# SMOOTH - A System for Mobility Training at Home for People with Parkinson's Disease

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# Declaration

I, the undersigned, declare that this work has not previously been submitted to this or any other University, and that unless otherwise stated, it is entirely my own work. I agree that Trinity College Library may lend or copy this thesis upon request.

# Acknowledgements

I have been waiting for this moment for so long. Sometimes, I even doubted that it would ever come. Now, with my thesis finally written the only thing left to do is to thank all the people that have helped me during the last four years. Without them this thesis would not exist!

It was a long journey full of small failures and big joys. On the way, I met a lot of wonderful people:

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# Abstract

Assistive technology has the capacity provide to people with limitations the opportunity to improve their quality of life and increase their independence in daily living. The promise of emerging pervasive computing technologies is that they will enable a new generation of assistive technologies to offer individuals the opportunity to stay in their homes for longer and manage everyday tasks without placing a significant burden on their caregivers.

Parkinson's disease is one of the most common neurodegenerative disorders. To date, there is no treatment for this disease. It progresses over time and only its symptoms can be treated. These symptoms include tremor, rigidity, problems with gait, and postural instability. Impairment of these functions influences the performance of everyday tasks and decreases the quality of life of sufferers. The range and variety of assistive technologies being researched and developed to support people with Parkinson's disease, as well as those that are commercially available, is growing. To date however, knowledge about the use of assistive technology by people with Parkinson's disease is limited. The aim of this work is to explore the use of emerging pervasive computing technologies to develop assistive technology to support people with Parkinson's disease.

The design of new assistive technology to support people with Parkinson's disease requires an identification of their difficulties and needs. To this end, we conducted a user survey of people with Parkinson's disease to investigate their problems and the assistive technology used or perceived to be relevant in everyday living. The physical limitations reported by the respondents were consistent with commonly reported problems for people with Parkinson's disease and include problems with mobility, physical strength and flexibility issues, gait disturbance, falls, and fatigue. In general, not many assistive technologies were used and there was no desire for any particular type of assistive device. However, the analysis showed a perceived benefit of the use of assistive technologies in daily living. Most of the participants reported problems with mobility and more than one third used assistive technology to improve their mobility. Changing location or body position are activities that humans tend to perform very often and it is desirable for them to be performed independently. In addition, the improvement of motor functions may influence other areas of life and therefore lead to an overall increase in quality of life. The results of the survey indicated the need for assistive technology that addresses mobility issues, commonly reported in Parkinson's disease.

People with Parkinson's disease typically avail of physiotherapy to address mobility issues. As re-

ported in the literature, physical exercises designed to improve posture maintenance, muscle strength, and balance, which are performed regularly, can have a positive impact on well-being. Because attending physiotherapy sessions can be problematic and expensive, best practice is to prescribe a set of exercises that can be performed by a patient at home. However, two issues with home-based physiotherapy arise. Firstly, the lack of supervision by a physiotherapist may result in improper exercise program execution. Secondly, patients may loose the motivation to sustain their exercise routine. This thesis investigates the feasibility of developing a system for mobility training at home. Such a system should facilitate the physiotherapist in monitoring patients' exercise routines, and provide the patients with feedback to assist them in proper exercise execution and encourage them to perform exercise sessions regularly.

To address this question we developed a system for mobility training at home - SMOOTH. The objective of the exercises supported by SMOOTH is to strengthen the core muscles, as research suggests that this leads to the improvement of posture, balance, and movement patterns and may lower the number of falls. SMOOTH was designed to be affordable, accurate, and unobtrusive. In addition, to enable people with Parkinson's disease to use the system independently at home, it was required to be safe, convenient, and intuitive. Due to user safety concerns, SMOOTH targets exercises on a chair. A number of previous systems detect activities by using wearable sensors and cameras. However, those techniques might not be suitable for a home-based system designed for people with Parkinson's disease considering their movement limitations and privacy issues. Our hypothesis is that a set of low-cost, fixed sensors are sufficient to measure exercise performance. To our knowledge no system supporting exercise monitoring using such sensors placed on a chair has been developed to date and there is therefore no study addressing its movement detection accuracy or user acceptance.

To address these issues, having built the system, a user study was conducted. The user study was divided into two parts. The first part, investigating the acceptance of SMOOTH, was conducted among physiotherapists and people with Parkinson's disease. The results show that potential users perceived SMOOTH to be useful in home-based physiotherapy. The second part, investigating the accuracy of SMOOTH, was conducted among healthy people and people with Parkinson's disease. The results indicate that the use of low-cost sensors placed on a chair enables the measurement of the exercise performance with accuracy above 91% for all the exercises addressed by SMOOTH but one.

# Publications Related to this Ph.D.

- Joanna A. Muras, Emma K. Stokes, and Vinny Cahill. A taxonomy of pervasive healthcare systems. In *1st International Conference on Pervasive Computing Technologies for Healthcare*, pages 1-10. IEEE, November 2006.

- Joanna A. Muras, Vinny Cahill, and Emma K. Stokes. Assistive technology in everyday living - A user survey of people with Parkinson's disease. *Technology and Disability*, 20(4):271-282, 2008.

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# Chapter 1

# Introduction

This thesis investigates the use of emerging pervasive computing technologies to develop assistive technology (AT) for people with Parkinson's disease (PD). PD is the second most common neurodegenerative disorder [Ben-Shomo et al., 1996]. It progresses over time and, to date, only its symptoms can be treated. To remain independent longer and improve overall well-being, people with PD can avail of AT that compensates for their functional limitations. An initial user survey identified that a common problem among people with PD is impaired mobility. This problem is typically addressed by exercise programmes in physiotherapy. However, attending physiotherapy sessions can be both expensive and inconvenient. For these reasons, physiotherapy exercises are often prescribed to patients to perform at home, with clear benefits such as the ability to perform exercises at times convenient to the patient, lower costs, and no need for travel. Unfortunately, there are also limitations including the lack of supervision by the physiotherapist, problems with sustaining motivation to perform the exercises regularly, and lack of social contact with the community, which might further influence motivation [Phillips et al., 2004]. According to the study presented by [Cohen-Mansfield et al., 2004] the most important factor for the participants was monitoring by a healthcare professional. Preferences related to other factors depended on the health and demographic characteristics of the participants. For example, cost aspects were not as important to more educated participants with higher incomes, while participants who lived alone were more interested in the social aspects of exercise programs.

To address some of this issues, a system for mobility training at home - SMOOTH - was developed. The purpose of SMOOTH is to facilitate the physiotherapist in monitoring patients' exercise routines, and provide the patients with feedback to assist them in correct exercise execution and also to encourage them to perform exercise sessions regularly. The objective of this thesis is to investigate the feasibility of exercise monitoring using low-cost, fixed sensors placed on a chair and to examine its accuracy and user acceptance. Potential benefits of such system include decreased physiotherapy costs, improved motivation to sustain exercise routines by patients, and improved facilities to monitor progress by physiotherapists.

This chapter begins with the characteristics of PD and the description of the most common prob-

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lems experienced by people with PD (Section 1.1). The next part of this chapter focuses on AT and its role for people with PD (Section 1.2) as well as on pervasive healthcare (Section 1.3). Section 1.4 briefly introduces the results of a user survey that we conducted to help identify AT that may be useful for people with PD. As the survey results identify a need to improve patients' mobility and the concept of home-based physiotherapy is introduced; its advantages and limitations outlined in Section 1.5. Following this, the concept of a system designed to support mobility training at home (SMOOTH) is introduced in Section 1.6. Finally, the contributions (Section 1.7) and a road map of the thesis (Section 1.8) are presented.

## 1.1 Parkinson's Disease

Neurodegenerative disorders, such as Alzheimer's disease, PD, Huntington's disease, and Multiple Sclerosis result from deterioration of neurons; all are progressive over time. Neurons in the brain and spinal cord are responsible for controlling various functions such as decision making, processing of sensory information, and movement. Neuronal degeneration can lead to limitations in all of these functions [Gowthaman et al., 2007]. Despite ongoing research exploring the causes of these neurodegenerative disorders, to date, they remain impossible to cure. All methods of treatment, which differ depending on disease, result only in limited relief and in delaying their progression [Bezprozvanny, 2009].

PD is the second most common neurodegenerative disorder [Ben-Shomo et al., 1996]. It results from the deterioration of dopamine containing cells of the substantia nigra, which is a brain structure located in midbrain. The exact cause of the disease is not known. Research suggests several different causes such as oxidative stress, toxins, genes, and age [Burkhardt and Weber, 1994]. To date, there is no definite test that allows the diagnosis of PD. The diagnosis is primarily based on history and a clinical examination. Therefore, there is a possibility of a person being initially diagnosed with PD and after development of additional symptoms the diagnosis being changed [National Collaborating Centre for Chronic Conditions, 2006, Gelb et al., 1999].

PD affects between 0.5% and 1% of the population aged 65-69 years and between 1% and 3% of the population over 80 years [Toulouse and Sullivan, 2008]. Its progressive nature and the lack of a cure for it suggests that its social and economic impact will increase over time. PD might result in a decrease in the quality of life of patients and their caregivers as well as an increased economic burden for society [Keranen et al., 2003]. According to a study conducted among the members of the United Kingdom Parkinson's Disease Society [McCrone et al., 2007] the costs related to PD include direct social care (5%), direct health care (15%), and informal care from family and friends (80%). For that reason it is important to enable people with PD to remain independent as long as possible which could reduce the burden on their caregivers and the overall cost of their healthcare [Mann et al., 1999, Schrag et al., 2006]. The promise of AT is to support people with disabilities in activities of daily living.

### 1.1.1 Symptoms

The symptoms of PD include limitations in motor and non-motor functions. Cardinal motor symptoms include tremor, rigidity, bradykinesia, gait disturbances and postural instability [Gelb et al., 1999]. Tremor in PD is called resting tremor because it usually appears when muscles are relaxed. The tremor initially has a frequency of 4-6 Hz although the frequency decreases and the amplitude increases over time [Hellwig et al., 2009]. In rigidity, the muscle tone is stiff and does not relax. This can cause a decrease in the range of motion and pain [MashhadiMalek et al., 2008]. Bradykinesia, also called 'slow movement', might influence gait functions and people suffering from it may walk with short, shuffling steps [Berardelli et al., 2001]. PD also involves symptoms such as delayed reactions, sudden stopping of ongoing movement, and difficulty initiating movements (referred as 'freezing'). A large number of studies have been done to characterise gait disturbances [Ferrarin et al., 2006]. The abnormalities in parkinsonian gait include a shortened stride length and reduced velocity. Gait cadence is not altered and it can be increased to compensate for stride length reduction. In addition, the trunk is often flexed forward and associated arm movements as well as the range of motion at the lower limb joints are reduced. Problems with balance are also reported in the literature [Benatru et al., 2008]. Postural instability is usually a sign of more advanced PD and might lead to a loss of independence due to falls and injuries. Parkinsonian posture is characterised by a moderate flexion of the knees and trunk with elbows bent and arms abducted. In addition, it can involve tilting of the trunk particularly when sitting or standing. Other symptoms reported by people with PD are speech and swallowing difficulties [Deane et al., 2001a]. They include monotony of pitch and volume, reduced stress and imprecise articulation resulting in improper silences and rushes of speech.

Non-motor symptoms are also very common in PD. Over half of patients suffer from more than one non-motor symptom [Witjas et al., 2002]. Impairments in non-motor functions affect people with PD and their families and might lead to even bigger complications in every day life than motor symptoms. Non-motor symptoms include fatigue, sensory, autonomic, and behavioural symptoms as well as sleep disorders [Pandya et al., 2008]. Fatigue is one of the most troubling symptoms in PD [Friedman et al., 2007]. It is combined with the feeling of continuous tiredness and lack of energy. To date, fatigue is not well understood and therefore under diagnosed. Sensory impairments involve off-period pain, paresthesia, and impaired sense of smell and vision. In general, autonomic problems increase with disease duration [Verbaan et al., 2007]. They include symptoms that relate to cardiovascular, gastrointestinal, urinary, thermoregulatory, and sexual functioning. Cognitive and behavioural symptoms involve depression, dementia, apathy, and anxiety. Most healthcare professionals obtain little training in diagnosing those symptoms in people with PD and therefore some of those functions, such as depression, are often under diagnosed [Anderson, 2002]. Sleeping disorders include daytime sleepiness and insomnia. PD patients often experience low total sleep time and frequent awakening. In addition, some of them suffer from intensive, unpleasant, and frightening dreams [Mehta et al., 2008].

Impairment in all the functions described in this section might influence the performance of every-

day tasks and decreases quality of life [National Collaborating Centre for Chronic Conditions, 2006]. The biggest influence on quality of life, according to the study [Schrag et al., 2000], are depression, disability, postural instability, and cognitive impairment. For that reason improvement of these limitations should become an important target in the treatment of the disease.

### 1.1.2 Treatment

As with other neurodegenerative disorders PD progresses over time and only its symptoms can be treated [National Collaborating Centre for Chronic Conditions, 2006]. Currently the most effective method of minimising the impact of motor symptoms is pharmacological treatment with levodopa, dopamine agonists, and MAO-B inhibitors [Thobois et al., 2005]. Even thought treatment with levodopa is the most reliable treatment of motor symptoms to date, it usually develops long-term complications. After 5 years of treatment, about half of people with PD develop motor fluctuations and dyskinesia [Jankovic, 2005]. Variations in levodopa intake as well as its short half-life (90–120 minutes) appear to influence motor fluctuations such as 'off-time' and 'on-time' effects, but its mechanism is not well understood. 'Off-time' refers to periods when the medication is not working well, which causes worsening of Parkinsonian symptoms. The term 'on-time' refers to periods of sufficient control of PD symptoms. To allow continuous levels of levodopa to enter the brain its intake can be enhanced by MAO-B inhibitors [Stern et al., 2004]. Research suggests that MAO-B inhibitors can reduce 'off-time' and therefore limit motor fluctuations. At the beginning, dopamine agonists have been used in conjunction with levodopa therapy to improve motor fluctuations [Ahlskog, 2003]. However nowadays, they are instead used as mono therapy at an early stage of PD due to their effect of delaying motor complications.

Motor complications caused by levodopa can be reduced by surgical treatments which involve destruction of parts of the brain nuclei (pallidotomy, thalamotomy, or subthalamotomy) [Thobois et al., 2005]. These procedures can improve dyskinesia, tremor, bradykinesia and rigidity [Nagaseki et al., 1986, Vitek et al., 2003]. They are usually employed when pharmacological treatment does not have a desirable effect. To avoid the destruction of parts of the brain nuclei, deep brain stimulation can be employed. This procedure involves insertion of electrodes to stimulate parts of the brain nuclei and is usually offered to people with PD who have severe motor symptoms [Genever, 2009]. It can be helpful in tremor, bradykinesia, dyskinesia, and rigidity reduction.

Some limitations associated with PD can be difficult to treat using medical and surgical methods. To overcome these difficulties, a variety of rehabilitative therapies are available [Gage and Storey, 2004]. Their purpose is to provide a person with PD with individual compensatory strategies addressing their limitations. Most of the people with PD, due to their age, lose on average 20% to 40% of their neuromuscular function which might accelerate the loss of mobility and therefore independence [Boelen, 2007]. Some studies suggest this loss can be regained by exercises [Doherty, 2003]. Prescription of physiotherapy is appropriate at all the stages of PD [Olanow et al., 2001]. Depending on the

stage, different mobility issues are addressed [Boelen, 2007]. At the early state focus is on optimising general strength, flexibility, balance, endurance, and prevention of impairments. The next stage addresses gait deviations and involves improvement of balance and 'freezing' avoidance. For patients with postural instability, prevention of falls is the main goal and for that reason balance training and compensatory strategies to prevent falls are introduced. For patients with severe disability great emphasis is placed on maximising flexibility and mobility to improve transfers from one position to the other as well as education of the caregivers in providing assistance.

Another therapy offered to people with PD is occupational therapy [Gage and Storey, 2004]. Its purpose is to teach patients how to modify their every day tasks to make them less difficult. The tasks include hygiene, dressing, eating, writing, cooking, and fall prevention. The strategies used might involve the use of AT or the appropriate arrangement of the living environment. Because people with PD may have problems with multitasking, they can also be taught methods to prioritise their attention while performing activities [Boelen, 2007]. Some studies suggest that, in conjunction with physiotherapy, occupational therapy leads to an overall quality of life improvement [Ellis et al., 2008].

As described in this section problems with speech and respiratory functions are common in PD. To improve voice and speech production in conjunction with pharmacological treatment, speech therapy has proved to be the most effective therapeutic method [Deane et al., 2001a]. Speech therapy techniques target two main categories: problems with swallowing and difficulties with speech. The techniques mainly address difficulties with speech by appropriate exercises [Gage and Storey, 2004]. However, they also include respiratory exercises, swallowing strategies, and the use of wearable biofeedback devices [Schulz and Grant, 2000].

## 1.2 Assistive Technology

AT is 'any item, piece of equipment, or product system, whether acquired commercially off the shelf, modified, or customised that is used to increase, maintain, or improve the functional capabilities of individuals with disabilities' [Public Law 100-407, 1988]. AT is applicable in many areas of life and can be used to support people in their living environments [Johnson et al., 2007, Mann, 2005]. It enables people to remain independent longer and reduces the cost of their healthcare [Mann et al., 1999] as well as the burden for their caregivers [Schrag et al., 2006].

AT can be beneficial for people with PD to cope with activities of daily living and it has the potential to allow them to remain independent longer and reduce the overall cost of their healthcare [Jutai et al., 2007]. Advances in technology have led to the development of a range of ATs to support people with PD [Constantinescu et al., 2007]. However, most of the available ATs are mechanical devices. They include devices to support communication, eating, drinking, writing, dressing, hygiene, lighting, mobility, and household tasks [Swann, 2008]. Some examples are special pens, adapted plates, lifters, and walking aids. The number of commercially available ATs is growing. In April 2001, ABLE-

DATA[1], the AT product database listed 27,000 assistive products (over 18,000 of which were currently available) [Scherer, 2002]. In June 2009, the same database listed 35,000 assistive products (over 22,000 of which are currently available). To date, despite the variety of ATs available, knowledge about their use and existence among people with PD is limited [Roelands et al., 2002, Constantinescu et al., 2007]. AT for mobility is the largest group of ATs [Scherer, 2002] and a number of studies focus on balance and mobility aids which include canes, walkers, and wheelchairs [Bateni and Maki, 2005]. Even though they can increase the confidence and safety of people with PD, as well as compensate for their limitations in some cases, they are abandoned soon after receiving them. The main reasons for this are difficulty or risk related to their use, inappropriate prescription, and inadequate user training [Agree et al., 2004]. For that reason it is essential to recognise individual user's limitations, abilities, and needs to adapt existing ATs to individual circumstances or design new ATs that would meet users' requirements and needs.

## 1.3 Pervasive Healthcare

Pervasive or ubiquitous computing is perceived as being the next generation of information and communication technologies [Weiser, 1991]. Its purpose is to support users in their every day activities by providing information, communication, and other services in an intelligent manner. Pervasive computing research covers a wide range of areas. These include distributed and mobile computing, sensor networks, human-computer interaction, and artificial intelligence [Reddy, 2006, Cook et al., 2009]. The promise of pervasive technologies is to embed computing infrastructure into the environment and to enable natural interaction with it [Grimm et al., 2001]. This integration allows the user to focus on their tasks and make them unaware of the assistance being provided by computing devices that are blended into the background. To achieve these goals pervasive computing has to address a number of challenges [Satyanarayanan, 2001]. In contrast to personal computers and dedicated devices, pervasive technology should be transparent to its users. Devices should be unobtrusive and inexpensive, and the infrastructure should adapt to environmental conditions and current users' needs [Estrin et al., 2002].

Pervasive healthcare is an emerging area that has the capacity to reduce long-term costs, improve quality of service, and increase independence of its users in daily living [Varshney, 2003]. It spans several areas of life such as transportation, communication, and safety and can support its users as well as their caregivers in a number of different manners including monitoring and guidance [Muras et al., 2006]. Smart homes equipped with sensors and reasoning algorithms are designed to make life easier and safer and can support their occupants in daily activities [Georgia Institute of Technology, 2009, Perry et al., 2004]. This can be accomplished by fall detection or behaviour monitoring. In case of an emergency, communication with appropriate authorities can be enabled [Axisa et al., 2005]. Devices such as automatic lighting control, tap and cooker monitors [Georgia Institute of Technology, 2009] that are able to switch devices off in case of emergency,

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[1]http://www.abledata.com

as well as ambient displays and speakers to inform occupants about scheduled appointments or tasks [Pollack et al., 2003] are all now available. Moreover, smart homes are not the only examples of using intelligent devices to improve the quality of life. Guides helping with a task by giving step-by-step instructions [Kautz et al., 2002], devices monitoring time and amount of medication taken [Jafari et al., 2005] and robotic interfaces combined with virtual reality environments for rehabilitation [Holden, 2005] are other examples of emerging pervasive healthcare technologies.

Due to advances in communication, information, and sensor technology it is possible to build systems that will monitor users' well-being at home and support the management of their medical condition in unobtrusive and transparent manner [Korhonen et al., 2003, Cooper et al., 2008]. Thus, pervasive healthcare has the potential to enable a new generation of ATs giving people with limitations the opportunity to manage everyday tasks on their own and stay in their homes longer.

## 1.4 Needs of People with Parkinson's Disease

To identify the difficulties and needs of people with PD in daily living we conducted a user survey of people with PD [Muras et al., 2008]. The aim of the survey was to explore individual circumstances of people with PD and investigate what kind of ATs may be useful for them. The survey investigated the views of participants about the ATs they use and obtained more specific information about features that would be worth developing or improving.

The results of the study were derived from a postal survey of randomly chosen members of a support group for people with PD (PALS)[2], which is a branch of the Parkinson's Association of Ireland. They show that physical condition was the biggest problem for the survey respondents. According to the survey results, the most common difficulty experienced by people with PD were limitations in mobility (88%). 59% of the respondents had problems with walking and over one third (39%) of all subjects used help to move around. Half (51%-53%) of the subjects reported problems in changing body position, e.g., getting up from the floor or standing up from a chair. Physical strength, flexibility and coordination was described as 'poor' or 'very poor' by 34%, 25% and 20% of the respondents, respectively. The majority of the subjects of the survey reported problems with fatigue, which is consistent with the findings of Chaudhuri et al. [Chaudhuri and Behan, 2000]. Over half of the participants (54%) suffered from fatigue 'frequently' or 'all the time' and 70% reported that they 'always' or 'often' become tired fast. Impairment of motor functions not only influences independence but might also lead to the risk of falls and injuries [Benatru et al., 2008]. Fear of falling is not only a characteristic for people with PD, but may also affect older people [Murphy et al., 2002]. For 81% of the respondents it was important to be able to contact someone in the case of a fall.

The results of the survey indicate a possible under-utilisation of ATs by people with PD. The participants, in general, did not use a large number of ATs. Devices that they used were mostly for walking, changing body position and helping them in self-care tasks. The reason for this could be

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[2]http://gofree.indigo.ie/~pdpals/

that most of the participants had mobility constraints and the devices mentioned above could greatly improve their independence and quality of life. Changing location or body position are activities that humans tend to perform very often and any limitation in movement functions can have a significant impact and may influence daily activities in a negative manner. The situation can be similar with self-care tasks, which have to be performed quite often and the natural behaviour is for people to perform them on their own, so any need for help from others may lead to inconvenience. Another reason for more the common use of this set of ATs may be awareness of their existence and familiarity with them [Constantinescu et al., 2007].

The results of the survey indicated the need for AT that would address mobility issues, commonly reported in PD. The improvement of motor functions may affect many areas of life and therefore lead to an overall increase in independence and the quality of life [Jutai et al., 2007, Schrag et al., 2000].

## 1.5 Home-based Physiotherapy

People with PD typically avail of physiotherapy to address mobility issues [Keus et al., 2009]. As suggested in the review presented by [Deane et al., 2001b], while most of the studies investigating the effectiveness of physiotherapy in PD found in the literature claimed a positive effect, they lacked sufficient evidence to support or reject the efficacy of physiotherapy in PD due to methodological flaws, e.g., choice of participants, and the small number of patients included in many of the studies. Despite a lack of conclusive evidence [Deane et al., 2001b, Keus et al., 2006] there are promising indications that physiotherapy can be beneficial for the support of people with PD and their well-being [de Goede et al., 2001, Ellis et al., 2005, Smidt et al., 2005]. The purpose of physiotherapy is to delay deterioration in motor functions and therefore allow people with PD to stay independent longer [King and Horak, 2009]. The main goals for people with PD are to improve limitations in balance, posture maintenance, agility, flexibility, and muscle strength [Goodwin et al., 2008]. To improve postural stability and muscle strength, which leads to a reduction in the number of falls, balance and high-resistance strength training can be performed [Hirsch et al., 2003]. Other types of training can aim at improvement of various aspects of gait and transfer techniques [Nieuwboer et al., 2002]. Physical exercises can also address particular difficulties in the execution of activities [Morris and Iansek, 1996] and improve specific motor functions such as accuracy and speed [Platz et al., 1998]. It is also good practice to perform physical exercises to keep up general fitness [Miyai et al., 2000]. As presented in [Canning et al., 1997] individuals with mild to moderate PD can maintain normal exercise training. In addition, the literature suggests that people with PD can improve their motor performance by repetitive exercises [Olanow et al., 2001, Montgomery, 2004].

Attending physiotherapy sessions may be problematic and expensive [Gage and Storey, 2004]. To reduce the cost of care, common practice is to prescribe a set of exercises that can be performed by a patient at home [Canning et al., 2009]. The study [Caglar et al., 2005] suggests the effectiveness of such an approach. The exercises address individual limitations and are prescribed keeping the patient's

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safety in mind. The exercise programmes are usually revised and adjusted on follow-up visits to meet user needs. Despite the positive impact of physical exercises, two issues arise with home-based physiotherapy: the lack of supervision by a physiotherapist, which might cause improper exercise program execution, and the loss of the motivation to sustain exercise routines by patients [Schoo et al., 2005]. Lack of motivation is reported to be a major cause of failure in maintaining exercise programmes [Loureiro et al., 2001]. Existing literature indicates that instructions and feedback given by the therapist are usually appreciated by the patient [Friedrich et al., 1996] and play an important role in both correct exercise execution and in keeping patients motivated [Caglar et al., 2005].

The findings above suggest that a system to support mobility training at home could be beneficial for people with PD and their physiotherapists. The advantage for the therapist would be the possibility of continuous monitoring of a patient's exercise routine and progress. The patients would be provided with clear instructions and feedback to assist them in correct exercise execution and encourage them to perform exercise sessions regularly [Loureiro et al., 2001]. This thesis investigates the feasibility of developing such a system.

## 1.6 The SMOOTH Concept

To address this question we developed SMOOTH. Several requirements were identified for SMOOTH. It should be affordable, accurate, and unobtrusive. These features could encourage people to purchase the system and sustain its regular use. In addition, to enable its independent use at home by people with PD it should be safe, convenient, and intuitive. The purpose of the system is to help improve the most common motor disturbances, which include muscle strength, balance and postural instability. Improvement of those functions leads to a reduction in the number of falls, injuries, and increased quality of life [Benatru et al., 2008]. Muscle weakness is one of the factors contributing to postural instability and for that reason the set of exercises supported SMOOTH aims to strengthen core and leg muscles [Falvo et al., 2008]. Core stability improves coordination of body movement and has a positive impact on posture and balance. A characteristic of home-based physiotherapy is the lack of supervision. As a consequence, safety concerns are paramount when a set of exercises to be performed at home is prescribed [Canning et al., 2009]. To prevent the risk of falls, SMOOTH targets exercises that can be performed while seated on a chair.

A number of systems to monitor postures and body movement has been developed. State of the art systems employ a variety of methods including decision trees, artificial intelligence, and statistical inference. They use miscellaneous sensors, however the majority utilise cameras and wearable accelerometers to collect data. Those techniques might not be suitable for a home-based system designed for people with PD. Placement of wearable sensors can be a problem when considering user convenience and the movement constrains often reported in PD. Placing cameras in the home environment can also be problematic due to the requirement for dedicated space and initial setup. At the time of the investigation, cameras in mobile phones or similar devices were not commonly used

among older people. As the study conducted by [Kurniawan, 2008] revealed, older people are usually passive mobile phone users and in general are afraid to use unfamiliar technology. If the setup of a camera-based system is too complicated it might be discouraging and lead to its abandonment. In addition, cameras situated in a home environment might be perceived to violate a user's privacy [Demiris et al., 2008]. Some work has been done to detect body posture from using data from a set of sensors placed on the chair. Nevertheless to our knowledge no system that would infer user movement from such sensors has been developed. As well as systems for movement and posture recognition, a number of systems for movement rehabilitation have been developed that do not require movement recognition. Existing systems for exercises at home employ novel haptic interfaces and virtual reality to provide users with feedback. However, to date most of them are expensive and their effectiveness is not fully recognised [Alamri et al., 2008].

To provide exercise monitoring and user feedback, SMOOTH consists of interfaces for a person with PD, physiotherapists and a central server to keep the data. The purpose of the therapist's interface is to prescribe appropriate exercises, adjust their parameters to the user's condition, and monitor the home exercise routine. The user interface helps a person with PD to follow the prescription, it provides instructions on how the exercise should be done, and informs users about their performance by providing visual and audio feedback. Our hypothesis is that a set of low-cost, fixed sensors is sufficient to measure exercise performance. For that reason, SMOOTH uses a chair augmented with the sensors to obtain information about its user. The sensors detect the force put on the seat and the distance from the back of the chair. On that basis current movement and position is detected. To interfere current user motion and adjust SMOOTH to their individual circumstances stochastic and probabilistic methods are utilised. The information about the current state is used to provide the user with feedback and monitor their exercise routine.

## 1.7 Thesis Contribution

To date there has been some research in the area of pervasive healthcare but to our knowledge there has been no detailed study of what kind of technology is desired by people with PD. This research focuses on identification of the pervasive technology that could be beneficial for people with PD and evaluation of its potential to improve their quality of life and overall well-being. Consequently, the main contributions of the thesis can be summarised as follows:

1. Identification of the difficulties and needs of people with PD in daily living. According to the user survey mobility limitations were the most common problem among the participants.

2. Identification of a home-based, pervasive AT that has the potential to be beneficial for people with PD. The user survey identified a need for the technology to address mobility issues. For that reason a system for mobility training at home - SMOOTH was developed.

3. Identification of the requirements for SMOOTH including hardware and software platform.

4. Design and implementation of a framework for SMOOTH. The following sentences added: The framework enables flexible acquisition and processing of sensor readings in regards to user characteristics as well as communication between system modules. In addition, the framework allows the definition and adaptation of exercises. To our knowledge, none of the systems found in the literature review present a complete framework that supports the functionality mentioned above.

5. Exploration of the feasibility to use a set of low-cost, fixed sensors placed on a chair to detect user movement and monitor exercise performance.

6. Evaluation of the exercise monitoring accuracy provided by SMOOTH, in particular:

   (a) current position or movement detection;

   (b) correct exercise repetition detection;

7. Evaluation of the user acceptance of SMOOTH by people with PD and physiotherapists, in particular:

   (a) user interface and feedback;

   (b) comfort of use;

   (c) general feelings about the system;

To empirically answer these questions for SMOOTH a user study with potential system users was conducted. The study was divided into two parts. The first part investigated the user acceptance of the system and employed a user survey. The second part investigated the accuracy of exercise monitoring provided by SMOOTH and included analysis of the data obtained during exercise sessions. The results indicate that the use of low-cost sensors placed on a chair enables the measurement of exercise performance with accuracy above 91% for all exercises addressed by SMOOTH but one. The outcome of the user surveys shows that the system obtained positive feedback from the potential users and they perceived it to be useful for home-based physiotherapy.

## 1.8   Thesis Outline

The remainder of this thesis is organised as follows. Chapter 2 presents a taxonomy of pervasive healthcare systems, which enables a better understanding of the connection between user needs and system features. Chapter 3 describes a user survey of people with Parkinson's disease. The survey recognises difficulties, needs, and views of the participants and identifies the assistive technology that has potential to be beneficial for people with PD. Chapter 4 reviews the state of the art in exercise monitoring and posture or movement detection. Chapter 5 presents the requirements, design, and architecture of SMOOTH. The design of the system and movement inference techniques are described in detail. The evaluation of SMOOTH is presented in Chapter 6. It includes the design of the user

study, data collection, analysis, and results. Finally, our conclusions and potential future work are discussed in Chapter 7.

# Chapter 2

# Taxonomy[1]

This chapter presents a taxonomy of pervasive healthcare systems. When the design of a pervasive healthcare system is considered an understanding of its intended users is essential. An appropriate user description leads to a better understanding of the user's needs and therefore a better design of the system. The purpose of the taxonomy is to provide common language for computer scientists and healthcare professionals (HCP) for the description of pervasive healthcare systems and to enable a better understanding of the connection between user needs and system features. To provide a common language for computer scientists and HCPs the taxonomy extends the International Classification of Functioning, Disability and Health (ICF) (WHO, 2001) [World Health Organisation, 2001]. The ICF is a multi-purpose framework for the classification of health and disability. The taxonomy identifies a number of properties of pervasive healthcare systems that are substantial when designing a system for people with disabilities. These properties were used to inform the design of SMOOTH.

The taxonomy was designed to provide a common language, improve understanding of the system features, and allow detailed description of a wide range of pervasive healthcare systems. The level of detail used to describe the system could be adjusted to the domain of its use resulting in better insight into system features and design.

The remainder of this chapter is organised as follows. The next part of this chapter outlines the contribution of the taxonomy (Section 2.1) and overviews related work (Section 2.2). Section 2.3 describes the structure of the ICF, its components and the relationships between them. Section 2.4 defines the structure of the taxonomy and describes the properties used for classification of pervasive healthcare systems. Section 2.5 presents a classification of existing pervasive healthcare systems, showing how they fit into the taxonomy described in this paper. Finally, Section 2.6 presents a summary of this chapter.

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[1]The content of this chapter has been published in [Muras et al., 2006].

## 2.1  Contribution of the taxonomy

The taxonomy is intended to provide a common language for computer scientists and HCPs for describing pervasive healthcare systems. This is expected to lead to a better understanding of the connection between user needs and system features. In addition to providing a basis for describing and classifying pervasive healthcare systems, the taxonomy may be useful in specifying strategic research directions. For example, the taxonomy is expected to expose novel combinations of system properties resulting in the identification of research issues to be addressed in the future.

## 2.2  Related work

The taxonomy identifies a large variety of properties of pervasive healthcare systems including their intended users' impairments and limitations, the environment and purpose of use of the systems as well as their inputs and outputs. In contrast, most existing work on classification of pervasive systems has focused on describing their properties only in terms of sensors, network structures and protocols.

In [Tilak et al., 2002] the authors presented a taxonomy of wireless micro-sensor network models that aids the definition of network architectures according to communication functions, data delivery models, and network dynamics. The taxonomy of wireless devices in [Cheekiralla and Engels, 2005] provides a classification according to five categories - communication, sensing, power, memory, and other features. This classification enables the definition of the structure, communication means and components of a pervasive network very precisely. However, when we consider pervasive systems, in the context of assistive technology (AT), defining their network architecture is not enough to describe and classify them. A higher-level approach was presented by Estrin et al. [Estrin et al., 2002] who defined three dimensions: scale, variability and autonomy in both time and space. These properties are oriented toward describing systems according to their perception of environment. While such approaches can be useful for the description and classification of pervasive systems, they still do not address enough properties to classify pervasive systems according to user conditions and needs.

A classification of technical aids for persons with disabilities can be found in ISO standard 9999:2002 [ISO, 2002]. This one-dimensional classification consists of three hierarchical levels. Each class, subclass or division consists of a code that allows the definition of a unique coding system for every family of device. The ISO standard also provides descriptions of the categories at each level. A new version of ISO standard 9999:2007 [ISO, 2007] called 'Assistive products for persons with disability' is connected with the ICF. It extends new product categories and match all described products with ICF domains.

## 2.3   International Classification of Functioning, Disability and Health

The ICF is based on the biopsychosocial model. The biopsychosocial model synthesises a medical model that views disability as a feature of the person and a social model that views disability as a socially-created problem. This approach enables all aspects of disability, which is always an interaction between features of the person and features of the overall context in which the person lives [World Health Organisation, 2001], to be described.
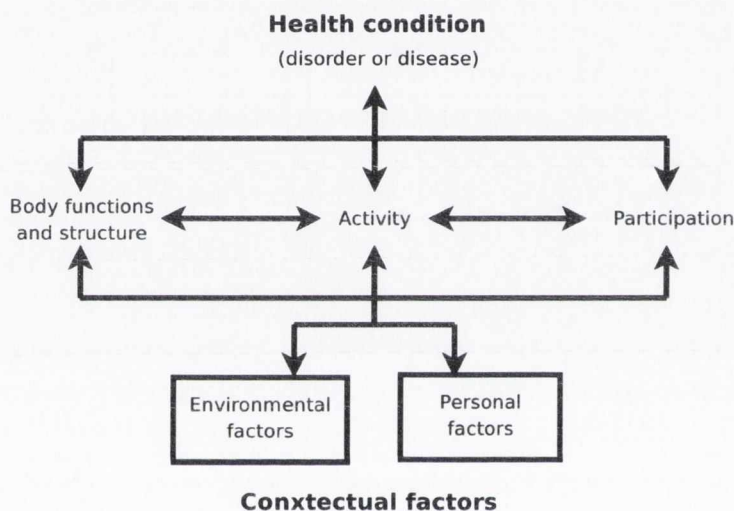


**Figure 2.1**: The model of disability that is the basis for ICF [World Health Organisation, 2001]

Figure 2.1 presents the model of disability that is the basis for the ICF. It considers disability and functioning as a result of interactions between health conditions (diseases, disorders and injuries) and contextual factors. The contextual factors are composed of external and internal factors. The external factors are called environmental factors and they represent the physical, social and attitudinal environment in which people live and conduct their lives. The internal factors are called personal factors and define the individual, their background, experience, overall behaviour pattern, character and other factors that influence how disability is experienced by the person. Figure 2.1 identifies the three levels of human functioning classified by the ICF: functioning at the level of the body or body part, the whole person, and the whole person in a social context. Disability therefore involves dysfunctioning at one or more of these same levels: impairments, activity limitations and participation restrictions [World Health Organisation, 2001].

The ICF offers a flexible framework for classification and description of human functioning and disability, for that reason, it was used as a basis for our taxonomy. Its hierarchical structure allows the choice of a suitable level of detail for describing a person and identifying impairments, activity limitations and participation restrictions.

## 2.4   Taxonomy

The root of our taxonomy, which is depicted in Figure 2.2 defines seven main feature categories, that allow us to describe a system according to its different properties. Categories A, B, and part of G were taken directly from the ICF and were not designed by us.
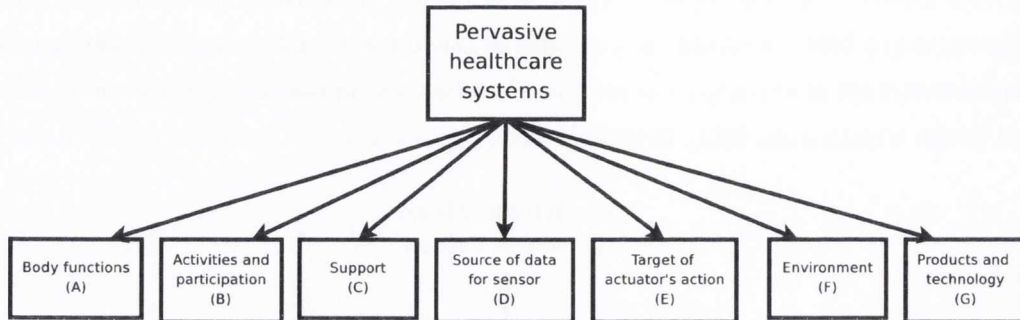


**Figure 2.2**: The root of the taxonomy

Two categories of the taxonomy provide the description of pervasive system properties according to potential user impairments, activity limitations and participation restrictions. Category A describes user impairments according to the physiological functions of body systems while category B allows the description of an assistive device according to the difficulties that a user may have in executing activities and involvement in life situations [World Health Organisation, 2001].

An important issue is defining who will be supported by the system. Classification according to feature C can distinguish systems designated for persons with disability, people living in the same house and, where appropriate, caregivers. This property influences the method used by the system to provide feedback. Some systems may support more than one class of person and the feedback provided can be different.

The next two categories (D and E) provide the description of the pervasive system according to its interaction with the user and the environment. Defined properties refer to the source of sensor readings and the outcome of system actions. The type of measurements taken by the system influences the manner in which the readings are processed and how the system's action is determined and triggered. When systems for people with disabilities are considered, the manner of user feedback is a crucial attribute according to which they can be classified.

The next category (F) describes the environment in which the system can be used. This property is important, since it implies the architecture of the pervasive network, types of network devices and communication protocols used.

The last category (G) of our taxonomy is the most complex one. It enables us to describe the system properties according to the manner in which the system assists the user and what areas of the user's life it supports. Six categories of system assistance have been identified, which are locator, guide, reminder, communicator, monitor and assistant. These categories describe the type of assistance desirable during activities of daily living, and each address different user needs. As identified in the

ICF, the areas in which this assistance might be used are daily living, indoor and outdoor mobility and transportation, communication, protection and health. This category therefore allows systems to be classified according to their precisely specified purpose.

In the next part of the chapter, the terms 'user' and 'participant' will be used interchangeable for the description of a person with a disability that makes use of a context-aware assistive device. The term 'caregiver' and 'carer' will be used for any person who provides assistance to the user.

### 2.4.1   Body functions

The body function categories define user impairments according to the physiological functions of body systems. This allows the categorisation of systems with respect to potential users' conditions. The type of user impairment implies the manner of feedback to the user. If a person has problems with hearing, the system should not use voice or sound to interact with this person. In contrast if a system is classified as an aid for blind people it should not use any visual feedback to its user [Ho et al., 2005]. This category also allows systems to be divided according to the manner in which their interface acts. The design of aids for persons with cognitive problems has to consider their characteristics and build interfaces that would be efficient for them [Kautz et al., 2002]. As shown in Figure 2.3, five distinct categories of body functions were directly taken from the ICF.
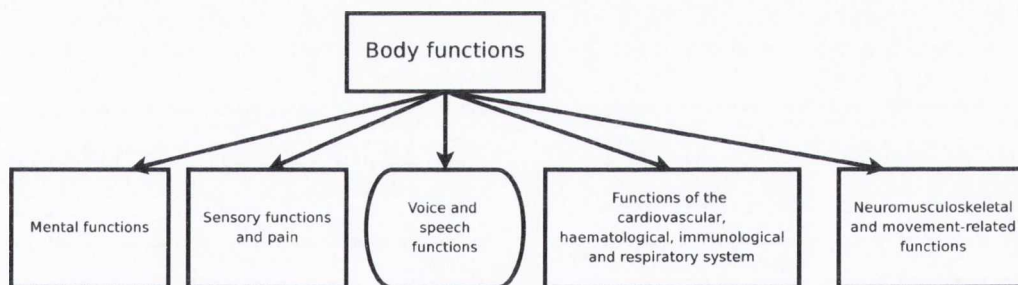


**Figure 2.3**: Body function categories [World Health Organisation, 2001]

#### 2.4.1.1   Mental functions

Mental functions allow us to describe functions of the brain. They are divided into two categories, which are global mental functions and specific mental functions, illustrated in Figure 2.4. Each category allow us to describe a user's mental impairments in more detail. *Global mental functions* define general functions of the brain and include function of consciousness, orientation, intellect, personality, energy and drive, and sleep. *Specific mental functions* include attention, memory, experience of self and time, and psycho-motor, emotional, perceptual, though, higher-level cognitive, calculation, sequencing complex movements functions as well as mental functions of language.
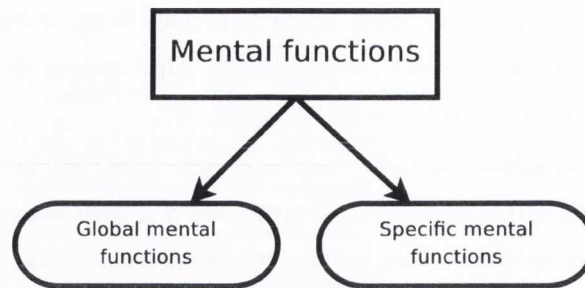
**Figure 2.4**: Mental function categories [World Health Organisation, 2001]

#### 2.4.1.2 Sensory functions and pain

Sensory functions and pain allow us to describe a system according to impairments in the users' senses. As illustrated in Figure 2.5, three categories were defined, which are seeing and related functions, hearing and vestibular functions, and additional sensory functions. *Seeing and related functions* include quality of vision, functions of sensing light and colour and visual acuity of distant and near vision as well as all impairments connected with vision.

To be consistent with the ICF, our taxonomy defines a category for *hearing and vestibular functions* which consists of the two categories: hearing and vestibular functions. *Hearing functions* include sound detection and discrimination, localisation of sound source and speech discrimination. *Vestibular functions* include sensory functions of the inner ear related to position, balance and determination of movement.

The last category *additional sensory functions* include the senses of taste, smell and touch as well as functions related to temperature and stimuli.
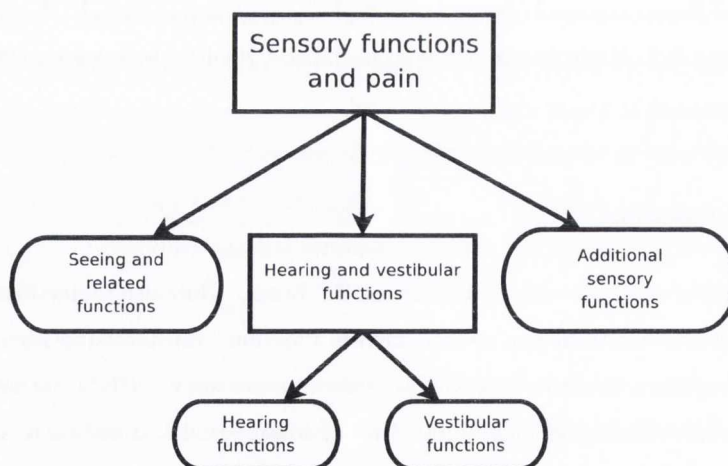


**Figure 2.5**: Sensory function categories [World Health Organisation, 2001]

### 2.4.1.3 Voice and speech functions

Voice and speech functions include production, quality and range of voice as well as the manner of speech such as fluency, rhythm or speed. Systems supporting these user impairments, if they interact with the user based on its speech, tend to use advanced algorithms for voice recognition.

### 2.4.1.4 Functions of the cardiovascular, haematological, immunological and respiratory systems

This category allows us to describe functions of the heart and blood vessels, blood production and immunity, and functions of respiration and exercise tolerance. As depicted in Figure 2.6, we have defined four different categories. *Functions of the cardiovascular system* include functions of the heart, blood vessels, and blood pressure. All cardiac problems are covered by this category. *Functions of the haematological and immunological systems* include blood production, oxygen and metabolite carriage, and clotting functions as well as functions of the body related to protection against foreign substances, including infections. *Respiration functions* cover inhaling and exhaling air into the lungs, the exchange of gases between air and blood and the muscles involved in breathing. *Additional functions and sensations of the cardiovascular and respiratory systems* include functions such as coughing, sneezing and yawning, exercise tolerance and various sensations connected with the heart and breath.
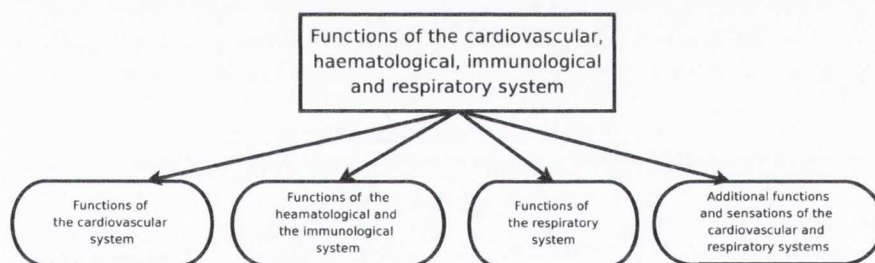


**Figure 2.6**: Functions of the cardiovascular, haematological, immunological and respiratory system categories [World Health Organisation, 2001]

### 2.4.1.5 Neuromusculoskeletal and movement-related functions

This category allows the description of potential user movement and mobility, including functions of the joints, bones, reflexes and muscles. As illustrated in Figure 2.7, three categories were defined, to better describe system properties. *Functions of the joints and bones* allow us to describe the pervasive system according to its potential user's mobility and stability of joints and bones. They include functions describing the range and ease of movement, and maintenance of structural integrity of a joint as well as the range and ease of movement of the scapula, pelvis, carpal and tarsal bones. *Muscle functions* allow us to describe an individual's muscle power as well as muscle tension and ability to sustain its contraction. The last category *movement functions* includes properties for identification of reflex, voluntary and involuntary movement control as well as related sensations and gait pattern.
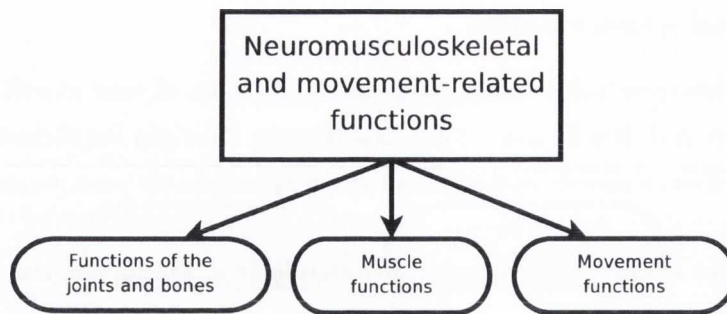
**Figure 2.7**: Neuromusculoskeletal and movement-related function categories [World Health Organisation, 2001]

## 2.4.2 Activities and participation

The activities and participation category provides the description of activity limitations and participation restrictions of potential system users. This category enables us to describe pervasive systems according to its user's constraints. It provides properties to define types of tasks that the user cannot manage. The type of user limitation and restriction puts various requirements on systems like, i.e., assistance with exercise. If we consider systems for rehabilitation they can support improvement of different user capabilities. One can aim to improve a user's ability to change body position, whereas another can intend to improve performance of daily routines by providing appropriate exercises [Holden, 2005]. As illustrated in Figure 2.8, five distinct categories of body functions were taken directly from the ICF.
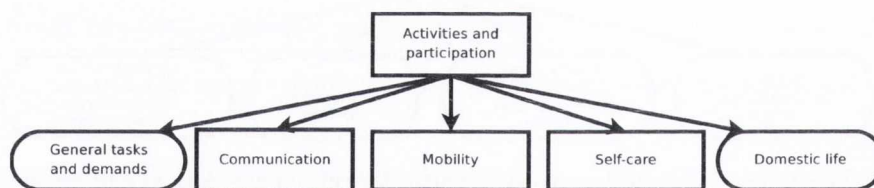


**Figure 2.8**: Activities and participation categories [World Health Organisation, 2001]

### 2.4.2.1 General tasks and demands

General tasks and demands allow us to describe the potential user of the system according to the manner in which he/she copes with single or multiple tasks, organising routines and handling stress. This category includes activities like managing and completing the requirements of day-to-day procedures or duties, such as budgeting time and making plans for activities throughout the day or preparing, initiating and arranging time and space, as well as carrying out coordinated actions in order to complete the requirements of day-to-day procedures or duties. In addition, this category also covers carrying out tasks demanding significant responsibilities and involving stress, distraction, or crises, such as exams or driving a car in heavy traffic.

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**2.4.2.2  Communication**

This category enables us to identify system's properties in relation to its user's restrictions or limitations in communication. They include receiving and producing messages, carrying on conversations, using communication devices, and use of spoken language, signs, and symbols. As illustrated in Figure 2.9, three distinct categories to better describe the system properties were taken from the ICF. *Communicating - receiving* covers comprehending the literal and implied meanings of symbols and drawings, messages in spoken and written language and ones conveyed by gestures. *Communicating - producing* includes producing the literal and implied meanings of messages that are conveyed through spoken and written language as well as gestures, symbols and drawings.

The last category *conversation and use of communication devices and techniques* was divided, as pictured in Figure 2.9 into two more accurate categories. *Conversation and discussion* include starting, sustaining and ending an interchange of thoughts and ideas, carried out by means of spoken, written, sign or other forms of language, with one or more people. *Using communication devices and techniques* allows us the description of the capacity to use telecommunication devices like phones and faxes, writing machines such as typewriters, and communication techniques like lip reading.
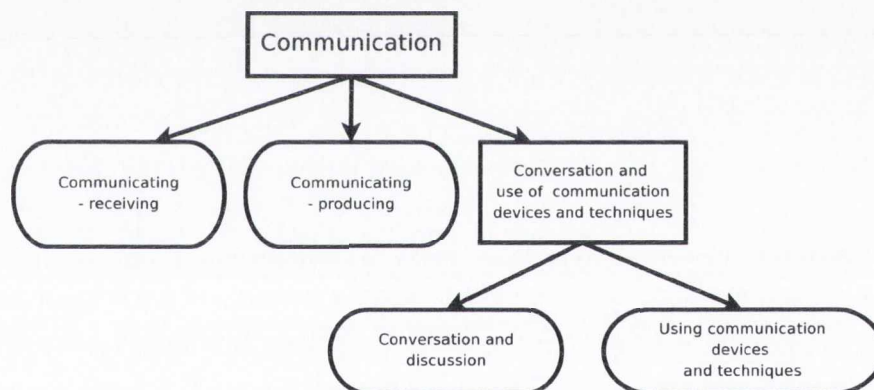


**Figure 2.9**: Communication categories [World Health Organisation, 2001]

**2.4.2.3  Mobility**

Mobility refers to every kind of intended movement of the human body. This category describes the change of body position or location by walking, running or climbing, and by using various forms of transportation. It also covers carrying, moving or manipulating objects. As shown in Figure 2.10, four categories are used. *Changing basic body position* includes performing and sustaining body position in such activities as lying down, squatting, kneeling, sitting, standing and bending as well as adjusting or moving the weight of the body or transferring oneself from one position to another. *Carrying, moving and handling objects* covers activities such as lifting and carrying objects with the hands, arms or on the shoulders, head, hip and back as well as pushing them with the legs or kicking. This category also describes properties of hand movements like picking up, grasping, manipulating or releasing,

and arm use like pulling, pushing, reaching, turning or twisting, throwing and catching. The next category allows the description of all aspects of *walking and moving*. It defines user limitations in distance and surface of walking, types of movement like crawling, climbing, running, jumping and swimming, moving in different locations within or outside the home and building, as well as using specific equipment like skis or wheelchairs. The last category *moving around using transportation* addresses the use of all means of transport, such as bus, boat, train or car including animals and animal-powered vehicles as a driver as well as a passenger.
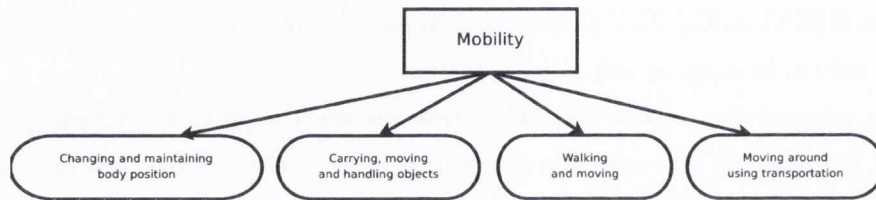


**Figure 2.10**: Mobility categories [World Health Organisation, 2001]

#### 2.4.2.4 Self-care

This category includes aspects of the user's ability to manage self-care activities. As illustrated in Figure 2.11, seven categories are specified. *Washing oneself* includes washing and drying one's whole body, or body parts like washing the hands, feet, face or hair, using methods, such as bathing, showering, and drying with a towel. *Caring for body parts* refers to looking after the skin, teeth, hair, fingernails and toenails. *Toileting* focuses on coordinating and managing the elimination of human waste (menstruation, urination and defecation), and cleaning oneself afterwards. *Dressing* covers all the activities involved in putting on and taking off clothes or shoes as well as their appropriate choice. *Eating* and *drinking* allows us to describe potential user ability to coordinate all the tasks and actions needed to consume served food or drink. The last category *looking after one's health* includes ensuring one's physical comfort, managing diet and fitness, and maintaining one's health by avoiding health risks, and following medical and other health advice.
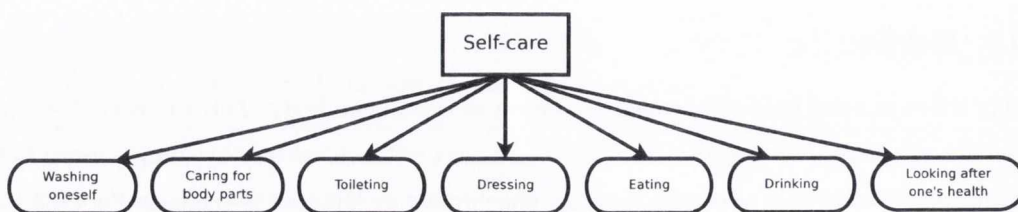


**Figure 2.11**: Self-care categories [World Health Organisation, 2001]

#### 2.4.2.5 Domestic life

This category enables the identification of the system properties according to its user's ability to carry out domestic and everyday actions and tasks. It includes acquiring a place to live, food, clothing and

other necessities also storing them, preparing meals, household cleaning and repairing, caring for personal and other household objects, using household appliances and assisting others.

### 2.4.3 Support

The support category in reference to pervasive healthcare systems allows the identification of who may benefit from the system. It does not necessarily have to be the person who is the direct target of the device's action. One device can support more than one person and not necessarily all of them have to be the target of its action. If we consider a device that informs a caregiver in case of emergency, it also helps its user to stay safe and well even if that person is not the direct target of the device's action [Axisa et al., 2005]. As illustrated in Figure 2.12, 3 different targets are depicted for support, which are the participant, caregiver and vicinity.
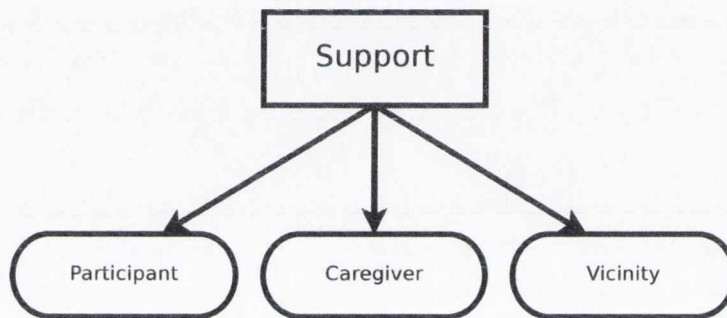


**Figure 2.12**: Support categories

#### 2.4.3.1 Participant

The participant can be described as a person with disabilities who is a user of the system. They can receive support from the pervasive assistive device in several manners. That can be adjusting appliances to user's preferences, warning about potential danger [Perry et al., 2004], reminding about some events or fixed appointments [Wu et al., 2005, Pollack et al., 2003], help with exercises [Holden, 2005], step-by-step guidance through some task or route [Kautz et al., 2002] or contacting a caregiver in case of emergency [Haigh and Kiff, 2004].

#### 2.4.3.2 Caregiver

The caregiver can be described as a person who supports, but not necessarily lives with, the user. For a caregiver the most important issue is the user's safety, so the advantage from using an assistive device could be informing them about emergency situations and the progress of daily routines or deviations from them [Haigh and Kiff, 2004, Consolvo et al., 2004]. The caregiver can also be a healthcare professional (HCP), who is in charge of the user's health and can, for example, be supported by obtaining measurements of vital signs for analysis [Axisa et al., 2005].

**2.4.3.3 Vicinity**

The vicinity can be described as people living with the user in the same flat, house or building, but who are not responsible for taking care of the user. They can be supported by pervasive systems that would manage domestic appliances and prevent them from causing damage like fire [Georgia Institute of Technology, 2009, Perry et al., 2004].

## 2.4.4 Source of data for sensor

This category allows the description of system properties related to the source of its sensors' readings and enables the classification of systems according to the kind of data that triggers its action. Depending on the purpose of the assistive device and its level of development various triggers can be used. If we consider a system that monitors vital signs its general purpose is to collect data from the user, however its action can be triggered by different factors. One of them could be time. In predefined periods of time outcome measurements could be sent to a storage server [Axisa et al., 2005]. In this case, gathered data could be used for later analysis of the user's health. In a second case, the system action could be triggered when collected readings indicate that there is danger to the user's health. In this case information about the risk could be sent to the appropriate authority [Haigh and Kiff, 2004]. Pervasive systems can use many sources as their input. Usually the more advanced the system is, the more information from different sources it uses. This category can classify the pervasive healthcare system according to its sensor readings. As illustrated in Figure 2.13, four distinct categories are depicted to describe the source of sensor readings, which are participant/individual, object, environment, and time.
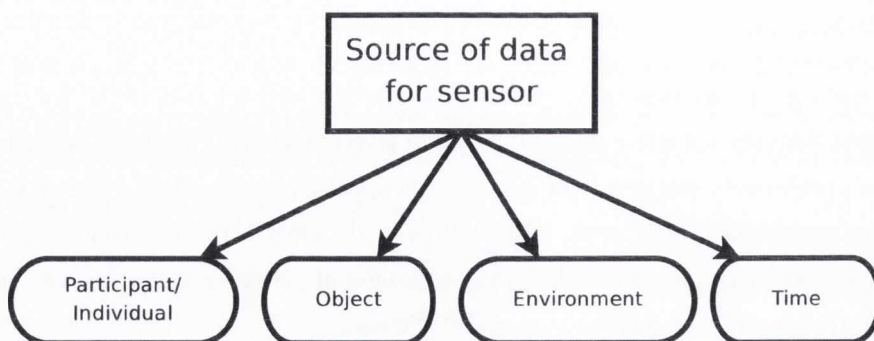


**Figure 2.13**: Source of data for sensor categories

**2.4.4.1 Participant/Individual**

This category describes systems that use the person as the source of their sensor readings. They can collect typed messages, information about the person's location [de Silva et al., 2005], body movements [Holden, 2005], and voice recordings as well as readings such as vital signs like blood pressure. In addition to whatever system action is triggered by the outcome of processing the data described

above, the user can also activate a device by pressing a button [Haigh and Kiff, 2004]. The source of collected measurements influences the type of sensors used. Depending on the system's purpose wearable or stationary sensors can be used for measurement collection.

### 2.4.4.2 Object

This category allows us to identify systems that use some objects as the source of their sensor readings. Examples of objects that could be used as the source of measurements are domestic appliances like ovens, beds, chairs, light switches, taps, or doors. The system's sensors can be embedded in the objects listed above or focused on them like cameras and they can collect data about the object's location, temperature, movement and state (for example, if a window is opened or an oven is on) [Perry et al., 2004].

### 2.4.4.3 Environment

This category describes systems that use sensor readings from a wider area using special data processing algorithms to receive useful information. As a result of this approach, a lot of different information can be obtained. Collected data can be used to recognise people, objects or activities [de Silva et al., 2005, Ho et al., 2005]. The data are usually obtained from cameras and microphones. These type of devices allow the data acquisition from a wide area. Systems classified in this category due to processing of gathered data are more likely to require higher processing power.

### 2.4.4.4 Time

The systems in this category, can use time readings in two ways. Information about the time can be used for saving other sensor readings with a time stamp that can be useful for later data processing and/or for obtaining an outcome that is situated in space-time [de Silva et al., 2005]. Collected data can be used to infer the probability of events or user activities that depend on day time or to place detected events in sequential order. The use of information about time can also be utilised to trigger reminders about some scheduled tasks.

## 2.4.5 Target of actuator's action

This category describes properties of a system's action. It enables the definition of what individual or object a device's outcome is executed. Pervasive systems can be used for gathering data for future analysis by a HCP, informing individuals about some events or fixed appointments or controlling some other device [Perry et al., 2004]. Depending on purpose of the system, the target of system feedback can vary. The aim of this category is to describe the final target of the system's action. As illustrated in Figure 2.14, four distinct categories are defined to describe the final recipient of a device's action, which are participant, caregiver, object, and data storage. For example, when reminding the participant about taking medicines, the ubiquitous assistive device can use text messages, sound or

blinking lights for this purpose [Ho et al., 2005, Haigh and Kiff, 2004]. All of the systems, regardless of the method of communication they use, whose purpose is informing the participant, are covered by the participant category.
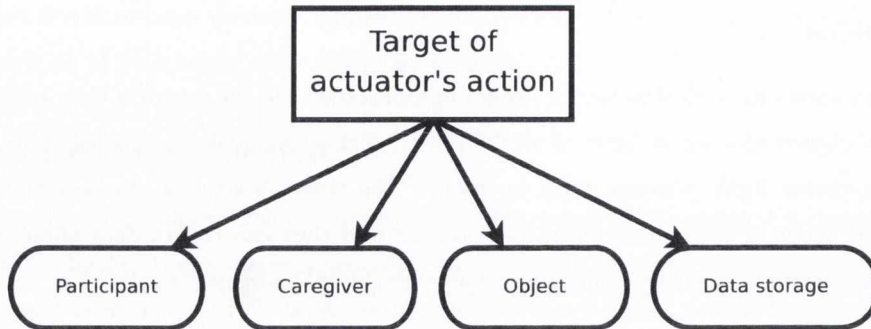


**Figure 2.14**: Target of actuator's action categories

### 2.4.5.1 Participant

This category describes systems in which the user is the recipient of the final action. This user can be instructed or reminded about some event, informed about some fact, e.g., that the front door is open, or in the case of using a computer can see the system's action on the screen [Feys et al., 2001]. Assistive devices can also provide assistance with the participant's activities. They can help with, e.g., walking, or medication delivery [Jafari et al., 2005].

### 2.4.5.2 Caregiver

This category defines the caregiver as the final recipient of a system's action. When considering the caregiver as a target of action, the main aim of assistive devices, may be to inform them in case of danger and about daily routine or some particular event like the participant leaving the house. The caregiver can obtain this information by phone, text message or email. As well as receiving emergency messages it may be possible to obtain periodic reports with vital-sign measurements such as blood pressure or heart and respiration rate.

### 2.4.5.3 Object

All domestic appliances, devices and equipment are included as objects. This category allows the description of all systems whose action is executed on an object. That could be automatic change of water temperature from the tap, light control or turning off the oven when it is no longer used [Georgia Institute of Technology, 2009]. The action may be triggered depending on environmental conditions and specific user presence or actions.

#### 2.4.5.4 Data storage

Data storage can be used for medical purposes as well as for saving the outcomes of monitoring either a room [de Silva et al., 2005] or a person [Axisa et al., 2005]. This category allows the description of systems that do not have a direct impact on their surrounding. Examples of such information could be checking if a participant took medicine or who entered some room in the last three hours.

### 2.4.6 Environment

This category defines where the pervasive system is used. This category provides the classification of systems according to the network architecture used, types of network devices and the manner in which they communicate. As illustrated in Figure 2.15, two main categories are identified, which are indoors and outdoors. This determines the range of system deployment. Environment characteristics also influence the accuracy of measurements that have to be taken to accomplish the objectives of the system.
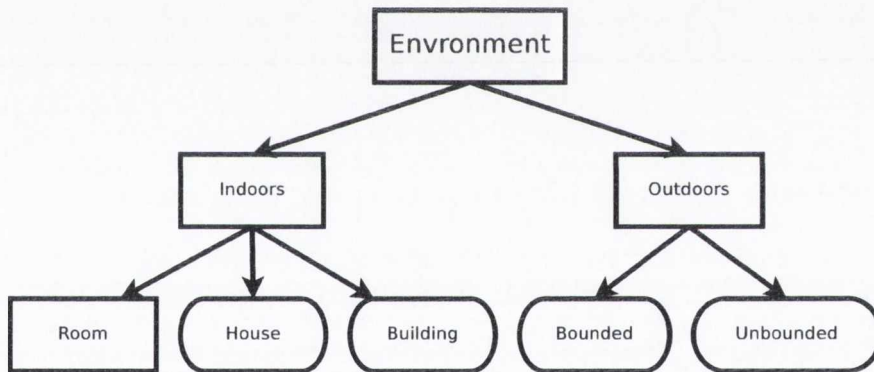


**Figure 2.15**: Environment categories

#### 2.4.6.1 Indoors

The characteristics of indoor environments allows the use of wireless communication technologies as well as cable connections. As illustrated in Figure 2.15, it distinguishes between room, house and building. These categories were defined to separate systems depending on their range of deployment and the manner in which they interact with their users. Technology utilised in a *house* aims to interact with its residents, so it is more likely that it is able to be customised to particular users. In contrast systems used in *buildings* are designated to support many unknown users. In this case, they are supposed to be more flexible and universal.

