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Classification of hand movements in motor execution and motor imagery tasks from EEG signals recorded with a low-cost recording system

Leonardo D. Ojeda[1], Jhon J. Pabon[1] and Javier M. Antelis[1]
[1]Tecnológico de Monterrey Campus Guadalajara, 45130 Zapopan, Mexico.

***Abstract*— This work studies the classification between rest and movement during motor execution and motor imagery of the left and/or right hand clenching from brain electroencephalography (EEG) signals recorded with a low-cost commercially available EEG recording system. Eleven healthy subjects participated in the study. EEG signals were recorded while the participants executed and imagined left and/or right clenching movements. The results showed the possibility to recognize between resting and movement.**

***Keywords*— Brain-Computer Interface, electroencephalography, motor execution, motor imagery, power spectral density.**

I. Introduction

Brain-Computer interfaces (BCI) have emerged as a new technology that aim to provide people with disabilities a new non-muscular communication channel for sending commands to the external world to control mobility devices [1]. These systems are based on the recording and processing of the brain activity in order to decode the user intention, which is then translated into control signals for a target application such as a spelling device, the control of a computer cursor, a tele-presence robot, a robotic wheelchair or a video game [2], [3], [4]. Most of BCIs are mainly based on non-invasive recording of the brain signals with the electroencephalogram (EEG) technique [5]. This is because this technique provides a unique access to the electrical brain activity with higher temporal resolution. This paper focuses on the study of EEG brain signals in the context of BCI systems.

So far, EEG-based BCI research is mainly focused on developing technology for patients with motor disabilities with diverse origins such as; brain stroke or spinal cord injury. However, most of the applications for these users are still in laboratory settings, in addition, real potential users have no easy access to such technology. Apart from the high complexity in the recognition of the user intention from the EEG signals, this is because EEG recording systems are expensive and not fully portable. For this reason, it is important to study and to validate BCI technology with low-cost EEG recording systems. Some previous works have addressed this research line [6], [7], [8].

To address these issues, this work studies the recognition between rest and movement during motor execution and motor imagery tasks from electroencephalographic signals recorded with a commercially available low-cost EEG system. Eleven right-handed healthy subjects participated in the experiments, which were based on the left- and right-hand execution and imagery of clenching movements. The goal was to evaluate the performance in the classification at the trial level between rest and execution/imagery of the hand movement. Results showed the possibility of using EEG signals recorded with a low-cost recording system that differentiates between rest and movement in motor execution and motor imagery tasks, which could be incorporated in brain-computer interface applications out of laboratory settings. The manuscript is organized as follows: section II describes the methods, section III describes the results, and finally section IV presents the conclusions and future work.

II. Materials and Methods

A. Participants

Eleven healthy students (nine males and two females) of the engineering school were recruited to participate in this study (age range, 20-24 years; mean $\pm$ std, 22 $\pm$ 2 years). All recruited participants were right-handed and had previously never participated in BCI or EEG recording experiments. All participants were duly informed about the content and aims of the study and consent forms were obtained from all of them.

B. Experiment

During the execution of the experiment, participants were comfortably seated in front of a computer screen with both forearms resting on their lap. Figure 1 shows a snapshot of a participant while performing the experiment. The whole execution of the experiment was controlled by visual cues presented on the screen, which instructed the participants in the execution of the task and sent synchronization signals to the EEG recording system. The experiment consisted of several trials in two different conditions: (i) motor execution of the left hand or right hand (clenching) at a natural and effortless speed, and (ii) motor imagery of the left hand or right hand (clenching) at the same natural and effortless speed. Prior to the execution of the experiment, the experimenter instructed the participants by describing the movements while executing or imagining them.

Each trial consisted of the time sequence depicted in figure 1. The first cue instructed the participants to rest and to adopt the initial position, which lasted three seconds (rest phase). The second cue randomly displayed an arrow pointing to the left or to the right and indicated the participants to perform the movement (motor execution or motor imagery) of the corresponding hand during three seconds (movement phase).

The last third cue indicated to the participants that they could relax and blink while maintaining the initial position, which also lasted three seconds (relax phase). Between the time of the first and third cues (rest and movement phases), participants were instructed to avoid blinking and perform movements with the eyes, head, arms or legs.

For each participant, the experiment was executed in four blocks (two blocks for each experimental condition) each including fifty trials, resulting in a total of two hundred trials (one hundred for each condition) of nine second each. After each block, participants were encouraged to rest as long as necessary to avoid fatigue.

