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CLOSING ONE'S EYES AFFECTS AMPLITUDE MODULATION BUT NOT FREQUENCY MODULATION IN A COGNITIVE BCI

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ABSTRACT: Cognitive brain-computer interfaces (BCIs) are an auspicious alternative to BCIs based on motor tasks for severely paralyzed patients, e.g., those in late-stages of amyotrophic lateral sclerosis. These patients, however, are often not able to volitionally control their eye lids: Undeliberate eye opening and closing affects modulation of theta- and alpha-rhythms, which impairs decoding performance in cognitive BCIs. Here, we demonstrate on EEG data recorded from nine healthy subjects that a cognitive BCI based on task-induced modulation of the frequency of the parietal alpha-rhythm is more robust to eye lid movements than a BCI based on amplitude modulation. Specifically, we instructed subjects to either open or close their eyes while performing cognitive tasks, and show that closing their eyes decreases decoding performance relative to the eyes-open condition for amplitude modulation but not for frequency modulation features. This insight has important consequences for the design of cognitive BCIs for severely paralyzed patients.

INTRODUCTION

Humans' capability to interact with the environment – whether via motion, sensation or communication – relies on the precise control of muscles. Several diseases may impair the capabilities of control. Temporary or partially reversible disturbances up to a complete degeneration of the necessary structures in the central nervous system can be the consequence in which case the (complete) locked-in state ((C)LIS) is the inevitable final condition of the patient [1].

In this condition the only remaining devices for communication are brain-computer interfaces (BCIs). Most of the well-established designs, however, trigger neural activity in brain areas that are impaired in some of these patients [2]. Amyotrophic lateral sclerosis (ALS) is characterized by a creeping degeneration of the upper and lower motor neurons impairing motor control already at the central level and hence neural activity therein [3, 4]. As well, long-lasting paralysis as a consequence of disorders on lower levels of motor control may likewise affect processing in central regions due to neuroplastic changes that result from omitted afferent projections [5–7]. It is apparent that under these circumstances motor imagery based BCIs are likely to be compromised. Because P300 speller systems [8] indirectly require motor control to shift the visual attention, they are, however, likewise affected. The degeneration of neurons in central sensorimotor areas may eventually impair the ability of oculomotor control [9] completing the locked-in state [10] and impeding the use of BCIs that directly or indirectly involve motor areas [11].

For these patients another class of BCIs, one that lacks any involvement of the very areas, is necessary in order to have a chance of establishing communication. Cognitive tasks that involve the imagination of goals of movements [12], language processing [13], working memory [14–16] and internal self-referential attention [17, 18] share this characteristic and have been shown to provide neural modulations useful as control signals. The big advantage of the cognitive strategy over another sensorimotor free approach – learning volitional control over certain neural activities through neurofeedback training [19, 20] – is that it can be used intuitively. Tasks like mental calculation, the imagination of words or remembering one's own past are convenient, under precise conscious control and feasible without training.

Functional MRI studies indeed suggest that performing tasks of this kind induces modulations of large-scale cortical networks which exhibit correspondent alterations in the ECoG and EEG signal [16, 21, 22]. Topographies show the involvement of frontal and parietal regions in line with networks related to higher cognitive functions like working memory, attention and self-referential thinking [14, 23, 24].

Despite this encouraging perspective, online communication with a CLIS patient using any of these tasks in an EEG- or even in a less artifactual ECoG-based BCI has failed to date [11]. A potential cause is directly related to the impairment and eventual complete loss of volitional eye(lid) movements once the CLIS state is entered [9, 10]. In this condition erratic and undeliberate eye closing and opening is likely to occur. Given the vast differences in the electrophysiological patterns resulting from closed and open eyes, it may likely be that classification accuracies based

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on these signals do not remain unscathed.

The most prominent electrophysiological change that accompanies eyes closed periods is the power increase in the alpha band of the EEG in occipital visual areas [25]. More elaborate investigations revealed, however, that the power of all of the common EEG frequency bands in virtually all brain regions is modulated and that a restriction of functional effects to visual processing is unlikely [26]. Specifically, Geller et al. found that besides alpha's up-modulation in occipital regions it is likewise affected in parietal regions and that a spatially diffuse low-frequency power increase (delta to beta) is accompanied by a high-frequency (gamma) decrease in some areas [27]. This indicates effects on large-scale cortical networks whose modulation is intended by cognitive BCIs.

