DWT-based Feature Extraction for Motor Imagery Classification

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Keywords: Brain Computer Interface, Discrete Wavelet Transform, Power Spectral Density.

Abstract

Brain computer systems interface (BCI) is a continuing and growing field in evolution. During the last decades, many laboratories have begun to explore technologies BCI as a new communication option for people with neuromuscular disabilities that prevent them from using conventional augmentative communication methods. In this work is presented a methodology for the classification of motor imagination, using features extracted from power spectral density (PSD) as feature extraction technique. Two approaches are evaluated, first computing PSD features from the raw data and the second, performing a decomposition by means of the discrete wavelet transform (DWT). Obtained classification results show that features obtained through PSD with DWT achieves an accuracy of 85%, a sensitivity of 90% and a specificity of 80% while the results obtained with PSD over the raw data has a precision of 70%, one sensitivity 60% and specificity of 80%. Demonstrating that the performance of the classifier with the proposed preprocessing stage was improved.

1 Introduction

Brain computer interface (BCI) systems are a continuous and growing field in evolution. A BCI system is a hardware and software communication system that allows cerebral activity to control computers or external devices. During the last decades, many laboratories have begun to explore BCI technologies as a new option of communication for people with neuromuscular disabilities which prevent them from using conventional communication methods [9]. BCI systems uses different neuroimaging techniques to record brain activity and translate certain characteristics, corresponding to the user's intentions, into commands for computer or other devices applications. The electroencephalogram (EEG) is the most widely used method to record the brain signals, because it is a noninvasive technique easy to handle, inexpensive and portable [10].

Patients in a late stage of amyotrophic lateral sclerosis (ALS) or suffering from a syndrome of captivity are not able to produce voluntary muscle movement [11], to solve these problems BCI-based imagery motor systems are investigated. In San Diego, California USA, was presented a non-motor imagery tasks classification EEG based brain computer interface (BCI) for wheelchair control. To this aim, two different features extraction methods, power spectral density (PSD) and Hilbert Huang Transform (HHT) energy, were compared to find the most suitable method with improved classification accuracy using a Genetic Algorithm (GA) based neural network classifier. The results from five subjects showed that using the original eight channels with three tasks, accuracy between 76% and 85% is achieved. With only two channels in combination with the best chosen task using a PSD feature extractor, the accuracy is reduced to between 65% and 79%. However, the HHT based method provides an improved accuracy between 70% and 84% for the classification of three discriminating tasks using two EEG channels [5].

A close approach was done in [7], where it was investigated a nonlinear approach for feature extraction of EEG signals in order to classify motor imagery for Brain Computer Interface (BCI). This approach was based on the Empirical Mode Decomposition (EMD) and band power (BP), the classification of motor imagery was performed by using two classifiers, Linear Discriminant Analysis (LDA) and Hidden Markov Models (HMMs). Obtained results showed that including EMD method allows the most reliable features and enhances the classification rate, than using only the direct BP approach, with an accuracy of about 83.12% and 78.29% respectively. Also in [4] is presented 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 studied. 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 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.

In the State of the art, some techniques based on spectral power density or power spectral density are used to extract features from EEG signals and combined with other methods, e.g. EMD. Although the results are promising, they need more experiments to obtain better classification accuracy. In this work a methodology for motor imagination classification is proposed. Classification over a set of features estimated by means of power spectral density (PSD) is compared against an approach with a preprocessing step, where the discrete wavelet transform is used to decompose the EEG signal into frequency bands and further analyzed by PSD. The methodology is tested in the 2003 data set BCI competition, which has data imagination motorboats of the left hand and the right with 140 recordings with 3 electrodes and 1152 samples. The results obtained show that the preprocessing stage of decompose the signal into frequency bands allows a better set of features than using the raw data in terms of accuracy, sensitivity and specificity values.

2 Materials and methods

2.1 Discrete wavelet transform (DWT)

The discrete wavelet transform (DWT) analyzes the signal at different frequency bands by decomposing of signal into a coarse approximation and detail information. The DWT can be described mathematically as a set of inner products between a finite-length sequence and a discretized wavelet basis. Each inner product results in a wavelet transform coefficient. Thus, the DWT can be expressed as:

$$Wf\left(j,k\right)=\sum_{N=0}^{N-1}f\left(n\right)\cdot\psi_{j,k}^{*}\left(n\right) \quad (1)$$

where $Wf\left(j,k\right)$ is a DWT coefficient; $f\left(n\right)$ is a sequence with length N ; the expression:

$$\psi_{j,k}\left(n\right)=\frac{1}{\sqrt{s_{o}^{j}}}\psi\left(\frac{n-s_{o}^{j}\cdot k}{s_{o}^{j}}\right) \quad (2)$$

is the discretized wavelet basis; and s_o^j and $s_o^j \cdot k$ are the discretized versions of the scale and translation parameters, respectively.

