# MOTOR IMAGERY BASED ON WAVELET POWER SPECTRUM FOR A BRAIN COMPUTER INTERFACE

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***Abstract:*** *A Brain Computer Interface (BCI) is often used to command devices and clinical applications. In this study a BCI based on wavelet power spectrum using motor imagery is implemented. Four motor tasks were used and the method proposed achieved success rate of 89% and ITR of 11.40 bit/min. The proposed method had statistical significance (p-value<0.05) and the size of effect was very high (>2.0) for sensitivity, specificity, accuracy and Kappa coefficient.*
***Keywords:*** *Wavelet Power Spectrum, Motor Imagery, Brain-Computer Interfaces, EEG.*

## Introduction

A BCI can be used for commanding devices, entertainment activities and medical applications. A BCI uses activation regions of the brain and transform these activation potentials in computer commands without using traditional ways (nerves, muscles or hormonal outputs). There are several paradigms to implement a BCI such as evoked potential which can be visual, auditory or somatosensory. The source of stimuli can be endogenous (volunteer provides the stimulus) or exogenous (the interface provides the stimulus)., where each paradigm presents its advantages [12].

Two types of brain rhythms are of importance for BCIs: mu (8-12 Hz) and beta rhythm (13-30 Hz), both originating in the sensorimotor cortex. Motor imagery can cause an eventrelated desynchronization (ERD) which performs an amplitude suppression, or event-related synchronization (ERS) which performs an amplitude enhancement in these two frequency bands. During motor imagery, the mu and beta ERDs occur mostly on the contralateral hemisphere at the onset of imagination, while the beta ERS occurs on the contralateral hemisphere at the offset of the imagination. Time-Frequency (TF) analysis is used to describe the distribution of signal energy as a function of both time and frequency. It provides a powerful tool for non-stationary signals processing and has been used for EEG signal analysis [1]–[4].

In our previous work [5] using two motor tasks from BCI III dataset IVa, Wavelet Power Spectrum (WPS) and Support Vector Machine (SVM) had the best performance compared other methods [5]. In this work, the motor imageryis based on WPS, which achieved the best results. Furthermore, an statistical analysis of the significance between the wavelet power spectrum and power density spectrum is here proposed.

## Materials and Methods

### *A. Experimental protocol*

The experimental protocol allows the acquisition of EEG signals for four motor tasks. Eight healthy volunteers participated in the experiment with provided written consent. EEG signals were acquired from Emotiv EPOC neuroheadset using fourteen electrodes on the scalp, placed according to the international 10/20 system: AF3, AF4, F3, F4, F7, F8, FC5, FC6, P7, P8, T7, T8, O1, O2. EEG channels were sampled with 128 Hz at 1.95 $\mu V$, which is the least significant bit voltage resolution. Regarding the experimental protocol, the volunteers were instructed to sit with his/her hands resting on his/her legs and observe the center of the screen. Text ”Rest” is then shown for eye fixation to avoid excessive artefact from eye movements. After 10 s, a text ”Mental task” indicates the start of the mental task. The mental task lasts 10 s, and then the text ”Rest” reappears indicating that the mental task is over. Therefore, 20 trials are taken with this same protocol, but during this phase the volunteer is instructed just to do not move or perform any of the four motor tasks:

- Baseline: in this task the subject only relaxes.
- Motor imagery of right/left arms: for the left/right arm task the subject is instructed to imagine the movement of the right arm in order to make inflexion and extension.
- Motor imagery of the right and left arm the same time: the subject must imagine the movement of his/her arms of the same time.

### *B. Power Spectral Density*

The Power Spectral Density (PSD) [6] is among the methods applied in characterizing brain activity patterns in EEG signals, and has already been used in many researches to study emotion recognition.