The specific paradigm under investigation in the present study utilizes activation and deactivation of the default mode network (DMN) triggered by self-referential thinking and mental calculation [18]. The DMN is a prominent example of a large-scale cortical network whose discovery is directly associated with the recording of brain activity during closed eyes conditions (EC) [24]. Since the common feature used for classification in BCIs is task-induced amplitude modulation (AM), the aforementioned may pose a significant problem for cognitive BCIs aiming to establish communication with patients lacking control over their eyelids. In that light, an interference between modulations induced by cognitive tasks and an EC-induced activation appears to be likely.

Recently, another property of the EEG signal was described to be similarly informative as AM in the context of BCIs. Jayaram et al. found that task-induced shifts of the pronounced peaks in the power spectra of EEG signals (FM) can be used to predict task conditions in motor imagery as well as in cognitive BCIs [28]. This finding provides a promising perspective for the design of communication systems for severely paralyzed patients. Here we test to what extend AM and FM based classification in a cognitive BCI is affected by the EC condition and whether this condition leads to structural differences of the task-induced AM compared to the open eyes condition (EO).

MATERIALS AND METHODS

Experimental Paradigm: The mental tasks performed by the participants were identical to those described in [18]. The experiment was composed according to a randomized block design. Each block consisted of $10+10$ randomized trials in which participants had to either memorize a personal positive experience or perform a mental subtraction task (trial-conditions). In total, four of these blocks had to be completed. During two of them participants were asked to keep their eyes open and during the other two to keep them closed (block-conditions). The order of block-conditions was randomized for each participant. Each trial started with the instruction to either recall a positive memory or successively subtract a given one-digit number from a given three-digit number. Trial length without instruction time was 35 s. Instructions were presented both visually and vocally on a computer screen and via headphones. Before each trial, a 5 s pause separated it from the preceding one. Experiments always began with 2×5 min of consecutive resting state recording, one in EO and the other in EC condition. During these participants were asked to relax and let their mind wander at will. Following, the experimental blocks began between which participants were allowed to have a break if desired.

Data Acquisition: The study was conducted at the Max Planck Institute for Intelligent Systems in Tübingen. Ten healthy subjects (5 female, 5 male) with a mean age of 26 ± 3 years participated and received an allowance of 12 € per hour. Before the start of the experiment participants had to fill out a consent and a questionnaire asking personal data, former experience with the use of BCIs, the presence of neurological disorders, drug abuse and level of fatigue. The experiment started after a detailed explanation of the task and a demonstration of the stimuli. Participants were seated in a chair at a distance of 1.25 m to the screen and asked to remain as still as possible and to minimize eye blinks during trials.

EEG was recorded at a sampling frequency of 500 Hz using actiCAP active electrodes (124 channels) and the BrainAmp amplifier (BrainProducts GmbH, Gilching, Germany). Electrodes were mounted according to the extended 10-20 system with the left mastoid electrode as the initial reference and the AFz-electrode as ground. Before data analysis, recordings were re-referenced to common average. Data streams were digitized and stored via OpenViBE [29], stimuli were implemented using a custom BCI GUI. After each experiment behavioral questions were asked to rate the perceived difficulty of performing the tasks in the different conditions on a scale between 1 and 10.

Data Analysis: Preprocessing of the data included band-pass filtering between 0.1 Hz to 45 Hz. Visual inspection lead to exclusion of one participant due to an abnormal shape of the power spectrum. No further artifact reduction was performed since the frequency band of interest is largely robust against the main sources of EEG artifacts [30]. Bandpower modulation and frequency modulation for each channel and trial were computed for the common alpha band (8 Hz to 13 Hz). The former via FFT and the latter according to the method described in [28]. This method relies on the analytic signal which is obtained through the Hilbert transform and provides