When we consider systems used in one particular room, they usually do not have as developed a structure and number of devices as ones placed all over a house or building. As illustrated in Figure 2.16, *room* can be better described using five more detailed categories, which are kitchen, bathroom,

living room, bedroom and other. All of these places put different requirements on a system which is placed in them and include different types of appliances. The most important issue for the systems placed in *bedrooms* is their users' privacy. Pervasive systems that are used in the *bathroom* must be unobtrusive to respect user's privacy, additionally they should be very reliable and react quickly, since this environment is potentially dangerous. The systems placed in kitchen should also be very reliable, due to the presence of appliances that are more likely to cause harm. They tend to use advanced processing algorithms and efficient user feedback, due to the relatively complex type of tasks supported. Context-aware assistive devices placed in *living rooms* are more likely to customise to user preferences quickly and accurately. The *other* category refers to systems, which are not placed in any of previously described rooms.
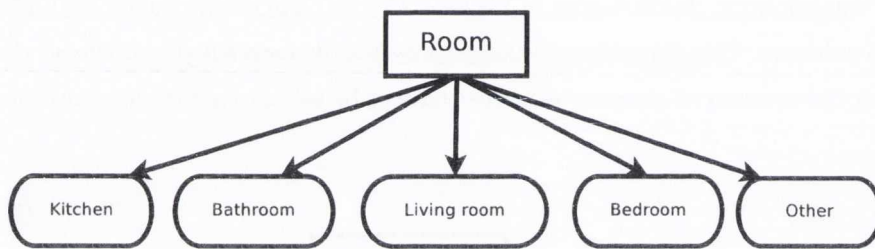


**Figure 2.16**: Room categories

#### 2.4.6.2 Outdoors

This category allows the description of the properties of systems that are used outside houses or buildings. In contrast to the systems working indoors, assistive devices used here will use technologies that require communication over a large area. Because the area of the system deployment is bigger than a house or building a very high level of accuracy of sensor's readings is not available. For that reason, in these kinds of systems mostly GPS technologies will be used. The pervasive systems that are applicable outdoors mostly use wireless sensors, due to user convenience and environment characteristics [Loh et al., 2004].

As depicted in Figure 2.15, two categories are defined, which are bounded and unbounded. The term *bounded* refers to an area that is restricted in some dimensions. That can be a garden outside a house, a car park or a football pitch. Technologies used to cover this space typically use sensors that are fixed to some static objects, for example, cameras. The term *unbounded*, in contrast, refers to the world at large. That puts demand on use of wireless and mobile technologies.

### 2.4.7 Products and technology

This category provides a description of pervasive healthcare systems according to two distinct aspects, which are the type of assistance provided and area of use. If we consider systems that guide users, information about the type of guidance is essential. If the device gives user directions about a route it

has different requirements to the device that gives step-by-step instructions to complete some activity [Kautz et al., 2002]. Some devices can have more than one function and can be used in more than one area. Smart homes [Perry et al., 2004, Georgia Institute of Technology, 2009] equipped with many context-aware devices can support user's memory with reminders and monitor its occupant well-being.
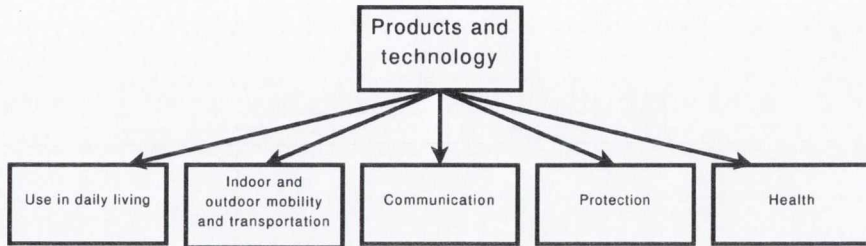


**Figure 2.17**: Products and technology categories [World Health Organisation, 2001]

### 2.4.7.1   Areas of use

To give a comprehensive view of device use, areas in which it can be used should be defined. The taxonomy specifies five areas of use [World Health Organisation, 2001], as illustrated in Figure 2.17. Depending on area, devices with different characteristics may be found.

- *Use in daily living*: It includes all the devices that can be used to help in activities of everyday living like cooking, washing, following a schedule, or controlling appliances.

- *Indoor and outdoor mobility and transportation*: This area contains all the devices that assist the user in changing the body position or its location. They can support physical impairments such as problems with walking as well as cognitive ones like finding the right way home.

- *Communication*: This includes all the devices that help to communicate with another person or device-like systems that provide simplified languages based on pictures or specialised computer interfaces.

- *Protection*: This area includes devices that prevent harm to the user and keep him remaining as safe as possible. This can be monitoring systems informing caregivers in case of any danger, appliance managers switching them off when needed or reminders about taking medication.

- *Health*: This area contains devices that support well-being or recovery. These can be devices for rehabilitation or vital signs monitoring.

### 2.4.7.2   Types of assistance

This category enables us to describe the pervasive healthcare systems according to their purpose of use. The pervasive assistive devices are designed to support various user needs. That could be reminding about some fixtures, locating missing objects or assistance with some tasks. Six categories are defined to describe distinct functions of the systems.

- *Locator*: The function of these devices is localisation of objects or people. The systems can help the participant to find necessary items or inform caregivers about a participant the location.

- *Guide*: These systems aim to give the user assistance needed to finish some task. They can support performing activities by giving step-by-step prompts or following the appropriate route by giving the right direction.

- *Reminder*: The assistance provided by these systems is reminding a user about scheduled events, actions or activities. Depending on user characteristics the type of device feedback can be different. That can be, e.g., text message or audio alarms.

- *Communicator*: The purpose of these systems is to provide communication between the system user and third parties. That can be contacting appropriate authorities in case of emergency or providing suitable language to enable mutual understanding of participant's conversations.

- *Monitor*: The function of these devices is surveillance of people or places. In case of people, things like vital signs, performed activities or mobile status can be monitored. In case of places, rooms or houses can be monitored and desired information like room occupancy can be received by data analysis.

- *Assistant*: The purpose of these devices is to aid their user in some particular activity, for example, haptic devices supporting computer use without hand tremor or devices that help with walking.

### 2.4.7.3 Relationship between areas of use and types of assistance

To provide more specific system descriptions, types of assistance are combined with areas of system use. This approach allows the creation of a relationship matrix, illustrated in Table 2.1. If relation between some areas of use and types of assistance exists it is marked with '•'. As pictured, not every function of assistance can be applied to all the areas, therefore the matrix defines possible connections. This assignment was based on a review of the literature and existing devices, however it is possible to add more assignments in case of such a need.

## 2.5 Classification of pervasive healthcare systems

In order to evaluate the taxonomy, several examples of applying the taxonomy to existing pervasive systems are illustrated in Table 2.2. The summarised systems were chosen to cover various properties like system purpose, user characteristics and technology used.

'The Activity Compass' [Kautz et al., 2002] is hand-held device whose purpose is to show the direction to a specified location. It can be used outdoors (GPS is used for the determination of user location) to pinpoint, for example, home, or indoors (infrared ID tags are used) to locate, e.g.,

| Areas of use | Types of assistance | Communicator | Reminder | Monitor | Locator | Guide | Assistant |
|---|---|---|---|---|---|---|---|
| Use in daily living | | • | • | • | | | • |
| Indoor and outdoor mobility and transportation | | | • | | | | • |
| Communication | | | | • | | | • |
| Protection | | • | | • | • | • | • |
| Health | | | | • | | • | • |

**Table 2.1**: Relationship between areas of use and types of assistance

a bathroom. It can be useful for people with Alzheimer's disease (wandering) or other users with orientation problems. 'The Orienting Tool' [Wu et al., 2005] is also a hand-held device designed to provide reminders for people with cognitive decline. 'The Tremor Control System' [Feys et al., 2001] was created to help people with hand tremor to use computer pointing devices by applying appropriate values to parameters like speed or gain. 'The In-home elder healthcare system' [Ho et al., 2005] that monitors patients' medication intake provides information about the amount of medication taken by the user and enables reminders if the user is in its vicinity and the time is appropriate. The last summarised pervasive system, 'The Millennium Home' [Perry et al., 2004] is the most complex one. Its purpose is to assist users in daily activities like controlling house appliances or adjusting them to the environmental state as well as monitoring its user and the house where it is deployed providing appropriate alarms in case of emergency.

## 2.6 Summary

This chapter presented a novel taxonomy of pervasive healthcare systems. The taxonomy identifies a set of fundamental properties that enable a system to be described according to user characteristics, its purpose and environment of use, as well as the technologies used. These properties are arranged in a hierarchical manner starting from the root of the taxonomy, which defines the relationships between all seven main feature categories. As a result of its hierarchical structure, the taxonomy is flexible and provides easy adjustment to description of new system properties. New categories and properties can be easily added depending on system characteristics. For that reason, the taxonomy may be extended for novel system properties without reorganisation of its existing structure. In addition, the taxonomy is based on the ICF, which provides standard language and a framework for the description of health and disability. The taxonomy is unique in considering the attributes of the users in a number of different ways. Existing work focuses on providing a framework designed either for the description of technologies used or user conditions. The set of properties covered by the taxonomy, that describe systems according to their environment and purpose of use as well as the technology applied and their

| | Activity Compass | Orienting Tool | Tremor Control System | In-home elder healthcare system | Millennium Home |
|---|---|---|---|---|---|
| Body functions | Global mental functions | Specific mental functions | Movement functions | Specific mental functions | Mental functions |
| Activities and participation | Walking and moving | General tasks and demands | Using communication devices and techniques | Looking after one's health | Changing and maintaining body position, Looking after one's health, Domestic Life |
| Support | Participant | Participant | Participant | Participant, Caregiver | Participant, Caregiver, Vicinity |
| Source of data for sensor | Participant | Participant, Time | Participant | Participant, Object, Time | Participant, Object, Environment, Time |
| Target of actuator's action | Participant | Participant | Participant | Participant, Data storage | Participant, Caregiver, Object, Data storage |
| Environment | Unbounded (PDA) | Unbounded, House, Building (PDA) | Room (computer) | Room (portable pad) | House |
| Products and technology | Indoor and outdoor mobility and transportation - Guide | Use in daily living - Reminder | Communication - Assistant | Protection - Reminder, Protection - Monitor | Use in daily living - Assistant, Protection - Monitor |

**Table 2.2**: Classification of pervasive healthcare systems

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potential users, provides a better framework for identification of system dimensions in more detail. As a result, it can be used for classification of pervasive healthcare systems, in which understanding characteristics of their potential user is essential.

The taxonomy was the basis of the creation of user survey 'Assistive technology in everyday living' described in the next chapter. In addition, the properties of pervasive healthcare systems defined in the taxonomy were used to inform the design of SMOOTH.

# Chapter 3

# User survey[1]

As presented in the introduction of this thesis, the range and variety of assistive technologies (ATs) being developed and researched as well as those that are commercially available is growing [Scherer, 2002]. To date, despite the variety of ATs that are available, knowledge about their existence and use among people with Parkinson's disease (PD) is limited [Roelands et al., 2002, Constantinescu et al., 2007]. To design and manufacture AT to support people with PD, identification of their needs is essential. For that reason our study engaged the community of people with PD to investigate their problems and the ATs used or perceived to be relevant in their everyday living. The previous chapter presented a taxonomy of pervasive healthcare systems designed to enable a better understanding of the connection between user needs and system features. Our study was designed on the basis of this taxonomy. The aim of the survey was to explore the individual circumstances of people with PD, as well as their ideas and opinions about AT that may be used for daily living.

The remainder of this chapter is organised as follows. Section 3.1 describes the design process and structure of the survey as well as the data collection procedure. Section 3.2 reports our results including those addressing the limitations in functions and activities of the participants, and their views on the AT use. This is followed (Section 3.3) by a discussion of the results. Next, survey limitations (Section 3.4) and conclusions (Section 3.5) are presented. On the basis of the survey results, Section 3.6 identifies AT that could be beneficial for people with PD. Finally, a summary of this chapter is presented.

## 3.1 Method

Several methods were identified in order to obtain information that could help to better understand user needs. They included direct interviews, phone interviews, postal surveys, and observation of daily living of the patients in their natural environment. The factor kept in mind during the choice of the study methodology was acquiring a representative sample of people with PD in different stadium of the

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[1]The content of this chapter has been published in [Muras et al., 2008].

disease. However, there were time and cost constraints, and approval from the ethics committee was required for the recruitment of participants and subject to the employment of appropriate methods of recruitment and protocols. In the case of personal contact, the recruitment process was more time consuming and the protocols were more strict, e.g., required the presence of healthcare professional, than in the case of a postal survey. In addition, it is more likely that people in poor condition would not be as eager to take part in the study if it required personal contact. For these reasons, this study employed a self-reported user survey methodology conducted by post in order to investigate the needs of people with PD. The study was approved by the Faculty of Health Sciences Research Ethics Committee, Trinity College Dublin.

### 3.1.1 Survey instrument design

The phase prior to the design of the user survey involved a systematic review of the literature to establish what AT may be available for use by people with PD. Articles for the review were compiled from a number of sources. Searches were performed in the databases of PUBMED[2], CINAHL[3], AMED[4], ScienceDirect[5] and the ACM Digital Library[6]. AT databases were also reviewed and included ABLEDATA[7], assistivetech.net[8], assistireland.ie[9], and Microsoft Accessibility[10]. This information was used to design the taxonomy described in previous chapter. The taxonomy in conjunction with the clinical experience of Dr. Stokes was employed to design the first version of the user survey. The initial version of the user survey was revised based on feedback from physiotherapists and occupational therapists working with people who have PD and further pilot studies of the survey instrument were conducted with people with neurological disorders from the Irish Wheelchair Association (IWA)[11].

### 3.1.2 User survey

The first part of the user survey consisted of a questionnaire to be completed by the person with PD intended to explore participants' individual circumstances and their views on the AT that they use for daily living. The questionnaire consisted of single and multiple-choice questions and Likert rating scales. This first part of the survey was designed to gather general information about the participants, e.g. age, gender, diagnosis and place of living, as well as more specific information about difficulties in daily living and the types and usability of AT used during specified activities of daily living.

The second part of the user survey aimed to explore participants' ideas and opinions about AT and their features. This part of the questionnaire consisted of open-ended questions only. This approach

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[2]http://www.pubmed.gov
[3]http://www.ebscohost.com/cinahl
[4]http://web.ebscohost.com/ehost
[5]http://www.sciencedirect.com
[6]http://portal.acm.org
[7]http://www.abledata.com
[8]http://assistivetech.net
[9]http://www.assistireland.ie
[10]http://www.microsoft.com/enable/at/
[11]http://www.iwa.ie

enabled participants to give more details about their views and experience.

### 3.1.3 Data collection

A survey of people with PD was conducted by post. The following inclusion criteria were used: (1) a diagnosis of PD; (2) ability to fill out the questionnaire independently; and (3) aged 18 or over. One hundred survey sets were delivered to a support group for people with PD (PALS)[12], which is a branch of the Parkinson's Association of Ireland, where they were sent to 100 out of 200 PALS members all over Ireland. Address labels were chosen at random, therefore participants recruited ranged from newly diagnosed to these with advanced-stage disease. Each survey set contained information about the purpose of the research, a consent form, and the questionnaire as well as a stamped envelope with return address to facilitate and encourage participants to fill out the questionnaire and send it back. The overall response rate during the data collection period (August, 2006 - November, 2006) was 59%.

### 3.1.4 Analysis of data

Quantitative data were coded and inputted into Excel where descriptive statistics were computed, Chi-squared and Fisher's Exact tests were employed to consider the relationships between categorical data. The qualitative data was reviewed by two researchers independently. Responses to open questions were reviewed by two researchers independently. They were categorised and themed separately and any disagreement between the categories of answers was resolved by discussion.

### 3.1.5 Limitations of methodology

There are a number of limitations related to the self-reported survey methodology [Razavi, 2001]. They include a tendency to agree with statements as presented (acquiescence bias), a tendency to respond consistently and avoid extreme sections of the scale (central tendency bias), and a tendency to answer questions in such a way as to represent oneself in a favourable light (social desirability bias). In self-reported surveys the measurements are subjective for each participant, which means that there is no common reference between ratings of participants, e.g., one person may rate their sight as good and another person having the same sight may rate it as very good. In addition, this user survey aimed at exploring participant's views on AT. It is plausible that some participants did not perceive particular devices they use on a daily basis as AT. Finally, the survey was conducted by post. Therefore, there might also be a non-responder bias. This methodology was chosen in order to obtain a fair representation of people with PD.

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[12]http://gofree.indigo.ie/~pdpals/

## 3.2 Results

This section presents the results obtained from the user survey. The remainder of this section is organised as follows. Section 3.2.1 presents general characteristics of the participants including their age and disease duration. Section 3.2.2 describes problems encountered in every day living including limitations, functions, and activity restrictions. Finally, Section 3.2.3 presents use of and user perspective on AT.

### 3.2.1 General characteristics

A total of 59 (25 men and 34 women) people with PD participated in the study. One person failed to report the year in which they were born and for that reason data from 58 subjects was used for characterisation of the participants' age, age of diagnosis and duration of disease. The mean participants' age was 58 years (range 35-77 years; standard deviation (SD)±10 years), the mean age of diagnosis was 49 years (range 20-67 years; SD±11 years) and the mean time since diagnosis of PD was nine years (range 1-33 years; SD±8 years). The distribution of participants' ages is illustrated in Figure 3.1a and disease duration in Figure 3.1b.



(a) Participants' age
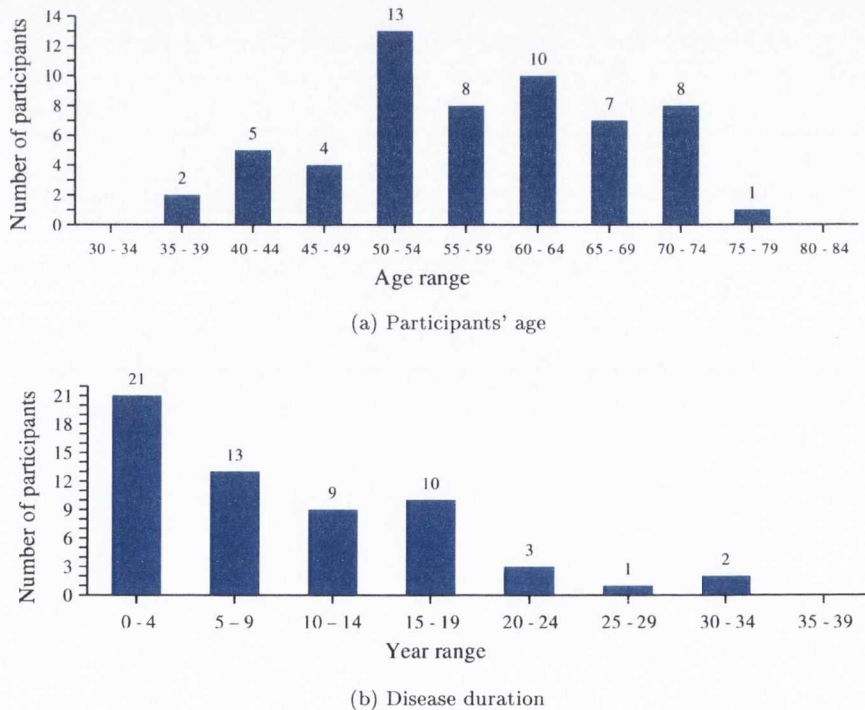


(b) Disease duration

**Figure 3.1**: Distribution of participants' age and their disease duration

Half (51%) of the 59 respondents lived with their spouse or partner, a small proportion (7%) lived with their children only, and almost a quarter (24%) lived with their spouse/partner as well as their children. The rest of the participants lived alone (12%) or with other people including parents and

siblings.

## 3.2.2 Limitations, functions, and activity restrictions

This section presents limitations, functions, and activity restrictions reported by the participants. The remainder of this section is organised as follows. Section 3.2.2.1 presents self-reported condition of several functions such as flexibility and physical strength. Section 3.2.2.2 describes problems with mobility, e.g., changing body position or transferring from one place to another. Section 3.2.2.3 and Section 3.2.2.4 report difficulties with self-care and household tasks, respectively. The relationship between physical strength, flexibility, problems with mobility, and self-care and household tasks is presented in Section 3.2.2.5. Finally, Section 3.2.2.6 describes relationship between tiredness and fatigue.

### 3.2.2.1 Self-reported condition

In Table 3.1 self-reported ratings of participants' memory, vision, hearing, quality of speech and physical condition are illustrated. A five-level Likert scale was employed to enable participants to rate their responses. The middle rating, which is usually supposed to be neutral, is labeled as 'good'. It results in three positive and two negative options and might have influenced the subjects' ratings. The functions and senses listed above were ordered from the highest rated (on top) to the lowest. To put them in order the ratings reported as 'excellent' and 'very good' were added for each function/sense and ratings reported as 'poor' and 'very poor' were subtracted from them. The items were ordered on the basis of the difference (from highest to lowest). Hearing, memory, and vision were the highest-rated. The lowest-rated functions were quality of speech, flexibility, and physical strength. A quarter (25%) of the participants rated their flexibility as 'poor' or 'very poor'. The term 'flexibility' was used in this survey as opposed to the term rigidity often associated with PD as the former is a commonly used lay term that incorporates both the rigidity that may be experienced by people with PD and general flexibility. The pilot revealed no difficulties with the use of this term. Quality of speech was reported as 'poor' or 'very poor' by 27% of the respondents. Physical strength was reported as the most common problem. One third (34%) of the respondents reported it as 'poor' or 'very poor' and only one fifth (19%) as 'very good' or 'excellent'.

### 3.2.2.2 Mobility

Only 12% of 59 respondents reported that they did not have any problems with changing body position and transferring from one place to another. Problems noted by the other respondents (88%) are illustrated in Figure 3.2. More men (92%) than women (85%) reported problems with mobility. The most common problem for both genders was walking and the majority of the respondents (59%) found it difficult. Half of them (51%-53%) had problems with changing body position including standing up from a chair, getting up from the floor, getting into/out of bed, and transferring in/out of

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| Function or sense | Excellent | Very good | Good | Poor | Very poor |
|---|---|---|---|---|---|
| Hearing | 15% | 27% | 47% | 8% | 2% |
| Memory | 12% | 32% | 37% | 19% | 0% |
| Vision | 9% | 22% | 53% | 16% | 0% |
| Coordination | 2% | 18% | 61% | 18% | 2% |
| Quality of speech | 7% | 19% | 47% | 27% | 0% |
| Flexibility | 4% | 19% | 53% | 23% | 2% |
| Physical strength | 5% | 14% | 47% | 32% | 2% |

**Table 3.1**: Overall self-reported ratings of participants' condition

a car. 36% of the respondents had problems with moving outdoors and these were more common than difficulties with moving indoors (29%). Going up/down the stairs was a difficult task for a quarter (24%) of the participants. A few respondents (8%) reported 'freezing' as a problem in daily living. Strength of the hand(s) was a problem for 41% of the respondents and hand movements were reported as a difficulty by one third (31%) of them.
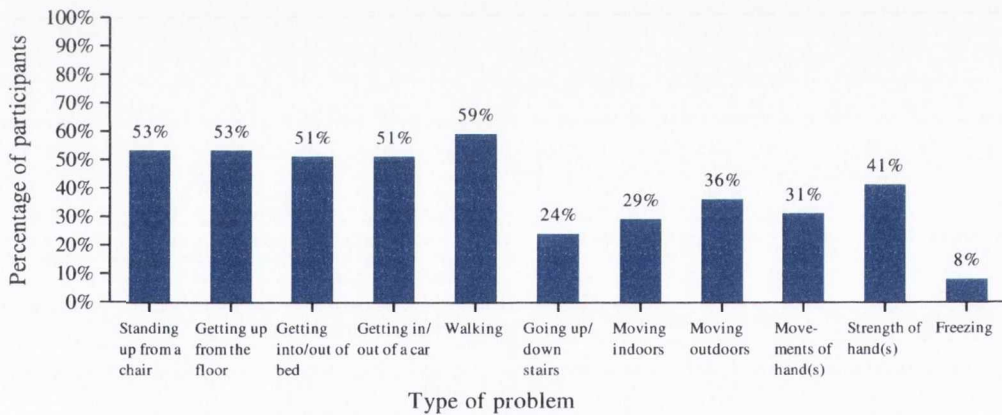


**Figure 3.2**: Problems with mobility

### 3.2.2.3   Tasks of self-care

As reported in Table 3.2, over half of the participants said that they did not have any difficulties with most self-care tasks. Two thirds of the participants (64%-69%) reported no problems with going to the bathroom, washing, and eating or drinking. Half of the subjects (53%) reported no problems with dressing. A quarter (21%-26%) found tasks of self-care difficult or needed more time to accomplish them but still managed on their own. Dressing, rather than any other of the tasks mentioned above, was the most common problem with one fifth (19%) of the respondents needing help from their caregivers. Only 2%-3% of the respondents used an AT.

| Task | Eating / drinking | Using bathroom | Washing | Dressing |
|---|---|---|---|---|
| Managed without difficulty | 69% | 66% | 64% | 53% |
| Managed with difficulty | 24% | 21% | 26% | 25% |
| Assistive device used | 2% | 3% | 2% | 2% |
| Help needed occasionally | 5% | 7% | 3% | 19% |
| Help needed all the time | 0% | 3% | 5% | 2% |

**Table 3.2**: Management of self-care tasks

#### 3.2.2.4 Household tasks

In Table 3.3, participants' problems with household tasks are illustrated. A minority of subjects had problems with washing up and preparing meals. 63% and 44% of survey respondents, respectively, managed to do the tasks listed without difficulty. 18% and 23%, respectively, experienced some difficulties but could still manage on their own. 9%-18% of survey respondents could not do them or needed the help of other people all the time. 63% of the subjects reported that they did not have any problems with doing washing up. More respondents had difficulties with preparing meals. 44% could do it on their own without any problems, 16% occasionally needed other people to help them, and 7% could not do the task at all. The most common, according to the survey respondents, were difficulties with doing shopping, carrying objects, and doing laundry. 58%-61% of the participants could complete these tasks on their own and 23%-36% could not do them or needed assistance all the time. Cleaning the house was also a significant problem among the survey respondents and a quarter (24%) of the participants could not manage it. More respondents, in general, found household tasks more difficult than tasks of self-care. Less than 5% of subjects always needed other people's help with self-care tasks, in comparison to 9%-36% of participants who needed another's help all the time or could not do household tasks at all.

| Task | Washing up | Prepare meals | Clean house | Carry objects | Laundry | Shopping |
|---|---|---|---|---|---|---|
| Managed without difficulty | 63% | 44% | 45% | 42% | 50% | 49% |
| Managed with difficulty | 18% | 23% | 19% | 16% | 11% | 12% |
| Assistive device used | 4% | 0% | 0% | 0% | 2% | 0% |
| Help needed occasionally | 7% | 16% | 12% | 19% | 11% | 4% |
| Help needed all the time | 2% | 11% | 14% | 14% | 16% | 25% |
| Not managed | 7% | 7% | 10% | 9% | 11% | 11% |

**Table 3.3**: Management of household tasks

### 3.2.2.5 Physical strength and flexibility

33% and 25% of the survey participants, respectively, reported their physical strength and flexibility as 'poor' or 'very poor'. Table 3.4 illustrates the relationship between physical strength, flexibility and number of people who had problems with self-care tasks. All eight subjects who reported problems with physical strength but not flexibility could manage self-care tasks such as eating/drinking, using bathroom, and washing on their own and without any use of AT, whereas some participants that reported problems with flexibility as well as those with a combination of flexibility and physical strength tended to use the help of other people to complete these tasks. As reported in Table 3.5, none of the participants who reported problems in both physical strength and flexibility could manage household tasks without any difficulty, whereas, some respondents with other conditions could do it. In addition, more people in this category could not complete household tasks at all.

As illustrated in Table 3.6, most respondents who reported problems with flexibility but not physical strength ($n = 4$) also had problems with mobility. Fewer participants who reported problems with physical strength only ($n = 8$) had problems with changing body position or moving around in comparison to other groups. There were no statistical relationships between users' ratings and tasks of self-care, household tasks, and problems with mobility.

### 3.2.2.6 Fatigue and tiredness

A common problem among the participants was fatigue and getting tired quickly. As reported in Table 3.7, 36% of the subjects said that they had ongoing fatigue 'frequently' and 18% declared it to be 'all the time'. More participants reported getting tired fast. 58% of the subjects got tired fast 'frequently' and 12% 'all the time'. For the purposes of analysis we assumed that participants had some condition (fatigue/tiredness) if they reported it 'always' or 'frequently'. As illustrated in Table 3.8, all participants who reported ongoing fatigue also reported getting tired fast. However, not all participants who reported getting tired fast also reported ongoing fatigue.

As reported in Table 3.9, problems with mobility (78%-83%) did not tend to depend on participants' condition; however more respondents with ongoing fatigue reported using AT or assistance of other people for mobility (48%) than the subjects who did not report ongoing fatigue (28%).

A significant difference was noted in the relationship between those reporting 'getting tired fast' and the presence or absence of ongoing fatigue - all those who reported ongoing fatigue also reported getting tired easily whereas only one third of those who did not have ongoing fatigue reported tiring quickly (X-square 26.37, $p = 0.000$). This did not differ across gender.

Categories of assistance and fatigue were collapsed to yield a 2x2 table, presence/absence of ongoing fatigue and independent/require assistance. No significant relationships were noted between fatigue and the use of assistance in the following tasks of self-care - going to the bathroom, washing or dressing. However, for eating/drinking, those who reported not requiring assistance reported ongoing fatigue in significantly greater numbers ($p = 0.002$).

| Problems with | Task | Eating / drinking | Using bathroom | Washing | Dressing | Number of participants |
|---|---|---|---|---|---|---|
| Flexibility and strength | Managed without difficulty | 1 | 2 | 1 | 0 | |
| | Managed with difficulty | 6 | 4 | 7 | 4 | |
| | Assistive device used | 1 | 0 | 0 | 1 | |
| | Help needed occasionally | 1 | 2 | 0 | 3 | |
| | Help needed all the time | 0 | 1 | 1 | 1 | 9 |
| Strength | Managed without difficulty | 6 | 7 | 7 | 4 | |
| | Managed with difficulty | 2 | 1 | 1 | 2 | |
| | Assistive device used | 0 | 0 | 0 | 0 | |
| | Help needed occasionally | 0 | 0 | 0 | 2 | |
| | Help needed all the time | 0 | 1 | 1 | 1 | 8 |
| Flexibility | Managed without difficulty | 2 | 1 | 2 | 1 | |
| | Managed with difficulty | 1 | 0 | 0 | 2 | |
| | Assistive device used | 0 | 2 | 1 | 0 | |
| | Help needed occasionally | 1 | 0 | 0 | 1 | 4 |
| | Help needed all the time | 0 | 1 | 1 | 0 | |

**Table 3.4**: Management of self-care tasks depending on condition

| Problems with | Task | Washing up | Prepare meals | Clean house | Carry objects | Laundry | Shopping | Number of participants |
|---|---|---|---|---|---|---|---|---|
| Flexibility and strength | Managed without difficulty | 0 | 0 | 0 | 0 | 0 | 0 | 9 |
| | Managed with difficulty | 3 | 3 | 4 | 1 | 2 | 1 | |
| | Assistive device used | 2 | 0 | 0 | 0 | 1 | 0 | |
| | Help needed occasionally | 2 | 3 | 2 | 1 | 2 | 0 | |
| | Help needed all the time | 0 | 2 | 0 | 3 | 0 | 4 | |
| | Not managed | 2 | 1 | 3 | 4 | 3 | 3 | |
| Strength | Managed without difficulty | 4 | 2 | 2 | 1 | 3 | 2 | 8 |
| | Managed with difficulty | 2 | 2 | 1 | 2 | 0 | 1 | |
| | Assistive device used | 0 | 0 | 0 | 0 | 0 | 0 | |
| | Help needed occasionally | 0 | 0 | 1 | 3 | 1 | 1 | |
| | Help needed all the time | 1 | 3 | 3 | 1 | 3 | 3 | |
| | Not managed | 0 | 0 | 0 | 0 | 0 | 0 | |
| Flexibility | Managed without difficulty | 3 | 2 | 1 | 1 | 1 | 1 | 4 |
| | Managed with difficulty | 0 | 0 | 0 | 0 | 0 | 0 | |
| | Assistive device used | 0 | 0 | 0 | 0 | 0 | 0 | |
| | Help needed occasionally | 0 | 1 | 1 | 1 | 1 | 0 | |
| | Help needed all the time | 0 | 0 | 1 | 1 | 1 | 2 | |
| | Not managed | 1 | 1 | 1 | 1 | 1 | 1 | |

**Table 3.5**: Management of household tasks depending on condition

| Problems with | Strength and flexibility | Strength | Flexibility |
|---|---|---|---|
| Standing up from a chair | 7 | 5 | 4 |
| Getting up from a floor | 7 | 4 | 4 |
| Getting into/out of bed | 8 | 4 | 4 |
| Transferring in/out of a car | 6 | 3 | 3 |
| Walking | 7 | 4 | 4 |
| Going up/down stairs | 3 | 0 | 3 |
| Moving indoors | 5 | 1 | 2 |
| Moving outdoors | 4 | 1 | 4 |
| Movements of hand(s) | 5 | 1 | 2 |
| Strength of hand(s) | 5 | 1 | 2 |
| Number of participants | 9 | 8 | 4 |

**Table 3.6**: Problems with mobility depending on condition

| Condition | Never | Rarely | Frequently | Always |
|---|---|---|---|---|
| I get tired fast | 14% | 16% | 58% | 12% |
| I have ongoing fatigue | 33% | 13% | 36% | 18% |

**Table 3.7**: Problems with getting tired and fatigue

Seventy per cent of respondents who reported that they were independent in preparing meals also reported ongoing fatigue, whereas 76% of those who sought assistance did not report ongoing fatigue ($p = 0.002$), these results, i.e., more fatigue in those not using assistance are consistent for all other household tasks except paying the bills - doing laundry ($p = 0.004$), doing shopping ($p = 0.002$) and carrying objects ($p = 0.000$), washing up ($p = 0.02$), house cleaning ($p = 0.01$).

### 3.2.3 Assistive technologies

This section presents use of ATs reported by the participants as well as participants' perspective on ATs they used or would like to use. The remainder of this section is organised as follows. Section 3.2.3.1 describes ATs used to complete self-care and household tasks. Section 3.2.3.2 and Section 3.2.3.3 present aids used to facilitate mobility and memory, respectively. Section 3.2.3.4 describes personal alarms and their importance to the subjects. Finally, Section 3.2.3.5 presents the participants' perspective on AT.

#### 3.2.3.1 AT in self-care and household tasks

As illustrated in Tables 3.2 and 3.3 only a few participants (up to two per task) used AT to help themselves in self-care or household tasks. Because the use of only very few AT was reported it is difficult to derive any conclusions about their usage. However, rather than AT, the survey respondents

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| Condition | I have ongoing fatigue | I do not have ongoing fatigue |
|---|---|---|
| I get tired fast | 29 | 9 |
| I do not get tired fast | 0 | 16 |

**Table 3.8**: Number of participants who reported tiring fast in relation to fatigue

| Condition | I have ongoing fatigue | I do not have ongoing fatigue |
|---|---|---|
| I get tired fast | 93% | 78% |
| I do not get tired fast | N/A | 81% |

**Table 3.9**: Percentage of participants who had problems with mobility

(5%-33%) did use the assistance of other people to help them in activities of daily living.

### 3.2.3.2 Mobility aids

More than one third (39%) of the 59 survey respondents said that they used assistance for mobility. As reported before, more men (92%) than women (85%) tended to have problems with mobility and it may be for that reason that more men (44%) than women (35%) used assistance for mobility. The most popular form of assistance was a cane (19%). 12%-15% of the subjects used other people's help, walkers, and manual wheelchairs. Only a few of them (2%-7%) used other AT to move around. These included tripods, crutches, scooters and AT to transfer in/out of bed. There was a difference in use of wheelchairs depending on gender. More women used manual (18%) as well as powered wheelchairs (6%) compared to 4% and 0% of men, respectively.

### 3.2.3.3 Memory aids

One third (34%) of the 53 participants who answered the question said that they used an AT to help their memory. Of note was that 54% of 59 respondents reported problems with their memory. The most common problem was remembering the names of people (42%). Less than one third of the respondents (29%) could not remember the location of objects and less than one quarter had problems with remembering what they did yesterday (20%) and last week (24%). 17% of the participants reported that they found it hard to remember about medication intake and 12% could not remember the names of objects. Few people mentioned that they were forgetting to eat their meals (7%) and did not remember other people's faces (3%). The most common memory aids were paper notebooks (19%) and mobile phones (15%). The majority of their users (19%-21%) found them 'very helpful' or 'helpful'. 13% of the participants used an alarm clock or timer to remind them about scheduled tasks or appointments. 4% of them found this kind of memory aid 'helpful' and 9% 'very helpful'. The most common reason for not using AT to help memory was 'no need to use them' and 53% of all participants responded in this way. Some of the participants responded that they did not have sufficient information about technologies to help their memory (15%) and 11% of them had never

heard of such technologies.

In the survey, the events about which respondents wanted to be reminded were investigated. The most commonly used memory aids were for scheduled appointments (30%) and taking medication (26%). One fifth (18%-21%) of the subjects used memory aids to remember shopping lists and things to do. Less than half of the participants (41%-43%) reported that they did not use any assistance, but thought that a technology to remind them about things to do, medication and scheduled appointments could be useful. One third (33%-34%) said that reminders of the location of objects and how to do various activities could be useful for them.

#### 3.2.3.4 Personal alarms

The majority (89%) of the 54 subjects who answered the question did not use any personal alarms. The reasons reported were absence of perceived need (65%), lack of sufficient information about existing technologies (22%), and prohibitive cost of AT (2%). In addition, it was reported by participants that the technologies were too complicated to be used and there was a lack of sufficient education in their use (2%). A number of respondents used automatic phone calls (6%) and voice messages (2%) as personal alarms and found them helpful.

In the survey, the importance of events for which an alarm should be triggered was also investigated. Most of the respondents (81%) said that it was 'very important' to them that someone was informed if they had fallen and could not get up. It was also 'very important' to 71% of the participants that their next of kin be contacted automatically if they had a medical condition and needed to contact someone but were unable. Only 14% of participants (18% of men and 12% of women) reported that it was not important to them for contact to be made with someone if they had a fall. Half of the participants (50%) considered alarms for taking medication as very important and one fifth (20%) as not important at all.

#### 3.2.3.5 User perspective on AT

In the second part of the survey participants' opinions and ideas in relation to AT were investigated. This part consisted of open-ended questions, so that participants could state their opinion in more detail. The data was transcribed and reviewed independently by two researchers. After analysis, six main categories of ATs were identified and agreed between the researchers. They were mobility, activities of daily living (ADLs), personal activities of daily living (PADLs), information technology (IT) technologies, safety technologies and 'other'. Because of the variety of answers, some of the categories required a more in depth analysis and for a better description of participants' views additional subcategories were defined. 'Mobility' includes technologies to assist in transfer from one place or position to another as well as doing exercises. 'ADLs' included home-care skills while 'PADLs' describe self-care skills including taking medication, dressing and using the bathroom. 'Safety technologies' include personal alarms and all technologies supporting the safety of their users and the IT category

includes technologies addressing problems with using a computer. AT mentioned in answers to all four questions included in this part of the survey are depicted in Figure 3.3 and described in more detail in the remainder of this section.
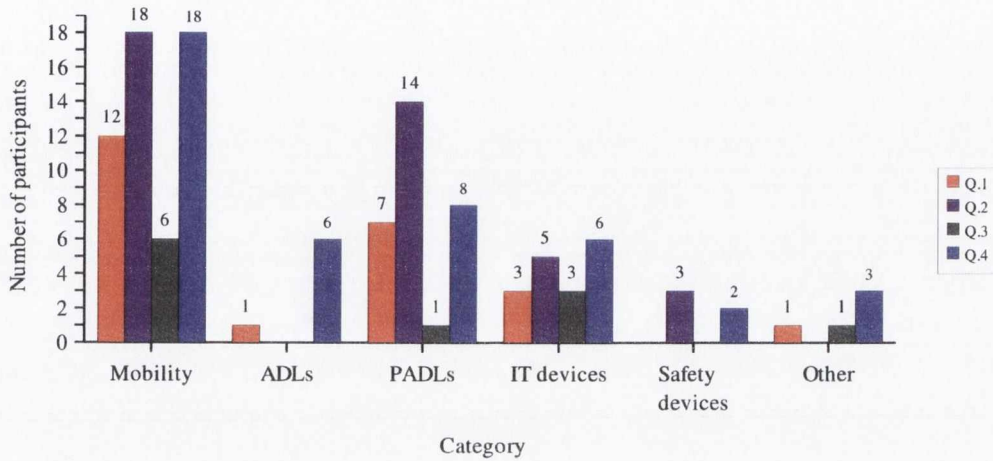


ADLs = Activities of daily living
PADLs = Personal activities of daily living

**Figure 3.3**: ATs reported in answers to open-ended questions

The aim of the first question was to obtain opinions about AT that the respondents did not like. Nineteen participants answered this question and identified 24 technologies that they did not like. Half of the technologies ($n = 12$) were designed for assistance in mobility. They included exercise bicycles, technologies for transferring in/out of bed ($n = 2$) and from one place to another ($n = 4$), e.g. wheelchairs, as well as aids for walking ($n = 5$), e.g. a walking frame or a cane. Seven technologies to help in PADLs were mentioned. They included technologies installed in bathrooms ($n = 5$), e.g., a bath lift or a grab rail for a shower, and aids in dressing ($n = 2$), e.g., putting on trousers or tights. The rest of the technologies reported by participants included those to help in ADLs ($n = 1$), using a computer ($n = 3$), e.g., speech recognition software, and other ($n = 1$). There were two reasons why the technologies were disliked. The first was insufficient utility of the technologies ($n = 6$). The second reason was pride and the fact that a person using a particular technology did not want other people to think that they are disabled ($n = 2$).

*'A cane which I don't like using - as it labels me, also it is not very effective (causes embarrassment)'*
(Participant no. 35).

The next question was about AT and their features that were liked and whether the respondents considered them helpful. Twenty seven participants identified technologies that were, in their opinion, useful. Eighteen of forty technologies mentioned in this question addressed problems with mobility including technologies for transferring in/out of bed ($n = 3$), e.g., hand grabs, and from one place to another ($n = 3$), special chairs ($n = 5$), e.g., rise recliner, as well as aids for walking ($n = 6$).

The respondents identified 14 technologies that were useful in doing their PADLs. They were used for dressing ($n = 4$), taking medication ($n = 6$), e.g., pill box, or installed in bathroom ($n = 4$), e.g., bath seat. Three people said that they found safety technologies, e.g. personal alarms, useful and five reported aids that helped them using a computer very helpful. The respondents identified ATs in general rather than their specific helpful features. One person mentioned that it was useful to have information about 'gadgets' available.

Eleven participants answered the question investigating the improvement of technologies to make them more useful. They suggested ten technologies that could be improved. Most ideas were reported for assistance in mobility ($n = 6$). They included size and weight reduction of wheelchairs as well as their battery performance (prevention of sudden discharge and longer life time). There were only a few improvement demands for walkers ($n = 1$), chairs ($n = 1$), and technologies for getting in/out of bed ($n = 1$). Three improvements for assistance in using a computer were reported. They included perfecting software, large keypads, and voice-activated computer programmes.

*'Could speech recognition software be perfected to cope with difficulties of speech in PD?'* (Participant no. 34).

One improvement for bath equipment was proposed. Two participants said that it would be useful to have better information and training on how to use technologies.

In the last question potential technologies that would be useful for participants were investigated. 29 respondents answered this question and reported 43 ATs. Most technologies ($n = 18$) were to help in mobility. They included technologies for changing body position ($n = 9$), transferring from one place to another ($n = 8$), and doing exercises ($n = 1$). Participants also thought that it would be helpful to use ATs for PADLs ($n = 8$). PADLs addressed dressing ($n = 2$), e.g., putting on socks, bath equipment ($n = 2$), and medication intake ($n = 4$). Support in ADLs was reported useful by six respondents and included, e.g. aids for writing, *'any to aid/improve my writing'* (Participant no. 15) or opening jars. Personal alarms were considered to be useful for two participants and six of them would be pleased to use electronic technologies like laptop or PDA and computer improvements, e.g., *'something to steady the mouse'* (Participant no. 17). Three other technologies including a vibrating massager, glasses for double vision, and technology to reduce tremor, *'some mechanical technology to reduce tremor in hands and arms'* (Participant no. 44), were mentioned. There was also need for information about technologies ($n = 2$).

## 3.3 Discussion

This section discusses the most important findings from the user survey. The remainder of this section is organised as follows. Section 3.3.1 gives overview of representation of the sample used in the study. The purpose of the survey was to obtain opinions about ATs used by people with PD. Thus, Section

3.3.2 discusses the use of ATs among the participants and their desirable improvements. Finally, Section 3.3.3 review personal alarms and fear of falling.

### 3.3.1 Sample representation

The physical limitations reported by respondents in this survey are consistent with commonly reported problems for people with PD [National Collaborating Centre for Chronic Conditions, 2006] and not unexpected given the age range and duration of disease reported by participants. Mobility issues, gait disturbance, falls and fatigue are all reported as a common problems among people with PD affecting many areas of daily living [Gelb et al., 1999, Chaudhuri and Behan, 2000, Adkin et al., 2003, Wild et al., 1981]. The results of the study show that fatigue was the most frequent problem for the survey respondents. Over half of the participants (54%) suffered from it 'frequently' or 'all the time' and 70% reported that they get tired fast 'often' or 'all the time'. This is consistent with the findings of Herlofsen and Larsen [Herlofson and Larsen, 2003] that reported that 50% of people with PD participating in their study had fatigue.

### 3.3.2 Assistive technologies

The purpose of the study was to investigate the use of AT among people with PD and their opinions about them. This has been not reported to date. In general, the survey respondents did not use many ATs. Only a few participants ($n = 5$) reported the use of ATs to help themselves in tasks of self-care and household tasks. In both kinds of task the assistance of other people was more commonly used than ATs and depending on the task, up to 20% and 33% of the survey respondents used the assistance of others in self-care and household tasks, respectively. The reason why ATs were not commonly used may be explained by the level of independence reported by the participants. As reported in previous sections over 60% of them could perform self-care and household tasks on their own independently. However, it is interesting to note that many more respondents used the assistance of other people to undertake such activities rather than using ATs. Low utilisation of ATs could be caused by several factors. These include lack of knowledge of existing technologies and the fact that some activities are not performed very often and there is no need for the participants to do them on their own. Another factor could be inappropriate design of ATs, which was reported by some participants in the open-ended part of the questionnaire. While it is not possible to draw a 'cause and effect' relationship, it is notable that those who reported not using assistance for certain tasks of daily living had a higher incidence of ongoing fatigue.

In the case of mobility a higher proportion of participants made use of ATs compared to the assistance of other people. Of note is that most of the technologies used by the survey participants were rather simple mechanical technologies and did not involve advanced computer technology. Over half of the participants (56%) used technologies such as canes or walkers and only 5% used automated technologies such as powered wheelchairs. The reason for the common use of technologies to improve

mobility could be, as reported before, that most of the participants (88%) had mobility constraints and the technologies mentioned above could greatly improve their independence and quality of life. Changing location or body position are activities that humans tend to perform very often and it is desirable for them to be performed independently. The reported use of simple mechanical technologies may be because they are widely available, commonly prescribed by healthcare professionals, and relatively inexpensive.

Despite the possibility that people affected by PD might suffer from cognitive impairment [Kida et al., 2007], to date there have been no 'definitive studies' of memory aids for them [Anderson, 2003]. These survey results show that 60% of the respondents, who did not use memory aids, reported lack of sufficient information about ATs for memory support as well as difficulties in their use. This indicates that they may not realise what useful technology is available or the utility of existing technologies may not meet the needs of people with PD. In addition, 41%-43% of participants said that even though they did not currently use any technologies to help their memory they noted that such technologies could be useful for them to support tasks such as scheduling appointments (41%), taking medication (42%), and 'things to do' (43%). In comparison, only 27% of the respondents, who did not use personal alarms, reported lack of sufficient information about them as well as difficulties in their use as a factor. A small proportion (up to 15%) used ATs to help themselves in activities such as medication management or gait monitoring, however, 51%-53% of the respondents who did not use any of those technologies declared that they could be useful for them. Few of the survey participants used ATs to support other daily activities such as writing.

The survey analysis showed a perceived benefit in the use of ATs to support a variety of activities. Jutai et al. [Jutai et al., 2000] noted a 'positive and strikingly similar' relationship between perceived and actual psychosocial impact of ATs to daily living in people with degenerative neuromuscular disease. This suggests that participants in our survey may be missing out on ATs that could possibly be very valuable to their independence and quality of life.

### 3.3.3 Personal alarms and falls

Gait disturbances as well as muscle weakness with postural instability [Adkin et al., 2003, Wild et al., 1981], which are common symptoms of PD, may lead to problems with balance and changing body position and potentially causing an increased risk of falls. The National Institute for Clinical Excellence (NICE) guidelines [National Institute for Clinical Excellence (NICE), 2004], which provide guidance on the use of medicines, appropriate treatments, and procedures used for diagnosis, propose that older people who have sustained an injurious fall should be informed of ways to cope should another fall occur. One way of minimising the impact of a fall is to prevent a 'long lie' [Simpson et al., 1998]. 'Best practice', as outlined by NICE, is to summon help if unable to get up in order to avoid a 'long lie' which itself can create further health problems, e.g., hypothermia. To minimise a 'long lie' personal alarms that

provide a communication link between the person who has fallen and their caregiver can be useful. The survey results show that for the majority (81%) of the participants it is very important to contact someone in a case of a fall for which the participant is unable to get up. However, the majority of the survey respondents (89%) did not use any personal alarms. The main reason given for that was absence of need (65%), which is an interesting fact considering that 81% of the participants were afraid that they would not be able to contact someone in case of emergency. More than one fifth (22%) of the subjects declared that they did not have sufficient information about existing technologies, a possible reason for their underutilisation.

## 3.4 Limitations

The response rate for this survey of 59% is consistent with mean response rates reported in medical journals [Asch et al., 1997] but the results should be interpreted in the context of a possible non-responder bias. While the sample size is small, the physical limitations described by participants suggest that the results may be generalised to people with PD in Ireland. In addition, the description of the sample of participants included people with a very recent diagnosis of PD and long-standing disease suggesting that it is a fair representation of people with PD. The survey instrument did not contain explicit cultural references which would preclude its use in other countries and cultures however one must consider that knowledge and availability of AT is informed by accessibility to AT which, in turn, may have socio-economic and political influences.

## 3.5 Conclusion

The limitations above notwithstanding, this survey is the first that explores the views and opinions of people with PD about AT. In light of current and future developments in the area of AT for people with disabilities, it provides an indicative set of opinions that can inform design and developments for people with PD. Engagement by designers and researchers with the community of people with PD will ensure that user-centred ATs become available. However, as the results suggest, there is a lack of knowledge about the availability of more advanced ATs that may support people with PD even though many respondents considered that such supportive technologies would be of use to them. For that reason, information dissemination about existing technologies appears to be essential. Methods of informing people with PD about ATs available should be improved which will lead to their broader use and improve independence and quality of life for people with PD in the future.

## 3.6 Identification of assistive technology

The survey results were expected to help in the identification of computer-based AT that would be the most beneficial for people with PD. The survey participants did not express the desire for any

| Potential AT | Supporting survey results |
|---|---|
| Fall detection and post-fall support system | • 88% of the participants reported problems with mobility;<br><br>• 51%-53% of the participants reported problems in changing body position;<br><br>• 85% of the participants reported that it is very important or important to contact someone in case of fall and unable to get up;<br><br>• 81% of the participants reported being afraid that they would not be able to contact someone in case of emergency. |
| System for mobility training at home | • 34% of the participants reported poor or very poor physical strength;<br><br>• 25% of the participants reported poor or very poor physical flexibility;<br><br>• 88% of the participants reported problems with mobility;<br><br>• 51%-53% of the participants reported problems in changing body position;<br><br>• 70% of the participants reported getting tired fast frequently or all the time;<br><br>• 54% of the participants reported fatigue frequently or all the time;<br><br>• all of these factors might influence ability to perform tasks of daily living. |

**Table 3.10**: Types of ATs potentially beneficial for people with PD

particular AT which would help them in activities of daily living and, which is also important, does not already exist. Notwithstanding, two general themes emerged from the survey results: problems with mobility and concerns related to the fear of falling. To address these themes we identified two types of ATs that we believe people with PD could potentially benefit from in everyday living. They are: a fall detection and post-fall support system, and a system for mobility training at home. The results from the user survey supporting such a choice are presented in Table 3.10.

To decide which AT would be more beneficial for people with PD their community was asked to form an opinion. The presentation of survey results was given to members of a support group for people with PD (PALS)[13], at a meeting held in March, 2007. To obtain their views a short survey with questions investigating the perceived usefulness of the two identified ATs was conducted among 24 participants who were present at the meeting. The results are presented below.

The first part of the survey investigated falls and fear of falling. More than half (54%) of the participants had fallen in past year and approximately the same amount (57%) was afraid of falling. 65% and 54% of the respondents considered falls and fear of falling, respectively, to be a problem and 25% of the participants had fallen and were unable to get up. The second part of the survey

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[13]http://gofree.indigo.ie/~pdpals/

investigated exercise execution at home. 65% of the respondents had been recommended to perform exercises by their healthcare professional. Less than half of the participants (45%) followed the recommendation most or all the time. 45% of the respondents performed exercises occasionally, and the remaining 10% rarely or not at all. Most of the participants (96%) declared that if an exercise system that would assist them in daily exercise routine was made available they would use it. Finally, questions related to the perceived benefit from both types of systems were posed in the survey. The answers are presented in Figure 3.4. In general, a significant majority of the survey participants (88% for fall detection and 100% for an exercise system) found both systems 'useful' or 'very useful'. More participants (83%) declared that an exercise system would be 'very useful' for them compared to 50% for a fall detection system.
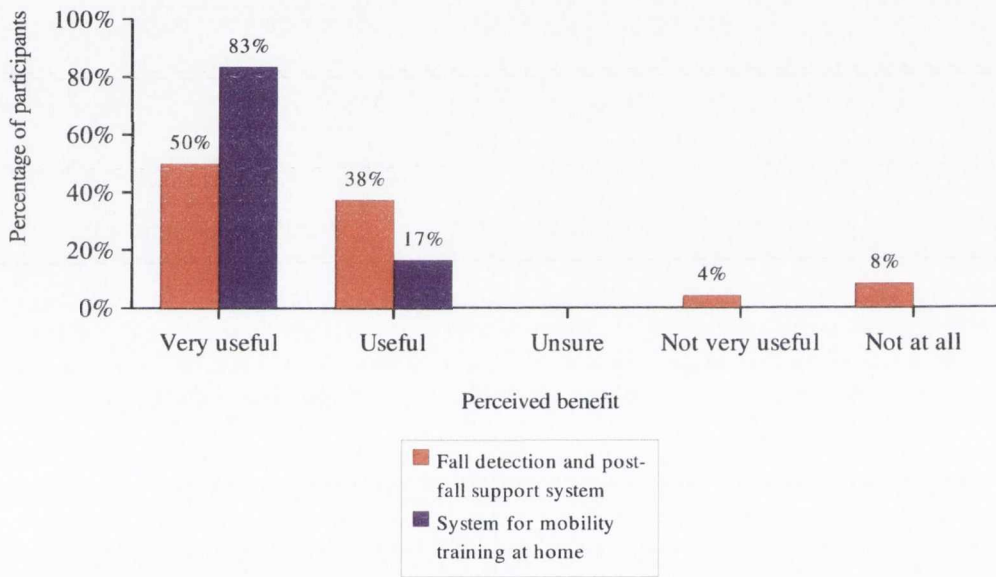


**Figure 3.4**: Perceived benefit from a fall detection and post-fall support system, and a system for mobility training at home

The feedback from the PD community suggests that a system for mobility training at home has a bigger perceived benefit than a fall detection and post-fall support system. As presented in the introduction to this thesis people with PD can avail of physiotherapy to address mobility issues [Keus et al., 2009] and therefore it is common practice to prescribe a set of exercises that can be performed by a patient at home [Canning et al., 2009]. The main goal of physical exercises prescribed to people with PD is improvement of limitations in balance, posture maintenance, agility, flexibility, and muscle strength [Goodwin et al., 2008]. Improvement of those functions should also lead to reduction in a number of falls and related injuries [Benatru et al., 2008]. In addition, the survey results and subsequent feedback from the PD community identified a need for AT to support exercise execution at home. For that reason SMOOTH - a system for mobility training at home for people with PD was developed and is described in the remainder of this thesis.

# 3.7 Summary

This chapter presented a user survey of people with PD. The aim of the survey was to explore the individual circumstances of people with PD, as well as their ideas and opinions about AT that may be used for daily living. A self-reported, user survey was designed. The results of the study were derived from a postal survey of randomly chosen members of the Parkinson's Association of Ireland. Analysis were conducted on data from 59 people. According to the survey results the majority of the participants reported problems with mobility (88%), fatigue (54%), and getting tired fast (70%). Problems with mobility included changing location (59%) and body position (51%-53%). 34% and 25% of respondents described their physical strength and flexibility, respectively, as 'poor' or 'very poor'. For 81% of participants it was important to be able to contact someone in a case of a fall. The results of this study indicate a possible underutilisation of ATs by people with PD.

# Chapter 4

# State of the Art

This thesis spans the two broad areas of exercise monitoring and posture or movement detection. This chapter gives an insight into both of these areas and reviews the current state of the art in each. In the review a number of computer-based systems to support users in performing exercise routines or to detect their current posture or activity are included. The inclusion and exclusion criteria used were slightly different for each area and for that reason they are presented at the beginning of the corresponding sections. The purpose of this chapter is to review approaches, challenges and results of work that has been done to date in these fields and on that basis inform the design of SMOOTH.

The remainder of this chapter is organised as follows. In Section 4.1 systems that were designed to monitor and support the performance of exercise routines are presented. Section 4.2 and 4.3 include work related to posture and activity recognition respectively. SMOOTH uses a chair equipped with sensors to classify movement. Thus, approaches that use a chair to detect posture are presented in Section 4.4. Finally, a summary of this chapter is presented in Section 4.5.

The most important concepts related to data processing for body posture and activity recognition are introduced in Appendix A. Appendix B provides theoretical background on the essential techniques applied in SMOOTH.

## 4.1 Exercise Monitoring

This section describes state-of-the-art systems designed to monitor exercise execution. Exercise is any activity that requires physical or mental effort and is repeated to improve health and maintain fitness [Dictionary, 2009]. In the review are included systems whose purpose is to provide users with feedback during independent exercise execution and assessment of the user's performance. Systems that supported passive movement, which is movement not requiring effort by the participant [Dictionary, 2009] were excluded from the review.

Two main categories of systems were identified: virtual environments (VE) for rehabilitation and exercise systems with movement recognition. The systems that belong to the first category, presented

in Section 4.1.1, utilise haptic interfaces manipulated by users to map their movement to a simulated environment with which they interact. User performance is assessed on the basis of position in VE, not on the basis of direct body position and movement of the user. The systems, that belong to the second category, presented in Section 4.1.2, recognise direct user movement and on that basis assess user performance and provide feedback.

## 4.1.1 Virtual environments for rehabilitation

Rehabilitation is a treatment, which assists recovery from injury, illness, or disease to as normal a condition as possible [Encyclopedia, 2009]. Recovery can be accomplished by modifying the environment in which patients live as well as by restoring their physical functions and skills or teaching them new skills by exercises. To facilitate rehabilitation a number of systems that utilise VEs and haptic interfaces have been developed [Holden, 2005]. Existing systems can be classified on the basis of two criteria: target and type of rehabilitation. The target of rehabilitation describes the part of the patient's body used to manoeuvre the haptic interface to the VE. It can belong to one of three groups: upper limb, lower limb, and other [Fujita and Kato, 2005]. Type of rehabilitation allows the description of the purpose of exercise, which is either restoring physical functions, e.g., range of movement and muscle strength, or restoring/teaching skills that are useful in activities of daily living, e.g., movement coordination and precision. The categories of VE for rehabilitation are presented in Figure 4.1.
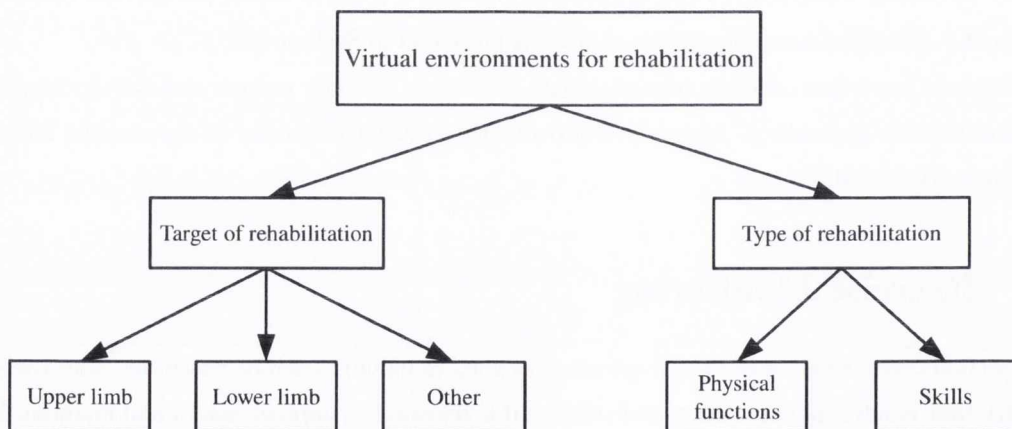


**Figure 4.1**: Virtual environments for rehabilitation

The review of VEs for rehabilitation is presented next. Section 4.1.1.1 presents systems for upper limb rehabilitation, Section 4.1.1.2 systems for lower limb rehabilitation, and Section 4.1.1.3 describes other systems. This is followed by a summary and discussion of all the systems in Section 4.1.1.4.

### 4.1.1.1 Upper limb

Upper limb rehabilitation is the most common area addressed by VEs for rehabilitation. For that reason the systems that belong to this category were grouped depending on the type of rehabilitation addressed. Systems designed to help users regain physical functions are presented in Section 4.1.1.1. Systems designed to allow users to learn new skills or regain lost skills are described in Section 4.1.1.1. This is followed by systems that aim to improve both physical functions and skills presented in Section 4.1.1.1.

**Physical functions**  The purpose of the system presented in [Jack et al., 2000] is to improve hand function in stroke patients. The system supports four simple exercises, which aim to improve range of motion, speed, finger movement isolation, and strength of hand. The parameters of the exercises, e.g., the required movement range can be adjusted to the user's characteristics. To enable the monitoring of hand motion the system utilises CyberGlove [Immersion Corporation, 2009]. The Rutgers Master II (RM-II) [Bouzit et al., 2002] is used to provide haptic force feedback. The pilot study conducted with control subjects suggested a number of improvements including exercise modification, presentation of user feedback, and design of haptic interface.

Subramanian et al. [Subramanian et al., 2006] present a system for upper limb rehabilitation after stroke that aims to improve pointing and reaching movement. The system simulates an elevator ride and the exercises supported by the system involve pressing appropriate buttons in the virtual elevator. To detect the position of the hand the Optorak Motion Capture System [Northern Digital Inc., 2009] is employed. A CyberGlove [Immersion Corporation, 2009] is utilised to obtain the position of the fingers. A head-mounted display is used to present the user with the simulation in a VE. To encourage the user to exercise the system provides the user with positive and negative feedback as well as instructions indicating the target goal. A pilot study was conducted with patients with hemiparesis, which is a weakness on one side of the body. The results suggest that movement in VEs performed to do some task might differ from movement that is done in order to accomplish the same task in reality.

Morrow et al. [Morrow et al., 2006] propose a low-cost system for hand rehabilitation post-stroke. The purpose of training is to improve range of finger motion, isolation of the movement, and speed of flexion. For that purpose two games were developed. In the finger range game the user is asked to flex their fingers so that the movement uncovers an image on the screen: the bigger the range of movement the more of the image can be seen. In the second game, the user is supposed to move the fingers with appropriate speed. If the goal is meet a virtual butterfly flies away from the hand. The system uses an Xbox [Microsoft Corporation, 2009] console and an inexpensive P5 game glove [Virtual Realities, Inc., 2009]. The P5 glove can track wrist position using infrared light emitting diodes and measure flexion of all fingers by employing resistive bend sensors. The P5 glove used in the study does not provide force feedback and is less accurate than its more expensive equivalents, e.g., the CyberGlove. For that reason fewer measurements of the hand movement can be taken. The

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overall cost of the system is less than $600. No evaluation of the system is presented in the paper.

Mali et al. [Mali and Munih, 2006] introduce a haptic interface for finger exercise (HIFE). The interface was designed for training for people after finger injuries. Two finger exercises were developed to increase finger strength and movement functions. They are a virtual damper, and a virtual spring. Different difficulty levels and exercise sets can be chosen for each user. The exercises focus on finger static forces, coordination of finger movement and contact force, finger-tip velocity, and precision. The user is provided with visual feedback during exercise execution. The haptic interface used in the finger exercises allows finger movement in the entire range of motion and can provide users with continuous force up to 10N. The accuracy and safety of the haptic interface was found sufficient for rehabilitation purposes. No study with people recovering from finger injuries was conducted.

**Skills** Webster et al. [Webster et al., 2001] present the Computer-Assisted Training (CAT) system for unilateral neglect patients created to improve wheelchair manoeuvring. The unilateral neglect is an effect of stroke in which the patient forgets about the weaker side of the body [Dictionary, 2009]. CAT includes a simulation of a wheelchair with training on obstacle avoidance. Participants navigate a virtual wheelchair using a 4-button hand controller. Depending on the user's performance, tasks related to visual perception of spatial relationships with different complexities can be used. CAT provides feedback about performance and guidance about correct movement. The evaluation of CAT was conducted with 20 unilateral neglect patients. The results suggest that some of the participants had difficulty in appropriate perception of the wheelchair pathway.

A group at the University of Nottingham designed a system for post-stroke rehabilitation that supervises making a hot drink [Hilton et al., 2002, Immersion Corporation, 2009]. The aim of the system is to support a user in practising sequential activities of daily living. The purpose of the exercise supported by the system is to complete all the sub-tasks required to make a hot drink. Prior to each sub-task, verbal instructions explaining each sub-task are given. When motion corresponding to the sub-task is sensed animation imitating the sub-task is played. The user can see each step of the activity on the screen and hear the corresponding sounds such as pouring water. If participants perform an inappropriate task or complete the task incorrectly, they are provided with corrections. The system consists of a tangible interface like a kettle or tap and a software application that guides the user through the particular steps of the activity. User actions are detected using a camera and sensors placed on the objects, e.g., a light sensor to detect intensity of ambient light. The pilot study was conducted with seven post-stroke patients.

The V-Store (Virtual Store) [Castelnuovo et al., 2003, Holden, 2005] provides a virtual shop. Its objective is to help improve the user's cognitive functions and to familiarise the user with stressful situations. The objective of the training provided by V-Store is to move fruit that can be found on virtual shelves from one basket to another. Before each trial, verbal commands, explaining to the user how to fill the baskets, are given through loudspeakers. The verbal commands consists of a number of steps to be completed with six levels of increasing complexity. Depending on the complexity level,

a number of distractions such as a telephone ringing are provided to increase time pressure. To move objects in the VE the participant uses an active force-feedback (AFF) joystick as a haptic device. No trials with potential users are described in the paper.

The VR Kitchen developed by Gourlay et al. [Gourlay et al., 2000] provides occupational rehabilitation for people with cognitive impairment following stroke and traumatic brain injury. The aim of the rehabilitation is to familiarise patients with the home environment and regain their ability to do simple daily living tasks, requiring safety and sustained attention. For example, the user must be aware of the danger of burning when touching a hot oven, and must also acknowledge that the kettle must not be turned on when empty. The VR Kitchen is a fully interactive simulation of a real kitchen and contains a sink, kettle, cup, coffee jar, microwave, power sockets, cupboards and drawers. The user performs a series of everyday tasks such as preparing a meal in a microwave oven, using kitchen appliances, and making tea. To interact with the appliances a VR glove was designed. It uses bend sensors attached to each finger and an electromagnetic tracking system to obtain hand orientation and position. The construction of the VR glove is basic. It does not provide force feedback and is not very accurate. Its resolution is low but it allows grasping or moving objects in the scene. A pilot study with nine patients with mild to moderate cognitive impairment was conducted. It suggests that after practise participants were able to satisfactory manoeuvre objects in the VE.

