SELECTION AND CLASSIFICATION METHODS FOR DETECTING IMAGINATION MOVEMENT AND SPONTANEOUS EEG SIGNALS: A STUDY OF METHODOLOGIES

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Abstract: The incorporation of pattern recognition techniques into Brain Computer Interface (BCI) systems has become an essential and promising field of research. This article analyzes and compares two new methodologies for classification of BCI signal into spontaneous and imaginary movements. Such methodologies are based on a combination of a feature selection technique with a learning algorithm. Comparing the results obtained in this study with those found in the literature, it can be said that they are similar with average success rate around 80 % and 90 % [8, 10-12].
Keywords: EEG, Brain Computer Interface, Artificial Neural Networks, Feature Selection.

Introduction

Identification of movement imagination have been broadly used in Brain Computer Interface (BCI). The application of BCI covers a wide range of areas, from games to the promotion of interaction among people with motor limitations, and with the environment that surround us [1,2,3]. In order to register brain activities, invasive and non-invasive techniques can be used. Signal acquisition can be achieved with electroencephalogram (EEG), which records the signals through sensors placed on the scalp of the subject [1,3,4].

As a response to external stimulus, the electrical activity recorded by the EEG is expected to suffer some change that, when synchronized in time and phase with the stimulus, generates the Event Related Potential (ERP). One of the goals of BCI is to obtain the ERP that is related to the movement imagination, as a response to external stimulation, and to generate a response action [5].

According to [6] BCI is composed of three components, as illustrated in Figure 1. First, an input device captures the brain activity (e.g. Electroencephalogram signal). Then, the raw input signal is recorded, preprocessed and converted (signal processing step) into commands for some output device: an electronic wheel chair, a prosthesis or a computer cursor.

However, the identification of ERP amid spontaneous electrical activity of the brain (Spontaneous EEG) is not trivial [7,8,9]. Several techniques, based in time and frequency, have been used in order to extract features of the input signals, and to classify them. Among the techniques more frequently used in the literature are: Energy band [2]; Magnitude-Squared Coherence - MSC [5]; K-Nearest Neighbor - KNN [8]; Parameters of Autoregressive Models [10]; Linear Discriminant Analysis - LDA [11]; Support Vector Machine - SVM [11]; Artificial Neural Networks [12]; Wavelet [13], among others. A general overview of EEG approaches to the problem can be found in [8].

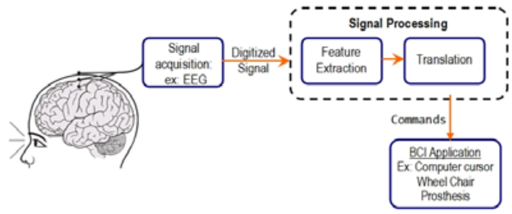

Figure 1: BCI components (adapted from [6]).

In this work we investigate two methodologies for signal classification in Spontaneous EEG and Movement imagination tasks. The first one combines T-test filter for ranking Fourier features with Multi-Layer Perceptron Neural Network classifiers. The results using these methodologies are then compared to another setting which is based on the Wavelet transform for ranking features and Support Vector Machines as will be described next.

Signal Acquisition Procedure

The database used in this work was collected in Federal University of Minas Gerais in the Biomedical Laboratory according to a protocol approved by the Local Ethics Committee. The signals were collected using 17 electrodes (Fcz, Fc1, Fc2, Fc3, Fc4, Cz, C1, C2, C3, C4, C5, C6, Cpz, Cp1, Cp2, Cp3, Cp4) placed according to International 10-10 System with reference at earlobes (A1 and A2 electrodes). Signal was recorded using the Brain-

Net BNT-36 (EMSA) Biological Amplifier with a frequency sampling of 600 Hz, band pass filter of 0.1-100 Hz and Notch Filter of 60 Hz.

Two different types of data were collected 1) Spontaneous EEG (no motor task) and 2) Movement Imagination up and down of the left index finger (MI EEG). The Spontaneous EEG record was during 15 minutes and the record of task of Imagination was during 20 minutes. The synchronization of the events was done using two LEDs (Light Emitting Diode), a red and a yellow one. Every trial was of duration of 14s (-4 to 10s). In moment -4s the red led was turned on to indicate attention for the subjects. At -1s, a yellow led was turned on to prepare individuals for the mental task. Finally, in moment 0s both LEDs were turned off and the subjects should do the mental task. After 10s another trial started. At the end of every session were collected M=42 and M=64 trials for Spontaneous EEG and for Imagination EEG, respectively. More information of the database can be found in [5]. The protocol can be visualized in Figure 2.

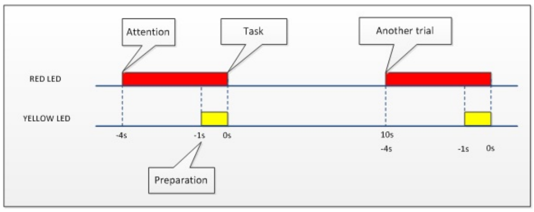

Figure 2: EEG signals were divided in synchronized trials of -0.7 to 2.3s where we found a cortical response to the imaginary movement task [5].

