Classification of Executed Upper Limb Movements by Means of EEG

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***Abstract*—This work presents the performance of a Linear Discriminant Analysis classifier that used EEG data from 3 different subsets of the signal, which was gathered during the execution of 4 upper limb movements. The mean Power of the signal, segmented in 8 EEG frequency bands, was used as the features for the classifier and the effect of spatial feature selection was also investigated. A non-conventional potential difference based on an 8-electrode clinical transversal setup was used in the acquisition of EEG signal during arm and hand movements, which were segmented in Movement Planning, Movement Execution and Steady Position. The results showed that the Movement Planning subset achieved the best classification accuracy, suggesting that the speed for a BCI can be improved by using pre-movement information. Spatial feature selection showed that non-motor areas should be considered as an information source. Best classification accuracy of right and left limbs was 67.95%, hands versus arms achieved 82.69%, and 49.36% of classification was the best result for the 4-class set up. Results are promising, however further experiments are required to obtain better classification accuracy and to generalize these conclusions.**

***Index Terms*—EEG, EEG Motor Signals, Pattern Recognition, Linear Discriminant Analysis (LDA), Power Spectral Density (PSD).**

I. Introduction

The possibility to use brain activity independently of muscles and peripheral nerves opened a way to develop Brain Computer Interfaces (BCI) as an assistive technology tool. Most of developed systems rely on one of these two types: motor imagery or visual evoked potential, both to be used by people with severe motor disabilities. Common applications include spelling devices, wheelchair, and neuromotor prostheses control. However, nowadays, entertainment applications as games and virtual reality interfaces are becoming more popular [1]–[11].

Although the imagination of a limb movement or a specific visual target that flashes or oscillates have been extensively used as source of study and processing, there are in the literature some works using brain motor signals, acquired during movement execution, as alternative, with similar classification accuracy [12]–[19].

Besides the possibility of applications with healthy users or with diminished motor capabilities, this line of research deals with a more natural behavior and contributes to the two major challenges that the area has faced: users have difficulties to learn how to control brain activity (EEG) and must be submitted to long training process, resulting sometimes in low efficiency and demotivation [8], [14] or users need to pay attention to the stimuli source instead of interacting with the environment [6], [11].

Furthermore, although EEG has the advantage of being non-invasive and can be considered a widely deployed technique, its low bit information rate implicates in low processing speed [20].

EEG motor signals regarding movement intention contains available information before a conscious decision to move that can be used to anticipate the execution of a command in a BCI system [14], [16], [21]–[23]. By means of the comparison of several techniques, the authors in [14] reached classification accuracy of 63% when combining Independent Component Analysis (ICA) with Power Spectral Density (PSD) and Support Vector Machine (SVM) to discriminate between right and left hand movements. In [16], the authors obtained 65% accuracy to classify movements in 2 groups, but it has decreased to approximately 40% when dealing with 4 groups.

Other researches relying on data obtained during the execution of movement can be found in the literature. The authors in [12] used ICA technique with a LDA to classify right and left wrist movements with over 70% accuracy, but when considering the four classes, classification rate ranged between 32% - 35%.

Several works commonly use a multi-channel electrode system to obtain EEG data from movement execution. Using a Hidden Markov model, [15] reported a classification rate ranged between 60% - 74% to identify index and little finger movements, but in many cases the author reported a lot of misclassification. Another example is the work presented by [19], which used power spectral feature in Alpha, Beta, and Theta bands with a SVM classifier, and obtained an average classification rate of 64% to distinguish between right and left hand movements.

In this context, this work proposed a non-conventional potential difference based on an 8-electrode clinical transversal setup to obtain EEG data during the execution of 4 upper limb movements and it presents a classification performance comparison for 3 different subsets of the signal, henceforth referred to as Movement Planning, Movement Execution and

Steady Position. The mean Power of the signal, evaluated in frequency domain (PSD), in each of the 8 EEG frequency bands and a Linear Discriminant Analysis-based classifier were used to distinguish between right/left hand closing and right/left arm flexion. This work also investigated the effect of spatial feature selection in the classification accuracy.

