Identification of motor imagery tasks using power-based connectivity descriptors from EEG signals

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***Abstract*—In recent years, functional connectivity has been studied through electroencephalography signals to analyze the patterns generated by the electrical conductions of the brain. In BCI systems, the paradigm of motor imagery has been used to generate patterns to identify the user's intention. However, the study of techniques that allow the correct identification and classification of such intention is still a challenge due to the low performance of algorithms for rehabilitation engineering applications. This study addresses the problem of binary identification of left and right-hand opening and closing motor imagery tasks. A method called Power-Based Connectivity (PBC) is proposed that correlates two reference channels in the central cortex (C_3 and C_4) with other channels located in the central area of the brain. The methods were evaluated using an EEG dataset of six subjects with no previous experience in BCI systems built at the Antonio Nariño University. The method was compared with a standard feature extraction method based on Power Spectral Density (PSD). It was used for evaluation accuracy and cohen's Kappa coefficients metrics. Maximum accuracy and cohen's Kappa coefficient of 0.7733 and 0.5488, respectively, were obtained using the Linear Discriminant Analysis (LDA) classifier. Finally, the proposed method was superior in performance and presents significant results in the alpha (α) frequency band and the combination of alpha (α) and beta (β). This leads to the conclusion that the proposed method is adequate for user intent identification in a motor imagery-based BCI system of users with no prior experience.**

***Index Terms*—Electroencephalography (EEG), Brain-Computer Interface (BCI), Motor Imagery, Power-Based Connectivity, Functional Connectivity.**

I. Introduction

A Brain-Computer Interface (BCI) is a system that provides a communication channel between the brain and computers to allow a user to control the environment in a way that is responsive with the user's intentions, without the need of using the peripheral nervous system [1], [2]. Traditionally, a BCI system is implemented mainly through different phases including acquisition, signal processing, classification, applications, among others [3], [4]. BCI systems have a range of applications in the fields of medicine, education, neuroergonomics, gaming, motor and communication rehabilitation, robotics, among others [5].

EEG Functional Connectivity can be defined as a relationship between brain sources or sensors located in the brain. EEG signals are commonly transformed to the frequency domain to estimate connectivity [6]. The higher the correlation between the signals, the more synchronized they are at the time of a movement or paradigm analyzed [7]. In the literature, it is mentioned that the most used method to estimate the connectivity between signals is the coherence that correlates the signals in the frequency domain through auto spectrum's and crossed spectrum's [7], [8].

A widely used paradigm in the literature to modulate patterns of Electroencephalography (EEG) signals to interact with a BCI system, correspond to the motor imagery (MI). MI consists of a mental or cognitive task in which the subject imagines the movement of one of his/her limbs without actually executing the movement, being the MI of the left and right hand one of the most explored [1], [8]. Brain activation during MI of hand movement elicited an increase or decrease of the spectral power of EEG signals at the central cortex of the brain within frequency bands between 8 and 30 Hz (Alpha (α) and Beta (β) band), that is known as Event-Related synchronization/desynchronization (ERS/ERD) [1].

In recent years, different EEG processing methods for the detection, feature extraction, and classification of MI tasks have been used to detect the user's intent, including Time-Frequency Analysis, Spectrum Analysis and Power Spectral Density (PSD) [9] with a performance average of 75%. Besides, methods based on connectivity have been implemented for detection of the motor intention of the subject through Coherence Spectrum, Phase Coupling, Entropy and Mutual Information of EEG signals [8], [10], [11], the Cross-Correlation with an EEG-reference-channel [12], [13] and the correlation of EEG with other signals [14] with performance average above 80%.

An open challenge for the scientific community in the implementation of MI-BCI systems is to detect the user's intention with a high classification rate, at this point, the importance of applying new methods is manifested that through the extraction of information facilitate the understanding of the behavior of the central nervous system with respect to certain stimuli (MI), applying these techniques in different fields of study, including rehabilitation engineering [15]. In this study, a method called Power-Based Connectivity (PBC) that relates EEG channels through correlation methods was implemented. For this, it was built an EEG dataset with 6 healthy subjects who have no previous BCI experience in the motor imagery task which consists of opening and closing the left or right hand. An algorithm based on Spearman's coefficient method was proposed to correlate the spectral power features of EEG signals from channels located in the motor cortex to identify two motor imagery movements. The Linear Discriminant Analysis (LDA) classifier was used, which was evaluated using Accuracy and Cohen's Kappa metrics. The results of this study allow to identifying that connectivity-based methods can outperform conventional methods highly reported in the literature. Additionally, the results show effects related to the connectivity between the reference electrodes and those located in the motor cortical area that are produced in the brain when right-hand or left-hand movements are imagined.