| Users | Sensitivity | Specificity | Accuracy_2 [%] | Kappa_2 | ITR [bits/min] | Accuracy_4 | Kappa_4 |
|---|---|---|---|---|---|---|---|
| **User 1** | 0.90 (0.57) | 0.97 (0.86) | 0.96 (0.79) | 0.87 (0.43) | 11.38 (10.33) | 0.90 (0.57) | 0.87 (0.43) |
| **User 2*** | 0.89 (0.63) | 0.96 (0.88) | 0.94 (0.81) | 0.85 (0.50) | 11.32 (10.45) | 0.89 (0.63) | 0.85 (0.50) |
| **User 3*** | 0.98 (0.86) | 0.99 (0.95) | 0.99 (0.93) | 0.97 (0.81) | 11.82 (11.18) | 0.98 (0 .86) | 0.97 (0.81) |
| **User 4** | 0.89 (0.57) | 0.95 (0.86) | 0.94 (0.78) | 0.85 (0.43) | 11.32 (10.32) | 0.89 (0.57) | 0.85 (0.42) |
| **User 5** | 0.86 (0.52) | 0.95 0.84) | 0.93 (0.76) | 0.81 (0.36) | 11.18 (10.25) | 0.86 (0.52) | 0.81 (0.36) |
| **User 6** | 0.71 (0.47) | 0.90 0.82) | 0.86 (0.74) | 0.61 (0.29) | 10.67 (10.17) | 0.71 (0.47) | 0.61 (0.30) |
| **User 7** | 1.00 (0.88) | 1.00 (0.96) | 1.00 (0.94) | 1.00 (0.83) | 11.98 (11.26) | 1.00 (0.88) | 1.00 (0.83) |
| **User 8** | 0.93 (0.47) | 0.98 0.82) | 0.96 (0.74) | 0.90 (0.30) | 11.50 (10.17) | 0.93 (0.47) | 0.90 (0.30) |
| **Average** | 0.89 (0.62) | 0.96 (0.87) | 0.95 (0.81) | 0.86 (0.49) | 11.40 (10.52) | 0.89 (0.62) | 0.86 (0.49) |
| **p-value** | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 |
| **d-effect** | 2.09 | 2.04 | 2.10 | 2.11 | 2.08 | 2.09 | 2.11 |

TABLE I: WPS and PSD performance on test data. Measurement performance for four imagery motor task. The user 2 and 3 are left handed.

The underlying principle of spectral analysis is a theorem stating that any function in time is a superposition of wave. Let $Af_i \sin 2\_f_it + \theta_i$ be the sinus wave at time t with amplitude Afi, frequency fi and phase i and so any function of time denoted by, for example, EEG(t) can be written as:

$$EEG(t) = \sum_{all\ frequencies\ f_i} \mathrm{A}\sin(2\pi f_I + \theta), \qquad (1)$$

when suitable coefficients for $Af_I$ (amplitudes) and $\theta_i$ (phases) are chosen. The power spectrum can be computed as the square of the amplitudes $A^2f'_I$ as a function of the frequency $f_I$, and it is commonly used as a measure of how strongly is a certain frequency $f_I$.

*C. Wavelet Power Spectral*

Although computing power spectral densities for EEGbased emotion recognition is a very popular method among the available feature extraction algorithms, it assumes that the signal over time periods is stationary. However, given the nonstationary signal due to the dynamic behaviour of EEGs, this would constrain the Fourier Transformation to extract salient features, which may be valuable to affect recognition. Other non-parametric methods of feature extraction can account for signal non-stationaries as they are found in the joint timefrequency domain, such as Wavelet features. Rather than analysing the signal dataset as a whole, wavelet provides a measure for local frequency analysis and thus providing information that is likely to be obscured by other alternative time-frequency methods, like Fourier analysis. The wavelet power spectrum [7] is computed through a so-called wavelet transform ψ (t), which, as a function of time, can be defined as:

$$\psi(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right), \qquad (2)$$

where $a$ denotes a scaling parameter for the frequency represented by the wavelet, and $b$ a shifting factor, i.e. the center point of the wavelet. At arbitrary scales between sampling intervals containing the times series, we refer to the continuous wavelet transform (CWT) of a function of time, f(t), expressed as:

$$W(f) = \int_{-\infty}^{+\infty} f(t)\overline{\psi(f)}, \qquad (3)$$

where factors $a$ and $b$ determine scale and center of the wavelet. Given the continuous wavelet transform, we are able to obtain the wavelet power spectrum by essentially squaring the CWT as $Pw = W(f)^2$.

