EEG Motor Imagery Classification of Upper Limb Movements

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Keywords: EEG, Band-power Extraction, Pattern Recognition, Linear Discriminant Analysis (LDA).

Abstract: C EEG channel data are usually used when building systems that aim at distinguishing among right and left hand movements. Few alternatives use multichannel systems when bigger sets of motor imagery are subject to classification and more inputs are required. In this context, this work proposes the use of 8 EEG channels (F,C,P, and O), disposed in a non-conventional set up, to classify up to 4 motor imagery of the upper limbs through a Linear Discriminant Analysis classifier. A spatial feature selection, prior to classification, is applied in order to improve the classification accuracy. For the many channel combinations tested, results suggest that, in addition to the motor areas, other brain areas should be considered. For the proposed system, the best classification accuracy was achieved when distinguishing between left arm and left hand (89.74%) and using only the electrodes in F areas. For the right versus left hand a 71.80% rate was obtained, with electrodes either in P and O areas or in F and P areas. To discriminate between arms and hands, independently of the body side, the best score was 83.33%, for F and P channels, whereas for right and left limbs the best score was 66.02%, with only P channels. The best classification accuracy for the 4 movement problem achieved 50.00%, using all electrodes.

1 INTRODUCTION

Brain Computer Interfaces (BCI) are communication systems that use the electrical brain activity as input of a system that will translate them into a control signal, for an external device, that represents the subject's wish. Originally, this technology was developed for people with severe motor disabilities and common applications include spelling devices, wheelchair, and neuromotor prostheses control. However, nowadays, entertainment applications for healthy users are gaining space, as applications for games and virtual reality interfaces (Hoffmann et al., 2007; Veen, 2009; Millan et al., 2010). BCI systems can be classified into two major categories depending on the signal that they use. Some are based on Endogenous Potentials, such as those used in imagined movement that are voluntarily generated by the user, and others are based on Exogenous Potentials that are externally induced by an stimuli (Veen, 2009).

The brain activity occurs in many regions of the brain, either on the cortex, basal ganglia, cerebellum, and thalamus, changing its oscillatory frequency according to the mental and physical states of the subject. The main bands or rhythms typically observable are: delta (1 - 4 Hz), theta (4 - 8 Hz), alpha (8 - 12 Hz), Beta (12 -28 Hz), and Gama above 28 Hz (Hoffmann et al., 2007; Hema et al., 2010).

The field of motor imagery has shown a predominant interest in the right and left hand movements using EEG from C3, Cz, and C4 channels. (Xu and Song, 2008) achieved $90\% - 92\%$ accuracy using Discrete Wavelets Transforms (DWT) and Autoregressive (AR) Model features with a Linear Discriminant Analysis (LDA) classifier, whereas (Hema et al., 2009) applied an Elman Neural Network over EEG 4 band power features, achieving an average classification of 72%. (Huang and Wu, 2010) used the average energy of the C3 and C4 channels, a Wavelet Package Transform, and the Quadratic Discriminant Analysis classifier achieving a maximum rate of 88.71%. (Kumar and Fumitoshi, 2010) proposed the use of a Relative Spectral Power as feature, applying it over the 5 EEG frequency bands. The classification rate using a LDA classifier was 76.43%, whereas (Dolezal et al., 2011), using the Power Spectral Density (PSD) with a Support Vector Machine (SVM), achieved 75% of classification.

With a 14-electrode set up, located around the motor area, the best results achieved by (Higashi et al., 2009), using correlation coefficients based on Rhythmic Component Extraction with a LDA classifier, ranged from 74.9% to 83%. Performing a spatial feature selection from a 64-electrode set up, (Xiao

Claudia F. Castro M., Pedro de O. P. Galhianne J. and Luna Colombini E. (2013).
EEG Motor Imagery Classification of Upper Limb Movements.
In *Proceedings of the International Conference on Bio-inspired Systems and Signal Processing*, pages 314-317
DOI: 10.5220/0004235003140317

et al., 2009) discriminated between two types of motor imagery among a set of four (right and left hand, foot, and tongue) using Energy Entropy of the Short-term Fourier Transform as feature. Comparing the performance of a Linear Discriminant classifier, a Back-Propagation Neural Network, and a SVM, the best accuracy was achieved by the Linear Discriminant classifier, with average classifications between 82.4% – 88%. With a set of 29-electrodes and using Independent Component Analysis prior to DWT to obtain the features, and Bhattacharyya distance matrices and scalp plots to classify, (Morash et al., 2008) reached an average classification around 35% to distinguish among the same four motor imagery classes.