II. Materials and Methods

A. Data Acquisition Setup and Procedure

The following material was used in the experiment: two Personal Computers (PCs), custom-made switch-based sensors and an electrodecap with an Octal Bio Amplifier (AdInstruments). Everything was connected to the 16/30 PowerLab acquisition system (AdInstruments) as shown in (Figure 1). A 60 Hz Notch filter and a band pass filter (0.5 - 120 Hz) with 1 kHz sampling frequency was the acquisition setup used with the PowerLab system.

Custom-made software, showing a list of instructions that indicate the movement to be executed, was running on PC-1. To ensure time synchronization between instruction presentation and acquisition, the PC's serial port was also connected to the recording unit. Sensors information allowed consistency checking by correlating the instruction presented to the volunteer with the actual executed movement and also determined the timestamps of the movement phase.

Based on the standard 10-20 electrode placement system, the following 8 channels were chosen: F3, F4, C3, C4, P3, P4, O1, and O2. The non-conventional potential difference based on a clinical transversal setup shown in Figure 2 was expected to provide better class discriminability.

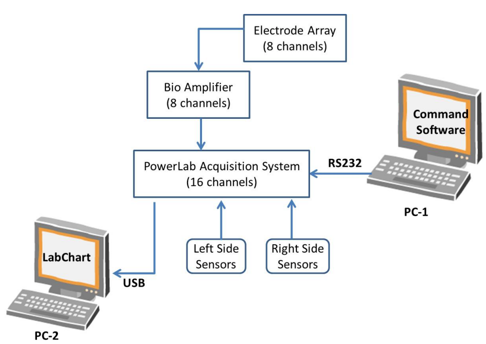

Fig. 1. Experimental setup.

One male subject, with no physical or mental restriction, participated in this experiment as volunteer, after sign the informed consent document, approved by COEP - USJT - No.088/2011.

The volunteer sat down in front of PC-1 with both hands and arms resting over the table and executed four sets of 15 instructions, consisted of left or right hand closing, left or right arm flexion. After executing a movement, when the instruction was removed from the screen, the volunteer had to return to the resting position. Each instruction remained on the screen for 5 s, with a 4 s blank screen between instructions.

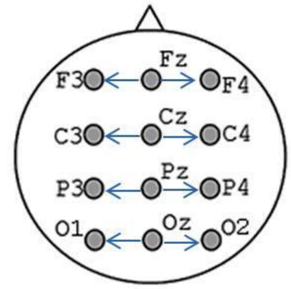

Fig. 2. Electrode set up.

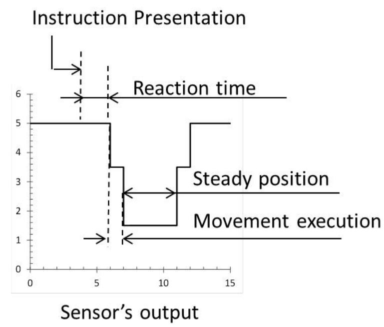

Fig. 3. Movement time synchronization.

Figure 3 shows the time course of the experiment. The subject presents a time delay to respond to the instruction, known as reaction time, during which movement execution is planned. This allowed the definition of 3 phases from the time of instruction presentation: Movement Planning, Movement Execution and Steady Position. A 1 s and 2 s data vectors length were selected for each phase.

B. Feature Extraction

The feature used in this experiment was the standard periodogram mean Power for each EEG frequency band shown in Table I.

TABLE I
EEG Frequency Bands (adapted from [18]).