This article is organized as follows: Section II presents the experimental methods where the protocol and the algorithmic proposal are described. Section III presents the results obtained, section IV presents the general discussion and finally, section V presents the conclusions and future works.

II. Methodology

A. Protocol

Six healthy subjects between 19 to 37 years old (average age of 26 years) who signed an informed consent form participated in this study. All participants were right-handed and none of them had previous experience in MI-BCI experiments. EEG acquisition was performed using 32-channels Nautilus equipment from G.Tec medical engineering GmbH, according to international 10-20 standard [16] at a sampling rate of 250 Hz, with gel-based electrodes. Impedance for all electrodes was kept below $30k\Omega$ by the use of electrically conductive gel and filtering was used during acquisition with a filter bandpass between 0.5 and 60 Hz. The visual indication was performed using a monitor and the BCI2000 software where the sequence to be performed was presented and synchronized with the EEG recording equipment. The protocol consisted of multiple repetitions (trials) with 9 seconds of duration, following the sequence presented in Fig. 1.

- The subject has to focus her/his gaze on the screen for 3 seconds.
- A visual instruction appears randomly indicating the limb to be imagined (left or right), where the subject proceeds to perform the imagination of opening and closing the corresponding hand, during 3 seconds. The subject should try not to blink during this phase.
- The subject enters the rest phase, for 3 seconds. The subject is allowed to blink.

The procedure was performed 12 times (trials) in one session (round). Ten sessions were performed, for a total of 120 trials. To avoid physical and mental fatigue, the subject rested between 1 and 2 minutes between each session.

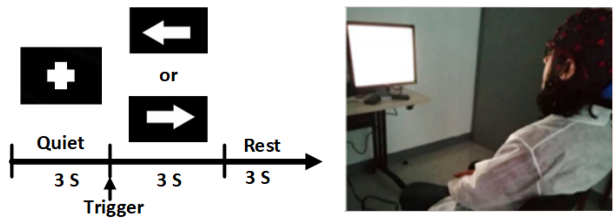

Fig. 1. EEG signal acquisition protocol sequence for motor imagery.

B. Data Analysis

EEG data analysis was performed to verify the contralateral behavior of the signals when the subjects imaging right or left-hand movement. For this purpose, EEG signals from FC_5, FC_1, FC_2, FC_6, C_3, C_z, C_4, CP_5, CP_1, CP_2 and CP_6 channels were filtered using an 8-order Butterworth filter in the $8-30$ Hz frequency band. Additionally, a Common Average Reference (CAR) filter was implemented to remove related noise on the electrodes located in the cortico-motor area. Subsequently, the Power Spectral Density (PSD) method was implemented using the Fast Fourier Transform (FFT) with a Hanning window of 1 second overlapped at 50% and a frequency resolution of 1 Hz.

After data analysis, a methodology presented in figure 2 was implemented, which consists of processing the EEG signals, extracting spectral power features, and correlating them by the Spearman method to subsequently identify the movement performed by the subjects.

C. Pre-processing

EEG signals were filtered using an 8-order Butterworth filter in the $8-30$ Hz frequency band. Additionally, it was used a notch filter to remove 60 Hz powerline interference and a CAR filter was implemented. EEG signals of motor imagery were segmented between 1 and 2.5 seconds for each trial per subject analyzed after the start of motor imagination (trigger) as showed in the Fig. 1.