A similar approach to that of V-Store, called virtual supermarket, is presented by [Josman et al., 2006]. The purpose of the system is to help post-stroke patients to regain skills that are needed in complex task execution. The training provided by the system consists of planning and purchasing items in a supermarket. The user is presented with a first-person perspective simulation of a medium-sized supermarket. Their task is to buy seven items from a list. The items are chosen by mouse clicks. Evaluation of the system was conducted with 26 post-stroke patients. The results showed big differences in participants' performance. In addition, a moderate relationship between the performance of participants and their executive functions (abilities to control and regulate behaviours) were found. The results suggest the potential of the virtual supermarket to be used in rehabilitation of post-stroke patients.

**Physical functions and skills** Popescu et al. [Popescu et al., 2000] present a system for orthopaedic rehabilitation. Orthopaedic rehabilitation is a treatment, which assists recovery from muscular and skeleton problems. The purpose of the system is to regain lost physical functions and skills by patients. To retrieve physical functions three exercises are modelled in a VE: squeezing a rubber ball, individual finger exercises (DigiKey), and simulation of putty. Exercises designed to retrieve skills include a peg board insertion game and a ball game in which the user is supposed to throw and catch a ball. The system utilises a magnetic tracker (Polhemus Fastrak [Polhemus, 2009]) and the Rutgers Master II (RM-II) glove [Bouzit et al., 2002] to track arm movements and to provide haptic force feedback. The platform presented in the paper facilitates remote monitoring, therefore patients can perform exercises at home.

Kuttuva et al. [Kuttuva et al., 2006] present a system, called the Rutgers Arm, for upper arm rehabilitation for post-stroke patients. The purpose of the system is to help patient to retrieve lost skills and physical functions by playing two therapeutic games. The objective of the pick-and-place game is to train motor coordination by moving a hand on a specified trajectory to pick up and place a ball on a target. During the exercise the user obtains ongoing auditory feedback. To improve hand-eye coordination the Breakout3D game was implemented. The objective of the game is to destroy a set of blocks by bouncing a virtual ball in the desired direction. Parameters of the game, such as ball size or speed, can be adjusted to each user. The Rutgers Arm consists of a 3D magnetic tracker (Polhemus Fastrak [Polhemus, 2009]) to track arm movements, a table that supports the patient's arm movement, and an arm rest. A pilot study was conducted with one person diagnosed with hemiparesis (weakness on one side of the body). The results show improvements in arm motor control and shoulder range of motion, which were maintained one week after finishing the trial. In addition, the system helped in the patient's motivation to sustain exercise routine.

In [Burdea et al., 2008] an improved version of the system presented in [Kuttuva et al., 2006], called the Rutgers Arm II, is introduced. The main difference is the replacement of the table with one that tilts in four directions and the replacement of the magnetic tracker with a vision-based tracking system, which uses an infrared camera. In addition, a treasure hunt game to improve arm endurance was implemented and included in the platform. Pilot trials were conducted with post-stroke patients. Performance of subjects was worse for larger tilt angles of the table.

A system for hand rehabilitation following stroke is presented by Alamri et al. [Alamri et al., 2008]. The purpose of the exercises supported by the system is to regain hand function. Five exercises were developed to improve various aspects of hand function. They include *handling a cup* (improving steadiness and hand-eye coordination), *arranging blocks* (improving dexterity and hand strength), *navigating a maze* (improving steadiness and hand-eye coordination), *squeezing a ball* (improving fingers strength), and *training with a dumbbell* (increasing gross motor skills and strength). The difficulty of all the exercises can be adjusted to the performance of each patient. The system relies on the CyberGrasp system [Immersion Corporation, 2009] for sensing hand position and providing force feedback. The feasibility of development the system was validated in a pilot study conducted with 10 participants.

A system for arm rehabilitation for Multiple Sclerosis (MS) patients is presented in [Coninx et al., 2008]. The purpose of the system is to provide arm training to people with MS. Three exercises were developed to meet this purpose: *a virtual car, book manipulation*, and *plate tapping*. The objective of the car game is to pilot the car through a predefined route. In the book manipulation task, the user has to grab a book and put it into an available space in a shelf. Several parameters can be changed depending on the user's condition. They include the size of the book, its placement and its weight. The aim of the tapping task is to move between two targets as fast as possible. The system utilises the PHANToM haptic device [Massie and Salisbury, 1994, SensAble Technologies, 2009]

to translate user movements into the VE. The PHANToM robot provides six degree-of-freedom input (ability to independently move forward/backward, up/down, left/right combined with rotation about three perpendicular axes) and force feedback through a stylus-like device. A pilot study conducted with MS patients shows that they did not have problems with transformation of their movements to the VE and commented positively on the system.

### 4.1.1.2 Lower limb

Boian et al. [Boian et al., 2002, Boian et al., 2003] present a system for ankle rehabilitation post stroke. The system facilitates participants performing exercises in a VE displayed on a PC screen. Movements in the VE are controlled by moving the foot and ankle. Two games were developed for patient training. In the first game, the user flies an air-plane through a set of 3D hoops. The system recognises nine different ankle positions and the position of the hoops can be changed by a therapist to reflect treatment goals. In the second game, the user navigates a boat. This exercise requires more accuracy from the user, as the boat must stay on the surface of the water. Parameters of both games can be adjusted to user characteristics, e.g., range of movement. The system enables recording of user performance and its remote analysis by the therapist. To translate the user's movement to the VE the Rutgers Ankle [Girone et al., 2001] is used. This is a haptic interface that consists of a pneumatic platform that senses the position of and supplies forces to the patient's foot. A pilot study of the system was conducted with three post-stroke patients who took part in four weeks of training. The participants improved the strength of some ankle muscles. In addition, the training had a positive impact on gait speed.

Fujita et al. [Fujita and Kato, 2005] introduce a system for rehabilitation of people with limited walking functions. The purpose of the system is to strengthen leg muscles and improve walking function. The system enables patients with insufficient muscle strength and postural stability to perform walking exercise at home. The user's steps are translated into the VE, which simulates a walk. While walking it is possible to meet other users of the system, which are presented as avatars in a virtual world, and talk to them. A change of walking direction can be accomplished by head inclination. To ensure the user's safety the exercise is performed in a lying position. Two air bags with pressure sensors were used to detect steps and translate them to the VE. An initial study shows that the energy consumption of walking exercise is 40% that of normal walking and therefore the distance has to be three times longer to obtain the same effect.

### 4.1.1.3 Other

Kizony et al. [Kizony et al., 2002] present an adaptation of the Gesture Xtreme VR system [Gesture Xtreme, 2009] for neurological rehabilitation. Four games were adapted for neurological rehabilitation to improve a user's cognitive and physical skills. They include: birds and balls, soccer, sharkbait, and snowboard. The Gesture Xtreme uses a digital camera to track movements of the

user's body and translate them to the VE. In that way, the user can see himself performing different functional tasks, e.g., catching and throwing the ball. The user must stay in a demarcated area and can observe his own motion on a large display or projected image. This kind of system allows the user to change body position without restriction, provided it is within the demarcated area. Because the user's movements are tracked by a camera and the system does not include any wearable device, it cannot provide haptic force feedback. The analysis of results of a pilot study with 10 patients after spinal cord injury showed that they had to put more effort into balance training in a VE than in conventional therapy. In addition, they are reported to have enjoyed the training and would like to repeat it.

Fitzgerald et al. [Fitzgerald et al., 2008] introduce a system for balance training. To provide the training, the open source Neverball game [Neverball, 2009] is used within the VE. The objective of the game is to tilt the ground in order to roll a ball though a set of obstacles in order to collect money tokens. The system employs a wobble board with fixed motion sensor [Xsens Technologies, 2009] to manoeuvre the ball in the VE. To evaluate the system, a study with 12 healthy subjects was conducted. The results show high usability of the system and the potential to be used in an exercise programme at home.

#### 4.1.1.4 Discussion

A summary of the systems used for rehabilitation presented above is shown in Table 4.1. The table describes the systems according to target group for rehabilitation, e.g., stroke patients or people with walking impairment, the target of rehabilitation, e.g., upper limb, lower limb or other, and type of rehabilitation which includes regaining physical functions or skills. In addition, the table includes information about the number of exercises implemented in the system and the haptic interface used to map the user's movements to the VE.

The current state of the art shows that VEs can be suitable for rehabilitation [Holden, 2005]. They can reduce the cost of healthcare and enable more patients to perform exercises at home. The major cause of failure of home-based therapy is that training without any interaction usually gets monotonous and the motivation of the user declines with time [Loureiro et al., 2001]. To prevent this, VEs can provide the user with information about their performance using different types of feedback, e.g., haptic, visual, and auditory. Exercise routines can be made more interesting and enjoyable by the development of various types of games [Ma et al., 2007]. In addition, user performance can be recorded and the therapist can use this information to better adjust exercise programs to user characteristics [Popescu et al., 2000].

As presented, sophisticated haptic interfaces have been created to enable therapy for people with various limitations. There are a number of issues related to those interfaces that can limit their use at home. Some of them might not be suitable for all users because of their size, weight or type of user limitation. As suggested in [Jack et al., 2000] the use of gloves can be problematic due to variations

in hand size, movement patterns and individual fit. At the moment, the setup and maintenance of some haptic interfaces can be complicated. For that reason there is often a need for the therapist to be present and for supervision of exercise sessions. Even though attempts to reduce the cost of the systems were made [Morrow et al., 2006], most of existing commercially available haptic devices as well as software platforms to develop games are still quite expensive. In addition, natural modelling of user movements in VE can also be challenging [Burdea, 2000].

**Table 4.1:** Summary of virtual environments for rehabilitation

| Reference | Target group | Number of exercises | Target of rehabilitation | Type of rehabilitation | | Haptic interface |
|---|---|---|---|---|---|---|
| | | | | Physical functions | Skills | |
| [Jack et al., 2000] | Stroke | 4 | Upper limb | ✔ | | CyberGlove; Rutgers Master II (RM-II) glove |
| [Subramanian et al., 2006] | Stroke | 1 | Upper limb | ✔ | | Optorak Motion Capture System; CyberGlove |
| [Morrow et al., 2006] | Stroke | 2 | Upper limb (fingers) | ✔ | | Xbox; P5 glove |
| [Mali and Munih, 2006] | Finger injuries | 2 | Upper limb (fingers) | ✔ | | HIFE |
| [Webster et al., 2001] | Stroke | 1 | Upper limb | | ✔ | 4-button hand controller |
| [Hilton et al., 2002] | Stroke | 1 | Upper limb | | ✔ | Camera; sensors placed on objects |

**Table 4.1:** Summary of virtual environments for rehabilitation

| Reference | Target group | Number of exercises | Target of rehabilitation | Type of rehabilitation | | Haptic interface |
|---|---|---|---|---|---|---|
| | | | | Physical functions | Skills | |
| [Castelnuovo et al., 2003] | Cognitive problems | 1 | Upper limb | | ✓ | Active force feedback joystick |
| [Gourlay et al., 2000] | Cognitive problems | ? | Upper limb | | ✓ | VR glove; mouse |
| [Josman et al., 2006] | Stroke | 1 | Upper limb | | ✓ | Mouse |
| [Popescu et al., 2000] | Orthopaedic | 5 | Upper limb | ✓ | ✓ | Polhemus Fastrak; Rutgers Master II glove |
| [Kuttuva et al., 2006] | Stroke | 2 | Upper limb | ✓ | ✓ | Polhemus Fastrak; |
| [Burdea et al., 2008] | Stroke | 3 | Upper limb | ✓ | ✓ | Vision tracking system |
| [Alamri et al., 2008] | Stroke | 5 | Upper limbs | ✓ | ✓ | CyberGrasp |
| [Coninx et al., 2008] | Multiple sclerosis | 3 | Upper limb | ✓ | ✓ | PHANToM robot |

**Table 4.1:** Summary of virtual environments for rehabilitation

| Reference | Target group | Number of exercises | Target of rehabilitation | Type of rehabilitation | | Haptic interface |
|---|---|---|---|---|---|---|
| | | | | Physical functions | Skills | |
| [Boian et al., 2002, Boian et al., 2003] | Stroke | 2 | Lower limb | ✔ | ✔ | Rutgers Ankle |
| [Fujita and Kato, 2005] | Walking impairment | 1 | Lower limb | ✔ | | Air bags with pressure sensors |
| [Kizony et al., 2002] | Neurological impairment | 4 | Other | ✔ | ✔ | Gesture Xtreme |
| [Fitzgerald et al., 2008] | Balance training | 1 | Other | | ✔ | Wobble board with MTx tracker |

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The use of VE in rehabilitation is a relatively new approach. Even though a number of studies have been conducted to measure its influence on user's performance there is still a need for extensive evaluation of its effects in comparison to traditional, well established practise [Alamri et al., 2008].

## 4.1.2 Exercise systems with movement recognition

Exercise systems with movement recognition in contrast to the systems described previously do not translate the user's movement to a VE. User performance is assessed on the basis of the body position and movement of the user. User feedback is provided on the same basis. This approach allows the user to perform exercises more naturally and without the need to manoeuvre any device.

The Stroke Rehabilitation Exerciser [Timmermans et al., 2007] is a home-based system developed to increase the efficiency of hand rehabilitation following stroke. The purpose of the exercises implemented in the system is to regain arm functions. The system consists of three elements: a motion sensing system along with user and therapist interfaces. It supports prescription of the exercises as well as guiding the user during exercise performance. It also provides the user the feedback about their performance.

When the user comes to the rehabilitation clinic and is assessed by the therapist, a set of exercises is prescribed. When the user performs the exercises from the training plan at home, he/she wears a set of wireless inertial sensors on the lower and upper arm as well as on the shoulder and torso. This configuration enables the system to measure joint angles, which are used to measure the user's performance. The readings from the sensors, as well as the exercise programme, are stored in the database and they can be accessed remotely by the user and therapist applications.

The sensor readings recorded during exercise are the basis for user feedback and progress reports for the therapist. The user interface is designed to be very simple with only a few elements. For each exercise, instruction videos on how to perform it are shown. While doing the exercise, the user is provided with a real-time animated figure and audio and visual feedback. After finishing, simple charts with information about performance are presented. The physiotherapist can see the report about the user's performance in conjunction with animated figures representing user motion. Reports include statistics such as the number of repetitions, change of joint angles over time and the duration and speed of movement.

To detect user posture the body model has to be adapted and sensors calibrated to each patient. The recognition of the start of each exercise is based on a fixed threshold on the difference in joint angle values over a time window. Potential executions are used to train a Bayesian classifier to recognise the start of the exercise. To recognise current hand position during exercise execution, algorithms like Dynamic Time Warping, which measures similarity between two sequences that may vary in time and speed, or HMM are used. No evaluation of the system is presented in the paper.

#### 4.1.2.1 Analysis

The concept of the system is almost identical to SMOOTH. The system consists of two modules for use by the patient and the physiotherapists and a central server to store the data. The patient is provided with instructions and feedback about the exercises and the physiotherapist can view the patients' progress. The main difference between the platforms is in the method of movement detection. The Stroke Rehabilitation Exerciser was designed for people after stroke and its objective was to increase the efficiency of hand rehabilitation. For that reason the authors use wearable inertial sensors placed on the arm, shoulder, and torso. The target group for SMOOTH are people with PD and the objective of their rehabilitation is different. Namely, to improve balance and posture by strengthening core muscles. Wearable sensors may not be suitable for people with PD due to often reported flexibility problems [Muras et al., 2008]. Similarly, probabilistic models are used for movement detection, but their input is based on readings from one type of sensors only and their output corresponds to hand joint angles. No actual models and feature calculation methods are presented. No user evaluation of this system has been reported.

## 4.2 Posture Recognition

In our review of posture recognition systems several techniques to recognise current body posture from sensor input were identified. Body posture, called also body position, is defined as the arrangement of body parts at a particular moment in time. The systems included in the review were classified depending on the sensor input to the system. The scope of the review was on the methods used to classify general body positions such as sitting or standing. Therefore techniques that focus on a particular body part, such as hand gestures, were not included in the review.

Five types of sensor input have been identified: proximity (Section 4.2.1), force (Section 4.2.2), acceleration (Section 4.2.3), strain (Section 4.2.4), and visual data (Section 4.2.5). Systems that recognise posture on the basis of visual data are the most common. For that reason they were divided intro two subcategories: general body postures (Section 4.2.5.1) and posture recognition with a 3D model (Section 4.2.5.2). The subcategories are described in more detail in Section 4.2.5. The categories of system for posture recognition are presented in Figure 4.2.

### 4.2.1 Proximity

Quawaider et al. [Quwaider and Biswas, 2008] introduce a wearable sensor network that identifies body postures based on the relative proximity of the sensors placed on the different body parts. The authors propose a method to distinguish between postures and activities by employing acceleration sensor readings. However, the scope of the paper is on detection of two postures (*sitting* and *standing*) using the proximity of wearable sensors. To measure proximity, the received signal strength indication (RSSI), which measures the power present in a received radio signal, is used. The sensor network
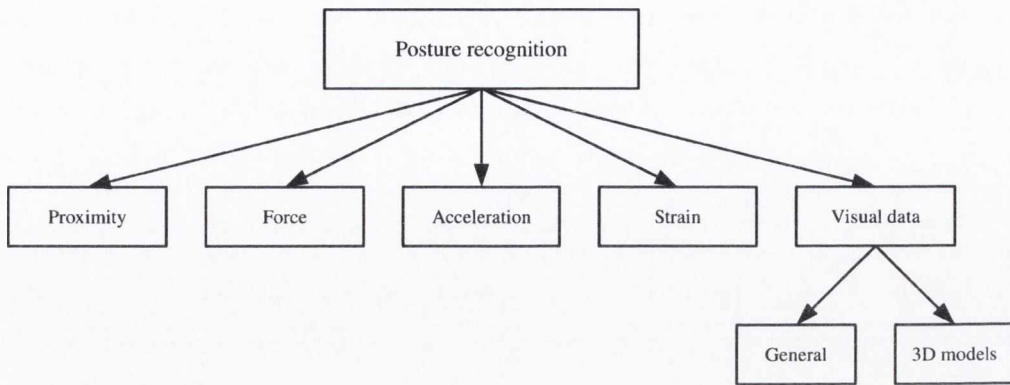
**Figure 4.2**: Categories of the systems for posture recognition

presented in the paper consists of four Mica2Dot motes [Crossbow Technology, 2009], which are modules used for enabling low-power wireless sensor networks, placed on the both the upper arms and the thighs. Each mote includes a 2-axis accelerometer and a radio transceiver.

To test recognition accuracy of sit and stand positions, data from three participants was acquired. They were asked to adopt 50 positions in a specific sequence. Initially classification of the postures was based on a set of fixed thresholds on RSSI values. However, the results revealed that the thresholds on RSSI values giving the best results were different for each participant. This means that no common, universal thresholds that would give the best results for all the participants could be set. To enable automatic adaptation to user characteristics, use of HMM was investigated. The RSSI values were transformed into a vector of binary values and used as input to the HMM. The size of the vector depended on the desirable granularity. The HMM approach obtained better results than the threshold method in all cases. Position recognition accuracy for the HMM approach varied from 88% to 94% depending on the subject.

#### 4.2.1.1   Analysis

Although this technique is interesting, the authors present results for discrimination between only two basic postures. As the authors mentioned there are several issues with the readings' accuracy. Firstly, the signal can be absorbed by garments and therefore its values can be distorted. Secondly, the accuracy of the sensor placement on the body is crucial. Therefore it might be problematic to distinguish between more similar postures using RSSI values.

### 4.2.2   Force

In [Hsia et al., 2008] a method to detect three different postures when lying on a bed is presented. The postures include *supine, lying on the left and lying on the right*. The system uses 16 long-narrow force resisting sensors (FSR [Interlink Electronics, 2009]) distributed uniformly on the upper part of a bed. The choice of sensors and its number was justified by the intention to develop a low-cost

solution as an alternative to expensive commercial alternatives. The posture recognition is conducted by a Bayesian classifier. Readings from each sensor are normalised and used in forming the feature vector $[k, s]$ which consists of two statistics: kurtosis ($k$) and skewness ($s$). Kurtosis is a measure of the variance in the readings. Skewness is a measure of the asymmetry of the readings. A Gaussian distribution is adopted to model the postures on the feature space.

To evaluate the system, data from two subjects was collected. They were asked to adopt two sets of positions. The first set consisted of lying positions with different hand position combinations (*on the body, at the body side, 45°/90° from the body*) for all three postures. The second set included a combination of hand positions (*on the body, at the body side, outstretched*) and lying angles (*parallel, 30° clockwise, 30° counterclockwise*). The results show that postures from the first set are classified with 100% precision. For the second set postures are classified with precision of 64.6%, 93.5%, 86.2% for supine, lying on the left and lying on the right, respectively. The results imply that lying angle influences the posture detection accuracy of the system.

#### 4.2.2.1 Analysis

The system presents a low-cost, unobtrusive attempt to detect lying positions. As the results suggest, the use of long sensors as well as the chosen characteristics might not be indicative enough to detect a variety of lying positions.

### 4.2.3 Acceleration

In [Harms et al., 2008] the authors present a posture and movement sensing platform (SMASH) developed to detect postures relevant to shoulder and elbow joint rehabilitation. The SMASH platform is integrated into a loose fitting long sleeve shirt. Currently the system uses 3-axial acceleration sensors placed on a person's body. A naive Bayesian classifier is used for recognition of postures. Mean acceleration values from the sensors are given as the input to the classifier and used as classification features.

To evaluate the system in terms of detection of arm postures that are appropriate for shoulder and elbow joint therapy, data from eight subjects was collected. The participants wore two 3-axis accelerometers - at the end of the sleeve and on the upper arm of the same side. The participants were asked to perform three sets of seven exercises. They included: abduction of arm, flexion/elevation of arm, rotation of arm, flexion of forearm, neck-grip, and flexion of forearm. Each exercise was divided into characteristic postures, which were recognised by the platform. In total 12 postures were identified and 288 posture samples were collected.

The system evaluation was conducted for three cases:

- *User-specific.* Learning and testing were conducted with samples from each user individually.

- *User-adapted.* Postures of all users were used for learning and testing.

- *User-independent.* Testing was conducted with samples from users that were not included in the learning set.

The overall accuracy of the system was 95% for user-specific, 94% for user-adapted, and 89% for user-independent tests. The user-specific learning performs the best, which is not surprising. The interesting observation is that the differences are not very big.

#### 4.2.3.1 Analysis

The authors have shown an approach to distinguishing between twelve upper-body postures using the readings from two accelerometers placed on one limb. The characteristic positions of seven exercises were chosen. On the basis of recognition of a sequence of positions, whether a repetition of a particular exercise occurred could be detected. Because the approach does not classify actual movement it might not be sufficient accurate to measure exercise performance. An additional problem is the automatic extraction of the postures from the data stream. The integration of the platform and shirt seems to be a good idea. This solution limits inconvenience in sensor placement.

### 4.2.4 Strain

Another garment equipped with sensors is introduced by Mattmann et al. [Mattmann et al., 2007]. It consists of strain sensors to detect 27 upper body postures. The strain sensors were developed by EMPA, Switzerland [EMPA, 2009]. Each sensor thread is of 0.3 mm diameter and its resistance linearly varies with strain. Twenty-one 2cm strain sensors were attached to the back of a commercially available catsuit using silicone film. A naive Bayes classifier was used to discriminate between the positions. The feature vector consists of 21 normalised strain sensor values. The values are normalised by subtraction of the mean value of all the sensors when in a base posture.

The system was tested on data from eight male participants. They were asked to perform each posture three times. Two sets of 27 postures were obtained from each participant. Similar to [Harms et al., 2008] three types of tests were conducted. 5-fold cross validation is used to split testing and training data. The system obtains overall accuracy of 97% for user-specific, 84% for user-adapted, and 65% for user-independent tests. As results show, the system achieves better outcomes for user specific training than for more general training.

#### 4.2.4.1 Analysis

The approach is similar to the one presented in [Harms et al., 2008]. The main difference is in the type of sensors used. The strain sensors require integration with a very tight garment. Apart from that limitation, a high recognition accuracy for user-specific training was obtained. This suggests that strain sensors might be usable for classification of even very similar upper body postures. Lower accuracy for user-independent tests suggests that position patterns differ for each user and user-specific training should be promoted.

### 4.2.5 Visual data

Recognition of posture from visual data is the most commonly reported method. These systems are classified into two categories. The first category consists of systems that use image characteristics to recognise general postures such as sitting or standing. The second category includes systems that use models of the human body to recognise body postures.

#### 4.2.5.1 General body postures

Spagnolo et al. [Spagnolo et al., 2003a, Spagnolo et al., 2003b] present an algorithm to detect three postures (*standing, bent,* and *squatted*) using data obtained from a camera. The system consists of two modules: human silhouette detection and posture recognition. To detect the human figure in a video sequence an adaptive background subtraction algorithm [Kanade et al., 1998] and shadow removal technique [P. Spagnolo and Distante, 2002] are utilised. Adaptive background subtraction methods are used for foreground object detection and are usually based on a pixel-based statistical model that is used for modelling the background and each pixel is updated on-line to adjust to background changes [Luo et al., 2007]. The authors propose histograms of horizontal and vertical projection as features used to clearly separate one posture from the other. The vertical projection is the sum of all of the rows, and the horizontal projection is the same operation applied to the columns. The histograms are used as an input to clustering algorithm in order to recognise the postures. The metric that is used for the clustering algorithm is based on Manhattan distance due to its fast computation. The evaluation of the system was conducted for a basic competitive learning algorithm [Theodoridis and Koutroumbas, 2006]. To evaluate the system 834 images of three postures (standing - 501, bent - 218, and squatted - 115) were collected. The images were taken outside the laboratory. The results show that the differences in posture detection for a different number of learning samples are small. Overall recognition rate is above 90% and is higher for differentiating between two postures rather than three, which is not surprising.

Buccolieri et al. [Buccolieri et al., 2005] describe a system that detects three body postures: *stand, bend,* and *squat.* Grey-level images are used as input to the system. The system consists of the following sequential units: data acquisition, motion detection, feature extraction, and postures classification. An ANN classifier with the radial basis function is employed in the system to recognise the postures. A radial basis function is a function whose value depends only on the distance from the origin. Three image features are used as the input to the classifier. The feature extraction consists of two levels of segmentation. Low-level segmentation is responsible for the initial evaluation of active contour (object outline) parameters and high-level segmentation for active contour calculation. The active contour calculation is based on the GVF-Snake approach presented in [Xu and Prince, 1998]. For evaluation purposes sequences of 500 images for standing, 220 for bending, and 110 for squatting were obtained. They were collected indoors and outdoors. The posture recognition rates for all three types of features are similar and are in the range between 92% and 97%.

A system that recognises four different human postures is presented in [Girondel et al., 2005b, Girondel et al., 2005a]. The postures recognised are: *standing, sitting, squatting,* and *lying.* The system consists of two threshold models that describe each posture in relation to the normalised distance between different parts of the human body. To detect body position the 'believe distribution', which is the orthogonal sum of two models, has to be calculated. To evaluate the system data from six people was obtained. 10 postures recorded for each participant were used in training the system. An overall accuracy of 88% is obtained for training data. For testing, data from six other people was collected. They were asked to perform seven postures. They could do them in more relaxed way, i.e., move their arms. The recognition accuracy for standing and lying is close to 100%. The body position confused the most is squatting with 44-70% detection rate. The overall recognition accuracy is equal to 81%.

Cucchiara et al. [Cucchiara et al., 2005] also introduce a probabilistic framework for detection of four basic postures: *standing, sitting, lying,* and *crouching.* The postures are divided into three view-based classes and therefore in fact 12 postures are classified by the system. The approach consists of two stages: posture classification performed frame-by-frame and 'temporally integrated' posture classification. A human silhouette (blob) is extracted from a video sequence using the SAKBOT system [Cucchiara et al., 2001, Cucchiara et al., 2003] and its projection onto the principal axes is computed and normalised. The projection is used in a machine-learning algorithm to create probabilistic projection maps (PPM). The PPMs are used by a Bayesian classifier to detect the postures. In the second stage a state transition graph (STG) is created to express probabilities for inter-state transitions and add temporal relationships between postures. The evaluation results show that user-specific training obtains better results than generic training. Recognition accuracy was tested for a Bayesian classifier with and without STG. The approach using time dependency (STG) achieved better position recognition accuracy of 97%.

Wang [Wang, 2006] introduces an algorithm for posture detection based on a video sequence from a camera. Three postures are recognised by the system: *sitting, standing,* and *lying.* The algorithm uses features calculated on a blob representing the human silhouette extracted from the video sequence. The features used in position recognition include: inner distance shape context (IDSC), fitted eclipse (FE), and projection histogram (PH). Their details are described in the paper. For posture detection a k-Nearest Neighbour(k-NN) classifier is used. Experiments were conducted with the data obtained from one participant for three viewing angles. During collection of data used for system training, not many variations from the three basic postures were allowed. During collection of data used for recognition accuracy testing, the subject could move more freely and change their position, e.g., move their limbs. To evaluate the approach video sequences in different scenes, clothes and random views were collected. A total of 23028 samples was collected. The tests of posture classification accuracy were conducted for each feature individually and a method proposed by the authors for feature fusion. The fusion was based on majority voting. The classification results were similar for all the features

tested individually and the worst accuracy was obtained by IDSC (78-100%). The best results were obtained by the fusion method (94-100%).

Juang and Chang [Juang and Chang, 2007] introduce a body posture classification method based on a fuzzy artificial neural network (ANN). Their system recognises four body postures: *standing, bending, sitting,* and *lying.* The fuzzy ANN used to recognise the positions is called SONFIN and is described in more detail in [Juang and Lin, 1998]. The feature vector, which represents body silhouette features, consists of silhouette length width ratio as well as discrete Fourier transform (DFT) coefficients. The body silhouette, given as the input of the system, is extracted from video using the method described in [Chien et al., 2002]. The choice of frequency domain allows the avoidance of problems with silhouette size (scaling) and its position (shifting) in the picture. Therefore normalised magnitudes of 20 of the most significant DFT coefficients calculated on horizontal and vertical projection histograms are included in the feature vector. To evaluate the system 20 samples for each posture were obtained. They were used for training of the SONFIN classifier. For testing, 100 additional samples for each posture were obtained. An overall recognition accuracy of 98% is reached. Another experiment revealed that for 10 training samples per posture the overall accuracy is 89%. The results show that the lower number of learning samples lowers the system accuracy.

**Analysis**  A summary of the systems used for general body posture detection from visual data presented above is shown in Table 4.2. The systems were summarised according to the number of postures recognised, the technique used for posture recognition, and the number of samples used in evaluation of system.

| Reference | Number of postures | Recognition technique | Total number of samples |
|---|---|---|---|
| [Spagnolo et al., 2003a, Spagnolo et al., 2003b] | 3 | Clustering | 834 |
| [Buccolieri et al., 2005] | 3 | ANN | 830 |
| [Girondel et al., 2005b, Girondel et al., 2005a] | 4 | Rule-based; belief distribution | ? |
| [Cucchiara et al., 2005] | 4 | Bayesian network | ? |
| [Wang, 2006] | 3 | k-NN | 23028 |
| [Juang and Chang, 2007] | 4 | Fuzzy ANN | 480 |

**Table 4.2**: Summary of systems for recognition of general body posture

The systems presented above distinguish between only three or four very different primitive postures. Even though some approaches obtained reasonably high detection accuracy, the precision of the approaches to distinguish between similar postures might not be sufficient for SMOOTH. Different methods are utilised for posture recognition. In

[Wang, 2006, Spagnolo et al., 2003a, Spagnolo et al., 2003b] clustering algorithms are used to separate postures on the basis of metrics calculated on the human silhouette extracted from the image. Neural networks are employed by [Buccolieri et al., 2005, Juang and Chang, 2007] and probability theory is used as base concept in [Cucchiara et al., 2005, Girondel et al., 2005b, Girondel et al., 2005a]. Several issues are identified by the authors. Using spatial features, which quantify the spatial pattern of visual data, is sensitive to the position and size of the human silhouette extracted from image. For example, the distance of the person from a camera makes a difference. Therefore the frequency domain, which represents the spectrum of the signal, and normalisation can be utilised to overcome this issue. Human silhouette extraction could also be complex and sensitive to various conditions, e.g., illumination. The person's orientation with respect to the camera is important. Depending on the viewing angle metrics could change significantly and detection accuracy could decrease. It is hard to determine which approach obtained the best results because the evaluation procedures and the number of the samples collected varied for each method.

#### 4.2.5.2 Posture recognition with 3D human model

Pellegrini et al. [Pellegrini and Iocchi, 2008] introduce a system to recognise human postures by matching them to 3D models of the human body. The system detects five different postures: *up, sit, bend, knee,* and *laid.* It consists of two modules: people localisation and tracking (PLT) and person posture recognition (PPR). The purpose of the PLT module is to extract the human silhouette and track it over time. To achieve this goal methods such as background subtraction or Kalman filters [Haykin, 2001] are used. The purpose of the PPR model is to track particular points of the human body, and classify postures using the 3D model of the human silhouette. The authors defined three principal points of the human body: head, pelvis, and the point at which the feet make contact with the floor. They are used to compute a feature vector that includes the angles of 4 joints and the person's height. Two different classifiers for posture discrimination were tested: maximum likelihood, and HMMs. The HMM takes into account the probability of the transition between postures. Probabilities for transitions between postures in the HMM were set empirically. To evaluate the system, data from seven subjects was collected. They were recorded using a stereo camera placed 3 meters above the ground. 26 video sequences were collected in total. The results suggest that the HMM classifier obtains better detection accuracy (86%-100%) than maximum likelihood (78%-100%).

An approach based on a 3D human model is also presented in Boulay et al. [Boulay et al., 2005]. The framework combines 2D methods with a 3D model in order to make recognition independent of the camera viewpoint. The system classifies four postures: *standing, sitting, bending,* and *lying.* To classify a set of postures 3D models for each of those postures have to be created. To describe human posture, the 3D model defined in [Vosinakis and Panayiotopoulos, 2001] is utilised. The model uses 9 joints to describe body postures: abdomen (1), shoulders (2), elbows (2), hips (2), and knees (2). On that basis, a set of 27 features (3 Euler angles for each joint) is defined to describe every posture

being recognised. The horizontal and vertical projection of 3D models generated for all possible angles and the human silhouette are calculated and used as model postures. The body position to be recognised is compared to them and classified as a model posture with the minimum distance. The system evaluation involved over 600 samples for four different postures collected in an office by a single camera. The results showed that the recognition accuracy for standing, sitting, bending, and lying was 96%, 86%, 95%, 98%, respectively. In [Boulay et al., 2006] the authors reduced the number of features from 27 to 23. The classification results for standing and sitting did not change whereas for bending and lying they dropped to 87% and 92%, respectively.

**Analysis** The approach to fit the human silhouette detected on a video sequence to a 3D model works well in differentiating between very distinct postures. Both models utilise the set of joint angles for human posture description. No systems that use 3D models to recognise more similar postures, e.g., sitting and sitting leaned forward were found. In that case, matching a human silhouette with the model could be much more challenging. For example, data from more than one camera might be needed to obtain desirable accuracy. That could lead to the setup of the system being impractical and requiring a designated space.

## 4.3 Activity Recognition

This section presents a review of approaches to recognising human activities from sensor readings. Systems that recognise activities cover many areas such as people tracking or detection of activities of daily living based on current location or objects currently used. Therefore only systems that allow the recognition of activities related to body movement, e.g., cycling or walking up the stairs, and changes in body position, e.g., standing up, are included in the review. The review is focused on discrimination between different activities, e.g., between walking and running, rather than analysis of one particular activity, e.g., length of steps while walking. Many systems included in this section, in addition to activity recognition, recognise postures. One difference between the systems included in this section and the previous section (posture recognition) is the method of calculation of sensor signal features. In activity recognition the features are usually calculated over a number of samples to differentiate between activities, whereas in the previous section they are calculated over sensor readings at a particular point.

Three types of sensor input have been identified: acceleration (Section 4.3.1), force (Section 4.3.2), and combinations of different readings (Section 4.3.3). The systems that recognise activity on the basis of acceleration are the most common group. For that reason they were divided intro four subcategories: postures and activities (Section 4.3.1.1), postures and transitions (Section 4.3.1.2), periodic activities (Section 4.3.1.3), and activities of daily living (Section 4.3.1.4). The subcategories are described in more detail in Section 4.3.1. The categories of the systems for activity recognition are presented in Figure 4.3.
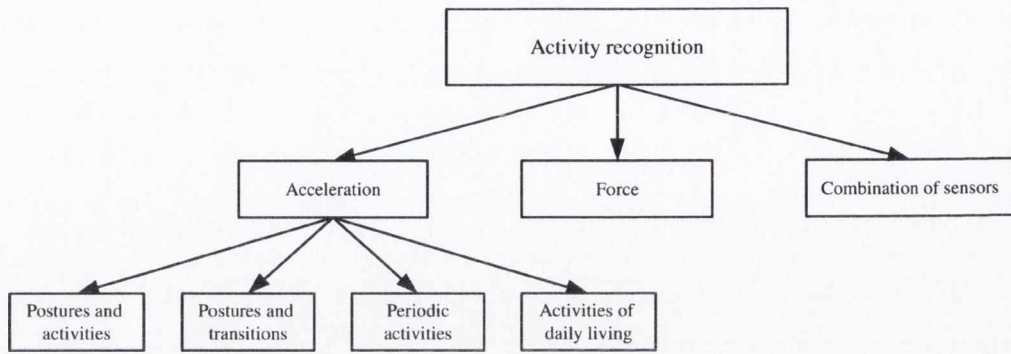
**Figure 4.3**: Categories of the systems for activity recognition

## 4.3.1 Acceleration

The use of wearable accelerometers is the most common sensing technique for activity detection. Acceleration allows the measurement of direction and speed of movement and miniaturisation of accelerometers allows them to be embedded into wearable items, e.g., bands or bracelets, and place them on different parts of body. That enables measurement of movement of the body parts which are related to the activity that is being performed. Some of the systems included in this section in addition to signals from acceleration sensors also use signals from gyroscopes, which measure orientation, and magnetometers, which measure the strength and/or direction of a magnetic field. Both of those measurements were used to calculate the orientation of the device, which can also be calculated from the acceleration signal.

This review has identified four general categories of systems that use data from acceleration sensors to recognise activities. The postures and activities category (Section 4.3.1.1) includes systems that differentiate between activities related to body movement, e.g., walking or running, and body postures, e.g., standing or sitting. A second category (Section 4.3.1.2) includes systems that recognise body positions, e.g., sitting or standing, and transitions between them, e.g., standing up. They might also include other activities related to body movement, e.g., falling. The two remaining categories include systems that recognise a number of periodic activities (Section 4.3.1.3), e.g., walking or ridding a bicycle, and activities of daily living (Section 4.3.1.4) such as watching television or fixing a car. Periodic activities are defined as continuously repeated sequences of movements.

### 4.3.1.1 Postures and activities

Most of the work in recognising basic posture and movement is based on the use of fixed thresholds and decision trees. Bussmann et al. [Bussmann et al., 1998] present an activity monitor (AM) that can recognise three postures: *standing, lying, sitting*, and *movement* in general. To recognise movement the system uses signals from four uni-axial accelerometers, which are placed on the upper part of both legs and the sternum. Fixed thresholds on differences in changes of acceleration are employed to distinguish between postures and movement. Fixed thresholds on acceleration values are employed

to distinguish between postures. The data collection to evaluate the system was divided into a spontaneous and standardised protocol. In the spontaneous protocol subjects performed activities of their choice for four hours in one room. In the standardised protocol the participants were asked to perform a predefined sequence of activities. In total 273 postures and movements were collected from three subjects. The overall recognition accuracy was 88% for the spontaneous protocol and 96% for the standardised one.

Another system for mobility monitoring is presented by Lyons et al. [Lyons et al., 2005]. It distinguishes between three basic postures: *sitting, standing,* and *lying* and *movement* in general. The system consists of two 2-axis accelerometers placed on the thigh and trunk. It recognises postures and movement based on a fixed threshold for the standard deviation of the accelerometer signal calculated over a 1-second window. If the activity is a body position, it can be identified depending on trunk and thigh angles. The angles are derived from the mean acceleration value calculated over the time window. To test the approach over 29 hours of data from one person was collected. The results show that overall recognition accuracy was in the range of 84%-95% for postures and equal to 97% for discriminating between movement and postures.

The systems described above distinguish between postures and movement in general, however they do not distinguish between different types of movement, e.g., walking or running. In [Jeong et al., 2007] the authors present a small, low-power activity monitoring system. The system differentiates between two postures (*standing/sitting, lying*) and three activities (*falling, running, walking*). It uses a signal from one 3-axis accelerometer placed on the waist. The algorithm uses a set of empirically-established thresholds for differential signal vector magnitude (DSVM) and current values of acceleration to recognise different postures and activities. DSVM is calculated according to the equation:

$$DSVM = \frac{1}{t}(\int_0^t (|\sum \sqrt{x_i^2 + y_i^2 + z_i^2}|)dt)$$

where $x, y, z$ are values of acceleration in three orthogonal (perpendicular) directions. To validate the system 100 samples were collected. The system obtained very high accuracy - above 96% for every posture/activity.

Ermes et al. [Ermes et al., 2008a] present a system that distinguishes between five postures/activities: *lying, sitting/standing, walking, running* and *cycling*. The system also uses a single 3-axis accelerometer but the accelerometer is placed on the trunk. A decision tree classifier is used to discriminate between the activities due to its simple implementation and low computational requirements. The time and frequency domain features of the sensor signal are used as input to the classifier. Time domain features describe signal changes over time and frequency domain features describe the spectrum of signal - the intensity of its frequency. The features are calculated every second over a sliding time window. The features include: frequency of the highest peak, spectral entropy (measurement of the disorder of signal spectrum), average value of signal, and its variance. To evaluate the approach at least 5 minutes of each activity was recorded for three subjects. 118 minutes of labelled activities were collected in total. The system reaches an average accuracy of 94%.

The most misclassified activities are walking and running for one of the subjects. This result could be caused by an inappropriate variance threshold for discrimination between those activities. The authors plan to use more sophisticated methods for thresholds establishment in the future.

A larger number of sensors are used in the study of activity and posture detection presented in [Foerster et al., 1999]. The system consists of four piezoresistive uni-axial accelerometers placed on four different locations on the participant's body: sternum, wrist, thigh, and lower leg. The frequency of changes in acceleration signal, which is calculated on data segments longer than 20s, as well as acceleration values are used to distinguish between the activities. Values are compared to values of model activities and the sample is classified as the activity from which the signal has the smallest difference. For the system evaluation 24 male university students were recruited. They were asked to perform nine of the following model postures/activities in the laboratory environment: *sitting, standing, lying supine, sitting and talking, sitting and operating a PC keyboard, walking, walking up stairs, walking down stairs,* and *cycling*. In addition, each participant spent about 50 minutes performing various postures/activities outside the laboratory. The results show that the overall misclassification of nine postures/activities performed in the laboratory environment was 4%. For postures/activities performed outside the laboratory misclassification was 33%. Problems in classification were mainly caused by the similarity of some postures/activities. For that reason some postures/activities were combined in the five following classes: *lying, sitting, standing, walking,* and *cycling*. Average misclassification of each class for the data collected outside the laboratory improved to 5%. After elimination of all data segments shorter than 40 seconds, which means that features were calculated over a sliding time window no shorter than 40 seconds, the average number of misclassified samples was 19% for nine activity classes and 5% for five. The test shows that classification results improved for longer data segments and smaller numbers of activity classes. The latter, according to the authors, may suggest that the number of sensors or signal features may not have been sufficient to distinguish between the initial set of postures/activities.

In [Foerster and Fahrenberg, 2000] the authors present a further investigation of the correlation between numbers of sensors placed on the body and the accuracy of activity recognition. Methods similar to those reported in [Foerster et al., 1999] are employed. Five uni-axial acceleration sensors for data collection are used. The study was conducted to distinguish between 13 postures/activities: 4 types of *sitting, standing,* 4 types of *lying,* 2 types of *walking, walking up and down stairs,* and *cycling*. A tree classifier is used to discriminate between postures/activities on the basis of the frequency of signal changes from different sensors. 31 participants were recruited in the study. They were asked to perform 3 repetitions of each of 13 postures/activities. The overall accuracy for the data obtained from the 5 sensors was 97%. Further tests were conducted for data obtained from two sensors, placed on sternum and thigh, and the activities were grouped into four categories: *sitting, standing, lying,* and *moving* in general. The overall recognition accuracy of each category was 99%.

More sophisticated mechanisms than fixed thresholds or decision tree classifiers have also been used

in posture and activity recognition. Wu et al. [Wu et al., 2007] describe a sensor network activity monitoring system (SAMS). The system recognises everyday activities performed in an apartment. They include 3 postures (*sitting, standing, and lying*) and 4 activities (*walking, ascending/descending stairs, swinging legs, and tapping the foot to the ground*). SAMS utilises signals from a 2-axis accelerometer to detect the activities. The activity recognition is divided into two levels. At the first level joint flexion angles are extracted from the acceleration signal using an extended Kalman filter [Haykin, 2001]. At the second level the flexion angles are used to recognise activities. Postures are categorised on the basis of thresholds for particular flexion angles. To distinguish between periodic activities, a set of HMMs corresponding to body segments is employed. The number of hidden states in a HMM applied in SAMS depends on the complexity of activity and was set empirically. The probability density function of transitions between states in the HMM is modelled as a Gaussian distribution. To validate the system seven wearable sensors were placed on one participant. The subject was monitored during the performance of activities in an apartment. The recognition accuracy of postures was 100% and activities was 93%.

In [Khan et al., 2008] authors present a framework of human activity recognition (HAR). HAR recognises four activities: *lying, standing, walking,* and *running*. It utilises a signal from one 3-axis acceleration sensor attached to the chest. Signal features correspond to the coefficients of autoregressive (AR) model. AR models are used in time series analysis to describe stationary time series. The feature vector consists of nine acceleration coefficients (3 AR coefficients for each acceleration axis) and can be augmented by two additional acceleration characteristics: magnitude of acceleration signal oscillations and tilt of the trunk. An ANN model is employed for the classification of activities. To evaluate the system data from seven healthy subjects was obtained. Training and testing samples are selected at random. The ANN is trained with 15 samples and tested for 35. The approach obtains overall accuracy between 59%-64% for a feature vector consisting only of AR coefficients. The accuracy improves to 99% when the two additional characteristics are added.

A framework based on several machine learning techniques is presented in [Thiemjarus and Yang, 2007]. The framework recognises 11 activities: *sitting (chair), standing, steps, sitting (floor), demi-plie, galloping left, skipping, galloping right, side kick, front kick,* and *walking*. It utilises four 2-axis accelerometers placed on ankles and legs to obtain the input signal. The framework reduces the number of features needed to detect particular activities by using an elimination algorithm and redundancy measure proposed by the authors. To validate the framework a 7-minute sequence of 11 activities from a single subject was acquired. The feature vector was calculated over a 2-second sliding window and consisted of 16 features: raw signals from all the sensors and the corresponding signal energy. 20% of the data was used to train the classifier and the rest to test it. Two types of classifiers were tested: an 11-state naive Bayes classifier and a corresponding multiple binary decision model. The overall recognition rate for both models was 77%. After the application of the elimination algorithm and the redundancy measure on binary decision variables the accuracy dropped to 73% for

9 features in the input vector.

**Analysis**    A summary of the systems used for posture and activity recognition from acceleration data presented above is shown in Table 4.3. The systems were summarised according to the number of accelerometers used to obtain data, the number of postures or activities recognised, the technique used for the recognition, and number of subjects used in evaluation of system.

| Reference | Number of accelerome-ters | Number of activities or postures | Recognition technique | Number of subjects |
|---|---|---|---|---|
| [Bussmann et al., 1998] | 4 uni-axial | 4 | Rule-based | 3 |
| [Lyons et al., 2005] | 2 2-axis | 4 | Rule-based | 1 |
| [Jeong et al., 2007] | 1 3-axis | 5 | Rule-based | ? |
| [Ermes et al., 2008a] | 1 3-axis | 5 | Decision tree | 3 |
| [Foerster et al., 1999] | 4 uni-axial | 9, 5 | Comparison to model postures/activities | 24 |
| [Foerster and Fahrenberg, 2000] | 5 and 2 uni-axial | 13, 4 | Decision tree | 31 |
| [Wu et al., 2007] | 1 2-axis | 7 | Rule-based; HMM | 1 |
| [Khan et al., 2008] | 1 3-axis | 4 | ANN | 7 |
| [Thiemjarus and Yang, 2007] | 4 2-axis | 11 | Bayesian network; multiple binary decision models | 1 |

**Table 4.3**: Summary of systems for recognition of postures and activities

The systems presented above used accelerometers placed on the body and are mainly based on fixed thresholds on acceleration metrics to distinguish between postures and activities. Even though the results suggest that this approach works well to differentiate between postures and movement in general, its application to certain movements, e.g., walking and running, is not optimal. One reason for this may can be that movement patterns vary for different individuals [de Leon and Sucar, 2002]. For example, one person can normally walk faster than another. To detect postures, tilt angles calculated from acceleration values are mainly employed. This solution obtains reasonable results for very different postures, e.g., sitting and lying, but as suggested, for more similar postures more sophisticated methods than fixed thresholds should be used. The number of sensors employed in the reported approaches is relatively small and for that reason the recognised activities and postures are coarse-grained. The results suggest that system accuracy may decrease as the number of activities it is required to distinguish increases.

**4.3.1.2 Postures and transitions**

As for posture and activity recognition, many of the approaches presented in this section are based on decision trees and thresholds set on the parameters of the acceleration signal. The common choice of decision trees as the classifier could be explained by their flexibility and simplicity. In [Najafi et al., 2003] the authors present a system that utilises one kinematic sensor, consisting of a gyroscope and a 2-axis accelerometer, attached to the chest to detect body postures and transitions between them. The study is based on the experiments and findings described in [Najafi et al., 2000]. The system detects the following postures *lying, walking, standing*, and *sitting* as well as postural transitions: *sit-to-lying, lying-to-sit, sit-to-stand*, and *stand-to-sit*. To detect activities a decision tree classifier is used. In the first step the data obtained from the sensors is segmented into 1 minute blocks, which are used to calculate a set of discrete wavelet transforms (DWTs) and trunk vertical displacements. In the second step the signal from different frequency ranges is reconstructed from a DWT. The recognition of current activity or posture is made on the basis of fixed thresholds on signal characteristics reconstructed from the DWT. Three types of tests were conducted to evaluate the system. In the first study 11 elderly subjects were asked to perform six different sequences consisting of the activities to be recognised. Overall specificity and sensitivity is in the range of 82%-100%. The recognition sensitivity is defined as the number of samples that are recognised properly divided by the number of samples that are recognised properly and the number of samples that are not recognised and should be. The recognition specificity is defined as a number of samples that are recognised and should not be divided by the number of samples that are recognised and should not be and a number of samples that are not recognised properly. In the second study 24 elderly persons were asked to change their body position in bed. For 144 postural transitions, and 30 transfers out of bed there was no detection error. In the third study, 45-60 minutes of daily activities were recorded from nine elderly subjects. Recognition accuracy over 90% was obtained.

Another framework for the classification of postures and movements is presented by Mathie et al. [Mathie et al., 2004]. The work is based on previous findings presented in [Mathie et al., 2002, Mathie et al., 2003]. The framework uses a signal from one waist-mounted 3-axis accelerometer to differentiate between 12 activities: *sit-to-stand, stand-to-sit, other movement, upright-to-lying, lying-to-lying, lying-to-upright, sitting, standing, lying face down, lying on back, lying on left side*, and *lying on right side*. Activity recognition is based on a binary decision tree. The binary decision tree consists of a number of decision and conclusion nodes. Conclusion nodes, which represent possible outputs, can be reached via a set of binary (yes/no) decision nodes. Decision nodes in the binary decision tree were established individually and included fixed thresholds, pattern matching and expert systems. To evaluate the system 1309 movement sequences from 26 subjects were collected. The participants were asked to perform a sequence of the following activities in a controlled environment: stand, lie supine, lie left side, lie face down, lie right side, stand, sit, stand, walk along a level corridor, stand, sit, stand, walk up a flight of stairs, walk down a flight of stairs, stand, sit, stand, walk along a level corridor,

and stand. Sensitivity and specificity of overall recognition accuracy was 98% and 99%, respectively.

A system for monitoring older people is introduced by Allen et al. [Allen et al., 2006]. The system recognises 8 activities: *standing, sitting, lying, stand-to-sit, sit-to-stand, stand-to-lie, lie-to-stand*, and *walking*. The input signal for the system is obtained from one 3-axis accelerometer placed on the waist and sampled at 45 Hz. The system is based on a Gaussian mixture model (GMM). A GMM is a probabilistic model for density estimation using a combination of mixtures, which are in fact Gaussian density functions. It can be used in unsupervised learning or clustering. For each activity a separate GMM, consisting of 32 mixtures, is trained using an expectation maximisation (EM) algorithm. To ensure adaptation to movement variation, the GMM can be trained using large numbers of samples from multiple users. The model can be adjusted to individual movement patterns using adaptive training based on Bayes methods (Bayesian adaptation) and user-specific data. The input vector to the GMM consists of 25 features calculated on acceleration values. To enable the recognition of short activities no frequency-domain features, which describe signal with respect to its frequency, are included in the vector. The evaluation of the approach was conducted on the data from six healthy, elderly subjects. The subjects were asked to perform the sequence of tasks consisting of 8 activities on a daily basis. On average each subject collected 340 instances of each activity or posture. 60% of the randomly chosen data is used to train and 40% to test the classifier. The results are compared to a decision tree classifier described in [Mathie et al., 2004]. The outcomes demonstrate overall 20% accuracy improvement. Further tests were conducted to investigate the effect of the system adaptation to the user characteristics. The average accuracy for subject-specific training of GMM (data of one subject used to train and test the classifier), subject-independent training of GMM (data of all the subjects but one used to train the classifier and tested for the subject not included in the training set) and GMM adjusted to subject characteristics by Bayesian adaptation was 88%, 77% and 92%, respectively.

One waist-mounted 3-axis accelerometer is also used in a real-time system to recognise postures and activities presented in [Karantonis et al., 2006]. The system recognises 12 activities: *sit-to-stand, stand-to-sit, lying, lying-to-sit, sit-to-lying*, three types of *walking*, three types of *falling*, and *circuit* (*sit-to-stand, walking, stand-to-sit, sit-to-lying, lying, lying-to-sit, sit-to-stand, walking, stand-to-sit*). The recognition of the activity is made by a decision tree classifier on the basis of fixed thresholds on the magnitude of signal oscillations and trunk tilt angle. To test the recognition accuracy, data from six healthy subjects was analysed. Each of them performed a set of 12 tasks. The data was logged with a frequency of 45 Hz. The overall detection accuracy was approximately 91%. The lowest accuracy was obtained for walking 83%.

In [Nyan et al., 2006] the authors present a system for activity detection using one 3-axis accelerometer integrated in the shoulder of a garment. The placement of the sensor and its integration with a garment is motivated by user comfort and safety. The system detects six following activities: *sit-stand, stand-sit, lie-sit, sit-lie, stairs up*, and *stairs down*. The recognition of the activities is based

on a decision tree classifier. The distinction between activities is done on the basis of fixed thresholds on acceleration values or characteristics related to a DWT. The DWT used in the system is calculated over a 7-second window. To evaluate the approach approximately 5 hours of data from each of six subjects recruited for the study was collected. The sensitivity and specificity for 1495 activity samples was 95% and 99%, respectively.

Yang et al. [Yang and Hsu, 2007] introduce an algorithm for real-time activity detection that uses data obtained from a wearable 3-axis accelerometer attached at belt level. Data are acquired with a frequency of 60 Hz. The activities detected by the system include three postures (*sitting, standing, lying*), four postural transitions (*sit-to-stand, stand-to-sit, lie-to-sit, sit-to-lie*) and *falls*. The recognition of postures and activities is done on the basis of thresholds set on acceleration values. Postures are recognised on the basis of tilt calculated over 0.5s window. The activities are recognised by a slope mapping technique, which maps data series into a binary sequence, applied in a 2.5s window. To evaluate the algorithm 10 subjects were recruited. They were asked to perform 5 activities: lying, sit-to-stand, stand-to-sit, sit-to-lie, lie-to-sit, and walking. The algorithm achieved recognition accuracy above 90%. The misinterpreted activities could be as a result of variations in the performance of a particular activity by one person as well as differences between activity performance among different people.

Salarian et al. [Salarian et al., 2007] describe a system to distinguish between four activities: *sitting, standing, lying*, and *walking* and two postural transitions *sit-to-stand* and *stand-to-sit*. The system is designed to work for healthy subjects and people with PD. The system uses three kinematic sensors. One sensor consisting of a gyroscope and a 2-axis accelerometer is placed on the trunk. Two gyroscopes are placed on two shins. The first step in signal processing is filtering to remove tremor, which is one of the symptoms in PD. To differentiate between postural transitions and activities a set of features such as the duration of a transition, the minimal value of the tilt of the trunk, and the range of the tilt is calculated. Those features are used to train two statistical classifiers. The first classifier is used to assign the probability of being in transition. The second one is used to discriminate between sit-to-stand and stand-to-sit transitions. To differentiate between sitting and standing periods a set of fuzzy rules was established. To evaluate the system, tests with 10 PD patients and 10 healthy subjects were conducted. 232 samples of various activities were collected from subjects with PD and 272 from control subjects. The recognition sensitivity of the activities obtained for people with PD is slightly worse than for control subjects 83%-99% and 96%-100%, respectively. The recognition specificity of the activities obtained for people with PD is almost the same for control subjects 97%-100% and 98%-100%, respectively. For postural transitions recognition sensitivity is 95% for control subjects and 84% for PD patients.

In contrast to simple decision trees more sophisticated methods for activity recognition can be used. Song et al. [kwang Song et al., 2008] present an activity recognition system to detect the daily activities of older adults using ANNs. The system recognises nine activities: *sit-to-stand, stand-to-*

*sit, lying, lying-to-stand, stand-to-lying, walking, running, sitting*, and four types of *falls*. It uses the signal from a 3-axis accelerometer placed on the waist. To recognise activities a multi-layer perceptron learnt by a back-propagation algorithm is employed. The input vector to the classifier includes 14 feature vectors. Each feature vector consists of a number of features that represent the acceleration signal. The features include acceleration and tilt values and are acquired during a 1 second period. To validate the method a total number of 5773 samples was collected from seven subjects. The overall activity recognition accuracy was 95%.

**Analysis**  A summary of the systems used for posture and transition recognition from acceleration data presented above is shown in Table 4.4. The systems were summarised according to the number of accelerometers used, the number of postures or activities recognised, the technique used for posture or activity recognition, and the number of subjects used in evaluation of system.

| Reference | Number of accelerometers | Number of activities or postures | Recognition technique | Number of subjects |
|---|---|---|---|---|
| [Najafi et al., 2003] | 1 unit (1 gyroscope; 1 2-axis accelerometer) | 8 | Decision tree | 11, 24, and 9 |
| [Mathie et al., 2004] | 1 3-axis | 12 | Decision tree | 26 |
| [Allen et al., 2006] | 1 3-axis | 8 | GMM | 6 |
| [Karantonis et al., 2006] | 1 3-axis | 12 | Decision tree | 6 |
| [Nyan et al., 2006] | 1 3-axis | 6 | Decision tree | 6 |
| [Yang and Hsu, 2007] | 1 3-axis | 8 | Rule-based | 10 |
| [Salarian et al., 2007] | 3 units (3 gyroscopes; 1 2-axis accelerometer) | 4 | Set of fuzzy rules; statistical classifiers | 20 |
| [kwang Song et al., 2008] | 1 3-axis | 9 | ANN | 7 |

**Table 4.4**: Summary of systems for recognition of postures and transitions

Most of the approaches use decision tree or rule-based models to recognise activities. The models usually involve manual adjustment of parameters. More automated approaches presented in this section are based on artificial intelligence, wavelet transformation, and probability theory. The wavelet transformation is very time consuming and for that reason is not suitable for real-time or near real-time systems. As suggested in [Allen et al., 2006], other features calculated in the frequency domain like Fourier transform are not suitable for short, non-periodic activity detection. The activities recognised by the systems include principal body positions as well as transitions between them. The number and type of activities as well as the evaluation protocols varied between the approaches therefore the

results can not be compared. However, the accuracy obtained by all the systems is usually over 90%, which is reasonably good. To evaluate some of the work the data was collected outside a controlled setting. The recognition accuracy for such data was lower, but its level was still acceptable.

### 4.3.1.3 Periodic activities

A number of systems focus on recognition of a number of actions that consist of regularly repeated sequences of movements such as running and cycling. Depending on the activity, movements can be repeated with different speed and have different characteristics, e.g., range. An ANN classifier is used in [Mantyjarvi et al., 2001] to recognise three walking activities *(level walking, walking upstairs, walking downstairs)* and their start/stop points. Two 3-axis accelerometers mounted on the right and left hip were used as a signal source. The purpose of the paper is to evaluate the influence of principal component analysis (PCA) and independent component analysis (ICA) on recognition accuracy. PCA and ICA are techniques used to reduce the number of features required to describe a signal. Four coefficients of a wavelet transform, which describe the signal with respect to its time and frequency, for each of six acceleration values form the feature vector. The feature vector is given as an input to a multi-layer perceptron, which is used to recognise the activities. To evaluate the system data from six subjects was collected. They were asked to follow a predefined scenario in an office environment. The results show that data processed by techniques to reduce the number of features in the feature vector (PCA and ICA) obtain better results than raw data. The recognition accuracy is 82%-90% and 61%-84%, respectively. There is no significant difference in results for PCA and ICA.

The comparison of different types of classifiers to recognise eight activities: *standing, walking, running, climbing up stairs, climbing down stairs, sit-ups, vacuuming*, and *brushing teeth* is presented by Ravi et al. [Ravi et al., 2005]. The signal from one 3-axial accelerometer placed on the waist is utilised to extract the signal features. The features are extracted over a 5.12 second sliding window. They include: mean, standard deviation, energy (sum of absolute signal values), and correlation of acceleration signal. Comparison of five base-level classifiers (decision tables, C4.5 decision trees, k-Nearest Neighbour (k-NN), support vector machine (SVM), naive Bayes) and five meta-level classifiers (boosting [Meir and Rätsch, 2003], bagging [Breiman, 1996], plurality voting, stacking with ordinary-decision trees, stacking with meta-decision trees [Todorovski and Džeroski, 2003]) is presented in the paper. Meta-level classifiers are used to obtain a final prediction from the base-level classifiers' prediction. The data was collected from two subjects during several days. The results show that meta-level classifiers performed better than base-level ones. The plurality voting technique obtained the best accuracy, from 91% to 100%. The energy was the least significant signal feature.

Huynh et al. [Huynh and Schiele, 2006] introduce a hybrid approach to activity recognition that combines a generative model, e.g., HMM, with a discriminative model, e.g., SVM. Generative models specify a joint probability distribution over observation and desired output of the model. Generative models model a full probability of all variables, whereas discriminative models model only dependence

of unobserved variables on observed variables. The system is designed to detect the eight following activities: *sitting, standing, walking, walking downstairs, walking upstairs, shaking hands, writing on the whiteboard,* and *typing on the keyboard.* Twelve 3-axis accelerometers are used to capture data. They are placed on the ankles, knees, elbows, shoulders, wrists, and hips. The generative model used in the study is multiple eigenspaces. Multiple eigenspaces are based on PCA and are employed to capture essential activity characteristics and reduce the sensor data used to describe the activity. A reduced set of data is used to create the feature vector. The feature vector is used as the input to train the discriminative classifier. The classifier is based on a SVM. SVMs are a set of supervised learning methods. The feature vector consists of the running mean and variance of the acceleration values calculated over 0.5s windows. In a previous study [Kern et al., 2003] the relationship between the the placement of sensors and the recognition accuracy of different activities by a Bayesian classifier was investigated. It was found that an increase in the number of sensors increases detection accuracy of complex activities. A data set of 18.7 minutes used in a previous study was employed in this study. The results show that the use of multiple eigenspaces can reduce the need for supervision and its integration with a SVM can increase overall system performance.

In [Ákos Fábián et al., 2007, Györbíró et al., 2009] the authors describe a system that uses three MotionBand devices and a mobile phone to recognise the six following activities: *resting, typing, gesticulating, walking, running,* and *cycling.* Each MotionBand device contains three 3-axial sensors: an accelerometer, a magnetometer, and a gyroscope. The sensors are placed on the dominant wrist, hip, and ankle. The set of activities to be recognised differs by the intensity of motion and therefore the feature vector consists of the variation in changes of the acceleration signal over time for each sensor. The variation of signal changes is calculated for every sample over a 2-second time window and normalised. To recognise activities six ANNs are employed. Each of them is trained to detect only one activity. The feature vector is given as an input to all of the ANNs. If more than one network reports activity detection, the activity with the biggest activation function value is considered to be detected. To evaluate the system three sets of data from one person were collected. Each set contained, on average, 1776 samples per activity. Due to the fact that movement often caused displacement of the sensors on the person's body, two types of feature vectors were investigated. For one vector, the variation of signal changes was calculated in all tree acceleration directions. For the other, it was a single intensity (signal amplitude) value for each sensor. The outcomes showed that average recognition accuracy for the feature vector consisting of single intensity values for each sensor was marginally greater. The activities that were recognised with the lowest accuracy were resting and gesticulating.

In [Krishnan and Panchanathan, 2008] the authors present an approach that takes into consideration temporal information between samples to recognise activity. Seven activities are recognised by the method: *walking, sitting, standing, running, cycling, lying down,* and *climbing the stairs.* Three accelerometers placed on the hip, dominant ankle, and dominant thigh are used to obtain the data. To

recognise the activities, sensor readings are grouped into frames consisting of a fixed number of samples. To improve classification of the frames, the method proposed by the authors combines temporal information about the distance between the frames denoted by a Gaussian distribution and similarity between current and past frames described by Euclidean distance. To calculate the feature vector, the acceleration stream is divided into 512 sample windows with 256 samples overlap. Statistical features like mean, variance, correlation or energy (sum of absolute values) of the sample values are calculated in that window. Boosted decision stumps (AdaBoost) [Freund and Schapire, 1995] and regularised logistic regression (RLogReg), which are discriminative classifiers used to recognise the activities, are adapted to the method proposed by the authors. Logistic regression is prediction of the probability of occurrence of an event by fitting data to a logistic logistic curve. The simplest logistic curve is a sigmoid function, which has 'S shape'. To validate the technique data from ten participants was collected. The best results are gained for three past frames utilised to classify a current frame. The tests conducted by the authors show that adding temporal information on top of the classifiers gives better results than without it. After adding temporal information AdaBoost and RLogReg classifiers obtained accuracy of 95% and 90%, respectively.

**Analysis**   A summary of the systems used for recognition of periodic activities from acceleration data presented in previous part of this section is shown in Table 4.5. The systems were summarised according to the number of accelerometers used in the system, the number of postures or activities recognised, the technique used for activities recognition, and the number of subjects used in evaluation of system.

| Reference | Number of accelerometers | Number of activities or postures | Recognition technique | Number of subjects |
|---|---|---|---|---|
| [Mantyjarvi et al., 2001] | 2 3-axis | 3 | ANN | 6 |
| [Ravi et al., 2005] | 1 3-axis | 8 | Comparison of different classifiers | 2 |
| [Huynh and Schiele, 2006] | 12 3-axis | 8 | SVM | ? |
| [Ákos Fábián et al., 2007, Györbíró et al., 2009] | 3 units (3-axis accelerometer, magnetometer, and gyroscope) | 6 | ANN | 1 |
| [Krishnan and Panchanathan, 2008] | 3 2-axis | 7 | Comparison (AdaBoost, RLogReg) | 10 |

**Table 4.5**: Summary of systems for recognition of periodic activities

To classify periodic activities machine learning methods and techniques that reduce a number of possibly correlated signal features are commonly used. The input features are usually calculated over time windows exceeding 1 second to capture characteristics of the signal in respect to its frequency. Because some of the features are calculated in the frequency domain their calculation can be time consuming. To detect relatively short, non-periodic activities in near-real-time long time windows and frequency characteristics might not be suitable.

