Head and eye movements influence the decoding of different reaching directions from EEG

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***Abstract*—Electroencephalography (EEG)-based brain-machine interfaces (BMI) have been proven effective for motor rehabilitation of severely paralyzed patients. The brain activity is classified and translated into a go vs no-go feedback (i.e., mobilizing, or not, the paralyzed limb). Patients performing the same movements but unrelated to their brain activity showed poorer or no recovery, which suggests that an accurate feedback expedites motor recovery. Being able to decode different movements from the EEG would allow providing a more accurate feedback, maximizing the rehabilitative potential. However, a dynamic rehabilitative environment with different types of movements would likely be accompanied by involuntary motions with the eyes and the head, which can contaminate the measured EEG signals. In this study we analyze how external movements associated with the task (i.e., eye or head movements) influence the performance of an EEG-based decoder of reaching movements. Our results reveal that different reaching directions could only be decoded when eye and head movements occur and only using low frequency features (delta band). In summary, this paper highlights the importance of carefully designing protocols to avoid eye and head movements to contaminate EEG signals.**

I. Introduction

Brain-machine interfaces (BMI) for motor rehabilitation of severely paralyzed patients have been proven to be effective [1]. Those studies showed that linking brain activity with the actual movement of the paretic limb promotes neuroplasticity, leading to motor recovery [2]. The electrical activity produced by the brain is recorded, usually in a non-invasive way via electroencephalogram (EEG), and translated into a binary feedback (i.e., go/no-go). Therefore, when patients try to move, an external rehabilitative device mobilizes their paralyzed limb, linking their brain activity and the actual movement. Importantly, other patients that received a sham feedback (i.e., same amount of time receiving therapy but unrelated to the brain activity) presented poorer or no recovery[1], [3]–[5]. Those findings highlight the importance of the link between brain activity and movement, and suggest that a more accurate feedback might boost the rehabilitative outcome of those interventions.

Extracting more detailed information about the movement performed would allow providing a more accurate feedback, potentially boosting the benefits of such an intervention. Previous invasive studies have already shown that directional information of reaching movements can be extracted from delta (<4 Hz) band [6]–[9]. Although this information could also be measured with EEG, several aspects have to be taken into account when interpreting those signals. Firstly, brain activity captured via EEG presents a much lower signal-to-noise ratio (SNR), leading to a less discriminant activity. More importantly, EEG recordings are easily contaminated by other external activity like eye or head movements (head and neck muscle activity and movement of the sensors and cables). Additionally, these contaminations mainly affect the delta band [10], [11]. This external activity can be substantially reduced by instructing the subjects. However, this approach can hardly be applied in rehabilitative BMI interventions with patients since overloading the task with too many instructions might compromise its outcome.

Recent offline studies have shown that the decoding of movements from the same limb can be performed using EEG. These findings represent an encouraging achievement that might take rehabilitative interventions to the next step. However, none of those methods has been applied in an online application so far. However, understanding how head and eye movements affect the decoding might be critical before moving these findings to practical applications.

The objective of this study is to analyze how involuntary movements associated with the task (i.e., eye or head movements) influence the performance of an EEG-based decoder to classify reaching movements. To do so, we compared the performance of a state of the art classifier when the task is performed under two conditions: one in which subjects were instructed not to move the head or eyes during the task, and other one in which subjects were free to follow their arm movements with their gaze and head orientation.

II. Methods

A. Experimental setup

Five right-handed healthy subjects (2 females, mean age 30,2 ± 3,4 years) without any neurological disease history participated in two experimental sessions. During the experiments, the subjects were comfortably seated in a chair with their right hand attached to a 7 degrees of freedom (DoFs) arm exoskeleton (Tecnalia, San Sebastian, Spain) and wearing an EEG cap (see Figure 1a). Subjects were instructed to perform reaching movements towards four different directions under two conditions: one in which the subjects were deliberately instructed to avoid head and eye movements during the task (constrained condition), and one in which they could perform the task freely, following their arm movements with their gaze and/or head (unconstrained condition—as patients would do during a rehabilitative intervention). In each session, the subjects performed 20 center-out reaching movements, divided in 5 runs of 5, to

