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Attention modulations of posterior alpha as a control signal for two-dimensional brain–computer interfaces

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ABSTRACT

Research on brain–computer interfaces (BCIs) is gaining strong interest. This is motivated by BCIs being applicable for helping disabled, for gaming, and as a tool in cognitive neuroscience. Often, motor imagery is used to produce (binary) control signals. However, finding other types of control signals that allow the discrimination of multiple classes would help to increase the applicability of BCIs. We have investigated if modulation of posterior alpha activity by means of covert spatial attention in two dimensions can be reliably classified in single trials. Magnetoencephalography (MEG) data were collected for 15 subjects who were engaged in a task where they covertly had to visually attend left, right, up or down during a period of 2500 ms. We then classified the trials using support vector machines. The four orientations of covert attention could be reliably classified up to a maximum of 69% correctly classified trials (25% chance level) without the need for lengthy and burdensome subject training. Low classification performance in some subjects was explained by a low alpha signal. These findings support the case that modulation of alpha activity by means of covert spatial attention is promising as a control signal for a two-dimensional BCI.

1. Introduction

A brain–computer interface (BCI) enables the processing of single-trial neuroimaging data in real-time. This has diverse applications such as communication and control by patients that suffer from severe disabilities, new forms of human-computer interaction, as well as novel methods of data-analysis in cognitive neuroscience (Wolpaw et al., 2002; Müller et al., 2004; Lebedev and Nicolelis, 2006; Waldert et al., 2008).

BCIs typically operate by distinguishing between well-defined mental states that are controlled by the subject. The main strategies that are used by non-invasive methods such as electroencephalography (EEG) and magnetoencephalography (MEG) are sensorimotor rhythms (Pfurtscheller and Neuper, 2001), slow cortical potentials (Birbaumer et al., 2000), event-related potentials (Farwell and Donchin, 1988), and (steady-state) visual evoked potentials (Sutter, 1992). Recently, it has been shown that posterior alpha activity is modulated by covert spatial attention (Worden et al., 2000). Specifically, covert shifts in visual attention are paired by alpha modulations in posterior sites, both contralateral (Sauseng et al., 2005; Thut et al., 2006; Yamagishi et al., 2005) and ipsilateral to the attended position (Worden et al., 2000; Kelly et al., 2006). Using off-line classification, Kelly et al. (2005) have demonstrated that the modulation of posterior alpha activity as a function of covert spatial attention may also act as a control signal for BCI. Specifically, it has been shown that binary classification is possible by using average alpha band power over the left (EEG channels PO7 and O1) and right (EEG channels PO8 and O2) hemispheres as input to linear discriminant analysis. Using this approach, an average classification rate of 73% across 10 subjects and a maximum of 87% for one subject was obtained, giving a maximum bit rate of 7.5 bits/min (see Section 2.3.3 for a description of these measures).

The aim of the present study is to examine whether covert spatial attention could also act as a potential signal for two-dimensional (2D) BCI control by increasing the number of orientations to which the subject may attend. This is motivated by the work of Rihs et al. (2007), who have shown that covert spatial attention follows a retinotopical organization. Most current BCI strategies offer one-dimensional (1D) BCI control and a 2D control signal significantly increases the applicability of brain–computer interfaces. Additionally, increasing the number of orientations may lead to a significant improvement in bit rate (McFarland et al., 2003; Santhanam et al., 2006). One of the few non-invasive studies in this direction is that of Wolpaw and McFarland (2004), where two components of the sensorimotor rhythm are independently controlled by the subject. However, in this study, 2D BCI control could only be attained after extensive subject training. In contrast, covert spatial attention

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promises to offer an alternative way of achieving 2D BCI control simply by covertly attending to the intended spatial location.

In order to examine the potential of our approach, we focus on the off-line analysis of electromagnetic brain activity data obtained for 15 subjects using magnetoencephalography. We used support vector machines (SVMs) to classify the averaged posterior alpha band power into the spatial orientation to which is covertly attended for both 1D and 2D BCIs. In order to obtain insight into the characteristics of brain activity that allow for BCI control, we differentiate well performing subjects from poorly performing subjects based on their individual classification performances; which we refer to as the *good* and *poor* subjects, respectively. Finally, it is examined how classification performance changes as a function of the delay period, during which subjects are covertly attending.