D. Feature Extraction

Feature extraction was performed using Welch's power spectral density method with the configuration of Welch's overlapped segment averaging spectral estimation. The PSD estimated by Welch's method employs a modified periodogram for each window segment where the average of these windows allows to obtain the PSD reducing the variability of the estimation by the averaging performed [17]. For this purpose,

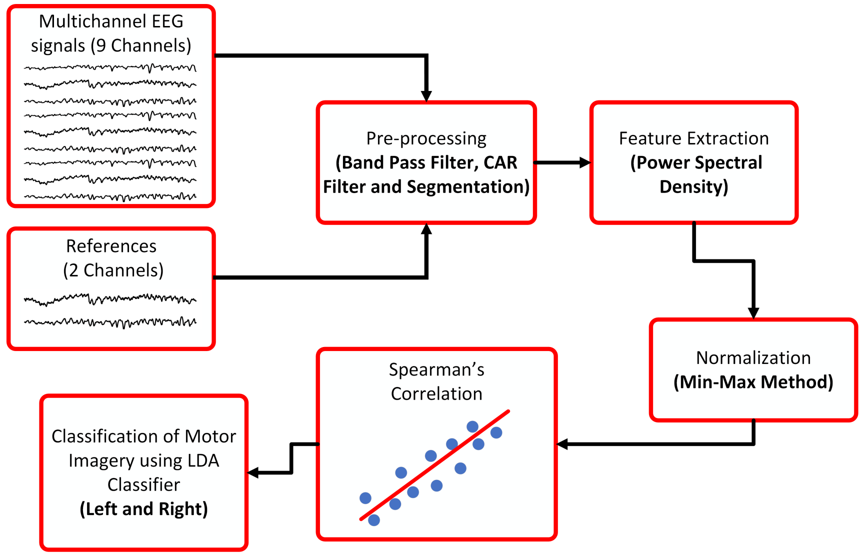

Fig. 2. Block diagram of the methodology followed for the identification of the hand motor imagery.

MATLAB software (version R2020b, Mathworks Inc) was used with a Hanning window of 1 second with an overlap of 50%. The spectral features of the EEG signals were divided into three separate frequency bands, corresponding to alpha (α, $8-13Hz$), beta (β, $14-30Hz$), and both ($8-30Hz$). The frequency resolution for each band was 0.5 Hz where each frequency band has a different feature vector size according to the length of each frequency band. The α band vector is 15 features long, the β band vector is 33 features long, and for both is of 49 features long.

E. Normalization

After feature extraction, a Min-Max Normalization method was implemented so that the spectral features span the range of $0-1$ for the correlation between the signals [18]. The normalization method is described by (1), where f_i represents the sample, f_{min} is the minimum value between features vector, f_{max} is the maximum value of the features vector, and f_n is the normalized value.

$$f_n = \frac{f_i - f_{min}}{f_{max} - f_{min}} \tag{1}$$

F. Correlation

To estimate the EEG functional connectivity, EEG signals of electrodes C_3 and C_4 were used as references according to obtained results of the data analysis and the literature [11]. Each reference channel was related to channels FC_5, FC_1, FC_2, FC_6, C_z, CP_5, CP_1, CP_2 and CP_6 for a total of 18 combinations. To correlate the normalized spectral power features between EEG channels, first, the normality of data was evaluated using the Shapiro-Wilk test to determine which correlation method is appropriate. For functional connectivity, Spearman's correlation coefficient method (Spearman's rho) was used taking into account that data did not have a normal distribution. It was set the $p-value$ to 0.05 significance to perform the analysis of the results with significant correlations. Finally, for each segmented data window, PSD features were extracted, normalized, and correlated according to the reference channels.

$$rho = 1 - \frac{6\sum d_i^2}{n(n^2-1)} \tag{2}$$

Spearman method is described by (2), where rho represents the correlation values between the range of -1 and 1, n is the number of the observation and d_i is the distance between the ranges of each observation of x_i and y_i [19]. Furthermore, for correlation data rho, the absolute value is applied.

G. Evaluation of algorithm proposal

The feature vector for classification of the proposed PBC method is formed as follows: the number of data (segments with significant correlations) by the number of channels combination (18 combinations). The proposed method was compared with a standard method for the identification of left and right-hand motor imagery movements [9], [20]. This method consists of a feature vector of spectral power values (PSD) of each frequency band for each EEG channel. The LDA classifier was used to identify the movements for both the proposed method and the standard method.

To assess the performance of both methods (PBC-LDA and PSD-LDA) the data was divided into 70% for training and 30% for evaluation where cross-validation with 5 folds was implemented.

