Microadaptivity within Complex Learning Situations – a Personalized Approach based on Competence Structures and Problem Spaces

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Abstract: In this paper, we present an approach to microadaptivity, i.e. to adaptivity within complex learning situations as they occur, e.g., in game-based learning. Integrating the competence-based knowledge space theory and the information-processing theory of human problem solving we developed a sound model as a basis for microadaptivity and continuous competence state monitoring. The architectural design of a first demonstrator is presented.

Keywords: Game-based learning, microadaptivity, competence space, problem space

Introduction

While adaptivity in Technology Enhanced Learning (TEL) has been an important topic in research and development for over a decade now, game-based learning is a rather recent advance in the field. The underlying idea is to make use of young people's motivation in computer games for learning purposes. If this is to be successful, the learning nature of the game should be as unapparent as possible.

On the other side, adaptation to the learners' individual knowledge is very important in learning. Its presence ensures that the learning game, based on the learner's actual state of knowledge, provides personalized challenges and support.

The ELEKTRA project (http://www.elektra-project.org/) aims to introduce a learner-centric, personalized approach to game-based learning. In this context it becomes apparent that, within the complex learning situations of a game, (i) the learner model must be continuously updated based on the learner's actions in the game and (ii) the interactions manifested by the game must be personalized with respect to the learner model.

In the following, we will present an approach to adaptation, based on psychological theories for structuring knowledge and for describing problem solving processes. After presenting these theories, we will present our approach to microadaptivity, i.e. adaptive and continuous assessment of the learners' knowledge, and interventions within (complex) learning objects [1]. Finally we will present the architectural design of a demonstrator which is currently being implemented.

1. **Theoretical Background**

1.1 Competence-based Knowledge Space Theory

The theory of knowledge spaces was originally developed by Doignon and Falmagne [2, 3] as a behaviourist approach to model the structure of a domain of knowledge. They represent such a domain by a set of test problems which is structured by a *prerequisite relation* (or *surmise relation;* "if a learner does not master problem *a*, we can surmise that s/he also will not master problem *b*"). The *knowledge state* of a learner is defined as the subset of test problems s/he can solve, and the set of all possible knowledge states which is restricted by the prerequisite relations is called a *knowledge space*. This model was originally developed for the adaptive assessment of knowledge but later was also successfully applied to technology enhanced learning, e.g. in the AdAsTra prototype [4] and the commercial ALEKS system (http://www.aleks.com/).

The investigation of the cognitive structures underlying the behaviourist knowledge spaces was later started by the group around Albert, and other groups. [5, 3]. For instance, Korossy [6] developed the competence-performance approach which was subsequently further developed leading to the competence-based knowledge space theory (CbKST) [7, 8]. According to CbKST, a domain of knowledge is described by a set of (abstract) skills or competences[1] which are structured by a prerequisite relation as described above. Skills are assigned to learning objects or test problems within this domain as required and as taught or tested competences. Based on the competence structures, suitable skills to be learned can be suggested for the individual learner, and based on the skill assignments, learning objects can be offered which fit best to the learner's current knowledge state. This approach was successfully implemented in the APeLS system [see, e.g., 9, 10] and is currently applied within the iClass project (see http://www.iclass.info/).

1.2 Information-Processing Theory of Human Problem Solving

In human problem solving, the core model of the information processing theory[11] can be summarized for our purpose as follows. The core idea is that of a *problem space*, the set of all *problem states* a task environment may take. When humans try to solve a problem they start at some *initial state*. Whenever the problem solver performs some action the problem state changes according to this action. Thus, the problem solver moves by his/her actions through the problem space. This model is strongly influenced by the finite automata model from theoretical computer science where the actions correspond to the alphabet of the automaton and the movements through the problem space are defined by the transition function.

There exist one or more problem states, the *solution states,* in which the problem is considered to be solved. In the automata analogy, they correspond to the final states. The problem states may be scored in a sense of *correctness* where the correctness of a problem state would increase with increasing proximity to a solution state. Similarly, actions are also scored by their *utility* where the utility of an action lies in its contribution to the correctness of the problem state.

