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Independent Brain Computer Interface Control using Visual Spatial Attention-Dependent Modulations of Parieto-occipital Alpha

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Abstract-**Parieto-occipital alpha band (8-14Hz) EEG activity was examined during a spatial attention-based brain computer interface paradigm for its potential use as a feature for left/right spatial attention classification. In this paradigm 64-channel EEG data were recorded from subjects who covertly attended to a sequence of letters superimposed on a flicker stimulus in one visual field while ignoring a similar stimulus in the opposite visual field. Increases in alpha band activity were observed over parieto-occipital cortex contralateral to the location of the ignored stimulus, consistent with previous reports, and the subsequent use of alpha band power over bilateral parieto-occipital sites as a feature yielded an average classification accuracy of 73% across 10 subjects, with highest 87%. The highest achievable bit rate from these data is 7.5 bits/minute.**

***Keywords* - BCI, EEG, spatial selective attention, alpha, gating**

I. INTRODUCTION

Brain Computer Interface (BCI) technology may offer the only feasible option for communication and environmental control for some individuals with very severe disabilities (e.g. amyotrophic lateral sclerosis or brainstem stroke) [1]. Existing BCI designs based on the electroencephalogram (EEG) rely on a variety of different EEG signal features. While some utilize exogenous event-related or evoked responses such as P300 potentials [2], motor-related potentials [3] and Visual Evoked Potentials (VEPs) [4,5] which are for the most part involuntary, other BCIs involve learned self-regulation of key cortical activity for production of responses on cue, for example slow cortical potentials [6] and oscillatory activity [7,8]. The former design, being reliant on natural involuntary responses, has the advantage of requiring no training, whereas the latter design normally demonstrates effectiveness only after periods of biofeedback training, wherein the subject learns to regulate the relevant activity in a controlled way. Current BCIs employing oscillatory activity normally utilize changes in ongoing EEG within certain frequency bands over certain areas of cortex, for example mu rhythms (8-12Hz) and beta rhythms (18-26Hz) over sensorimotor cortex [7,8]. These changes occur in response to higher cognitive operations – in the examples of the Wadsworth and Graz BCIs [7,8] subjects employ motor imagery (imagination of movements or relaxation of parts of the body), and the changes in sensorimotor rhythms which occur as a result are harnessed to provide control.

Another example of top-down modulation of oscillatory activity is the reactivity of alpha band (8-14Hz) activity to attention [9,10]. In particular, alpha has been reported to index sensory gating during a biased attentional state [11,12]. In [12], alpha band activity was examined during the cue-stimulus interval of a visual spatial cueing paradigm involving bilateral stimuli. Focal increases of alpha band activity were seen over occipital cortex contralateral to the direction of the to-be-ignored stimulus, reflecting anticipatory biasing of visual spatial attention.

Visual selective attention pertains to the brain's ability to identify and focus on certain components of visual input to be processed preferentially at a given time. In particular, *spatial* selective attention refers to the mechanism by which locations in visual space are selected for enhanced processing [13]. This can be carried out independent of gaze direction, i.e. components in peripheral vision may be selected for processing just as those in foveal vision. The term *covert attention* is used to describe attentional selection of regions of visual space outside the central foveal region.

An interesting question arising from the abovementioned results of recent neuroscience research [11,12] is whether modulations in alpha band power affected by shifts in covert attention, can be harnessed in real-time and used as the control mechanism for a BCI.

In this paper the authors present results of experiments in which subjects deployed spatial attention on cue to one of two bilateral locations in order to count target presentations at that location. Simple alpha power features extracted from bilateral parieto-occipital scalp sites are used to determine whether the observed separability in alpha oscillations can be harnessed for control, without the subject having had previous training.

II. METHODOLOGY

A. Subjects

Ten subjects aged between 22 and 30 participated in the study. All had normal or corrected-to-normal vision.