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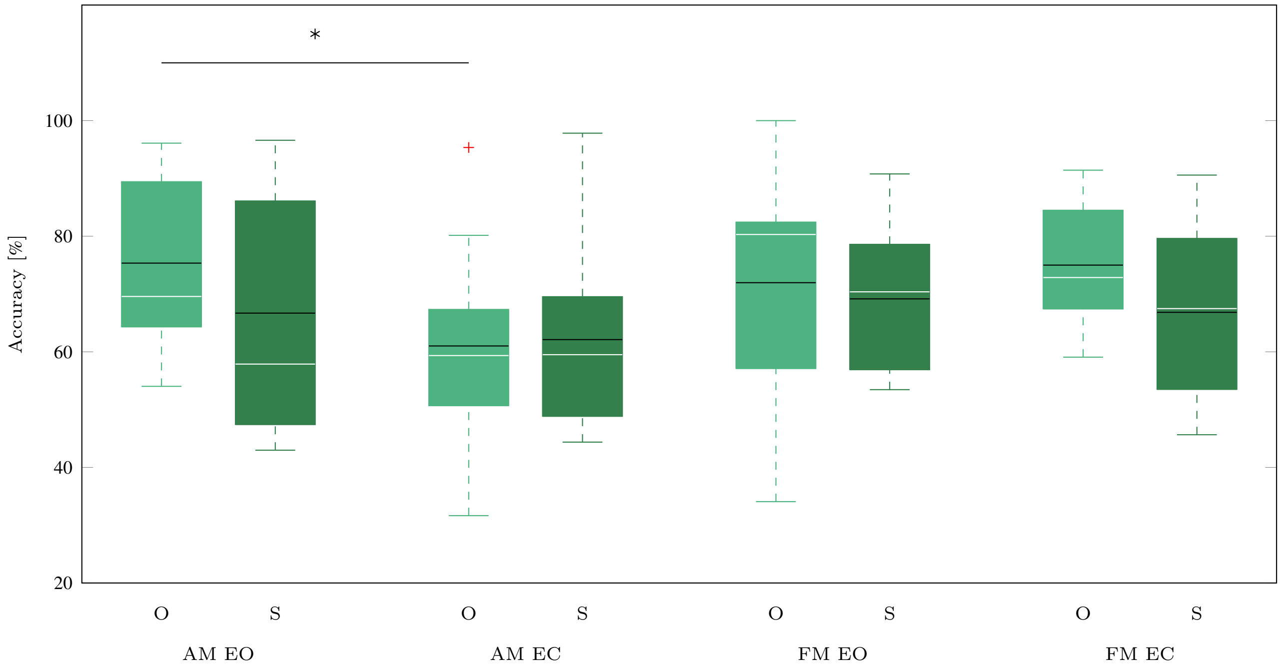

Figure 1: Distributions of the performance across participants for the different features (AM/FM), block- (EO/EC) and classification-conditions (O/S). Black lines mark the mean and white the median accuracy. Difference between AM EO O and AM EC O is significant ($p_{median} = 0.038$).

phase information. Derivation of the instantaneous phase with respect to time yields the instantaneous frequency. To obtain the location of a trial's alpha peak its data was band-pass filtered between the alpha band and the median of each data point's estimate used as the instantaneous frequency of that trial. Linear discriminant analysis was used for classification. According to the paradigm's underlying hypothesis concerning the involved brain areas, classification was based on channel Pz and channel Fz providing a two dimensional feature space. Classification accuracy of each participant and condition was computed by 100 repetitions of 10-fold cross validated LDA (random split). Mean values across repetitions are reported. To test the significance of classification against chance level permutation tests were used, i.e. class labels were randomly permuted 1000 times and for each iteration the classification accuracy was calculated again. The fraction of values greater than or equal to the original accuracy constitutes the p-value. An analog procedure was used to test the differences between conditions. Here the difference between the means across participants of two conditions was used as test statistic and its value was calculated 1000 times by randomly splitting the combined set of accuracies into sets of equal size. The fraction of differences greater or equal to the original difference constitutes the p-value. Permutation tests were calculated for each of the LDA repetitions separately yielding distributions of p-values for each comparison whose median value is the reported.

To further probe the differences between the block-conditions the classification accuracies obtained by using the condition's own classifier, i.e., training and prediction based on the same data set (O condition), and the accuracies obtained by swapping the classifier (S condition), i.e., training on the EC data and predicting EO data and vice versa, were compared. Perceived difficulties of the tasks in different conditions were compared using the non parametric Wilcoxon rank sum test.