2. Methods

2.1. Subjects

Fifteen healthy subjects (mean age 28 ± 8.6; six females) participated in the experiment. All subjects had (corrected to) normal vision. Four males and two females were left-handed and the remaining subjects were right-handed. The study was approved by the local ethics committee and written informed consent was obtained from the subjects according to the Declaration of Helsinki.

2.2. Task

The subjects viewed a screen with a central fixation cross and four squares at 7.5° of visual angle to the top, right, bottom, and left of the fixation cross. At regular intervals, a small arrow appeared at the location of the fixation cross in order to indicate the direction to which subjects should covertly attend without moving their eyes away from the fixation cross. A total of 128 trials were collected per condition over eight subsequent sessions, interspersed by 1 min rests. Each trial started with the presentation of the cue for 400 ms, after which subjects had 2500 ms to covertly attend to the indicated direction. After this delay period, the square at the indicated direction turned either green or red for 40 ms. In order to facilitate task engagement and to behaviourally measure task compliance, the subjects were asked to count the number of times the target location turned green over all eight sessions. There was a 1500 ms rest between trials (Fig. 1). The task was implemented in Presentation (Neurobehavioral Systems Inc., Albany, CA, USA).

2.3. MEG acquisition

Electromagnetic brain activity was recorded using a CTF MEG System (VSM MedTech Ltd., Coquitlam, British Columbia, Canada), which provides whole-head coverage using 275 DC SQUID axial gradiometers. The planar gradient was approximated for each sensor using the signals calculated from a sensor and its neighboring sensors, effectively emulating a setup with planar gradiometers (Bastiaansen and Knosche, 2000), simplifying interpretation of sensor-level data since the greatest activation will be located above the source (Hämäläinen et al., 1996). Bipolar EEG channels were used to record horizontal and vertical eye-movements as well as the cardiac rhythm. All signals were sampled continuously at 1200 Hz. Head position was monitored using three coils that were placed at the subject's left ear, right ear, and nasion. The data were analyzed using Matlab 7 (Mathworks, Natick, MA, USA) and FieldTrip, which is an open source toolbox for the analysis of neurophysiological data that has been developed at the F.C. Donders Centre for Cognitive Neuroimaging (http://www.ru.nl/fcdonders/fieldtrip). Data were downsampled from 1200 to 300 Hz. For each trial, the power spectrum was computed in the 5–70 Hz frequency range using a Hanning window for the period from −500 to 2500 ms after cue offset using 100 ms intervals. For the frequency bands that acted as input to the classifier, we applied an adaptive sliding time window of five cycles for each frequency, resulting in an adaptive smoothing of $\Delta f = 3/2$.

2.3.1. Feature selection

In order to simplify the classification task, we reduced the dimensions of the spectral data by preselecting sensors, frequencies and temporal intervals. We focused on alpha band power (8–14 Hz) in occipito-parietal channels only, based on findings of (Kelly et al., 2005). The temporal interval was chosen to range from 500 to 2500 ms after cue offset in order not to include stimulus locked evoked response. The resulting data were further reduced by averaging power over frequencies as well as time. The motivation for this step is that alpha band power was the signal of interest and averaging over the delay period should increase the signal-to-noise ratio if the signal is sufficiently stationary (Proakis and Manolakis, 2006).

2.3.2. Classification

In order to use the data for BCI purposes, we distinguished single trials into one of the four classes *top*, *right*, *bottom*, or *left*. For single trial data we used standardized (zero mean and standard deviation of one) log-power spectra as input to the classifier. We differentiate between the 1D task, where the goal is to discriminate between covert attention to two different orientations, and the 2D task, where the goal is to discriminate between covert attention to left, right, upper, and lower visual field. For the 1D task, we chose that pair of orientations which showed the best classification performance per subject (e.g., for Subject 1 it was easiest to discriminate between up and down whereas for Subject 2 it was easiest to discriminate between right and bottom). Finally, in order to rule out the possibility that we classified based on eye movements, we also used the standardized log-power spectra for the two EOG channels which measure horizontal and vertical eye movement as the basis for classification.