### 4.3.1.4 Activities of daily living

In [Bao and Intille, 2004] the authors present a study on the recognition of 20 real-life activities. They include activities such as: *walking, walking carrying items, sitting and relaxing, working on computer, standing still, eating or drinking, watching television, reading, running, bicycling, stretching, strength-training, scrubbing, vacuuming, folding laundry, lying down and relaxing, brushing teeth, climbing stairs, riding elevator,* and *riding escalator*. The system utilises five 2-axis accelerometers to classify the activities. They are placed on the hip, wrist, arm, ankle, and thigh. The features from the acceleration signal are calculated over a 6.7s sliding window. They include mean value, energy, spectral entropy (a measure of the disorder of the signal spectrum), and correlation of the signal. A number of classifiers was tested (decision table, k-Nearest-Neighbour, decision tree C4.5, and naive Bayes). To evaluate the classifiers, the accuracy of activity recognition and the influence of the number of sensors and their placement on it, data from 20 subjects was collected. Two types of data were obtained: semi-naturalistic, and specific. For semi-naturalistic data collection, subjects had to perform a number of activities listed on a worksheet. Subjects were not aware what was the exact activity because only the goal of each activity was known to them. For example, subjects were asked to 'use the web to find out what the world's largest city in terms of population is' rather that 'work on the computer'. For specific data collection subjects performed the 20 activities and all of them were explained to them in detail. The classifiers were trained on specific data and tested on semi-naturalistic data. The best results were obtained by a C4.5 decision tree classifier. The results showed that recognition accuracy for user-specific training was better (77%) than for leave-one-subject-out training (73%). The reason for that could be differences in activity patters of each participant. Additional tests of activity recognition accuracy after reduction of the number of sensors were conducted. The results indicated that using only thigh and wrist, and hip and wrist pairs showed less than a 5% decrease in recognition accuracy compared to all five accelerometers.

In [Zappi et al., 2007] the authors present an approach to recognising ten gestures carried out by workers in a car assembly line using acceleration data from acceleration sensors placed on the body. The method uses data acquired from 19 3-axial acceleration sensors placed at regular distances on both hands. The system consists of two separate modules. The first module classifies the current gesture on the basis of readings from one sensor. Therefore, one such module for each sensor used by the method is needed. A HMM is used to recognise current gesture in this module. Each HMM

(one for each sensor) consists of four hidden states which are fully connected. The feature vector given as the input to the HMM consists of acceleration direction (positive, negative, or null). The second module fuses the gestures detected by the HMM for each sensor to infer the final gesture. Two classifiers were tested for fusion: a majority voting scheme and a naive Bayesian fusion method. In naive Bayes fusion all gestures detected by the HMM for each sensor form a vector which is given as the input to the naive Bayes classifier. The final gesture is detected on the basis of previously learnt probability relationships between outputs of HMMs and actual gestures. To evaluate the system each of the ten activities was performed 19 times by a single subject. The results show that the detection accuracy increases with the number of wearable sensor nodes and for 19 nodes was equal to 93% for majority voting and 98% for the naive Bayes classifier.

**Analysis** Distinguishing between a number of real life activities can be challenging. The systems presented above classify up to 20 activities. In contrast to posture and movement detection methods, the systems are based on training rather than on fixed thresholds. This approach enables adjustment to user-specific movement patterns, which may be different for each user, and therefore desirable for real-life activities. To obtain the accuracy required they use a larger set of wearable sensors than the work described in previous sections. The use of more sensing elements can make the systems more accurate, because there is more data describing a particular activity. However, on the other hand their placement becomes more problematic.

### 4.3.2  Force

Headon et al. [Headon and Curwen, 2001] introduce a method for activity recognition using ground reaction force (GRF). GRF refers generically to any force exerted by the ground on a body in contact with it. Seven activities are classified by the system: *crouch, sit, jump, step, rise to stand, drop land*, and *static position*. The approach is based on the idea that the force experienced by the floor is dependent on the acceleration of the body acting upon it. By comparing GRF to body weight it can be decided whether the body acceleration was acting downwards or upwards. For that reason the system requires calibration with the weight of the participant, which is done automatically by an adaptive weight estimator. The Active Floor [Addlesee et al., 1997], which consists of floor tiles placed on load cells, is used as the sensory input. To recognise activities HMMs are used. The signal features are calculated over a 20ms time window from the sensor input and normalised by the user's body weight. The features include the mean, standard deviation and slope of the signal as well as their first and second order derivatives over time, which represent changes of the signal over time. The feature vector is used as an input to a HMM classifier. The number of states in the HMM might be different for each activity and was set empirically. To evaluate the system a number of samples were collected and used to train and test the system recognition accuracy. The results showed almost 100% accuracy for each of seven activities.

#### 4.3.2.1 Analysis

The basic idea of the system is that it is possible to detect body movement from force sensors. The features calculated to obtain the feature vector use only weight accumulated in a single point to distinguish between actions and therefore the activities that the system can detect are much more coarse-grained. As presented, the system is dependent on the weight of the user. For that reason the system employs a mechanism to adjust its parameters to the user weight. The set of activities distinguished by the system would not be suitable for people with PD. In addition, its deployment in the home environment would be problematic.

### 4.3.3 Combinations of sensors

Because accelerometers allow the measurement of direction and speed of user's movement, they were the most common source of data used to recognise activities. Their readings were often combined with readings from different types of sensors such as position or sound sensor to recognise activities. This section gives insight into systems that combine readings from accelerometers with different types of sensors to recognise activities.

#### 4.3.3.1 Acceleration and position

Ogris et al. [Ogris et al., 2005] present methods for gesture recognition using data from wearable motion and location sensors. The methods are employed to detect 21 gestures performed during fixing a bicycle. The scope of the paper is to compare different methods of fusion of motion and location sensor data. Motion sensors include accelerometers and gyroscopes. The location (3D coordinates) of ultrasonic devices placed on the body is calculated using an ultrasonic location system, which consists of at least three ultrasonic beacons placed at predefined locations. As the authors pointed out, some of the gestures are periodic, e.g., screwing, whereas others are not, e.g., assembling some parts. For that reason, the system presented in the paper consists of two subsystems: a location-based classification module and a motion-based classification module. The *location-based classification* utilises features obtained from the ultrasonic location system. The feature vector given as an input to a classifier, is calculated over a 1-second sliding window and consists of the coordinates of all the ultrasonic devices placed on the body. Two classifiers, a C4.5 decision tree and k-NN are tested for accuracy of gesture recognition in location-based classification module. The *motion-based classification* consists of two modules: model and frame-based classifications. For the model-based classification raw data from accelerometers and gyroscopes are used. For each gesture a dedicated HMM is trained. To reflect the continuous nature of the input each node in the HMM is modelled by a single Gaussian distribution. The number of states in the HMM, which was set empirically, corresponds to the complexity of the task and varies from 5 to 7. For the frame-based classification features like mean, variance, and median of acceleration signal over the sliding time window are calculated and form the feature vector that is passed to the classifier. As a classifier, C4.5 is chosen because of its low computational complexity.

Majority over decision is applied to recognise the gesture.

The authors propose three methods of sensor fusion:

- *Plausibility analysis.* The *motion-based classification* is applied and the 3 most likely gestures are selected. For each gesture an error from the position learnt by the ultrasonic sensors is calculated. If the error from the position is within an acceptable range the gesture recognised by *motion-based classification* module with the highest probability is taken as the one being recognised.

- *Joint feature vector.* The vector consisting of ultrasonic and motion features is used as an input to the *frame-based classification.*

- *Classifier fusion.* The classification is based on ranking from location and motion-based classification.

To evaluate the system three ultrasonic sensors [Hexamite, 2009] for location measurement and nine acceleration sensors with gyroscopes [Xsens Technologies, 2009] placed at several body positions are used. Nine data sets consisting of 21 gestures were recorded and labelled. To better understand the nature of the data the gestures were grouped into categories by their similarity. The values in brackets represent outcomes for groups of categories. The results show that location-based classification had average detection accuracy of 59% (82%) for the C4.5 classifier and 60% (85%) for k-NN. The recognition accuracy is not very high. This may be as a result of the number of tasks and the fact that some of them were very similar. For that reason results obtained for grouped tasks are better. The best results for the frame-based model were accomplished by the k-NN classifier and were equal 84% (90%). As predicted, activity recognition accuracy for non-periodic tasks was higher than for periodic ones. On the other hand the model-based approach had the worst results for periodic tasks and its average classification accuracy was 65% (78%). The most successful strategy was classifier fusion with 89% (95%) accuracy. Even though it is 1% worse than plausibility analysis it obtains similar results for each gesture. The tests show that additional information from ultrasonic sensors improves the results by 6% in comparison to the outcomes from motion sensors only.

In [Stiefmeier et al., 2006] the authors extend the research described above on the data from six participants. 21 similar gestures are recognised and the same types of sensors are used placed in slightly different locations. Three types of tests were conducted:

- *Intra.* Samples from an individual user were used for training and data from the same user for testing.

- *Inter.* Samples from all the subjects were used for training and testing.

- *External.* Testing was conducted for a user not included in the training set.

The results show that there is no significant difference between intra, inter, and external tests. Position classification is around 15% better than the motion classification and it varies from 55% to 73%. Classifier fusion is less accurate than position classification alone.

**Analysis**   The authors present the interesting idea of combining readings from acceleration sensors placed on different body parts with readings determining the position of the body parts. The set of activities chosen for the system consists of very similar actions but despite that the approach obtains reasonably high accuracy. In contrast to systems based on readings from the accelerometers only, non-periodic activities can also be classified by this system. The system consists of several wearable sensors and ultrasonic beacons deployed in the room. Even though the system has the potential to classify movements related to the exercise set prepared for SMOOTH, this set of sensors does not make it very mobile and convenient to use in terms of sensor placement and user convenience.

### 4.3.3.2   Acceleration and speed

Ernes et al. [Ermes et al., 2008b] introduce a system for daily activity and sports recognition. The study was based on findings described in [Parkka et al., 2006]. The aim of the paper is to compare the results of activity recognition in supervised and unsupervised settings for the following set of nine activities: *lying, sitting and standing, walking, running, Nordic walking, rowing with a rowing machine, cycling with an exercise bicycle, cycling with a real bicycle,* and *playing football.* The supervised setting includes activities performed in a laboratory with accurate labelling of these activities made by a supervisor. the unsupervised setting includes activities performed outside the laboratory with labelling of the activities made by the subject. The system uses signals obtained from two accelerometers placed on the hip and wrist, and a GPS receiver. The feature vector is calculated within a 1-second window. It consists of time-domain features (mean, variance, median, skew, kurtosis, 25% percentile, and 75% percentile) and frequency-domain features (estimation of power of the frequency peak and signal power in different frequency bands). In addition, the feature vector includes speed calculated from GPS data. Four classifiers for activity recognition were evaluated in the paper:

1. *Custom decision tree* using a simple threshold mechanism to detect activities.

2. *Automatically generated decision tree.* A structure similar to the *custom decision tree,* however rules were generated by the 'treefit' function from the Matlab Statistics Toolbox [The MathWorks, Inc., 2009].

3. *Artificial neural network (ANN)* consisting of one hidden layer (15 nodes) with the back propagation algorithm used for learning.

4. *Hybrid model,* which according to the authors, combines all the best features of the previous three methods. Its structure is similar to the *custom decision tree,* but decision nodes are replaced by ANNs.

Data for the study was collected from 12 subjects in both supervised and unsupervised settings. In total 68 hours of data were used. The outcomes show that the hybrid model obtained the best results with a total classification accuracy for the data collected under both supervised and unsupervised settings equalling 89%. For the model trained and tested with data collected in a supervised setting a total accuracy of 90% was noted. For the model trained with data collected in a supervised setting and tested with data collected in an unsupervised setting, the total accuracy was 72%.

**Analysis**    This approach distinguishes between periodic activities on the basis of time and frequency-domain features as well as the speed of the person. The information about current speed obtained from GPS is not meaningful for monitoring of exercises performed at home. The authors investigated recognition accuracy of activities performed without supervision. This approach obtained worse results than activities performed under supervision. A hybrid model that obtained the best accuracy for activity detection is decision tree based. Such a structure might be more difficult to implement for data obtained from more than one type of sensor. In addition, the tree structure highly depends on the set of activities to be recognised and for that reason adding or removing an activity involves rebuilding the tree structure.

### 4.3.3.3   Acceleration and other

Lester et al. [Lester et al., 2005] propose a hybrid approach to recognising activities using readings from different types of sensors placed at a single body location. The sensors measure acceleration, light, sound, humidity, and pressure. The approach combines the advantages of a static discriminative classifier to detect activities with a generative classifier to capture temporal dependency. Decision stump, which is a machine learning model consisting of a single-level decision tree, is used as discriminative classifier to recognise activities. The feature vector includes: fast Fourier transform (FFT) coefficients, cepstral coefficients (they model spectral energy distribution), spectral entropy (measure of the disorder of signal spectrum), band pass filter coefficients, integrals, mean, and variance of the signal. To select the most meaningful features and reduce the feature set, the AdaBoost algorithm is used. In empirical analysis it was found that a selection of 50 of the most meaningful features is optimal. For each activity a separate HMM is trained as a generative model and the classification is based on the HMM that detects the activity with the highest probability. To evaluate the system 12 hours of data were recorded from two participants over a period of six weeks. Ten activities were recognised: *sitting, standing, walking, jogging, walking up/down stairs, walking, riding a bicycle, driving a car,* and *riding an elevator up/down.* Comparison of different classifiers (naive Bayes, decision stump classifier, HMM with decision stump and with raw data) is presented in the paper. The highest classification accuracy was obtained by the HMM with decision stump classifier and was equal to 95%. In [Lester et al., 2006] further tests were conducted. The data was collected from 12 individuals. The sensors were worn in 3 different locations: wrist, waist, and shoulder. 8 activities were investigated: *sitting, walking, standing, walking up/down the stairs, riding elevator up/down,*

and *brushing teeth*. The results showed that classifiers trained by a sensor placed on a single body location obtained slightly better results than by three sensors trained altogether. For classifiers trained only with the accelerometery signal the overall accuracy was approximately 65% compared to 90% for acceleration, sound and barometric pressure. The results suggest that no customisation to the specific user is needed.

Maurer et al. [Maurer et al., 2006] present eWatch, a multi-sensor platform to detect activities of every day living. eWatch contains four sensors: a 2-axis accelerometer, a light sensor, a temperature sensor, and a microphone. The system is designed to distinguish between six activities: *sitting, standing, walking, ascending stairs, descending stairs*, and *running*. The features of the sensor signal are calculated every 0.5 seconds on a 4-second sliding window. They include: mean, standard deviation, variance, cumulative histogram, inter-quartile range, and crossing rates of the signal. The most meaningful features for the activities are chosen by the Correlation based Feature Selection (CFS) algorithm from the WEKA toolkit [Weka, 2009]. A number of classifiers was evaluated. Namely a C4.5 decision tree, k-NN, and naive Bayes. Because of the good balance of accuracy and computational complexity a C4.5 classifier was chosen for further tests. Six subjects took part in the evaluation of the system. They wore six sensors which were placed on the left wrist, belt, necklace, in the right trousers pocket, shirt pocket, and bag. Using all the features from all the sensors obtains the best result. It varied from 85% to 92% depending on the sensor location. For comparison, the activities detected using only the acceleration signal showed only 61%-86% accuracy.

In [Yang and Hsu, 2007] a system to recognise activities from readings obtained from the Bodymedia Armband [Bodymedia, 2009] is presented. The Armband includes five types of sensors: a 2-axis accelerometer, a heat flux sensor, a galvanic skin response sensor, a skin temperature sensor, and a thermometer. 24 different measurements can be obtained from those sensors. To recognise the activities a fuzzy Bayesian network is used. For each sensory reading a fuzzy membership function based on mean value and standard deviation is created. The membership values are used as an input to a fuzzy Bayesian network that infers the activity being performed. The training of the Bayesian network is also adapted to fuzzy data. To evaluate the system, 5500 samples of the following activities were collected: *walking, running, exercising, eating, reading, studying, playing, resting*, and *sleeping*. They were labelled and randomly chosen for training and testing of the Bayesian classifier. The results show that the fuzzy Bayesian classifier behaves slightly better than a discrete one. The recognition accuracy is 74% and 70%, respectively. A further set of tests revealed that recognition accuracy was better for both types of signals (acceleration and physiological) (74%) compared with acceleration (45% accuracy) or physiological signals (61% accuracy) separately. As predicted the acceleration signal contained more meaningful data to distinguish between periodic activities. Worse recognition results using data from accelerometers compared to sensors reading physiological signals might be caused by the set of activities used in the evaluation which contained more non-periodic activities than periodic ones.

**Analysis**    All the approaches presented combine information from acceleration sensors with either physiological, e.g., body temperature, or environmental sensors, e.g., ambient light. The choice of sensors is highly dependent on the set of tasks to be detected. Neither physiological nor environmental sensors provide any information about user body movement during exercise.

## 4.4    Sensing Chairs

In this section a review of chairs designed to sense the body position of their occupant is presented. To date and to our knowledge no chairs used to detect user movement have been developed. Sensing chairs are divided into two categories depending on the sensors used as input to the system: force sensors (Section 4.4.1) and force and distance sensors (Section 4.4.2). A summary of the systems is presented in Section 4.4.3.

### 4.4.1    Force sensors

Force sensors placed on a chair have been commonly used to detect the body position of its occupant. Placement of the sensors on the seat or back of the chair allows pressure distribution on these areas to be measured. On the basis of pressure patterns different body positions can be recognised.

#### 4.4.1.1    Seated posture recognition by low-cost sensors

Kamiya et al. [Kamiya et al., 2008] introduce a chair equipped with low-cost sensors to identify sitting postures. The system utilises an 8 x 8 grid of force sensors (Flexiforce [Tekscan, Inc., 2009]) placed on a seat to determine nine seated postures. The postures include:

1. Normal.

2. Leaning forward.

3. Leaning backward.

4. Leaning right.

5. Right leg crossed.

6. Leaning right with right leg crossed.

7. Leaning left.

8. Left leg crossed.

9. Leaning left with left leg crossed.

The pressure values from the 64 sensors form the feature vector. The feature vector is used to train and test a SVM algorithm, which is used to recognise the current posture. To solve the problem of dependency on individuals two types of normalisation of the feature vector are introduced:

- *Position.* The feature vector is subtracted from the feature vector for the *normal posture.*

- *Weight.* The feature vector is divided by the sum of its 64 values.

Data for system validation were collected from ten male students. They were asked to perform the sequence of nine positions listed above. After each position the participants were supposed to return to the normal position. Each subject did five trials, so a total of 450 samples were obtained from each subject.

Two types of tests were conducted:

- *Person-unknown.* The data of nine subjects was used for training (4050 frames) and the one not included in the set for testing (450 frames).

- *Person-known.* The individual data from each person was used to train and test the classifier.

For each test the effect of the normalisation method was investigated. The results are shown in Table 4.6. Recognition accuracy was greater for the person-known than the person-unknown test, which is not surprising. The feature vector normalisation had an insignificant influence on the person-known test results. For the person-unknown test the results were improved by 3%.

| Test | Case | Accuracy |
|---|---|---|
| Person-unknown | Without normalisation | 90.6% |
|  | Normalised (position) | 93.0% |
|  | Normalised (+weight) | 93.9% |
| Person-known | Without normalisation | 98.4% |
|  | Normalised (position) | 98.8% |
|  | Normalised (+weight) | 98.9% |

**Table 4.6**: Classification results for nine postures

**Analysis** The authors used 64 force sensors which is almost 3 times more than SMOOTH. Our system was designed to be inexpensive and operate in real time. Even though inexpensive force sensors were used in the approach, any increase in their number can increase computation time as well as the overall cost of the system. Because the sensors were placed only on the seat, recognition of some positions in which the trunk position is crucial, e.g., leaned forward, might be limited. The normalisation techniques proposed by the authors seem to improve overall system performance. However, the difference in accuracy for the person-known approach is marginal. The system detection accuracy is high but it detects only postures and therefore there is no comparison of detection accuracy for actions classified by SMOOTH.

**4.4.1.2    Seated posture recognition using sensor mat**

Tan et al. [Tan et al., 2001] present a sensing chair equipped with pressure mats manufactured by Tekscan [Tekscan, 2009] to detect postures. The mats were placed on the back and seat of an office chair. They consist of 4032 (2 mats x 42 x 48 grid) sensing elements in total. Because a pressure map is similar to a grey-scale image, pattern recognition algorithms employed in computer vision are used for data processing. The data collected by the sensor is pre-processed by filtering and normalisation. The initial feature vector consists of 4032 pressure values (number of sensing elements). To reduce the number of values in the feature vector PCA is used. The reduced vector is used to restore the original vector. Values after restoration are compared against the values of model postures and the sample is classified as the posture for which the difference is the smallest.

Evaluation of the sensing chair was conducted for single and multiple users. For the single user a trial of 14 sitting postures was performed. Each posture was repeated 10 times. The system classified sitting postures with overall accuracy of 95%. The postures included:

1. Seated upright.

2. Leaning forward.

3. Leaning left.

4. Leaning right.

5. Right leg crossed (with knees touching).

6. Right leg crossed (with right foot on left knee).

7. Left leg crossed (with knees touching).

8. Left leg crossed (with left foot on right knee).

9. Left foot on seat pan under right thigh.

10. Right foot on seat pan under left thigh.

11. Leaning left with right leg crossed.

12. Leaning right with left leg crossed.

13. Leaning back.

14. Slouching.

For the multi-user trial, data from 30 subjects was collected. The trial was restricted to 10 positions. Each participant performed each posture five times. 1500 samples in total were used to create the model postures database. To evaluate detection accuracy two trials were conducted:

- *Familiar subjects.* 200 additional samples (one sample per posture per subject) were collected from 20 subjects, who had participated in the data collection for the model postures. The overall recognition accuracy was 96% and varied depending on position from 90% for leaning back to 100% for slouching. Classification time and accuracy increased with the number of features included in the reduced feature vector.

- *Unfamiliar subjects.* 400 additional samples were collected from new eight subjects (five samples per posture per participant). The overall recognition accuracy was lower in comparison to the familiar subjects test and was equal to 79%.

In [Zhu et al., 2003] further investigation of seated posture recognition is described. The authors introduce a function based on sliced inverse regression (SIR), which is a method for reduction of the number of features in a feature vector needed to describe some data [Duan and Li, 1991]. A comparison of different methods for feature vector reduction is presented in the paper. They include: k-NN, PCA, LDA, and SIR. For the same test data as in the previous study, the results show that PCA and SIR produce the best results. The differences between them are insignificant.

**Analysis**  As presented the approach obtained good accuracy for 14 postures. The reason for this could be the use of an expensive sensor mat with over 150 times more sensing elements than SMOOTH. The placement of a pressure mat on the back of the seat can only detect pressure when contact with the mat maintained. Using the mat it is not possible to detect how far the user's back is from the back of a chair. The dimension reduction methods employed in the system are suitable for the selection of the most representative signals for each posture. However, several issues arise. The methods reduce a data set significantly and might not be useful for already reduced sets of data. Their operation time might be time consuming and therefore not suitable for real-time recognition. Finally, recognition based on the difference from model postures might not be appropriate for activity recognition, because of larger variations in readings for the same activity.

### 4.4.1.3  Seated posture recognition by robust, low-cost, and non-intrusive sensing

Mutlu et al. [Mutlu et al., 2007] propose a methodology for recognition of seated postures using two sensor mats (Tekscan [Tekscan, 2009]) placed on the seat and on the back of a chair. The mats consists of 4032 pressure sensors in total. The methodology presented in the paper is used to design an accurate system for the classification of seated postures of unfamiliar subjects. The method for seated posture recognition applies techniques to reduce the size of the feature vector. In addition, it enables hardware cost reduction by the use of a near-optimal sensor placement algorithm for the selection of optimally located sensors. The system discriminates among a set of 10 of the following postures:

1. Left leg crossed.

2. Right leg crossed, leaning left.

3. Leaning back.

4. Leaning forward.

5. Leaning left.

6. Leaning right.

7. Left leg crossed, leaning right.

8. Seated upright.

9. Right leg crossed.

10. Slouching.

The feature vector proposed by the authors contains two sets of features, which take into consideration the location and quantity of pressure applied. On that basis a feature vector consisting of 51 features is created. The feature vector is used to train a posture recognition classifier, which is based on logistic regression.

The proposed approach utilises input from a large number of high-resolution sensors, and for that reason computation of features in near-real-time is performance demanding. To reduce its cost, a near-optimal sensor placement algorithm is introduced. The classifier learns the correlation between measurements from selected sensors and feature values. Its aim is to select sensor locations, for which feature reconstruction would be as accurate as possible.

Two sets of experiments to evaluate the system were conducted. The first set of experiments used the data collected using sensor mats. The second used the data collected by a prototype of a sensing chair equipped with low-cost sensors developed by the authors. For the first experiment sensor readings collected from 26 males and 26 females were used. The system was trained on the data from 23 males and 23 females and tested on the data from the remaining six participants. To reduce the number of features used for position recognition a SVM based algorithm is used. Maximum posture detection accuracy of 86% was reached by the subset of 30 features, and thereafter the top 30 features were used for further experiments, which aimed to evaluate the sensor placement algorithm. A number of tests were conducted in order to select the number and placement of the sensors providing the most meaningful data. The best position recognition accuracy was 87% and was obtained by 31 sensors. For all 4032 sensors classification accuracy was the same as for 19 and was 82%. On that basis the hardware design was limited to set of 19 sensors. To compare the performance of the different classifiers the data from 19 near-optimally placed sensors, selected by the method proposed by the authors, were used. The accuracy comparison is presented in Table 4.7. The best position recognition accuracy was obtained by the SimpleLogistic [Landwehr et al., 2003] classifier.

| Multi-layer perceptron | Naive Bayes | SimpleLogistic | Support vector machine |
|:---:|:---:|:---:|:---:|
| 79.1% | 74.9% | 82.5% | 78.5% |

**Table 4.7**: 10-fold cross-validation results for classification accuracy of four classifiers

The second set of tests was conducted with the use of a prototype chair equipped with 19 near-optimally placed low-cost force sensing resistors (FSR [Interlink Electronics, 2009]). As the feature vector, force values from 19 sensors were used. The chair prototype and sensor placement is pictured in Figure 4.4. Sensor data were collected from 20 participants (10 males and 10 females). Each participant was asked to perform 10 positions on 10 occasions. Data from 9 males and 9 females were used to train the SimpleLogistic classifier. Data from the remaining two participants were used for testing. An overall position recognition accuracy of 78% was achieved.
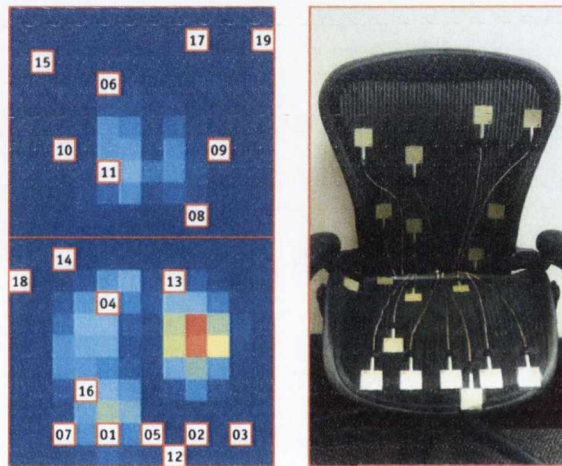


**Figure 4.4**: Final near-optimal placement of the sensors (on the right) and the prototype of the system with FSR sensors (on the left) [Mutlu et al., 2007]

**Analysis** The technique for near-optimal sensor placement presented in the paper obtained reasonably good results. It is interesting that the most meaningful readings are obtained from the sensors placed near the edge of the seat. The sensor placement obtained by the technique depends on the data given as the input to the system. That means that sensor placement might vary depending on participants, postures and chair type. Nevertheless, the placement of sensors on a chair used in SMOOTH was based on the findings in the paper. The posture recognition accuracy for the prototype with 19 sensors is only slightly less than for the design which used a sensor mat. The classifier for the chair prototype was trained with data obtained from low-cost sensors and instead of a set of 30 features as in the previous test, raw sensor values were used as the input. In addition, the sensors used in the prototype had different characteristics. These factors may influence overall system performance. For that reason, it would be interesting to see what results were obtained for different sensor configurations and for different classifiers when using the prototype with 19 low-cost sensors.

### 4.4.2 Force and distance sensors

Knight et al. [Knight et al., 2008] present the gesture recognition interactive technology (GRiT) designed to prevent a patient from falling when they attempt to stand up from a chair. The system is equipped with two types of sensors: force sensitive resistors (FSR [Interlink Electronics, 2009]) placed on a seat (12 sensors) and arm rests (2 sensors) of a chair and capacitive proximity sensors, which measure a distance, placed on the back of the chair (7 sensors). The readings from the sensors are used to extract the following features: static back position, forward leaning angle, total bottom pressure, bottom pressure distribution, armrest pressure as well as their change over time. The authors suggest the use of a probabilistic model to detect following postures: *sitting down, sitting, forward lean, slouching, high movement, attempting to exit, standing up*, and *falling out of chair*. Appropriate voice, visual or remote alarms are associated with each position detected by the system to prevent the patient from standing up from the chair or to inform the personnel about the attempt. Neither the actual model nor its evaluation are presented in the paper.

#### 4.4.2.1 Analysis

The system uses force sensors to obtain the pressure distribution on the seat and arm rests of the chair and distance sensors to measure the user's distance from the back of a chair. Even though the set of features derived from the sensor readings is presented there is no explanation as to how the features are actually calculated. In addition, no exact probabilistic model for position inference and its evaluation is presented.

### 4.4.3 Summary

A summary of the systems using sensors placed on a chair to recognise its occupant's posture's presented above is shown in Table 4.8. The table describes the systems according to the number and type of sensors used, their placement on a chair, the number of postures recognised, and the recognition technique. In addition, the table includes information about the number of samples and participants used to evaluate the systems.

All sensing chairs presented in this section detect body position at a particular moment in time. The detection of movement in this way can be achieved by classification of characteristic positions, e.g., if a sitting position is followed by a standing position the transition can be classified as a standing up movement. Such a method, however, does not recognise the movement itself but only its outcomes, which might be inappropriate for an exercise support system. The approach used in SMOOTH aims to classify the movement in order to assess if the exercise is performed in a correct way. In contrast to the systems described in this section, SMOOTH was designed not only to detect body positions but also to detect body transitions using metrics calculated over a period of time.

| Reference | Number and type of sensors | Placement of sensors | Number of postures | Recognition technique | Total number of samples | Number of subjects |
|---|---|---|---|---|---|---|
| [Kamiya et al., 2008] | 64 force sensors | Seat | 9 | SVM | 4500 | 10 |
| [Tan et al., 2001] | 4032 force sensors | Seat and back | 14, 10 | Comparison to model postures | 140, 2100 | 1, 38 |
| [Zhu et al., 2003] | 4032 force sensors | Seat and back | 10 | Comparison to model postures | 2500 | 50 |
| | 4032 force sensors | Seat and back | 10 | SVM | ? | 52 |
| [Mutlu et al., 2007] | 19 force sensors | Seat and back | 10 | Comparison (multi-layer perceptron, naive Bayes, SimpleLogistic, and SVM) | ? | 52 |
| | 19 force sensors | Seat and back | 10 | SimpleLogistic | 2000 | 20 |
| [Knight et al., 2008] | 14 force and 7 distance sensors | Seat, arm rests, back | 8 | Probabilistic model | ? | ? |

**Table 4.8**: Summary of systems using sensing chairs to recognise postures

## 4.5 Summary

This chapter reviewed the current state of the art in the two areas of exercise monitoring and posture or movement detection. Systems that used chairs equipped with sensors to recognise their occupant's position were also reviewed.

As presented in [Loureiro et al., 2001] the main reason for not sustaining exercise routines at home is lack of motivation. For that reason it is important to the keep the user motivated, which might lead to more frequent exercise execution. As observed, feedback while doing exercise seems to have a positive impact on motivation level. The systems presented in this chapter use audio, visual or haptic feedback to inform users about execution of exercises. In addition, some of the systems provide users with instructions on how exercises should be performed. Most of the systems for exercise use some kind of haptic interface to track user movements. As the review shows some of the devices can be cumbersome and not fit all the users. For that reason, a more natural and better solution could be the use of unobtrusive sensors to detect user movement and position.

The systems of this type presented in this review used various types of sensors to obtain data about their users and the environment. The sensors include force, distance and proximity sensors, accelerometers, video cameras as well as sensors obtaining information like temperature or position. Placement of sensors differs depending on their type and the information to be obtained. Two main types of sensor placement were identified: on the body, e.g., accelerometers, and stationary, e.g., cameras. In addition, the number of sensors used in the systems and their position varied. As evaluation results suggest, sensor position is highly dependent on the activities and postures to be recognised.

The review shows that various reasoning techniques are used to recognise a user's position and movement. They include decision trees, HMM, Bayesian networks, ANN, and fuzzy logic. Some approaches presented in this chapter used learning techniques to adjust the system to the characteristics of its users whereas others assumed characteristics and set classification thresholds a priori. Because the systems presented classify various sets of activities, use a different number and placement of sensors as well as different amounts of data in the evaluation process it is hard to decide which technique obtains the highest recognition accuracy.

This chapter gives insight into metrics what are used as the input into reasoning algorithms. In general, the metrics are dependent on two factors: whether the system detects movement and the type of sensors used to obtain the data. In addition, some of the systems were designed to chose a set of the most meaningful features from a much larger feature set. The features were calculated in the time domain, frequency domain or both. As suggested, frequency domain features are appropriate for periodic movement detection. However, a number of samples from a relatively long time window are needed for their calculation. For that reason, they might not be suitable for real-time or near real-time systems like SMOOTH.

The literature review suggests that movement patterns might differ from person to person. For

that reason learning techniques are used by some of the approaches to adjust the system to the characteristics of their users. As evaluation results show, user-specific training obtains higher recognition accuracy than user-independent training and for that reason this approach is adopted in SMOOTH.

The review shows that current state-of-the-art activity-recognition techniques are mostly based on readings obtained from wearable acceleration sensors. Even though the recognition accuracy for simple periodic activities is reasonably high, the recognition of short, non-periodic activities is still limited. In addition, systems that detect complex activities usually require larger numbers of sensors placed on the person's body, which can be a problem for people with movement limitations. These two factors make wearable accelerometers unsuitable for potential users of SMOOTH.

In state-of-the-art posture recognition methods the use of cameras and video stream processing is the most common approach. Current systems focus on basic posture recognition and there is a lack of work on detection of more complex body postures. In addition, the use of cameras at home can violate privacy [Demiris et al., 2008] and therefore they might not be freely used by SMOOTH users.

This review has provided evidence that systems for exercises that provide their user with feedback can be beneficial and encourage users to sustain their exercise routine. To date however, no low-cost exercise system to strengthen core muscles suitable for home use by people with movement limitations has been developed.

Current state-of-the-art sensing chairs show that it is possible to detect their occupant's position from fixed sensors. To our knowledge, no system that detects activities from low-cost set of sensors placed on a chair has not been developed to date. There is therefore a need to research the feasibility of activity monitoring using such sensors and explore movement detection accuracy and user acceptance.

# Chapter 5

# Design

The literature review (Chapter 4) provides evidence that, to date, no low-cost exercise system designed to strengthen core muscles, which is suitable for home use by people with movement limitations, and no system that detects activities using low-cost sets of sensors placed on a chair have been developed.

Our hypothesis is that a set of low-cost, fixed sensors are sufficient to measure exercise performance. To test this hypothesis several related questions have to be answered. What is the set of exercises that should be supported by the system? What sensors can be used to monitor the execution of these exercises? Finally, what approach should be used to measure exercise performance? This chapter answers these questions, identifies the key requirements for SMOOTH, and presents the design of the system.

The remainder of this chapter is organised as follows. In Section 5.1 requirements for SMOOTH are presented. Section 5.2 presents the set of exercises supported by the system and introduces the approach used by SMOOTH to measure exercise performance. Section 5.3 addresses the choice of sensors for SMOOTH, experiments conducted to evaluate different options, and the final decision about the sensor set and its placement. Finally, it gives an overview of the extraction and selection of signal features. Section 5.4 describes the approach used to monitor exercise performance. It includes the justification for and description of the inference technique based on dynamic Bayesian networks (DBNs) used to detect movement and initial experiments conducted to verify the ability of the inference technique to monitor exercise execution. In addition, it provides a detailed description of techniques used in conjunction with inference such as discretisation. Section 5.5 describes operation of the system and the roles of the physiotherapist and patient. Section 5.6 presents the user interfaces designed for the physiotherapist and patient. Finally, a summary of this chapter is presented in Section 5.8.

## 5.1 Requirements

Based on discussions with physiotherapists the following requirements were defined for SMOOTH.

1. **Affordable (R. 1)** - One of the assumptions of the project was that the system would be made

available for acquisition by people with Parkinson's disease (PD) for home use. The possession of the system at home should enable patients to perform exercises at times that are convenient for them and save the need for travel. One of the factors influencing acquisition of assistive technology (AT) is its cost [Meng and Lee, 2006]. For that reason it is important to minimise the cost of the system components and position the overall system in an affordable price range. To date, no study investigating affordability for an exercise system for people with PD has been found. For that reason, it is difficult to define an affordable price range for the system. However, this requirement implies that the cost of the system should be reduced by reduction of the cost of its components. This research focused on the reduction of system cost by reduction of the cost of sensing elements, i.e., number and price.

2. **Accurate (R. 2)** - To properly assist users, the system should be able to measure exercise performance accurately. Accurate measurement is important for two reasons. Firstly, user feedback depends on exercise measurement accuracy. If a user performs an exercise incorrectly the system should detect this and provide the user with appropriate advice. In addition, the system should not classify an exercise as incorrect if it was performed properly. Such behaviour might lead to user frustration and abandoning of the system and exercise routine. Secondly, accurate exercise measurement is the basis for information about the performance of user exercise routines for the physiotherapist. Inaccurate measurement leads to a discrepancy between the system and reality and therefore potentially gives false insight into patient exercise programme execution.

3. **Unobtrusive (R. 3)** - As reported in [Roelands et al., 2002], some users feel embarrassed using AT, which might lead to the abandonment of the device. For that reason, the device should look natural, i.e., sensors used to detect user movement should not be noticeable, and the use of technology should be transparent to the user, i.e., tasks like collection and transfers of data should be done in the background without attracting the user's attention. In addition, the sensors used by the system should not be perceived as violating user's privacy as might be the case, for example, with cameras [Demiris et al., 2008].

4. **Safe (R. 4)** - The safe use of the system is a major concern. The system is designed for use by people with PD for mobility training. As mentioned in previous chapters one of the symptoms of PD is motor-function impairment. This includes various mobility limitations and posture instability, which might increase the risk of falls and injuries [Benatru et al., 2008]. In addition, the system is designed to be used at home without additional assistance and therefore it is essential to keep patient safety in mind when an exercise programme is prescribed [Canning et al., 2009]. To meet safety concerns and not put the user's health at risk, the system address exercises that can be performed in a chair.

5. **Convenient (R. 5)** - The system is designed to be used by people with PD at home without

any additional assistance. Therefore, system maintenance can not be troublesome and no other people should be needed to use the system. People with PD should be able to start and carry on their exercise routine by themselves. Once the system is set up it should be ready to use without any additional installed every time the user wants to exercise. In addition, users should feel comfortable during training and there should be no restrictions on their movements. For that reason and due to commonly reported difficulties in dressing by people with PD [Abudi et al., 1997], the use of wearable sensors and tight garments should be limited.

6. **Intuitive (R. 6)** - The target group for the system are people with PD. Because of the characteristics of the disease they are usually advanced in years [Eeden et al., 2003] and therefore are not always familiar with the newest technologies. It is important to design a user interface that is very natural to use. That should lead to minimal need for training on how to use the system or no need for the training at all. A complex user interface may discourage users from using the system [Renaud and van Biljon, 2008] and in consequence be contrary to the purpose of the system. In addition, user feedback provided by the system should be natural and self-explanatory so that the user can concentrate on correct exercise execution.

7. **Portable (R. 7)** - It should be possible to use the system by different users in different locations without substantial difficulty to set it up for each user. Such a design would allow a number of users to use the same device, e.g., in a nursing home, or to move device from one place to the other. In addition, the system should provide the physiotherapist with data about exercise performance regardless of its location and the number of users.

8. **Adaptable (R. 8)** - As noted in the literature review, different people might move in different ways [de Leon and Sucar, 2002]. Movement may depend on, for example, the height and weight of people. Moreover, people with PD often suffer from movement limitations [Gelb et al., 1999] and therefore the way that they perform the same exercise may differ significantly. To recognise movement patterns properly it is essential that the system adapts to the individual circumstances of its user.

SMOOTH addresses all the requirements described in this section. The application of the requirements and the design of the system are described in the next part of this chapter.

## 5.2  Set of exercises

In the previous section the set of requirements for SMOOTH was presented. On this basis a set of exercises to be supported by the system was identified. To fulfil the safety requirement **(R. 4)** only exercises that can be performed while sitting in a chair were considered. The choice of exercises was preceded by visits to a number of physiotherapy sessions for people with PD[1] in order to give the

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[1]The physiotherapy sessions took place in Royal Hospital Donnybrook, Dublin 4, Ireland.

researcher better insight into the exercises prescribed to people with PD to be performed at home. The final selection of exercises was made after consultation with physiotherapists working with people with PD including members of PROP[2]. In addition, a list of potential difficulties with execution of the exercises was established by consultation with the physiotherapists in order to give better insight into parameters that could be used to measure exercise performance. The final set of eight exercises for SMOOTH, their description, and the list of potential difficulties with their execution are presented in Table 5.1.

**Table 5.1**: Set of exercises for SMOOTH

| # | Exercise | Description | Potential difficulties for people with PD |
|---|----------|-------------|-------------------------------------------|
| 1 | Marching in sitting | Sit upright in your chair. While sitting, lift your right knee as high as possible and put it down. Lift your left knee as high as possible and put it down. Repeat 10 times. | • No feet clearance. <br> • Reduced number of repetitions. <br> • Loss of balance to contralateral side of lift. <br> • Compensation for weak hip flexors by excessive trunk extension to help lift leg. <br> • Gradual reduction in amplitude of movement as exercise progresses. |
| 2 | Hip walking in sitting | Sit upright in your chair. Try not to lean forward. While sitting, lift your right hip off the chair and put it down. Then lift your left hip off the chair and put it down. Repeat 10 times. | • Sliding. <br> • Sliding in conjunction with leaning against back of chair. <br> • Inability to isolate one side to lift. <br> • Gradual reduction in amplitude of movement as exercise progresses. |

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[2]Physiotherapy Research & Older People Group, Department of Physiotherapy, Trinity College Dublin

**Table 5.1**: Set of exercises for SMOOTH

| # | Exercise | Description | Potential difficulties for people with PD |
|---|----------|-------------|-------------------------------------------|
| 3 | Abduction of the right leg | Sit upright in your chair. Try to stay upright. While sitting, lift right knee as high as possible and move it as far away from your left knee and foot as possible. Put it down for a moment. Lift it once more and move it back to starting position. Repeat 10 times. | • Sliding.<br>• No feet clearance.<br>• Rotation of trunk to follow abduction of leg.<br>• Internal rotation of the hip. |
| 4 | Abduction of the left leg | Sit upright in your chair. Try to stay upright. While sitting, lift left knee as high as possible and move it as far away from your right knee and foot as possible. Put it down for a moment. Lift it once more and move it back to starting position. Repeat 10 times. | • Sliding.<br>• No feet clearance.<br>• Rotation of trunk to follow abduction of leg.<br>• Internal rotation of the hip. |
| 5 | Leaning to the right | Sit upright in your chair. Try not to bend forward. While sitting, reach with your left hand towards the floor as far as possible. Return to the starting position. Repeat 10 times. | • Bending forward.<br>• Reduced range of movement.<br>• Inability to return to midline.<br>• Lifting leg on contralateral side to maintain balance. |

**Table 5.1**: Set of exercises for SMOOTH

| # | Exercise | Description | Potential difficulties for people with PD |
|---|----------|-------------|-------------------------------------------|
| 6 | Leaning to the left | Sit upright in your chair. Try not to bend forward. While sitting, reach with your right hand towards the floor as far as possible. Return to the starting position. Repeat 10 times. | • Bending forward.<br>• Reduced range of movement.<br>• Inability to return to midline.<br>• Lifting leg on contralateral side to maintain balance. |
| 7 | Leaning forward | Sit upright in your chair. While sitting, slowly lean forward as far as possible. Try to touch your toes with your hands. Return to the starting position. Repeat 10 times. | • Reduced range of movement.<br>• Inability to return to starting position. |
| 8 | Sit to stand | Sit upright on the edge of your chair. Lean slowly forward and stand up. Then slowly sit down. Repeat 10 times. | • Position not upright (hunched).<br>• Swinging - moving trunk back and forth in order to stand up.<br>• Not smooth move.<br>• Fatigue.<br>• Uncontrolled sitting down.<br>• Inability to extend hips and knees fully in standing. |

## 5.2.1 Assessment of exercise performance

As presented in previous chapters the main goal of SMOOTH is to monitor exercise performance. This information is used to:

- provide users with feedback;

- provide physiotherapists with information about user performance.

To meet this goal, a mechanism to assess whether the exercise is performed properly should be developed. As presented in Table 5.1 each exercise consists of a number of movements, e.g., 'leaning forward' consists of sitting, leaning forward, and returning to starting position. The individual movements during an exercise are referred to as movement phases and are described in more detail in Section 5.4.3. If the movements appear in an appropriate sequence a repetition of the exercise happens. The measurement of execution of the exercise can be expressed as the number of correct, also called also proper, repetitions completed. A repetition is considered to be performed properly if the movements of which an exercise consists are, according to a physiotherapist and given user limitations, performed correctly and appear in a valid sequence. Thus, the assessment of correctness of the repetition can be based on:

1. the particular movements that are performed;

2. the sequence of these movements.

For example, when performing 'leaning forward' the patient might not be able to return to the starting position, which means that there is a movement missing to complete the exercise. On the other hand, during execution of 'sit to stand', swinging might occur. That means that all the correct movements are present during the exercise, however their sequence is distorted.

The number of correct repetitions completed during exercise is the metric that is used by SMOOTH to measure exercise performance. On this basis a person with PD can be made aware of their performance and a physiotherapist can assess the progress of the patient. The types of interaction with users and user feedback used in SMOOTH will be discussed in more detail in Section 5.6.1. A detailed description of correct exercise repetition detection is presented in Section 5.4.4.

## 5.3  Sensors

The previous section presented a set of eight exercises that are supported by SMOOTH. The next step in answering the hypothesis that a set of low-cost, fixed sensors are sufficient to measure exercise performance was to identify a set of sensors and signal features that would enable measurement of these exercises. The remainder of this section is organised as follows. Section 5.3.1 introduces possible sensor types that can be used to monitor exercise execution and then discusses their match to the requirements defined for SMOOTH (see Section 5.1). Section 5.3.2 describes experiments conducted on sensor types that fulfil the requirements in order to investigate the feasibility of their use in SMOOTH. The final set of sensors used by SMOOTH and their placement is introduced in Section 5.3.3. Section 5.3.4 presents movement patterns obtained from sensor readings during exercise. This is followed by the description of signal features calculated in SMOOTH and their use (Section 5.3.5 and Section 5.3.6). Finally, a summary is presented in Section 5.3.7.

## 5.3.1  Choice of sensors

The literature review revealed several types of sensors that are used to detect activity and body position. A sensor set used by SMOOTH has to fulfil the system requirements presented in Section 5.1 and enable measurement of exercise performance. Three essential requirements in terms of sensor choice were determined, namely, the sensors used by the system should be affordable **(R. 1)**, unobtrusive **(R. 3)**, and convenient **(R. 5)**. As mentioned previously, it was difficult to define an affordable price range for the system. This research focused on the use of sensors to measure exercise performance, therefore in terms of affordability the focus was on the cost of the sensors used in SMOOTH. A number of systems available on the market were investigated and on the basis of the cost of the sensors they used, it was assumed that €1000 was a reasonable starting point for the sensor set used in the system prototype. This cost could probably be further reduced in a commercially available product. Unobtrusiveness and convenience requirements are closely connected to potential users of the system and their perceived privacy and comfort during use. The comparison of sensor types used in state-of-the-art systems against the requirements for SMOOTH is presented in Table 5.2.

As presented in Table 5.2 two types of sensors fulfil all the requirements defined for SMOOTH. They are force and distance sensors. Both of them can be purchased from a range of suppliers and fixed to a surface to detect user movement. Accelerometers, proximity, position, and strain sensors were excluded from further investigation due to the fact that they must be placed on the user's body to detect its movement. In addition, the cost of position sensors was prohibitive. As reported earlier, placement of wearable sensors can be problematic because of movement limitations related to PD and reported problems in dressing [Abudi et al., 1997, Muras et al., 2008]. Cameras were not suitable for SMOOTH because they could be perceived by user's as violating privacy when used in the home environment [Demiris et al., 2008]. In addition, they required dedicated space and setup. Even though pressure mats have much higher accuracy than most of the commercially available force sensors, their cost is also prohibitive, and therefore they were excluded from further tests. Finally, readings from GPS and environmental sensors used by state-of-the-art systems [Lester et al., 2005, Lester et al., 2006, Yang and Hsu, 2007, Ermes et al., 2008b] were not applicable because the information provided by them, e.g., temperature, is not relevant to monitoring of exercises performed in a chair.

## 5.3.2  Experiments

As presented in the previous section two types of sensors were identified to have potential to be suitable for SMOOTH. The purpose of the experiments described in this section was to investigate the feasibility of the use of force and distance sensors to monitor the set of eight exercises presented in Table 5.1. The results are presented below.

| Type of sensor | Requirement | | | Comments |
|---|---|---|---|---|
| | Affordable | Unobtrusive | Convenient | |
| Force sensor | ✔ | ✔ | ✔ | Suitable; price in range from $6 to $25 per unit [Trossen Robotics, 2009]. |
| Accelerometer | ✔ / ✗ | ✔ | ✗ | Wearable; price in range from $5 to $500 per unit [Analog Devices, Inc., 2009]. |
| Position sensor | ✗ | ✔ | ✗ | Wearable tags; price approximately €300 per unit (wearable tag or beacon) [Hexamite, 2009]; another available equivalent - price over €10000 [Ubisense, 2009]. |
| Distance sensor | ✔ | ✔ | ✔ | Suitable; price in range from $29 to $65 per sonar and from $12 to $22 per IR unit [Trossen Robotics, 2009]. |
| Proximity sensor | ✔ | ✔ | ✗ | Wearable; price approximately $150 per unit [Crossbow Technology, 2009]. |
| Strain sensor | ? | ✔ | ✗ | Wearable; not commercially available - developed by EMPA [EMPA, 2009]. |
| Camera | ✔ | ✗ | ✔ | Privacy issues; dedicated space and setup required. |
| Pressure mat | ✗ | ✔ | ✔ | Price over €10000 [Tekscan, 2009, Xsens Technologies, 2009]. |
| *GPS* | | | | Not applicable. |
| *Environmental sensor* | | | | Not applicable. |

**Table 5.2**: Choice of sensors for posture and activity detection

### 5.3.2.1 Force sensors

For force detection FlexiForce Force Sensors (manufactured by Tekscan, Inc.) [Tekscan, Inc., 2009] were used. The manufacturer provides three models of the sensors suitable for use under different loads:

1. A201-1 (0 - 1 lb.; 0- 4.4N)

2. A201-25 (0-25 lb.; 0- 110N)

3. A201-100 (0-100 lb.; 0- 440N)

Each model was tested for the range of pressures that could be detected in relation to the pressure distribution of a person performing exercises in a chair. A number of sensors was placed on the seat of a wooden chair and while the researcher performed the exercises described in Table 5.1 the sensor readings were observed. On the basis of the readings the A201-1 model seemed to be the most suitable sensor for the system. For that reason, the A201-1 is the only force sensor that was investigated further. To investigate the accuracy of the sensors the same weight was put on sixteen A201-1 sensors and measurements were taken. The measurements were repeated five times for each sensor. The sensor readings differed by 7% for a weight equal to approximately half of the maximal load for the sensor. It was also noticeable that after removal of the weight there was a few second delay before the reading returned to the initial state. In addition, there were minor variations of the values for the initial states among the sensors.

### 5.3.2.2 Distance sensors

Two types of distance sensors were used for the tests:

1. Sonar Ranger SRF10 (manufactured by Devantech) [Devantech, 2009] - This sensor detects a single object that is in a range of from 3cm to 6m in line with the sensor. To check its accuracy an object was moved several times in the range of the sensor and the distance was measured. Initial tests with the use of a solid object showed that the accuracy of the sensor is high. However, a further set of tests revealed that the detection accuracy of objects covered in textiles, e.g., a cotton T-shirt, was insufficient. The reason for that could be the absorption of ultrasonic pressure waves by textiles. Therefore the use of a sonar sensor was discarded.

2. IR Distance Sensors (manufactured by Sharp)[Sharp, 2009] - Two models of IR distance sensors with different ranges were selected for the tests:

   - GP2D120 (1.57 - 11.81 inches; 4 - 30cm)

   - GP2D12 (4 - 30 inches; 10 - 80cm).

   An object covered in textile (a cotton T-shirt) was placed at several different distances from the sensor. Each reading was repeated five times. The results are presented in Figures 5.1a and

5.1b. As shown, variance in the readings collected during the trials is very small and might be related to human error in the distance measurement. This suggests that readings from both types of sensors are repeatable and the measurement error is marginal. As a result, uncertainty of the system, specifically physical randomness and indeterminism (see Section 5.4.1), in respect to distance sensor readings is low. It was also noticed that when sensors are placed closer than 10 cm vertically and 25cm horizontally they interfere with each other and their readings are distorted. Because of the detection range, model GP2D120 was chosen to be used in the system.

### 5.3.2.3 Summary

This section described experiments performed with force and distance sensors to measure their accuracy, limitations, and the feasibility of their use in the system. On the basis of the experiments FlexiForce Force Sensor A201-1 and IR Distance Sensor GP2D120 were identified to be suitable for SMOOTH. A description of their placement is presented in the next section.

## 5.3.3 Sensor placement

Having identified two types of sensors, the next step was to determine their number and placement to monitor the set of exercises to be performed in a chair (see Table 5.1). Because of convenience (**R. 5**) and unobtrusiveness (**R. 3**) requirements, all the sensors are placed on a chair. That allows users to move without any additional limitations and makes starting exercise sessions more convenient. The remainder of this section describes the exact placement and number of force and distance sensors used in the system.

### 5.3.3.1 Force sensors

The purpose of force sensors is to detect the distribution of the user's weight during exercise. For that reason force sensors were placed on the seat of the chair. Their placement was based on experiments and findings of Mutlu et al. [Mutlu et al., 2007] which indicate that uniform or random sensor placement is not necessarily the optimal one. The experiments described in Section 5.3.2.1 show that there was 7% variation in sensor readings. To minimise the impact of the variation, instead of using values from individual sensors, the average value of a number of sensors was used. To average sensor readings, eight areas that are crucial for identification of leg movements and changes to body weight distribution were identified empirically by a number of experiments. The experiments involved performance of a set of the exercises addressed by SMOOTH by the researcher and examination of the sensor readings. The bigger the change in the sensor readings, the better their placement. The number of force sensors belonging to each area varies from two to four. In total 24 A201-1 force sensors were placed in these areas. The placement of the sensors on a chair is pictured in Figure 5.2.

In order to extract signal features (see Section 5.3.5) the mean values of the pressure sensors belonging to each of the eight areas are used in further processing.
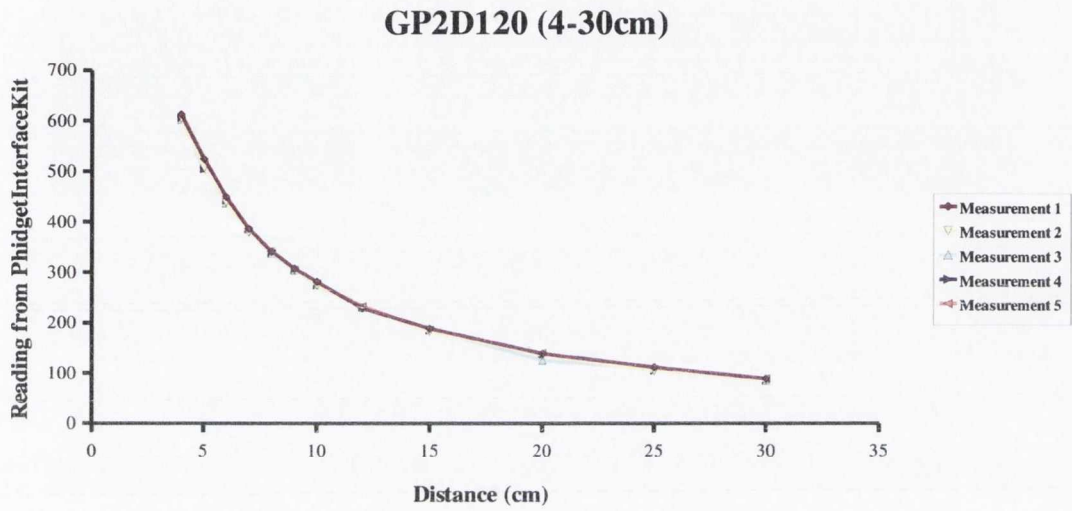
(a) GP2D120
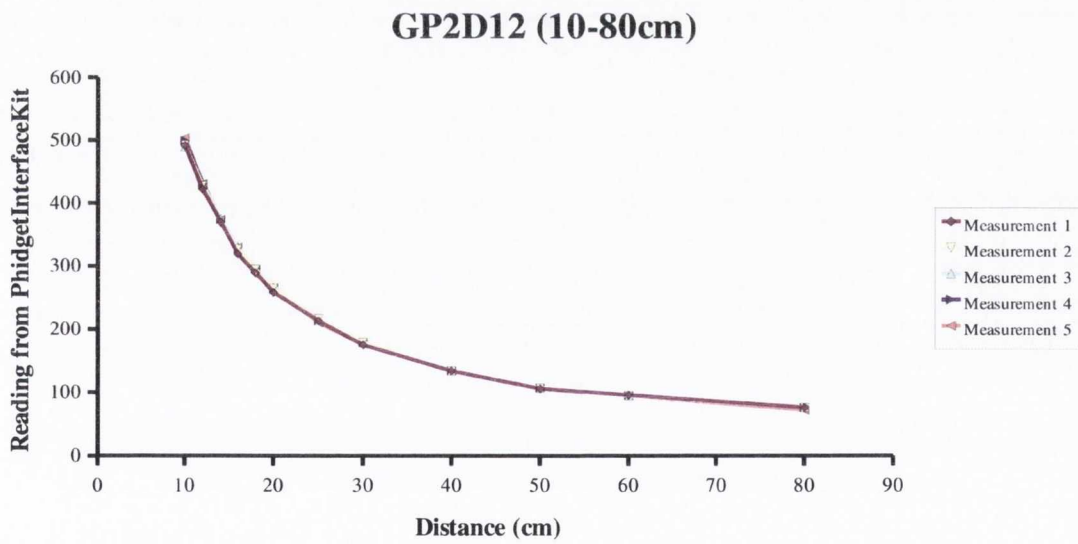


(b) GP2D12

**Figure 5.1**: Accuracy of sensor readings in relation to the distance

(a)                                              (b)
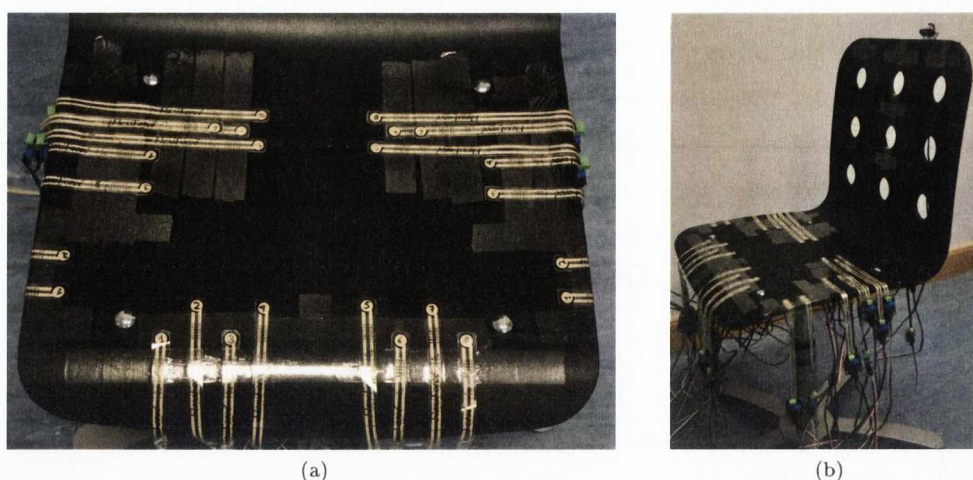
**Figure 5.2**: Placement of twenty-four A201-1 force sensors on a chair

### 5.3.3.2   Distance sensors

The purpose of the distance sensors is to detect the distance of the user's back from the chair and for that reason they were placed on the back of the chair. The number of sensors that it was possible to place on the chair was limited by mutual inference between the sensors occurring if they were placed too close to each other (see Section 5.3.2.2). In addition, the minimum distance detected by the GP2D120 distance sensor is 3cm. For that reason and for user comfort sensors should be placed 3cm away from the back of the chair. The final placement of five GP2D120 distance sensors was limited by the type of chair used in SMOOTH and identified empirically. The chair had nine holes in the back. Different combinations of sensors were placed facing those holes. The combination in which the sensors did not interfere with each other and their readings changed during performance of exercises addressed by SMOOTH were chosen. The placement of the sensors on a chair is pictured in Figure 5.3.

In order to extract signal features the raw values of the distance sensors are further processed as described in Section 5.3.5.

### 5.3.4   Movement patterns

Having identified a set of sensors for SMOOTH and their placement, to justify their choice, sensor readings for the set of eight exercises supported by the system were recorded. The main goal was to identify if movement patterns that could be recognised by the system emerge. Several repetitions of each exercise were performed by one person and the sensor readings recorded during it are presented in Figures 5.4 - 5.9.

It can be clearly seen that there are patterns in the sensor readings that are related to the movement phases of each exercise and that they differ between exercises. The next step was to identify a technique that would allow their detection and on that basis monitor exercise performance. The choice of the

(a)                                              (b)
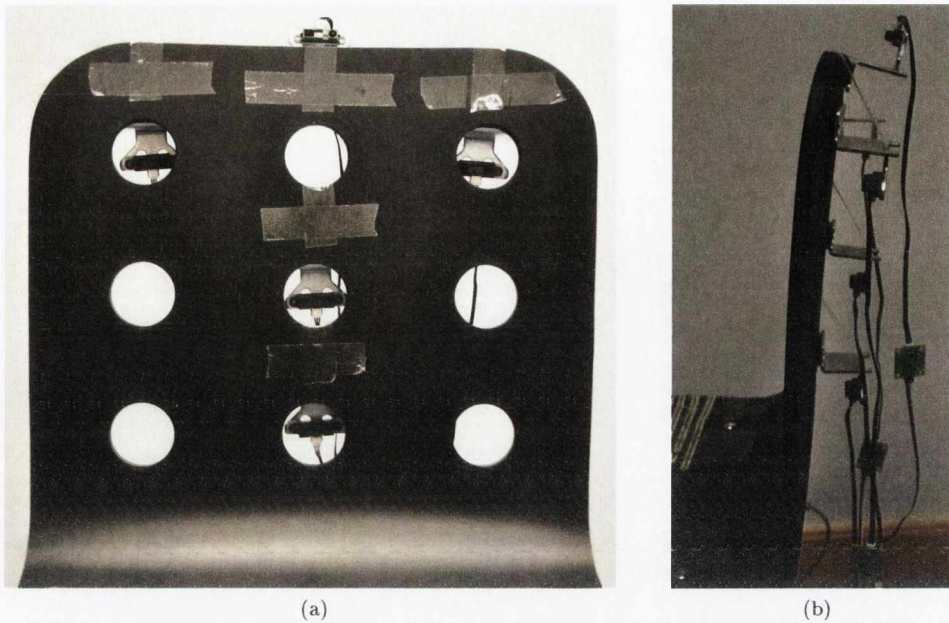
**Figure 5.3**: Placement of five GP2D120 distance sensors on a chair
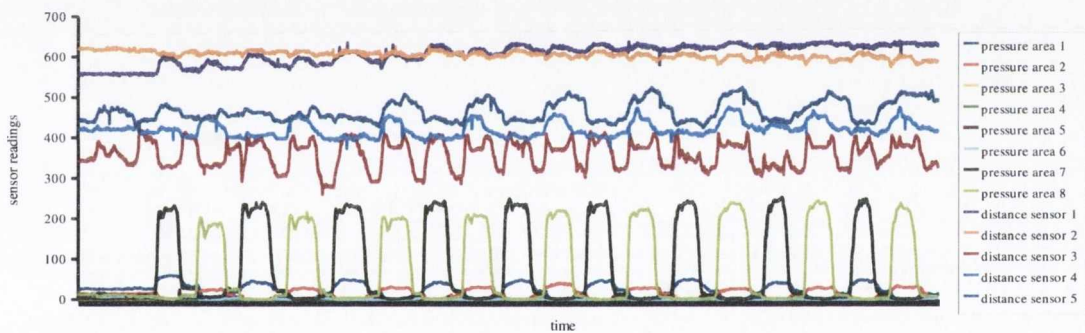


**Figure 5.4**: Movement patterns in sensor readings - Marching in sitting

technique and its detailed description is presented in Section 5.4.

### 5.3.5   Feature extraction

To infer movement from sensor readings (see Section 5.4), signal features, that allow discrimination between the different movement phases during the exercise (see Section 5.4.3), should be defined. The literature review shows that to represent changes in signals over time, sensor readings can be grouped into sliding time windows, and signal features can be calculated over these windows. The size of the sliding time window as well as the number of overlapping samples depends on the activity to be detected and signal features to be calculated. It differs among reviewed studies. For example, in [Headon and Curwen, 2001] to detect 7 activities from the Active Floor [Addlesee et al., 1997] a 20ms time window is used and metrics such as mean, standard deviation and slope as well as their first and second order regression are calculated. In [Ákos Fábián et al., 2007, Györbíró et al., 2009]
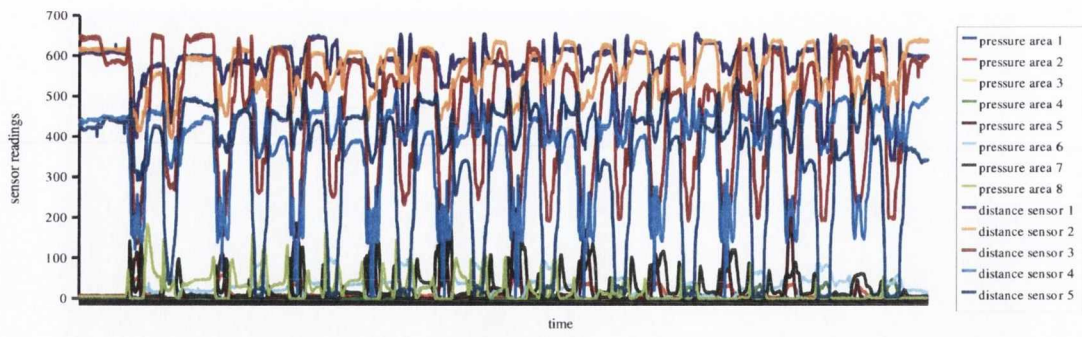
**Figure 5.5**: Movement patterns in sensor readings - Hip walking in sitting
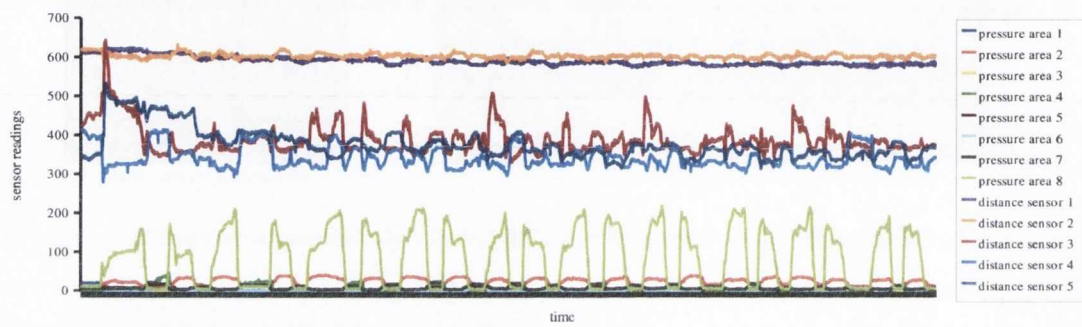


**Figure 5.6**: Movement patterns in sensor readings - Abduction of the left/right leg
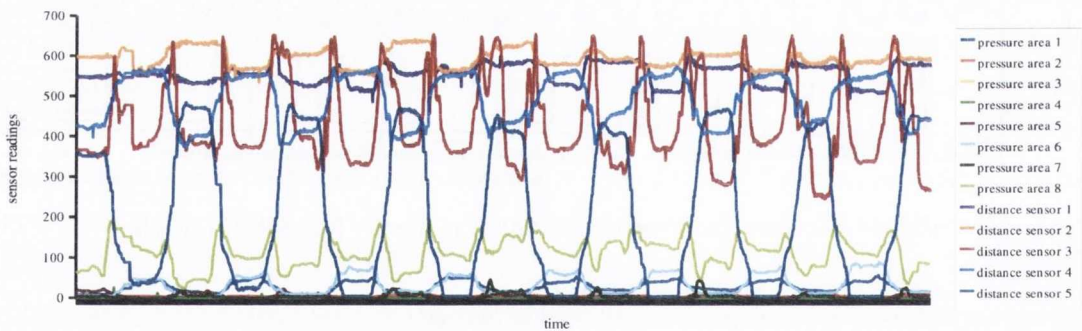


**Figure 5.7**: Movement patterns in sensor readings - Leaning to the left/right
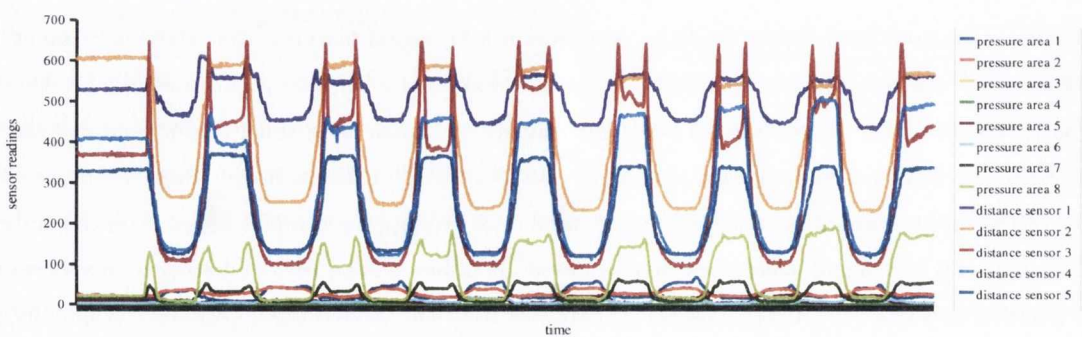


**Figure 5.8**: Movement patterns in sensor readings - Leaning forward
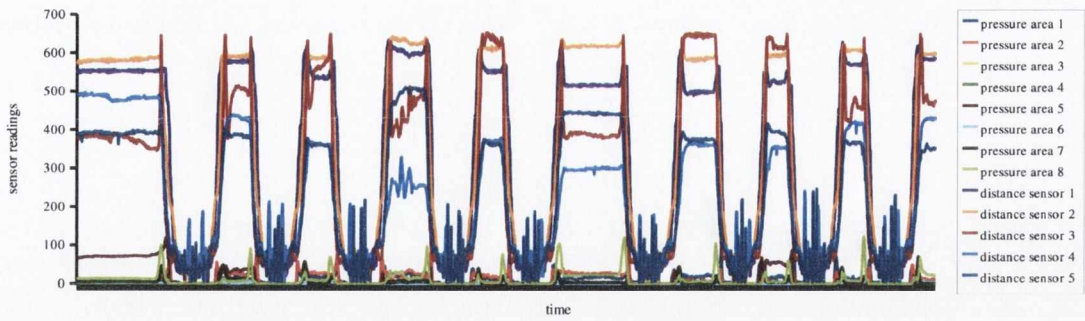
**Figure 5.9**: Movement patterns in sensor readings - Sit to stand

to detect 6 activities from 3 MotionBand devices a 2s time window is used and acceleration variation is calculated.