H. Evaluation Metrics

The evaluation metrics implemented for the feature extraction methods validation were the accuracy (Acc) and the Cohen's Kappa coefficient (κ). Evaluation metrics are describe in (3) and (4) which are configured for binary classification [21], [22].

$$Acc = \frac{\sum_{i=1}^{l} \frac{TP_i + TN_i}{TP_i + FN_i + FP_i + TN_i}}{l} \quad (3)$$

$$\kappa = \frac{\sum_{i=1}^{l} \frac{Acc_i - P_{ei}}{1 - P_{ei}}}{l} \quad (4)$$

Where TP are the true positives, TN are the true negatives, FN are the false negatives, FP are the false positives, P_e is the aleatory accuracy and l is the total number of classes.

I. Statistical Analysis

For this study, a two-sample t-test using Matlab (version R2020b, Mathworks Inc.) was implemented to calculate the significant differences between the results of evaluation metrics of the proposed method (PBC-LDA) and the standard method (PSD-LDA) by each frequency band analyzed. Nevertheless, the type of distribution and the homogeneity of the variances of the data was determined before applying the t-test. For this purpose, the Shapiro-Wilk and Levene test was applied.

A Two-sample t-test was applied after verifying the results of evaluation metrics follow normal distribution values and homogeneous variances. A $p-value$ was established at 0.05. The alternative hypothesis consists in that proposed methods are significantly better than standard methods to classify motor imagery of right and left hand, and the null hypothesis otherwise. For this purpose, the results of the two implemented metrics are considered for each frequency band implemented (α, β, and both).

III. Results

Fig. 3 and Fig. 4 present the results of the data analysis, where Fig. 3 presents the average PSD features for C_3 and C_4 channels of subject 4, and Fig. 4 presents the head maps of the PSD features normalized by the z-score method in the analyzed channels.

According to [1], the motor imagery of right and left-hand movements is elicited contralaterally at the cerebral cortex, mainly in the C_3 and C_4 channels. This means that in the frequency band $8-30$ Hz an ERD (decrease in power) occurs in the C_4 channel when the subject imagines the left-hand movement and an ERD occurs in the C_3 channel when the subject imagines the right-hand movement. This behavior can be seen in Fig. 3 and Fig. 4.

After calculating the correlations between all frequency bands and channels described in table I, it was identified the correlations where the highest value was obtained. Fig. 5 shows the connectivity between the EEG channels and the reference channels for each frequency band analyzed. Confidence intervals at 95% are presented to identify the variability of the results among whole subjects. In the figure, it is presented for α the correlation of the C_3 channel with FC_2 and the correlation of C_4 with CP_5. For β, C_3 correlates with FC_1 and C_4 with CP_6. Finally, in both band, C_3 correlates with FC_5 and C_4 with CP_6. It can be observed

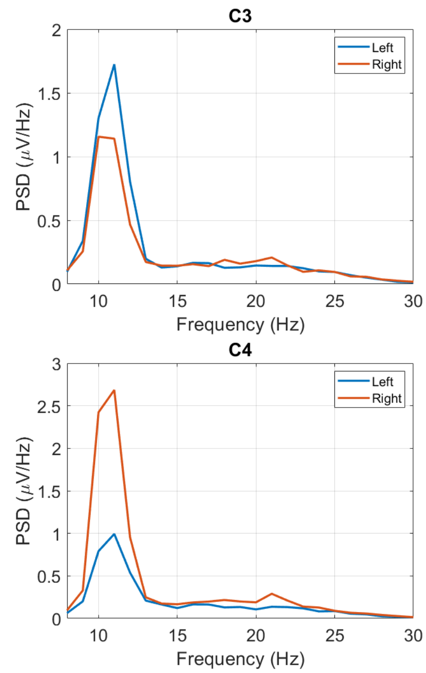

Fig. 3. Average PSD of left and right-hand motor imagery of α and β bands from channels C_3 and C_4 for the subject 4.

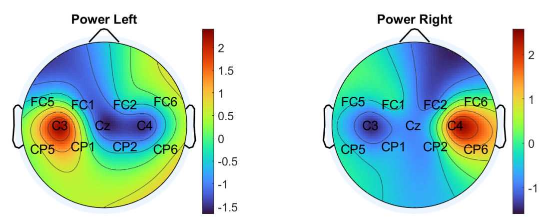

Fig. 4. Head map of left and right-hand motor imagery of α band at motor cortex channels location for subject 4.

that when the subject imagines the right-hand movement there is a higher correlation in C_3 than in C_4, and if the subject imagines the left-hand movement there is a higher correlation in C_4 than in C_3. This means that there is a contralateral behavior (higher correlation) represented in the correlation data when imagining hand movements.

