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Discriminating Between Attention and Mind Wandering During Movement Using EEG

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Abstract

Attention, and conversely mind wandering, are believed to be important factors in physical rehabilitation. We propose an experimental protocol to investigate if it is possible to discriminate between attention and mind wandering during passive movements of lower limbs using EEG. We performed time-frequency analysis of the gathered data and designed a simple brain-computer interface (BCI) based on oscillatory features. The designed BCI achieved average accuracy of 75% in single trials, on a sample of five healthy subjects.

1 Introduction

Attention is believed to be an important cognitive factor in physical rehabilitation [7]. Conversely, repetitive tasks – which are typical of rehabilitation regimes – can induce inattentive cognitive states, termed *mind wandering* [6]. These considerations are relevant in, e.g., motor rehabilitation after stroke, where repetitive task-specific practice is a common intervention [3]. Therefore, an EEG-based brain-computer interface (BCI), capable of discriminating between attention and mind wandering, might prove useful in a number of different settings. In classical rehabilitation, the therapist could use such a device as a window into the patient's cognitive state, guiding the exercise regime. In the robot-assisted rehabilitation scenario, attention level could be used as an additional control signal, adhering to the human-in-the-loop concept. Additionally, such a device might allow to more rigorously answer research questions on the role of attention in rehabilitation.

We are building on the work described in [1]. The referenced work has shown that a distractor task (specifically, counting backwards by threes) modulates desynchronization of sensori-motor rhythms (SMR) and that a classifier can be designed to discriminate between attended and unattended passive movements of upper limbs, with an accuracy of around 75%.

Our approach differs from prior work in the way we defined the conditions: instead of contrasting attention with distraction by an artificial mental task, we contrast attention with a mind wandering state, more realistically modeling the rehabilitation scenario. Furthermore, we focus on a specific aspect of attention – the kinesthetic sensation of the movement – trying to disentangle it from other aspects like visual attention. Lastly, in this study we focused on the lower limbs instead of upper, envisioning the application of the developed BCI to a gait-rehabilitation robot.

2 Methods

2.1 Experimental Protocol and Data Collection

Five healthy male participants (age range: 23 – 28 years old) volunteered in the experiment. Subjects were seated in front of a screen with their feet strapped to an electrical mini bike that

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was used to actuate passive movements. The view of participants' feet was obscured to prevent confounds with visual attention. EEG recording was carried out with 30 channels (positioned according to the 10-10 system). TMSi Refa 32 amplifier was used with 256 Hz sampling rate and linked ears average reference.

Each subject was exposed to two experimental conditions. In the first condition subjects were instructed to pay attention to the kinesthetic sensation of the passive movement – we denote this as the "Passive Movement with Attention" (PMA) condition. In the second condition (denoted PMR – "Passive Movement with Relaxation") subjects were instructed to relax, ignore the movement and let their mind wander. For both conditions subjects were instructed not to make muscle contractions themselves and to not visualize or imagine the movements.

The recording sessions were divided into 6 blocks, each consisting of 10 consecutive trials of one, and 10 consecutive trials of the other condition. The ordering of conditions within blocks was semi-randomized, with 3 blocks having PMR, and 3 having PMA trials first. Before each block the subjects were informed what type of trials follows and could take a pause. The duration of trials was 15 seconds: for the first 5 seconds (baseline period) the message "Rest" was displayed; during the next 10 seconds the mini bike was working and a fixation cross was displayed. A sound cue, played 500 ms prior to the appearance of the fixation cross, prompted the experiment operator to turn on the bike. The sound was also audible to the subject. Recording time was around 50 minutes, and 60 trials per condition were collected.

2.2 Time-Frequency Analysis

To verify whether attention and mind wandering have an effect on sensori-motor rhythms, we performed time-frequency analysis of collected data. Before the time-frequency decomposition, data was preprocessed: zero-phase IIR filter with the pass band between 1 and 40 Hz was applied; data was segmented into 15 s long trials, with 5 s before the appearance of the fixation cross and 10 s after; artifactual trials were excluded on the basis of visual inspection (on average 20% of trials were rejected).

Event-related spectral perturbation (ERSP) [2] was calculated with Morlet wavelets. For baseline correction all the spectrum estimations were divided with the mean spectrum of the -3 s to -1 s period of all the trials. Using a divisive baseline, we are assuming a gain model of task activity: power in the task period is a modulation of power in the baseline period.

2.3 Classification

To check how well PMA trials can be discriminated against PMR trials we utilized a simple bandpower BCI design. In the preprocessing step signals were filtered with a causal FIR filter with the pass band from 8 to 35 Hz (capturing the alpha and beta bands that are relevant for SMR). Next, several different spatial filtering variants were applied: no spatial filter (all 30 channels used); surface Laplacian with 4 closest neighbors applied to all the channels; selection of 7 electrodes over the motor cortex (FC1, FC2, C3, Cz, C4, CP1, CP2); only channel Cz with a surface Laplacian. In feature extraction the logarithm of variance in the period of 1 to 8 s after the appearance of the fixation cross was calculated (resulting in 30, 7 or 1 feature, depending on the spatial filter). No artifact rejection was performed, i.e. all the recorded trials were used. An LDA classifier was then trained and tested on this data. The classifier was regularized using covariance shrinkage (with the regularization parameter determined analytically; see [5]). The classifier performance was then estimated using a 5-fold chronological cross-validation scheme [4], with 5 trials before and after the testing block omitted from the training set.