RESULTS

Average performance across participants of all conditions was significantly above the chance level of 50 % (p-values not reported here). Fig. 1 shows the accuracy distributions across participants for each block- and classification-condition based on AM and FM within the alpha band at channels Pz and Fz.

Table 1: Mean (top) and median (bottom) accuracies across participants separated by trial- and block-condition in correspondence with Fig. 1 (values in [%]).

AM EO		AM EC		FM EO		FM EC	
O	S	O	S	O	S	O	S
75.3	66.7	61	62.1	72	69.2	75	66.8
69.6	57.9	59.4	59.5	80.3	70.4	72.9	67.5

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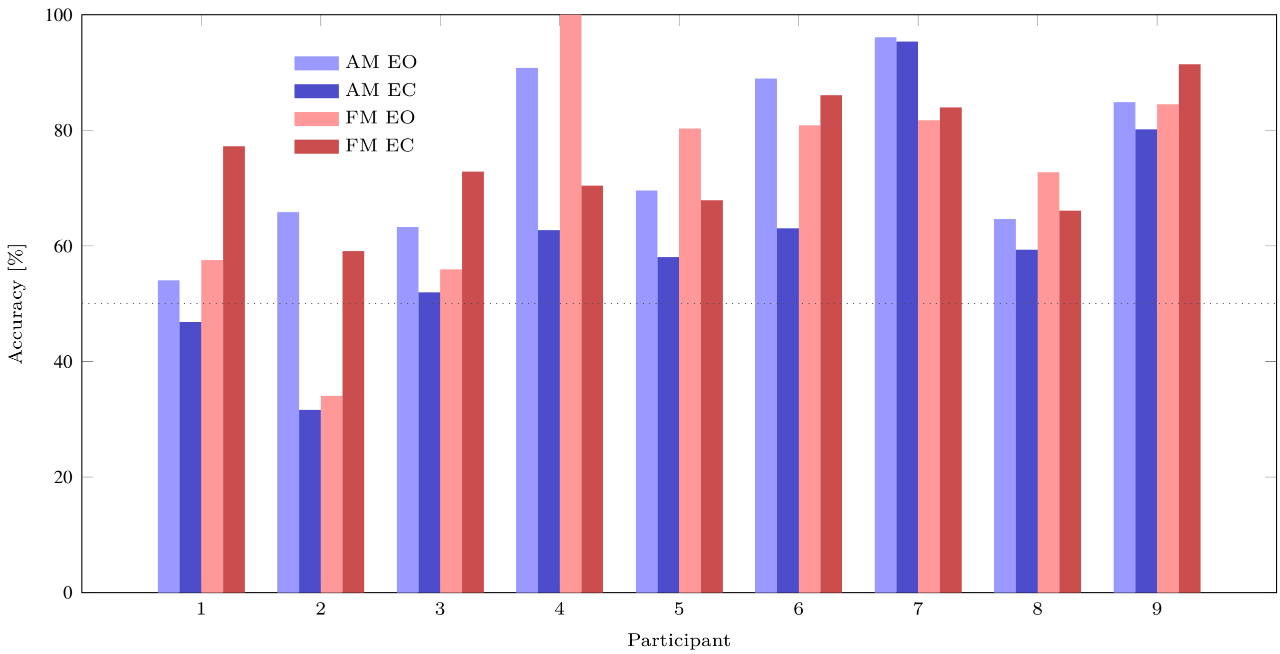

Figure 2: Individual performances separated by feature and block-condition. Dashed line marks chance level. AM EO: amplitude modulation in the eyes open condition. AM EC: amplitude modulation in the eyes closed condition. FM EO: frequency modulation in the eyes open condition. FM EC: frequency modulation in the eyes closed condition.

Tab. 1 shows the corresponding mean (top) and median (bottom) values. A significant difference between the EO and the EC condition was observed if classification was based on the AM feature in the O classification-condition (72 of the 100 p-values obtained by LDA iterations were smaller or equal to 0.05, $p_{median} = 0.038$). No significant differences were found neither between block-conditions if classification was based on the FM feature nor between the O and S classification-conditions of both features. Importantly, classification performance based on FM is on average roughly the same as based on AM, though, considering the individual accuracies shown in Fig. 2, the feature which performs better varies from participant to participant.