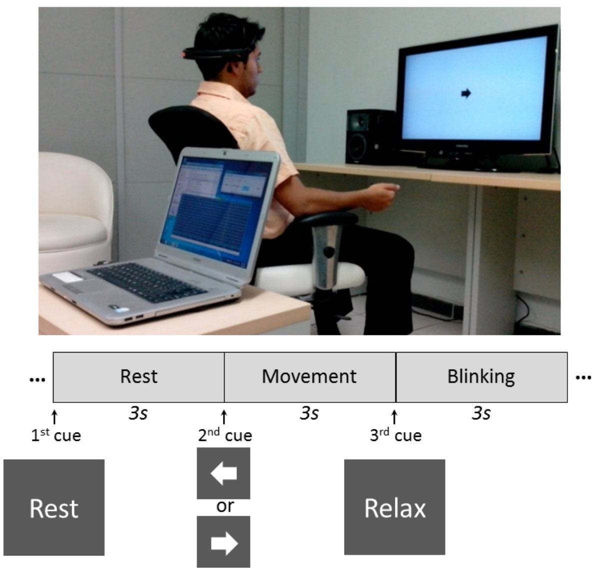

Fig. 1. Top: Snapshots of the experimental setup showing a participant with the EEG recording system while performing the experiment. Bottom: Temporal sequence of one trial during the execution of the experiment.

C. Data Recording System

EEG signals were recorded from 14 scalp locations according to the international $10/20$ system using the low-cost commercially available Emotiv EPOC Neuroheadset system. Signal were recorded at a sampling frequency of $128Hz$ with two reference electrodes CMS (on the left side) and DRL (on the right side), and no filtering was applied. The impedance for all electrodes was kept below $5k\Omega$. During the whole execution of the experiment this process was controlled by the experimenter. The signal acquisition and the visual application that controlled the execution of the experiment were developed under BCI2000 platform [9].

D. Data preprocessing

For each participant, the EEG signals were segmented in trials of 9 seconds using the second cue as reference, therefore; each trial lasted from -3 to 6 seconds. Visual inspection was applied to all trials and trials contaminated with electrooculographic (EOG) or electromyographic (EMG) activity were discharged. Subsequently, each trial was trimmed from -3 to 3 seconds, thus the time interval $[-3, 0)s$ corresponds to the rest phase while the time interval $[0, 3)s$ corresponds to the movement phase. EEG signals were bandpass-filtered from 0.5 to $60Hz$ using a zero-phase shift filter and common average reference (CAR) filter. After this preprocessing, on average 90 ± 7 trials (minimum of 83 and maximum of 96 trial) per participant and condition were kept and used for further data analysis.

E. Data analysis: r-squared

The differences of the power spectral density (PSD) between the rest and the movement phases were evaluated separately for each experimental condition using the r-squared analysis [10]. The power spectral density was computed from the EEG activity of each electrode (separately for each trial in both, the rest phase and movement phase) for the frequency range between 2 and $40Hz$ at a resolution of $1Hz$ using the fast Fourier transform (FFT) with overlapping Hamming-windowed epochs. Finally, the r-squared values for each electrode and frequency were computed as the square Pearson's linear correlation coefficient between the values of the power spectral density and the labels of -1 and $+1$ for the rest phase and the movement phase, respectively.

F. Features and classification

The aim for each experimental condition was to recognize separately, between rest and movement (i.e. to identify at the trial level whether the user is resting or executing/imagining the hand clenching).

Features were computed using the power spectral density (PSD) as done for the r-squared analysis. Features computed in the rest phase ($[-3, 0)s$) were labeled as $rest$ while features computed in the movement phase ($[0, -3)s$) were labelled as $movement$. The power spectral density of frequencies contained within the $\alpha : [8 - 14]Hz$ and $\beta : [15-30]Hz$ motor-related frequency bands presenting the highest r-squared values were selected by visual inspection for each participant, electrode and experimental condition. Finally, features were z-score normalized.

The classification model was based on the Support Vector Machine (SVM) technique as this classifier is extensively used in EEG-based motor tasks recognition [11]. We assessed the SVM with a Radial Basis Function Kernel with hyper-parameters set to $C = 1$ and $\sigma = 0.5$ using the freely-available LIBSVM software package [12].

G. Evaluation Process and Metrics

The classification between $rest$ and $movement$ was assessed using each channel individually, the full set of 14 channels and the subset of 6 channels that presented the higher r-squared values and are closest to the motor cortex ($FC5$, $FC6$, $F3$, $F4$, $F7$ and $F8$). Thus, sixteen classification scenarios were evaluated for each subject and experimental condition.

The performance of the classifier in each scenario was assessed by a ten-fold cross-validation procedure individually for each participant. In each case, the total set of trials was sampled without replacement to construct a mutual exclusive training and testing folds. The cross-validation procedure was complete when all ten combinations of train and tests sets were validated. To measure performance in each fold, the decoding accuracy or DA was computed as the percentage of correctly predicted trials.