B. Experimental set-up

Subjects were seated 60cm from a CRT monitor on which was displayed two white rectangular stimuli situated bilateral to a central fixation cross on a black background, as shown in Figure 1. As the paradigm employed in this study was designed originally to elicit steady-state evoked potentials (SSVEPs) the left rectangle was flickered at 14Hz and the right rectangle was flickered at 17Hz.

More importantly for this study, however, the task of target detection was also employed, as a means of examining the static allocation of visual spatial attention. In the center

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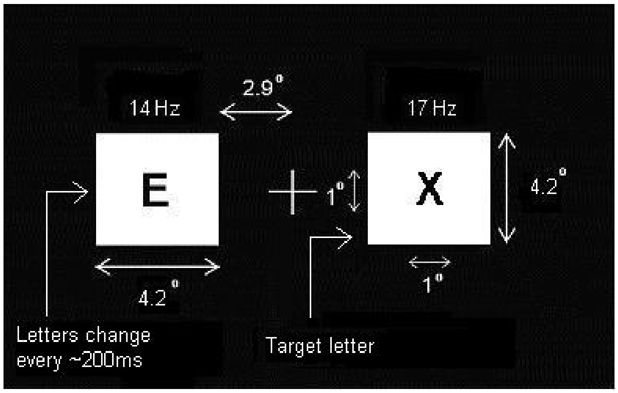

Fig. 1. Stimulus display.

of each of the white rectangles, letters from "A" through "H" were presented in a random pattern, replicating the visual spatial attention paradigm employed in [14]. Embedded in the sequence of letters was the target letter "X", occurring with equal probability (~0.11). Subjects were instructed to keep count of target presentations during each trial and report this number on completion of the trial. This provides a behavioral measure of spatial attention performance in terms of error rates and ensured that spatial attention mechanisms are engaged in the correct way. The letter in each rectangle was changed after 3 flicker cycles of the white rectangle on which it was superimposed. The letter in each rectangle subtended a visual angle of 1° both vertically and horizontally. The rectangles were situated 2.9° bilateral to the central fixation cross (cross to medial edge), centered on the horizontal meridian, and subtended a visual angle of 4.2° both vertically and horizontally.

Continuous EEG signals were recorded from 64 electrode positions referenced to location AFz, filtered over the range 0 – 134 Hz and digitized at a rate of 512Hz using the BioSemi Active Two system. In addition horizontal electrooculographic (EOG) data were recorded using two electrodes placed at the outer canthi of the eyes.

C. Procedure

Each subject underwent a total of five sessions, each lasting under 5 minutes. Each trial started with a red warning stimulus lasting 0.5s, followed by a cue stimulus consisting of a white fixation cross of the same size with an arrow on the left or right arm, lasting 0.5s. Depending on the direction of the arrow, the subject was instructed to covertly attend to the left or right rectangle while strictly maintaining fixation on the central fixation cross for 8s. Following the attend period a green fixation cross was presented for 5s, signifying a rest period. Each session consisted of 20 trials, with an equal number cued left as cued right, in random order.

D. Feature Extraction

From each 8s attend period three 3.52s segments were extracted using rectangular windows starting at 0, 2 and 4 seconds, each of which counted as a single case for training and classification. For each segment the Fast-Fourier Transform (FFT) was calculated at 2 pairs of electrode locations, PO7 and O1 over the left hemisphere and PO8 and O2 over the right hemisphere. The 3.52s segment duration was chosen so that it contained an integral number of cycles of the 14Hz stimulus, thus confining the SSVEP power to a single frequency bin. The mean power over the alpha range (8-14Hz) was then calculated at each electrode location. This calculation was carried out by averaging over the corresponding frequency bins, up to but not including that containing the SSVEP peak. Alpha power for each hemisphere was determined by averaging over the corresponding pairs of electrodes.

The following two-dimensional and one-dimensional features were then extracted for each case:

$$F2d(n) = \left(X^{L}{}_{\alpha}(n), X^{R}{}_{\alpha}(n)\right), \quad (1)$$

$$F1d(n) = \log\left(\frac{X^{L}{}_{\alpha}(n)}{X^{R}{}_{\alpha}(n)}\right), \quad (2)$$

where $X^{L}{}_{\alpha}$(n) is the alpha band power over the left hemisphere for case *n*.