Analysis of the behavioral data suggested no difference in the perceived difficulty of performing the memory or the mental calculation task in EO or EC conditions ($p_{Memory} = 0.53$, $p_{Calculation} = 0.85$).

DISCUSSION

We could show that discriminability between trials with mnemonic content and those without based on AM in the common alpha range significantly drops in the EC condition compared to the EO condition. This is not the case for classification based on FM; here distinguishability between trial-conditions is roughly the same in the EO and the EC condition. Furthermore, classification based on FM meets the level of the well established AM, concerning the median values FM even exceeded AM by more than 10 %, proving it to be a very promising feature for the use in BCIs. Although our initial hypothesis that a classifier trained on trials of the EC condition but applied to EO data performs significantly worse than the condition's own classifier was not met, results still indicate a downswing and, in addition, that the downswing is stronger for AM than for FM (comparing AM EO O/AM EO S and FM EO O/FM EO S in Fig. 1). If significant, this effect would have been evidence for the hypothesis that task related AM exhibits diverging structures in the two block-conditions impairing the classifier and contributing to the failure of current BCI systems to establish communication with patients lacking control over their eyelid movements.

From another perspective, though, the fact that the classifier trained on EC data performed better if applied to EO data than if applied to EC data itself sheds new light on the issue. It suggests that training the LDA model on either EO or EC data resulted in a similarly oriented decision boundary and, hence, that orientation of the task-induced AM in the EC condition was preserved but less pronounced in comparison with the EO condition.

Another possible explanation for the accuracy drop from AM EO to AM EC is that it is more difficult to concentrate on the cognitive tasks during EC periods causing a weaker modulation of the neural activity. The rational behind this explanation is that closing one's eyes might increase the likeliness

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of mind-wandering and/or effects of fatigue leading to a weaker involvement with the tasks. However, probing the ratings of perceived difficulty to that effect suggests no difference between block-conditions. Furthermore, in the case of a behavioral cause the accuracy drop in the EC condition should likewise be observable if classifying the FM feature. Taken together, these arguments speak in favor of a genuine effect within the alpha band caused by an interference of the EC related up-modulation and the task-induced modulations.

The strong up-modulation of the alpha band during EC periods is a result of a corresponding synchronization of neural activity. A straightforward explanation for the observed drop is, hence, that alpha synchrony is largely saturated during the EC condition and that modulation atop triggered by the cognitive task is therefore less effective. This is in line with the hypothesis that the orientation of the modulation is preserved in the EC condition but less pronounced. An interference of that kind is supported by fMRI studies suggesting effects of EC periods on the topology of large-scale networks [31,32]. Xu et al. report that the EC condition leads to a higher global processing efficiency compared to EO and relate this to an activation of the "introceptive" network which includes the DMN. Including the assumed correlates of DMN activation in the EEG [17,33] these findings provide neurophysiological evidence.

In light of this argumentation it remains unclear why classification is not impaired if based on FM. Assuming the activation of the DMN along with EC as well as along with self-referential thinking and further that this activation reflects in an alpha power increase in either case it may be expected that FM would suffer the same fate. Nonetheless our results indicate a dissociation between AM and FM which can be explained by three settings. First, there is one neural network whose activity is likewise triggered by the EC condition and by the task but unlike AM task-induced FM is effective atop EC-induced effects. Second, there is one neural network but FM is only induced by the tasks and not by closing and opening the eyes, or third, there are two distinct neural networks involved one of which features AM and the other FM. Considering a study by Thuraisingham et al. the second option can likely be rejected. Estimating the instantaneous frequency of EEG recordings during EO and EC conditions via an Hilbert-Huang transform they were able to distinguish with an high level of accuracy between those two conditions [34]. This points to the significance of our results. As in contrast to AM, the task-induced FM withstands the block-condition related FM described by Thuraisingham et al. – whether because of the involvement of two distinct neural networks or whether effective modulations atop the EC-induced modulation –, FM should be among the routinely considered features when designing communication systems for severely paralyzed patients.

CONCLUSION

Frequency modulation appears to be a more consistent feature than amplitude modulation across eyes open and eyes closed periods in a cognitive BCI that relies on modulations of parietal alpha rhythms. This property might help to improve BCI systems for patients who lost control over oculomotor functions.

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