*D. Support Vector Machine*

SVM applies discriminate hyperlanes to detect classes. The attempt of the SVM to maximize margins from the closest data training points is distinguishable, whose function behaves as the nearest preparation fact. A SVM classification using linear decision boundaries is referred as a linear SVM. In a simple, binary class problem with separable data, the best hyperplane is found as the one with the largest margins between the two classes. The training data comprise a set of points (vectors) xifor some dimension d, where xi 2 Rd and their corresponding categories (or labels) yi for which yi = 1. To find the best hyperplane, we define the decision boundary as:

$$w^Tx + b = 0 \qquad (4)$$

where $w \in R^d$ and $w^Tx$ is the inner dot product of $w$ and $x$, and $b$ is a real number. Anything above the decision boundary should have label 1, i.e., $x_i$ such that $w^Tx + b > 0$ will have the corresponding yi = 1.

*E. Measurement Performance*

The performance measurement used here draws information from the confusion matrix [8], such as follows:

- Accuracy is the success rate of the classifier. The accuracy defined for this paradigm is above the random value for four classes (71% expected value).

- ITR (Information Transfer Rate) is a standard measurement of communication systems, meaning the amount of information transferred per unit of time. ITR depends on both speed and accuracy and it is defined by Equation 5.

$$B = log_2 N + P log_2 P + (1 - P) log_2 \left(\frac{1-P}{N-1}\right), \qquad (5)$$

where N is the number of classes, P is the success rate of correct classifications. The measurement unit for ITR is [bits=s], but it can be determined in [bits=min] multiplying the result by the selection speed, i.e, the number of selections performed by the system in one minute. It is normally ranged between 5 to 25 [bits/min] for a mental tasks.

- Kappa coefficient is a parameter that represents the concordance between the targets and the prediction values. In this sense, the index used here was proposed for Cohen. The Kappa coefficient is defined in Equation 6:

$$Kappa = \frac{\sum_{i=1}^{q} p_{ii} - \sum_{i=1}^{q} p_{i-}p_{-i}}{1 - \sum_{i=1}^{q} p_{i-}p_{-i}}, \qquad (6)$$

where $\sum_{i=1}^{q} p_{ii}$ is the accuracy, and $\sum_{i=1}^{q} p_{i-}p_{-i}$Pq is the percentage due to chance. $Kappa > 0.61$ indicates good concordance to four classes; therefore the expected accuracy should be > 71%.
- Sensitivity and specificity are measurements that provide information about the particular class detection ability (true positive or negative condition). The sensitivity and specificity are calculated in Equations 7 and 8.

$$Sensitivity = \frac{TP}{TP + FN} \qquad (7)$$

$$Specificity = \frac{TN}{FP + TN}, \qquad (8)$$

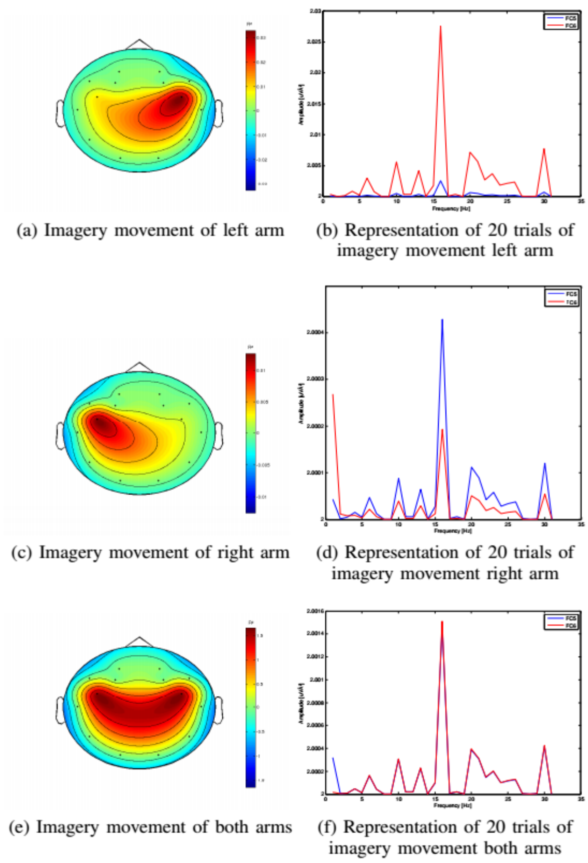
where TP is referred as true positive, FN false negative, TN is true negative and FP is false positive. Sensitivity and specificity are used in two class problems; in which the expected values should be above 81%.