In order to classify the single trials, we use a support vector machine with a linear kernel (Vapnik, 1995). Assume we have acquired $n$trials. The input x_i to the classifier for trial i is the averaged standardized log-power per channel, whereas the output y_i of the classifier is a binary class label (−1 for condition A versus +1

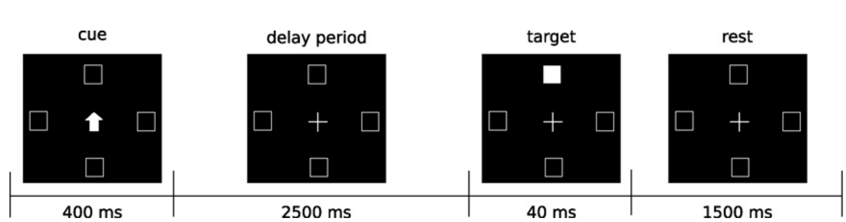

Fig. 1. The subject should covertly attend to the location indicated by the cue for a period of 2500 ms. A target or non-target appears for 40 ms at the indicated location. Subjects should keep track of the number of observed targets.

for condition B). The objective then is to find the minimizer (Hastie et al., 2001):

$$\underset{\beta_0,\beta}{\operatorname{argmin}} \sum_{i=1}^{n} \max(0, 1 - y_i(\beta_0 + x_i^T \beta)) + \lambda ||\beta||^2.$$

The regularization parameter λ controls how strongly parameters in β are pushed towards zero and was determined based on initial empirical testing. Once the parameters β_0 and β are found given a suitable value for λ, a new example x can be classified as: $y = \mathrm{sign}(\beta_0 + x^T \beta)$.

In order to use the above approach for non-binary classification when distinguishing all four orientations in the 2D case, we will use a *one-against-one* approach, where the classification problem is reduced to a set of binary classification problems (one for each of the six possible orientation pairs). A separate SVM is thus used for each binary classification problem and new examples are assigned to the class that receives the most votes from the individual SVMs. The method has been implemented in the open source FieldTrip classification module, which can be obtained from http://ftp.fcdonders.nl/pub/fieldtrip/modules.

2.3.3. Evaluation

Evaluation of the obtained results is based on two different measures. We use both classification rate (CR), which is simply the percentage of correctly classified trials, and bit rate or information transfer rate (ITR) to get an estimate of the amount of information that is conveyed per unit of time (bits/min) (Dornhege et al., 2007):

$$\mathrm{ITR} = \frac{I(Z;Y)}{\text{trial duration in minutes}}$$

where $I(Z;Y)$ stands for the mutual information between the user intent Z (actual class) and classification output Y (predicted class). The ITR allows one to measure the dependence of information transfer on trial length. In order to obtain a robust estimate of classification performance, we report average results based on tenfold cross-validation. This boils down to splitting the data into 10 mutually exclusive subsets and testing each individual subset while training a classifier on the remaining subsets.

Significance levels of classification performance were computed by comparing classifier outcomes with the outcomes of a classifier that assigns each trial to the class with highest prior probability (amounting to random guessing for uniform priors) using a one-sided binomial test (Salzberg, 1997). Performance differences were assessed using a two-sided Wilcoxon rank sum test.

3. Results

3.1. Classification results

Fig. 2 shows the classification rates and information transfer rates for all 15 subjects on both the 1D and 2D tasks. We find for the 1D case that classification rates are above the 50% chance level for all subjects, with a mean classification rate of 69%, ranging from 57% to 86%. Classification performance was significantly different from random guessing for all subjects with exclusion of Subject 12. For the 2D case, all subjects performed above the chance level of 25%, with a mean classification rate of 41%, although there is a sharp drop in performance between subjects, ranging from 29% to 69% correctly classified trials. Classification performance was significantly different from random guessing for all subjects except Subjects 14 and 15.