[1] The terms "skill" and "competence" have often been used synonymously by different authors in the context of KST extensions.

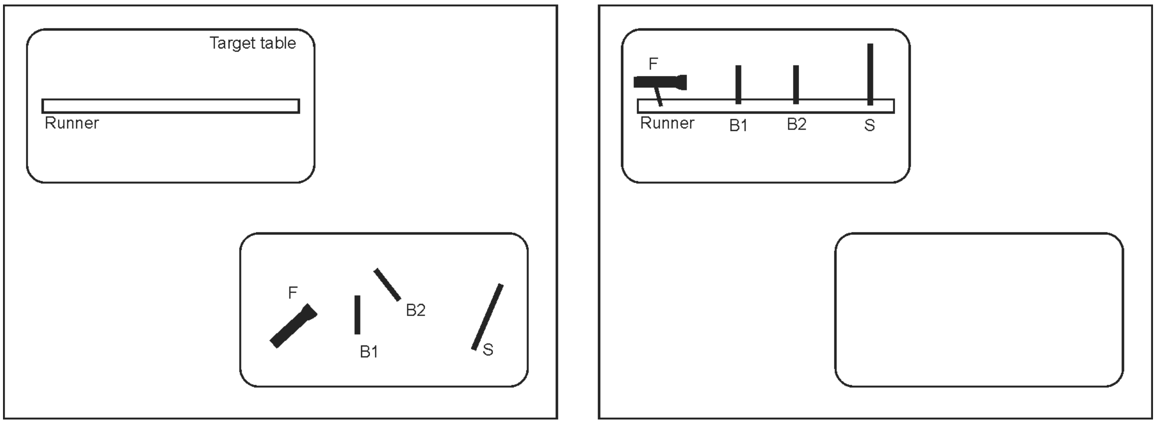

Fig. 1. The "blinds in a row"

2. Microadaptivity in Game-based Learning

Based on the theoretical foundations introduced above we have developed an integrated formal description for game-based learning situations. We will introduce this formal description using an example in the field of optics from the ELEKTRA project.

In this example, the learner has to place a flashlight (F), two blinds (B1 and B2), and a screen (S) in the right order onto a runner such that the light is narrowed by the blinds and hits the screen in a small ray of light. Figure 1 depicts the scene schematically, in the initial state (left side) the four objects are on a separate table, and at the end (right side) they should be positioned on the ruler in the right order and pointing into the right direction.

2.1 Basic Formal Framework for Microadaptivity

Actions in computer games (and thus also in game-based learning) mostly involve moving objects in the virtual scene[2]. Therefore, the (current) state of the problem solving process can be described by a vector of the *positions* of all *objects*. An *action* would then be to move an object to another position. This would, however, lead to infinite problem spaces and sets of actions. Therefore, we introduce *position categories* for each object thus keeping the problem space finite. In our example, we define four position categories. For each object, we might have (P_1) the object is on the runner in the correct position, (P_2) the object is on the runner but in a false position, (P_3) the object is on the target table but not