While the 1-dimensional feature should capture the expected lateralized behavior, the 2-dimensional feature was also employed to investigate whether taking a ratio caused a loss of information.

E. Classification

Linear discriminants were used as the classifier model for this study, providing a parametric approximation to Bayes' rule [15]. Optimization of the linear discriminant model is achieved through direct calculation and is very efficient thus lending itself well to real-time applications.

Performance of the LDA classifier was assessed using 10-fold cross validation [15]. This scheme randomly divides the available data into 10 approximately equal sized, mutually exclusive "folds". For a 10-fold cross validation run, 10 classifiers are trained with a different fold used each time as the testing-set, while the other 9 folds are used for the training data. Cross validation estimates are generally pessimistically biased, as training is performed using a sub-sample of the available data.

F. Information Transfer Rate

One objective measure of BCI performance is the bit rate, as defined in [16]. For a trial with *N* possible symbols in which each symbol is equally probable, the probability (*P*) that the symbol will be selected is the same for each symbol, and each error has the same probability, then the bit rate can be calculated as follows:

$$\text{Bits / symbol} = \log_2 N + P \cdot \log_2 P + (1-P) \cdot \log_2 \frac{1-P}{N-1} \quad (3)$$

$$\text{Bit Rate} = \text{Bits / symbol} * \text{symbols / minute} \quad (4)$$

In the assessment of information transfer in this study we take each 3.52s segment as a separate case. We define *P* as the classification accuracy achieved and the number of symbols sent per minute is set at, 60 / 3.52 = 17.

III. Results

Table I shows the classification accuracies achieved by all ten subjects over five sessions for both the 2-dimensional and 1-dimensional feature, as well as average performance across subjects for both features. Subjects are listed in order of performance, with highest accuracy first. Subjects 1 through 4 achieved accuracies in excess of 80% while only subjects 7 through 10 failed to achieve above 70% for either feature. For all subjects the 1-dimensional feature gives a performance that is at least comparable to the 2-dimensional feature.

Average information transfer rates were calculated for all subjects across all sessions using (3) and (4). Subjects 1-4 obtained bit rates in excess of 6 bits/min for at least one feature with subject 1 obtaining a bit rate of 7.5 bits/min using the 1-dimensional feature.

To test the relationship between classification accuracy and behavioral performance on the task, the correlation between the accuracies using the 1-dimensional feature listed in Table I and the number of errors in counting during the experiments was calculated. No correlation (r=–0.1, p=0.73) was found.

Based on the recorded EOG, prior to classification, any segments during which there was eye movement exceeding 1° visual angle were rejected. This resulted in a mean rejection rate of 7% (range 7-67).

TABLE I
CLASSIFICATION ACCURACIES FOR ALL SUBJECTS OVER 5 SESSIONS.

Subject	*F*1d	*F*2d
1	86.9%	85.7%
2	83.8%	83.7%
3	83.7%	82.7%
4	82.6%	85.5%
5	76.1%	74.1%
6	71.7%	72.9%
7	67.3%	66.0%
8	69.6%	59.3%
9	61.5%	59.6%
10	55.7%	58.5%
Average	73.9%	72.8%

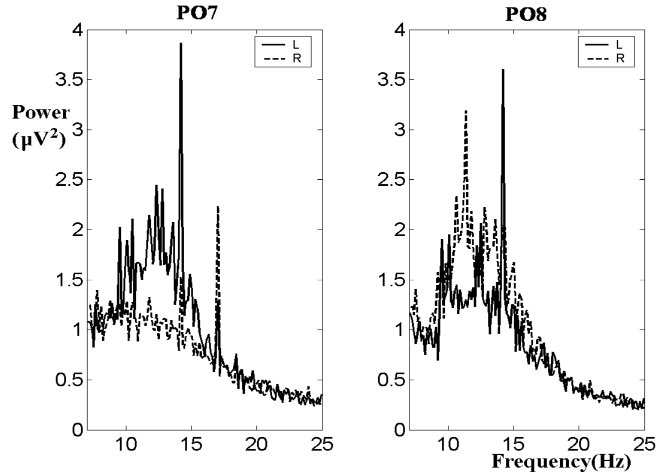

Fig. 2 Frequency spectra for attend-left (L) and attend-right (R) trials for subject 1 at electrode locations PO3 and PO4.