Although the classification rates for the 1D task always outperform those of the 2D task, it can still be beneficial to use the 2D task. First, moving from a 1D to a 2D task increases the range of possible BCI applications (e.g., two-dimensional cursor control). Second, even though classification rates are lower, the maximum number of bits that can be transmitted per unit of time is higher for the 2D task (20.0 bits/min) as compared with the 1D task (12.5 bits/min). Both results improve the maximum bit rate of 7.5 bits/min reported in (Kelly et al., 2005). This is illustrated by the information transfer rates reported in Fig. 2. Note however that there is no significant difference between the ITRs for the 1D and 2D task according to a two-sided Wilcoxon rank sum test ($p = 0.05$). This is due to the fact that differences between ITRs for both tasks are small for poorly performing subjects.

In order to rule out the possibility that classification performance was based on brain signatures that reflect eye movement, we attempted to classify eye movement directly. The average classification rate obtained using the EOG signals for the 1D case and 2D case was 57% and 27%, respectively which are both only slightly above chance level and significantly below the average classification rates of 69% and 41% obtained using posterior alpha as computed with a two-sided Wilcoxon rank sum test ($p = 0.05$). Classification perfor-

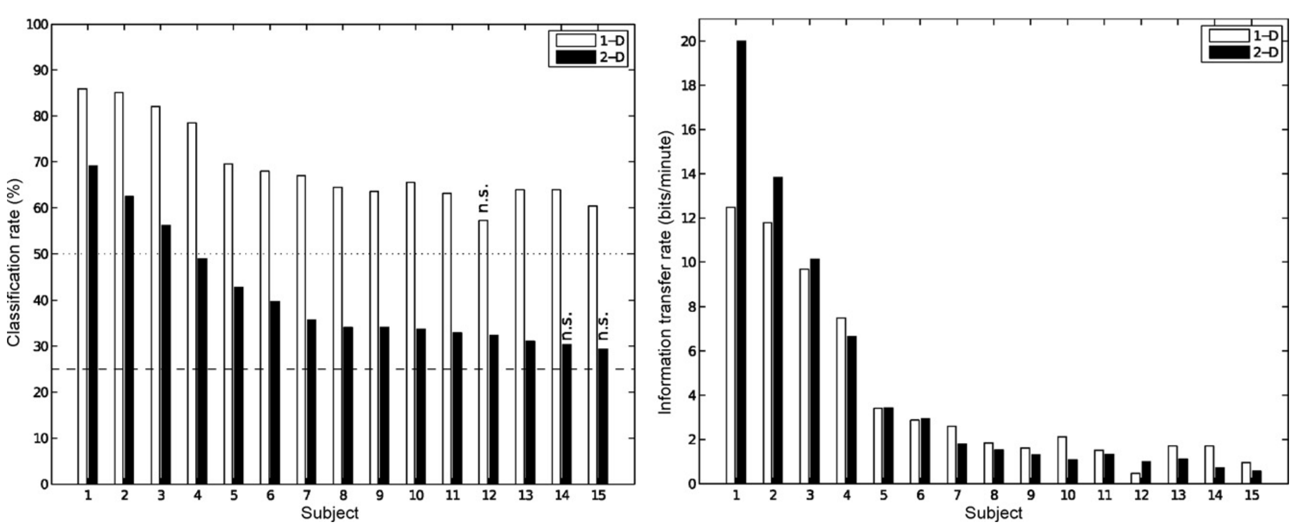

Fig. 2. Classification rates and information transfer rates for all subjects on the one- and two-dimensional tasks, sorted according to performance on the two-dimensional task. For the one-dimensional task, we selected per subject that pair of orientations which showed highest classification rate. Classification performance was significantly different from random guessing for all subjects except Subject 12 in the 1D case and for all subjects except Subjects 14 and 15 in the 2D case (one-sided binomial test, $p = 0.05$). Dotted and dashed lines show chance level performance for the 1D and 2D case, respectively.