State-of-the-art systems use three types of domain to calculate signal features over time window: time, frequency, and time-frequency as described in more detail in Appendix A. The literature review suggests that frequency domain, which emphasise the frequency characteristics of the signal, might be useful to detect periodic activities. However, they do not perform well for non-periodic activities, such as the movement phases (see Section 5.4.3) defined for SMOOTH. In addition, signal transformation to the frequency domain usually requires samples collected over a longer period of time to show the frequency characteristic of an activity [Bao and Intille, 2004], e.g., walking or running. For those reasons the signal features used in SMOOTH are calculated in the time domain.

The set of signal features for SMOOTH is required to differentiate between static postures like *sitting upright* and movements like *moving the trunk forward*. In addition, it has to indicate the direction of movement. For example, it has to differentiate between *moving the trunk forward* and *moving the trunk backward*. Finally, it has to make a distinction between different positions such as *sitting upright* and *standing*. On the basis of these requirements the following signal features calculated over a sliding time window are included in the feature set used in SMOOTH:

1. *Mean.* The mean is the arithmetic average of a set of values. For a finite set of samples $x_1, x_2, \ldots, x_n$ it is given by:
$$\mu = \frac{1}{n} \sum_{i=1}^{n} x_i$$

2. *Difference.* This feature is defined as the difference between the mean value of the signal over the current time window $(t)$ and the mean value over the previous time window $(t-1)$. It is given by the equation:
$$d = \mu_t - \mu_{t-1}$$

3. *Standard deviation.* This is a measure of the variability or dispersion of a data set. A low standard deviation indicates that the signal samples tend to be very close to the same value (the mean), while a high standard deviation indicates that the data are spread out over a large range of values. In the case where $X$ takes random values from a finite sample set $x_1, x_2, \ldots, x_n$, with

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each value having the same probability and $\mu$ being their mean value, the standard deviation is given by:

$$s = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \mu)^2}$$

### 5.3.6 Feature selection

The most meaningful features, which describe the sensor signal in the most meaningful way, to be used to infer the current movement phase might differ depending on the exercise. For example, in 'leaning forward' features calculated over the signals from the distance sensors, which correspond to the movement of the back, are crucial, whereas they are not relevant in 'marching in sitting'. It could be assumed that all the features calculated on all the sensor readings can be used to infer the current movement phase. This approach however, could increase the complexity of the DBNs used for inference in SMOOTH (see Section 5.4.5), not necessary providing better results. To reduce model complexity, SMOOTH includes a simple mechanism to select meaningful features which are given as the input to inference module. The features are selected on the basis of training and testing sets (see Section 5.4.5.2). Initially, the feature set includes 39 different features: 3 features $\{\mu, d, s\}$ calculated over the set of 13 sensor readings (8 pressure areas and 5 distance values). Only the features that change over the sample set are selected and used to infer current movement phase. This means that the structure of each DBN depends on the data collected during the training phase (see Section 5.4.5.2) and might differ for each user and exercise.

### 5.3.7 Summary

This chapter presented the choice of sensors for SMOOTH and their placement. A number of different types of sensors was identified in the literature review, however, only force and distance sensors met the requirements for and are used in SMOOTH. The sensor set consists of twenty-four A201-1 force sensors placed on the seat of a chair and five GP2D120 distance sensors placed on the back of the chair. Data recorded for this sensor set while performing eight exercises defined for SMOOTH suggest that movement patterns emerge from sensor readings and that there is potential for their detection. Three types of features from the sensor readings are calculated over a sliding time window. They are the mean, difference, and standard deviation of each signal. The most meaningful features are selected on the basis of samples collected from the individual users.

## 5.4 Monitoring of exercise performance

The purpose of this section is to present the approach to monitoring exercise performance used in SMOOTH. As noted in Section 5.2.1 exercise performance in SMOOTH is assessed by measuring the number of correct repetitions of an exercise completed. However, detection of the number of exercise

repetitions performed from sensor readings can be challenging and involves recognition of the sequence of movements corresponding to the different phases of each exercise. As presented in Section 5.3.4 readings from the set of sensors chosen for SMOOTH suggest that there are identifiable patterns corresponding to the different movement phases of the exercises. A key challenge described in this section is the design of the movement phase inference technique used in SMOOTH and detection of correct exercise repetitions based on outputs from the inference module.

The remainder of this section is organised as follows. Section 5.4.1 motivates the use of DBNs as the movement phase inference technique to be used in SMOOTH. Following that, initial experiments to justify the use of Bayesian techniques as an inference mechanism for SMOOTH are presented in Section 5.4.2. Section 5.4.3 describes the movement phases for each exercise addressed by SMOOTH in detail. Following that, an overview of the use of DBNs to detect correct exercise repetition is introduced in Section 5.4.4. Section 5.4.5 describes the DBNs used in SMOOTH in more detail including their structure and learning process. In Section 5.4.6 discretisation of signal features is described. Finally, a summary of this section is presented.

### 5.4.1 Selection of inference technique

One of the requirements defined for the system in Section 5.1 is adaptivity (**R. 8**). People with PD often have movement limitations and therefore their individual ranges of movement might differ [Gelb et al., 1999]. In addition, [de Leon and Sucar, 2002] note that different people might perform the same activity in a different way, e.g., slower or faster. For that reason the inference technique used in SMOOTH should have the capability of adjusting its parameters to individual user circumstances. This means that it should be able to learn how to recognise the movement patterns of different users during exercise. As mentioned in Section 5.2.1 the metric to assess exercise performance used in SMOOTH is the number of correct exercise repetitions completed. In order to teach the system correct movement patterns, an expert that assesses the correctness of exercise execution and labels sensor data with the corresponding phases is needed. The role of the expert is played by a physiotherapist. On the basis of labelled data the inference module can then learn the relationship between sensor readings and the movement of the user and recognise the current phase of the exercise.

The key challenge for the inference module is to detect the current phase of exercise from low-level sensor data. Data obtained from the sensors used by SMOOTH can be uncertain and the inference module should cope with that. Korb et al. [Korb et al., 2003] describe three types of uncertainty that can occur in systems:

1. *Ignorance.* This is related to the lack of understanding of how a system operates or the lack of information. The lack of information can be caused by the fact that the system has a limited number of sensing elements and therefore data obtained from them are incomplete and does not include all relevant information. The set of sensors used in SMOOTH is limited to those described in Section 5.3.3, which means that some substantial information might not be included

in their readings.

2. *Physical randomness or indeterminism.* This refers to noisy data. Even if everything was known about the system there would still be a possibility of erroneous readings from the sensors. This could be caused by the sensor's inaccuracy, hardware faults or connection errors. The accuracy of the force sensors used in SMOOTH is not very high and therefore they can be indeterministic to a certain level. In general sensors are burdened by two forms of uncertainty [Page and Sanderson, 1995]:

   (a) Absolute sensing uncertainty, which is related to absolute sensor accuracy. For example, readings from one sensor might differ depending on environmental conditions, e.g., temperature of the sensor.

   (b) Incremental sensing uncertainty, which corresponds to the sensor's relative accuracy. For example, the resolution of a sensor might be limited and not be able to capture a change.

3. *Vagueness.* This refers to the vagueness of assertions. Sometimes it might be hard to classify a human as rich or not, or brave or not. In SMOOTH vagueness relates to the fact that sometimes it can be hard to define strict boundaries between movement phases in an exercise. For example, when people are standing up it might be hard to decide where the boundary between sitting and standing lies.

State-of-the-art systems for posture and activity recognition, described in the previous part of this thesis, use a broad spectrum of inference techniques. Evaluations of posture and activity recognition accuracy provided for these techniques are insufficient to draw any conclusion about their performance in relation to the detection of movement during exercise in a chair. To address the problems described above and fulfil the requirements for the inference module in SMOOTH Bayesian techniques can be applied. The remainder of this section compares Bayesian networks (BNs)/dynamic BNs (DBNs) to other inference techniques used in state-of-the-art systems and justifies the choice of DBNs as the inference technique used in SMOOTH.

As noted in Appendix A, a decision tree classifies patterns as one of a number of defined classes. For that reason, there is no mechanism that would allow the degree of belief that some particular pattern belongs to one class or the other to be assessed. This lack of capability is not desirable considering the uncertainty and vagueness with which SMOOTH has to deal and the fact that it might sometimes be difficult to decide if a repetition of an exercise is done correctly or to determine the boundary of movement phases.

Johansson et al. [Johansson and Falkman, 2008] presents advantages of BNs over fuzzy inference rules. In fuzzy logic, in contrast to BNs, there is no way to handle uncertain evidence explicitly. For that reason, BNs are better suited to deal with uncertainty than fuzzy logic. Fuzzy membership functions and fuzzy inference rules for SMOOTH could be very difficult to define due to the lack of knowledge about exact dependencies between sensor readings and movement phases.

In general, rule-based systems are based on logical inference and have three properties [Russell and Norvig, 2003]:

- *Locality.* In logical systems, when rule $A \Rightarrow B$ is defined, given evidence $A$ it is possible to conclude $B$ without worrying about other rules. In probabilistic systems all the evidence has to be considered.

- *Detachment.* Once logical prof for proposition $B$ is found, it can be used regardless of the way in which it was derived. In probability, the source of evidence is important for subsequent reasoning.

- *Truth-functionality.* In logic, complex sentences can be divided and their truth can be calculated from the components. In probability theory, such an approach is not applicable.

These three properties make rule-based systems inappropriate for reasoning under uncertainty. Even though several attempts have been made to introduce uncertain reasoning to the systems, they have not provided desirable results, and therefore this approach is no longer recommended [Russell and Norvig, 2003].

Correa et al. [Correa et al., 2009] state that BNs have a number of advantages over artificial neural networks (ANNs). BNs are more intuitive and allow fast construction while there are no principled methods for choosing network parameters for ANNs such as the number of hidden layers, the number of neurons in these layers, and the activation function. In addition, the learning algorithm used in ANNs does not guarantee the convergence to a global minimum and is prone to over-fitting and under-fitting, when too much or not enough data for learning is used [Russell and Norvig, 2003].

Linear discriminant analysis (LDA) is based on discriminative models, which do not allow to generate samples from the joint distribution and therefore handling missing data is often more complicated in these models. The problem with LDA is that a small training error does not guarantee a small testing error, because the linear discriminant is not effectively determined unless the number of samples is several times greater than the dimensionality of the feature space. Linear discriminants are also not sufficiently general to handle challenging pattern recognition [Duda et al., 2000]. Recognition of movement patterns in SMOOTH might be challenging due to data being obtained from many different types of sensors, lack of knowledge about the dependence between the readings and movement phases, and the changes of the readings over time to capture movement.

As also presented in Appendix A, nonparametric models recognise postures/activities on the basis of similarity to other postures/activities. This means that classification of unfamiliar, according to the system classification function, samples might have a big classification error. In addition, nonparametric models do not cope well with noisy data, and reasoning under uncertainty [Alpaydin, 2004]. For that reason, they are not a suitable inference technique for SMOOTH.

Oliver et al. [Oliver and Horvitz, 2005] presents several advantages of DBNs over HMMs. The most important are better learning of dependencies between variables and better resistance to loss of

some of the observations. The purpose of the inference module in SMOOTH is to detect the current phase of movement during the execution of the exercise. To assess accuracy of exercise execution, movement phases are modelled as independent events and all of them can be performed improperly. However, the current movement phase might still depend on sensor readings at different points of time. For that reason DBNs are more suitable to infer activities in SMOOTH than HMMs.

BNs have been used with some success by other researchers to recognise postures and activities [Thiemjarus and Yang, 2007, Kern et al., 2003, Yang and Hsu, 2007, Hsia et al., 2008] [Harms et al., 2008, Cucchiara et al., 2001, Cucchiara et al., 2003, Cucchiara et al., 2005]. From this evidence, DBNs were chosen to be used for the recognition of movement phases and the detection of correct exercise repetitions in SMOOTH. At the time of choice of inference technique for SMOOTH the perceived advantages of DBNs were:

1. They provide resistance to loss of some of the observations and reasoning under uncertainty.

2. They provide a graphical model that is easy to understand and modify.

3. The model naturally represents casual relationships between sensor readings and movement phases.

4. The learning process is relatively simple and its results should improve with more data.

## 5.4.2   Initial experiments

To verify the ability of BNs to monitor exercise execution in SMOOTH a small-scale experiment was designed. The purpose of the experiment was to investigate the feasibility of using BNs to recognise static postures related to exercises that could be performed in a chair from the A201-1 force and GP2D120 distance sensor readings. Five distance sensors and sixteen force sensors mounted on a chair were used in the experiment. This section describes the postures considered, the BN used in the experiment, and the results.

### 5.4.2.1   Postures

The set of postures for the experiment was based on the set of exercises described in Section 5.2. The body position for each posture was broken down into the position of the trunk and the position of the lower limbs resulting in the fourteen positions described in Table 5.3 being assessed in the experiment.

**Table 5.3**: Body posture descriptions

| # | Trunk position | Lower limb position | Description |
|---|---|---|---|
| 1 | Away | Away | Away from the chair. |
| 2 | Sitting upright | Both legs down | The participant is seated upright in the chair with his/her back resting against the back rest. His/her feet are resting on the floor, hips and knees are flexed to 90 degrees and his/her ankles are in the neutral position. |
| 3 | Sitting upright | Right leg up | In this position, the participant is required to elevate the right thigh and knee from the chair. The knee remains flexed to 90 degrees. The participant is seated upright in the chair with his/her back resting against the back rest. |
| 4 | Sitting upright | Left leg up | In this position, the participant is required to elevate the left thigh and knee from the chair. The knee remains flexed to 90 degrees. The participant is seated upright in the chair with his/her back resting against the back rest. |
| 5 | Sitting upright | Right leg abducted | This position requires slight hip flexion to clear the right thigh off the chair. The participant is seated upright in the chair with his/her back resting against the back rest. |
| 6 | Sitting upright | Left leg abducted | This position requires slight hip flexion to clear the left thigh off the chair. The participant is seated upright in the chair with his/her back resting against the back rest. |
| 7 | Leaning to the right | Left side up | This position involves elevation of the left leg and buttocks from the chair and simultaneously transferring the weight onto the opposite side. |
| 8 | Leaning to the left | Right side up | This position involves elevation of the right leg and buttocks from the chair and simultaneously transferring the weight onto the opposite side. |

**Table 5.3**: Body posture descriptions

| # | Trunk position | Lower limb position | Description |
|---|---|---|---|
| 9 | Leaning to the right | Both legs down | This position involves movement of the trunk to the right, which involves movement of the shoulder towards the hip on other side. The participant's feet are resting on the floor, hips and knees are flexed to 90 degrees and his/her ankles are in the neutral position. |
| 10 | Leaning to the left | Both legs down | This position involves movement of the trunk to the left, which involves movement of the shoulder towards the hip on other side. The participant's feet are resting on the floor, hips and knees are flexed to 90 degrees and his/her ankles are in the neutral position. |
| 11 | Slouched | Both legs down | In this position the participant is requested to protract the shoulder girdle and flex the cervical and upper thoracic spine. His/her feet are resting on the floor, hips and knees are flexed to 90 degrees and his/her ankles are in the neutral position. |
| 12 | Leaning forward | Both legs down | In this position the participant is required to flex the trunk at the thigh. His/her feet are resting on the floor, hips and knees are flexed to 90 degrees and his/her ankles are in the neutral position. |
| 13 | Rotating to the right | Both legs down | The person is required to rotate his/ her trunk and look over his/her right shoulder. His/her feet are resting on the floor, hips and knees are flexed to 90 degrees and his/her ankles are in the neutral position. |

**Table 5.3**: Body posture descriptions

| # | Trunk position | Lower limb position | Description |
|---|---|---|---|
| 14 | Rotating to the left | Both legs down | The person is required to rotate his/ her trunk and look over his/her left shoulder. His/her feet are resting on the floor, hips and knees are flexed to 90 degrees and his/her ankles are in the neutral position. |

### 5.4.2.2 Bayesian network

The purpose of inference module was to detect the lower limb and trunk position. It consisted of two BNs that had the same structure. The first infers the lower-limb position and the second the position of the trunk for each body posture. This separation was introduced to reduce the number of inferred body positions in each BN. As presented in [Foerster et al., 1999] reduction in the number of possible outputs of an inference module can improve recognition accuracy. Each network consists of 8 nodes corresponding to the inputs from the pressure sensors and 4 nodes corresponding to the inputs from the distance sensors. Because sensor readings are continuous, discretisation parameters for each node have to be established. In order to investigate the influence of the number of discretisation categories, two different sets of discretisation thresholds were used in the experiments. The thresholds were set to fixed values and these values were determined empirically. In order to obtain the threshold values a number of trials was conducted with data acquired from the researcher. The threshold values that obtained the highest position recognition accuracy were chosen. Two sets of discretisation thresholds, called parameters, were applied to two separate inference modules, referred as 'module 1' and 'module 2'. Each module consisted of two BNs that inferred 'lower limb position' and 'trunk position'. Nodes corresponding to sensor readings are discretised into less states in 'module 1' (see Figure 5.10a) than in 'module 2' (see Figure 5.10b). The parameters for the BNs used in the experiment are shown in Figure 5.10.

### 5.4.2.3 Methodology

Five people (2 females and 3 males) aged between 25-35 took part in the experiment. All the positions were demonstrated to them and all their questions answered. The chair was adjusted to the participants high before each experiment. Two sets of the 14 positions listed in Table 5.3 were performed by each participant in a chair. The first set was used to learn and the second set to test the inference module. Each position was performed five times in each of the two sets. The sensor readings were
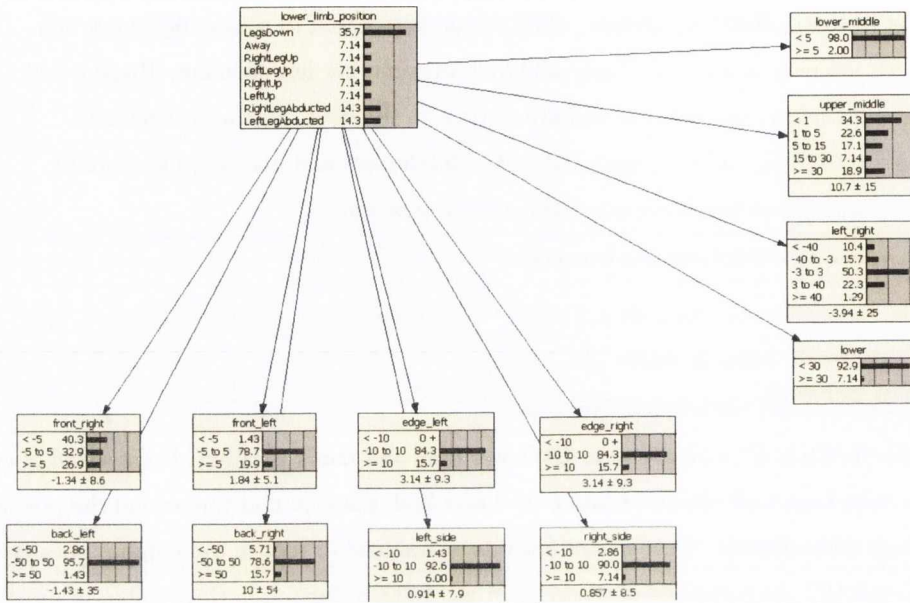
(a) Module 1 parameters
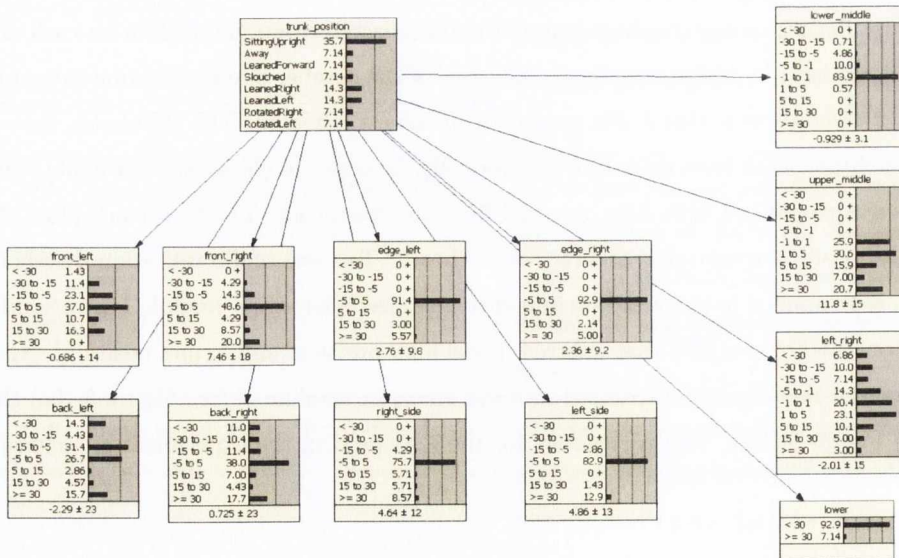


(b) Module 2 parameters

**Figure 5.10**: BNs used in experiments

logged with a frequency of 5 Hz and each participant was asked to stay in each position for three seconds. After each trial the sensors were re-calibrated, which meant that the participant had to come back to the neutral position (position number 2 from Table 5.3) and stay in that position for 5 seconds. The purpose of calibration was adjustment to the weight of the participant.

### 5.4.2.4 Results

Evaluation of position detection included two types of tests:

1. *User-specific.* Learning and testing were conducted with samples from each user individually.

2. *User-independent.* Testing was conducted with samples from the user that was not included in the learning set.

The average error rates for recognition of the 14 positions from the 5 participants are shown in Table 5.4 for the user-specific test and in Table 5.5 for the user-independent test.

| Participant | Module 1 | | Module 2 | |
|:---:|:---:|:---:|:---:|:---:|
| | Trunk position | Lower limb position | Trunk position | Lower limb position |
| 1 | 7.71% | 11.43% | 5.714% | 14.14% |
| 2 | 12.29% | 11.29% | 13.43% | 22.29% |
| 3 | 0.00% | 15.43% | 4.143% | 24.14% |
| 4 | 11.71% | 17.14% | 12.86% | 13.86% |
| 5 | 13.57% | 17.86% | 26.71% | 13.57% |

**Table 5.4**: Error rates for position recognition for user-specific test

| Participant | Module 1 | | Module 2 | |
|:---:|:---:|:---:|:---:|:---:|
| | Trunk position | Lower limb position | Trunk position | Lower limb position |
| 1 | 15.00% | 17.86% | 15.71% | 19.29% |
| 2 | 35.00% | 21.43% | 37.14% | 22.14% |
| 3 | 12.14% | 22.86% | 8.571% | 17.14% |
| 4 | 27.14% | 30.00% | 24.29% | 30.71% |
| 5 | 16.43% | 22.14% | 10.00% | 17.14% |

**Table 5.5**: Error rates for position recognition for user-independent test

The results obtained from the experiment suggest that it is feasible to use BNs to detect body postures from pressure and force sensors mounted on a chair. The results show that overall recognition rates obtained by 'module 1' for the user-specific tests are slightly better than by 'module 2'. Overall recognition error for 'module 1' and in a user-specific test equals 9% and 14.5% for trunk position and lower limb position, respectively. Overall recognition error for 'module 2' in user-specific tests equals 12.5% and 17.5% for trunk position and lower limb position, respectively. The results show that

overall recognition rates obtained by 'module 1' in user-independent tests are slightly worse than by 'module 2'. Overall recognition error for 'module 1' in user-independent tests equals 21% and 22.5% for trunk position and lower limb position, respectively. Overall recognition error for 'module 2' in user-independent tests equals 19% and 21% for trunk position and lower limb position, respectively. In general, both modules obtained comparable results. That suggests that a lower number of states for network nodes is a valid solution and provides similar results. In general, the user-specific tests obtained better results than user-independent tests, which is not surprising and is consistent with the literature [Bao and Intille, 2004, Harms et al., 2008]. The final finding is that the error rates differ significantly depending on the participant. That suggested that use of fixed thresholds to discretise node values might not be an optimal solution. A more flexible solution that would adjust discretisation parameters to user characteristics should be sought in order to obtain more uniform results.

### 5.4.2.5 Summary

The results obtained in the experiments show that Bayesian inference is a suitable technique for detection of static postures on the chair from the set of sensors used in SMOOTH. For that reason the BNs are adapted to measure exercise performance in SMOOTH. Their design and final inference model are presented below.

### 5.4.3 Movement phases

Turaga et al. [Turaga et al., 2008] propose a distinction between simple and complex activities. The authors refer to simple activities as motion patterns usually lasting a short period of time, i.e., tens of seconds, and call them *actions*. On the other hand *activities* are defined as more complex sequences of actions. The boundaries for this categorisation are not very strict and mostly depend on interpretation. In Section 5.2.1 we stated that to monitor exercise performance each exercise can be divided into a number of movement phases in order to detect correct repetition of the exercise. Relating this to the categorisation proposed by Turaga et al. we can refer to an exercise as an activity, which consists of a number of simpler motions, movement phases, that can be called actions. In order to detect correct exercise repetition we divided each exercise addressed by SMOOTH (see Table 5.2) into various numbers of consecutive movement phases. The correctness of this division has been reviewed with physiotherapists. The set of exercises addressed by SMOOTH with their corresponding movement phases is presented in Table 5.6.

**Table 5.6**: Movement phases for the exercises addressed by SMOOTH

| # | Exercise | Movement Phases |
|---|----------|-----------------|
| 1 | Marching in sitting | 1. Sitting upright. |
|   |          | 2. Moving right knee up. |
|   |          | 3. Right knee up. |
|   |          | 4. Moving right knee down. |
|   |          | 5. Sitting upright. |
|   |          | 6. Moving left knee up. |
|   |          | 7. Left knee up. |
|   |          | 8. Moving left knee down. |
| 2 | Hip walking in sitting | 1. Sitting upright. |
|   |          | 2. Moving to the left. |
|   |          | 3. Moving to the right. |
|   |          | 4. Sitting upright. |
|   |          | 5. Moving to the right. |
|   |          | 6. Moving to the left. |
| 3 | Abduction of the right leg | 1. Sitting upright. |
|   |          | 2. Moving right knee up. |
|   |          | 3. Right knee up. |
|   |          | 4. Moving right knee down. |
|   |          | 5. Right leg abducted. |
|   |          | 6. Moving right knee up. |
|   |          | 7. Right knee up. |
|   |          | 8. Moving right knee down. |

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**Table 5.6**: Movement phases for the exercises addressed by SMOOTH

| # | Exercise | Movement Phases |
|---|---|---|
| 4 | Abduction of the left leg | 1. Sitting upright. |
| | | 2. Moving left knee up. |
| | | 3. Left knee up. |
| | | 4. Moving left knee down. |
| | | 5. Left leg abducted. |
| | | 6. Moving left knee up. |
| | | 7. Left knee up. |
| | | 8. Moving left knee down. |
| 5 | Leaning to the right | 1. Sitting upright. |
| | | 2. Leaning to the right. |
| | | 3. Leaned to the right. |
| | | 4. Leaning back to the left. |
| 6 | Leaning to the left | 1. Sitting upright |
| | | 2. Leaning to the left |
| | | 3. Leaned to the left |
| | | 4. Leaning back to the right |
| 7 | Leaning forward | 1. Sitting upright. |
| | | 2. Moving trunk forward. |
| | | 3. Leaned forward. |
| | | 4. Moving trunk backward. |

**Table 5.6**: Movement phases for the exercises addressed by SMOOTH

| # | Exercise | Movement Phases |
|---|----------|-----------------|
| 8 | Sit to stand | 1. Sitting upright. |
| | | 2. Moving trunk forward. |
| | | 3. Standing. |
| | | 4. Moving trunk backward. |

The movement phases presented in Table 5.6 are used in the DBNs (see Section 5.4.5) as states for a movement phase node and are inferred from nodes corresponding to features of the sensor input. The movement phases of each exercise correspond to the particular movements that can be distinguished in the exercise. The number of movement phases in each exercise differs from four to eight.

### 5.4.4 Exercise repetition detection

Each exercise repetition consists of a number of movement phases. If the correct movement phases appear in the correct order a repetition is counted. The movement phases and their correct order for each exercise are presented in Table 5.6. This section presents the main features of the use of DBNs to detect correct exercise repetition. The structure of the DBNs is described in more detail in Section 5.4.5.3.

The model used in SMOOTH is based on the naive Bayes structure, which is a standard approach for inference of activity based on a set of observed signal features [Russell and Norvig, 2003]. In addition, to indicate movement the model utilises the information from the previous time window. For that reason DBNs were employed. The purpose of the DBNs used in SMOOTH is accurate recognition of the current movement phase from sensor input. To fulfil the accuracy requirement (**R. 2**) the DBNs should detect movement phases with the smallest possible error and indicate if exercise has been performed properly.

The current movement phase can be detected improperly due to many reasons. These include limited sensor accuracy and noise in the data, lack of essential information from the sensor input, and human error related to labelling of learning samples (see Section 5.4.5.2). In SMOOTH, the priority is to classify movement as correct if there is a reasonably high chance that the movement was performed properly. Otherwise the user could become frustrated that in spite of correct exercise execution the exercise repetition was classified as incorrect. This could lead to abandonment of the device. For that reason, two different DBNs are generated for each exercise addressed by SMOOTH. The first DBN recognises the most probable current movement phase out of all the movement phases defined for the
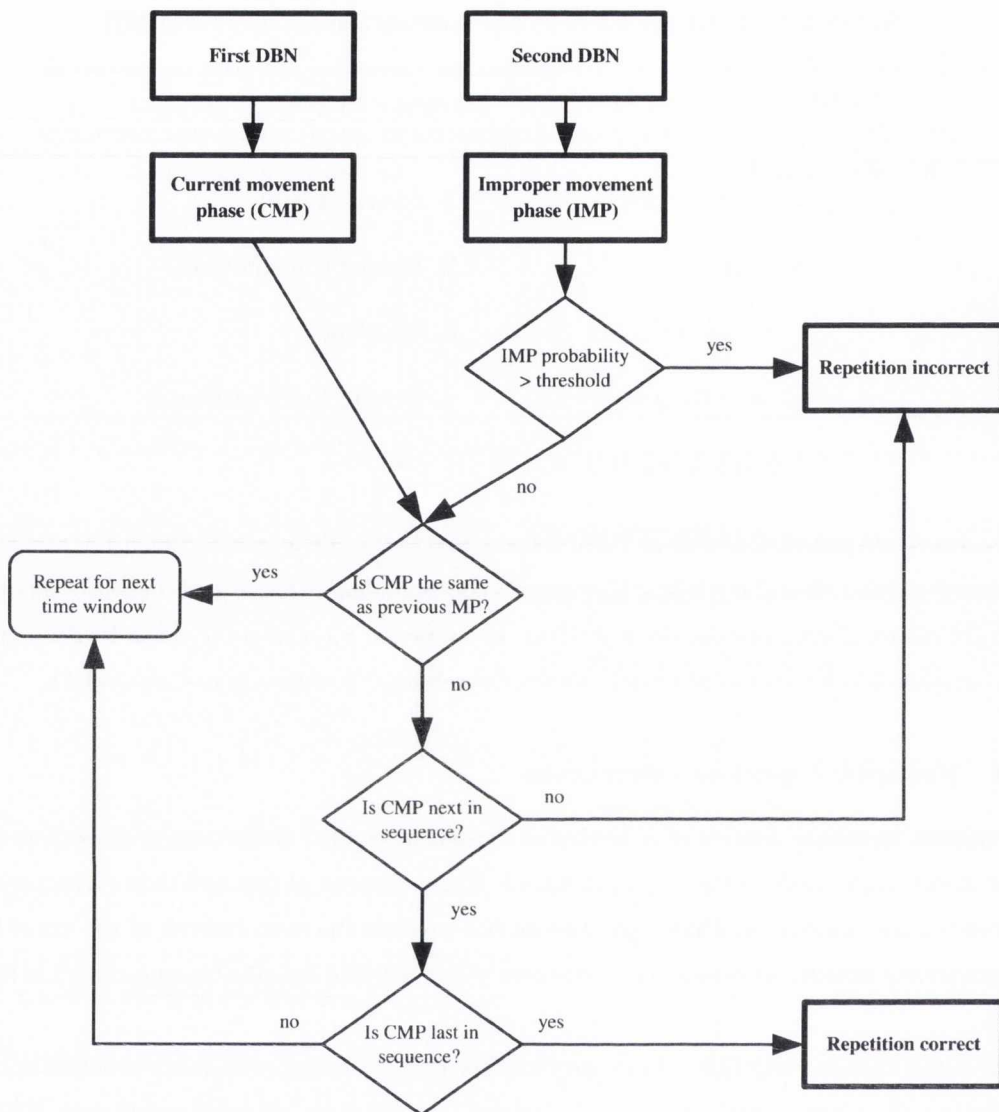
**Figure 5.11**: Exercise repetition detection schema

exercise. The second DBN detects the probability of the current movement phase being performed incorrectly.

Figure 5.11 presents an overview of exercise repetition detection from the movement phases inferred by the two DBNs. The correct phase sequence is pre-defined for each exercise and presented in Table 5.6. For example, the valid order of phases for 'sit to stand' is: *sitting upright, moving trunk forward, standing*, and *moving trunk backward*. Each DBN infers the movement phase separately from the same sensor readings. If the second DBN detects an incorrect movement phase with belief exceeding some defined threshold, exercise execution is considered to be incorrect. Otherwise, it is examined if the current movement phase detected by the first DBN using the sensor readings from the current time window is the same as the movement phase detected in previous time window. If so, the inference is repeated for the next time window. If not, it is examined if the current movement phase is the

next phase in the sequence defined for a particular exercise. If not, then the exercise repetition is considered to be incorrect. If so, it is examined if the current movement phase is the last phase in the sequence. If it is, then a correct exercise repetition is counted. If not, the inference is repeated for next time window.

## 5.4.5 Dynamic Bayesian network for SMOOTH

The general approach for movement phase inference from sensor inputs applied in SMOOTH is presented in Figure 5.12. Sensor readings are pre-processed (see Section5.3.3) and a set of signal features is calculated over a sliding time window (see Section 5.3.5). The selected signal features (see Section 5.3.6) are discretised (see Section 5.4.6.1) and given as the value of the input nodes to the DBNs in order to infer the current movement phase and the probability of its correct execution.
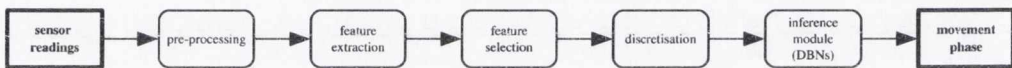


**Figure 5.12**: Current movement phase inference schema

The following part of this section presents the mechanism used for learning within the inference module in order to fulfil the adaptivity **(R. 8)** requirement, and the structure of the DBNs used in SMOOTH.5.4.5.1

### 5.4.5.1 Learning movement phases and parameters

DBNs can learn probability parameters relating to existing dependencies between their nodes in a supervised manner. This means that a set of training samples that map sensor inputs to the desired outputs of the network in needed. To create such a set for the DBNs used in SMOOTH an expert that can match the movement during exercise execution, which is the source of sensor inputs, and the movement phases presented in Table 5.6 is required. As noted previously, in SMOOTH, the role of the expert is performed by physiotherapists. During the system training phase the user is asked to perform two sets of the exercises to be prescribed, called the training and testing samples, and the physiotherapist marks the corresponding movement phases as the exercise progresses. This data set is used to update the probability parameters and therefore adapt the DBNs to individual characteristics of the user **(R. 8)**. The acquisition and use of the training and testing samples are described in more detail in Sections 5.4.5.2 and 5.4.6.1, respectively.

Both DBNs used to recognise phases of a particular exercise are learnt separately with data collected from the user and labelled by the physiotherapist in a training phase. The learning process involves adjustment of two types of parameters: discretisation parameters (see Section 5.4.6.1), and conditional probability tables (CPTs) in nodes in order to infer current movement phase. However, the sample sets used to learn each DBN differ (see Section 5.4.5.2). This means that discretisation parameters as well as CPTs for each node are optimised to give the best movement phase recognition

accuracy for a particular set of training and testing samples and might differ for both DBNs.

### 5.4.5.2 Training and testing samples

Labelled training and testing sample sets used to learn the first DBN are obtained during the training phase and can be used without any modifications. However, to learn the second DBN, samples of incorrect behaviour during a particular exercise have to be collected in order to allow the association of sensor readings with incorrect movement. Collection of incorrect movement samples during exercise execution might be difficult, unnatural, and inconvenient. In general, users are encouraged to do exercises properly and for that reason any incorrect movements are usually corrected by physiotherapists and should be avoided. Having that in mind, the mechanism for acquisition of incorrect samples was designed to utilise samples collected during execution of other exercises. For example, *moving trunk forward* is a valid movement phase in the 'leaning forward' exercise, however during 'leaning to the left' execution of such a movement should be classified as *incorrect*. Using this approach, samples collected for other exercises can be relabelled in such a way that if some movement phase is not present in a particular exercise its label is changed to *incorrect*. Modified training and testing sample sets are used as input data to the learning process of the second DBN. In the set of exercises for SMOOTH, 21 different movement phases have been identified. The movement phases and the exercises to which they belong are presented in Table 5.7. If a particular movement phase does not belong to the exercise it is considered to be incorrect for the purpose of the preparation of training and testing sample sets for this exercise.

**Table 5.7**: Correct movement phases for exercises for SMOOTH

| # | Movement phase | Phase correct in |
|---|---|---|
| 1 | Sitting upright | • All the exercises. |
| 2 | Moving right knee up | 1. Marching in sitting. |
|   |   | 2. Abduction of the right leg. |
| 3 | Right knee up | 1. Marching in sitting. |
|   |   | 2. Abduction of the right leg. |
| 4 | Moving right knee down | 1. Marching in sitting. |
|   |   | 2. Abduction of the right leg. |
| 5 | Moving left knee up | 1. Marching in sitting. |
|   |   | 2. Abduction of the left leg. |

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**Table 5.7**: Correct movement phases for exercises for SMOOTH

| # | Movement phase | Phase correct in |
|---|---|---|
| 6 | Left knee up | 1. Marching in sitting. |
| | | 2. Abduction of the left leg. |
| 7 | Moving left knee down | 1. Marching in sitting. |
| | | 2. Abduction of the left leg. |
| 8 | Moving to the right | 1. Hip walking in sitting. |
| 9 | Moving to the left | 1. Hip walking in sitting. |
| 10 | Right leg abducted | 1. Abduction of the right leg. |
| 11 | Left leg abducted | 1. Abduction of the left leg. |
| 12 | Leaning to the right | 1. Leaning to the right. |
| 13 | Leaned to the right | 1. Leaning to the right. |
| 14 | Leaning back to the left | 1. Leaning to the right. |
| 15 | Leaning to the left | 1. Leaning to the left. |
| 16 | Leaned to the left | 1. Leaning to the left. |
| 17 | Leaning back to the right | 1. Leaning to the left. |
| 18 | Moving trunk forward | 1. Leaning forward. |
| | | 2. Sit to stand. |
| 19 | Leaned forward | 1. Leaning forward. |
| 20 | Moving trunk backward | 1. Leaning forward. |
| | | 2. Sit to stand. |
| 21 | Standing | 1. Sit to stand. |

**5.4.5.3   Structure**

As noted previously, there are two DBNs created for each exercise addressed by SMOOTH. Each of the DBNs consists of a number of input nodes, referred as feature nodes, that represent features of the sensor input signals (see Section 5.3.5). The DBNs differ in the number of states in the output node, referred as the phase node, that represents the current movement phase. In the first DBN the states of the phase node correspond to the movement phases defined for a particular exercise. This network is used to recognise the current movement phase. In the second DBN an extra output state corresponding to improper execution of the current movement phase is added. This network is used to recognise whether the current movement phase has been performed properly. For example, in the first DBN created for 'leaning forward', the phase node has 4 states: *sitting upright, moving trunk forward, leaned forward*, and *moving trunk backward*. In the second DBN one additional *incorrect* state is added to indicate incorrect exercise execution. Therefore, for 'leaning forward', the phase node has 5 states: *sitting upright, moving trunk forward, leaned forward, moving trunk backward*, and *incorrect*. Both DBNs are generated separately from the learning and testing samples described in the previous section

Figure 5.13 shows the DBN used for inference of the current movement phase in SMOOTH. The network consists of a number of nodes representing signal features from force and distance sensors. Each feature node has a number of discrete states described in Section 5.4.6.1 in more detail. These nodes are connected to the node representing the current movement phase. As noted previously, DBNs in SMOOTH are based on a naive Bayes classifier, therefore the feature nodes are independent from each other given movement phase. As indicated in Section 5.3.5, features $\{\mu, d, s\}$ for each sensor are calculated over a sliding time window in the current time slice $t$. Therefore each sliding time window consists of a number of readings $j = 1, \ldots, k$. Let $\{x_1^{t_j}, x_2^{t_j}, \ldots, x_n^{t_j}\}$ be sensor readings from a number of sensors $i = 1, \ldots, n$ at time $t_j$. Mean value $\mu_i^t$ and standard deviation $s_i^t$ in current time slice for sensor $x_i$ are calculated as follows $\mu_i^t = \frac{1}{k}\sum_{j=1}^{k} x_i^{t_j}$ and $s_i^t = \sqrt{\frac{1}{k}\sum_{j=1}^{k}(x_i^{t_j} - \mu_i^t)^2}$. Difference $d_i^t$ is calculated by subtraction of the mean value of previous time slice $\mu_i^{t-1}$ from the mean value in the current time slice $\mu_i^t$, and given by $d_i^t = \mu_i^t - \mu_i^{t-1}$. As noted in Section 5.3.3, in SMOOTH sensors placed on the seat of the chair are grouped into eight pressure areas and the mean values of each area are used as an input for feature calculation. Such a solution was based on the low-accuracy of the sensors and empirical results. Therefore, the features are calculated for $n = 13$ sensor readings (8 pressure areas and 5 distance values).

Figure 5.14 shows a sample DBN generated for 'leaning forward' exercise using training and testing samples obtained from the researcher. 33 of 39 features were selected in the feature selection process (see Section 5.3.6) therefore 33 feature nodes are connected to the phase node.

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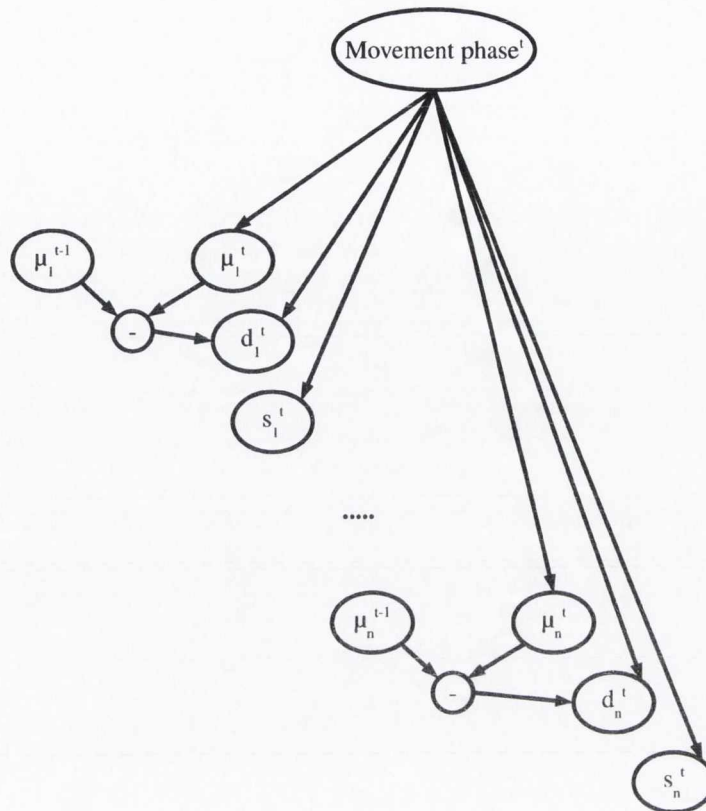
**Figure 5.13**: DBN used in SMOOTH

## 5.4.6 Discretisation

The set of signal features available to be used in the inference module of SMOOTH presented in Section 5.3.5 consists of 3 features $\{\mu, d, s\}$. Each of these features can take any value from the real number domain, which means that their values are continuous. The naive Bayes classifier used in the system requires the estimation of probabilities and continuous node values are not so easy to manage, as they often take too many different values for a direct estimation of frequencies. To avoid this, a normal distribution of the continuous values can be assumed, but this hypothesis does not always provide an optimal solution [Gelman et al., 1995]. In addition, as presented in Appendix B most BN tools allow only discrete values of nodes in order to learn probability parameters. For that reason the continuous values of signal features used in SMOOTH need to be divided into a number of intervals to allow the adjustment of DBN parameters to user characteristics. This process of division of continuous variables into intervals is usually termed discretisation. Unfortunately, the number of ways to discretise a continuous value is infinite [Kotsiantis and Kanellopoulos, 2006]. Therefore the key challenge in SMOOTH is to find a set of thresholds to divide the range of feature values into a small number of intervals.

The most straightforward method for data discretisation is establishment of fixed thresholds in order to create a small number of intervals. The thresholds can uniformly divide the data range into
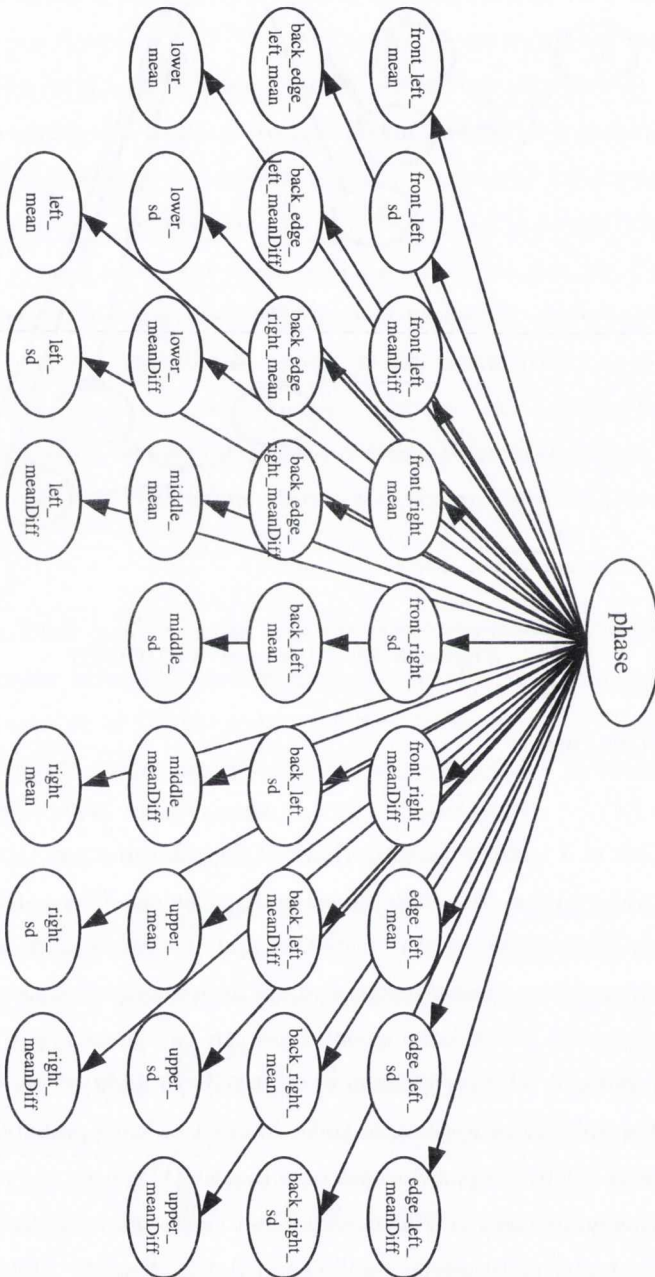
**Figure 5.14:** Sample DBN generated for 'leaning forward'

intervals or can be decided empirically. Even though this might work reasonably well in some cases, the initial experiments presented in Section 5.4.2 show that this approach does not work well for the set of sensors used in SMOOTH. The reason for this can be differences in the physical characteristics of people, e.g., they have different heights and weights. In addition, movement patterns differ for different people. For example, people can perform a movement with different speeds and have different ranges of movement. These issues might be crucial when designing a system for people with PD, who often have movement limitations [Gelb et al., 1999]. To improve the accuracy of inference in SMOOTH, and therefore fulfil accuracy requirement **(R. 2)**, it is important to discretise the signal features in a more flexible way. As a flexible optimisation tool, genetic algorithms (GAs), which are nowadays widely applied to tackle a number of real-world optimisation problems, can be used to discretise continuous data [Chen et al., 2006]. In principle, GAs select the fittest individuals from the current population on the basis of defined criteria and generate the new population by employing recombination and mutation. GAs are described in more detail in Appendix B.

### 5.4.6.1 Discretisation of features for SMOOTH

SMOOTH uses GAs in order to discretise signal features and adjust DBN parameters to the characteristic of individual users. The first step is to define the problem to be solved by a GA. The problem is how to divide continuous data from sensor signal features $\{\mu, d, s\}$ into intervals. Such a division would enable the DBNs to learn probability parameters for dependencies between the signal features and movement phases to obtain the highest accuracy of movement phase inference. To answer this question and enable GA application in SMOOTH, a chromosome (solution representation) and objective function (criteria for the evaluation of the quality of solutions) have to be defined.

In the DBNs defined for SMOOTH each node related to sensor readings represents one of the features $\{\mu, d, s\}$ calculated from the input of a particular sensor. Discretisation of features from different sensors in the same way is not necessarily the most optimal solution. For example, the value range and behaviour of a distance sensor placed on the back of the chair is different from a force sensor placed on its seat. In addition, during exercise a different range of pressures is applied to different areas of the seat and therefore the force sensors placed on them. For simplicity and based on the results of initial experiments, the smallest reasonable number of states for each feature was chosen in order to discretise continuous values of the features. Features, their ranges, the number of intervals which corresponds to the number of states in the DBN feature nodes, and their relation with parameter $n$ are presented in Table 5.8. Consequently, each chromosome encodes the value of $n$ that match the discretisation thresholds for each feature. Each parameter $n$ corresponds to a particular feature node in the DBNs used to infer the current movement phase in SMOOTH. Parameters for each feature node in the first population are initialised randomly from the range of this feature values obtained from training and testing sample sets (see Section 5.4.5.2). As noted in Section 5.3.6, the number of feature nodes depends also on training and testing samples. The number of parameters

encoded in the chromosome corresponds to the number of feature nodes used in the Bayesian model and for that reason, the size of the chromosomes might differ depending on the model.

| Feature | Value range | Number of states | States in relation to parameter $n$ |
|---|---|---|---|
| mean $\{\mu\}$ | $\mu \epsilon < 0, \infty)$ | 2 | $< 0, n), < n, \infty)$ |
| difference $\{d\}$ | $d \epsilon (-\infty, \infty)$ | 3 | $(-\infty, -n), < -n, n), < n, \infty)$ |
| standard deviation $\{s\}$ | $s \epsilon < 0, \infty)$ | 2 | $< 0, n), < n, \infty)$ |

**Table 5.8**: Number of states for feature nodes

The choice of objective function should be related to the purpose of discretisation. In the case of SMOOTH the data are discretised in order to learn the DBN's probability parameters and obtain the highest accuracy of movement phase inference. In other words, the objective of the GA is to search for the DBN whose discretisation parameters provide the highest inference accuracy. Consequently, movement phase inference accuracy is the objective function. The higher the value the more accurate the DBN is and the more chromosomes representing it should be selected to breed the next generation. To calculate the value of the objective function each chromosome is transformed into a DBN. The DBN is learnt using training samples (see Section 5.4.5.2) collected from a user in the training phase and tested against testing samples (see Section 5.4.5.2) collected from the same user. The movement phase detection accuracy from this test is the value of the objective function. Two separate sample sets for learning and testing are used to introduce diversity of user movement to the parameter learning process. Because even correct repetitions of a particular exercise can differ from each other, the diversity is needed in order to learn a variety of correct movement patterns.

### 5.4.7 Summary

This section described the technique used in SMOOTH to monitor exercise performance. Assessment of exercise execution is based on the number of correct repetitions completed. A repetition is defined as a valid sequence of the correct consecutive movement phases. To detect the current movement phase and assess its correctness DBNs were chosen because of their suitability for reasoning under uncertainty. The DBNs utilised in SMOOTH consist of movement-phase nodes and nodes that represent features from the sensor signal. Three types of features from the sensor readings calculated over a sliding time window are used as the input to DBNs. The feature nodes used in DBNs are selected on the basis of samples collected in a training phase from the user for a particular exercise. The values of feature nodes are discretised using GAs and dependencies between sensor readings and movement phases are also learnt from data acquired in a training phase.

## 5.5   Operation

SMOOTH is designed to support people with PD in their exercise routines and enable their physiotherapist to review their progress. The purpose of this section is to describe in more detail the roles of the users, people with PD and their physiotherapists, in the system and what tasks that they are expected to perform.

### 5.5.1   Physiotherapists

The physiotherapist has four roles defined in the system:

1. choice of exercises;

2. calibration of the device to meet the user's characteristics;

3. prescription of an exercise programme;

4. review of exercise programme execution.

When a person with PD comes to a consultation, the physiotherapist examines the patient and depending on their condition prescribes a set of exercises that should be performed by this person at home. The patient is instructed on how the exercises should be performed. To calibrate the system, two sets of each exercise prescribed have to be performed under the supervision of the physiotherapist. The movement phases (see Table 5.6) are marked by the physiotherapist as the exercise progresses. The supervision of the physiotherapists ensures that exercises are performed properly and training and testing samples with corresponding labels, to be used in system calibration, are collected. Following that the physiotherapist determines the number of repetitions, sets, and frequency of each exercise to be performed by the user at home. When the user returns home, the system is ready to exercise.

The correct number of repetitions of each exercise performed by a user at home can be reviewed by the physiotherapist at any time. When the patient consults the physiotherapist they can review execution of the exercise programme and change the exercises and their prescription if necessary. If the range of patent motion changed remarkably or new exercises were added to the exercise programme the calibration process for these exercises should be executed once more.

### 5.5.2   People with Parkinson's disease

The role of people with PD in the system is to execute the exercise programme, prescribed by the physiotherapist during a consultation, and at home. To support the user, SMOOTH provides the user with feedback during the exercise, which helps to perform the appropriate number of exercise repetitions. In addition, the user is provided with information about the execution of the exercise programme and on that basis can decide, which exercises should be performed. During each session the number of correct exercise repetitions is recorded and can be reviewed by physiotherapist at any time.

## 5.6 Graphical user interfaces

This section begins with a general description of possible user interactions with the system and gives insight into the type of feedback used in SMOOTH. To enable the operations described in the previous section the applications for the user and physiotherapist were implemented. To fulfil the intuitiveness requirement **(R. 6)** the applications for user and the physiotherapist were designed to have very simple graphical user interfaces (GUIs) and intuitive operations. The following part of this section describe GUIs in more detail.

### 5.6.1 User feedback

As presented in the literature review there are a number of ways to interact with system users including voice, visual, and haptic feedback. SMOOTH was designed to be used at home therefore a number of common interfaces such as digital picture frames, personal computers, and television sets were considered as user feedback devices. In addition, a number of interactions such as visual and audio clues before and during the exercises were considered. However, to define the most appropriate and convenient form of user feedback and user feedback device for SMOOTH as well as the user interface further research should be conducted including iterative design and consultation with people with PD. This research focused on investigating the feasibility of measuring an exercise routine using inexpensive sensors placed on a chair rather than on the design of a user interface. The user interface was built mainly for evaluation purposes and can be considered the first iteration of the user interface design process.

### 5.6.2 Physiotherapist interface

Figure 5.15 presents the initial physiotherapist interface screen. It enables the physiotherapist to manage the patients, i.e., to add and remove them from the system and to change their details. To start working with a particular patient, the patient must be chosen from the list and the 'continue' button pressed.

To enable calibration of the device to a user's characteristics the logging interface presented in Figure 5.16 was designed. The interface allows the choice of an exercise for which the system should be calibrated and selection of the sample set (training or testing). After pressing the 'start logging' button sensor readings start being recorded. The physiotherapists can mark movement phases as an exercise progresses by clicking the 'next phase' button or buttons corresponding to the appropriate movement phase, e.g., 'moving trunk forward'. In the sample screen the 'leaning forward' exercise, which consists of four movement phases (see Table 5.6), was selected to be calibrated.

Following logging and marking the sensor readings, the physiotherapist can prescribe an exercise programme appropriate for the user. The exercise programme prescription screen is shown in Figure 5.17. Once an exercise is selected to be included in an exercise programme the following parameters

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**Figure 5.15**: Patient choice screen
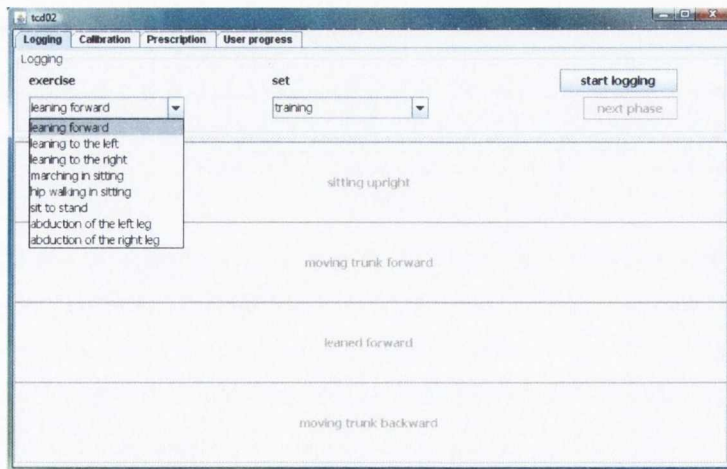


**Figure 5.16**: Logging screen

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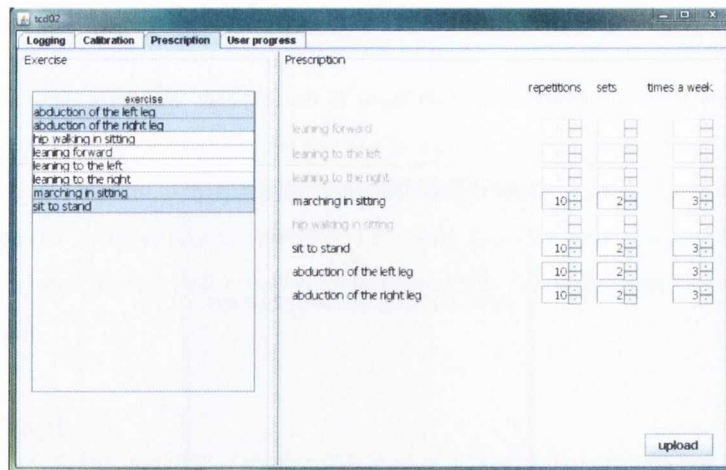
**Figure 5.17**: Exercise programme prescription screen

can be adjusted:

- number of repetitions in one set;

- number of sets to be performed in a day;

- number of days a week when the exercise programme should be performed.

To change the exercise programme, a new set of exercises and their parameters should be selected. In the sample screen, four exercises were selected to be included in the exercise programme: 'abduction of the right leg', 'abduction of the right leg', 'marching in sitting' and 'sit to stand'. For each of them, two sets of 10 repetitions to be performed three times a week were prescribed.

Two types of charts were designed to enable the physiotherapists to review user progress. Figure 5.18a presents a chart that shows the number of exercise sets performed each day during last week/month. The pink bars indicate that last week the 'leaning forward' exercise was performed on three days: two sets on the first day, one set on the second day, and two sets on the third day. As described in the example above (Figure 5.17), two sets to be performed three times a week were prescribed. This means that the user did five of six sets prescribed (over 80%), which is indicated by the blue line. Figure 5.18b presents a chart that shows the number of correct exercise repetitions performed in each set in the last week/month. The pink bars indicate that last week five sets of the 'leaning forward' exercise were performed and the number of repetitions in each set varied from 9 to 10. The blue line indicates that 10 repetitions to be done in each set were prescribed.

### 5.6.3 User interface

The user interface was not the major research question of the thesis and was mainly built for evaluation purposes. For that reason, devices other than a PC (as used in the system evaluation) were not given deeper consideration and the interface was not designed to benefit from their potential features. User

(a) Number of sets
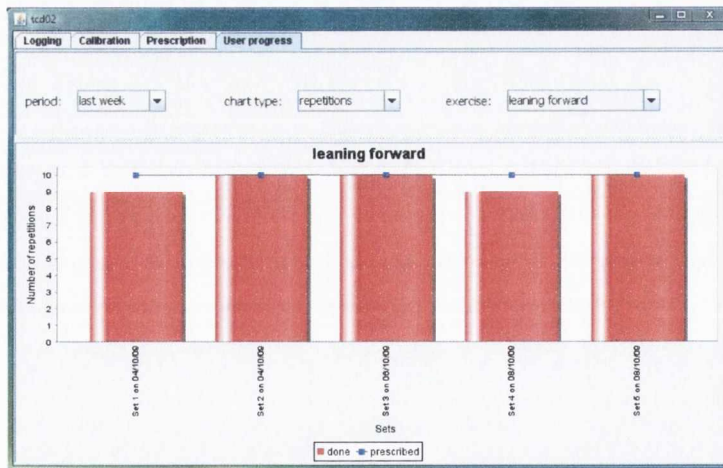


(b) Number of repetitions

**Figure 5.18**: User progress screen
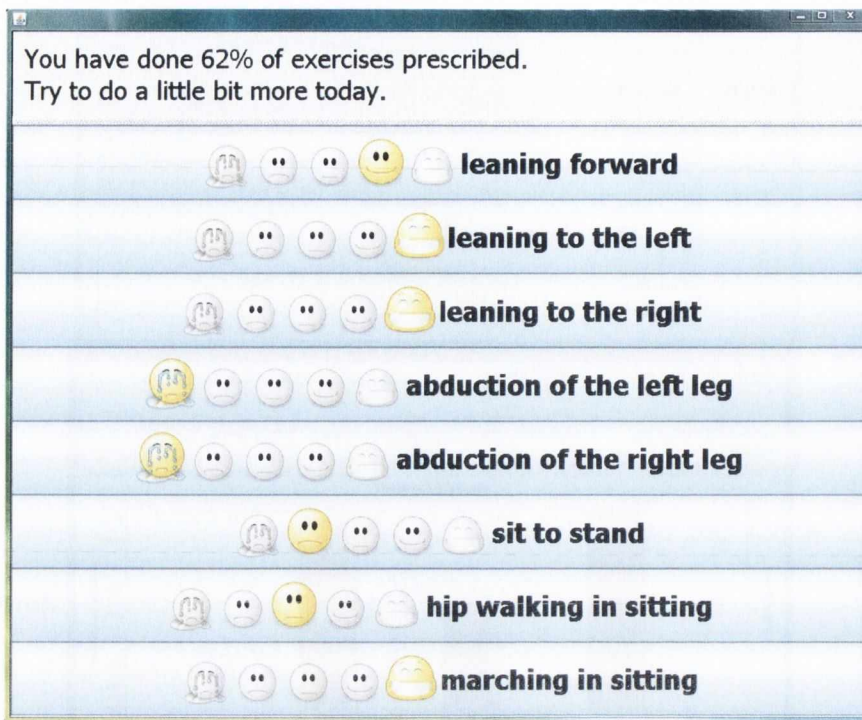
**Figure 5.19**: Progress screen

interaction with the system aimed at being convenient and simple. However, the user interface was neither designed in cooperation with people with PD nor based on previous consultations with them. The main reasons for this were time constraints and the fact that it was not the main aim of this study.

Figure 5.19 shows a progress screen with which a user is presented after starting the application at home. The list of exercises prescribed by the physiotherapists and their parameters are downloaded automatically from the data server (see Section 5.7). The icons next to each exercise indicate how well the user met the exercise prescription in the last week. For example, the 'happy icon' next to 'marching in sitting' shows that enough repetitions of this exercise were done. The 'sad icon' next to 'abduction of the right/left leg' indicates that not enough repetitions of these exercise were done and the user should do more repetitions. In general, the happier the icon next to a particular exercise, the better the user has met the prescription. On the top of the screen general information about the exercise programme is presented. To start a particular exercise user should press the corresponding button. After that a voice message describing the selected exercise is played.

After starting an exercise the user is presented with the screen shown in Figure 5.20. In the sample screen the user selected the 'leaning forward' exercise. Five repetitions of this exercise to be done in each set were prescribed. To make interaction with the user more natural, the application for the user provides the user with visual and voice feedback. As repetition progresses the red progress bar turns green. During the exercise the user is provided with voice feedback, which includes messages such as 'come back to starting position' and 'continue the exercise'. After each correct repetition, the counter

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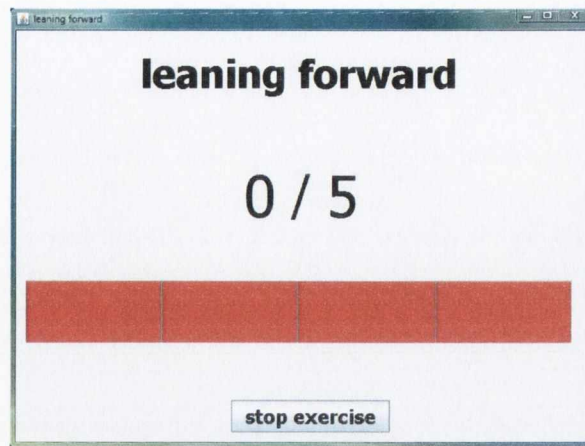
**Figure 5.20**: Exercise screen

of repetitions performed is increased and a voice message 'well done' is played. When the user exceeds the number of repetitions prescribed for one set, a message 'you have reached prescribed amount of repetitions' is played. After pressing the button 'stop exercise' the user is presented with the progress screen (Figure 5.19) in which the icons and messages on the top of the window have been updated according to user progress.