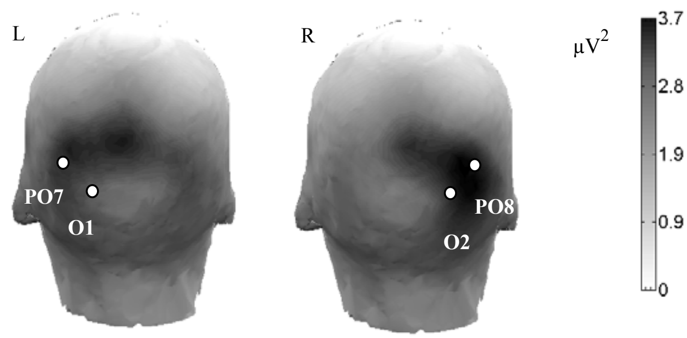

Fig. 3 topographic maps of alpha band power for attend-left (L) and attend-right (R) trials grand averaged across all 10 subjects.

Fig. 2 shows attentionally modulated frequency spectra at channels PO7 and PO8 for subject 1. Fig. 3 shows grand average topographic maps of alpha power from which contralateral inhibitory alpha increases can be seen.

IV. Discussion

The results of this study show that, by tracking bilateral parieto-occipital alpha modulations, binary decision-making using covert attention to visual stimuli is possible. Fig. 2 illustrates the increase in alpha band power over the hemisphere contralateral to the ignored stimulus, for subject 1. The 14 and 17Hz SSVEP peaks can be seen in this figure, however due to the narrow bandwidth of these peaks it is clear that they did not influence the value of the alpha band power feature.

As can be seen from Table I not all subjects achieved accuracies that would be deemed acceptable for use in a BCI. Although the behavioral measure of attention did not correlate with the accuracies obtained using the alpha band power it is worth noting that subjects 8-10 each performed below average behaviorally. While this alone does not explain why these subjects performed poorly, it was also found that these subjects had either a minimal amount of alpha activity or very narrow band alpha activity.

While the peak bit-rate of 7.5 bits/min is encouraging it is not as high as for other current independent BCI designs [1]. It is worth noting that the bit rate defined in equations (3) and (4) is designed to encourage accuracy over speed, therefore by improving accuracy by using intervals longer than the ~3.5s segments used in this study, higher bit rates could be achieved. Alternatively, the amount of time given to a subject to make a binary decision could be extended by generating a cumulative running sum of the 1-dimensional feature obtained from each segment within each trial.

Scalp locations from which alpha band power was measured was fixed across subjects in this study, determined from inspection of the grand average alpha topographies in Fig. 3. Thus these results are conservative, and it is probable that with selection of subject-specific electrode location, accuracies would be further increased. Also, future research will determine whether SSVEP modulations as observed in [14] can be combined with alpha band power to provide improved performance.

The novelty of this design lies in the fact that it utilizes oscillatory activity in a way similar to previous BCI studies [7,8], but subjects are able to perform well without training. Although this study utilizes spatial attention mechanisms that are naturally developed in every day situations, it is possible that training within the specific framework of this BCI paradigm using real-time feedback would serve to significantly improve accuracies over time.

V. Conclusion

Alpha band modulations affected by visual spatial attention can be employed successfully for control in a Brain Computer Interface. This provides a novel independent BCI design which relies in no way on the normal output pathways of peripheral muscles and nerves, and thus may have considerable impact on alternative communication and control technology for the disabled.

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