It can be noticed that there is a prevalence of using only C3 and C4 channels to distinguish between two motor imagery, mostly restricted to the right and left hand movements, with a few alternatives using multichannel systems aiming at classifying a bigger set of motor imagery. In this context, this work proposes the use of 8 EEG channels (F,C,P, and O), disposed in a non-conventional set up, to classify up to 4 motor imagery of the upper limbs with a LDA classifier. A spatial feature selection is applied, prior to classification, in order to verify the best electrode combination to improve classification performance.

2 MATERIALS AND METHODS

During the experiment, an able body subject was seated on a comfortable arm chair, with the body relaxed. Six series of 5 repetitions of 4 random command sequences were given: close right hand, close left hand, flex right arm, flex left arm, those which should be imagined. EEG was recorded at 1000 Hz using a Bioamplifier plus PowerLab 16/30 configuration from AdInstruments, according to the approved protocol (COEP - USJT - No.088/2011).

The signal, from each of the 8-channel set up, was acquired transversally from electrodes Fz, Cz, Pz, Oz to electrodes F3, F4, C3, C4, P3, P4, O1, and O2 (Figure 1). A segment of 2.5 s of each execution was selected and the Spectral Power Magnitude Averages in different frequency bands were computed as features, as follows: alpha (8 - 12 Hz), Beta1 (12 - 16 Hz), Beta2 (16 - 20 Hz), Beta3 (20 - 28 Hz). For the Gamma band, the effect of different configurations were investigated: (1) 28 - 32 Hz; (2) 28 - 64 Hz; (3) 28 - 100 Hz; (4) Gamma1 (28 - 32 Hz), and Gamma2 (32 - 64 Hz); (5) Gamma1 (28 - 32 Hz), Gamma2 (32 - 64 Hz), and Gamma3 (64 - 100 Hz). A spatial feature selection was also performed aiming to find efficient electrode combinations that carry useful and discriminative information.

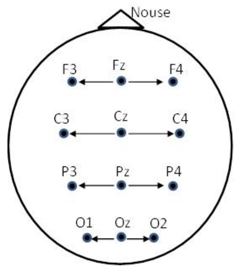

Figure 1: Electrode channel set up.

A classifier based on Linear Discriminant Analysis (LDA) was used in order to distinguish different groups of data. Experiments were performed to discriminate each of the motor imagery: right hand versus left hand, right arm versus left arm, right arm versus right hand, left arm versus left hand, hands versus arms, and right limb versus left limb. LDA is a well known technique based on linear combinations of the ratio between two covariances: between-class scatter matrix and the within-class scatter matrix. It usually results in a reliable classification accuracy, requiring a few number of samples and a low computational cost if compared to other classification methods such as Neural Networks.

3 RESULTS AND DISCUSSION

The classification accuracies achieved for each frequency band when varying the boundaries of the Gamma frequency band are shown in Figure 2. In general, the impact of this variation was low, below 5%, specially when aiming at discriminating among the four movements, right arm and right hand, left arm and left hand, and between right and left limbs. Nevertheless, the increase of the upper band boundary (28 - 64 Hz, 28 - 100 Hz) or the use of the total frequency band (28 - 32 Hz, 32 - 64 Hz, 64 - 100 Hz) resulted in a diminished classification accuracy to distinguish between right and left hand or right arm and right hand. The increase of the upper boundary had also a negative effect into the classification rate to differentiate between right and left arm. However, this situation generated the best discrimination rate between left arm and left hand or arms versus hands. Although small, the effect of the gamma band configuration is different for each experiment. This suggests an investigation a priori and an appropriate use depending on the ultimate goal.

The classification rates achieved by the application of the LDA can be shown in Figures 3 and 4. Figure 3 shows the classification accuracies reached

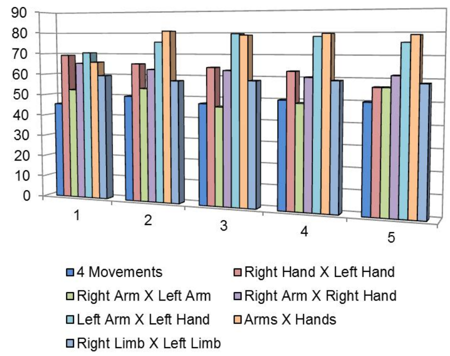

Figure 2: Classification accuracies for each frequency band varying the Gamma frequency boundaries (1) 28 - 32 Hz; 2) 28 - 64 Hz; 3) 28 - 100 Hz; 4) Gamma1 (28 - 32 Hz), and Gamma2 (32 - 64 Hz); 5) Gamma1 (28 - 32 Hz), Gamma2 (32 - 64 Hz), and Gamma3 (64 - 100 Hz).

considering all channels. The best average classification was 78.85%, obtained when distinguishing between motor imagery related to hands and arms, independently of the body side, followed by a 75.64% of classification for left arm versus left hand. The classification accuracy when distinguishing between right and left hands, a common problem presented in the literature, was 56.43%, the same value achieved to distinguish between right and left arms, whereas the 4 movements problem reached 50.00% accuracy.

