XXVI Congresso Brasileiro de Engenharia Biomédica
Armação de Búzios – RJ – Brasil
October 21st to 25th, 2018

Investigation of EEG signals generated by motor imagery for application in BCIs

C M Mendes[1*], C A Stefano Filho[1], G Castellano[1]
[1]Neurophysics Group, IFGW, UNICAMP, Campinas, Brazil
**mendes.caique@outlook.com*

Background, Motivation and Objective. A brain-computer interface (BCI) is a system that measures brain activity in order to translate it into commands that operate an application. Electroencephalography (EEG) has been the most used technique in BCI systems to record brain activity. One of the strategies to generate the signals captured by EEG is motor imagery (MI), that may be seen as the mental rehearsal of a motor task without its execution, allowing, in principle, the control of a BCI device. In this study, we sought to investigate how the brain response of users during MI happens, by analyzing a database of EEG signals in which healthy subjects were asked to imagine the movement of their right and left hands. Our goal has been to recognize patterns associated with this task, through a spectral evaluation of different segments of the signal.

Methods. Sixty-four channel EEG data of eight healthy subjects (7 men, age 24 ± 4 years) were provided by a previous database collected by our group. The project was approved by the local ethics committee and all subjects gave their written consent. The datasets consisted of MI-based acquisitions for right and left hands, with blocks of rest in between. A single task or rest block lasted 10 s, within a set of nine rest blocks and four blocks of each type of imagination per trial – totalizing 170 s for each *run* (Figure 1). The electrodes were distributed on the scalp in a 10/20 positioning system. A standard preprocessing procedure was used for the signals: bandpass filtering (0.5 to 50 Hz), identification and removal of bad channels (channels with a low recording signal-to-noise ratio), exclusion of artifactual portions of the data, and common average reference (CAR) filter. The criteria for the removals were, mainly, visual inspection of extreme amplitudes and/or lack of correlation with other channels. Estimates of power spectral density (PSD) of the signal were calculated per second for μ and β bands (8 to 30 Hz), singly and combined, and then used as features for classification. The classifier used was k-nearest neighbors (k-NN), given the simplicity of its implementation. Since we aimed to analyze different segments of the signal, we compared the features from the first second of each block (PSD1s) with the first two seconds (PSD2s) and the features from the entire block (PSD10s). Signal from electrodes C1, C2, C3, C4 and Cz were considered so far, owing to their proximity to sensorimotor regions of the brain.

Results. Figures 2 and 3 show the performance of the k-NN classifier, in terms of average accuracy, for μ and β bands combined. In Figure 2, "group A" indicates classification among "rest", "right hand MI" and "left hand MI" possibilities; while "group B" indicates classification between "rest" and "MI" (i.e., right hand plus left hand MI) possibilities. Other frequency bands analyses showed similar results. Figure 3 shows individual classification rates for "rest" and "MI" tasks.

Discussion and Conclusions. As shown in Figure 2, the accuracy rates obtained with k-NN classification are very similar to random – that would be 33% for "group A" and 50% for "group B" – regardless of the feature used. Figure 3 shows a slightly satisfactory accuracy rate to correctly classify MI (above 59%), mainly when one considers PSD2s and PSD10s, but this does not apply to classification of rest blocks (below 50%). We believe that this happened due to: (1) inter-subjects variability, since we used the samples from all the subjects together, in order to have enough samples to study the different segments of the signal; (2) choice of a low complexity classifier for the analysis of high complexity data; (3) data use from few electrodes; (4) difficulty of one's brain to comprehend what would be a "motor rest", inherent to the MI paradigm. Next steps would be to manage the variability of response between subjects, perhaps considering reducing the number of samples for individual analysis. In addition, it would be interesting to implement another classifier, such as LDA (Linear Discriminant Analysis).

Figures and Tables.

Figure 1. Data acquisition paradigm

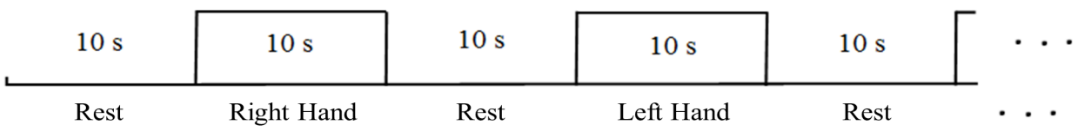


Figure 2. Performance of the classifier: μ and β bands (8-30 Hz)

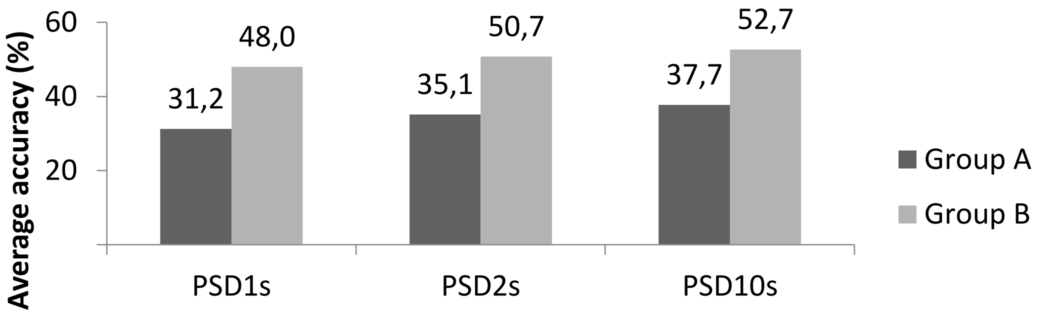
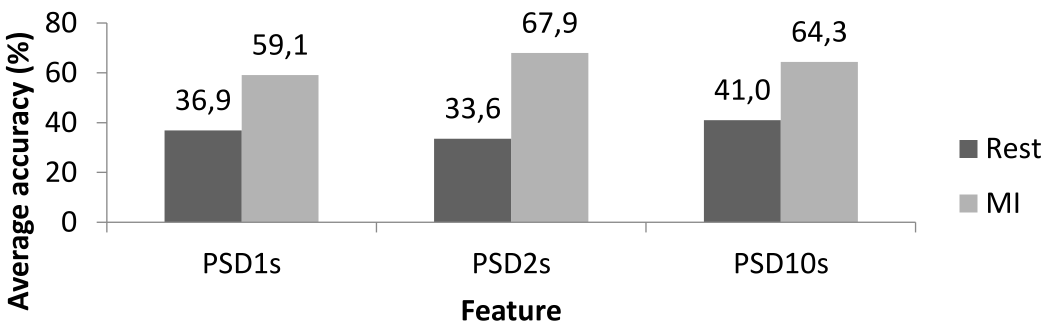


Figure 3. Comparision between Rest and MI accuracy rates: μ and β bands (8-30 Hz)



Acknowledgment. This work has been supported by FAPESP (Fundação de Amparo à Pesquisa do Estado de São Paulo), grants 2017/09451-6 and 2013/07559-3, and FINEP (Financiadora de Estudos e Projetos), grants 01.10.0449.00 and 01.16.0067.00.

Keywords. Electroencephalography; motor imagery; brain-computer interface.