## 5.7 System architecture

The overall system architecture is pictured in Figure 5.21. SMOOTH consists of a user module for the home environment, a healthcare professional (HP) module for the clinical environment, and a data server. The data server is used to store calibration data obtained during a learning session and exercise statistics. In addition, it enables the exchange of data between the user and HP modules. The data server is introduced to fulfil the portability requirement **(R. 7)**, so that the system is independent of the location of its users. The HP and user modules consist of a chair equipped with sensors that is connected through an appropriate interface to the feedback device. For feedback separate applications for the HP and user were developed (see Section 5.6). The chair used by the user at home and by the physiotherapist to calibrate the system is equipped with the same set of sensors.

The system architecture is based on a client-server model. The server runs the application to store the data obtained from clients and provides clients with appropriate data. The clients, i.e., user and HP modules, can be distributed and access the server simultaneously. The server application as well as client modules were implemented in Java therefore every environment that implements Java Virtual Machine should be compatible. The clients communicate with the server using web services running on the server. This approach enables reliability, flexibility, and re-use, e.g., by a web interface presenting data collected on the server. The data obtained from the client applications is stored in the database. The data collected by the HP application includes user details, calibration data, and details of the exercise prescription. The data collected by the user application includes the time and number

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**Clinical environment**
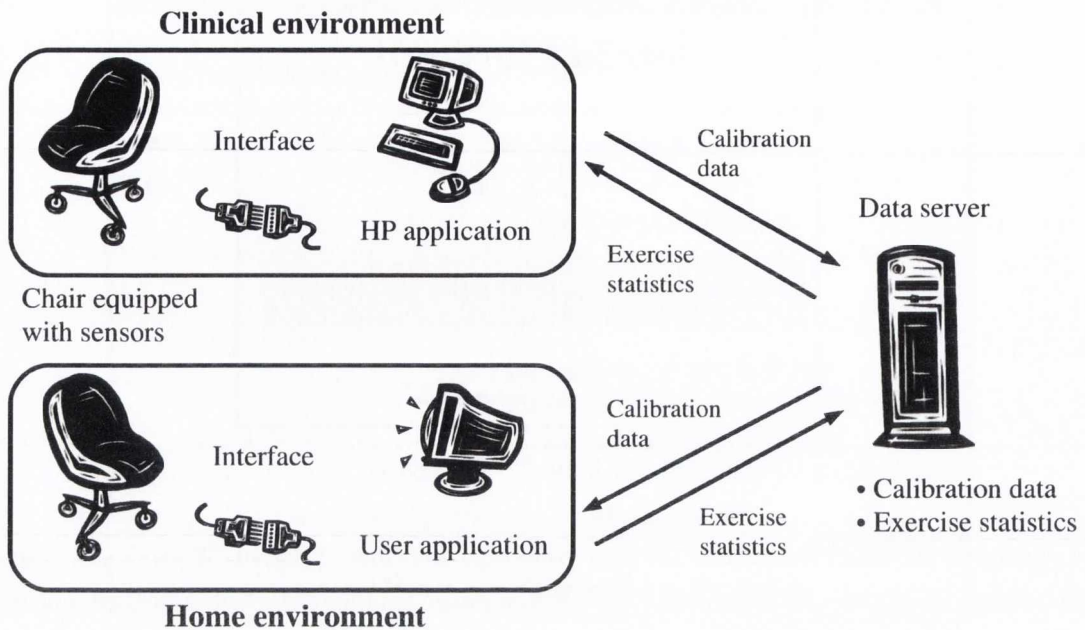


Figure 5.21: System architecture overview

of exercise repetitions executed by the user. The exercises and appropriate movement phases as well as other configuration details were defined in an XML file to promote flexibility of the application.

### 5.7.1  Realisation

The server and client applications described in this thesis were fully implemented. The server was implemented using J2EE technologies such as web services, Enterprise Java Beans, and Java Persistence API to communicate with the MySQL database used to store the data. User and HP modules were implemented in Swing as standalone desktop applications. They used a local database (SQLite) to store the data and when the connection to the server was available the data was synchronised automatically using web services available on the server.

## 5.8  Summary

To answer our hypothesis that a set of low-cost, fixed sensors are sufficient to measure exercise performance SMOOTH has been designed. At the beginning of this chapter key requirements for the system were identified. On that basis, a set of exercises and sensors as well as techniques for monitoring exercise performance were selected and are described in this chapter.

Because of safety concerns the set of exercises for SMOOTH includes only exercises that can be performed on a chair. Eight exercises were included in the set. They are: marching in sitting, hip walking in sitting, abduction of the right/left leg, leaning to the right/left, leaning forward, and sit to stand.

The literature review identified several sensor types that could be used to monitor exercise performance. All of them were compared against the system requirements and those meeting the criteria were tested. On the basis of the results two types of sensors were used in the system: force and distance. Five distance sensors were placed on the back of a chair and twenty-four force sensors on the seat in order to detect the current movement phase of the system user. Their readings were used as the input to the exercise monitoring module.

The number of correct repetitions completed was used to measure exercise performance. Each exercise was divided into a number of movement phases. An exercise repetition happens if the correct phases occur in the correct order. To detect the current movement phase a number of techniques were considered and DBNs were selected. DBNs are based on probability theory and enable inference based on uncertain data and provide mechanisms for learning to adapt to users' individual movement patterns. Two DBNs for each exercise were created to infer the current movement phase and assess its correctness. Each DBN uses three types of features calculated over a sliding time window on sensor readings. To discretise continuous features and optimise the accuracy of the DBN, GAs were used. GAs are a flexible optimisation tool and are nowadays widely applied to tackle a number of real-world optimisation problems. The data for selection of feature nodes and learning of the DBNs parameters are obtained during a training phase, during which the patient is asked to perform a set of exercises in a chair, which are labelled by a physiotherapist.

# Chapter 6

# Evaluation

SMOOTH was designed to meet needs of people with Parkinson's disease (PD) and their physio-therapists. The purpose of this chapter is to present the assessment of the accuracy of the exercise monitoring implemented in SMOOTH and the user acceptance of the system. User studies are vi-tally important in the development of novel technologies and forms of interaction to seek the views of their potential future users and optimise their design [Kranz et al., 2007] and so form the core of the evaluation of SMOOTH.

This chapter begins with a presentation of the requirements for the system as defined in the previous chapter and discusses how they were addressed in SMOOTH. Section 6.2 outlines the objectives of our user study including the research questions that it was trying to answer. In Section 6.3 the design of the user study to ensure that the analysis of its results answered the research questions is presented. Two user studies were undertaken to meet the evaluation objectives. Evaluation of user acceptance of the system, including data collection and analysis of the data, are presented for physiotherapists in Section 6.4.2 and for people with PD in Section 6.4.3. A study designed to measure the accuracy of exercise monitoring is presented in Section 6.5. Finally, a summary of this chapter is presented in Section 6.6.

## 6.1 Realisation of Requirements

This section presents how the requirements defined in the previous chapter are addressed by SMOOTH.

1. **Affordable (R. 1)** - As presented in Section 5.3.1, it was difficult to define an affordable price range for an exercise system. In addition, this research only produced a prototype of the system. Its cost would likely be reduced if components were purchased in bulk for manufacture. To investigate the amount that people would pay for SMOOTH as well as the prices of commercially available products further research is needed. Finally, this work focused on the use of sensors to measure exercise execution therefore estimation of the system cost is restricted to an estimation of the sensor cost. To make the system affordable, the approach was to use a possibly low

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number of inexpensive sensors. The set of sensors for SMOOTH consists of twenty-four A201-1 force sensors [Tekscan, Inc., 2009] and five GP2D120 distance sensors [Sharp, 2009]. At the time of purchase, the price of the force sensors was \$24.40 per unit and the distance sensors \$21.99 per unit [Trossen Robotics, 2009]. The units included all cables and boards needed to connect them to a PhidgetInterfaceKit [Trossen Robotics, 2009], which was used to convert the analog sensor readings to a digital representation and could be directly plugged in to a processing unit via a USB port. It was possible to connect eight sensors to one PhidgetInterfaceKit therefore four PhidgetInterfaceKits were used in the system. The price was \$62.20 per unit. The total cost of the sensor set used by SMOOTH is summarised in Table 6.1. As presented, the cost equals \$944.35 which is approximately Euro 640.56 using the exchange rate from 13 October 2009 [OANDA, 2009].

| Unit | Unit price | Quantity | Total price |
|---|---|---|---|
| A201-1 force sensor | \$24.40 | 24 | \$585.60 |
| GP2D120 distance sensor | \$21.99 | 5 | \$109.95 |
| PhidgetInterfaceKit | \$62.20 | 4 | \$248.80 |
| **Total cost** | | | **\$944.35** |

**Table 6.1**: Cost of sensor set used by SMOOTH

2. **Accurate (R. 2)** - As noted in Section 5.2.1, accuracy in SMOOTH is related to measurement of correct exercise repetition. To fulfil the accuracy requirement a number of techniques have been applied in SMOOTH. As described in Section 5.4.4, two dynamic Bayesian networks (DBNs) were used to detect correct repetition of each exercise. The first DBN recognises the current movement phase and the second DBN the probability of its correctness. The literature review [Bao and Intille, 2004, Harms et al., 2008] and initial experiments (see Section 5.4.2) suggest that a user-specific approach to parameter learning obtains better results. For that reason, as described in Section 5.4.5.1, learning of DBNs parameters was conducted for each user individually using samples from the particular user.

3. **Unobtrusive (R. 3)** - As stated in Section 5.3.1, unobtrusiveness is related to privacy as perceived by the user during the use of the device, as well as embedding the technology in the environment to make it less noticeable to the user. To fulfil the requirement for unobtrusiveness, force and distance sensors placed on the chair were used in SMOOTH. This enables integration of the sensors with the device in a way that might not be as noticeable to the user. In addition, no evidence that force and distance sensors violate a user's privacy has been found in the literature. The communication between the sensors and the user feedback device was carried out using a wireless connection therefore it was transparent to the user. The data transfers were automated and did not require additional actions from the user.

4. **Safe (R. 4)** - As stated in Section 5.2, to fulfil the safety requirement and not put the user's health at risk SMOOTH addresses only exercises that can be performed while sitting in a chair.

5. **Convenient (R. 5)** - To fulfil the convenience requirement, SMOOTH uses sets of sensors that are mounted on a chair. For that reason there is no need for configuration involving placement of sensors on the body and there are no restrictions on user movements. The sensors are calibrated automatically during the training phase (see Section 5.4.5.1) therefore there is no need for their calibration before each exercise. In addition, all the settings needed for starting to exercise are downloaded/uploaded automatically (see Section 5.6).

6. **Intuitive (R. 6)** - As mentioned in Section 5.6, to fulfil the intuitiveness requirement applications for people with PD and physiotherapists were designed to have very simple graphical user interfaces (GUIs) and intuitive handling.

7. **Portable (R. 7)** - As presented in Section 5.7, to fulfil the portability requirement the architecture of SMOOTH involves a data server used for information exchange between system users. This means that the system is independent of the location of its users.

8. **Adaptable (R. 8)** - As noted in Section 5.4.1, to adjust system parameters to individual user circumstances DBNs were chosen as the inference technique used in SMOOTH. As described in Section 5.4.5.1, DBNs can learn probability parameters relating to existing dependencies between sensor readings and movement phases from training and testing sample sets of a particular user. In addition, as described in Section 5.4.6.1, genetic algorithms (GAs) were applied in order to reflect the physical characteristics and the movement patterns of a particular user.

## 6.2 Objectives of the User Study

To evaluate the following system requirements: accuracy **(R. 2)**, unobtrusiveness **(R. 3)**, convenience **(R. 5)**, and intuitiveness **(R. 6)** a user study was designed. The objectives of the user study were to establish:

1. **O.1** - User acceptance **(R. 3, R. 5,** and **R. 6)** of the system by people with PD and physiotherapists, in particular with respect to:

   (a) user interface and feedback;

   (b) comfort and simplicity of use;

   (c) general feelings about the system.

2. **O.2** - The accuracy **(R. 2)** and performance of the system in monitoring exercise routines, in particular:

   (a) current movement phase recognition;

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(b) correct exercise repetition detection.

## 6.3 Design of the User Study

To meet the objectives described above the user study was divided into two parts. The first part evaluated user acceptance of the system, which is presented in Section 6.4. The second part evaluated exercise monitoring accuracy, which is presented in Section 6.5.

SMOOTH targets two groups of users: people with PD and physiotherapists. For that reason to evaluate the user acceptance of the system two user studies were undertaken. Each study had a similar methodology, i.e., exposure to the system followed by a questionnaire investigating users' opinions about the system. The questionnaire is described in more detail in Section 6.4.1. The study with physiotherapists was conducted prior to the study of people with PD to obtain suggestions for potential changes and improvements to better meet the needs of people with PD. Most of the physiotherapists included in the study worked with people with PD on a daily basis. For that reason, their opinions about the system operation, set of exercises, number of movement phases in each exercise, user interface and feedback as well as the suitability of the system for people with PD were essential before trials with the patients. Data collection, study results, their discussion, suggested system improvements and their application to SMOOTH are described in Section 6.4.2. Following that, the study investigating acceptance of SMOOTH by people with PD is presented in Section 6.4.3. Similarly, it includes data collection methods and study results, which are followed by a discussion.

To evaluate exercise monitoring accuracy a study with healthy subjects and people with PD was designed. To obtain data for the study, sensor readings were recorded during exercise sessions. They were used in a number of tests conducted for different parameters such as the size of the sliding time window used to calculate signal features and the belief threshold above which the movement phase was assumed to be incorrect (see Section 5.4.4). The purpose of the tests was to measure the accuracy of movement phase recognition and the accuracy of proper exercise repetition detection.

The study was approved by the Faculty of Health Sciences Research Ethics Committee, Trinity College Dublin.

## 6.4 User Acceptance

To fulfil objective **O.1** (see Section 6.2) this part of the evaluation explores user views about the system. This section begins with a description of the survey instruments used to obtain opinions about the system (Section 6.4.1) and is followed by the description of the user studies conducted with physiotherapists (Section 6.4.2) and people with PD (Section 6.4.3). Finally, a summary of this section is presented in Section 6.4.4.

### 6.4.1 Survey instruments

This part of the study employed a self-reported user survey methodology.

#### 6.4.1.1 Design

Two separate user surveys were designed to investigate the views of the two groups of potential users, i.e., physiotherapists and people with PD, on the system. The design of the user surveys was based on the purpose and requirements for SMOOTH described in previous chapters of this thesis. This information in conjunction with the clinical experience of Dr. Stokes was employed to design the first version of the user survey. The initial version of the user survey was revised based on feedback from physiotherapists during a pilot study.

#### 6.4.1.2 User surveys

Both user surveys consist of a questionnaire to be completed by the participants after a demonstration of the operation of the system oriented towards that participant's role. The questionnaires aim to explore subjects' views on the system from the user perspective. It includes questions related to user interface and feedback, comfort and simplicity of use and general feelings about the system. Both questionnaires use a Likert scale with 6 ordered response levels anchored at 'strongly disagree' and 'strongly agree' and consist of 9 or 10 questions, respectively. An additional open-ended question for other comments is included to enable participants to give more detailed opinions about their views and experience.

### 6.4.2 Physiotherapists

This section presents the study investigating the user acceptance of the system by the physiotherapists. The remainder of this section describes data collection (Section 6.4.2.1), results of their analysis (Section 6.4.2.2), a discussion (Section 6.4.2.3), and proposed system improvements (Section 6.4.2.4).

#### 6.4.2.1 Data collection

The following inclusion criteria were used: (1) degree in physiotherapy; and (2) experience in working with patients. Physiotherapists working with people with PD identified through professional networks[1,2] were invited to participate in the study. In addition, Dr. Stokes contacted physiotherapists already known to her. The project was explained to them, including their role, and any pertinent questions were answered. One week later, they were contacted again and if they agreed to participate, written consent was requested on a formal consent form. The meeting with participants was scheduled at a time convenient to them. During the session the purpose of the system was explained to the participants and its operation, including the applications for physiotherapists and people with

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[1] Physiotherapy Research & Older People Group, Department of Physiotherapy, Trinity College Dublin
[2] Dublin Physiotherapy Research Hub, which is part of the National Physiotherapy Research Network (NPRN)
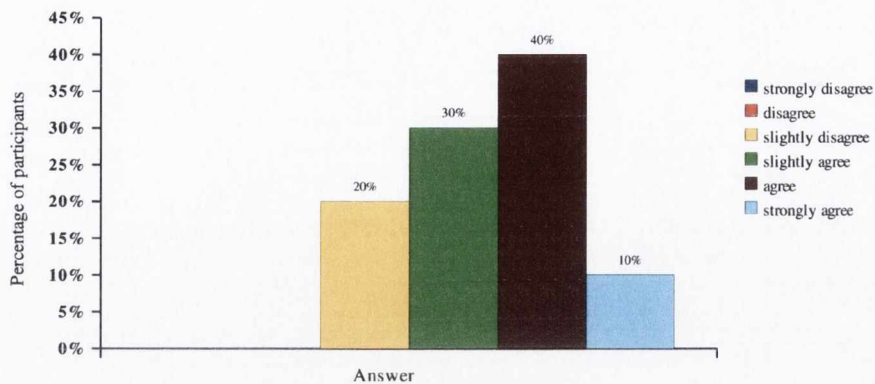
**Figure 6.1**: Question 1 - I found the seat appropriate for the treatment.
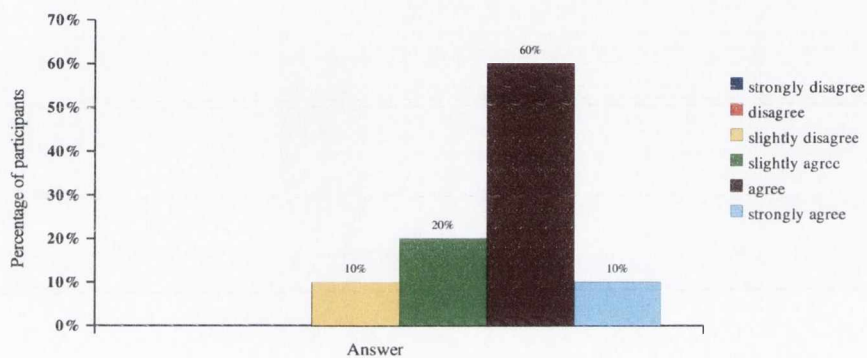


**Figure 6.2**: Question 2 - Overall I found the system easy to use.

PD, was demonstrated. The demonstration of the application designed for people with PD included execution of exercises supported by the system performed by the researcher. Following that subjects were asked to fill in the questionnaire. 10 physiotherapists agreed to participate in the study.

#### 6.4.2.2 Results

The first question investigated the suitability of the chair chosen for SMOOTH. In general, participants agreed that the chair chosen for the treatment was appropriate. 40% and 10% of the subjects 'agreed or 'strongly agreed' with the suitability of the chair, respectively. 30% 'slightly agreed' and 20% 'disagreed' with that. The reason for perceived inappropriateness of the chair was lack of arm rests. The distribution of participants' answers is illustrated in Figure 6.1.

The second question investigated if the system was perceived to be easy to use. In general, most of the subjects (90%) agreed that SMOOTH is easy to use. 10%, 50%, and 20% of the participants 'strongly agreed', 'agreed', or 'slightly agreed' with that, respectively. The remaining 10% of the subjects 'slightly disagreed'. The distribution of participant's answers in illustrated in Figure 6.2.

The third question investigated if the instructions on the screen were unclear to the participants. 50% and 40% of the subjects 'disagreed' or 'strongly disagreed' that the instructions were not clear, respectively. The remaining 10% of subjects 'slightly agreed' with that. The distribution of participant's
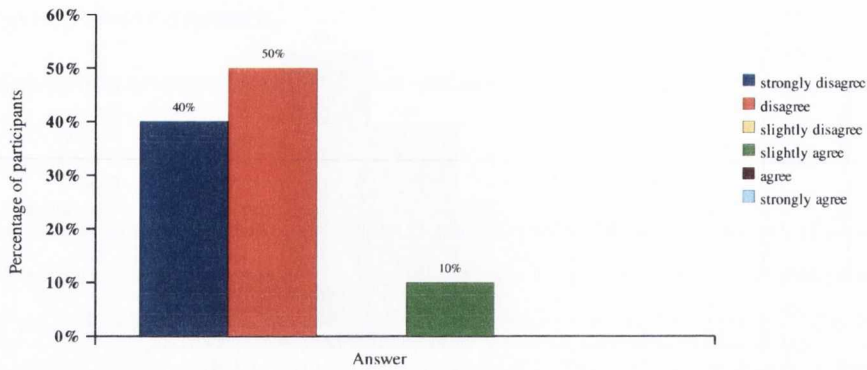
**Figure 6.3**: Question 3 - The instructions on the screen were not clear to me.
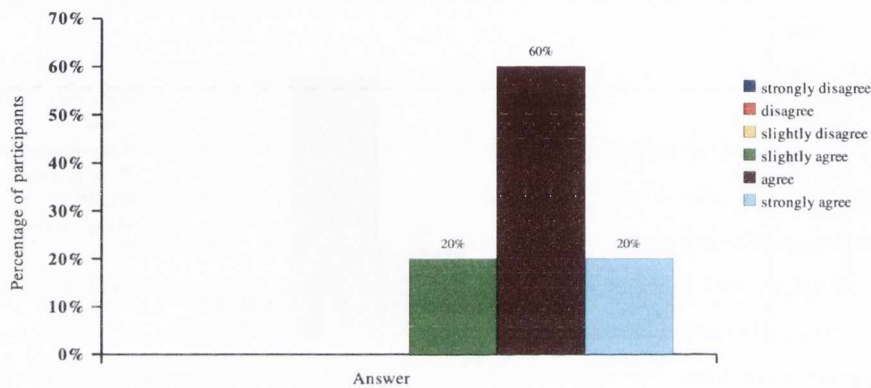


**Figure 6.4**: Question 4 - I found creation and change of a set of exercises for a patient easy to use.

answers in illustrated in Figure 6.3.

The fourth question investigated if the participants perceived prescription of exercises easy to use. In general, all of the subjects agreed that creation of an exercise programme prescription was easy to use. 20%, 60%, and 20% of the participants 'strongly agreed', 'agreed', or 'slightly agreed' with the statement, respectively. The distribution of participant's answers in illustrated in Figure 6.4.

The fifth question investigated if the participants perceived the possibility of review of a patient's exercise routine useful. Most of the subjects (70%) 'strongly agreed' that review of a patient's progress is useful for them. 20% and 10% of the participants 'agreed' and 'slightly agreed' with that, respectively. The distribution of participants' answers is illustrated in Figure 6.5.

The sixth question investigated if the participants found the manner by which the information about patient progress is presented to them to be appropriate. In general all of the participants agreed that the presentation of patients' progress was appropriate. 40%, 50%, and 10% of the participants 'strongly agreed', 'agreed', or 'slightly agreed' with that, respectively. The distribution of participants' answers is illustrated in Figure 6.6.

The seventh question investigated if the participants found marking of movement phases during the system training phase inconvenient. Generally, most of the participants disagreed that marking movement phases was inconvenient. 10%, 40%, and 10% of the subjects 'strongly disagreed', 'dis-
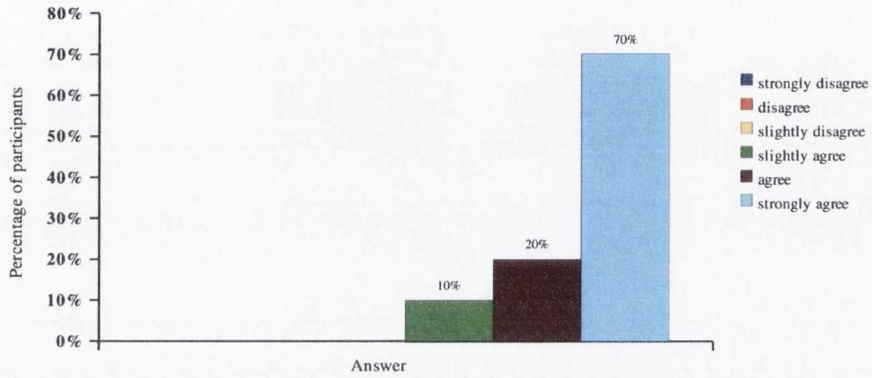
**Figure 6.5**: Question 5 - I liked that I can review the progress of each participant.
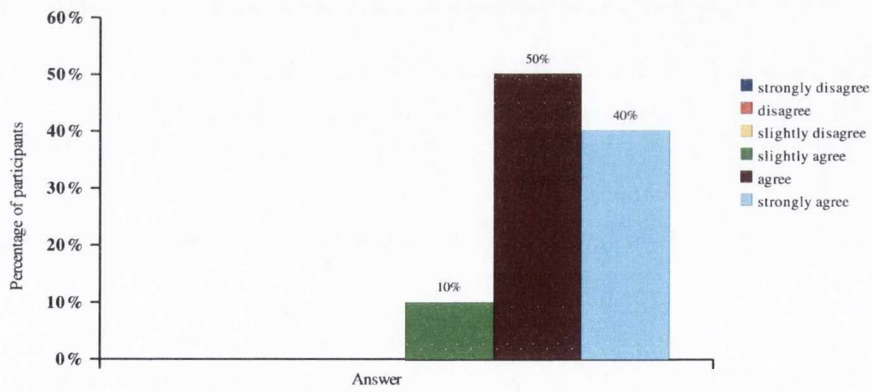


**Figure 6.6**: Question 6 - I found the method of presenting information about patient's progress appropriate.
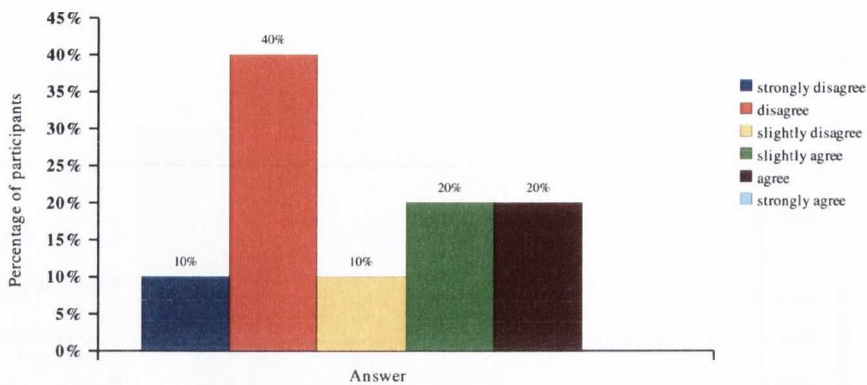
**Figure 6.7**: Question 7 - I found marking different movement phases inconvenient.
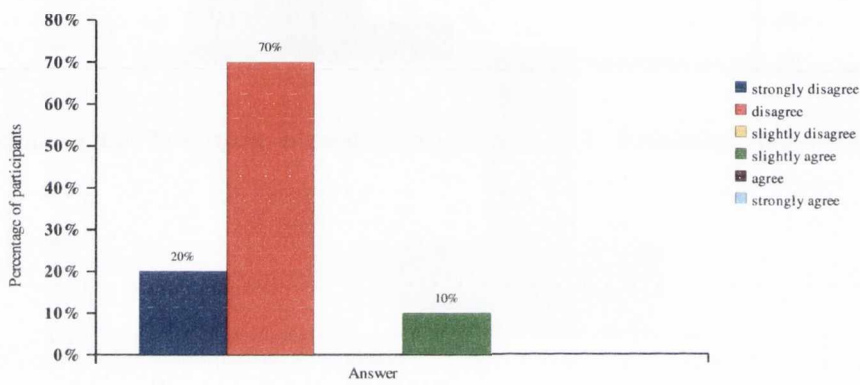


**Figure 6.8**: Question 8 - I do not think that the patient's movement was detected properly.

agreed', or 'slightly disagreed' with that, respectively. The remaining 40% of the participants 'slightly agreed' and 'agreed' with that. The distribution of participants' answers is illustrated in Figure 6.7.

The next question investigated the perceived correctness of movement detection. The system was trained prior to the exercise session with data obtained from the researcher and during the session exercises were demonstrated by the researcher. Most of the participants (70%) 'disagreed' and 20% 'strongly disagreed' that the movement was not detected properly. The remaining 10% of the subjects 'slightly agreed' with that statement. The distribution of participants' answers is illustrated in Figure 6.8.

The penultimate question investigated if the participants found the patients' interface easy to use. All the participants agreed that patient's interface was easy to use. 30%, 50%, and 20% of the subjects 'strongly agreed', 'agreed', or 'slightly agreed' with that, respectively. The distribution of participants' answers is illustrated in Figure 6.9.

The final question investigated if the subjects would recommend the system to a patient with PD. Half of the participants would 'possibly' recommend the system. 30%, 10%, and 10% of the subjects would 'probably', 'very probably', and 'definitively' recommend it, respectively. The distribution of participants' answers is illustrated in Figure 6.10.
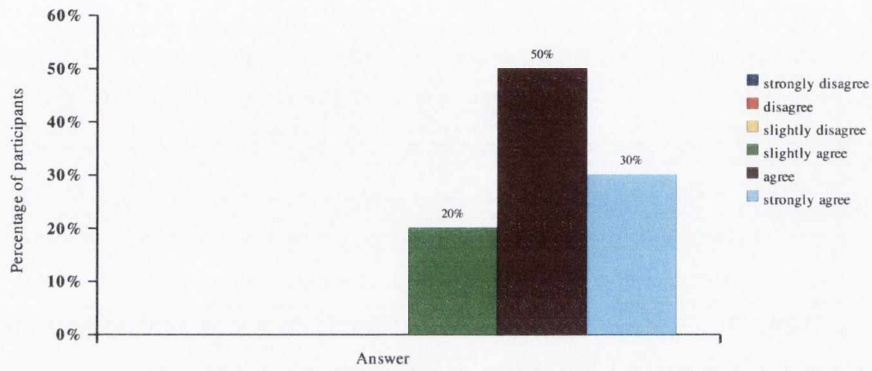
**Figure 6.9**: Question 9 - I found the patient's interface easy to use.
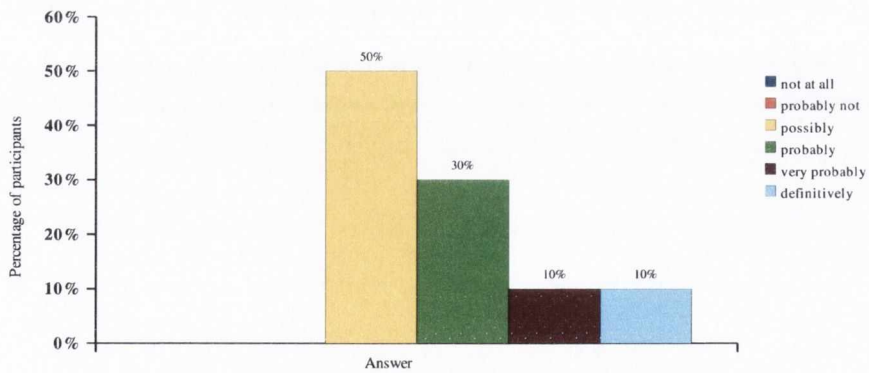


**Figure 6.10**: Question 10 - If the system was made available I would recommend it to a patient with PD.

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In the open-ended question the participants expressed their comments in relation to the system. Six themes were identified from their answers as follows.

Two participants said that they would recommend SMOOTH '*to younger, less disabled*' patients (Participant no. 8) or patients '*at an early diagnosis*' (Participant no. 7). One participant suggested that the exercises supported by the system should be more specific to people with PD. They should include trunk rotation rather than abduction of the legs. Three participants mentioned division of exercises into movement phases. They felt that '*some of the exercises had too many phases and would be difficult for the patient to follow*' (Participant no. 5), the division into movement phases should '*encourage a smooth, continuous movement*' (Participant no. 4) and there should be '*less of sustained hold at each phase*' (Participant no. 2). One participant said that to encourage continuous movement '*perhaps a visual or verbal queueing about the sequence of movements would be beneficial*' (Participant no. 3). Two participants expressed their opinions about the chair used in SMOOTH. Both preferred that the chair had arms, '*I would prefer if the chair had arms due to concerns to postural stability*' (Participant no. 9). Finally, two participants commented on the general purpose of the system. They thought that it is '*interesting and novel*' (Participant no. 5) and it '*does look very promising*' (Participant no. 9).

### 6.4.2.3 Discussion

The purpose of this part of the evaluation of SMOOTH was to investigate the opinions of physiotherapists about the system and to obtain feedback that identified potential improvements to better meet the needs of people with PD. The opinions of the participants were used to evaluate the system.

In general, the participants found the system convenient to use **(R. 5)**. Most of the participants (90%) found the overall system easy to use. Marking of movement phases during exercise execution in the training phase was found to be convenient by 60% of the participants. Reasons for lack of reported convenience might be a large number of movement phases identified for the exercises and lack of practise. The seat was found appropriate for the duration of the treatment by 80% of the subjects. The remaining 20% 'slightly disagreed' with that and suggested that the chair should have arm rests.

The system was perceived to be intuitive **(R. 6)** and the GUI designed for physiotherapists got positive feedback. Most of the participants (90%) said that the interface was self-explanatory and clear to them. All of the participants said that the creation of an exercise set was easy. Similarly, all of the physiotherapists thought that the presentation of the information related to the number of exercises done by the patients at home was appropriate and gave a good insight into the patient's exercise routine. In addition, all of the participants found the GUI designed for patients and the user feedback during exercise to be appropriate.

All of the physiotherapists that participated in the study liked the possibility of monitoring patient's progress as well as being able to review the number of exercises actually done by the patient.

They said that this knowledge would be useful for them to modify the rehabilitation programme.

Most suggestions during the study were related to the division of the exercises into movement phases. Conversation during the evaluation of the system and comments written in the user surveys revealed that most of the participants felt that the system should encourage fast movement in order to resist the bradykinesia (slow movement) often reported in PD [Berardelli et al., 2001]. In addition, the execution of exercises should be more rhythmic and should not contain sustained holds such as *leaned forward* (see Table 5.6). The reason for that was to avoid 'freezing' (difficulty initiating movement), which is one of the common symptoms of PD [Berardelli et al., 2001]. In general, the number of movement phases in the exercises was found to be too large and therefore difficult to follow by people with PD. Some of the participants suggested that the exercise set should be more related to problems with general body posture and muscle stiffness common in PD [MashhadiMalek et al., 2008]. They suggested to replace 'abduction of the right/left leg' exercise with 'trunk rotation'. Actual improvements to the system made on the basis of the feedback from physiotherapists are presented in Section 6.4.2.4.

None of the survey participants said that they would not recommend SMOOTH to people with PD, which suggests a perceived potential of the system. However, the level of confidence in the recommendation is not very strong - half of the participants would 'possibly' recommend it. There might be a number of reasons for that. They include perceived problems with division of exercises into movement phases, which is related to exercise execution, lack of armrests and therefore inappropriateness of the chair (20% slightly agreed that the chair was inappropriate), and finally the fact that the chair is a prototype and sensors placed on it are connected using cables, which might not look very user friendly and reliable. It is possible that improvements introduced to the system (see Section 6.4.2.4) would increase confidence in recommendation of SMOOTH to people with PD, however, a further study should be conducted in order to investigate this.

### 6.4.2.4 System improvements

Before study with people with PD the feedback from physiotherapists was analysed, which resulted in a list of possible changes to the system. The improvements that were applied to the system are described in the following part of this section.

On the basis of the comments obtained from physiotherapists that participated in the study, we decided to exchange 'abduction of right/left leg' exercises (see exercise no. 3 and 4 in Table 5.1) to 'trunk rotation to the left/right' exercises to better meet the usual exercise programme prescribed for people with PD. The description of the exercises added and the potential difficulties with their execution by people with PD, which were established by consultation with the physiotherapists, are presented in Table 6.2.

| # | Exercise | Description | Potential difficulties for people with PD |
|---|----------|-------------|-------------------------------------------|
| 3 | Trunk rotation to the right | Sit upright in your chair. While sitting, turn your shoulders to right side as far as possible. Turn your head and body as well. Return to the starting position. | • Position not upright. <br><br> • Reduced range of movement - turning head only. <br><br> • Knees follow the trunk. |
| 4 | Trunk rotation to the left | Sit upright in your chair. While sitting, turn your shoulders to left side as far as possible. Turn your head and body as well. Return to the starting position. | • Position not upright. <br><br> • Reduced range of movement - turning head only. <br><br> • Knees follow the trunk. |

**Table 6.2**: Exercises added to SMOOTH

In addition, three participants suggested changes in the movement phases. Feedback from them suggested that the number of phases in each exercise should be reduced and phases that required sustained hold should be removed. The set of eight exercises addressed by SMOOTH with the movement phases updated accordingly is presented in Table 6.3.

The list of correct movement phases, which is used for training and testing sample creation (see Section 5.4.5.2), for the new set of exercises addressed by SMOOTH was changed according to Table 6.3.

The improvements described above were applied to SMOOTH before the study involving people with PD. The study is described in the following part of this section.

### 6.4.3 People with Parkinson's disease

This section presents the study investigating the user acceptance of the system by the people with PD. The remainder of this section describes data collection (Section 6.4.3.1), results of their analysis (Section 6.4.3.2), and a discussion (Section 6.4.3.3).

#### 6.4.3.1 Data collection

The following inclusion criteria were used: (1) diagnosis of PD; (2) ability to do the set of exercises on a chair designed for SMOOTH; (3) ability to answer the questions in the questionnaire independently; and (4) aged 18 or over. People with PD were identified through a support group for people with PD (PALS)[3], which is a branch of the Parkinson's Association of Ireland, and a number of previous studies. They were sent information about the purpose of the study and an acceptance form to be returned if they agreed to participate in the study. A stamped envelope with return address was included. Potential participants were provided with the contact details of the researcher in the

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[3]http://gofree.indigo.ie/~pdpals/

| # | Exercise | Movement Phases |
|---|----------|-----------------|
| 1 | Marching in sitting | 1. Sitting upright. <br> 2. Moving right knee up. <br> 3. Moving right knee down. <br> 4. Moving left knee up. <br> 5. Moving left knee down. |
| 2 | Hip walking in sitting | 1. Sitting upright <br> 2. Moving to the left. <br> 3. Moving to the right. |
| 3 | Trunk rotation to the right | 1. Sitting upright. <br> 2. Rotation of trunk to the right. <br> 3. Rotation of trunk back to the left. |
| 4 | Trunk rotation to the left | 1. Sitting upright. <br> 2. Rotation of trunk to the left. <br> 3. Rotation of trunk back to the right. |
| 5 | Leaning to the right | 1. Sitting upright. <br> 2. Leaning to the right. <br> 3. Leaning back to the left. |
| 6 | Leaning to the left | 1. Sitting upright. <br> 2. Leaning to the left. <br> 3. Leaning back to the right. |
| 7 | Leaning forward | 1. Sitting upright. <br> 2. Moving trunk forward. <br> 3. Moving trunk backward. |
| 8 | Sit to stand | 1. Sitting upright. <br> 2. Moving trunk forward. <br> 3. Standing. <br> 4. Moving trunk backward. |

**Table 6.3**: Updated movement phases for exercises addressed by SMOOTH
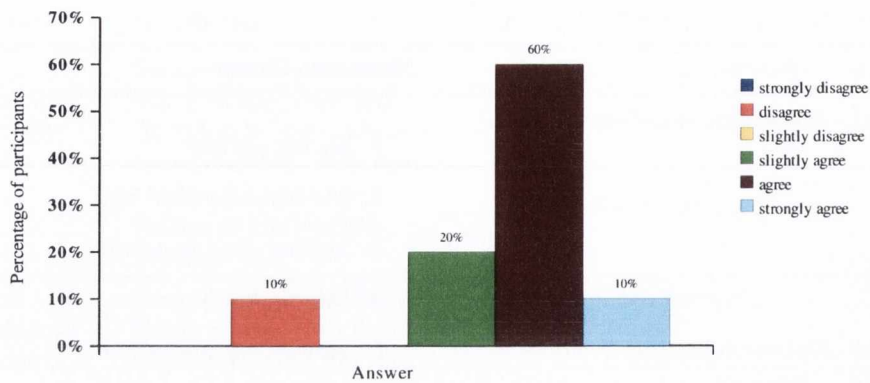
**Figure 6.11**: Question 1 - I found the seat comfortable for the duration of treatment.

participation leaflet in case they wished to seek further information. Thereafter, the subjects who returned the acceptance form were contacted again and the study was explained to them in more detail. They were asked questions related to their condition in order to assess their suitability for the study. If they agreed to participate, written permission was requested on a formal consent form. The individual meeting with participants was scheduled at a time convenient to them. During the meeting the purpose of the system was explained to the participants and the operation of the application for people with PD was demonstrated. After that, the participants were asked to perform a number of exercises on a chair. The number of exercises and procedure is described in more detail in Section 6.5.2. A physiotherapist was present during each session and supervised the exercise execution. During exercise execution the subjects had an opportunity to use the application designed for people with PD. Following that subjects were asked to fill in the questionnaire (see Section 6.4.1.2). 10 people with PD agreed to participate in the study.

#### 6.4.3.2 Results

The first question investigated the suitability of the chair chosen for SMOOTH. In general, participants agreed that the chair chosen for the treatment was appropriate. 60% and 10% of the subjects 'agreed or 'strongly agreed' with suitability of the char, respectively. 20% and 10% 'slightly agreed' or 'disagreed' with that, respectively. The distribution of participants' answers is illustrated in Figure 6.11.

The second question investigated if the system was perceived to be easy to use. In general, most of the subjects (90%) agreed that the system is easy to use. 30%, 50%, and 10% of the participants 'strongly agreed', 'agreed', or 'slightly agreed', respectively. 10% 'disagreed' with that statement. The distribution of participants' answers is illustrated in Figure 6.12.

The third question investigated if the images/icons on the screen and the voice instructions were clear to the participants. 50% and 30% of the subjects 'strongly agreed' or 'agreed' that the images/icons and voice instructions were clear, respectively. The remaining 20% of the subjects 'slightly disagreed' (10%) or 'disagreed' (10%) with that. The distribution of participants' answers is illustrated in Figure 6.13.
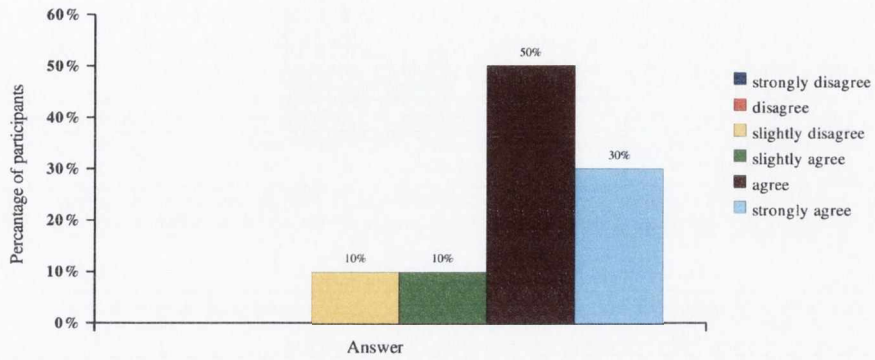
**Figure 6.12**: Question 2 - Overall I found the system easy to use.
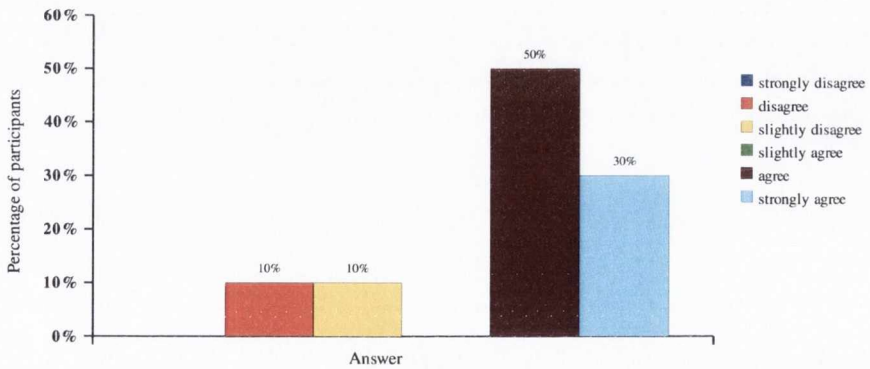


**Figure 6.13**: Question 3 - The images on the screen and voice instructions were clear to me.
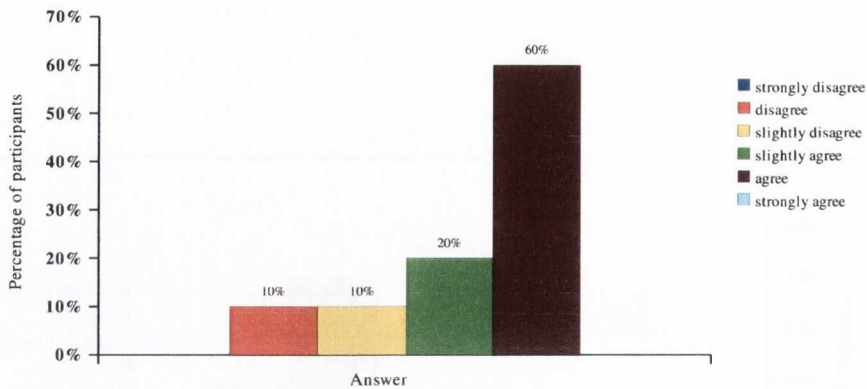
**Figure 6.14**: Question 4 - The images on the screen helped me to indicate whether I followed my exercise prescription.
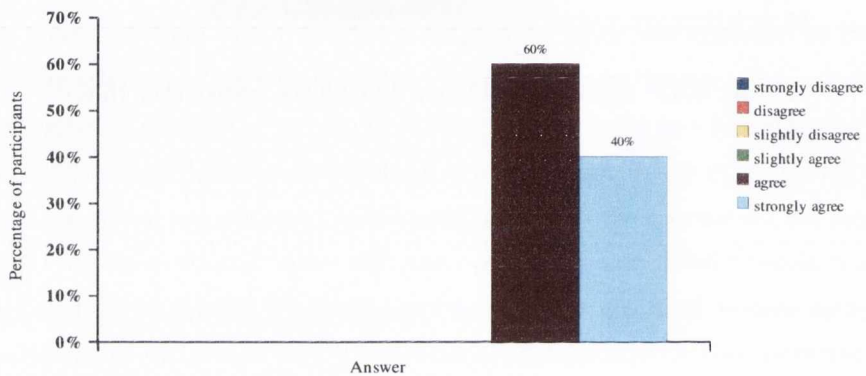


**Figure 6.15**: Question 5 - I liked that my physiotherapist can review how often I perform my exercises.

The fourth question investigated if the participants perceived the images/icons on the screen to be helpful to indicating whether they followed their exercise prescription. In general, most of the subjects (80%) either 'agreed' (60%) or 'slightly agreed' (20%) that the images were helpful. The rest of the participants (20%) either 'slightly disagreed' (10%) or 'disagreed' (10%) with that. The distribution of participants' answers is illustrated in Figure 6.14.

The fifth question investigated if the participants perceived the possibility of their progress been reviewed by a physiotherapist to be useful. In general, all of the subjects liked the idea of a possible review of their progress. 40% and 60% of the subjects 'strongly agreed' and 'agreed' with that, respectively. The distribution of participants' answers is illustrated in Figure 6.15.

The sixth question investigated if the participants thought that their movement was detected incorrectly. Generally, 40% of the participants disagreed that their movement was not detected properly. Half of these 'strongly disagreed' (20%) and another half 'disagreed' (20%). The remainder of the subjects (60%) either 'slightly agreed' (30%) or 'agreed' (30%) that their movement was not detected properly. The distribution of participants' answers is illustrated in Figure 6.16.

The seventh question investigated if user feedback made the exercise routine more enjoyable. All
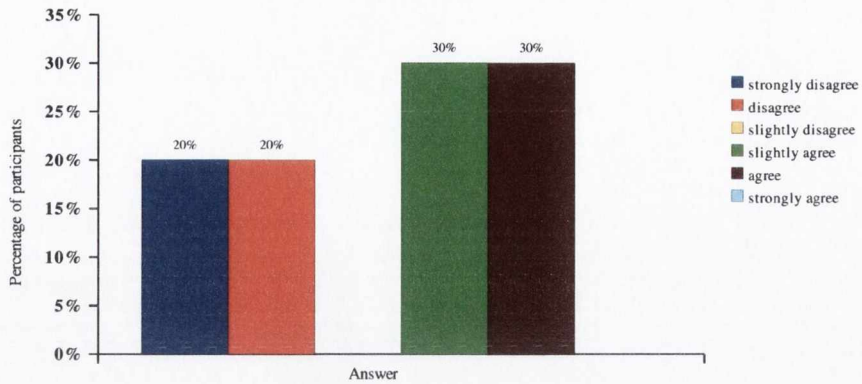
**Figure 6.16**: Question 6 - I do not think that my movement was detected properly.
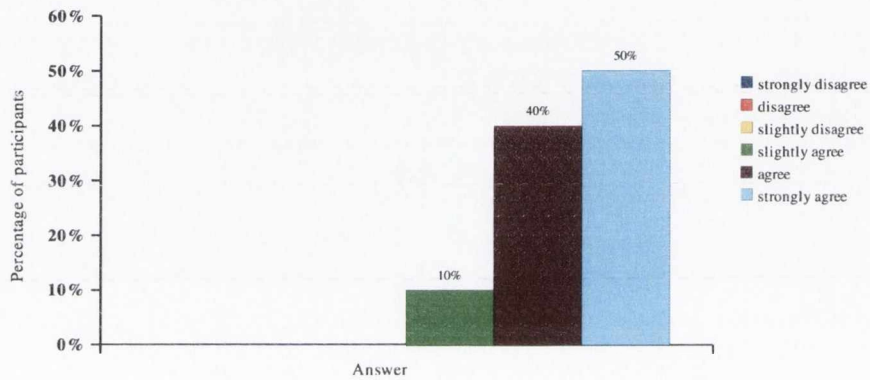


**Figure 6.17**: Question 7 - This treatment was more enjoyable than performing exercises at home on my own.

of the participants stated that this kind of treatment was more enjoyable than performing exercises at home on their own. 50%, 40%, and 10% of the subjects 'strongly agreed', 'agreed', or 'slightly agreed' with that, respectively. The distribution of participants' answers is illustrated in Figure 6.17.

The next question investigated if a system like SMOOTH would encourage the participants to sustain their exercise routine. All of the participants stated that this kind of system would encourage them to do exercises more often. 30%, 60%, and 10% of the subjects 'strongly agreed', 'agreed', or 'slightly agreed' with that, respectively. The distribution of participants' answers is illustrated in Figure 6.18.

The final question investigated if the system was made available would the participants use it. In general, most of the subjects (90%) said that they would use it. 50%, 30%, and 10% of the subjects 'strongly agreed', 'agreed', or 'slightly agreed' with that, respectively. The remaining 10% of the participants said that they would 'probably not' use it. The distribution of participants' answers is illustrated in Figure 6.19.

In the open-ended question the participants expressed their comments in relation to the system. Four themes were identified from their answers as follows. Three participants stated that '*it was very enjoyable*' experience (Participant no. 4) and the system '*has good potential*' (Participant no. 9).
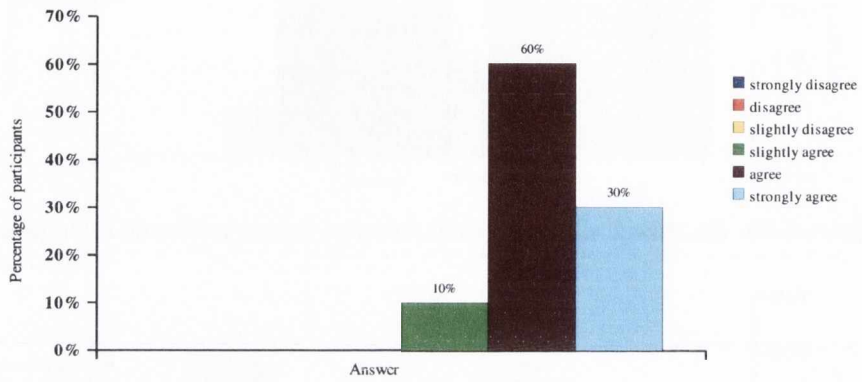
**Figure 6.18**: Question 8 - I think the system would encourage me to do my exercises more often.
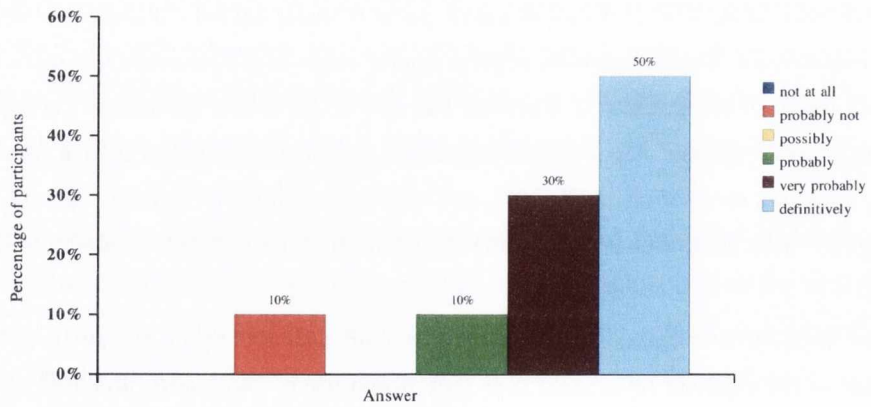


**Figure 6.19**: Question 9 - If the system was made available I would use it.

Five comments in relation to the user feedback given by the system were provided. They said that the voice feedback was annoying ($n = 2$), '*I found voice from PC annoying*' (Participant no. 5), and '*voice needs to be louder*' (Participant no. 6) ($n = 1$). One participant stated that '*it should be easier to indicate when exercise should be started*' (Participant no. 7). To better illustrate the exercise '*an image of figure doing the exercise or movement*' (Participant no. 8) was suggested by one participant. On the other hand one participant said that the exercises were '*clearly illustrated*' (Participant no. 9). The last theme was related to the encouragement given by the system. Two participants suggested that doing exercises should be more rewarding, '*perhaps introduce rewards for completing exercises*' (Participant no. 5). Two participants said that the system encouraged them to do exercises, '*it was encouraging to see the numbers coming up on the screen*' (Participant no. 10). One person commented on the chair used in the system. It was suggested that '*the chair needs to be adjustable and needs arm rests*' (Participant no. 6).

### 6.4.3.3  Discussion

The purpose of this part of the evaluation of SMOOTH was to investigate the opinions of people with PD about the system and obtain feedback that could identify potential improvements to be made to the system in the future to better meet user needs. The opinions of the participants were used to evaluate the system.

The participants found the system convenient to use **(R. 5)**. Most of the participants (90%) found the overall system easy to use. Similarly, the seat was found appropriate for the duration of the treatment by 90% of the subjects.

In general, the system was perceived to be intuitive **(R. 6)** and the GUI and user feedback designed for people with PD was appropriate. Most of the participants (80%) said that images/icons on the screen and voice instructions were self-explanatory and clear to them. The remaining 20% of the subjects stated either that there should be less voice feedback ($n = 1$) or that voice instructions were not loud enough; one could not see the images on the screen because she forgot her glasses ($n = 1$). Most of the participants (80%) said that the images/icons helped them to follow their exercise prescription.

All of the participants liked the possibility that the physiotherapist can review how often they performed the exercises. Similarly, all of the subjects found the training using the system more enjoyable than performing exercises at home on their own and thought that the system would encourage them to do exercises. Subjects' responses could however be biased by a number of psychological factors stemming from the visit to the lab, the presence of the researcher, and a novelty effect related to the fact that subjects who took part in the study were more likely to be enthusiastic about new technology. To reduce this bias a more extensive study should be conducted wherein participants are chosen at random, they are able to use SMOOTH independently at home, and participant's views on the system are collected via an anonymous survey. Such a study was not conducted due to time constraints.

Most suggestions during the study were related to the user feedback provided by the system. Conversation during evaluation of the system, observation of system behaviour during participants exercising and comments written in user surveys revealed that the voice feedback provided by the system should be slightly modified. The voice messages after each correct repetition were found to be confusing due to the delay with which they were played. For example, when the exercise repetition were performed quickly, occasionally there was a lag between the message for completion of the actual repetition and starting the next movement. This could be avoided by either removing voice messages after each repetition or shortening them. Each exercise was always preceded by voice instructions describing it. It was noticed that some participants got confused as to when they should start the exercise and they were starting as soon as they could hear the voice instructions. As suggested, there could be a light turning green to indicate the start of the exercise or a message '*3, 2, 1, go!*' (Participant no. 7). Some participants also suggested that doing exercises should be more rewarding. For example, if the user does all the exercise repetitions prescribed the message 'congratulations!' should be played (Participant no. 7). Finally, the inclusion of an animated figure showing the exercise or movement was suggested.

More than half of the participants (60%) 'slightly agreed' or 'agreed' that their movement was detected incorrectly. This could be caused by the fact that a predetermined set of the parameters was used to demonstrate the operation of the system to the participants. A duration of a time window was set to 0.25s, and the belief threshold to 90%, because for those parameters the system performed well for the researcher. As presented in Section 6.5, those parameters were not the most optimal. For that reason, to investigate perceived accuracy of the system, further study should be conducted.

Most of the participants (90%) said that if the system was made available they would use it. The remaining 10% of the subjects said that they would probably not use the system because they prefer other forms of physical activity, e.g., gardening. No additional comments about feeling uncomfortable or being embarrassed by using the system were stated. For that reason, it was concluded that the system was perceived to be unobtrusive **(R. 3)**.

### 6.4.4 Summary

This section presented a study designed to fulfil objective **O.1** (see Section 6.2) and to investigate user acceptance of SMOOTH. 10 physiotherapists and 10 people with PD took part in the study. The study explored user views about the system and obtained information needed for the evaluation of the system. In addition, the study identified a number of possible improvements to the system. Three system requirements (see Section 6.1) were evaluated by the user study: unobtrusiveness **(R. 3)**, convenience **(R. 5)**, and intuitiveness **(R. 6)**. All of these requirements received positive feedback from the physiotherapists and the people with PD that participated in the study.

## 6.5 Exercise Monitoring Accuracy

To fulfil objective **O.2** (see Section 6.2) this part of the evaluation investigated the accuracy and performance of the system. This section begins with a description of the evaluation metrics used to assess the accuracy of the system (Section 6.5.1). This is followed by a description of the data collection (Section 6.5.2) and a presentation of the generation of the learning and testing samples used (Section 6.5.3). Section 6.5.4 presents the results from the study and is followed by a discussion (Section 6.5.5). Finally, a summary of this section is presented in Section 6.5.6.

### 6.5.1 Evaluation metrics

To evaluate the exercise monitoring accuracy **(R. 2)** of SMOOTH two metrics were used:

1. *Accuracy of movement phase recognition.* The accuracy of movement phase recognition is defined by the number of samples that were recognised correctly by the first DBN (see Section 5.4.4) as a proportion of the total number of samples used in a test. The samples correspond to the signal features calculated over the sliding time windows.

2. *Accuracy of correct repetition detection.* The accuracy of correct repetition detection is calculated as the number of exercise repetitions detected by the system. The target number of repetitions to be performed for each exercise was 10. Some participants performed more than 10 repetitions of each exercise. One exercise was done 13 times, one exercise 12 times, and nine exercises were performed 11 times. The confusion of the participants was caused by the user application not necessarily showing the number of repetitions corresponding to the number of repetitions actually performed. To compare the results, the number of repetitions detected by the system was normalised and calculated by a proportion of the number of repetitions detected by the system to the number of repetitions actually performed by the user and multiplied by 10. For example, if the participant performed 13 repetitions and 13 of them were detected by the system the normalised number of repetitions was 10. However, when the participant performed 10 repetitions and 13 of them were detected by the system the normalised number of repetitions was 13. During each exercise session the numbers of actual and correct repetitions were noted by the supervising physiotherapist (see Section 6.5.2). According to the physiotherapist, the number of actual repetitions was equal to the number of correct repetitions for all the participants.

Two parameters were investigated during the tests: the size of the sliding time window used to calculate signal features and the belief threshold above which movement was considered to be incorrect.

### 6.5.2 Data collection

The data for the study was collected from each participant during one exercise session. Two types of subjects participated in the study: people with PD and healthy subjects. The detailed description

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| Participant | Gender | Age [years] | Height [cm] | Weight [kg] |
|:-:|:-:|:-:|:-:|:-:|
| 1 | female | 28 | 180 | 78 |
| 2 | male | 31 | 172 | 65 |
| 3 | male | 29 | 182 | 85 |
| 4 | male | 29 | 189 | 95 |
| 5 | male | 41 | 175 | 85 |
| 6 | male | 33 | 175 | 70 |
| 7 | female | 23 | 173 | 60 |
| 8 | female | 23 | 172 | 59 |

**Table 6.4**: Healthy people that participated in the study

| Participant | Gender | Age [years] | Years since PD diagnosis | Height [cm] | Weight [kg] |
|:-:|:-:|:-:|:-:|:-:|:-:|
| 1 | male | 71 | 8 | 170 | 73 |
| 2 | male | 64 | 33 | 170 | 76 |
| 3 | male | 72 | 9 | 170 | 70 |
| 4 | male | 55 | 5 | 180 | 101 |
| 5 | male | 54 | 4 | 180 | 72 |
| 6 | female | 67 | 12 | 155 | 64 |
| 7 | female | 42 | 10 | 164 | 67 |
| 8 | male | 55 | 5 | 162 | 70 |
| 9 | male | 61 | 10 | 180 | 67 |
| 10 | female | 47 | 7 | 163 | 57 |

**Table 6.5**: People with PD that participated in the study

of the recruitment of people with PD is presented in Section 6.4.3.1. Each participant was asked to perform eight exercises on the chair as listed in Table 6.3. The exercise session with people with PD was supervised by a physiotherapist. Each exercise was described by the physiotherapist to the participant. Three sets of 10 repetitions of each exercise were performed by each participant. During the exercise, sensor readings were recorded and marked with the corresponding movement phases by the researcher. Such a setting was chosen because of the practise required to correctly mark movement phases as exercise progresses. The order of the exercises was randomised for each participant. The reason for that was to avoid bias related to fatigue and tiredness, which can increase as the exercises progress. 2 of 3 sets collected were used to learn the parameters of the DBNs. Following that, each participant was asked to perform a fourth set of 10 repetitions of each exercise using the user application that provided visual and voice feedback. The number of repetitions actually performed by each participant was called out by the physiotherapists and noted, for normalisation purposes (see Section 6.5.1). The number of repetitions considered to be correct, according to the physiotherapist, was also noted. During exercise execution sensor readings were recorded, but they were not marked

with movement phases. 8 healthy subjects and 10 people with PD participated in the study. Their characteristics are presented in Table 6.4 and Table 6.5, respectively.

### 6.5.3  Samples

As mentioned previously, two parameters were investigated during the tests: the size of sliding time window and the belief threshold. Investigated parameters for the time windows and belief thresholds are presented in Table 6.6 and Table 6.7, respectively. The parameters were chosen empirically, based on knowledge of the domain. The data were logged with a frequency of 100Hz.

| # | Size *[samples]* | Overlap *[samples]* | Duration |
|---|---|---|---|
| 1 | 10 | 0 | 0.1s |
| 2 | 25 | 5 | 0.25s |
| 3 | 50 | 10 | 0.5s |
| 4 | 100 | 25 | 1s |

**Table 6.6**: Investigated parameters of sliding time windows

| # | Belief threshold |
|---|---|
| 1 | 100% |
| 2 | 95% |
| 3 | 90% |
| 4 | 70% |
| 5 | 50% |

**Table 6.7**: Investigated parameters of belief thresholds

In total, 3 sets of 10 repetitions of each of the 8 exercises for each participant were used to evaluate the accuracy of the movement phase recognition. Two sets were used to learn the parameters of the DBNs, and the third set was used for testing. To obtain more uniform results three combinations of these sets, which are presented in Table 6.8, were used in the tests. To evaluate correct exercise repetition detection, two sets were used to learn the parameters of the DBNs, and the fourth set (without movement phases marked) was used for testing. Each trial, which was learning the parameters of the DBNs and testing their recognition accuracy, was repeated 5 times. The reason for this was to get average results, because GAs used in discretisation (see Section 5.4.6.1) are non-deterministic, i.e., for the same inputs they can produce different outputs. The mean and standard deviation (SD) of the results from all the trials are used in the further part of this chapter.

All the samples described in Section 6.5.2 were collected from the healthy subjects. Two people with PD had difficulties with some exercises. Those exercises included: 'Sit to stand' ($n = 2$), 'Hip walking' ($n = 1$), and 'Marching in sitting' ($n = 1$). The difficulties included fatigue and problems

| # | Sets used for learning | Set used for testing |
|---|---|---|
| 1 | 1, 2 | 3 |
| 2 | 2, 3 | 1 |
| 3 | 3, 1 | 2 |

**Table 6.8**: Combinations of sets used in tests

in estimating the number of actual repetitions. For that reason, the samples corresponding to the exercises above were not included in the tests.

### 6.5.4 Results

To measure the accuracy of exercise monitoring in SMOOTH a number of tests was conducted. The tests included investigation of dependencies between participants, exercises, different parameters such as the size of the time window and belief threshold, and the evaluation metrics (see Section 6.5.1). The results are presented in the following part of this section.

#### 6.5.4.1 Exercises and duration of time windows

Figure 6.20a and Figure 6.20b show the accuracy of the movement phase recognition, depending on the exercise and the duration of the time window, for healthy subjects and participants with PD, respectively. For both, healthy subjects and participants with PD, as the duration of time window (excluding the 1s time window) increased, so the recognition accuracy increased. The best results were obtained by a 0.5s time window used to calculate signal features. The worst results were obtained by the 1s time window. For the healthy subjects, the differences between phase recognition accuracy among the exercises are relatively small. The average accuracy for all the exercises is above 80% (0.5s time window). For people with PD, 'marching in sitting' obtained the lowest accuracy (68%). Movement phases in all other exercises were recognised with similar accuracy, which was, similarly to healthy subjects, above 80% (0.5s time window). The phase recognition accuracy for the 1s time window that obtained the lowest results, was above 70% for all the exercises. The variation in the phase recognition accuracy was generally bigger for participants with PD.

Figure 6.21a and Figure 6.21b show the accuracy of correct repetition detection, depending on the exercise and the duration of time window, for healthy subjects and participants with PD, respectively. The results were generated for a belief threshold equal to 100%, because it obtained the best results. This means that the second DBN was not used to detect incorrect repetitions and only the sequence of movement phases recognised by the first DBN was taken into consideration (see Section 5.4.4). The number of repetitions detected decreases as the duration of the time window increases, therefore the highest results are obtained for a 0.1s time window. The detection of repetitions of 'marching in sitting' was considerably smaller than for other exercises and equal to 5.8 and 3.3 repetitions (0.1s time window) for healthy subjects and participants with PD, respectively. Possible reasons for the
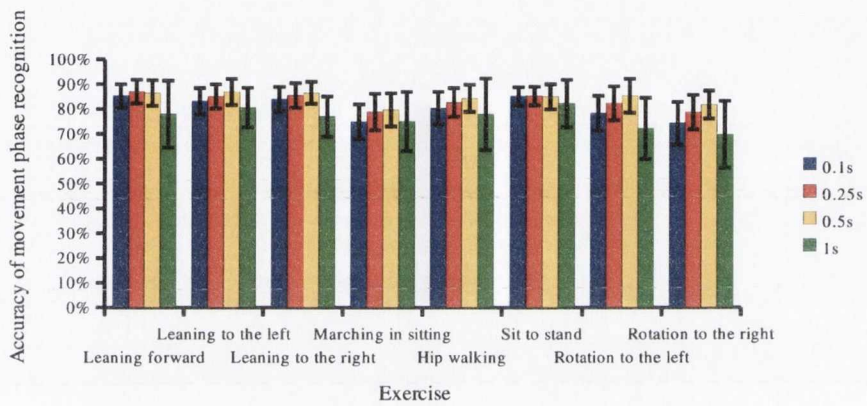
(a) Healthy participants


(b) Participants with PD

**Figure 6.20**: Accuracy of movement phase recognition dependent on exercise and duration of time window

(a) Healthy participants
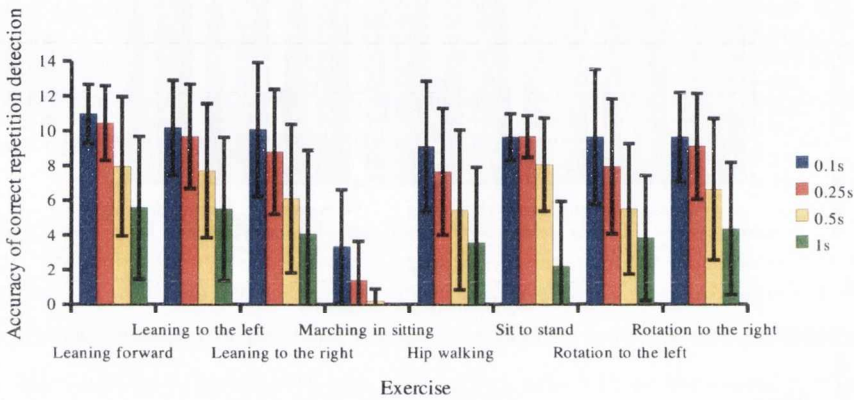


(b) Participants with PD

**Figure 6.21**: Accuracy of correct repetition detection dependent on exercise and duration of time window

poor results obtained for the 'marching in sitting' exercise are discussed in more detail in Section 6.5.5. The number of repetitions detected among other exercises was similar and differed from 9.8 to 10.4 repetitions and from 9.1 to 11 repetitions (0.1s time window) for healthy subjects and participants with PD, respectively. Similar to previous tests, the variation in detection accuracy across the trials was slightly bigger for participants with PD.