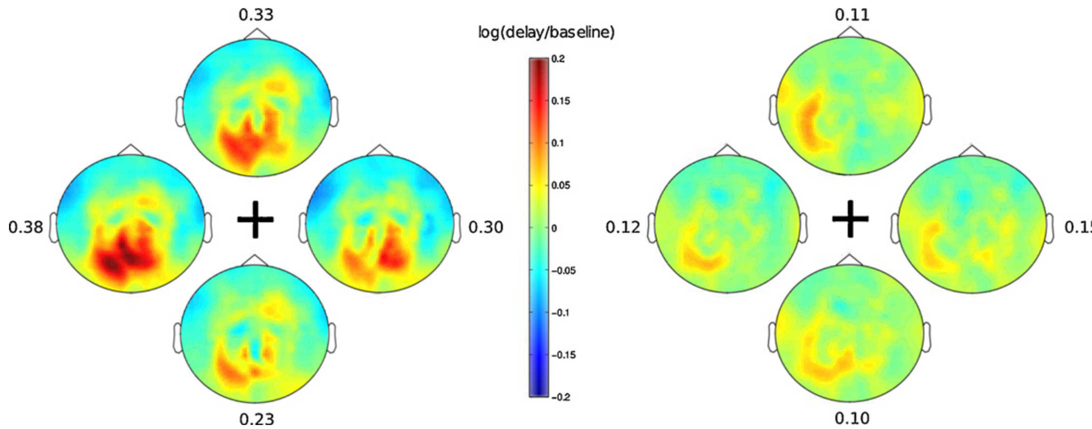

Fig. 3. Log of the alpha power (8–14 Hz) for the covert attention conditions (top, right, bottom, left) from 500 to 2500 ms after cue offset divided by the log of the alpha power in the −500 to −400 ms baseline period for the best (left) and worst (right) five subjects. Average log(delay/baseline) of occipito-parietal channels is shown per orientation.

mance was low but significantly different from random guessing for Subjects 2, 5, 7, and 11 in the 1D case and Subject 2 in the 2D case as computed with a one-sided binomial test ($p = 0.05$). Note that some improvement over random guessing is unsurprising since EOG does not exclusively measure ocular activity but is also sensitive to brain activity (in particular horizontal EOG channels).

3.2. Differences in alpha power

In order to understand which subject characteristics may account for good or bad performance on the BCI tasks, we distinguished the best five subjects from the worst five subjects according to classification rate. Fig. 3 depicts relative increases and decreases in alpha power from 500 to 2500 ms after cue offset as compared with a baseline period for good and poor subjects. Average log(delay/baseline) of occipito-parietal channels is shown per orientation. Increase in posterior alpha activity for good subjects is 2.6 times higher than that of poor subjects on average and shows a strong positive correlation with classification rate ($r = 0.61$). High alpha power at baseline is less indicative of increased classification rate ($r = 0.30$). For the left and right conditions, this increase is mainly located ipsilateral to the direction of covert attention. This is consistent with findings that alpha synchronization reflects active inhibition of visual distractors in the contralateral hemifield. For the poor subjects, in contrast, increases and decreases in alpha activity are of much lower magnitude and less localized to posterior sites.

Fig. 4 shows an alternative representation of the same data. Here, we observe for the good subjects that posterior activity starts to increase at about 1500 ms after cue offset, whereas no such increase is apparent for the poor subjects. Furthermore, although the increase is strongest in the alpha band, this increase is a broad band phenomenon, ranging from the delta to the lower gamma band. Evoked response is stronger in poor subjects and does not show the decrease in power in the 10–50 Hz range that can be observed for the good subjects.

3.3. Differentiating between orientations

The previous analysis has shown that covert attention indeed leads to modulation of posterior alpha. However, in order to let SVMs distinguish the direction of covert attention, it is required that these modulations depend on this directionality. Fig. 5 shows differences in modulations depending on the direction of covert attention. Note that we depict all six possible pairwise differences together with their classification performances averaged over good and poor subjects, respectively. Pairwise differences are shown in terms of the logarithm of alpha power in the first condition divided by alpha power in the second condition. The reported classification rates are obtained when distinguishing between two orientations using a support vector machine.