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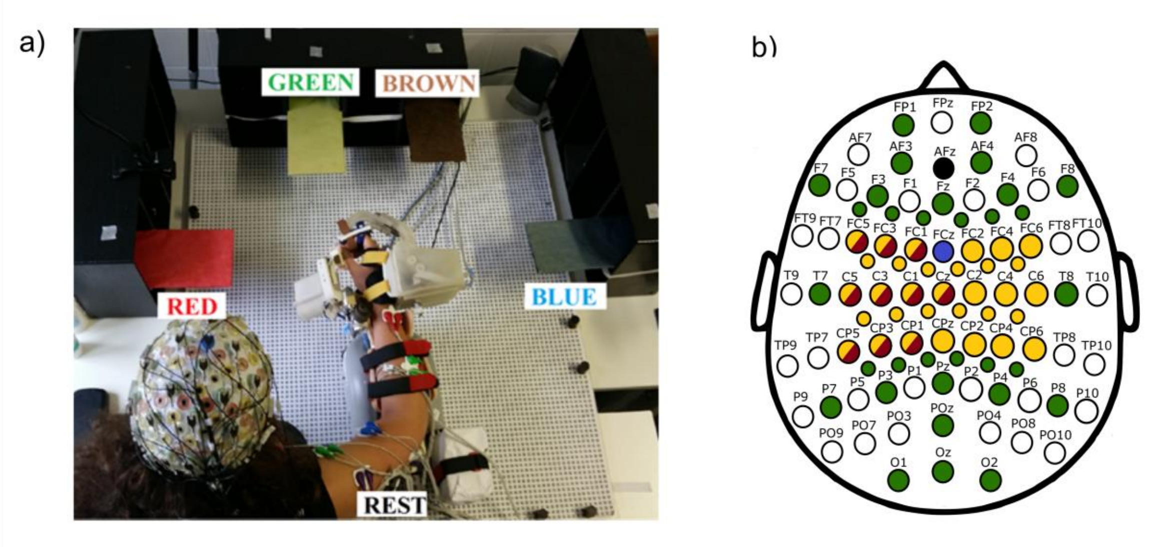

Figure 1. (a) Experimental set-up. Subject wearing the exoskeleton while performing a reaching movement towards the green target. (b) EEG montage. Electrodes included in the recording displayed in green color. Yellow color indicates the electrodes used for the CAR filter. The electrodes colored as red, further referred as contralateral motor cortex electrodes, were used for the subsequent feature extraction and classification processes.

each of the four targets placed in front of them. The task onset, as well as the target to be reached, was presented to the subject via auditory cues, according to the following trial structure: a rest period of 2-3 seconds was followed by an auditory cue indicating the color of the target to be reached. Two seconds after, a "go" cue indicated the beginning of the movement. Subjects had 3 seconds to reach the target and go back to the initial position. Thus, trials had an average duration of 7.5 seconds.

B. *Data acquisition*

The EEG data was recorded from 64 channels (ActiCap, Brain Products GmbH, Germany) following the montage shown in Figure 1b, with AFz and FCz as ground and reference, respectively. Electrooculographic activity (EOG) was recorded using four passive electrodes. The impedances of EEG and EOG signals were kept below 5 kΩ during the recording sessions. EEG data was recorded at 1000 Hz (BrainAmp, Brain Products GmbH, Germany). Additionally, kinematic activity from the 7 DoF of the exoskeleton was recorded from its sensors at 18 Hz. Before any other preprocessing, kinematic activity was resampled to 1000 Hz using cubic interpolation to match the EEG and EOG signals.

C. *Preprocessing and onset extraction*

EEG signals were downsampled to 100 Hz after applying a 45 Hz low-pas filter (4^{th} order Butterworth). Subsequently, signals were re-referenced by using a customize common average reference (CAR): from all the channels independently, we subtracted the mean of all the channels placed over the motor cortex (see Figure 1b). The trials were aligned based on the movement onset extracted from the kinematics of the robot. Thus, the onset was set when the kinematic activity showed activation above 5% of its maximum activity during this trial (similar to [12]).