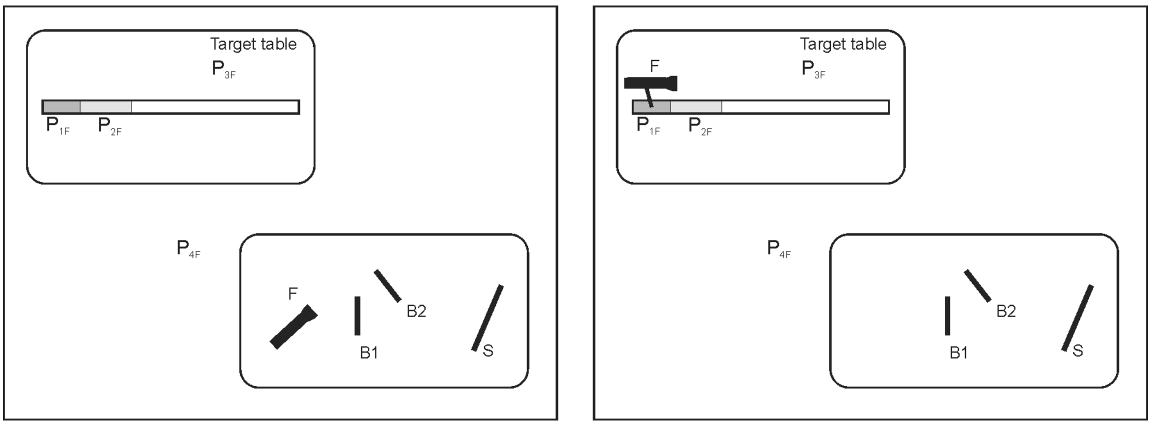

Fig. 2. Position categories for the flashlight.

[2] This holds also for many objects where we normally do not think of movements. If we think, e.g., of switching a light on and off, we often speak of the position of a switch.

on the runner, and (P_4) the object is not on the target table[3]. Figure 2 shows the four position categories for the flashlight.
We define actions as equivalent to the resulting position categories, i.e. for each object *o* and each of its position categories p_{io} we have an action a_{io} which means "move object *o* into its position category p_{io}."

Looking at the correctness of problem states, we derive it as an integration of correctness values of the single objects and their position categories. In our example, we might assign, e.g., for each object *o* a correctness value of 1.00 to the position category p_{1o}, a value of 0.60 to p_{2o}, and a value of 0.05 to the categories p_{3o} and p_{4o}. For integrating the single correctness values different interpretations are possible. The only necessary conditions to the integration function are (i) that it maps into the interval [0,1] and (ii) monotonicity holds in all positions. Starting, e.g., from a rule "the problem state is correct (i.e. it is a solution state) if all positions are correct" we come up with a logical conjunction which might be implemented by the minimum function as it is usual in the area of fuzzy logics.

So far, we have described the gaming (or problem solving) part of the framework. Looking at the CbKST part, we start with a set of *competences* and a *prerequisite relation* on this set. The link between the CbKST and gaming parts is reached through the skill assignment. In pure CbKST we have test problems which are either solved or not. In the context of gaming, however, we have actions which are fully correct, fully incorrect or something in between. For the (partially or fully) correct actions, we have to specify skills required to perform these actions, and for the (partially or fully) incorrect actions, we have to specify skills apparently missing for a learner performing these actions.

Figure 3 shows the resulting ontological structure combining problem solving model and CbKST, thus connecting the underlying formal psychological model with the microadaptivity implementation through ontological reasoningin the ELEKTRA demonstrator.. For each object, several possible position categories are defined, and for each position category, the skills required for performing the action and the skills missing when performing the action are specified. The learner, on the other side, has skills and has a skill state.

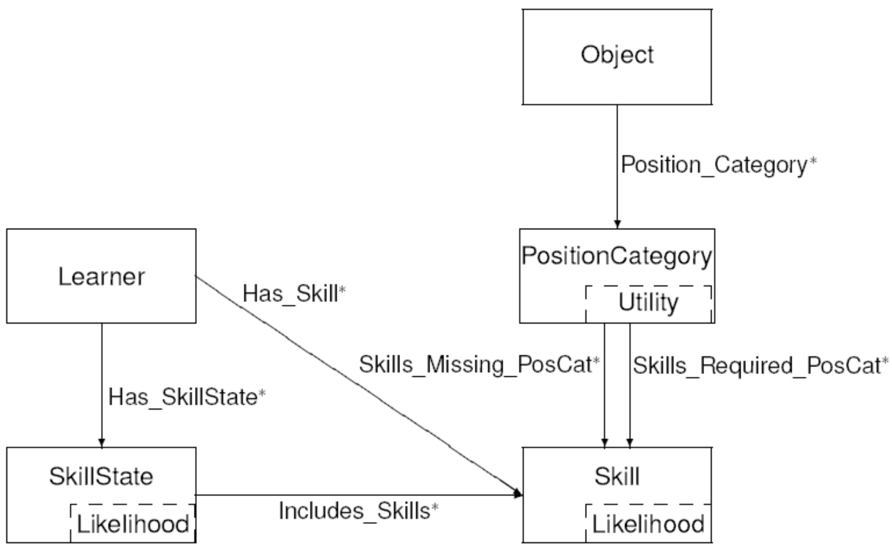

Fig. 3. Ontological Structure for microadaptivity

[3] The number of position categories may differ in other contexts, e.g. for a switch which may have just two

In the following, we will describe how the framework described by this ontological structure can be used for continuous, implicit skill assessment and for microadaptivity.