With regard to the pairwise differences for the best five subjects, attention modulations of alpha activity can be seen for each pair and modulation is restricted to posterior channels. Alpha syn-

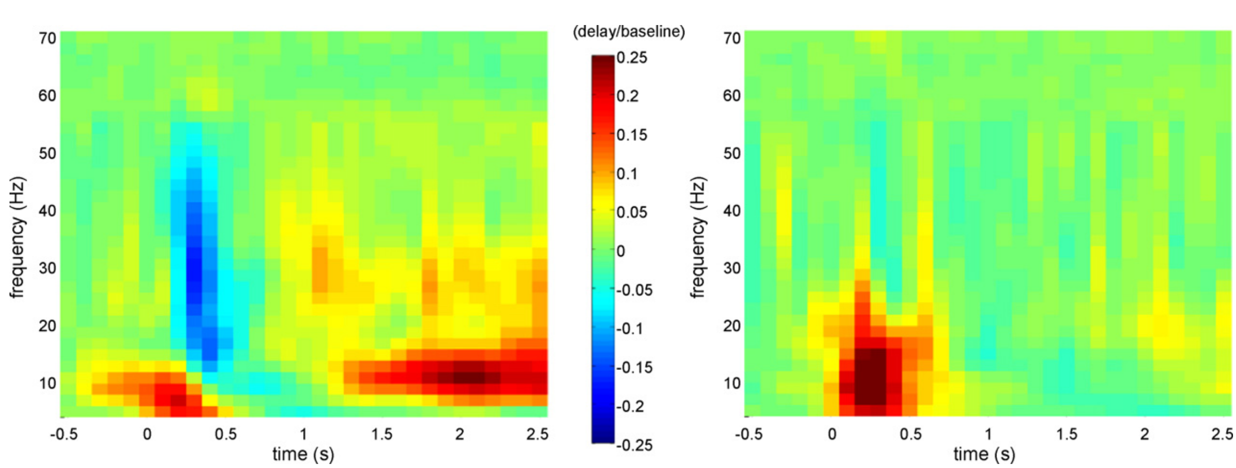

Fig. 4. Log of the power (5–70 Hz) in occipito-parietal channels for the covert attention conditions (top, right, bottom, left) from −500 before to 2500 ms after cue offset divided by the alpha power in the −500 to −400 ms baseline period for the best (left) and worst (right) five subjects.

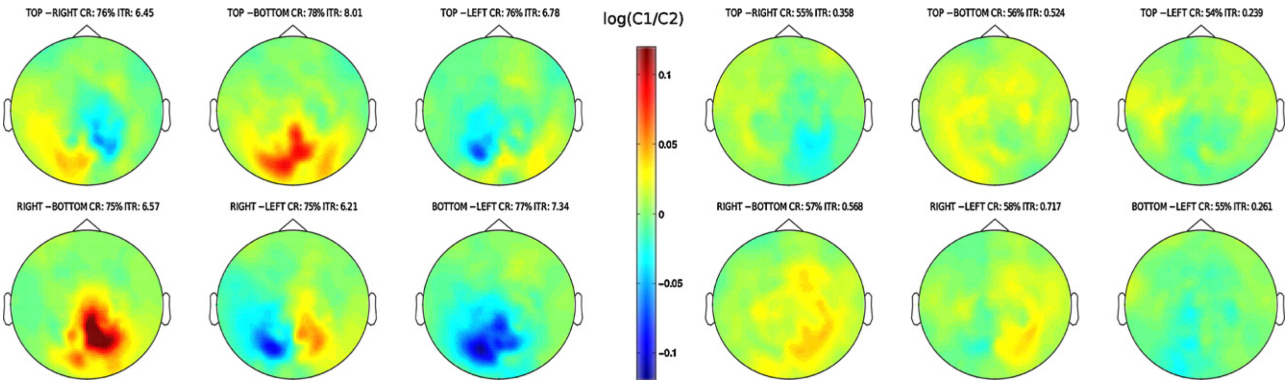

Fig. 5. Pairwise differences between conditions C1 and C2 in terms of classification performance and alpha band power (8–14 Hz) from 500 to 2500 ms after cue offset, averaged over the best (left) and worst (right) five subjects.