TABLE I
Correlation of the reference channels with the channels located at the motor cortex.

Bands	Reference Channels	EEG Channels
α $(8-13Hz)$	C_3 C_4	FC_5, FC_1, FC_2, FC_6, C_z, CP_5, CP_1, CP_2 and CP_6
β $(14-30Hz)$	C_3 C_4	
α and β $(8-30Hz)$	C_3 C_4	

Fig. 6 and Fig. 7 show the behavior of standard methods based on PSD features and the proposed method based on

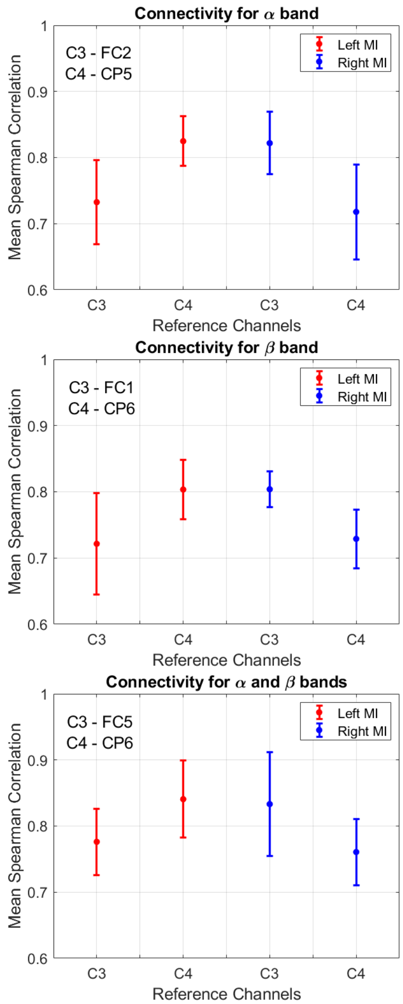

Fig. 5. Correlation behavior between channels with 95% confidence intervals of subject data for each frequency band (α, β, *both*). It is presented the correlation of C_3 (Reference channel) with channels FC_2, FC_1 and FC_5, and for C_4 (Reference channel) it is presented for CP_5, CP_6, CP_6, respectively for each band.

PBC. The yellow box represents the behavior of the α band, the blue box represents the behavior in the β band and the red box represents the behavior in both bands (8 and 30 Hz). It can be observed that the proposed method for each band provides better results according to the evaluation metrics than the standard method implemented for each band. Furthermore, the results of the statistical analysis are presented in the table II.

TABLE II
RESULTS OF STATISTICAL ANALYSIS BETWEEN THE PROPOSED AND STANDARD METHODS WITH THE LDA CLASSIFIER.

Methods Comparison	**Accuracy**	κ
PBC-α vs PSD-α	†	†
PBC-β vs PSD-β	$\sim$	$\sim$
PBC-All vs PSD-All	†	†

Note: $\sim$ non-significant; † $p < 0.05$.

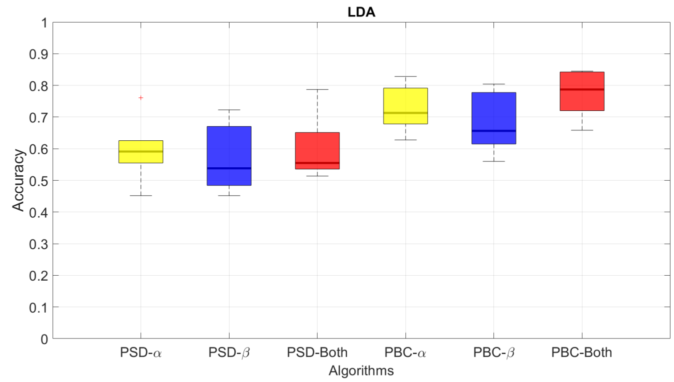

Fig. 6. Box diagram of the Accuracy for the evaluated methods in this study using the LDA classifier.