The statistical significance of the DA was assessed using the binomial cumulative distribution at the $\alpha = 0.05$ significance level [13]. This level provides the boundary from which the DA is statistically significant above chance level, which is important as the chance level is sensible to the number of trials.

III. RESULTS

A. Data analysis

The r-squared analysis of the EEG activity revealed differences, for both the resting and the movement conditions. These results, across all subjects and trials, are presented in figure 2. This analysis shows differences in the power spectral density between the rest phase and the movement phase mainly in frontal and frontal-central electrodes ($FC5$, $FC6$, $F3$, $F4$ 78 and $F8$, which are the closest to the motor cortex), and in the motor-related frequency bands (between $10Hz$ and $30Hz$). Importantly, note that these differences are stronger in the movement execution condition than in the movement imagery condition.

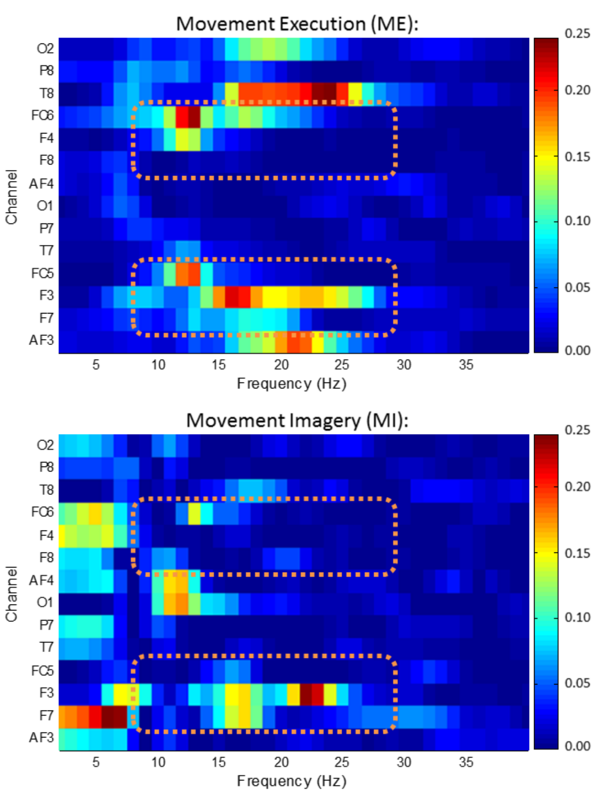

Fig. 2. r-squared analysis across all subjects and trials for both, movement execution and movement imagery conditions. Results are presented for all electrodes (vertical axis) and from 2 to $40Hz$ at a resolution of $1Hz$ (horizontal axis). In both experimental conditions, differences in the power spectral density between the relax and movement phases are observed in the frontal and frontal-central electrodes and in motor-related frequency bands.

B. Classification accuracy

Figure 3 shows, for both experimental conditions and for all classification scenarios, the decoding accuracy DA results averaged across all subjects. For the movement execution condition, DA is significant above chance level ($p < 0.05$) for all classification scenarios except for electrodes $AF4$ and $P8$. The higher DA is achieved when using the full set of channels and the subset of best channels ($DA = 79\%$ and $DA = 78\%$, respectively), while when using a single channel; the best performance is achieved with electrode $FC5$ ($DA = 69\%$). For the movement imagery condition, DA is significant above chance level ($p < 0.05$) solely when using electrodes $F3$, $O1$, $AF4$, $O2$, the full set of channels and the subset of best channels. As in the movement execution condition, the higher DA is achieved when using the full set of channels and the subset of best channels ($DA = 74\%$ and $DA = 72\%$, respectively). When using a single channel, the best performance is achieve with electrode $AF4$ ($DA = 63\%$). These results also show that irrespective of the classification scenario, the higher classification rates are achieved in the movement execution condition, rather than in the movement imagery condition.