DWT decomposition can be seen as a set of high-pass and low-pass filters in a filter bank. Following the filtering, the signal is decimated by a factor of two. The outputs of the low-pass branch are called wavelet approximation coefficients, and the outputs of the high-pass branch are called wavelet detail coefficients. The wavelet decomposition can be iteratively performed until a maximum scale is reached. The maximum scale is dependent on the signal length and the wavelet basis length[3].

2.2 Power Spectral Density (PSD)

Power spectral density (PSD), describes how to the power of a signal or time series is distributed with frequency. Since signal with nonzero average power is not square integrable, the Fourier transforms do not exist in this case. The PSD is the Fourier transform of the autocorrelation function of the signal.

The power of a signal in a given frequency band can calculated by integrating over positive and negative frequencies. The definition of power spectral density generalizes in a straight manner to finite time series with $1 \leq n \leq N$,such as signal sampled at discrete times $xn = x\left(n\Delta t\right)$ for a total measurement period $T = N\Delta t$ [8].

$$S\left(e^{jw}\right)=\frac{1}{2\pi N}\left|\sum_{n=1}^{N}x_{n}e^{-jwn}\right|^{2} \quad (3)$$

3 Experimental Framework

3.1 Dataset

Used Dataset was provided by Department of Medical Informatics, Institute for Biomedical Engineering, University of Technology Graz [2]. It was recorded from a normal subject *(female, 25 yrs)* during a feedback session. The subject sat in a relaxing chair with armrests. The task was to control a feedback bar by means of imagery left or right hand movements. The order of left and right cues was random. Figure 1 shows the timing of the experiment. The first $2s$ was quite, at $t = 2s$ an acoustic stimulus indicates the beginning of the trial, the trigger channel ($\#4$) went from low to high, and a cross (“+”) was displayed for $1s$; then at $t = 3s$, an arrow (left or right) was displayed as cue. At the same time the subject was asked to move a bar into the direction of the cue. The feedback was based on AAR parameters of channel $\#1$ ($C3$) and $\#3$ ($C4$), the AAR parameters were combined with a discriminant analysis into one output parameter.

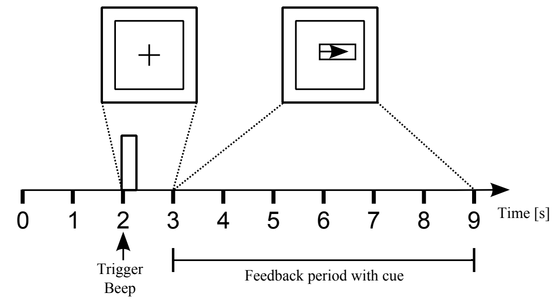


Figure 1. Timing of the experiment

The recording was made using a G.tec amplifier and a Ag/AgC1 electrodes. Three bipolar EEG channels channels (anterior ‘+ ’, posterior ‘-’) were measured over $C3$, Cz and $C4$ Figure 2. The EEG was sampled with 128Hz, it was filtered between 0.5 and 30Hz. The experiment consists of 7 runs with 40 trials each. All runs were conducted on the same day with several minutes break in between. Since one half of the dataset are provided for training there are 140 trials of $9s$ length.

3.2 Data pre-processing and decomposition

Given that the first $3s$ are irrelevant (quiet state and cross displaying), EEG signals are used from second 3rd to 9th. For the comparison approach, the signal is decomposed into frequency bands using the discrete Wavelet transform. The number of levels of decomposition was chosen on the basis of the dominant frequency components of the signal. According to imag-

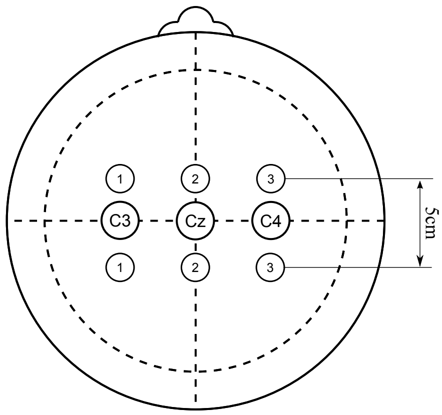


Figure 2. Electrode placement

Decomposed signal	Frequency range (Hz)	Rhythms
A5	0 – 2	Delta (δ)
D5	2 – 4	Delta (δ)
D4	4 – 8	Theta (θ)
D3	8 – 16	Alpha (α)
D2	16 – 32	Beta (β)

Table 1. Frequencies corresponding to different levels of decomposition for Daubechies order 4.

ined right/left hand movements, we chose the level of 5 and the wavelet of Daubechies order 4 [6]. As a result, the EEG signal is decomposed into the details D2-D5 and approximation A5 for each of the three electrodes. The ranges of different frequency band are shown in Table 1.