Bands	Frequency range (Hz)
δ	$0-4$
α_1	$4-8$
α_2	$8-12$
β_1	$12-14$
β_2	$14-18$
β_3	$18-25$
γ_1	$25-32$
γ_2	$32-70$

PSD was calculated using the Equation 1, where: $S_p(f)$ is the Periodogram, T_s is the sampling interval, N is the number of samples, f is the signal frequency and $x[n]$ is discretized amplitude of each sample, while the mean Power P_m can be calculated by Equation 2, where: $S(k)$ is the sample periodogram values and f_1 and f_2 are the lower and upper frequency limits within the mean is considered [18].

$$S_p(f) = \frac{T_s}{N}\left(\sum_{n=1}^{N} x[n] * e^{-j2\pi f n T}\right)^2 \tag{1}$$

$$P_m = \sum_{k=f_1}^{f_2} S(k) \tag{2}$$

Electrode combination that resulted in the best classification was determined by spatial feature selection, which removed one or more electrodes in pairs according to brain's region, always keeping the central ones (C3, Cz and C4). Since the number of electrode combinations are small, an extensive search algorithm was used to implement this feature selection procedure.

C. Classification Technique

Data was classified into groups according to movement side (left or right) and limb movement (hand or arm) or yet into four movements (right arm, right hand, left arm, and left hand) using Fisher's Linear Discriminant Analysis (LDA). This method was chosen due to its simple implementation and its low computational resources requirements and because it's a widely deployed method providing good results. Besides that, the main purpose of this research is to demonstrate that it's possible to use movement related EEG signals to improve a BCI overall response time and usability.

LDA is a technique for pattern recognition that finds linear combinations used to separate samples from a data set into classes of objects by maximizing between-class separability, while minimizing their within-class variability. The between-class (S_b) and within-class (S_w) scatter matrices can be calculated by Equations 3 and 4, where: g is the number of classes, N_i the number of samples in class X_i, $\bar{x_i}$ the mean of class X_i and $\bar{x}$ the total mean vector considering all the samples of all the g classes [24], [25].

$$S_b = \sum_{k=1}^{g} N_i(\bar{x_i} - \bar{x})(\bar{x_i} - \bar{x})^T \tag{3}$$

$$S_w = \sum_{k=1}^{g} \sum_{x_k \in X_i} (\bar{x_k} - \bar{x_i})(\bar{x_k} - \bar{x_i})^T \tag{4}$$

By finding a projection matrix that maximizes the ratio of the determinant defined by Equation 5, LDA can find boundaries that separate the groups. This is possible since P_{LDA} is the solution for an Eigen system. Assuming that S_w is a non-singular matrix, according to Fisher's criterion, it is maximized when the P_{LDA} projection matrix is composed of eigenvectors of $S_w^{-1}\ S_b$ with at most $(g-1)$ nonzero corresponding eigenvalues [24], [25].

$$P_{LDA} = argmax_P \frac{P^T S_b P}{P^T S_w P} \tag{5}$$

Leave one out technique was chosen to determine the samples for training and test whereas euclidean distances were used for class assignment.

III. Results

Considering 1 s data vector and all 8 channels setup showed that Movement Planning phase obtained the best average classification accuracies, being 76.29%, 67.32%, and 47.44% for the classification for hands versus arms, right versus left limbs and for 4-class movements. Figure 4 summarizes these results.

While keeping C electrodes in the setup, spatial feature selection was implemented, resulting in the combination that culminated in the best classification accuracy, as shown in figure 5. The use of electrodes only in C areas to distinguish between hands versus arms and right versus left limbs was a common factor when dealing with data from Movement Execution phase and O electrodes had to be added to allow the recognition of four groups of movements. Although the other movement phases did not show a clear pattern regarding electrode removal, it could be noticed that accuracy was improved when a small number of electrodes were considered.

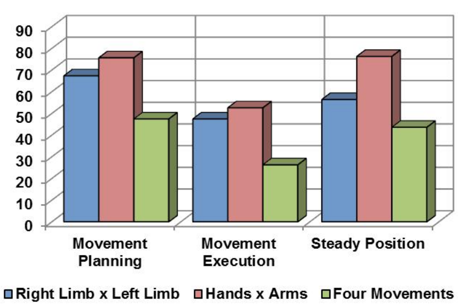

Fig. 4. Average Classification Accuracy for 1 s data vector considering the 8-channel set up .