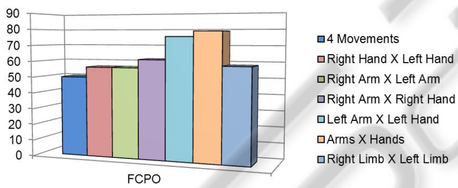

Figure 3: Classification accuracies using a LDA classifier over the F, C, P, and O channels.

The results for the spatial feature selection, showed in Figure 4, improved all classification accuracies except for the 4 Movement problem, which is the most complex among those presented. The classification accuracy to distinguish between left arm and left hand movement imagination achieved 89.74%, using only the electrodes in the F areas, whereas for the right versus left hands a 71.80% rate was obtained with electrodes either in P and O areas or in F and P areas. To distinguish between arms and hands, independently of the body side, the best score was 83.33%, considering only F and P channels. For the discrimination between right and left limbs, the best score was 66.02% with only P channels. It is important to mention that these two last experiments were performed with groups assembled with mixed data: there was no equivalent movement imagination for both limbs.

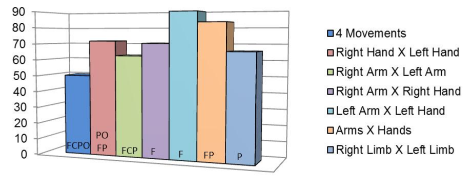

Figure 4: Best classification accuracies after spatial feature selection.

In the predominant protocol for motor imagery, the BCI systems use only C3, Cz, and C4 signals to distinguish right versus left hands (Hema et al., 2009; Xu and Song, 2008; Xiao et al., 2009; Huang and Wu, 2010; Kumar and Fumitoshi, 2010; Dolezal et al., 2011). This is justified by the fact that when the subject performs an upper limb motor imagery the considered waves in the contra-lateral electrode concentrates more energy, while in the same side the energy is suppressed (Xiao et al., 2009).

Despite the fact that this work has used a non-conventional electrode set up, the spatial feature selection process suggests that other brain regions should be considered. Most of the experiments with better classification rates have not used the electrodes in C areas after applying the spatial feature selection. Specifically, the best average classification accuracy achieved to distinguish between right and left hands used electrodes in F and P areas or in P and O areas. To distinguish between right arm and right hand or left arm and left hand, the best accuracy was achieved using only F channels. When dealing with arms versus hands classification, electrodes in F and P areas demonstrated the best results, and for right versus left limbs, only P channels were used to achieve a similar performance. The frontal cortex (F area) is related to activities of planning movements, the parietal cortex (P area) is an area of association for proprioceptive information also related to movement control, whereas the visual cortex (O area) could be used in order to visualized the execution of the movement.

Another point that must be considered is that, according to (Veen, 2009), the comparison among BCI systems suggests that there is a trade-off between speed and accuracy: slower systems that consider a long period of data demonstrate higher accuracies than faster ones. This can be related to the number of features samples that are available to the classifier, supplying it with more useful information about the motor imagery. Another point refers to the period of time that the subject has to learn how to use motor imagery. The use of BCI in real applications, during device control, provides continuous feedback to the subject regarding the action that is implemented. This process enables the subject to learn how to better use the motor imagery control. Some researchers considering a feedback stage and this training can provide a performance improvement (Veen, 2009).

In this work no feedback was provided to the subject and a 2.5 s data period was considered, that comparatively to others (Xu and Song, 2008; Kumar and Fumitoshi, 2010; Huang and Wu, 2010; Dolezal et al., 2011) is a short period. Nevertheless, the classification rates were consistent or even higher than those achieved by other systems.

On the other hand, the lower accuracies achieved for the classification between right and left arm, right and left limbs, and also to distinguish the four motor imagery set up, situations that were not found in the literature for comparison, need further investigation. Maybe a higher period of time and other electrodes could be considered to provide more information to the classifier. Other features and classifiers might be tested in order to evaluate their performances under this environment set up.

4 CONCLUSIONS

This work presented a motor imagery classification system that uses a non-conventional electrode set up and a spatial feature selection aiming at distinguishing up to four upper limb motor imagery. The results suggest that in addition to the motor areas (C3 and C4) other brain areas should be considered. New sets of experiments were proposed to classify between left arm and left hand movement imagination and to discriminate between arms and hands, resulting in high classification accuracy. Furthermore, the classification of 4 upper limb motor imagery was evaluated and, for that, the results have shown that further improvements, such as the use of more electrodes, the increase of the data period, and the use of other features and classifiers are required. Finally, in order to generalize the results, experiments with more subjects are necessary.

ACKNOWLEDGEMENTS

The authors would like to thank FEI, CNPq and FAPESP for supporting.

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