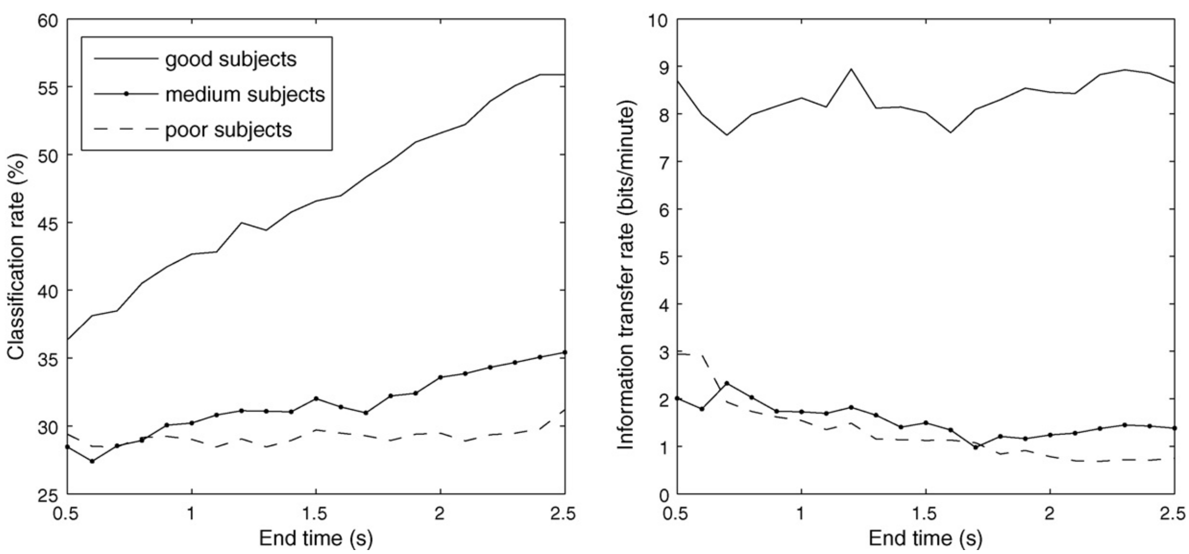

Fig. 6. Classification rate and information transfer rate averaged over good, medium, and poor subjects (tenfold cross-validated) as the end time of the delay period is varied. Start time is 500 ms after cue offset.

chronization/desynchronization is clearly observable for the right versus left condition. Distinguishing between covert attention to the top and bottom visual fields is easiest on average (CR: 78%, ITR: 8.01) although performance differences between conditions in terms of classification rate or information transfer rate are small. Estimated classification parameters for individual subjects indicate that there is considerable between-subject variation even though global patterns are similar. For the worst five subjects, attention modulations of alpha activity are not restricted to posterior channels and an order of magnitude smaller as compared with the best five subjects. Distinguishing between covert attention to the left and right visual fields is easiest on average (CR: 58%, ITR: 0.72) although performance differences between conditions are again negligible.

3.4. Classification performance as a function of delay

Finally, we examined how average classification performance for 2D BCIs changed as a function of the length of the delay period. Fig. 6 shows results for good, medium, and poor subjects. For good subjects, we observe a steep increase in classification rate as the delay period increases while information transfer rate remains constant due to the increase in time associated with a classification. For the poor subjects there is almost no change in classification rate as a function of the delay, leading to a decrease in information transfer rate. Medium subjects are intermediate between these two extremes.

4. Discussion

In this paper, we have shown for the first time that modulations of posterior alpha can be used to distinguish multiple orientations of covert spatial attention on the single trial level. Since we are able to discriminate not only horizontal but also vertical shifts in covert attention at the single trial level, this opens up the possibility of using the signal for two-dimensional BCI control. This extends previous results by Kelly et al. (2005), who have shown that binary (one-dimensional) BCI control based on covert attention is feasible, and previous results by Rihs et al. (2007), who have shown that covert spatial attention is retinotopically organized. Classification performance for the 1D case was comparable with the results of Kelly et al. (2005).