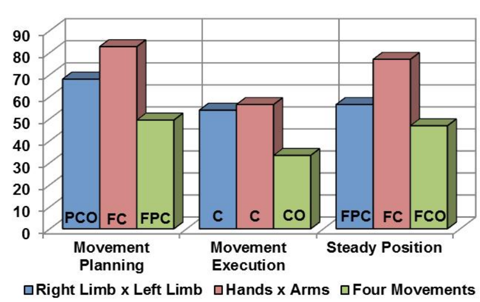

Fig. 5. Best average classification accuracy for 1 s data vector after spatial feature selection.

It was possible to achieve an improvement of up to 26.8% for the 4 movements with data obtained from Movement Execution phase, when electrodes in C and O areas were in use. To distinguish between right and left limbs the best improvement was 14% during the same phase, whereas considering hands versus arms, the best improvement occured during Movement Planning phase, with 9%.

Considering the 2 s data vector, best average classification accuracy was 68.59% to discriminate right limbs from left limbs in the Steady Position phase, 75.64% for hands versus arms during the Planing phase, whereas the 4 movement problem achieved 47.44% accuracy during the Steady Position phase. These results are shown in figure 6.

Spatial feature selection has improved best results up to 10% when using 2 s data vector, with different electrode combinations when compared with 1 s data vector, as can be seen in figure 7.

Fig. 6. Average Classification Accuracy for 2 s data vector considering the 8-channel set up .

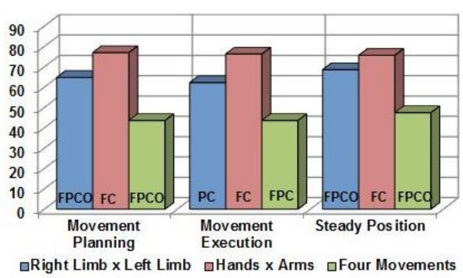

Fig. 7. Best average classification accuracy for 2 s data vector after spatial feature selection.

As γ_2 upper frequency limit increases, classification accuracy was improved for all classes considered, as can be seen in figure 8. Similar behavior, but with low improvements, was observed using the 2 s data vector, as shown in 9.

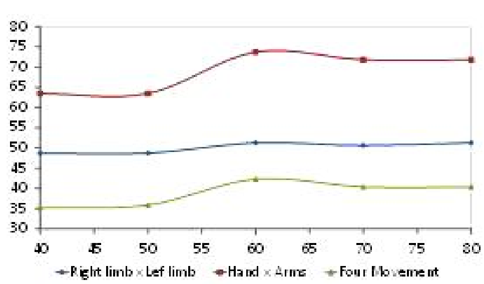

Fig. 8. Classification accuracy tendency for 1 s data vector as γ_2 upper frequency limit increases.

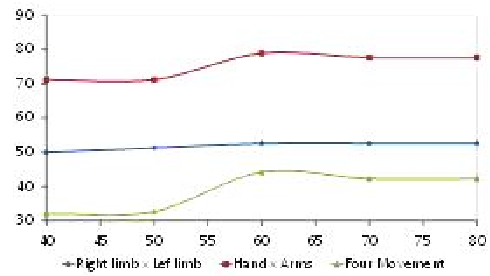

Fig. 9. Classification accuracy tendency for 2 s data vector as γ_2 upper frequency limit increases.

IV. Discussion

Even considering groups assembled with mixed data from hand and arm and a non-conventional potential difference based on a clinical transversal set up, the right and left limb classification, with data from Planning Movement phase, achieved an accuracy of 67.32%. This value is consistent with those achieved by [3], [5], with rates ranging from 63% to 65% for the classification of right and left hands.