#### 6.5.4.2 Participants and size of time windows

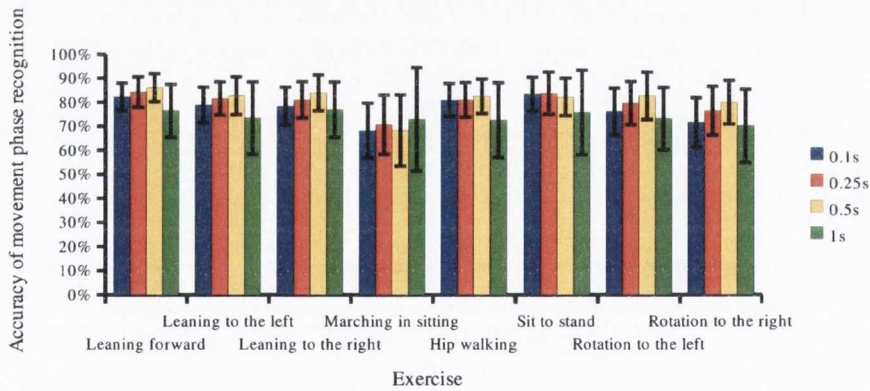Figure 6.22a and Figure 6.22b show the accuracy of movement phase recognition, depending on the participant and the duration of the time window, for healthy subjects and participants with PD, respectively. With respect to the exercises, the recognition accuracy for all the participants increased as the duration of time window (excluding 1s time window) increased, which is not surprising given the previous results. The best results were obtained for the 0.5s time window used to calculate signal features. The worst results were obtained for the 1s time window. The phase recognition accuracy varied from 81% to 86% for healthy subjects (0.5 time window). The worst results were obtained by

(a) Healthy participants



(b) Participants with PD

**Figure 6.22**: Accuracy of movement phase recognition dependent on participant and duration of time window

participant no. 8. For participants with PD, the phase recognition accuracy varied from 75% to 86% (0.5 time window). The poorest results were obtained by participants no. 3, 6, and 9. The variances in recognition accuracy across the trials were generally bigger for participants with PD.

Figure 6.23a and Figure 6.23b show the accuracy of the correct repetition detection, depending on the participant and the duration of the time window, for healthy subjects and participants with PD, respectively. As previously, the results were generated for a belief threshold equal to 100%. With respect to the exercises, the number of repetitions detected for all the participants decreased as the duration of the time window increased, which is not surprising given the previous results. The highest results were obtained for 0.1s time window. For the healthy subjects the number of repetitions detected was similar and varied from 9.2 to 10.3 (0.1s time window). For participants with PD, the lowest number of repetitions was detected for participant no. 9 and was 6.8 (0.1s time window). For all other subjects the number of repetitions varied from 8.3 to 11.2 (0.1s time window). Similar to previous tests, the variation in detection accuracy was bigger for participants with PD.
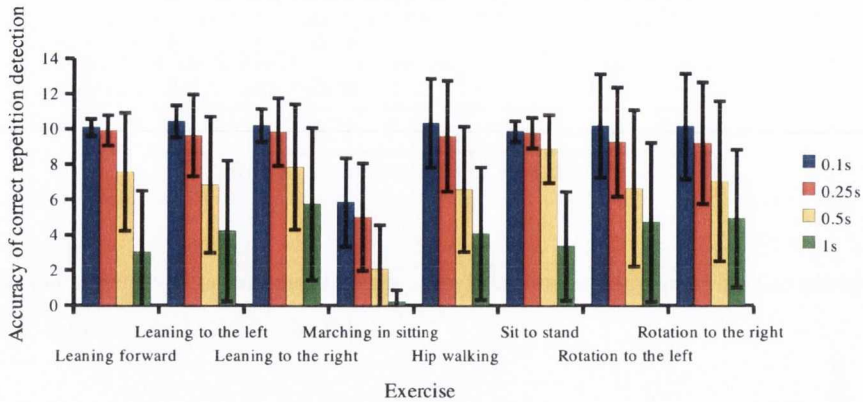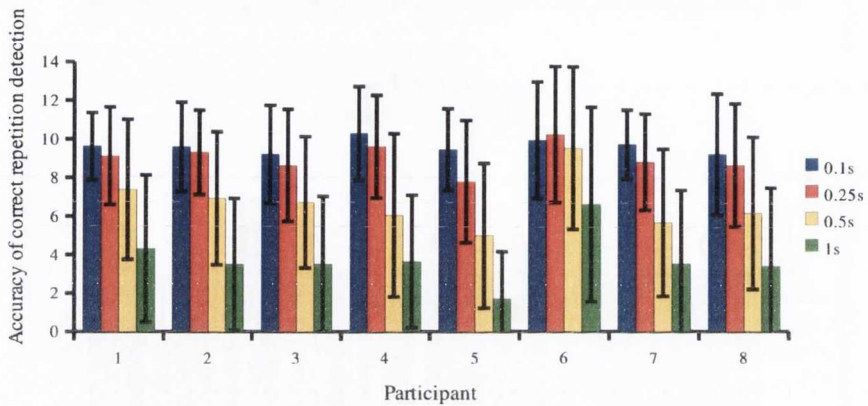
(a) Healthy participants
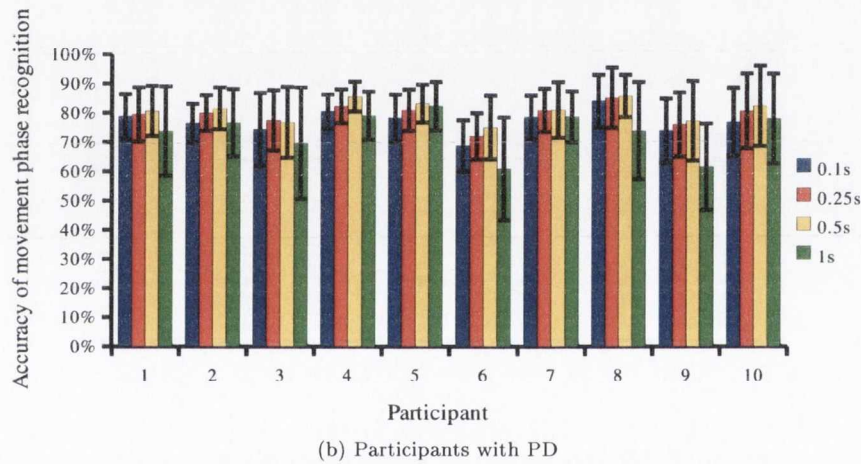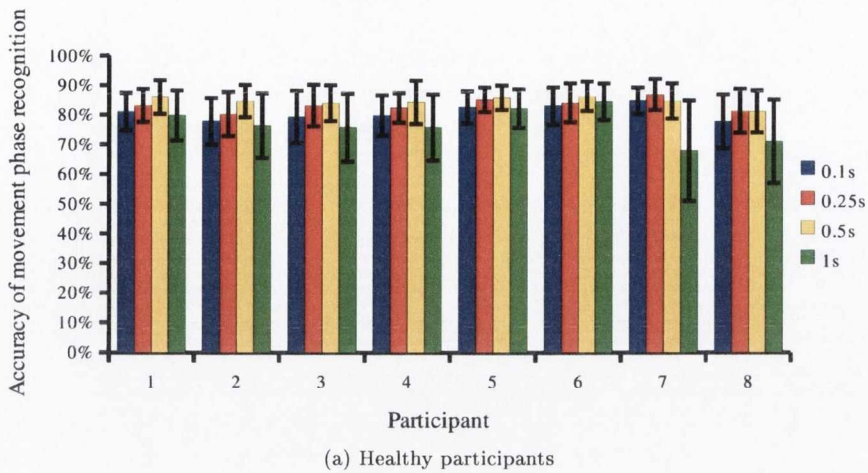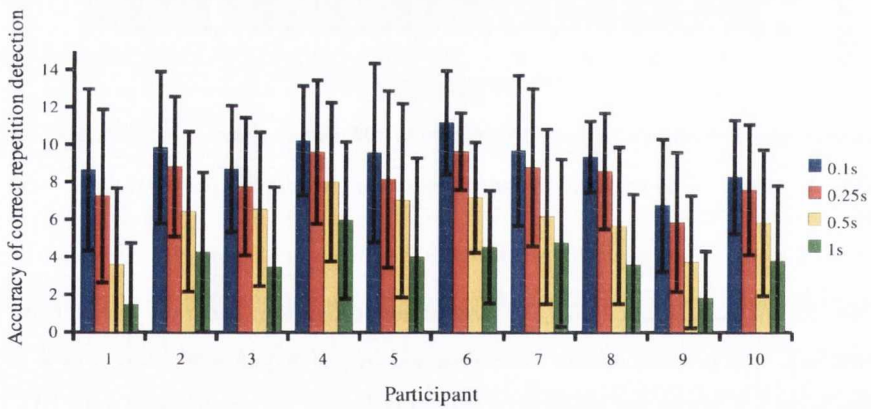


(b) Participants with PD

**Figure 6.23**: Accuracy of correct repetition detection dependent on exercise and duration of time window

### 6.5.4.3 Exercises and belief thresholds

Figure 6.24a and Figure 6.24b show the accuracy of correct repetition detection, depending on the exercise and the belief threshold, for healthy subjects and participants with PD, respectively. The results presented were generated for 0.1s time window, which according to previous tests, obtained the highest number of repetitions detected by the system. In general, the number of the repetitions detected by the system across all the exercises was similar for healthy subjects and participants with PD except 'hip walking' and 'marching in sitting'. For healthy subjects, the system detected in general more repetitions of these exercises than for participants with PD. The difference in results varied from 1.2 to 3.1 repetitions depending on the belief threshold. In addition, the variance across the results was bigger for participants with PD. The exercise that obtained the worst results was 'marching in sitting', which is consistent with previous findings. In general, the number of repetitions detected by the system decreased as the belief threshold decreased. The decrease rate depended on the exercise. The smallest decrease rate was noted for 'sit to stand'. The differences in the number of exercise repetitions recognised depended on the belief threshold and were 0.3 repetitions and 0.2 repetitions for healthy subjects and participants with PD, respectively. In addition, the smallest variance across the trials was also noticed for 'sit to stand'. For the rest of the exercises, the decrease rate was similar with a slightly smaller one for 'leaning forward'.

## 6.5.5 Discussion

The purpose of this part of the evaluation of SMOOTH was to investigate the accuracy of movement recognition archived by the system, in particular movement phase recognition and correct repetition detection. The results were used to evaluate the accuracy of the system **(R. 2)**.

Two metrics were used to evaluate the movement recognition accuracy of SMOOTH: movement phase recognition and correct repetition detection. As presented in the previous section, the duration of the sliding time windows that obtained the best results differed for both metrics. Current movement phase was recognised with the highest accuracy for signal features calculated over a 0.5s time window, whereas the highest number of correct exercise repetitions was detected for a 0.1s time window. There might be two reasons for this finding. The first reason is that human error might occur during the labelling of movement phases. Of note, is that the movement phases were labelled as the exercises progressed. The shorter the duration of the time window used for feature calculation the more accurate the labelling should be. For example, if marking a movement phase is delayed 0.2s this means that in case of a 0.1s time window there is high chance that 2 samples will be misclassified by the system and in case of a 0.5s time window there is high chance that none of the samples will be misclassified. The second reason is the fact that using a 0.1s time window to calculate signal features means that more samples are generated for one exercise set. To detect the number of exercise repetitions, a sequence of movement phases in the correct order is required. The more samples there are, the bigger the chance that they will form a sequence that will be recognised as an exercise repetition. The metric used in

(a) Healthy participants
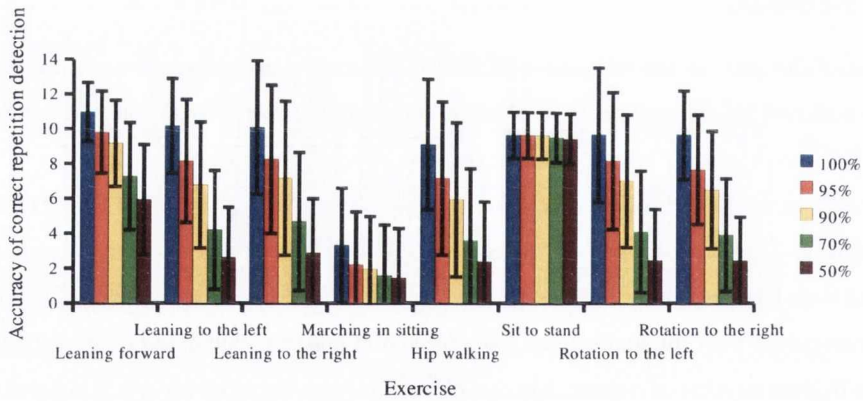


(b) Participants with PD

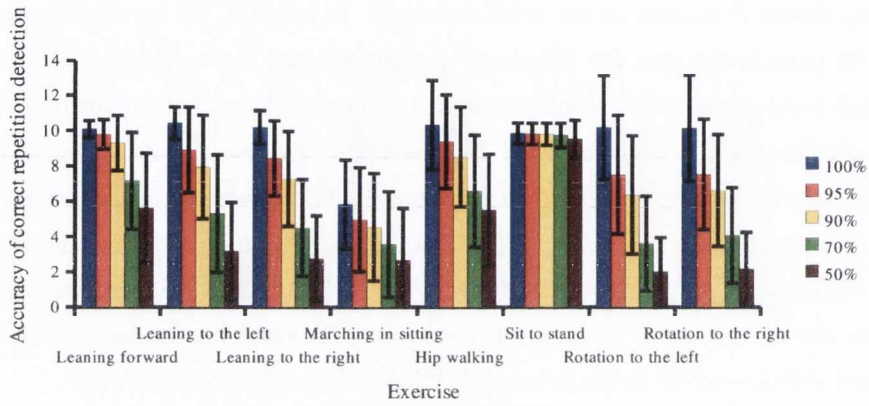**Figure 6.24**: Accuracy of correct repetition detection dependent on exercise and belief threshold

SMOOTH to assess exercise performance is the number of correct exercise repetitions completed. As presented in Figure 6.21, using a 0.1s time window in signal feature calculation allows the detection of a number of repetitions, which varies from 9.1 to 11 depending on the exercise and excluding 'marching in sitting'. For 'marching in sitting' the number of repetitions detected is much lower and equals 5.8 and 3.3 repetitions for healthy subjects and participants with PD, respectively. For that reason, a 0.1s time window used to calculate signal features is to be preferred over 0.5s time window.

The smallest variance in the number of repetitions detected across different trials was for 'sit to stand'. In addition, as presented in Figure 6.24, 'sit to stand' had the smallest decrease in the rate of number of repetitions detected depending on the belief threshold. What is interesting, as presented in Figure 6.21, is that the accuracy of the movement phase recognition in 'sit to stand' did not differ significantly from other exercises. This might by caused again by human error that may occur during the labelling of movement phases. Such an error might result in a component of a new movement phase being labelled as part of the movement phase prior to its commencement. This means that even if movement phases are not detected properly their sequence might still be undistorted and lead to correct exercise repetition detection. In addition, the fact that movement phases in 'sit to stand' are highly distinguishable from each other might be relevant to small variance across the trials.

The exercise that obtained the worst results for healthy subjects and participants with PD was 'marching in sitting'. Depending on the participant, the number of 'marching in sitting' repetitions detected for the 100% belief threshold varied from 3.5 to 8.3 and from 0 to 8.7 (0.1s time window) for healthy subjects and participants with PD, respectively. This means that differences in the number of repetitions detected are smaller among healthy subjects. No relationship between the number of repetitions detected and participants' weight, height, age, and disease duration (where applicable) was found. This might suggest that the accuracy of repetition detection depends on the way the exercise was performed. For example, some participants performed the exercise faster than others. In such cases, it was difficult for the researcher to mark movement phases accordingly. In addition, 'marching in sitting' was the only exercise where trunk position was not important to distinguish between movement phases. The pressure sensors used in SMOOTH have, in general, lower accuracy than distance sensors. This suggests that the exercises for which readings from pressure sensors only are crucial for phase recognition are detected with lower accuracy than exercises for which readings from pressure and distance sensors are important.

There are no significant differences between the results obtained among healthy subjects. The results obtained among participants with PD are also similar to each other. There are no significant differences in the average movement recognition accuracy between healthy subjects and participants with PD except 'marching in sitting' and 'hip walking'. Participants with PD obtained slightly worse results for both of those exercises. In addition, there is bigger variance across the trials in the results obtained from participants with PD. This might be related to factors such as age and general condition.

Figure 6.24 presents the number of correct exercise repetitions recognised by the system depending

on the belief threshold. The best results are obtained for the threshold set to 100%, which means that the second DBN is not indicating incorrect movement phase occurrence. These results are not surprising given that there are no additional restrictions on the movement phase being correct. To investigate the influence of belief threshold on the number of correct repetitions detected by the system, the physiotherapist assessed the number of correct exercise repetitions during the exercise execution with user application (see Section 6.5.2). All the repetitions of all the participants were assessed as being correct. For that reason, it is hard to draw any conclusions about the influence of belief threshold on the detection of incorrect exercise repetitions. To investigate this parameter in more detail the study which would collect samples of incorrect exercise executions should be conducted.

### 6.5.6 Summary

This section presented a study designed to fulfil objective **O.2** (see Section 6.2) and investigate the movement recognition accuracy of SMOOTH. The study investigated two metrics: accuracy of movement phase recognition and accuracy of correct repetition detection. 8 healthy subjects and 10 people with PD took part in the study. The results were used to evaluate the accuracy requirement **(R. 2)**. The results suggest that the number of correct exercise repetitions detected by SMOOTH, which is used as a metric to measure exercise performance, is within a range from 9.1 to 11 repetitions for all the exercises excluding 'marching in sitting'. 'Marching in sitting' obtained lower results. In general, there were no significant differences between healthy subjects and participants with PD.

## 6.6 Summary

This chapter presented an evaluation of SMOOTH. It started with a discussion about how the system requirements were addressed in the system design. To assess accuracy **(R. 2)**, unobtrusiveness **(R. 3)**, convenience **(R. 5)**, and intuitiveness **(R. 6)** of the system a user study was designed. The user study was divided into two parts. The first part aimed to investigate user acceptance of the system and therefore evaluate the following requirements: unobtrusiveness **(R. 3)**, convenience **(R. 5)**, and intuitiveness **(R. 6)**. The second part aimed to investigate exercise monitoring accuracy and therefore evaluate the accuracy requirement **(R. 2)**. The results suggest the realisation of the requirements **(R. 3)**, **(R. 5)**, and **(R. 6)** by SMOOTH as evidenced by the positive feedback from the physiotherapists and people with PD who participated in the study. Furthermore, the results show that the detection accuracy **(R. 2)** is within range from 9.1 to 11 repetitions for both, healthy subjects and people with PD, and all the exercises excluding 'marching in sitting'. The perceived system accuracy for the parameters that obtained the best results should be investigated in further study. In addition, the results indicate that the use of low-cost sensors placed on a chair enables the measurement of the exercise performance with accuracy above 91% for all the exercises addressed by SMOOTH but one.

The evaluation presented in this chapter could be extended to home-based trials in order to in-

vestigate issues such as continuity of training, enjoyment, and general user experience. Such a study would require participants to have their own copy of SMOOTH at home and to perform exercises on a daily basis for a longer period of time as prescribed by a physiotherapist. Such a study could also result in valuable user feedback and further suggestions for improvements to SMOOTH, as well as investigating the effects of the training on participants' conditions.

# Chapter 7

# Conclusions

The research presented in this thesis explored the use of emerging pervasive computing technologies to develop assistive technology (AT) for people with Parkinson's disease (PD). More specifically, it focused on investigating the feasibility of exercise monitoring using low-cost, fixed sensors placed on a chair and examined its accuracy and user acceptance.

Chapter 1 presented motivation for this work and introduced the basic concepts related to this thesis. Chapter 2 presented a taxonomy of pervasive healthcare systems. Chapter 3 described a user survey of people with PD. The survey and subsequent feedback from the PD community identified the potential use of AT to assist people with PD in mobility training at home and facilitate physiotherapists with monitoring of their progress. Chapter 4 reviewed the state of the art in exercise monitoring and posture or movement detection. Current state-of-the-art systems show that it is possible to detect a person's position from fixed sensors mounted on a chair but that no system that detects activities from a low-cost set of sensors placed on a chair has been developed to date. To research the feasibility of activity monitoring using such sensors, SMOOTH - a system for mobility training at home - was developed. Chapter 5 presented the requirements, design, and architecture of SMOOTH including the techniques used for monitoring exercise performance. Chapter 6 presented the evaluation of the system, which included a user study designed to assess the accuracy of the system and its user acceptance. The remainder of this chapter summarises the main contributions of this work and outlines suggestions for future research.

## 7.1 Contributions

This work identified the difficulties and needs of people with PD in daily living. A user survey was employed in order to obtain this information. The results of the user survey suggest that mobility limitations were the most common problem among the participants. The majority of the participants reported problems with mobility (88%), fatigue (54%), and getting tired fast (70%). Problems with mobility included changing location (59%) and body position (51%-53%). 34% and 25% of respondents

described their physical strength and flexibility, respectively, as 'poor' or 'very poor'. For 81% of participants it was important to be able to contact someone in a case of a fall. In addition, the results of this study indicate a possible underutilisation of ATs by people with PD.

This work identified a home-based, pervasive AT that has the potential to be beneficial for people with PD. To identify the AT, the results from the user survey and the opinions of the PD community were used. The survey participants did not express the desire for any particular AT that would help them in activities of daily living and, which is also important, does not already exist. However, two potential types of ATs emerged from the survey results. They are: a fall detection and post-fall support system, and a system for mobility training at home. To decide which AT would be more beneficial for people with PD, their community was asked to form an opinion. The feedback from the PD community suggests that a system for mobility training at home would be the most beneficial. Therefore, the work presented in this thesis focused on development and evaluation of SMOOTH.

This work identified the key requirements for SMOOTH including the hardware and software platform. SMOOTH should be affordable, accurate, and unobtrusive. These features would encourage people to obtain the system and sustain its regular use. In addition, to enable its independent use at home by people with PD it should be safe, convenient, and intuitive. The purpose of SMOOTH was to help improve the most common motor disturbances, which include muscle strength, balance and postural instability. Those requirements led to development of a system that uses a set of low-cost, fixed, sensors placed on a chair to monitor exercise performance.

In order to explore the feasibility of using a set of low-cost, fixed sensors placed on a chair to detect user movement and to monitor exercise performance SMOOTH was developed. This work identified a set of exercises to be addressed by SMOOTH, a set of sensors to be used by the system including their placement as well as an approach to the assessment of exercise performance. The exercise performance was assessed by the number of correct exercise repetitions completed. To detect correct exercise repetitions, each exercise addressed by SMOOTH was divided into a number of movement phases. If the correct movement phases appeared in the appropriate order, the exercise repetition was detected to have happened. A number of techniques such as dynamic Bayesian networks and genetic algorithms were applied to detect proper exercise repetition. Detailed descriptions of their application was presented in this thesis. In addition, this work described the architecture of the system and design of user interfaces for physiotherapists and people with PD.

To evaluate the system a user study was conducted. The purpose of the study was to evaluate exercise monitoring accuracy provided by SMOOTH and its acceptance by potential users. The study was divided into two parts. To evaluate user acceptance of the system a user survey with physiotherapists and people with PD was conducted. The results show that SMOOTH received positive feedback from the physiotherapists and the people with PD that participated in the study and was perceived to be useful in home-based physiotherapy. To evaluate the monitoring accuracy of SMOOTH a study with healthy people and people with PD was conducted. The results indicate that

the accuracy of correct exercise repetitions detected by SMOOTH is above 91% for all the exercises excluding 'marching in sitting', which obtained the lowest results. This suggests that our hypothesis that a set of low-cost, fixed sensors are sufficient to measure exercise performance is valid.

## 7.2 Future work

This thesis focused on the development and evaluation of SMOOTH. To evaluate the system a user study was conducted. The feedback from potential users suggested a number of improvements that could be made to the system. The results obtained from physiotherapists indicate that marking movement phases during exercise execution was perceived to be the biggest issue related to the system. For that reason, it would be useful to replace supervised learning, which needs all the samples to be labelled, with semi-supervised learning, which needs a small number of labelled samples. The results obtained from people with PD indicate that minor changes to the user interface could be made. The changes include: an animated icon presenting the exercises, reduction/modification of voice feedback, a clear indication when an exercise should be started, and the provision to participants of more encouragement after doing all the exercises that were prescribed.

The data obtained from the user study was not sufficient to complete an in-depth exploration of the influence of the belief threshold on the indication of improper exercise execution. For that reason, more extensive user studies should be designed to investigate this issue as well as how users perceived the accuracy of the system and their views after long term use of SMOOTH at home.

SMOOTH addressed a set of eight exercises that could be performed on a chair. The set of exercises could be extended to include also exercises that are prescribed not only to people with PD but healthy people or people having different conditions. Furthermore, different sensor types could be investigated to monitor exercises that can be performed not only on a chair but, for example, on a bed.

Lack of motivation is the main reason for not sustaining exercise routines at home [Loureiro et al., 2001]. User study revealed that encouragement was an important factor for the participants and some of them suggested that doing exercises should be more rewarding. For that reason, different, more motivating, forms of interaction with the user should be explored. For example, social networks that would allow the monitoring of other users and therefore introduce competition factor, which according to [Roelands et al., 2002] might have positive impact on motivation.

Finally, SMOOTH used a number of correct exercise repetitions to measure exercise performance. This information could be extended with additional statistics, e.g., time needed to complete the exercise, that would give a physiotherapist better insight into user's performance. Therefore, future research could address exploration of additional statistics to monitor exercise performance and methods of their measurement.

# Appendix A

# Data processing

The purpose of this section is to introduce the most important concepts underlying body posture and activity recognition systems. A general schema for the processing of sensor data in order to recognise activity or body posture is shown in Figure A.1. Each step is introduced in more detail in the remainder of this section.
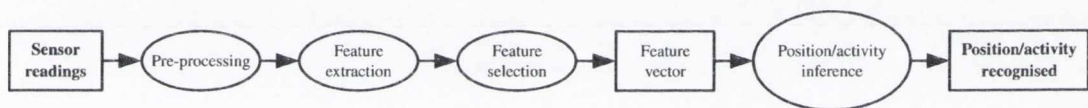


**Figure A.1**: General schema for activity/posture recognition

## A.1 Pre-processing

Data pre-processing describes any type of processing of data to prepare it for another processing procedure. The purpose of pre-processing is the preparation of data obtained from sensors for calculation of signal features. Depending on the sensors it might not be included in the process of activity/position recognition. For example, systems that obtain data from cameras process video streams in order to extract human silhouettes from them.

## A.2 Feature extraction

Feature extraction, also referred to as feature calculation, involves extraction of characteristics of the sensor signal that allow its description in order to distinguish between the postures/activities to be recognised by a system. The features can be calculated in on of three domains:

1. *Time.* No transformation is needed. Features are calculated from a number of samples that belong to a sliding time window.

2. *Frequency.* The purpose of a transformation into the frequency domain is to determine the frequency content of the signal in order describe the spectrum of a signal [Semmlow, 2008]. The most straightforward and commonly used technique in the systems reviewed is a Fourier transform. Fourier analysis is based on the fact that a waveform can be decomposed into a series of sinusoids of different frequencies. It maps the amplitude of the sinusoid to a single point on a spectrum's magnitude curve, and the phase of the sinusoid to a single point on a spectrum's phase curve. The series of sinusoids can be expressed by a mathematically equivalent series of sines and cosines:

$$a(m) = \frac{1}{T} \int_0^T x(t) \, cos(2\pi m f_1 t) dt$$

$$b(m) = \frac{1}{T} \int_0^T x(t) \, sin(2\pi m f_1 t) dt$$

where $f_1 = \frac{1}{T}$ is the period of the waveform, and $m$ is a set of integers: $m = 1, 2, 3, \ldots$ defining the family member. The original signal can be reconstructed from the sinusoidal components by the following equation:

$$x(t) = \frac{a_0}{2} + \sum_{m=0}^{\infty} a(m) \, cos(2\pi m f_1 t) + \sum_{m=0}^{\infty} b(m) \, sin(2\pi m f_1 t)$$

3. *Time-frequency.* The time-frequency domain is a generalisation and refinement of the Fourier analysis, in which frequencies are constant over time. The technique used in the systems reviewed in the remainder of this chapter to transform a signal from the time to the time-frequency domain is wavelet transform or its discrete version, discrete wavelet transform (DWT). A wavelet transform is the representation of a function by wavelets [Semmlow, 2008]. In wavelet analysis, a variety of function families may be used, but the family member (daughter wavelet) always consists of enlarged or compressed versions of the basic function (mother wavelet). This approach can be expressed by the *continuous wavelet transform (CWT)*:

$$W(a, b) = \int_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{|a|}} \Psi * (\frac{t - b}{a}) dt$$

where $b$ translates the function across $x(t)$, and $a$ varies the time scale of the probing function $\Psi$. A DWT is any wavelet transform for which the wavelets are discretely sampled. Wavelets provide a compromise between time and frequency and allow the signal description in both the time and the frequency domain.

The features can be calculated either on the signal at particular point in time or on a number of consecutive samples, called a sliding time window. The features might use metrics such as the mean value, standard deviation or maximum value of the signal.

## A.3   Feature selection

Feature selection includes techniques that are used to select a subset of the most meaningful features that describe a signal. The main purpose of these techniques is to minimise redundancy in and reduce the size of the data. Some systems might not include this step and instead use all the features calculated in the previous step. In that case, it is assumed that all of them are meaningful. Methods used for feature selection can be simple, e.g., if some feature changes over time for a particular data set, it is selected, or more sophisticated, e.g., principal component analysis (PCA) and independent component analysis (ICA). Features selected in this step form a feature vector that describes sensor readings. The feature vector is given as an input to an inference module.

## A.4   Activity/position inference

Activity/position inference involves recognition of activity/position from sensor data. State-of-the-art systems, described in the following part of this chapter, use a broad spectrum of inference techniques to infer activity/position from some feature vector. A brief introduction of the techniques follows:

- *Decision trees.* A decision tree is a hierarchical data structure that enables the classification of signal patterns through a sequence of rules [Duda et al., 2000]. A decision tree consists of a root node that is linked to other nodes. Nodes can be linked to other nodes or leaf nodes that have no other links. The classification of a pattern starts from the root node, which assesses some attribute of the pattern. Based on the outcome, the appropriate link is followed. The procedure is repeated for each node until a leaf node is reached meaning that the pattern has been classified. The links should be mutually exclusive so that only one link can be followed from any node. A decision tree classifies patterns into one of a number of defined classes, which means that there is no partial membership of other classes. To generate the decision tree the C4.5 algorithm can be used [Quinlan, 1993].

- *Fuzzy logic.* Fuzzy logic is based on the idea that human thinking is not necessary two-valued or multi-valued but can include fuzzy truths [Adeli and Hung, 1995]. Fuzzy logic operates on fuzzy sets. A fuzzy set $A$ is defined as a collection of pairs:

$$A = \{(x_i, \mu_A(x_i)),\ i = 1, 2, \ldots, n\}$$

where $\mu_A(x_i)$ is called the membership function and represents the level of membership of variable $x_i$ of fuzzy set $A$. This means that variable $x_i$ can belong to more than one fuzzy set and the membership to each of these sets can be only partial. A fuzzy inference system usually consists of a set of fuzzy rules. The rules are usually given in the form:

*IF variable IS property THEN action.*

Inference in fuzzy systems is performed by application of fuzzy operations to set of fuzzy rules. The fuzzy operations include: fuzzy complement $(cA(x_i, \mu_A(x_i)) = 1 - A(x_i, \mu_A(x_i)))$, fuzzy intersections $((A \cap B)(x_i, \mu_{A \cap B}(x_i)) = min(A(x_i, \mu_A(x_i)), B(x_i, \mu_B(x_i))))$, and fuzzy unions $((A \cup B)(x_i, \mu_{A \cup B}(x_i)) = max(A(x_i, \mu_A(x_i)), B(x_i, \mu_B(x_i))))$.

- *Artificial neural networks (ANNs).* ANNs provide a mathematical model of biological neural networks [Hecht-Neilsen, 1990]. The model tries to simulate the structure and operation of the networks. An ANN consists of an interconnected group of artificial neurons, which are usually structured as a number of layers (input layer, a number of hidden layers, and an output layer) of connected artificial neurons and weights assigned to each connection. The weights are set in a learning process. For example, the back-propagation algorithm a supervised learning method that changes connection weights in order to minimise the error of the entire output. Input data are processed by propagation through the layers. ANNs are adaptive and can change their structure based on external or internal information that flows through the network during the learning phase. They can be used to model complex relationships between inputs and outputs or to find patterns in data. ANNs might differ with an activation function. The activation function of a neuron defines the output of that neuron given an input or set of inputs. An ANN with a number of layers can also be referred to as a multi-layer perceptron.

- *Linear discrimination.* Linear discriminant analysis (LDA) is a method used in machine learning and statistics to find a linear combination of features that allows the differentiation between two or more activities/postures [Duda et al., 2000]. A linear classifier recognises activities/postures on the basis of the value of the linear combination of the features while minimising the recognition errors.

- *Nonparametric models.* Nonparametric models, in contrast to parametric models like LDA, do not make assumptions about inputs [Alpaydin, 2004]. In fact, all that nonparametric models assume is that similar inputs have similar outputs. For that reason, their structure is not specified a priori but is instead determined from data. The term nonparametric does not mean that such models completely lack parameters but that the number and nature of the parameters are flexible and not fixed in advance. The nonparametric models recognise postures/activities on the basis of similarity to other postures/activities used to train the system in the past. As the measurement of similarity, for example, Euclidean distance between model samples and samples to be recognised (the straight-line distance between two points) can be used.

- *Bayesian Networks (BNs).* Bayes' theorem is based on probability theory, which makes it suitable for reasoning under uncertainty. BNs can be considered as a mechanism for applying Bayes' theorem to complex problems [Korb et al., 2003]. BNs provide a graphical model that represents probabilistic relationships between variables. This means that given values of some variables, it is possible to calculate the probability of occurrence of different values of others. In addition,

BNs have the capability of adjusting their parameters in a learning process. BNs are described in more detail in Section B.1.

- *Hidden Markov models (HMMs)*. A HMM is a statistical model and is considered to be a specialised form of dynamic BN (DBN) [Duda et al., 2000]. A DBN is a BN that represents probabilistic relationships between variables at different points of time. A HMM defines a finite set of states with transition probabilities between these states. States in the HMM can be visible or not directly visible - hidden. The visible states in the HMM correspond to its outputs. To find transition probabilities between states of the HMM, the Baum-Welch algorithm [Baum et al., 1970] can be used. In the activity recognition domain a HMM can model a user's action as a set of states with a probability of transitions between them over time.

Techniques for mapping sensor readings to activity/position is also referred as classification. The classifiers described above are called base-level classifiers. Some of the systems can involve more than one base-level classifier to infer activity/position. For example, many classifiers of different types can be used for sensor fusion, which combines sensor readings obtained from different sources. Such classifiers are referred as meta-level classifiers and are used to obtain a final prediction from the base-level classifiers prediction. Meta-level classifiers include techniques such as boosting [Schapire, 1990] (iterative learning weak classifiers and adding them to a final strong classifier), bagging or bootstrap aggregating [Breiman, 1996] (averaging several predictors) or majority voting (selection of one of a number of alternatives, based on which has the most votes).

# Appendix B

# Techniques applied in SMOOTH

This section provides the theoretical background of two essential techniques applied in SMOOTH: DBNs (Section B.1), which are used as for inference, and genetic algorithms (GAs) (Section B.2), which are used for optimisation of discretisation parameters.

## B.1 Probability and Bayesian networks

The probability calculus was invented in the $17^{th}$ century by Fermat and Pascal to model uncertainty in gambling. The basic element of the language used in probability theory is a random variable. Every random variable has a set of values that it can accept. The values can be continuous or discrete. Continuous random variables take values from the real numbers. Discrete random variables, including Boolean random variables as a special case, take values from a finite set of values. The values must be mutually exclusive and exhaustive. An example of a discrete random variable is a coin $C$. If we toss a coin the outcome will be equal to one of two values $< heads, \ tails >$. Those values are mutually exclusive, e.g., the coin can only be in one state at a time, and exhaustive, e.g., the set of states defines all possible outcomes of the toss. If $C = tails$ is the proposition that the coin lands tails up, then the probability of that event is given by $P(C = tails)$. For a fair coin, the probability of heads and tails is the same and in that case is $P(C = tails) = 0.5$.

The foundations of probability theory were laid by Andrey Nikolaevich Kolmogorov and can be expressed by three fundamental axioms [Russell and Norvig, 2003]:

1. All probabilities are between 0 and 1. For any proposition X,

$$0 \leq P(X) \leq 1.$$

2. Necessarily true propositions have probability 1, and necessarily false propositions have probability 0.

$$P(true) = 1 \qquad P(false) = 0.$$

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3. The probability of combined evens can be expressed as,

$$P(X \cup Y) = P(X) + P(Y) - P(X \cap Y).$$

Any function satisfying the above axioms is a probability function.

A crucial aspect in probability theory is conditional probability. It is expressed by the equation:

$$P(X|Y) = \frac{P(X \cap Y)}{P(Y)}.$$

That is, given that the event $Y$ occurs, the probability that event $X$ will also occur is $P(X|Y)$. The concept is shown in Figure B.1, where conditional probability of $X$ on $Y$ is the ratio of the common area ($P(X \cap Y)$) to the area representing $P(Y)$.
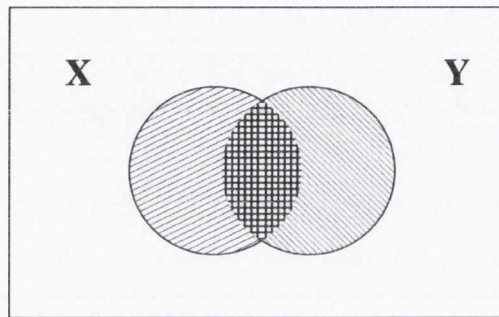


**Figure B.1**: Conditional probability $P(X|Y) = P(X \cap Y)/P(Y)$ from [Korb et al., 2003]

Another important property is independence or marginal independence. Two events $X$ and $Y$ are probabilistically independent ($P(X \perp Y)$) whenever conditioning on one leaves the probability of the other unchanged. It is described by following equation:

$$P(X \perp Y) \equiv P(X|Y) = P(X)$$

The independence is symmetrical, which means that $P(X \perp Y) \equiv P(Y \perp X)$. For example, 2 rolls of a die are normally independent. This means that getting 1 with a first roll will not lower the probability of getting 1 on the second roll and the probability is still equal to $1/6$. For dependent events the occurrence of one event will change the probability that the other will occur. For example, there is a box with 5 black balls and 5 white balls. We draw one ball and then without putting it back draw another one. The probability that the second ball is black depends on the colour of first ball. If the first ball is black then the probability of the second ball being black is $4/9$, but if first ball is white then probability of the second ball being black is $5/9$.

Conditional independence generalises the concept of independence of $X$ and $Y$ given some additional event $Z$:

$$X \perp Y|Z \equiv P(X|Y, Z) = P(X|Z).$$

Conditional independence is used when the event $Z$ tells us everything that $Y$ does about $X$ and possibly more. It means that once $Z$ is known, learning $Y$ is uninformative.

The final concept introduced in this section is joint probability. Joint probability is the probability of occurrence of two or more events in conjunction. A full joint probability distribution specifies the probability of every combination of events and is given by $P(X_1 = x_1 \wedge X_2 = x_2 \wedge \ldots \wedge X_n = x_n) \equiv P(x_1, x_2, \ldots, x_n)$. A full joint probability distribution can be expressed by conditional probabilities using the chain rule, which is described by the following equation:

$$P(x_1, x_2, \ldots, x_n) = P(x_1) * P(x_2|x_1) * P(x_3|x_1, x_2) * \ldots * P(x_n|x_1, \ldots, x_{n-1}) = \prod_i P(x_i|x_1, \ldots, x_{i-1}).$$

### B.1.1   Bayesian networks

BNs are graphical models that represent the full joint probability distribution of a set of random variables (continuous or discrete) and allow reasoning about an uncertain domain. BNs consist of sets of nodes and arcs (links). Nodes in BNs represent random variables and arcs connecting pairs of nodes, represent the direct dependencies between them. The only constraint on the arcs allowed in a BN is that they can not form any directed cycles. Such graphs are are called directed acyclic graphs (DAGs). BNs are generally oriented to handling discrete variables and continuous variables can be discretised for most purposes. For example, temperatures can be divided into ranges of a number of degrees. Assuming discrete variables, the strength of the relationship between variables is modelled by conditional probability tables (CPTs) associated with each node. Modelling with BNs requires the assumption of the Markov property. That means that all direct dependencies in the system are shown via arcs, and no additional dependencies are present. However, even though arcs are present in the model they can be nullified in the CPT, which implies lack of dependency. The Markov property implies that the value of particular node in BN depends only on its parent nodes. This fact reduces the joint probability in a BN to the following equation:

$$P(x_1, x_2, \ldots, x_n) = \prod_i P(x_i|Parents(X_i)).$$



(a) Causal chains          (b) Common cause          (c) Common effect
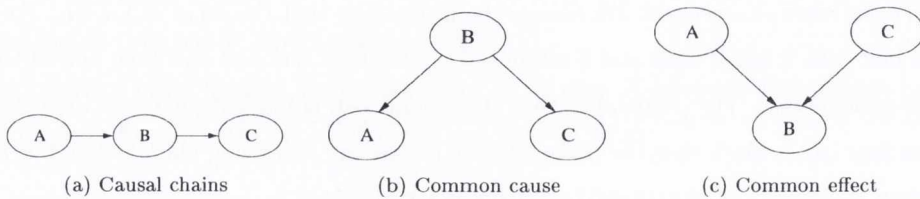
**Figure B.2**: Conditional independencies in BNs from [Korb et al., 2003]

BNs that satisfy the Markov property explicitly express conditional independence in probability distributions. In BNs 3 types of conditional independence, which are shown in Figure B.2, can be observed [Korb et al., 2003]:

1. *Causal chains.* A causal chains of three nodes, where $A$ causes $B$ which in turn causes $C$ is

shown in Figure B.2a. Conditional independence in this network can be expressed as:

$$P(C|A \wedge B) = P(C|B) = P(A \perp C|B).$$

This means that the probability of $C$, given $B$, is exactly the same as the probability of $C$, given both *A and B*. Knowing that $A$ has occurred does not change our belief about $C$ if we already know that $B$ has occurred.

2. *Common cause*. Two variables $A$ and $C$ having a common cause $B$ is shown in Figure B.2b. Common causes can be expressed as the same conditional independence structure as casual chains:

$$P(C|A \wedge B) = P(C|B) = P(A \perp C|B).$$

If there is no evidence about $B$, then learning that $A$ is present will increase the chances of $B$ which will in turn increase the probability of $C$. However, if we already know about $B$, then additional information about $A$ will not tell us anything about $C$.

3. *Common effect*. A common effect is represented by a network in B.2c in which the effect (node $B$) has two causes ($A$ and $C$). Common effects (or their descendants) produce the exact opposite conditional independence structure to casual chains and common causes. That is, the parents are marginally independent ($A \perp C$), but become dependent given information about the common effect:

$$P(A|C \wedge B) = P(A|C) \equiv \neg P(A \perp C|B)$$

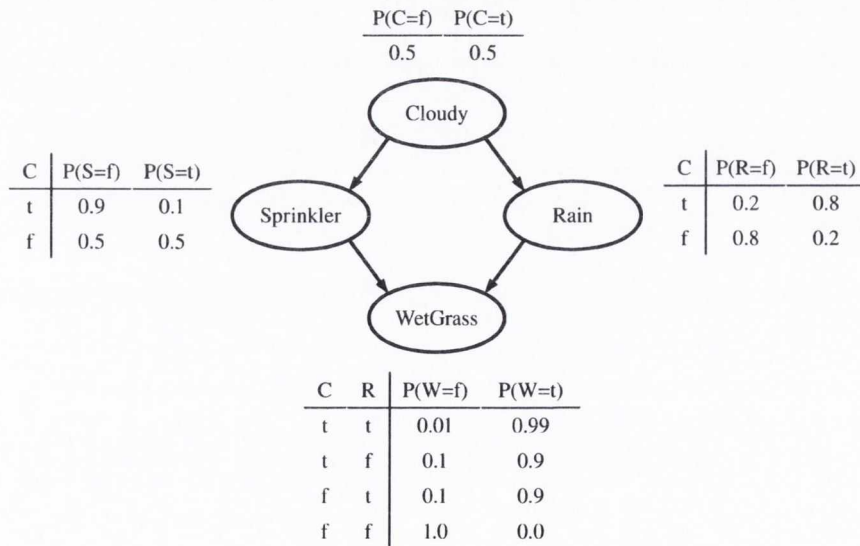

**Figure B.3**: Example of BN

An example BN is shown in Figure B.3. It models 4 Boolean random variables: *Cloudy, Sprinkler, Rain*, and *WetGrass*. The fact of the day being *Cloudy* affects the probability of the *Sprinkler* being

on and the probability of *Rain*. *Sprinkler* and *Rain* furthermore affect the probability of grass being wet *(WetGrass)*.

| $C$ | $S$ | $R$ | $W$ | $P(C)$ | $P(S|C)$ | $P(R|C)$ | $P(W|S \wedge R)$ | $P(C \wedge S \wedge R \wedge W)$ |
|---|---|---|---|---|---|---|---|---|
| t | t | t | t | 0.5 | 0.1 | 0.8 | 0.99 | 0.0396 |
| t | t | t | f | 0.5 | 0.1 | 0.8 | 0.01 | 0.0004 |
| t | t | f | t | 0.5 | 0.1 | 0.2 | 0.9 | 0.009 |
| t | t | f | f | 0.5 | 0.1 | 0.2 | 0.1 | 0.001 |
| t | f | t | t | 0.5 | 0.9 | 0.8 | 0.9 | 0.324 |
| t | f | t | f | 0.5 | 0.9 | 0.8 | 0.1 | 0.036 |
| t | f | f | t | 0.5 | 0.9 | 0.2 | 0 | 0 |
| t | f | f | f | 0.5 | 0.9 | 0.2 | 1 | 0.09 |
| t | t | t | t | 0.5 | 0.5 | 0.2 | 0.99 | 0.0495 |
| t | t | t | f | 0.5 | 0.5 | 0.2 | 0.01 | 0.0005 |
| t | t | f | t | 0.5 | 0.5 | 0.8 | 0.9 | 0.18 |
| t | t | f | f | 0.5 | 0.5 | 0.8 | 0.1 | 0.02 |
| t | f | t | t | 0.5 | 0.5 | 0.2 | 0.9 | 0.045 |
| t | f | t | f | 0.5 | 0.5 | 0.2 | 0.1 | 0.005 |
| t | f | f | t | 0.5 | 0.5 | 0.8 | 0 | 0 |
| t | f | f | f | 0.5 | 0.5 | 0.8 | 1 | 0.2 |

**Table B.1**: Joint probability table

The join probability table for this network is shown in Table B.1. Conditional probabilities *(P(C)*, *P(S|C)*, *P(R|C)*, *P(W|S ∧ R))* can be simply read from CPTs for each node in the BN and the joint probability distribution *(P(C ∧ S ∧ R ∧ W))* is their product from the chain rule. Note that the sum of all joint probabilities equals 1 which means that they are mutually exclusive and exhaustive. Any possible probability of interest can be derived from the table.

For example, we could calculate the probability of grass being wet *(P(W = t))* having no other evidence by summing all rows where $W = t$. That gives $P(W = t) = 0.0396 + 0.009 + 0.324 + 0 + 0.0495 + 0.18 + 0.045 + 0 = 0.6471$. Given no evidence, the probability of grass being wet is 65%. The probability of some event's occurrence without any evidence is called its prior probability. In contrast, the probability after observing some evidence is called the posterior probability.

In BNs we can perform predictive reasoning, i.e., from new information about causes to new beliefs about effects. For example, we could calculate how the fact that there is no rain *(R = f)* affects the probability of the grass being wet *(W = t)*. In that case the joint probability can be expressed as $P(W = t|R = f)$ and can be calculated by summing joint probabilities from all the columns where $W = t$ *and* $R = f$ and dividing this sum by the sum of joint probabilities from all the columns where $R = f$. That gives $P(W = t|R = f) = \frac{P(W=t \wedge R=f)}{P(R=f)} = \frac{0.009+0+0.18+0}{0.009+0.001+0+0.09+0.18+0.02+0+0.2} = 0.378$. Given that there is no rain the probability of grass being wet has decreased to 38%.

In contrast to predictive reasoning, we can perform diagnostic reasoning, i.e., reasoning from symptoms to cause. For example, we could calculate the probability of it being cloudy *(C = t)* given no rain *(R = f)*. We can derive the equation needed for the calculation of this probability

$(P(C = t|R = f))$ from the conditional probability:

$$P(X|Y) = \frac{P(X \cap Y)}{P(Y)} \Rightarrow$$

$$P(X \cap Y) = P(X|Y) * P(Y) \Rightarrow P(X \cap Y) = P(Y|X) * P(X) \Rightarrow$$

$$P(Y|X) = \frac{P(X \cap Y)}{P(X)}.$$

In our case $P(C = t|R = f) = \frac{P(C=t \wedge R=f)}{P(R=f)}$ and join probabilities can be read from table $P(C = t|R = f) = \frac{P(C=t \wedge R=f)}{P(R=f)} = \frac{0.009+0.001+0+0.09}{0.009+0.001+0+0.009+0.18+0.02+0+0.2} = 0.238$. The probability of being cloudy when it is not raining is 24%. Those examples demonstrate that BNs can be used to calculate the probability of occurrence of any event given an available set of observations.

In pervasive computing BNs can be used to estimate current activity based on input from a set of sensors in the environment. The basic BN structure is presented in Figure B.4, where activity to be detected is the parent of all sensor nodes. This type of classifier is called a naive Bayes classifier and in this case assumes that sensor nodes are independent from each other given activity. Despite its simplicity it works surprisingly well [Korb et al., 2003]. To infer activity, diagnostic reasoning is used. Activity is perceived to cause sensor readings therefore we infer cause (activity) from symptoms (sensory input). To query the activity, sensor readings are sampled and their values are assigned to corresponding nodes. Then the update of probabilities for the activity is performed given the sensor values.
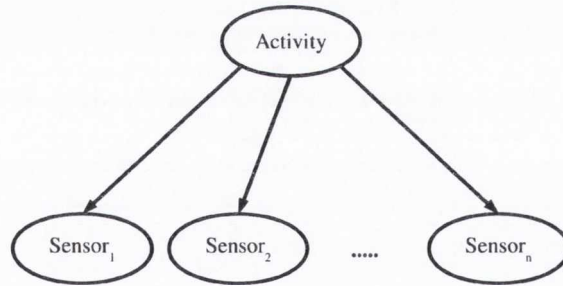


**Figure B.4**: Example of BN in pervasive computing

## B.1.2  Dynamic Bayesian networks

BNs model probabilistic dependencies between sets of random variables at a particular point of time or during a specific time interval. They do not explicitly model temporal relationships between variables. The only way to model the relationship between the current value of a variable and its value at a different point of time, is to add another variable with a different name. To explicitly model temporal relationships BNs can be generalised into DBNs, which model probabilistic and temporal relationships between variables while enabling reasoning under uncertainty [Korb et al., 2003].

Let a BN consist of a set of $n$ variables at a point of time $X = \{X_1, X_2, \ldots, X_n\}$. To construct a DBN each variable $X_i$ is considered at to a point in time $t$ so $X_i^t$ represents variable $X_i$ at time $t$ where $0 \le t \le T$. In that case the DBN consists of $T$ sets of time dependent variables $X^t = \{X_1^t, X_2^t, \ldots, X_n^t\}$. If the current time step is represented as $t$ then the previous time step would be represented as $t - 1$, and the next time step as $t + 1$. The corresponding DBN variables can be expressed as:

- Current time step: $X = \{X_1^t, X_2^t, \ldots, X_n^t\}$

- Previous time step: $X = \{X_1^{t-1}, X_2^{t-1}, \ldots, X_n^{t-1}\}$

- Next time step: $X = \{X_1^{t+1}, X_2^{t+1}, \ldots, X_n^{t+1}\}$

Each time step is called a time-slice and corresponds to a sliding time window.

DBNs are defined by the following specification [Neapolitan, 2003]:

1. An initial BN consists of an initial DAG $G_0$ containing variables in $X^0$ and an initial probability $P^0$ of these variables.

2. A transition BN that is a template consisting of a transition DAG $G_\rightarrow$ containing variables in $X^t \cup X^{t+1}$ and a transition probability distribution $P_\rightarrow$ that assigns a conditional probability of every value of $X^{t+1}$ given every value of $X^t$. This means that a transition probability specifies all conditional probabilities given by equation:

$$P_\rightarrow(X^{t+1} = x^{t+1} | X^t = x^t).$$

3. The DBN containing the variables that constitute the $T$ random vectors consists of the DAG composed of DAG $G_0$ and for $0 \le t \le T$ DAG $G_\rightarrow$ evaluated at $t$ and the following joint probability:

$$P(x^0, \ldots, x^T) = P_0(x^0) \prod_{t=0}^{T-1} P_\rightarrow(x^{t+1} | x^t).$$

All information needed to predict the world state at time $t$ is contained in the description of the world at time $t - 1$. No information from earlier times is needed. Therefore, the process has the Markov property.

An example of a DBN for activity recognition, which is an extension of the BN presented in Figure B.4, is shown in Figure B.5. The initial BN has the same structure, however to extend it with temporal information time-slices have been added. Time-slices correspond to different points in time and in the example they represent the previous $t - 1$, current $t$, and next $t + 1$ points in time. Usually DBNs are not extended to other time-slices, because they become very large too quickly. In the example, the current state (activity) depends on evidence (sensory input) from the previous time-slice, and affects the particular observations (sensors) at current time-slice.
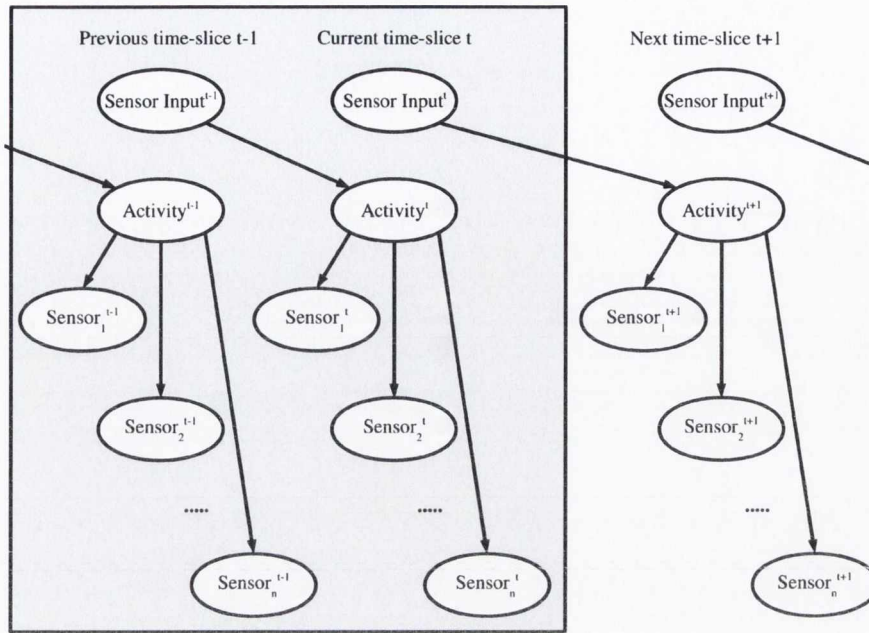
**Figure B.5**: Example of DBN in pervasive computing

## B.1.3   Parameter learning for Bayesian networks

A BN including a CPT for each node and arcs representing dependencies between nodes can be based on the beliefs of a domain expert or can be learnt from previously observed data. There are two types of learning associated with BNs: structure and parameter learning. The goal of structure learning is to learn dependencies (arc structure) between the nodes of the network. The aim of parameter learning is to learn probability parameters for existing dependencies between nodes , i.e., CPTs. Probabilities that are learnt from the data are called relative frequencies. In SMOOTH it is assumed that dependencies exist only between sensor inputs and movement phases, and sensor inputs are independent from each other given movement phase. For that reason structure learning is not further discussed.

Suppose we have an experiment that can have two outcomes. Let random variable $X$ have two values $x_1$ and $x_2$ that are possible outcomes of the experiment. We assume that it is possible to represent our belief about the relative frequency of $X = x_1$ by a random variable $F$ that takes values from range $[0, 1]$. The expected value $E(F)$ is defined to be an estimate of the relative frequency. If we knew that the relative frequency of $X = x_1$ was $f$ such that $P(X = x_1|F = f) = f$ then

$$P(X = x_1) = \int_0^1 P(X = x_1|F = f)\, P(f) df = \int_0^1 f\, P(f) df = E(F).$$

This situation is presented by the BN in Figure B.6. Such a network is called an augmented BN.

P(f)



P(X=x₁ | F=f)=f
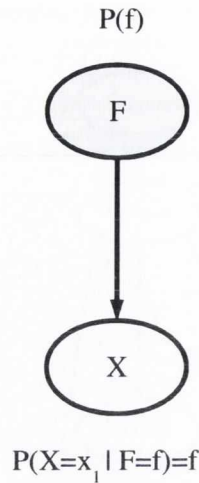
**Figure B.6**: Augmented BN representing probability distribution of $F$

### B.1.3.1   Binomial variables

Binomial variables are variables that have two values. The simplest possible BN is one consisting of a single binomial variable $X$. The purpose of a learning process is to estimate relative frequencies $E(F)$ for both possible values $\{x_1, x_2\}$ of the variable $X$. The probability distribution for $F$ can be modelled as a beta distribution, which provides natural way of quantifying prior believes about relative frequencies and allows their easy update given the evidence [Neapolitan, 2003]. A beta distribution with shape parameters $a, b, N = a + b$ where $a, b \geq 0$ is defined in terms of the gamma function:

$$P(f) = beta(f; a, b) = \frac{\Gamma(N)}{\Gamma(a)\,\Gamma(b)} f^{a-1}(1-f)^{b-1} \qquad 0 \leq f \leq 1.$$

If the relative frequency $F$ has beta distribution with parameters $a, b, N = a + b$ then

$$P(X = x_1) = E(F) = \frac{a}{N}.$$

For a BN with variable $X$ that can take one of the values $x_1$ or $x_2$ we can think about parameters $a$ and $b$ as the counts of each outcome $x_1$ and $x_2$ and $N$ as total number of both outcomes. For example, we toss a fair coin $C$ with two possible outcomes *heads* and *tails* and observe 60 *tails* in 100 tosses. The expected value $E(F)$ of the probability $P(C = tails) = \frac{60}{100} = 0.6$. The probability distribution $P(f)$ is given by the beta distribution $beta(f; 60, 40)$. In addition to providing the expected value of the probability, the beta distribution represents the strength of an belief in this probability given the number of observations. Figure B.7 shows 3 sample beta distributions of belief in $P(C = tails) = 0.6$ after a different number of observations, Figure B.7a after 10, Figure B.7b after 100, and Figure B.7c after 1000. It can be seen that the more observations we have, the more focused the distribution is and therefore represents stronger belief in the estimate.

Easy updates of beta distribution can be used to continually learn the probability distribution for $F$ from the observed data $d$. Let $a$ and $b$ be a number of previous observations and $s$ and $t$ a number

(a) beta(f; 6, 4)

(b) beta(f; 60, 40)

(c) beta(f; 600, 400)
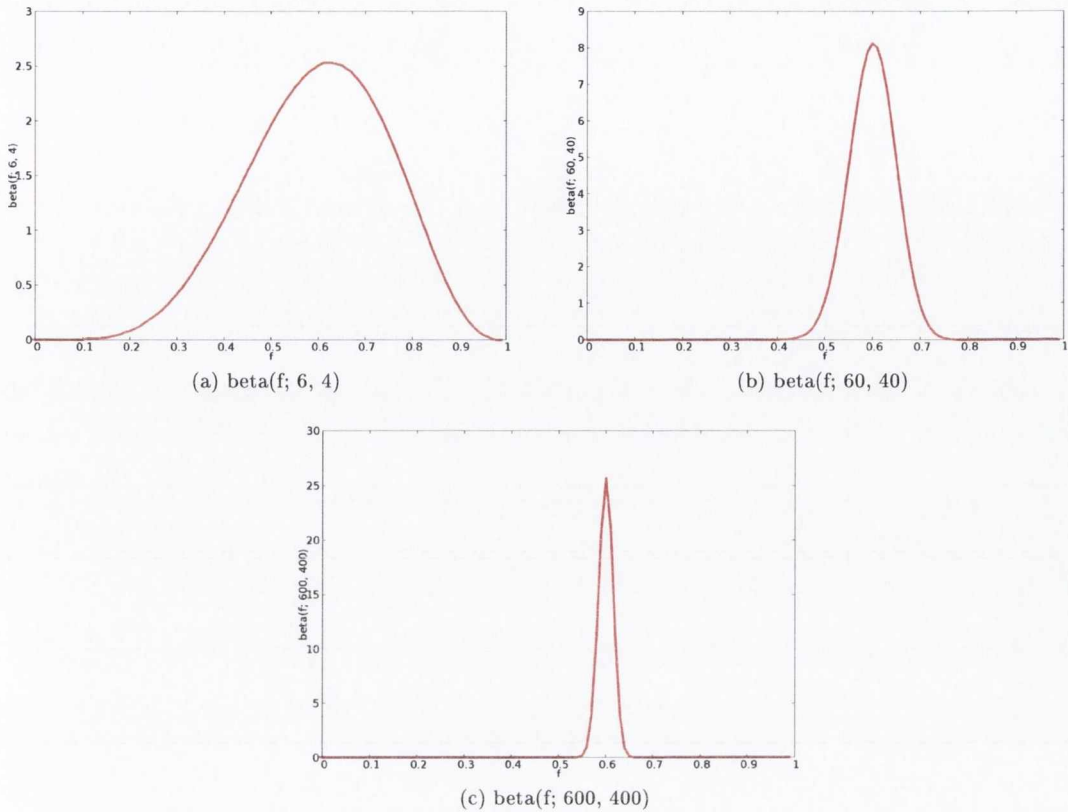
**Figure B.7**: Beta distribution

of new observations of values $x_1$ and $x_2$, respectively. The probability distribution of $F$ conditional on data $d$ is called the updated density function and given by following beta distribution:

$$P(f|d) = beta(f; a + s, b + t).$$

The posterior estimate of the relative frequency for $X = x_1$ and sample of size $M + 1$ is given by:

$$P(X^{M+1} = x_1|d) = E(F|d).$$

In the example of coin tossing presented earlier, the beta distribution of belief in $P(C = tails)$ after 10 observations (6 for *tails* and 4 for *heads*) is given by $beta(f; 6, 4)$. Subsequently, after an additional 90 observations (54 for *tails* and 36 for *heads*) the updated density function is given by $beta(f; 6 + 54, 4 + 36) = beta(f; 60, 40)$ and, finally, after 1000 observations in total (600 for *tails* and 400 for *heads*) by $beta(f; 600, 400)$. As presented in Figures B.7 the belief about the estimate of relative frequencies gets stronger with the number of observations.

In the previous part of this section, the learning probability distribution in a BN with a single binomial variable was presented. It can be extended to a BN with more variables by generalisation of the augmented BN (see Figure B.6), which can be determined by the following [Neapolitan, 2003]:

1. A DAG $G = (V, E)$ where $V = \{X_1, X_2, \ldots, X_n\}$ and each $X_i$ is random variable.

2. For every $i$, an auxiliary parent variable $F_i$ of $X_i$ and density function $P_i$ of $F_i$. Each $F_i$ is a root and has no edge to any variable except $X_i$. The set of all $F_i$s is denoted by $F$ given by:

$$F = F_1 \cup F_2 \cup \cdots \cup F_n.$$

3. For every $i$, for all values $pa_i$ of the parents $PA_i$ in $V$ of $X_i$, and all values $f_i$ of $F_i$, a probability distribution of $X_i$ conditional on $pa_i$ and $f_i$.

### B.1.3.2 Multinomial variables

Multinomial variables are variables that have more than two values. Methods used for learning binomial variables can be extended to discrete multinomial variables by use of a Dirichlet density function [Gelman et al., 1995] that is the multivariate generalisation of the beta distribution. The Dirichlet distribution with parameters $a_1, a_2, \ldots, a_r$ and $N = \sum_{k=1}^{r} a_k$, where $a_1, a_2, \ldots, a_r$ are integers $\geq 0$, is given by:

$$Dir(f_1, f_2, \ldots, f_{r-1}; a_1, a_2, \ldots, a_r) = P(f_1, f_2, \ldots, f_{r-1}) = \frac{\Gamma(N)}{\prod_{k=1}^{r} \Gamma(a_k)} f^{a_1-1} \ f^{a_2-1} \ f^{a_r-1}$$

$$where \quad 0 \leq f_k \leq 1, \sum_{k=1}^{r} f_k = 1.$$

The random variables $f_1, f_2, \ldots, f_{r-1}$ represent probabilities for $r$ values of the node.

If relative frequencies $F_1, F_2, \ldots F_r$ have a Dirichlet distribution with parameters $a_1, a_2, \ldots, a_r$, $N = \sum_{k=1}^{r} a_k$ then for $1 \leq k \leq r$

$$P(X = x_k) = E(F_k) = \frac{a_k}{N}.$$

For a BN with a variable $X$ that can take one of the values $x_1, x_2, \ldots, x_k$ we can think about parameters $a_1, a_2, \ldots, a_k$ as the counts of occurrence of the $k^{th}$ value in $N$ trials. For example, we roll a dice $D$ with 6 possible outcomes $\{1, 2, 3, 4, 5, 6\}$ and and observe 20 1s, 15 2s, 15 3s, 15 4s, 15 5s, and 20 6s in 100 tosses. The expected value $E(F_1)$ of the probability that 1 is rolled is $P(D = 1) = \frac{20}{100} = 0.2$. Probability distribution $P(f_1, f_2, f_3, f_4, f_5)$ is given by Dirichlet distribution $Dir(f_1, f_2, f_3, f_4, f_5; 20, 15, 15, 15, 15, 20)$.

Similar to the beta distribution the Dirichlet distribution can be used to update the probability distribution for $F_k$ from the observed data $d$. Let $a_1, a_2, \ldots, a_k$ be the number of previous observations and $s_1, s_2, \ldots, s_k$ number of new observations of corresponding values $x_1, x_2, \ldots, x_k$. The probability distribution of $F_k$ conditional on data $d$ is given by following the Dirichlet distribution:

$$P(f_1, f_2, \ldots, f_{k-1}|d) = Dir(f_1, f_2, \ldots, f_{k-1}; a_1 + s_1, a_2 + s_2, \ldots, a_k + s_k).$$

In order to learn an entire network the Spiegelhalter and Lauritzen method can be applied [Korb et al., 2003]. This method is the most broadly used and is available in the standard BN tools. Two main assumptions related to the algorithm are that parameters should be mutually independent

and can be represented as a Dirichlet distribution. The later implies that values of nodes in a BN must be discrete. For that reason continuous variables, e.g., temperature or time, have to be discretised to be used by this learning algorithm. In pervasive BNs, the variable independence assumption is already guaranteed by the Markov property and assumed as general practise for the BN as a whole.

