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Selecting features for BCI control based on a covert spatial attention paradigm

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ABSTRACT

Covert attention to spatial locations in the visual field is a relatively new control signal for brain–computer interfaces. Previous EEG research has shown that trials can be classified by thresholding based on left and right hemisphere alpha power in covert spatial attention paradigms. We reexamine the covert attention paradigm based on MEG measurements for fifteen subjects. It is shown that classification performance can be improved by applying sparse logistic regression in order to select a subset of the sensors specific to each subject as the basis for classification. Furthermore, insight is gained into how classification performance changes as a function of the length of the attention period and as a function of the number of trials. Classification performance steadily increases as the length of the attention period over which is averaged is increased, although this does not necessarily translate into higher bit rates. Good classification performance using early components of the attention period may be related to evoked response. With regard to the number of used trials, classification performance became maximal after 150 samples had been obtained, requiring a training time of approximately eleven minutes under the current experimental paradigm.

1. Introduction

Brain–computer interfaces (BCIs) depend on the detection of changes in task-related activity as the subject moves from one mental state to the other. This implies that task-related changes must be strong enough and stable over time in order to be useable as a control signal for BCI. It is well-known that a steady-state visual evoked potential (SSVEP), induced by an external stimulus oscillating at a particular frequency, can drive a BCI (Allison, McFarland, Schalk, Zheng, Jackson, & Wolpaw, 2008; Middendorf, McMillan, Calhoun, & Jones, 2000; Sutter, 1992). Recently, Kelly, Lalor, Reilly, and Foxe (2005) have shown that the external stimulus might not be required and covert attention to spatial locations in the visual field alone may be sufficient to drive a BCI. They were the first to demonstrate that shifts in covert spatial attention between the left and right visual hemifield can be picked up on the single trial level. This accomplishment is based on the fact that covert shifts in visual attention are paired by alpha-desynchronisation in posterior sites contralateral to the attended position (Sauseng et al., 2005; Thut, Nietzel, Brandt, & Pascual-Leone, 2006; Yamagishi, Goda, Callan, Anderson, & Kawato, 2005) as well as alpha-synchronisation ipsilateral to the attended position (Kelly, Lalor, Reilly, & Foxe, 2006; Worden, Foxe, Wang, & Simpson, 2000).

Kelly et al. (2005) demonstrated that by using alpha power (8–14 Hz) over left and right hemispheres based on 3.52 s windows of EEG data as input to a linear discriminant analysis classifier, a maximum bit rate of 7.5 bits per minute could be achieved. Covert spatial attention is a promising paradigm for BCI control since it is natural for the subject to orient ones attention to the direction of intended control. Furthermore, little training time is required in order to attain acceptable results. However, at present the paradigm remains relatively unexplored.

In this study, we examine the paradigm using data obtained with a 275 channel MEG system for fifteen subjects. To our knowledge, this is the first time covert spatial attention is examined as a paradigm for brain–computer interfacing using MEG as a modality. Our goal is to improve classification performance by using a feature selection approach. We assume that alpha (de)synchronisation over an attention period is indeed the signal of interest, but in contrast to Kelly et al. (2005), the optimal channels are assumed to be subject specific and will be identified using sparse logistic regression (van Gerven, Hesse, Jensen, & Heskes, 2009). Examples of other feature selection approaches in BCI research are Millán, Franzé, Mouriño, Cincotti, and Babiloni (2002), Schröder, Bogdan, Rosenstiel, Hinterberger, and Birbaumer (2003), Lal et al. (2004), Schröder et al. (2005) and Hoffman, Yazdani, Vesin, and Ebrahimi (2008). We compare the results of sparse logistic regression with a method that is analogous to that of Kelley et al. We also examine

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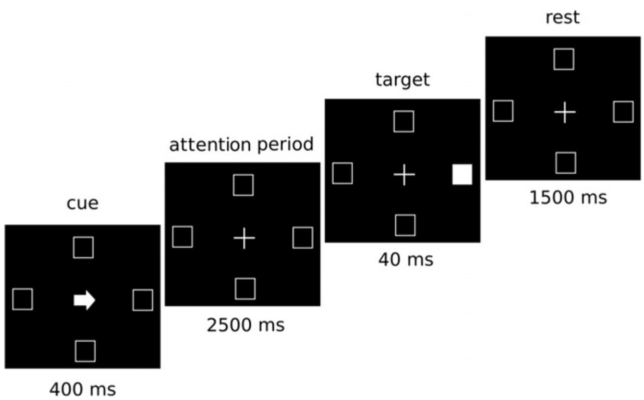

Fig. 1. Timeline of a trial in the covert attention experiment. Subjects had to attend to one of the target squares and keep track of whether or not the target square turned green at the end of the attention period.

how classification performance changes as a function of the length of the attention period and as a function of the number of trials. The hope is that the improved classification performance due to the selection of more optimal features and a better insight into the optimal attention period and number of trials leads to a more widespread use of this promising BCI paradigm.