Non-invasive 2D BCI control has been demonstrated before using the independent modulation of two components of the sensorimotor rhythm but this required lengthy training times (Wolpaw and McFarland, 2004). Although classification rates decreased as we moved from 1D to 2D control, bit rates increased to a maximum of 20 bits/min for the best subject. This compares favourably to the maximum bit rate of 17 bits/min obtained by the 2D BCI of McFarland et al. (2003) and is competitive with the bit rates that can be obtained using non-invasive methods in general (Wolpaw et al., 2002).

The fact that classification of eye movement failed, strengthens our belief that posterior alpha really reflects brain-derived activity and can thus be used as the basis for BCIs. We are confident that the measured alpha activity is not related to eye movement since, if this were the case, classification rates should increase rather then decrease when classifying based on EOG. The fact that classification rates based on EOG are slightly above chance level in some subjects might be explained by bleed-in of posterior alpha activity.

Our analysis has been performed at the sensor level. Alternatively, one could consider localizing the sources of the alpha activity and then apply a spatial filter (Van Veen et al., 1997). A classifier can then be applied to the output of the spatial filters. We do however not expect this approach to perform better than the classification approach applied to the sensor data. Spatial filtering will linearly recombine the sensor data but this will also be realized by the linear recombination of the sensor data when the linear support vector machine is used. Hence, there is no a priori reason to believe that source-level analysis would be superior to the sensor-level analysis presented here.

A comparison between well performing and poorly performing subjects has shown that good performance is linked to a stronger and more localized increase in posterior alpha. This is in line with findings of Rihs et al. (2009), who have shown that subjects with low alpha power at baseline failed to show task-related alpha modulations. The inability of some subjects to achieve BCI control, referred to as BCI illiteracy, is not inconsistent with findings of other BCI studies. For example, up to 20% of subjects may fail to achieve control in BCIs based on motor imagery (Nijholt et al., 2008). Next to these physiological differences, motivational factors might account for differences in performance as some subjects reported that it was hard to maintain concentration throughout the sessions. This is supported by a weak positive correlation ($r = 0.1$) between classification performance and task compliance as measured in terms of the difference between the actual and reported number of targets. Finally, since results were obtained with little to no subject training we expect further improvements in achievable bit rate with subject training.

Looking at pairwise differences, it was found that differences in classification performance are small for different pairs. For the best five subjects we do find that distinguishing top from bottom is somewhat easier than distinguishing left from right, while the reverse pattern is true for the worst five subjects. One could argue that the described classification performance for 2D BCI control can be attained even if not all orientations are distinguishable from one another. For example, random guessing for orientation to the bottom visual field and perfect prediction for the remaining three orientations may lead to a high classification rate but does not constitute a proper 2D control signal. That this is not the case is motivated by the fact that all six pairwise classifications were significantly different from random guessing for the good subjects.

Classification performance as a function of the delay period has shown that good subjects show qualitatively different behaviour compared with the rest. For good subjects, the bit rate remained fairly constant as the length of the delay period is varied. This implies that we can transmit an equal amount of information using fast and unreliable classification or slow and reliable classification. Which mode of operation is preferred depends on the actual BCI application.

The analysis presented in this paper also suggests that classifiers can be used to obtain additional insight into the characteristics of task-related activity at the single trial level. For example, classification performance (such as classification rate or information transfer rate) can be used as an objective measure to select those subjects that clearly show task-related activity which facilitates subsequent interpretation of the data (cf. grand averages in Fig. 5).

Concluding, we have shown that covert spatial attention may serve as a natural control signal for 2D BCIs that does not require lengthy training times and leads to high bit rates. These characteristics make covert spatial attention a promising new paradigm for BCI control. Our future aim is to 'close the loop' and use the paradigm in actual on-line BCI applications for both healthy and disabled users.

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