2.2 Realizing continuous, implicit skill assessment

As already mentioned before, the original aim in developing knowledge space theory was the adaptive assessment of knowledge, and assessment procedures have been an ongoing research topic [see 12, 13, 14]. However, skill assessment in the gaming context differs in one very important aspect from these procedures, i.e. the assessment is not based on posing test problems to the learner. Instead, we have a *continuous and implicit assessment*, i.e. the assessment is based on interpreting the learners' activities with respect to their skill state. As a consequence, the assessment works directly on the skill level, this is in comparison with previous attempts at skill assessment that worked in two steps by first determining a performance state and then mapping it onto a skill state.

The basic idea of the classical assessment procedures in knowledge space theory is to have likelihood estimates over the knowledge space, i.e. estimating the likelihood for each knowledge state that it is the current state of the learner. Based on these likelihoods, the assessment procedure selects a problem to be posed to the learner according to its optimal diagnostic value and afterwards updates the likelihoods according to the observed response. These updates may follow the Bayesian update rule or a generalized version of it [15, 13]. This loop of selecting test problems and updating the likelihoods is continued until the likelihood mass is refined to a sufficient extent to a single knowledge state. The learner model can be defined as the likelihood distribution over the knowledge space.

In game-based learning, however such an explicit assessment is not wanted since it would disturb the nature of the game. Instead we have an implicit and continuous assessment, i.e. each of the learners' actions should lead to an update of the likelihood distribution and, thus, of the learner model. As a consequence, the assessment consists of the following four steps.

1. The learner performs an action, i.e. s/he moves an object.
2. The action is interpreted by the required and missing skills of the object's new position category.
3. The likelihoods of the skill states are updated according to the new positive (required skills) and negative (missing skills) evidence.
4. The likelihoods of the individual skills (of being mastered by the learner) are computed analogously to margin probabilities.

For the likelihood update, again the generalized version of the Bayesian update rule, the *multiplicative rule* [15] is used. It applies parameters defining how strong the updating effects should be. In this context of implicit assessment, these parameters will probably be much smaller than in the classical, explicit assessment procedure. Currently, simulation studies are under way to determine "good" values for these parameters.

Underlying this approach to assessment is the assumption that the game-based learning takes place within a learning environment. When the learner enters a learning game situation, an initial likelihood distribution is retrieved from this learning environment. While the learner is active within the learning game, the implicit and continuous assessment as described above takes place, and at the end of the game situation, the new likelihood distribution is returned to the environment.

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positions (and position categories), "on" and "off".

2.3 Realizing microadaptivity through adaptive interventions

The original idea behind developing the concept of microadaptivity was to present adaptive hints to the learner depending on her/his progress in the learning game situation. This idea has been generalized to the concept of adaptive interventions some of which depend on the learner's skill state while others do not [1]. In the following, we will simply give an example list of types of adaptive interventions and triggering events or conditions.

- A *skill activation adaptive intervention* may be applied if a user gets «stuck» in some area of the problem space and some skills are not used although the user model assumes that the user masters these skills.
- A *skill acquisition adaptive intervention* may be applied in a similar situation where, however, the user model assumes that the user does not master the unused skill.
- Basically independent of the model is the application of *motivational adaptive interventions*. These might be applied, e. g., if the user does not act at all for a certain, unexpectedly long time.
- *Assessment clarification adaptive interventions* may be applied, e. g., if the user's actions give contradicting support for and against the assumption of him/her mastering a certain skill.

The conditions under which a certain adaptive intervention is given are to be developed on the basis of pedagogical rules; however, these rules will apply the microadaptivity framework and utilise the learner model obtained through the assessment within the framework.