## B.2 Genetic algorithms

GAs are a search technique used in computing to find solutions to general optimisation and search problems. GAs are modelled on the mechanism of natural genetic systems and try to imitate some of the processes observed in natural evolution [Pal and Wang, 1996]. GAs are executed iteratively on a set of coded solutions, called a *population*, with 3 basic genetic operators: *selection/reproduction*, *crossover*, and *mutation*. To find an optimal solution to some problem, a GA starts from a set of assumed solutions, called *chromosomes*, and evolves to a better set of solutions over a number of iterations, called *generations*. In each iteration, the objective function, representing *fitness* criteria, determines the suitability of chromosomes to be selected for reproduction. In that way better chromosomes are selected and worse chromosomes eliminated on the basis of their fitness. In the next step genetic operators are applied and the outcome chromosomes create a new population, which is used as an input to the next iteration. The process is usually stopped when a solution that satisfies certain criteria is found, a fixed number of generations is reached, or the highest ranking solution's fitness has reached a plateau such that successive iterations no longer produce better results. A schematic diagram visualising a basic genetic algorithm is shown in Figure B.8.

The components of which a GA typically consists are described in more detail below [Pal and Wang, 1996]:

- *Chromosome.* A chromosome refers to a possible solution. Traditionally, solutions are represented in binary as strings of 0s and 1s, but other encodings are also possible. For example, a chromosome can be coded as 010011.

- *Population.* To solve an optimisation problem, a GA starts with a chromosome representation of the parameter set $\{x_1, x_2, \ldots, x_p\}$. A set of such chromosomes in a generation is called the population. The size of the population can be constant or vary across generations. The initial population is usually chosen randomly and its size depends on the nature of the problem. For example, the population can consists of 4 chromosomes and be expressed as $\{010111, 100001, 101010, 000100\}$.

- *Encoding/decoding mechanism.* This is the mechanism used to convert the parameter values of the possible solution to the chromosome representation. Decoding is the reverse process.

- *Objective/fitness function.* The choice of objective function depends on the problem. The objective function is used to choose the best chromosomes to reproduce in the next generation.
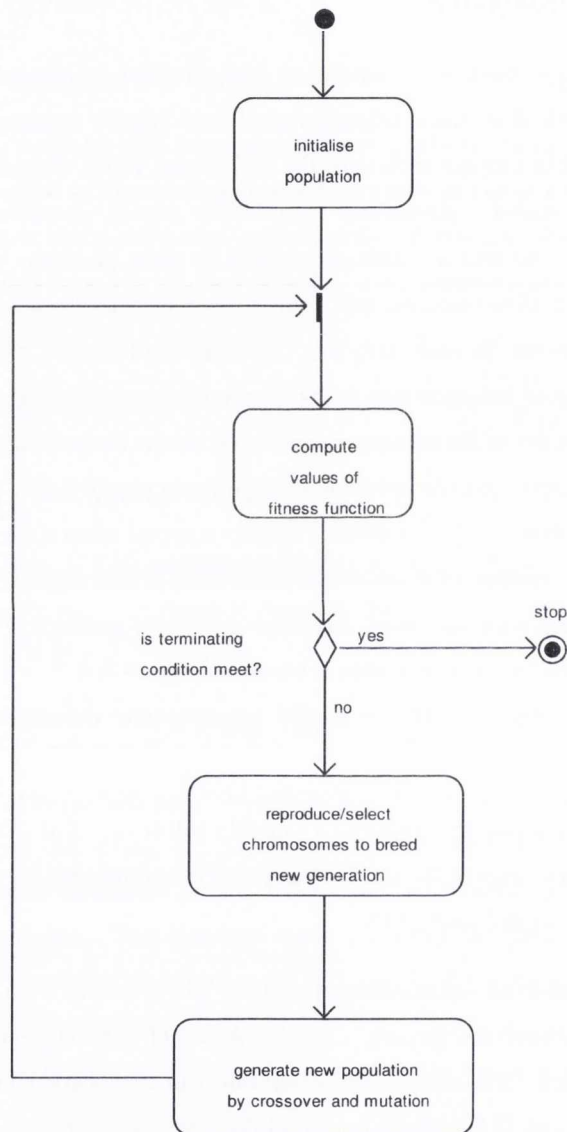
**Figure B.8**: Basic steps of genetic algorithm from [Pal and Wang, 1996]

It is chosen in such a way that highly fitted chromosomes (possible solutions) have high fitness values. For example, the objective function can be the number of 1s in a chromosome.

- *Selection/reproduction procedure.* This procedure selects individual chromosomes to breed a new generation. The number of copies of each chromosome is proportional to its fitness value. Popular selection methods include roulette wheel selection and tournament selection. In roulette wheel selection, all chromosomes are placed on a 'roulette wheel' and the size of the area they occupy depends on their fitness function. The higher value of the fitness function, the bigger area a particular chromosome occupies. Afterwards, a chromosome is selected for crossover at random. Tournament selection involves running several selections, called tournaments, among a few chromosomes chosen at random from the population. The winner of each tournament, which is the fittest chromosome, is selected for crossover. Most selection methods are stochastic and designed in such a way that a small proportion of less fit chromosomes is selected. This allows the diversity of the population to be maintained, and prevents premature convergence on poor solutions.

- *Crossover/recombination.* This is a genetic operator used to exchange information between 2 randomly chosen chromosomes. Crossover consists of 3 steps: selection of pairs of chromosomes, determination of crossover probability, and interchange of segments between the chromosomes. The number of segments and their length depends on the crossover technique. The most popular techniques are: one-point, two-point, multi-point, and uniform crossover. For example, in one-point crossover a single point on two chromosomes is selected. All data beyond that point in either chromosome is swapped between the two chromosomes. Let $a$ and $b$ be chromosomes that are selected by the one-point crossover technique with crossover position $k = 5$:

$$a = 01001111$$

$$b = 01110000$$

then new chromosomes created by application of this technique are:

$$a' = 01000000$$

$$b' = 01111111$$

- *Mutation.* This is a genetic operator used to introduce genetic diversity into a population. In mutation a random position of a random chromosome is selected and replaced by another value from a set of values defined for the chromosome. Mutation allows the algorithm to avoid local minima by preventing the population from becoming too similar, which might slow or even stop the evolution. Sometimes, mutation allows information lost in previous generations to be regained. For example, let $a$ be chromosome selected for mutation:

$$a = 01001101$$

if mutation occurs in position $k = 2$ then the new chromosome is:

$$a' = 00001101$$

- *Probabilities of performing genetic operations.* Probabilities of crossover or mutation can be set to a fixed value or adapt to the environment. Because mutation occurs occasionally its probability should be very low - typically between 0.001 and 0.01. Crossover occurs more often, and its typical value usually varies between 0.6 and 0.9 [Goldberg, 1989].

Recently, GAs have been applied to solve problems in many domains such as business, science, and engineering [Davis and Mitchell, 1991]. The following characteristics enhance their application in optimisation and searching [Pal and Wang, 1996]:

- GAs work simultaneously allowing the introduction of parallelism into the computational procedure.

- GAs work with a coded parameter set, therefore a possible search space can be controlled by varying a coding mechanism.

- In GAs, the search space does not have to be continuous.

- GAs use an objective function as the only criteria and do not need any additional information.

- GAs use a probabilistic set of rules not deterministic ones.

# Bibliography

[Abudi et al., 1997] Abudi, S., Bar-Tal, Y., Ziv, L., and Fish, M. (1997). Parkinson's disease symptoms - patients' perceptions. *Journal of Advanced Nursing*, 25:54–59.

[Addlesee et al., 1997] Addlesee, M., Jones, A., Livesey, F., and Samaria, F. (1997). The orl active floor [sensor system]. *IEEE Personal Communications*, 4(5):35–41.

[Adeli and Hung, 1995] Adeli, H. and Hung, S.-L. (1995). *Machine learning: neural networks, genetic algorithms, and fuzzy systems*. Wiley.

[Adkin et al., 2003] Adkin, A. L., Frank, J. S., and Jog, M. S. (2003). Fear of falling and postural control in parkinson's disease. *Movement Disorders*, 18(5):496–502.

[Agree et al., 2004] Agree, E. M., Freedman, V. A., and Sengupta, M. (2004). Factors influencing the use of mobility technology in community-based long-term care. *J Aging Health*, 16(2):267–307.

[Ahlskog, 2003] Ahlskog, J. E. (2003). Slowing parkinson's disease progression: recent dopamine agonist trials. *Neurology*, 60(3):381–389.

[Ákos Fábián et al., 2007] Ákos Fábián, Győrbíró, N., and Hományi, G. (2007). Activity recognition system for mobile phones using the motionband device. In *MOBILWARE '08: Proceedings of the 1st international conference on MOBILe Wireless MiddleWARE, Operating Systems, and Applications*, pages 1–5, ICST, Brussels, Belgium, Belgium. ICST (Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering).

[Alamri et al., 2008] Alamri, A., Eid, M., Iglesias, R., Shirmohammadi, S., and Saddik, A. E. (2008). Haptic virtual rehabilitation exercises for poststroke diagnosis. 57(9):1876–1884.

[Allen et al., 2006] Allen, F. R., Ambikairajah, E., Lovell, N. H., and Celler, B. G. (2006). Classification of a known sequence of motions and postures from accelerometry data using adapted gaussian mixture models. *Physiol Meas*, 27(10):935–951.

[Alpaydin, 2004] Alpaydin, E. (2004). *Introduction to Machine Learning*. The MIT Press.

[Analog Devices, Inc., 2009] Analog Devices, Inc. (2009). http://www.analog.com.

[Anderson, 2002] Anderson, K. E. (2002). Nonrecognition of depression in parkinson's disease. *Curr Neurol Neurosci Rep*, 2(4):293–295.

[Anderson, 2003] Anderson, K. E. (2003). Dementia in parkinson's disease. *Current Treatment Options in Neurology*, 6(3):201–207.

[Asch et al., 1997] Asch, D. A., Jedrziewski, M. K., and Christakis, N. A. (1997). Response rates to mail surveys published in medical journals. *Journal of Clinical Epidemiology*, 50(10):1129–1136.

[Axisa et al., 2005] Axisa, F., Schmitt, P. M., Gehin, C., Delhomme, G., McAdams, E., and Dittmar, A. (2005). Flexible technologies and smart clothing for citizen medicine, home healthcare, and disease prevention. 9(3):325–336.

[Bao and Intille, 2004] Bao, L. and Intille, S. S. (2004). Activity recognition from user-annotated acceleration data. *Pervasive Computing*, pages 1–17.

[Bateni and Maki, 2005] Bateni, H. and Maki, B. E. (2005). Assistive devices for balance and mobility: benefits, demands, and adverse consequences. *Arch Phys Med Rehabil*, 86(1):134–145.

[Baum et al., 1970] Baum, L. E., Petrie, T., Soules, G., and Weiss, N. (1970). A maximization technique occurring in the statistical analysis of probabilistic functions of markov chains. *The Annals of Mathematical Statistics*, 41(1):164–171.

[Ben-Shomo et al., 1996] Ben-Shomo, Y., Finnan, F., Allwright, S., and Smith, G. D. (1996). The epidemiology of parkinson's disease in the republicof ireland: observations from routine data sources. *Irish Medical Journal*, 86(6):190–194.

[Benatru et al., 2008] Benatru, I., Vaugoyeau, M., and Azulay, J.-P. (2008). Postural disorders in parkinson's disease. *Neurophysiol Clin*, 38(6):459–465.

[Berardelli et al., 2001] Berardelli, A., Rothwell, J. C., Thompson, P. D., and Hallett, M. (2001). Pathophysiology of bradykinesia in parkinson's disease. *Brain*, 124(Pt 11):2131–2146.

[Bezprozvanny, 2009] Bezprozvanny, I. (2009). Calcium signaling and neurodegenerative diseases. *Trends Mol Med*, 15(3):89–100.

[Bodymedia, 2009] Bodymedia (2009). http://www.bodymedia.com.

[Boelen, 2007] Boelen, M. (2007). The role of rehabilitative modalities and exercise in parkinson's disease. *Dis Mon*, 53(5):259–264.

[Boian et al., 2002] Boian, R. F., Deutsch, J. E., Burdea, G. C., and Lewis, J. (2002). Virtual reality-based system for ankle rehabilitation post stroke. In *Proceedings of the First International Workshop on Virtual Reality Rehabilitation (Mental Health, Neurological, Physical, Vocational)*, pages 77–86.

[Boian et al., 2003] Boian, R. F., Deutsch, J. E., Lee, C. S., Burdea, G. C., and Lewis, J. (2003). Haptic effects for virtual reality-based post-stroke rehabilitation. In *HAPTICS '03: Proceedings of the 11th Symposium on Haptic Interfaces for Virtual Environment and Teleoperator Systems (HAPTICS'03)*, page 247, Washington, DC, USA. IEEE Computer Society.

[Boulay et al., 2005] Boulay, B., Bremond, F., and Thonnat, M. (2005). Posture recognition with a 3d human model. In *Proc. IEE International Symposium on Imaging for Crime Detection and Prevention ICDP 2005*, pages 135–138.

[Boulay et al., 2006] Boulay, B., Brémond, F., and Thonnat, M. (2006). Applying 3d human model in a posture recognition system. *Pattern Recogn. Lett.*, 27(15):1788–1796.

[Bouzit et al., 2002] Bouzit, M., Popescu, G., Burdea, G., and Boian, R. (2002). The rutgers master ii-nd force feedback glove. In *Proceedings of the 10th Symposium on Haptic Interfaces for Virtual Environment and Teleoperator Systems (HAPTICS'02)*, pages 145–152. IEEE.

[Breiman, 1996] Breiman, L. (1996). Bagging predictors. *Mach. Learn.*, 24(2):123–140.

[Buccolieri et al., 2005] Buccolieri, F., Distante, C., and Leone, A. (2005). Human posture recognition using active contours and radial basis function neural network. In *Proc. IEEE Conference on Advanced Video and Signal Based Surveillance AVSS 2005*, pages 213–218.

[Burdea et al., 2008] Burdea, G., Fensterheim, D., Cioi, D., and Arezki, A. (2008). The rutgers arm ii rehabilitation system. In *Proc. Virtual Rehabilitation*, pages 76–76.

[Burdea, 2000] Burdea, G. C. (2000). Haptics issues in virtual environments. In *CGI '00: Proceedings of the International Conference on Computer Graphics*, page 295, Washington, DC, USA. IEEE Computer Society.

[Burkhardt and Weber, 1994] Burkhardt, C. R. and Weber, H. K. (1994). Parkinson's disease: a chronic, low-grade antioxidant deficiency? *Med Hypotheses*, 43(2):111–114.

[Bussmann et al., 1998] Bussmann, J. B., Tulen, J. H., van Herel, E. C., and Stam, H. J. (1998). Quantification of physical activities by means of ambulatory accelerometry: A validation study. *Psychophysiology*, 35(5):488–496.

[Caglar et al., 2005] Caglar, A. T., Gurses, H. N., Mutluay, F. K., and Kiziltan, G. (2005). Effects of home exercises on motor performance in patients with parkinson's disease. *Clin Rehabil*, 19(8):870–877.

[Canning et al., 1997] Canning, C. G., Alison, J. A., Allen, N. E., and Groeller, H. (1997). Parkinson's disease: An investigation of exercise capacity, respiratory function, and gait. *Archives of physical medicine and rehabilitation*, 78.

[Canning et al., 2009] Canning, C. G., Sherrington, C., Lord, S. R., Fung, V. S. C., Close, J. C. T., Latt, M. D., Howard, K., Allen, N. E., O'Rourke, S. D., and Murray, S. M. (2009). Exercise therapy for prevention of falls in people with parkinson's disease: a protocol for a randomised controlled trial and economic evaluation. *BMC Neurol*, 9:4.

[Castelnuovo et al., 2003] Castelnuovo, G., Priore, C. L., Liccione, D., and Cioffi, G. (2003). Virtual reality based tools for the rehabilitation of cognitive and executive functions: the v-store. *PsychNology Journal*, 1(3):310–325.

[Chaudhuri and Behan, 2000] Chaudhuri, A. and Behan, P. O. (2000). Fatigue and basal ganglia. *Journal of the Neurological Science*, 179:34–42.

[Cheekiralla and Engels, 2005] Cheekiralla, S. and Engels, D. (2005). A functional taxonomy of wireless sensor network devices. In *Second IEEE/CreateNet Workshop on Broadband Advanced Sensor Networks (BaseNetS 2005)*, The University of Nottingham.

[Chen et al., 2006] Chen, C.-H., Liu, W.-N., and Chen, Y.-P. (2006). Adaptive discretization for probabilistic model building genetic algorithms. In *GECCO '06: Proceedings of the 8th annual conference on Genetic and evolutionary computation*, pages 1103–1110, New York, NY, USA. ACM.

[Chien et al., 2002] Chien, S.-Y., Ma, S.-Y., and Chen, L.-G. (2002). Efficient moving object segmentation algorithm using background registration technique. 12(7):577–586.

[Cohen-Mansfield et al., 2004] Cohen-Mansfield, J., Marx, M. S., Biddison, J. R., and Guralnik, J. M. (2004). Socio-environmental exercise preferences among older adults. *Prev Med*, 38(6):804–811.

[Coninx et al., 2008] Coninx, K., Raymaekers, C., Boeck, J. D., Weyer, T. D., Alders, G., Gijbels, D., Eijnde, B. O., and Feys, P. (2008). Using the phantom device for rehabilition of the arm in ms patients: a case study. In *Proceedings of 6th International Conference on Methods and Techniques in Behavioral Research Measuring Behavior 2008*, pages 148–149.

[Consolvo et al., 2004] Consolvo, S., Roessler, P., and Shelton, B. E. (2004). The CareNet display: Lessons learned from an in home evaluation of an ambient display. In *Lecture Notes in Computer Science - UbiComp 2004: Proceedings of 6th International Conference on Ubiquitous Computing*, volume 3205, pages 1–17. Springer Berlin/Heidelberg.

[Constantinescu et al., 2007] Constantinescu, R., Leonard, C., Deeley, C., and Kurlan, R. (2007). Assistive devices for gait in parkinson's disease. *Parkinsonism Relat Disord*, 13(3):133–138.

[Cook et al., 2009] Cook, D. J., Augusto, J. C., and Jakkula, V. R. (2009). Review: Ambient intelligence: Technologies, applications, and opportunities. *Pervasive Mob. Comput.*, 5(4):277–298.

[Cooper et al., 2008] Cooper, R. A., Dicianno, B. E., Brewer, B., LoPresti, E., Ding, D., Simpson, R., Grindle, G., and Wang, H. (2008). A perspective on intelligent devices and environments in medical rehabilitation. *Med Eng Phys*, 30(10):1387–1398.

[Correa et al., 2009] Correa, M., Bielza, C., and Pamies-Teixeira, J. (2009). Comparison of bayesian networks and artificial neural networks for quality detection in a machining process. *Expert Systems with Applications*, 36(3, Part 2):7270 – 7279.

[Crossbow Technology, 2009] Crossbow Technology (2009). http://www.xbow.com.

[Cucchiara et al., 2001] Cucchiara, R., Grana, C., Neri, G., Piccardi, M., and Prati, A. (2001). *Video-based Surveillance Systems: Computer Vision and Distributed Processing*, chapter The Sakbot system for moving object detection and tracking. Kulwer.

[Cucchiara et al., 2003] Cucchiara, R., Grana, C., Piccardi, M., and Prati, A. (2003). Detecting moving objects, ghosts, and shadows in video streams. 25(10):1337–1342.

[Cucchiara et al., 2005] Cucchiara, R., Grana, C., Prati, A., and Vezzani, R. (2005). Probabilistic posture classification for human-behavior analysis. *IEEE Transactions on Systems, Man and Cybernetics, Part A: Systems and Humans*, 35(1):42–54.

[Davis and Mitchell, 1991] Davis, L. D. and Mitchell, M. (1991). Handbook of genetic algorithms. *Van Nostrand Reinhold*.

[de Goede et al., 2001] de Goede, C. J., Keus, S. H., Kwakkel, G., and Wagenaar, R. C. (2001). The effects of physical therapy in parkinson's disease: A research synthesis. *Archives of physical medicine and rehabilitation*, 82:509–515.

[de Leon and Sucar, 2002] de Leon, R. D. and Sucar, L. E. (2002). Continuous activity recognition with missing data. In *Proc. 16th International Conference on Pattern Recognition*, volume 1, pages 439–442 vol.1.

[de Silva et al., 2005] de Silva, G. C., Oh, B., Yamasaki, T., and Aizawa, K. (2005). Experience retrieval in a ubiquitous home. In *CARPE '05: Proceedings of the 2nd ACM workshop on Continuous archival and retrieval of personal experiences*, pages 35–44. ACM Press.

[Deane et al., 2001a] Deane, K. H., Whurr, R., Playford, E. D., Ben-Shlomo, Y., and Clarke, C. E. (2001a). Speech and language therapy for dysarthria in parkinson's disease. *Cochrane Database Syst Rev*, (2):CD002812.

[Deane et al., 2001b] Deane, K. H. O., Jones, D., Playford, E. D., Ben-Shlomo, Y., and Clarke, C. E. (2001b). Physiotherapy versus placebo or no intervention in parkinson's disease. *Cochrane Database of Systematic Reviews*, 3(CD002817).

[Demiris et al., 2008] Demiris, G., Hensel, B. K., Skubic, M., and Rantz, M. (2008). Senior residents' perceived need of and preferences for "smart home" sensor technologies. *Int J Technol Assess Health Care*, 24(1):120–124.

[Devantech, 2009] Devantech (2009). SRF10. http://www.acroname.com/robotics/parts/R241-SRF10.html.

[Dictionary, 2009] Dictionary (2009). The american heritage dictionary of the english language. http://dictionary.reference.com.

[Doherty, 2003] Doherty, T. J. (2003). Invited review: Aging and sarcopenia. *J Appl Physiol*, 95(4):1717–1727.

[Duan and Li, 1991] Duan, N. and Li, K. (1991). Slicing regression: A link-free regression method. *Annals of Statistics*, 19(2):505–530.

[Duda et al., 2000] Duda, R. O., Hart, P. E., and Stork, D. G. (2000). *Pattern Classification (2nd Edition)*. Wiley-Interscience.

[Eeden et al., 2003] Eeden, S. K. V. D., Tanner, C. M., Bernstein, A. L., Fross4, R. D., Leimpeter, A., Bloch, D. A., and Nelson, L. M. (2003). Incidence of parkinson's disease: Variation by age, gender, and race/ethnicity. *American Journal of Epidemiology*, 157(11):1015–1022.

[Ellis et al., 2005] Ellis, T., de Goede, C. J., Feldman, R. G., Wolters, E. C., Kwakkel, G., and Wagenaar, R. C. (2005). Efficacy of a physical therapy program in patients with parkinson's disease: A randomized controlled trial. *Archives of physical medicine and rehabilitation*, 86:626–632.

[Ellis et al., 2008] Ellis, T., Katz, D. I., White, D. K., DePiero, T. J., Hohler, A. D., and Saint-Hilaire, M. (2008). Effectiveness of an inpatient multidisciplinary rehabilitation program for people with parkinson disease. *Phys Ther*, 88(7):812–819.

[EMPA, 2009] EMPA (2009). Swiss federal laboratories for materials testing and research.

[Encyclopedia, 2009] Encyclopedia (2009). http://www.answers.com.

[Ermes et al., 2008a] Ermes, M., Parkka, J., and Cluitmans, L. (2008a). Advancing from offline to online activity recognition with wearable sensors. In *Proc. 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society EMBS 2008*, pages 4451–4454.

[Ermes et al., 2008b] Ermes, M., Parkka, J., Mantyjarvi, J., and Korhonen, I. (2008b). Detection of daily activities and sports with wearable sensors in controlled and uncontrolled conditions. *IEEE Transactions on Information Technology in Biomedicine*, 12(1):20–26.

[Estrin et al., 2002] Estrin, D., Culler, D., Pister, K., and Sukhatme, G. (2002). Connecting the physical world with pervasive networks. *Pervasive Computing, IEEE*, 1(1):59–69.

[Falvo et al., 2008] Falvo, M. J., Schilling, B. K., and Earhart, G. M. (2008). Parkinson's disease and resistive exercise: rationale, review, and recommendations. *Mov Disord*, 23(1):1–11.

[Ferrarin et al., 2006] Ferrarin, M., Carpinella, I., Rabuffetti, M., Calabrese, E., Mazzoleni, P., and Nemni, R. (2006). Locomotor disorders in patients at early stages of parkinson's disease: a quantitative analysis. *Conf Proc IEEE Eng Med Biol Soc*, 1:1224–1227.

[Feys et al., 2001] Feys, P., Romberg, A., Ruutiainen, J., Davies-Smith, A., Jones, R., Avizzano, C. A., Bergamasco, M., and Ketelaer, P. (2001). Assistive technology to improve PC interaction for people with intention tremor. *Journal of Rehabilitation Research and Development*, 38(2):235–243.

[Fitzgerald et al., 2008] Fitzgerald, D., Trakarnratanakul, N., Dunne, L., Smyth, B., and Caulfield, B. (2008). Development and user evaluation of a virtual rehabilitation system for wobble board balance training. In *Proc. 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society EMBS 2008*, pages 4194–4198.

[Foerster and Fahrenberg, 2000] Foerster, F. and Fahrenberg, J. (2000). Motion pattern and posture: correctly assessed by calibrated accelerometers. *Behav Res Methods Instrum Comput*, 32(3):450–457.

[Foerster et al., 1999] Foerster, F., Smeja, M., and Fahrenberg, J. (1999). Detection of posture and motion by accelerometry: a validation study in ambulatory monitoring. *Computers in Human Behavior*, 15(5):571–583.

[Freund and Schapire, 1995] Freund, Y. and Schapire, R. E. (1995). A decision-theoretic generalization of on-line learning and an application to boosting. In *EuroCOLT '95: Proceedings of the Second European Conference on Computational Learning Theory*, pages 23–37, London, UK. Springer-Verlag.

[Friedman et al., 2007] Friedman, J. H., Brown, R. G., Comella, C., Garber, C. E., Krupp, L. B., Lou, J.-S., Marsh, L., Nail, L., Shulman, L., Taylor, C. B., and on Fatigue in Parkinson's Disease, W. G. (2007). Fatigue in parkinson's disease: a review. *Mov Disord*, 22(3):297–308.

[Friedrich et al., 1996] Friedrich, M., Cermak, T., and Maderbacher, P. (1996). The effect of brochure use versus therapist teaching on patients performing therapeutic exercise and on changes in impairment status. *Phys Ther*, 76(10):1082–1088.

[Fujita and Kato, 2005] Fujita, K. and Kato, S. (2005). Development of on-bed lower extremity exercise system for use with networked virtual space. In *Proc. 27th Annual International Conference of the Engineering in Medicine and Biology Society IEEE-EMBS 2005*, pages 2563–2566.

[Gage and Storey, 2004] Gage, H. and Storey, L. (2004). Rehabilitation for parkinson's disease: a systematic review of available evidence. *Clin Rehabil*, 18(5):463–482.

[Gelb et al., 1999] Gelb, D. J., Oliver, E., and Gilman, S. (1999). Diagnostic criteria for parkinson disease. *Archives of Neurology*, 56(1):33–39.

[Gelman et al., 1995] Gelman, A., Carlin, J., Stern, H., and Rubin, D. (1995). *Bayesian Data Analysis*. Chapman and Hall.

[Genever, 2009] Genever, R. W. (2009). Deep brain stimulation for patients with advanced parkinson disease. *JAMA*, 301(19):1985; author reply 1985–1985; author reply 1986.

[Georgia Institute of Technology, 2009] Georgia Institute of Technology (2009). The Aware Home Research Initiative. http://awarehome.imtc.gatech.edu.

[Gesture Xtreme, 2009] Gesture Xtreme (2009). http://www.intertekme.com.

[Girondel et al., 2005a] Girondel, V., Bonnaud, L., Caplier, A., and Rombaut, M. (2005a). Static human body postures recognition in video sequences using the belief theory. In *Proc. IEEE International Conference on Image Processing ICIP 2005*, volume 2, pages II-45–8.

[Girondel et al., 2005b] Girondel, V., Caplier, A., and Bonnaud, L. (2005b). A belief theory-based static posture recognition systems for real-time video surveillance applications. In *Proc. IEEE Conference on Advanced Video and Signal Based Surveillance AVSS 2005*, pages 10–15.

[Girone et al., 2001] Girone, M., Burdea, G., Bouzit, M., Popescu, V., and Deutsch, J. E. (2001). A stewart platform-based system for ankle telerehabilitation. *Auton. Robots*, 10(2):203–212.

[Goldberg, 1989] Goldberg, D. E. (1989). *Genetic Algorithms in Search, Optimization and Machine Learning*. Addison-Wesley Longman Publishing Co., Inc., Boston, MA, USA.

[Goodwin et al., 2008] Goodwin, V. A., Richards, S. H., Taylor, R. S., Taylor, A. H., and Campbell, J. L. (2008). The effectiveness of exercise interventions for people with parkinson's disease: a systematic review and meta-analysis. *Mov Disord*, 23(5):631–640.

[Gourlay et al., 2000] Gourlay, D., Lun, K., and Liy, G. (2000). Virtual reality and telemedicine for home health care. *Computers & Graphics*, 24(5):695–699.

[Gowthaman et al., 2007] Gowthaman, R., Gowthaman, N., Rajangam, M. K., and Srinivasan, K. (2007). Database of neurodegenerative disorders. *Bioinformation*, 2(4):153–154.

[Grimm et al., 2001] Grimm, R., Davis, J., Hendrickson, B., Lemar, E., MacBeth, A., Swanson, S., Anderson, T., Bershad, B., Borriello, G., Gribble, S., and Wetherall, D. (2001). Systems directions for pervasive computing. In *Proc. Eighth Workshop on Hot Topics in Operating Systems*, pages 147–151.

[Györbíró et al., 2009] Györbíró, N., Ákos Fábián, and Hományi, G. (2009). An activity recognition system for mobile phones. *Mob. Netw. Appl.*, 14(1):82–91.

[Haigh and Kiff, 2004] Haigh, K. Z. and Kiff, L. M. (2004). The independent lifestyle assistant (I.L.S.A.): AI lessons learned. In *IAAI'04: Proceedings of Innovative Applications of Artificial Intelligence Conference*, pages 852–857. American Association for Artificial Intelligence.

[Harms et al., 2008] Harms, H., Amft, O., Tröster, G., and Roggen, D. (2008). Smash: a distributed sensing and processing garment for the classification of upper body postures. In *BodyNets '08: Proceedings of the ICST 3rd international conference on Body area networks*, pages 1–8, ICST, Brussels, Belgium, Belgium. ICST (Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering).

[Haykin, 2001] Haykin, S. (2001). *Kalman Filtering and Neural Networks*. Wiley-Interscience.

[Headon and Curwen, 2001] Headon, R. and Curwen, R. (2001). Recognizing movements from the ground reaction force. In *PUI '01: Proceedings of the 2001 workshop on Perceptive user interfaces*, pages 1–8, New York, NY, USA. ACM.

[Hecht-Neilsen, 1990] Hecht-Neilsen, R. (1990). *Neurocomputing*. Addison Wesley.

[Hellwig et al., 2009] Hellwig, B., Mund, P., Schelter, B., Guschlbauer, B., Timmer, J., and Lucking, C. H. (2009). A longitudinal study of tremor frequencies in parkinson's disease and essential tremor. *Clin Neurophysiol*, 120(2):431–435.

[Herlofson and Larsen, 2003] Herlofson, K. and Larsen, J. (2003). The influence of fatigue on health-related quality of life in patients with parkinson's disease. *Acta Neurol Scand*, 107:1–6.

[Hexamite, 2009] Hexamite (2009). http://www.hexamite.com/.

[Hilton et al., 2002] Hilton, D., Cobb, S., Pridmore, T., and Gladman, J. (2002). Virtual reality and stroke rehabilitation: A tangible interface to an every day task. In *4th International Conference on Disability Virtual Reality and Associated Technologies*, pages 63–70, Veszprem, Hungary.

[Hirsch et al., 2003] Hirsch, M. A., Toole, T., Maitland, C. G., and Rider, R. A. (2003). The effects of balance training and high-intensity resistance training on persons with idiopathic parkinson's disease. *Archives of Physical Medicine and Rehabilitation*, 84(8):1109–1117.

[Ho et al., 2005] Ho, L., Moh, M., Walker, Z., Hamada, T., and Su, C.-F. (2005). A prototype on RFID and sensor networks for elder healthcare: Progress report. In *E-WIND '05: Proceeding of the 2005 ACM SIGCOMM workshop on Experimental approaches to wireless network design and analysis*, pages 70–75. ACM Press.

[Holden, 2005] Holden, M. K. (2005). Virtual environments for motor rehabilitation: Review. *Cyberpsychology & behavior*, 8(3):187–211.

[Hsia et al., 2008] Hsia, C.-C., Hung, Y.-W., Chiu, Y.-H., and Kang, C.-H. (2008). Bayesian classification for bed posture detection based on kurtosis and skewness estimation. In *Proc. 10th International Conference on e-health Networking, Applications and Services HealthCom 2008*, pages 165–168.

[Huynh and Schiele, 2006] Huynh, T. and Schiele, B. (2006). Towards less supervision in activity recognition from wearable sensors. *10th IEEE International Symposium on Wearable Computers*, pages 3–10.

[Immersion Corporation, 2009] Immersion Corporation (2009). http://www.immersion.com.

[Interlink Electronics, 2009] Interlink Electronics (2009). http://www.interlinkelectronics.com.

[ISO, 2002] ISO (2002). Technical aids for persons with disabilities: Classification andterminology.

[ISO, 2007] ISO (2007). Assistive products for persons with disability: Classification and terminology.

[Jack et al., 2000] Jack, D., Boian, R., Merians, A., Adamovich, S. V., Tremaine, M., Recce, M., Burdea, G. C., and Poizner, H. (2000). A virtual reality-based exercise program for stroke rehabilitation. In *Assets '00: Proceedings of the fourth international ACM conference on Assistive technologies*, pages 56–63, New York, NY, USA. ACM.

[Jafari et al., 2005] Jafari, R., Dabiri, F., Brisk, P., and Sarrafzadeh, M. (2005). Adaptive and fault tolerant medical vest for life-critical medical monitoring. In *SAC '05: Proceedings of the 2005 ACM symposium on Applied computing*, pages 272–279. ACM Press.

[Jankovic, 2005] Jankovic, J. (2005). Motor fluctuations and dyskinesias in parkinson's disease: clinical manifestations. *Mov Disord*, 20 Suppl 11:S11–S16.

[Jeong et al., 2007] Jeong, D.-U., Kim, S.-J., and Chung, W.-Y. (2007). Classification of posture and movement using a 3-axis accelerometer. In *Proc. International Conference on Convergence Information Technology*, pages 837–844.

[Johansson and Falkman, 2008] Johansson, F. and Falkman, G. (2008). A comparison between two approaches to threat evaluation in an air defense scenario. In *MDAI '08 Sabadell: Proceedings of the 5th International Conference on Modeling Decisions for Artificial Intelligence*, pages 110–121, Berlin, Heidelberg. Springer-Verlag.

[Johnson et al., 2007] Johnson, G. R., Faragher, R., Gore, P., Orpwood, R., Schep, K., and Toussaint, O. (2007). Full reports of the sector panels - Technology. In *AGEACTION "Changing Expectations of Life"*, pages 89–104. Institute for Ageing and Health, Newcastle University.

[Josman et al., 2006] Josman, N., Hof, E., Klinger, E., Marie, R., Goldenberg, K., Weiss, P., and Kizony, R. (2006). Performance within a virtual supermarket and its relationship to executive functions in post-stroke patients. pages 106–109.

[Juang and Chang, 2007] Juang, C.-F. and Chang, C.-M. (2007). Human body posture classification by a neural fuzzy network and home care system application. *IEEE Transactions on Systems, Man and Cybernetics, Part A*, 37(6):984–994.

[Juang and Lin, 1998] Juang, C.-F. and Lin, C.-T. (1998). An online self-constructing neural fuzzy inference network and its applications. 6(1):12–32.

[Jutai et al., 2007] Jutai, J., Coulson, S., Teasell, R., Bayley, M., Garland, J., Mayo, N., and Wood-Dauphinee, S. (2007). Mobility assistive device utilization in a prospective study of patients with first-ever stroke. *Arch Phys Med Rehabil*, 88(10):1268–1275.

[Jutai et al., 2000] Jutai, J., Rigby, P., Ryan, S., and Stickel, S. (2000). Psychosocial impact of electronic aids to daily living. *Assistive Technology*, 12(2):123–131.

[Kamiya et al., 2008] Kamiya, K., Kudo, M., Nonaka, H., and Toyama, J. (2008). Sitting posture analysis by pressure sensors. In *Proc. 19th International Conference on Pattern Recognition ICPR 2008*, pages 1–4.

[Kanade et al., 1998] Kanade, T., Collins, R. T., Lipton, A. J., Burt, P., and Wixson, L. (1998). Advances in cooperative multi-sensor video surveillance.

[Karantonis et al., 2006] Karantonis, D., Narayanan, M., Mathie, M., Lovell, N., and Celler, B. (2006). Implementation of a real-time human movement classifier using a triaxial accelerometer for ambulatory monitoring. 10(1):156–167.

[Kautz et al., 2002] Kautz, H., Arnstein, L., Borriello, G., Etzioni, O., and Fox, D. (2002). An overview of the assisted cognition project. In *AAAI'02: Proceedings of workshop on Automation as Caregiver: The Role of Intelligent Technology in Elder Care*.

[Keranen et al., 2003] Keranen, T., Kaakkola, S., Sotaniemi, K., Laulumaa, V., Haapaniemi, T., Jolma, T., Kola, H., Ylikoski, A., Satomaa, O., Kovanen, J., Taimela, E., Haapaniemi, H., Turunen, H., and Takala, A. (2003). Economic burden and quality of life impairment increase with severity of pd. *Parkinsonism & Related Disorders*, 9(3):163 – 168.

[Kern et al., 2003] Kern, N., Schiele, B., and Schmidt, A. (2003). Multi-sensor activity context detection for wearable computing. In *In Proc. EUSAI, LNCS*, pages 220–232.

[Keus et al., 2006] Keus, S., Bloem, B., van Hilten, J., Ashburn, A., and Munnek, M. (2006). Effectiveness of physiotherapy in parkinson's disease: The feasibility of a randomised controlled trial. *Parkinsonism and Related Disorders*.

[Keus et al., 2009] Keus, S. H. J., Munneke, M., Nijkrake, M. J., Kwakkel, G., and Bloem, B. R. (2009). Physical therapy in parkinson's disease: evolution and future challenges. *Mov Disord*, 24(1):1–14.

[Khan et al., 2008] Khan, A. M., Lee, Y. K., and Kim, T. S. (2008). Accelerometer signal-based human activity recognition using augmented autoregressive model coefficients and artificial neural nets. In *Proc. 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society EMBS 2008*, pages 5172–5175.

[Kida et al., 2007] Kida, Y., Tachibana, H., Takeda, M., Yoshikawa, H., and Okita, T. (2007). Recognition memory for unfamiliar faces in parkinson's disease: Behavioral and electrophysiologic measures. *Parkinsonism and Related Disorders*, 13(3):157–164.

[King and Horak, 2009] King, L. A. and Horak, F. B. (2009). Delaying mobility disability in people with parkinson disease using a sensorimotor agility exercise program. *Phys Ther*, 89(4):384–393.

[Kizony et al., 2002] Kizony, R., Katz1, N., Weingarden, H., and Weiss, P. L. (2002). Immersion without encumbrance: adapting a virtual reality system for the rehabilitation of individuals with stroke and spinal cord injury. In *ICDVRAT 2002: Proceedings of 4th International Conference Series on Disability, Virtual Reality and Associated Technologies*, pages 55–62.

[Knight et al., 2008] Knight, H., Lee, J.-K., and Ma, H. (2008). Chair alarm for patient fall prevention based on gesture recognition and interactivity. In *Proc. 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society EMBS 2008*, pages 3698–3701.

[Korb et al., 2003] Korb, K. B., , and Nicholson, A. E. (2003). *Bayesian Artificial Intelligence (Chapman & Hall/Crc Computer Science and Data Analysis)*. Chapman & Hall/CRC, 1 edition.

[Korhonen et al., 2003] Korhonen, I., Parkka, J., and Van Gils, M. (2003). Health monitoring in the home of the future. 22(3):66–73.

[Kotsiantis and Kanellopoulos, 2006] Kotsiantis, S. and Kanellopoulos, D. (2006). Discretization techniques: A recent survey. *GESTS International Transactions on Computer Science and Engineering*, 23(1).

[Kranz et al., 2007] Kranz, M., Spiessl, W., and Schmidt, A. (2007). Designing ubiquitous computing systems for sports equipment. In *Pervasive Computing and Communications, 2007. PerCom '07. Fifth Annual IEEE International Conference on*, pages 79–86.

[Krishnan and Panchanathan, 2008] Krishnan, N. and Panchanathan, S. (2008). Analysis of low resolution accelerometer data for continuous human activity recognition. In *Proc. IEEE International Conference on Acoustics, Speech and Signal Processing ICASSP 2008*, pages 3337–3340.

[Kurniawan, 2008] Kurniawan, S. (2008). Older people and mobile phones: A multi-method investigation. *International Journal of Human-Computer Studies*, 66(12):889 – 901. Mobile human-computer interaction.

[Kuttuva et al., 2006] Kuttuva, M., Boian, R., Merians, A., Burdea, G., Bouzit, M., Lewis, J., and Fensterheim, D. (2006). The rutgers arm, a rehabilitation system in virtual reality: a pilot study. *Cyberpsychol Behav*, 9(2):148–151.

[kwang Song et al., 2008] kwang Song, S., Jang, J., and Park, S. (2008). A phone for human activity recognition using triaxial acceleration sensor. In *Proc. Digest of Technical Papers. International Conference on Consumer Electronics ICCE 2008*, pages 1–2.

[Landwehr et al., 2003] Landwehr, N., Hall, M., and Frank, E. (2003). Logistic model trees. pages 241–252.

[Lester et al., 2006] Lester, J., Choudhury, T., and Borriello, G. (2006). *A Practical Approach to Recognizing Physical Activities.*

[Lester et al., 2005] Lester, J., Choudhury, T., Kern, N., Borriello, G., and Hannaford, B. (2005). A hybrid discriminative/generative approach for modeling human activities. In *In Proc. of the International Joint Conference on Artificial Intelligence (IJCAI*, pages 766–772.

[Loh et al., 2004] Loh, J., Schietecat, T., Kwok, T. F., Lindeboom, L., and Joore, P. (2004). Technology applied to address difficulties of alzheimer patients and their partners. In *Proceedings of the conference on Dutch directions in HCI*. ACM Press.

[Loureiro et al., 2001] Loureiro, R., Amirabdollahian, F., Coote, S., Stokes, E., and Harwin, W. (2001). Using haptics technology to deliver motivational therapies in stroke patients: Concepts and initial pilot studies. In *In Proceedings of EuroHaptics 2001.*

[Luo et al., 2007] Luo, R., Li, L., and Gu, I. Y. H. (2007). Efficient adaptive background subtraction based on multi-resolution background modelling and updating. In *PCM*, pages 118–127.

[Lyons et al., 2005] Lyons, G. M., Culhane, K. M., Hilton, D., Grace, P. A., and Lyons, D. (2005). A description of an accelerometer-based mobility monitoring technique. *Med Eng Phys*, 27(6):497–504.

[Ma et al., 2007] Ma, M., McNeill, M., Charles, D., McDonough, S., Crosbie, J., Oliver, L., and McGoldrick, C. (2007). Adaptive virtual reality games for rehabilitation of motor disorders. In Stephanidis, C., editor, *HCI (6)*, volume 4555 of *Lecture Notes in Computer Science*, pages 681–690. Springer.

[Mali and Munih, 2006] Mali, U. and Munih, M. (2006). Hife-haptic interface for finger exercise. *Mechatronics, IEEE/ASME Transactions on*, 11(1):93–102.

[Mann, 2005] Mann, W. C. (2005). *Smart Technology for Aging, Disability and Independence: The State of the Science*. Wiley.

[Mann et al., 1999] Mann, W. C., Ottenbacher, K. J., Fraas, L., Tomita, M., and Granger, C. V. (1999). Effectiveness of assistive technology and environmental interventions in maintaining independence and reducing home care costs for the frail elderly. a randomized controlled trial. *Arch Fam Med*, 8(3):210–217.

[Mantyjarvi et al., 2001] Mantyjarvi, J., Himberg, J., and Seppanen, T. (2001). Recognizing human motion with multiple acceleration sensors. In *Proc. IEEE International Conference on Systems, Man, and Cybernetics*, volume 2, pages 747–752 vol.2.

[MashhadiMalek et al., 2008] MashhadiMalek, M., Towhidkhah, F., Gharibzadeh, S., Daeichin, V., and Ahmadi-Pajouh, M. A. (2008). Are rigidity and tremor two sides of the same coin in parkinson's disease? *Comput Biol Med*, 38(11-12):1133–1139.

[Massie and Salisbury, 1994] Massie, T. H. and Salisbury, K. J. (1994). Phantom haptic interface: a device for probing virtual objects. volume 55-1 of *Proceedings of the 1994 International Mechanical Engineering Congress and Exposition*, pages 295–299, Massachusetts Inst of Technology, Cambridge, United States. ASME.

[Mathie et al., 2002] Mathie, M., Lovell, N., Coster, A., and Celler, B. (2002). Determining activity using a triaxial accelerometer. In *Proc. Second Joint [Engineering in Medicine and Biology 24th Annual Conference and the Annual Fall Meeting of the Biomedical Engineering Society] EMBS/BMES Conference*, volume 3, pages 2481–2482 vol.3.

[Mathie et al., 2004] Mathie, M. J., Celler, B. G., Lovell, N. H., and Coster, A. C. F. (2004). Classification of basic daily movements using a triaxial accelerometer. *Med Biol Eng Comput*, 42(5):679–687.

[Mathie et al., 2003] Mathie, M. J., Coster, A. C. F., Lovell, N. H., and Celler, B. G. (2003). Detection of daily physical activities using a triaxial accelerometer. *Med Biol Eng Comput*, 41(3):296–301.

[Mattmann et al., 2007] Mattmann, C., Amft, O., Harms, H., Troster, G., and Clemens, F. (2007). Recognizing upper body postures using textile strain sensors. In *Proc. 11th IEEE International Symposium on Wearable Computers*, pages 29–36.

[Maurer et al., 2006] Maurer, U., Smailagic, A., Siewiorek, D., and Deisher, M. (2006). Activity recognition and monitoring using multiple sensors on different body positions. In *Proc. International Workshop on Wearable and Implantable Body Sensor Networks BSN 2006*, pages 4pp.–116.

[McCrone et al., 2007] McCrone, P., Allcock, L. M., and Burn, D. J. (2007). Predicting the cost of parkinson's disease. *Movement Disorders*, 22(6):804–812.

[Mehta et al., 2008] Mehta, S. H., Morgan, J. C., and Sethi, K. D. (2008). Sleep disorders associated with parkinson's disease: role of dopamine, epidemiology, and clinical scales of assessment. *CNS Spectr*, 13(3 Suppl 4):6–11.

[Meir and Rätsch, 2003] Meir, R. and Rätsch, G. (2003). An introduction to boosting and leveraging. pages 118–183.

[Meng and Lee, 2006] Meng, Q. and Lee, M. (2006). Design issues for assistive robotics for the elderly. *Advanced Engineering Informatics*, 20(2):171–186. Engineering Informatics for Eco-Design.

[Microsoft Corporation, 2009] Microsoft Corporation (2009). Xbox. http://www.xbox.com.

[Miyai et al., 2000] Miyai, I., Fujimoto, Y., Ueda, Y., Yamamoto, H., Nozaki, S., Saito, T., and Kang, J. (2000). Treadmill training with body weight support: its effect on parkinson's disease. *Archives of physical medicine and rehabilitation*, 81.

[Montgomery, 2004] Montgomery, E. B. (2004). Rehabilitative approaches to parkinson's disease. *Parkinsonism and Related Disorders*, 10:S43–S47.

[Morris and Iansek, 1996] Morris, M. E. and Iansek, R. (1996). Characteristics of motor disturbance in parkinson's disease and strategies for movement rehabilitation. *Human Movement Science*, 15:649–669.

[Morrow et al., 2006] Morrow, K., Docan, C., Burdea, G., and Merians, A. (2006). Low-cost virtual rehabilitation of the hand for patients post-stroke. In *Proc. International Workshop on Virtual Rehabilitation*, pages 6–10.

[Muras et al., 2006] Muras, J. A., Stokes, E. K., and Cahill, V. (2006). A taxonomy of pervasive healthcare systems. In *1st International Conference on Pervasive Computing Technologies for Healthcare*, pages 1–10. IEEE.

[Muras et al., 2008] Muras, J. A., Stokes, E. K., and Cahill, V. (2008). Assistive technology in everyday living - a user survey of people with parkinson's disease. *Technology and Disability*, 20(4):271–282.

[Murphy et al., 2002] Murphy, S. L., Williams, C. S., and Gill, T. M. (2002). Characteristics associated with fear of falling and activity restriction in community-living older persons. *Journal of the American Geriatrics Society*, 50(3):516–520.

[Mutlu et al., 2007] Mutlu, B., Krause, A., Forlizzi, J., Guestrin, C., and Hodgins, J. (2007). Robust, low-cost, non-intrusive sensing and recognition of seated postures. In *UIST '07: Proceedings of the 20th annual ACM symposium on User interface software and technology*, pages 149–158, New York, NY, USA. ACM.

[Nagaseki et al., 1986] Nagaseki, Y., Shibazaki, T., Hirai, T., Kawashima, Y., Hirato, M., Wada, H., Miyazaki, M., and Ohye, C. (1986). Long-term follow-up results of selective vim-thalamotomy. *J Neurosurg*, 65(3):296–302.

[Najafi et al., 2000] Najafi, B., Aminian, K., Loew, F., Blanc, Y., and Robert, P. (2000). An ambulatory system for physical activity monitoring in elderly. In *Proc. Conference On Microtechnologies in Medicine and Biology, 1st Annual International 2000*, pages 562–566.

[Najafi et al., 2003] Najafi, B., Aminian, K., Paraschiv-Ionescu, A., Loew, F., Bula, C., and Robert, P. (2003). Ambulatory system for human motion analysis using a kinematic sensor: monitoring of daily physical activity in the elderly. 50(6):711–723.

[National Collaborating Centre for Chronic Conditions, 2006] National Collaborating Centre for Chronic Conditions (2006). *Parkinson's disease: national clinical guideline for diagnosis and management in primary and secondary care*. London: Royal College of Physicians.

[National Institute for Clinical Excellence (NICE), 2004] National Institute for Clinical Excellence (NICE) (2004). *Clinical practice guideline for the assessment and prevention of falls in older people*. Royal College of Nursing.

[Neapolitan, 2003] Neapolitan, R. E. (2003). *Learning Bayesian Networks*. Prentice Hall.

[Neverball, 2009] Neverball (2009). http://neverball.org.

[Nieuwboer et al., 2002] Nieuwboer, A., Weerdt, W. D., Dom, R., and Bogaerts, K. (2002). Prediction of outcome of physiotherapy in advanced parkinson's disease. *Clin Rehabil*, 16(8):886–893.

[Northern Digital Inc., 2009] Northern Digital Inc. (2009). http://www.ndigital.com.

[Nyan et al., 2006] Nyan, M. N., Tay, F. E. H., Manimaran, M., and Seah, K. H. W. (2006). Garment-based detection of falls and activities of daily living using 3-axis mems accelerometer. *Journal of Physics: Conference Series*, 34:1059–1067.

[OANDA, 2009] OANDA (2009). The currency site: Foreign exchange services and trading. www.oanda.comm.

[Ogris et al., 2005] Ogris, G., Stiefmeier, T., Junker, H., Lukowicz, P., and Troster, G. (2005). Using ultrasonic hand tracking to augment motion analysis based recognition of manipulative gestures. In *Proc. Ninth IEEE International Symposium on Wearable Computers*, pages 152–159.

[Olanow et al., 2001] Olanow, C. W., Watts, R. L., and Koller, W. C. (2001). An algorithm (decision tree) for the management of parkinson's disease (2001): treatment guidelines. *Neurology*, 56(11 Suppl 5):S1–S88.

[Oliver and Horvitz, 2005] Oliver, N. and Horvitz, E. (2005). A comparison of hmms and dynamic bayesian networks for recognizing office activities. In Ardissono, L., Brna, P., and Mitrovic, A., editors, *User Modeling 2005 - 10th International Conference - UM 2005*, pages 199–209. Springer.

[P. Spagnolo and Distante, 2002] P. Spagnolo, A. Branc, G. A. and Distante, A. (2002). Fast background modeling and shadow removing for outdoor surveillance. In *Visualization, Imaging, and Image Processing*, pages 668–671.

[Page and Sanderson, 1995] Page, L. and Sanderson, A. (1995). Robot motion planning for sensor-based control with uncertainties. In *Robotics and Automation, 1995. Proceedings., 1995 IEEE International Conference on*, volume 2, pages 1333–1340 vol.2.

[Pal and Wang, 1996] Pal, S. K. and Wang, P. P. (1996). *Genetic Algorithms for Pattern Recognition.* CRC Press, Inc., Boca Raton, FL, USA.

[Pandya et al., 2008] Pandya, M., Kubu, C. S., and Giroux, M. L. (2008). Parkinson disease: not just a movement disorder. *Cleve Clin J Med*, 75(12):856–864.

[Parkka et al., 2006] Parkka, J., Ermes, M., Korpipaa, P., Mantyjarvi, J., Peltola, J., and Korhonen, I. (2006). Activity classification using realistic data from wearable sensors. 10(1):119–128.

[Pellegrini and Iocchi, 2008] Pellegrini, S. and Iocchi, L. (2008). Human posture tracking and classification through stereo vision and 3d model matching. *J. Image Video Process.*, 2008(2):1–12.

[Perry et al., 2004] Perry, M., Dowdall, A., Lines, L., and Hone, K. (2004). Multimodal and ubiquitous computing systems: Supporting independent-living older users. 8(3):258–270.

[Phillips et al., 2004] Phillips, E. M., Schneider, J. C., and Mercer, G. R. (2004). Motivating elders to initiate and maintain exercise. *Arch Phys Med Rehabil*, 85(7 Suppl 3):S52–7; quiz S58–9.

[Platz et al., 1998] Platz, T., Brown, R. G., and Marsden, C. D. (1998). Training improves the speed of aimed movements in parkinson's disease. *Brain*, 121:505–514.

[Polhemus, 2009] Polhemus (2009). http://www.polhemus.com/.

[Pollack et al., 2003] Pollack, M. E., Brown, L., Colbry, D., McCarthy, C. E., Orosz, C., Peintner, B., Ramakrishnan, S., and Tsamardinos, I. (2003). Autominder: An intelligent cognitive orthotic system for people with memory impairment. *Robotics and Autonomous Systems*, 44(3-4):273–282.

[Popescu et al., 2000] Popescu, V., Burdea, G., Bouzit, M., Girone, M., and Hentz, V. (2000). Pc-based telerehabilitation system with force feedback. *IEEE Transactions on Information Technology in Biomedicine*, 4:45–51.

[Public Law 100-407, 1988] Public Law 100-407 (1988). The technology related assistance for individuals with disabilities act of 1988. 29 U.S.C. Sec. 3002(a)(2).

[Quinlan, 1993] Quinlan, J. R. (1993). *C4.5: Programs for Machine Learning (Morgan Kaufmann Series in Machine Learning).* Morgan Kaufmann, 1 edition.

[Quwaider and Biswas, 2008] Quwaider, M. and Biswas, S. (2008). Body posture identification using hidden markov model with a wearable sensor network. In *BodyNets '08: Proceedings of the ICST 3rd international conference on Body area networks*, pages 1–8, ICST, Brussels, Belgium, Belgium. ICST (Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering).

[Ravi et al., 2005] Ravi, N., Dandekar, N., Mysore, P., and Littman, M. L. (2005). Activity recognition from accelerometer data. *American Association for Artificial Intelligence.*

[Razavi, 2001] Razavi, T. (2001). Self-report measures: An overview of concerns and limitations of questionnaire use in occupational stress research. Papers 01-175, University of Southampton - Department of Accounting and Management Science.

[Reddy, 2006] Reddy, Y. (2006). Pervasive computing: Implications, opportunities and challenges for the society. In *Proc. 1st International Symposium on Pervasive Computing and Applications*, pages 5–5.

[Renaud and van Biljon, 2008] Renaud, K. and van Biljon, J. (2008). Predicting technology acceptance and adoption by the elderly: a qualitative study. pages 210–219.

[Roelands et al., 2002] Roelands, M., Oost, P. V., Buysse, A., and Depoorter, A. (2002). Awareness among community-dwelling elderly of assistive devices for mobility and self-care and attitudes towards their use. *Social Science & Medicine*, 54(9):1441–1451.

[Russell and Norvig, 2003] Russell, S. and Norvig, P. (2003). *Artificial Intelligence: A Modern Approach*. Prentice Hall.

[Salarian et al., 2007] Salarian, A., Russmann, H., Vingerhoets, F., Burkhard, P., and Aminian, K. (2007). Ambulatory monitoring of physical activities in patients with parkinson's disease. 54(12):2296–2299.

[Satyanarayanan, 2001] Satyanarayanan, M. (2001). Pervasive computing: vision and challenges. *IEEE Personal Communications*, 8(4):10–17.

[Schapire, 1990] Schapire, R. E. (1990). The strength of weak learnability. *Mach. Learn.*, 5(2):197–227.

[Scherer, 2002] Scherer, M. J. (2002). The change in emphasis from people to person: introduction to the special issue on assistive technology. *Disabil Rehabil*, 24(1-3):1–4.

[Schoo et al., 2005] Schoo, A., Morris, M., and Bui, Q. (2005). The effects of mode of exercise instruction on compliance with a home exercise program in older adults with osteoarthritis. *Physiotherapy*, 91(2):79–86.

[Schrag et al., 2006] Schrag, A., Hovris, A., Morley, D., Quinn, N., and Jahanshahi, M. (2006). Caregiver-burden in parkinson's disease is closely associated with psychiatric symptoms, falls, and disability. *Parkinsonism & Related Disorders*, 12:35–41.

[Schrag et al., 2000] Schrag, A., Jahanshahi, M., and Quinn, N. (2000). What contributes to quality of life in patients with parkinson's disease? *J Neurol Neurosurg Psychiatry*, 69(3):308–312.

[Schulz and Grant, 2000] Schulz, G. M. and Grant, M. K. (2000). Effects of speech therapy and pharmacologic and surgical treatments on voice and speech in parkinson's disease: a review of the literature. *J Commun Disord*, 33(1):59–88.

[Semmlow, 2008] Semmlow, J. L. (2008). *Biosignal and Medical Image Processing*. CRC Press.

[SensAble Technologies, 2009] SensAble Technologies (2009). http://www.sensable.com.

[Sharp, 2009] Sharp (2009). IR Distance Sensors. http://www.acroname.com.

[Simpson et al., 1998] Simpson, J., Harrington, R., and Marsh, N. (1998). Managing falls among elderly people. *Physiotherapy*, 84:173–177.

[Smidt et al., 2005] Smidt, N., de Vet, H. C. W., Bouter, L. M., Dekker, J., Arendzen, J. H., de Bie, R. A., Bierma-Zeinstra, S. M. A., Helders, P. J. M., Keus, S. H. J., Kwakkel, G., Lenssen, T., Oostendorp, R. A. B., Ostelo, R. W. J. G., Reijman, M., Terwee, C. B., Theunissen, C., Thomas, S., van Baar, M. E., van 't Hul, A., van Peppen, R. P. S., Verhagen, A., van der Windt, D. A. W. M., and Group, E. T. (2005). Effectiveness of exercise therapy: a best-evidence summary of systematic reviews. *Aust J Physiother*, 51(2):71–85.

[Spagnolo et al., 2003a] Spagnolo, P., Leo, M., Attolico, G., and Distante, A. (2003a). Posture recognition in visual surveillance of archeological sites. In *Proc. IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS 2003)*, volume 2, pages 1542–1547.

[Spagnolo et al., 2003b] Spagnolo, P., Leo, M., Leone, A., Attolico, G., and Distante, A. (2003b). Posture estimation in visual surveillance of archaeological sites. In *Proc. IEEE Conference on Advanced Video and Signal Based Surveillance*, pages 277–283.

[Stern et al., 2004] Stern, M. B., Marek, K. L., Friedman, J., Hauser, R. A., LeWitt, P. A., Tarsy, D., and Olanow, C. W. (2004). Double-blind, randomized, controlled trial of rasagiline as monotherapy in early parkinson's disease patients. *Mov Disord*, 19(8):916–923.

[Stiefmeier et al., 2006] Stiefmeier, T., Ogris, G., Junker, H., Lukowicz, P., and Troster, G. (2006). Combining motion sensors and ultrasonic hands tracking for continuous activity recognition in a maintenance scenario. In *Proc. 10th IEEE International Symposium on Wearable Computers*, pages 97–104.

[Subramanian et al., 2006] Subramanian, S., Knaut, L., Beaudoin, C., McFadyen, B., Feldman, A., and Levin, M. (2006). Virtual reality environments for rehabilitation of the upper limb after stroke. In *Proc. International Workshop on Virtual Rehabilitation*, pages 18–23.

[Swann, 2008] Swann, J. (2008). Parkinson's disease part 3: assistive devices. *British Journal of Healthcare Assistants*, 2(3):111–114.

[Tan et al., 2001] Tan, H. Z., Slivovsky, L. A., and Pentland, A. (2001). A sensing chair using pressure distribution sensors. *IEEE/ASME Transactions on Mechatronics*, 6(3):261–268.

[Tekscan, 2009] Tekscan (2009). http://www.tekscan.com.

[Tekscan, Inc., 2009] Tekscan, Inc. (2009). FlexiForce Force Sensors. http://www.tekscan.com/flexiforce/flexiforce.html.

[The MathWorks, Inc., 2009] The MathWorks, Inc. (2009). Matlab statistics toolbox. http://www.mathworks.com.

[Theodoridis and Koutroumbas, 2006] Theodoridis, S. and Koutroumbas, K. (2006). *Pattern Recognition, Third Edition*. Academic Press.

[Thiemjarus and Yang, 2007] Thiemjarus, S. and Yang, G.-Z. (2007). An autonomic sensing framework for body sensor networks. In *BodyNets '07: Proceedings of the ICST 2nd international conference on Body area networks*, pages 1–8, ICST, Brussels, Belgium, Belgium. ICST (Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering).

[Thobois et al., 2005] Thobois, S., Delamarre-Damier, F., and Derkinderen, P. (2005). Treatment of motor dysfunction in parkinson's disease: an overview. *Clin Neurol Neurosurg*, 107(4):269–281.

[Tilak et al., 2002] Tilak, S., Abu-Ghazaleh, N. B., and Heinzelman, W. (2002). A taxonomy of wireless micro-sensor network models. *SIGMOBILE Mob. Comput. Commun. Rev.*, 6(2):28–36.

[Timmermans et al., 2007] Timmermans, A., Saini, P., Willmann, R., Lanfermann, G., te Vrugt, J., and Winter, S. (2007). Home stroke rehabilitation for the upper limbs. In *Proc. 29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society EMBS 2007*, pages 4015–4018.

[Todorovski and Džeroski, 2003] Todorovski, L. and Džeroski, S. (2003). Combining classifiers with meta decision trees. *Mach. Learn.*, 50(3):223–249.

[Toulouse and Sullivan, 2008] Toulouse, A. and Sullivan, A. M. (2008). Progress in parkinson's disease–where do we stand? *Progress in Neurobiology*, 85(4):376 – 392.

[Trossen Robotics, 2009] Trossen Robotics (2009). http://www.trossenrobotics.com.

[Turaga et al., 2008] Turaga, P., Chellappa, R., Subrahmanian, V., and Udrea, O. (2008). Machine recognition of human activities: A survey. 18(11):1473–1488.

[Ubisense, 2009] Ubisense (2009). http://www.ubisense.net.

[Varshney, 2003] Varshney, U. (2003). Pervasive healthcare. *Computer*, 36(12):138–140.

[Verbaan et al., 2007] Verbaan, D., Marinus, J., Visser, M., van Rooden, S. M., Stiggelbout, A. M., and van Hilten, J. J. (2007). Patient-reported autonomic symptoms in parkinson disease. *Neurology*, 69(4):333–341.

[Virtual Realities, Inc., 2009] Virtual Realities, Inc. (2009). http://www.vrealities.com/.

[Vitek et al., 2003] Vitek, J. L., Bakay, R. A. E., Freeman, A., Evatt, M., Green, J., McDonald, W., Haber, M., Barnhart, H., Wahlay, N., Triche, S., Mewes, K., Chockkan, V., Zhang, J.-Y., and DeLong, M. R. (2003). Randomized trial of pallidotomy versus medical therapy for parkinson's disease. *Ann Neurol*, 53(5):558–569.

[Vosinakis and Panayiotopoulos, 2001] Vosinakis, S. and Panayiotopoulos, T. (2001). Simhuman: A platform for real-time virtual agents with planning capabilities. In *IVA '01: Proceedings of the Third International Workshop on Intelligent Virtual Agents*, pages 210–223, London, UK. Springer-Verlag.

[Wang, 2006] Wang, L. (2006). From blob metrics to posture classification to activity profiling. In *Proc. 18th International Conference on Pattern Recognition ICPR 2006*, volume 4, pages 736–739.

[Webster et al., 2001] Webster, J. S., McFarland, P. T., Rapport, L. J., Morrill, B., Roades, L. A., and Abadee, P. S. (2001). Computer-assisted training for improving wheelchair mobility in unilateral neglect patients. *Archives of Physical Medicine and Rehabilitation*, 82(6):769–775.

[Weiser, 1991] Weiser, M. (1991). The computer for the 21st century. *Scientific American*.

[Weka, 2009] Weka (2009). http://www.cs.waikato.ac.nz/ml/weka/.

[Wild et al., 1981] Wild, D., Nayak, U. S., and Isaacs, B. (1981). How dangerous are falls in old people at home? *British Medical Journal*, 282(6260):266–268.

[Witjas et al., 2002] Witjas, T., Kaphan, E., Azulay, J. P., Blin, O., Ceccaldi, M., Pouget, J., Poncet, M., and Cherif, A. A. (2002). Nonmotor fluctuations in parkinson's disease: frequent and disabling. *Neurology*, 59(3):408–413.

[World Health Organisation, 2001] World Health Organisation (2001). *International Classification of Functioning, Disability and Health: ICF*. Geneva, Switzerland: WHO.

[Wu et al., 2007] Wu, J. K., Dong, L., and Xiao, W. (2007). Real-time physical activity classification and tracking using wearble sensors. In *Proc. 6th International Conference on Information, Communications & Signal Processing*, pages 1–6.

[Wu et al., 2005] Wu, M., Baecker, R., and Richards, B. (2005). Participatory design of an orientation aid for amnesics. In *CHI '05: Proceedings of the SIGCHI conference on Human factors in computing systems*, pages 511–520. ACM Press.

[Xsens Technologies, 2009] Xsens Technologies (2009). http://www.xsens.com/.

[Xu and Prince, 1998] Xu, C. and Prince, J. (1998). Snakes, shapes, and gradient vector flow. 7(3):359–369.

[Yang and Hsu, 2007] Yang, C.-C. and Hsu, Y.-L. (2007). Algorithm design for real-time physical activity identification with accelerometry measurement. *33rd Annual Conference of the IEEE Industrial Electronics Society (IECON 2007)*, pages 2996–3000.

[Zappi et al., 2007] Zappi, P., Stiefmeier, T., Farella, E., Roggen, D., Benini, L., and Troster, G. (2007). Activity recognition from on-body sensors by classifier fusion: sensor scalability and robustness. In *Proc. 3rd International Conference on Intelligent Sensors, Sensor Networks and Information ISSNIP 2007*, pages 281–286.

[Zhu et al., 2003] Zhu, M., Martinez, A. M., and Tan, H. Z. (2003). Template-based recognition of static sitting postures. In *Proc. Conference on Computer Vision and Pattern Recognition Workshop CVPRW '03*, volume 5, pages 50–50.