3 Results

In Fig. 1 we are showing the results of time-frequency analysis for all the subjects, for the electrode Cz which displayed strongest movement-related spectral changes. At a qualitative level we observe that for all the subjects passive movement produced a prominent desynchronization in the upper beta band with a spatial distribution concentrated over the central electrodes. For some subjects a desynchronization in the alpha band could also be observed, but with a more diffuse spatial distribution (possibly caused by the contribution of occipital or temporal rhythms in the alpha band, and not by the mu rhythm). For subject 3 we could also observe a synchronization at around 30 Hz that increased in bandwidth during the course of a trial.

Averaging ERSP values over 1-8 s time window and over alpha and beta bands (selected for each subject by visual inspection) yielded significant differences between the PMA and PMR conditions for subjects 3 and 4 in both bands (two-sample t-test at $\alpha = 0.05$, Bonferroni corrected).

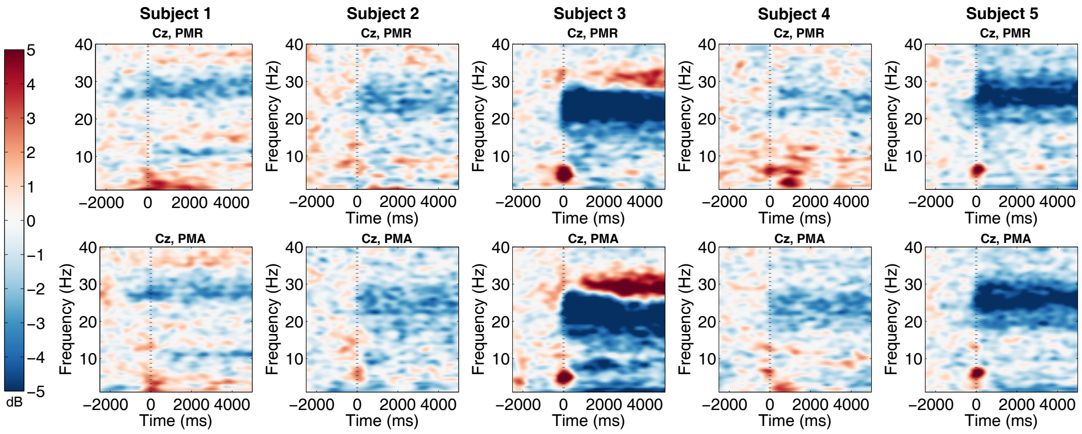

Figure 1: ERSP maps for all subjects, for electrode Cz. Upper plots show ERSPs for the PMR condition, and the lower ones for the PMA condition.

In Fig. 2 we present the cross-validated classification accuracy for different spatial filter choices. The results show that it was possible to discriminate between the PMA and PMR conditions significantly above chance level for all the subjects with a suitably chosen spatial filter. The average accuracy for the best performing design (with 30 channels and Laplacian spatial filter applied) was 75%. Given the small sample size, the average results should be taken with caution, but they do seem to suggest that it is beneficial to also include channels other than those over the motor cortex.

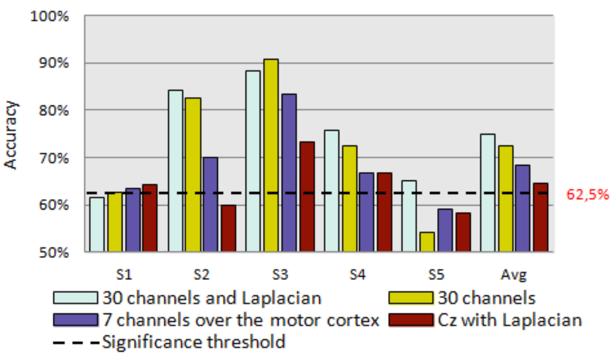

Figure 2: Mean cross-validation accuracy of classifiers with different spatial filters. The dashed line marks the significance threshold for a binomial test (at $\alpha = 0.05$ significance level and with Bonferroni correction).

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4 Discussion

For a sample of five subjects we found that it is possible to discriminate between attention and mind wandering during passive movement of lower limbs. With a simple BCI design based on bandpower features we were able to obtain average accuracy of 75% on single trials, in line with results for upper limbs by [1]. However, time-frequency analysis suggested different levels of SMR (de)synchronization for only two subjects.

While we tried to model realistically attention during rehabilitation, the "stop-go" nature of the trial-based experiments might not be very conducive to mind wandering. Also, unlike in our experiment, mind wandering is usually not intentional. Therefore, the experimental protocol we propose should be validated as a calibration session for an online BCI with continuous feedback. Our results also suggest that it is beneficial for classification to include features not only from the channels over the motor cortex. The question of whether the classifier is using class-specific information from other brain regions, or is using the additional features to cancel out class-unrelated noise, is left to be answered by future studies with source localization techniques. Another possibility is the existence of an uncontrolled confound in our experimental design – we find this explanation unlikely, due to the fact that the trials had the same external stimuli, and were semi-randomized.

Our future research efforts are motivated by several observations from this study: the subjects might have difficulties in complying with the protocol (inability to ignore the movement or to attend to it consistently); there might be discriminatory information in regions other than the motor cortex, and in frequency bands other than the alpha and beta bands; there is considerable variation in performance from subject to subject. We intend to address this questions, respectively, by using the proposed protocol as a calibration session for online BCI operation, by using optimized spatio-spectral features, and by analyzing subject-to-subject and session-to-session transfer of knowledge.

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