3. Implementing microadaptivity within the ELEKTRA project

The microadaptivity framework developed in the previous section is currently implemented within the ELEKTRA project. In this section, we will briefly present the architecture of the resulting system with respect to the microadaptivity realization. This architecture is shown in Fig. 4.

The architecture consists of four modules or engines. The learner is connected to the ELEKTRA system through the *game engine* (GE). It provides the non-adaptive parts of the game, and as such it is also the user interface to the system. The GE provides information on the learner's action in the game to the *skill assessment engine* (SAE). The SAE updates the learner model (i.e. the skill state likelihoods) according to the procedure proposed in Section 2.2 and the information it has in the skill ontology. The resulting information about the learner's skill state and its changes are then forwarded to the *Educational Reasoner* (ER), the pedagogical part of microadaptivity. Based on pedagogical rules and learning objectives, the ER gives recommendations on adaptive interventions to the *adaptation realization* (AR) module which maps the abstractly formulated educational recommendations onto more concrete game recommendations. In this mapping process, data on game elements and information on previously given recommendations are considered. The game recommendations are then forwarded to the GE which realises them as concrete adaptive interventions in the game.

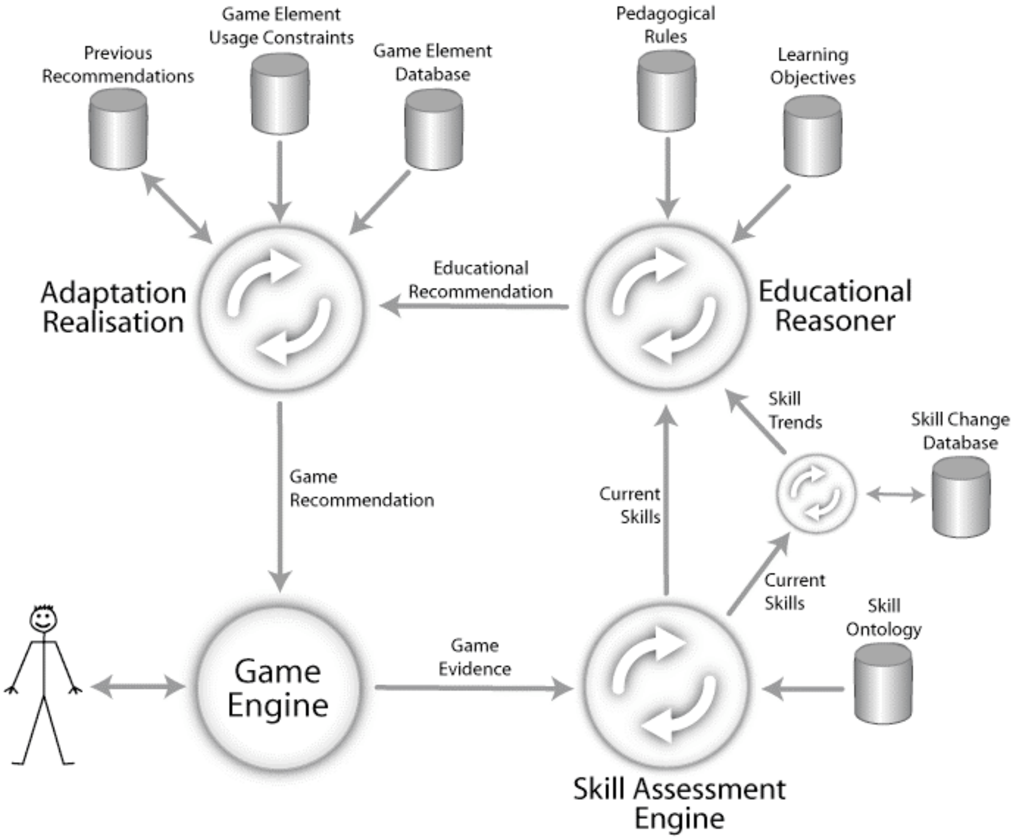

Fig. 4. ELEKTRA architecture for microadaptivity

4. **Discussion**

In this paper, we have given a snapshot of current developments on microadaptivity within the ELEKTRA project. Based on well accepted psychological models for problem solving and for skill structures, we have developed a framework for microadaptivity, i.e. for adaptivity within complex learning objects. The software architecture for the implementation has been presented.