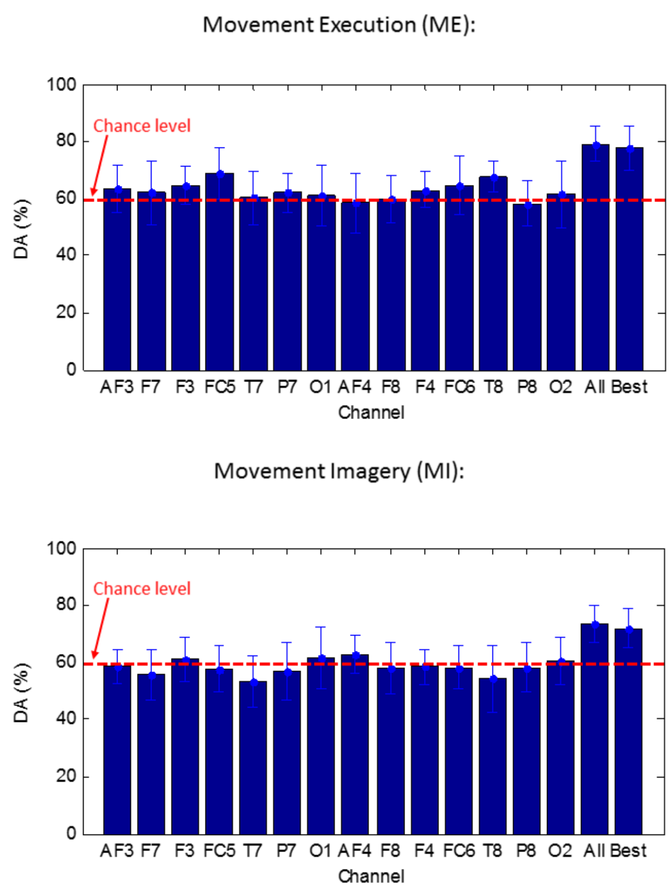

Fig. 3. Decoding accuracy DA results averaged across all subjects for both experimental conditions (movement execution and movement imagery) and for all classification scenarios. In both conditions, the best performance is achieved with the full set of channels and the subset of best channels. Red dotted lines represent the bound for which DA is significant above chance level (59%).

Figure 4 shows, the decoding accuracy DA results for both experimental conditions, averaged across all subjects for the three best classification scenarios: the best channel, the full set of channels and the subset of best channels. In both conditions, the best performance is achieved when using the full set of channels (79% and 74% for movement execution and movement imagery, respectively), while the lower performance is achieved when using the best channel (69% and 63% for movement execution and movement imagery, respectively). In addition, these results confirm that the performance is higher in the movement execution condition (69%, 79% and 78% for the best channel, the full set of channels and the subset of best channels, respectively) than in the movement imagery condition (63%, 74% and 72% the best channel, the full set of channels and the subset of best channels, respectively).

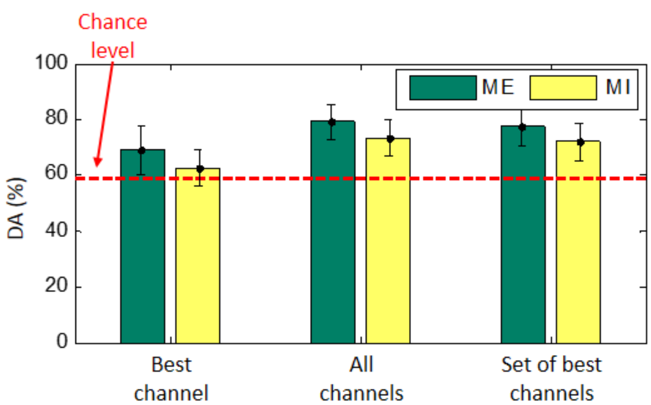

Fig. 4. Decoding accuracy DA results averaged across all subjects for both experimental conditions (movement execution and movement imagery) and for the three best classification scenarios: the best channel, the full set of channels and the subset of best channels.

IV. CONCLUSIONS

This work studied the classification between $rest$ and $movement$ during motor execution and motor imagery of the left and/or right hand clenching from brain signals recorded with a low-cost EEG recording system. Although it is a motor task, wasn't used electrodes on this area, because the EEG system used in the experiments doesn't have it.

On the one hand, the r-squared analysis of the power spectral density of the recorded EEG signals revealed that, in both, hand movement execution and hand movement imagery, the stronger differences between $rest$ and $movement$ are observed in electrodes $FC5$, $FC6$, $F3$, $F4$ $F7$ and $F8$, and in the motor-related $alpha$ and $beta$ frequency bands. Those electrodes are located in the fronto and fronto-central scalp regions and correspond precisely to the closest electrodes of the motor cortex. In addition, the differences between $rest$ and $movement$ are stronger in hand movement execution than in hand movement imagery, this is because the power spectral activity is more prominent during actual movements than during imagined movements.

On the other hand, the classification was evaluated using power spectral features for each channel solely, the full set of channels and the subset of best channels. In both experimental conditions, the higher classification rates were achieved when using the full set of channels and the subset of best channels. In addition, those electrodes that provided the best classification performance were those located closest to the motor cortex. Finally, the results showed that movement execution condition outperforms the movement imagery condition in all the evaluation scenarios, which agrees with the results of the r-squared analysis and is due to the fact that the power spectral activity during movement is more prominent in real movements than in imagined movements.

In summary, this study shows the possibility of using a low-cost EEG recording system to recognize between $rest$ and $movement$ in motor execution and motor imagery tasks, which could be used as the basis for a low-cost and fully portable brain-computer interface, based on motor-related mental tasks. Future work involves the use of the classification model that uses the full set of electrodes to provide two mental commands to control a robotic wheelchair based on motor imagery, as well as the evaluation of the recognition of four motor mental states.

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