D. *Feature extraction*

Two one-second epochs were extracted per trial: one between -5 and -4 seconds to characterize rest and one between 0 and 1 second to characterize movement (being t = 0 the kinematic onset). Features were extracted from the electrodes placed over the contralateral motor cortex (Figure 1b). To analyze how head and eye movements affect different features commonly used in BMI, we analyzed separately two features: the movement related cortical potentials (MRCP) and the event-related desynchronization (ERD) of the alpha and beta rhythms [13], [14].

MRCP: The EEG signals were band pass filtered ([0.05-2] Hz) using a 1st order Butterworth following [15]. After that, temporal features were extracted by downsampling the epochs to 10 Hz, therefore obtaining 10 features per electrode. Note that, to avoid the effect of the transient response of the filter, the signals were filtered before extracting the epochs (therefore this effect is produced only at the beginning of the signal instead of in all the epochs).

ERD: After multiplying the epochs by a Hamming window, a 16th order autoregressive model was solved using Burg's algorithm to calculate the power spectral density (PSD). Posteriorly, the mean logarithmic power for the alpha (([7-13] Hz) and beta ([14-25] Hz) bands was computed, resulting in a set of 2 features per electrode.

E. *Classification and metrics*

We configured two different classifiers: a binary classifier to discriminate movement execution from rest and a multiclass classifier to decode the 4 different reaching movements. Notice that, while the binary classifier was trained using the two epochs previously described, the multiclass was trained only with the epoch between 0 and 1 second (since this is the epoch that contains brain activity related with the reaching movements). For both classifiers, a linear support vector machine (SVM) was implemented. To assess the performance of the classifier, a block-based N-fold cross validation procedure was implemented. Four blocks (160 trials, 320 epochs) were used to train the classifier, and the remaining one (40 trials, 80 epochs) was kept for testing. The features were z-score normalized, resulting in a set of values with zero mean and unit variance. Mean and std values extracted from the training set were used to normalize the epochs of the test set. For all the trials assigned to the test dataset, the epoch between 0 and 1 (being t = 0 the kinematic onset) was classified by the binary and the multiclass classifiers independently. For both of them, the percentage of epochs correctly classified was computed to evaluate the performance of the classifier. Thus, for the binary classifier, this metric represents the percentage of movement executions correctly detected, and for the multiclass classifier, the percentage of reaching movements correctly decoded. This process was repeated iteratively so that all the blocks were included once in the test set.

F. *Artifact rejection methods*

To study if the presence of these contaminations affects the performance of the decoder, we applied state of the art artifact removal techniques. First, ocular artifacts were removed by applying a regression-based method. This method cleans the EEG signals by decorrelating EEG and EOG signals assuming that the recorded EEG is a linear combination between both (see [16] for a more detailed description). Secondly, a variance-based method was applied to remove the most contaminated epochs from the training dataset. This method computes the power in delta ([0.1-4] Hz) and gamma ([30-45] Hz) bands, where motion and muscular artifacts occur [11], [17]. Then, an epoch is rejected if any of those two values is larger than three standard deviations from the mean. More information about how to apply this method can be found in [18].

III. RESULTS

A. *Decoding motor execution and reaching directions*

Figure 2a summarizes the performance of the binary classifier for both the constrained and the unconstrained condition. In the constrained condition, using MRCP and ERD features yielded similar results of almost 80% of correctly classified epochs. Similar values were obtained in the unconstrained condition, with almost 80% for both features. Interestingly, the performance for each type of feature was similar between the constrained and unconstrained conditions..

Figure 2b shows the performance obtained by the multiclass classifier under the constrained and the unconstrained condition. In the constrained condition, the performances of the classifier using both features remained at the chance level (i.e., 25 % for 4 classes). In contrast, for the unconstrained condition, the performance obtained using MRCP features reached almost 70%, while the performance of the ERD features presented values at almost chance level.

B. *Influence of artifact removal on performance*

Figures 2c and 2d illustrate the performance obtained with the binary and multiclass classifiers, respectively, after artifact removal. No differences could be observed in the binary classification between MRCP and ERD features for any of the conditions studied with and without applying artifact removal. However, in the multiclass classification under the unconstrained condition, the accuracy showed a drop of 30% when using MRCP features. The results obtained when using ERD features did not vary after applying artifact removal for any of the conditions.