However, microadaptivity is still in an early stage of research and development, and many open issues remain. The underlying framework uses some simplifying assumptions like the identity of position categories and actions which means that an action can move only one object. Based on the experiences in the ELEKTRA project, the framework will be generalised within and beyond the domain of game-based learning.

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References

[1] Kickmeier-Rust, M. D., Peirce, N., Conlan, O., Schwarz, D., Verpoorten, D., & Albert, D. (in press). Immersive digital games: The interfaces for next-generation e-learning. In *Proceedings of the HCI International 2007, 22-27 July 2007, Beijing*, Lecture Notes in Computer Science. New York, Heidelberg: Springer.

[2] Doignon, J.-P. & Falmagne, J.-C. (1985). Spaces for the assessment of knowledge. *International Journal of Man-Machine Studies*, *23* ,175-196.

[3] Doignon, J.-P. & Falmagne, J.-C. (1999). *Knowledge Spaces*. Berlin: Springer-Verlag.

[4] Dowling, C. E., Hockemeyer, C., & Ludwig, A. H. (1996). Adaptive assessment and training using the neighbourhood of knowledge states. In Claude Frasson, Gilles Gauthier, & Alan Lesgold, editors, *Intelligent Tutoring Systems*, pp. 578-586, Berlin: Springer Verlag.

[5] Albert, D. & Lukas, J., editors (1999). *Knowledge Spaces: Theories, Empirical Research, Applications*. Mahwah, NJ: Lawrence Erlbaum Associates.

[6] Korossy, K. (1999). Modeling knowledge as competence and performance. In Dietrich Albert & Josef Lukas, editors, *Knowledge Spaces: Theories, Empirical Research, Applications*, pp. 103-132. Mahwah, NJ: Lawrence Erlbaum Associates.

[7] Hockemeyer, C. (2003). Competence Based Adaptive E-Learning in Dynamic Domains. In F. W. Hesse & Y. Tamura (Eds.), *The Joint Workshop of Cognition and Learning through Media–Communication for Advanced E-Learning (JWCL)*, pp. 79–82. Berlin.

[8] Heller, J., Steiner, C., Hockemeyer, C., & Albert, D. (2006). Competence-Based Knowledge Structures for Personalised Learning. *International Journal on E-Learning*, 5(1), 75-88.

[9] Albert, D., Hockemeyer, C., Conlan, O., & Wade, V. (2001). Reusing adaptive learning resources. In C.-H. Lee et al., editor, *Proceedings of the International Conference on Computers in Education ICCE/SchoolNet2001*, volume 1, pp. 205-210.

[10] Conlan, O., Hockemeyer, C., Wade, V., & Albert, D. (2002). Metadata Driven Approaches to Facilitate Adaptivity in Personalized eLearning systems. *The Journal of Information and Systems in Education*, 1, 38–44.

[11] Simon, H. A. (1978). Information-processing theory of human problem solving. In W. K. Estes, editor, *Handbook of Learning and Cognitive Processes, vol. 5, Human Information Processing*, pp. 271-295. Hillsdale, NJ: Lawrence Erlbaum Associates.

[12] Degreef, E., Doignon, J.-P., Ducamp, A., & Falmagne, J.-C. (1986). Languages for the assessment of knowledge. *Journal of Mathematical Psychology*, *30* ,243-256.

[13] Doignon, J.-P. (1994). Probabilistic assessment of knowledge. In Dietrich Albert, editor, *Knowledge Structures*, pp. 1-56. New York : Springer Verlag.

[14] Dowling, C. E. & Hockemeyer, C. (2001). Automata for the assessment of knowledge. *IEEE Transactions on Knowledge and Data Engineering*, *13*, 451-461.

[15] Falmagne, J.-C. & Doignon, J.-P. (1988). A class of stochastic procedures for the assessment of knowledge. *British Journal of Mathematical and Statistical Psychology*, *41* ,1-23.