**Results and Discussion**

Figure 1 shows the brain topography representation and the WPS for channels placed above the motor region (FC5 and FC6). The determination coefficient R2 is shown and the baseline is correlated with each specific task. Each motor task activates the contra-lateral region. Volunteers 2 and 3 are left handed and their activation region was ipsi-lateral. The performance measurement was obtained for the PSD in α and β bands, and for the WPS in the frequency band was 2-32Hz with a scaling factor of 0.5hz and using a ”Morlet” wavelet function [9].

*A. Statistical Performance*

A statistical analysis is necessary to validate the proposed feature extraction method. The Wilcoxon



(a) Imagery movement of left arm (b) Representation of 20 trials of imagery movement left arm

(c) Imagery movement of right arm (d) Representation of 20 trials of imagery movement right arm

(e) Imagery movement of both arms (f) Representation of 20 trials of imagery movement both arms

Fig. 1: Representation imagery movement for left and right arms

Signed-Ranks test (WSR) is the non-parametric alternative to the parametric paired sample t-test, when the assumption of normality is not met. WSR is used to evaluate the difference between the means of dependent samples (i.e., PSD WPS) [10]. The effect size calculation was conducted by using Cohens description of common effect sizes, which included small (deffect= 0.2), medium (d-effect=0.5), large (d-effect=0.8), very large (d-effect=1.2), and huge (d-effect=2.0). Table I shows the measurement for evaluating the performance of WPS and PSD methods.

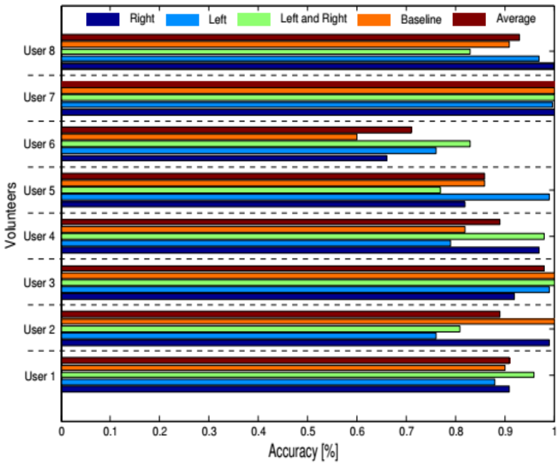



Fig. 2: Performance for four motor imagery task using WPS.

This table presents the PSD feature extraction methods values inside the parenthesis, and WPS values are presented outside it. The accuracy for two classes (Accuracy 2) is higher than four classes, thus allowing its use to switch BCIs or for a hybrid BCI.

Accuracy and Kappa coefficient for four motor tasks are good, except for volunteer 1, 5 and 6. The statistical significance (p-value) is <0.05 for all performances measurement. The null hypothesis was rejected for all cases due to the high effect size (d-effect), that is greater than two. Figure 2 shows the performance for each volunteer in each motor task. As expected, the baseline and movement imagery of both arms had the worst performance. The baseline low performance is due to the difficult of providing the same pattern for non-specific tasks. The movement imagery of both arms should be contra-lateral, because it is always easier to imagine the movement of the predominant arm. The movement imagery of the right arm had the best performance.

## Conclusions

Wavelet power spectrum presents better performance than power spectrum density for motor mental task recognition. It has been found, unlike [4], that the Morlet wavelet seems to be better suited [9]. This difference was validated through statistical significance in several measurements. The BCI implemented in this work is designed to be used to control an avatar in a virtual enviroment, and for robotic telepresence control. The motor imagery can be used as a neurofeedback tool. When a volunteer provides a good pattern, the feature extraction method gets dimension reduction and a better data representation.

## Acknowledgment

Authors thank CAPES and CNPq for funding (process 133707/2013-0). The first author also thanks the School of Electrical and Electronic Engineering Graduated Program of the University of Valle (Colombia).

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