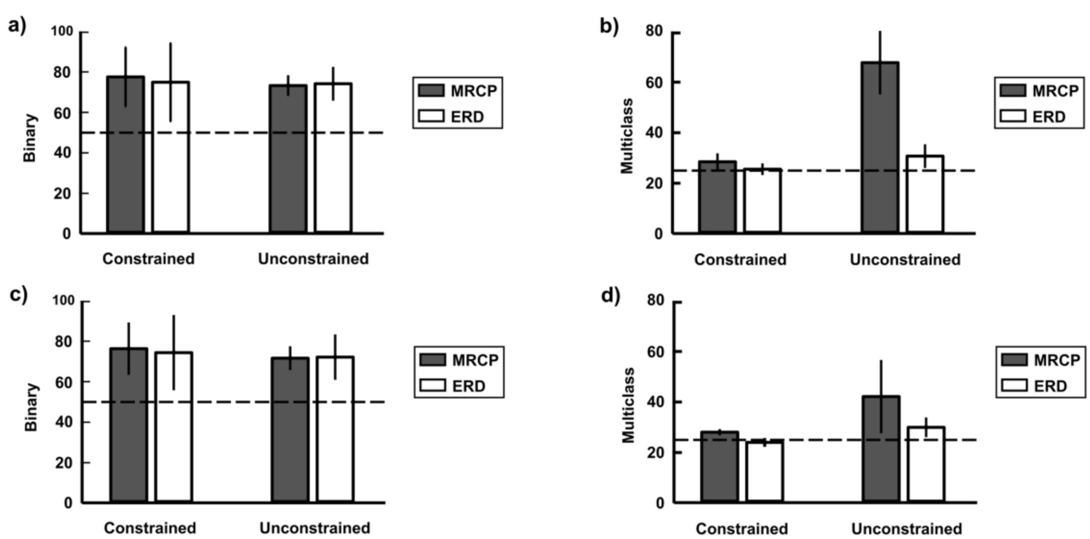

Figure 2. Decoding accuracy of the binary and multiclass classifiers. Gray bars indicate the performance using MRCP features and white bars using ERD. (a) Binary classification results obtained without using any artifact removal technique. (b) Multiclass classification results obtained without using any artifact removal technique. (c) Binary classification results obtained after artifact removal. (d) Multiclass classification results obtained after artifact removal.

IV. Discussion and Conclusion

With a growing interest in EEG-based BMIs to train different movements of the upper limb, the present study investigates how movement-related artifacts (i.e., head or eye movements) influence the output of the BMI. We proposed an investigation in which we compared the decoding results when the subjects avoided moving their head and eyes during the task, versus when they performed the task freely. Furthermore, to recreate a realistic application of a BMI for upper limb, the experiment was performed in a rehabilitative-like setup that includes several reaching movements and a rehabilitative arm exoskeleton. Our results show that reaching movements could only be decoded using low-frequency features, MRCP features, and only during the condition in which head and eye movements occurred and potentially contaminated the EEG signals. Notably, the average performance of the binary did not change between conditions suggesting that the presence of these head and eye movements did not affect the decoding of movement execution.

Applying state of the art techniques to remove the most contaminated epochs lead to very similar results for go vs no-go classification. and only MRCP features in the unconstrained condition lead to a multiclass classification above chance level. However, the performance of the multiclass classification for the MRCP features in the unconstrained condition, in which subjects could move freely, showed a 30% drop in performance when artifacts were removed. The fact that the binary classification was not affected by removing those epochs suggests that the classification is not relying on eye and/or head movement activity to “miss-detect” movement. However, the drop in performance observed in the multiclass classification indicates that this external activity (head and eye movements) is providing discriminative information that can bias the results.

These findings do not imply that different reaching movements cannot be decoded from EEG activity, but underlines the importance of designing protocols so that the influence of such external signals can be controlled. Nonetheless, the here presented analysis was performed under specific conditions (reaching movements) and with a limited amount of subjects and thus these results need to be interpreted with caution.

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