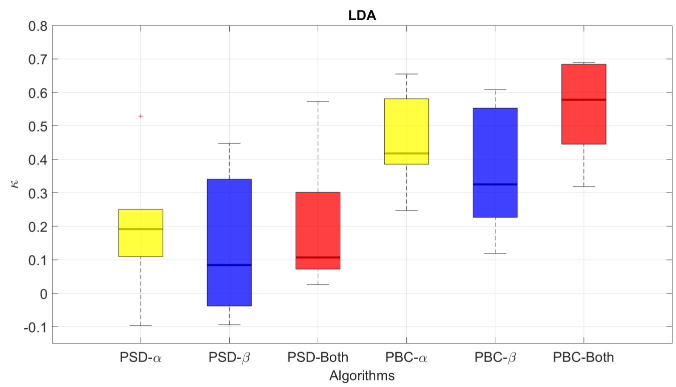

Fig. 7. Box diagram of the Cohen's Kappa coefficient (κ) for the evaluated methods in this study using the LDA classifier.

IV. DISCUSSION

According to the results obtained in this study, the Power-based connectivity (PBC) methods provide adequate identification of motor imagery regarded right and left hand with averages accuracy of approximately: 0.73 $\pm$ 0.07 (PBC-α), 0.68 $\pm$ 0.09 (PBC-β) and 0.77 $\pm$ 0.08 (PBC-Both). While the standard methods based on PSD obtained average accuracy of approximately: 0.59 $\pm$ 0.10 (PSD-α), 0.57 $\pm$ 0.11 (PSD-β), and 0.60 $\pm$ 0.12 (PSD-Both), see Fig. 6. On the other hand, the proposed method outperforms the standard method considering Cohen's Kappa coefficient, where the PBC method had a behavior of 0.45 $\pm$ 0.15, 0.36 $\pm$ 0.19 and 0.55 $\pm$ 0.15 on the frequency bands α, β and both respectively. While the PSD method had a behavior of 0.19 $\pm$ 0.20, 0.14 $\pm$ 0.21 and 0.19 $\pm$ 0.20 on the frequency bands α, β and both, respectively. Fig. 7.

Reported methods in literature based on connectivity through cross-correlation or coherence using reference channels [11], have provided accuracy of approximately 0.94 [12], 0.79 [8], 0.85 and 0.66 [13] but using advanced techniques as spatial filters and complex classifiers. On the other hand, experiments based on the classification of motor imagery for subjects with no experience in BCI systems have reported accuracy of around 0.79 [23]. According to the table II, it is possible to see that the proposed method has a behavior significantly better than standard methods on the α band and using both bands ($p-value < 0.05$), for the β band the behavior, is superior for PBC but not significant ($p-value > 0.05$). Finally, the proposed method had the best performance using the information of both frequency bands (α+β) and the worst performance was on the β band, however, the evaluation of the metrics are acceptable for the classification.

Obtained connectivity results present a contralateral behavior showing a higher correlation in the C_3 channel when the subject imagines the right hand and in C_4 when the subject imagines the left hand. The correlation between the channels was greater than 0.7 in the ipsilateral results and greater than 0.8 in the contralateral results according to Fig. 5. The correlation between the signals increases the dimensionality of the data, which can lead to an improvement in the identification of movements. Nevertheless, increasing the number of reference channels increases the dimensionality of the data. The proposed method was based on Spearman's correlation taking into account the normality conditions for the application of Pearson's correlation coefficient. In addition, to our knowledge, Spearman's correlation has not yet been used for connectivity-based command identification. However, connectivity-based systems for motion identification are still under investigation to find methods that allow an effective application in rehabilitation engineering.

V. Conclusions

It is possible to conclude that the connectivity-based method can increase the performance in motor imagery task detection in comparison to the traditional methods. Additionally, the results show effects related to the connectivity between the reference electrodes and those located in the motor cortical area that are produced in the brain when right-hand or left-hand movements are imagined. For this study, the method based on Spearman's correlation was an adequate descriptor for identifying the user's intention. This method could be applied in online BCI system in combination with neurorehabilitation techniques to benefit people with disabilities, additionally, it could provide tools for understanding brain-behavior during other types of stimuli. Further research will focus on generalizing the method with more sample subjects and on the experimental implementation of the method.

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