2. Data collection

Fifteen healthy subjects (mean age 28 $\pm$ 9; 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. The subjects viewed a screen with a central fixation cross and four squares at 7.5 degrees of visual angle to the top, right, bottom, and left of the fixation cross. For the present analysis, we focused on a subset of the data. A total of 256 trials were collected in eight sessions for subjects covertly attending (i.e., without moving their eyes from the fixation cross) during an attention period of 2.5 s to the left or right square, as indicated by an arrow that pointed to the intended direction for 400 ms. There was a rest period of 1500 ms between each trial. In order to keep subjects engaged, they were required to count the number of times the target square turned green as opposed to red for 40 ms at the end of the attention period (Fig. 1).

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 although for the current experiments only 86 posterior (occipito-parietal) channels were used. Additionally, vertical and horizontal eye-movements were recorded using two bipolar EEG channels. The data was analysed using FieldTrip.[1] The planar gradient was approximated for each sensor using the signals calculated from a sensor and its neighbouring sensors (Bastiaansen & Knosche, 2000). Data was detrended and downsampled from 1200 Hz to 300 Hz. No further artifact rejection was performed since our methods should be useable in (noisy) online BCI settings. For each trial, the power spectrum was computed in the 8 Hz to 14 Hz range using a Hanning window for the period from −0.5 to 2.5 s with 100 ms intervals. We applied an adaptive time window of five cycles for each frequency ($\Delta T = 5/f$) and an adaptive smoothing of $\Delta f = 1/\Delta T$. We used normalised (z-transformed) log power per channel averaged over time and frequency as input to the classifier and defined 0.5 to 2.5 s after cue offset as the attention period in order to counteract the influence of evoked potentials due to the cue. Hence, an attention period consisted of two seconds of covert attention.

[1] FieldTrip is an open-source package for the analysis of electrophysiological data (http://www.ru.nl/fcdonders/fieldtrip).

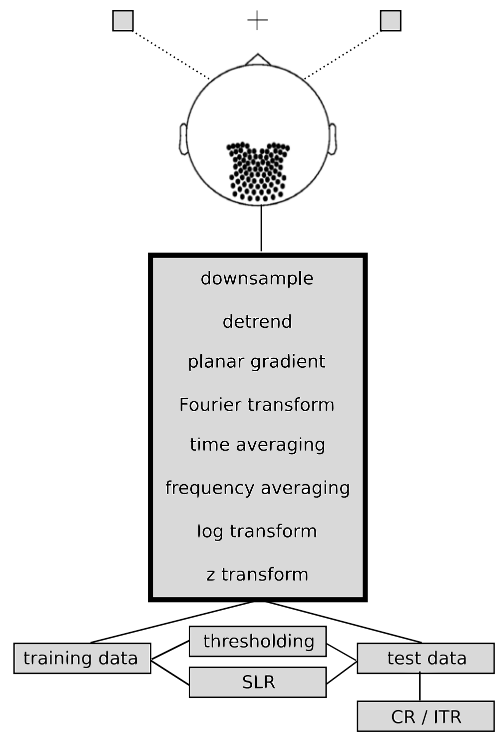

Fig. 2. The subjects were covertly attending to either the left or right visual hemifield. Posterior channels were measured and transformed using the FieldTrip toolbox. Part of the data is reserved for training and part of the data is reserved for testing. Classifiers were taught from training data using the thresholding and SLR algorithms (see accompanying text). Classification performance was evaluated using the test data in terms of classification rate (CR) and information transfer rate (ITR) using a five-fold cross-validation scheme.

In order to test classification performance we used five-fold cross-validation where data was split five times into 80% training data and 20% test data and average results are reported. In order to optimise parameters an additional inner cross-validation was used where optimal performance was determined using 20% of the training data. Fig. 2 depicts how the data is measured, transformed, and finally used for classification.

3. Classification methods

3.1. Lateralisation index

Kelly et al. (2005) obtained the best results using the logarithm of the left hemisphere (EEG electrodes PO7 and O1) alpha power divided by the right hemisphere (EEG electrodes PO8 and O2) alpha power, averaged over the attention period, as input to a linear discriminant analysis algorithm. As a rough approximation to this strategy, we use the average over left and right occipito-parietal MEG channels in order to represent left and right hemisphere alpha power (8–14 Hz). We refer to the log of right divided by left hemisphere alpha power as the *lateralisation index*. This lateralisation index will be used as input to logistic regression as a classifier. We used logistic regression instead of discriminant analysis in order to facilitate the comparison with the other method used in this paper.[2] Logistic regression will effectively

[2] Preliminary experiments which varied regions of interest and frequency range indicated that occipito-parietal channels and 8–14 Hz band power indeed gave best performance for our data sets. The use of different classifiers based on the lateralisation index gave comparable results.