Another classification issue problem has also been proposed. The classification between hands and arms achieved higher accuracy (75.64%). Maybe the use of the potential difference based on a clinical transversal setup has contributed to this result. According to [26], [27], there is a somatotopically pattern associated with different cortical limb representations that may be highlighted by this configuration.

However, despite the 4-class movement set up has achieved 47.44% of classification, which is higher than those presented by [16], that reached approximately 40% accuracy using the same movement phase, these low classification rates show the difficult task to distinguish among a set of movements.

The number of electrodes may represent another point to be considered. The availability of useful information from other brain areas or the better resolution within a specific area in multi-channel electrode systems can contribute to higher classification accuracies, despite the use of spatial feature selection, which reduces the amount of data. Using data obtained during Movement Execution, after feature selection the rates were 53.85% and 56.41% for the right and left limb classification and hands versus arms, respectively. These rates are a little lower than those achieved by [12], [15], [19] with rates ranging from 60% to 70% for the classification of right and left hands. However, besides the fact that the classification groups have mixed data, the number of electrodes used were considerably lower than the number of electrodes used in the mentioned works with 21, 64 and 122 channels, respectively.

Although several works use only electrodes in C areas, multi-channel system have shown that non-motor areas should be considered as information providers. The results of this work suggest that the use of information restricted from motor areas may be adequate for studies during movement execution and for a simple classification problem. However, during Movement Planning, Steady Position phases or for a more complex classification problem, the addition of non-motor areas may increase classification accuracy. Considering 1 s data vector, the classification results achieved after the spatial feature selection were improved to 67.95%, 82.69%, and 49.36% for the right and left limb classification, hands versus arms and for the 4-movement set up, respectively, using data from Movement Planning phase.

Another relevant result is that planning phase presented better classification accuracy for all groups for the 1 s data vector, but there's almost no difference in phases classification accuracy for any group for the 2 s data vector. One possible explanation to this behaviour is that overlapping is smaller in former case.

To corroborate with the importance of the Movement Planning Phase, there are other researches showing that the intention of the movement, extracted from EEG signals, can be used to anticipate future actions based on the fact that there is information available before a conscious decision to make a move [14], [16], [21]–[23]. The work in [21] suggests that the Readiness Potential can be used to detect the beginning of the process of deciding whether to perform a movement and that this fractional seconds occurs before the actual exercise, without, though, clearly indicate a default time, whereas in [22] the movement intention was detected around $500ms$ before actual onset.

By increasing γ_2 upper frequency limit it can be noticed that, for any type of movement, and for both data vector length, there are important accuracy improvements around 60 Hz. This is in accordance with [13], where the authors suggest that higher gamma band frequency (50-80Hz) has a prominent hole in classification.

Finally, considering that the resolution of the PSD, used in this research, was 0.5 Hz for the 2 s data vector and 1 Hz for 1 s data vector and that, usually, the researchers use a resolution between 0.1 and 0.2 Hz, the results obtained are quite satisfactory, since the classification rates achieved, in the present work, were in the same range when comparing to the others. Also, the overlap of data between different phases of movement due to the duration of the data vectors compared to the short periods of the Movement Planning and Movement Execution phases constitute a practical problem that was still not overcome. Despite the possibly negative contribution to the results, preventing the exploitation of the full potential of the proposed method, this did not implicate in results lower than those commonly observed in the literature.

V. Conclusion

Using a non-conventional potential difference based on an 8-electrode clinical transversal setup, a performance comparison among EEG data from 3 different phases during the execution of 4 upper limb movements was presented in this work. Movement Planning phase has brought the best results, suggesting that speed and classification accuracy for BCI can be improved using pre-movement information presented in this research. Additionally, the use of EEG signals related with movement execution seems to be a good way to improve BCI usability, since it is more intuitive and natural for its users and does not require long and demotivating training sessions, while yet providing classification accuracies that are compatible with the literature. Spatial feature selection results also indicated that non-motor areas should be considered as valuable sources of information for classification purposes. Although these results are promising, further experiments are required to generalize these conclusions and obtain better classification accuracies.

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