3.3 Feature Extraction

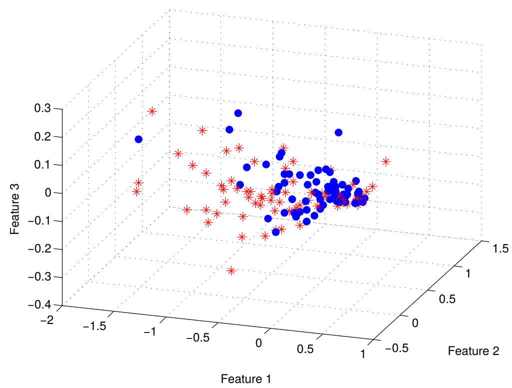
To extract relevant information from EEG signals and characterize the motor imagination of left/right hands two approaches was taken. As a first approach, each raw signal from electrodes $C3$, Cz and $C4$ were analyzed by PSD and such features were concatenated into a single vector. Comparison approach extract a set of feature for each level of decomposition (details (D2-D5) and approximation (A5)) creating a single vector by stacking the features of each one of the three electrodes.

3.4 Classification

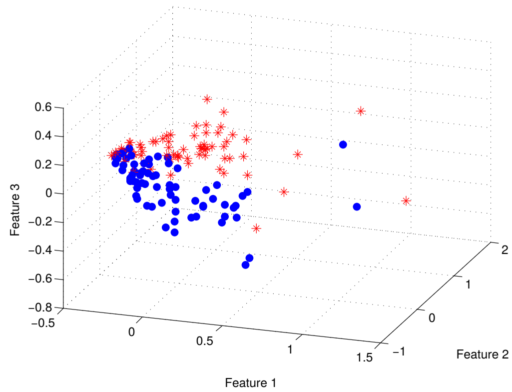
Due to the high amount of features, principal component analysis (PCA) technique is used to reduce data dimension. This, aiming to provide better classification accuracy and reduce the computational cost. PCA is set to retain 99% of data variance. It is worth to note that dimension reduction is done for all the characterization techniques described before. Besides, an SVM is used for the classification stage. Since it has free parameters, a suitable tuning must be done. Thus, a two-dimensional exploration for all the possible values of the SVM trade-off constant C and the kernel band-width σ is carried out by means of a Particle Swarm Optimization (PSO) meta-heuristic [1]. To avoid over-training of the models, a cross-validation of ten folds is performed. The limits of the search space were defined as (10^{-3},10^{4}) for σ and (1,10^{-6}) for C. Additionally, the number of particles for the search was set to 10, while the maximum number of iterations was set to 20.

4 Results and Discussion

Scatterplots for both considered feature extraction approaches are shown in Figure 3. Specifically, in the Figure 3(a) is depicted PSD features over raw EEG signal. A strong overlapping among classes is present, exhibiting that despite belonging to different classes, some samples has similar information. Such overlapping prevents a proper classification performance. From the foregoing, it can be concluded that another method is required to separate and improve classification features. In Figure 3(b) is shown the scatterplot of the features computed by means of PSD, when data has a preprocessing stage of decomposition with DWT. Although there is a region with some overlapping between classes, most of the samples for different classes are separable from each other, which improves classification result.



(a) PSD over raw EEG



(b) PSD with DWT

Figure 3. Scatterplots for considered feature extraction methods.

Classification performance is summarized in terms of accuracy, sensitivity and specificity and shown in Table 4. Since a 10 fold cross-validation was done, results are presented as mean value with standard deviation. It is worth to note how the preprocessing stage with DWT enhances both the classification accuracy and the sensitivity, from 70% to 85% and from 60% from 90%, respectively. While the specificity remains the same (80%), it it should be noted that the standard deviation is less when using DWT decomposed levels, leading to more stable specificity results.

	PSD over raw EEG	PSD with DWT
Accuracy	0.7 ± 0.174	$\mathbf{0.85 \pm 0.103}$
Sensitivity	0.6 ± 0.188	$\mathbf{0.9 \pm 0.118}$
Specificity	0.8 ± 0.225	$\mathbf{0.8 \pm 0.154}$

Table 2. Classification performance

5 Conclusions

A methodology for the classification of the left-right hands movement imagination was proposed, achieving a result of 85% accuracy, which is comparable with some results of the State of the art. EEG recordings from three electrodes are analyzed. It was demonstrated how, for this type of motor imagery tasks, a decomposition stage using power spectral density as a feature extraction technique over the wavelet decompositions allows to obtain more information in the bands, which improves the performance of the classifier in terms of accuracy, sensitivity and specificity. It is worth notice that the used database contains only information of one single subject, in BCIs the control is user dependent and not all subjects can perform perfect control of the system.

As future work it would be interesting to study other types of decomposition such as EMD or band-frequency filtering. Besides, further experiments with the proposed methodology for tasks addressed by BCI systems should be done, and explore the methodology with more users.

Acknowledgments

This work is carried out under grants provided by Programa Nacional de Jóvenes Investigadores e Innovadores - 2014 (COLCIENCIAS) and Programa de financiación de Becas de Doctorado Nacional convocatoria 647 COLCIENCIAS.

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