Methodology

The proposed methodology in this paper can be divided into three main steps: (1) Processing of EEG signal, (2) Selection of the relevant features; and (3) Classification.

In the experiments we used the signals drawn from electrodes C1, C2, C3, C4 and Cz. As described in Section Signal Acquisition Procedure, data was collected from seven different volunteers. For each subject, five signals of each category were collected. Accordingly, the dataset consists of 70 signals, being 35 of spontaneous movement and 35 of imaginary movement. The first procedures applied to raw signal were: signal averaging (see Figure 3) and Fast Fourier transform (FFT) in order to identify the main frequency components (see Figure 4).

Signal processing with FFT intends to find some useful information (the band Delta (0.5 - 4 Hz) and band Theta 4 - 8 Hz) which could provide some clue about dissimilarities between the different class of signals. Analyzing the FFT signal (see Figure 4), one can be observe that there is no useful information after 100 Hz. One can also observe that most of the useful information is concentrated in the first 20 Hz. Thus, we chose to work with two ranges: 1) 0 - 100 Hz; 2) 0 - 20 Hz. This procedure resulted in 4 different data sets described as follows: 1) This dataset uses the 100 initial components and T-test to select the 40 most relevant features; 2) This dataset uses the 100 initial components and T-test to select the 20 most relevant features; 3) This dataset uses the 100 initial components and T-test to select the 10 most relevant features; 4) This dataset uses the 20 initial components and T-test to select the 2 most relevant features.

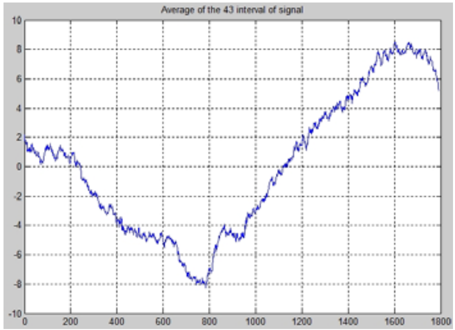

Figure 3: Average of the signal.

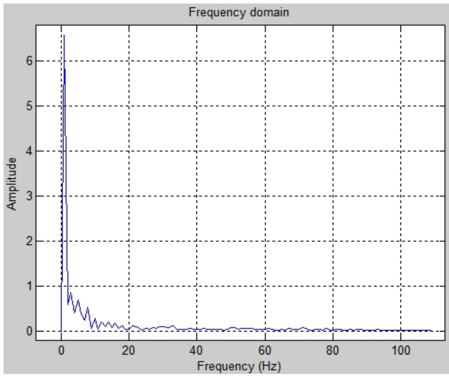

Figure 4: Fast Fourier Transform of the average signal.

For the range 0 - 20 Hz, it was observed according to results obtained by the T-test (see Figure 5), that the second and third features contained enough information to describe the categories.

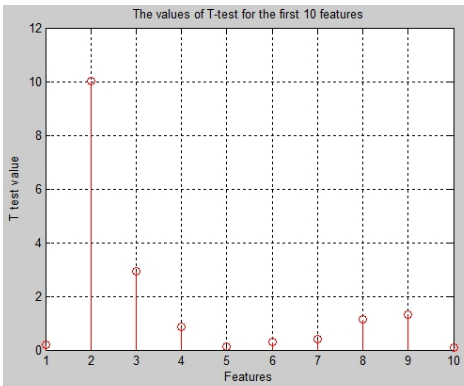

Figure 5: Value of the T-test for the first 10 features.

Methodological Setting I - Figure 6 presents a general diagram of the proposal methodology in order to classify the signal in Spontaneous and Imaginary Movement.

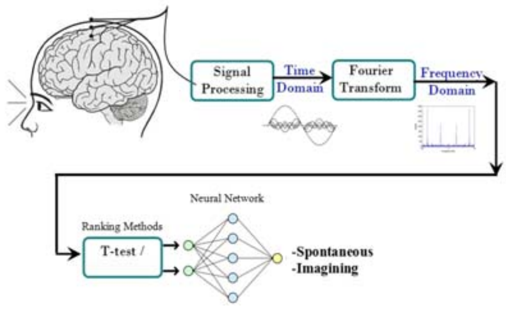

Figure 6: Diagram of the methodology proposed.

1) **Feature Selection with T-test Filter:** Figure 7 shows the signals extracted from electrode C1 for imaginary and spontaneous categories before the signal processing stage. Figure 8 presents FFT with respect to imaginary movement signals drawn from electrode C1.

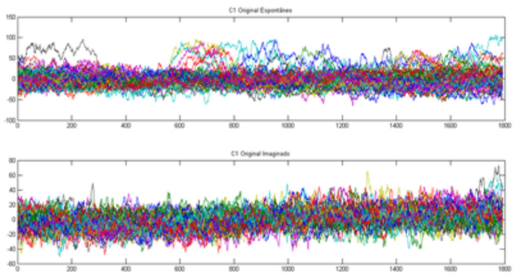

Figure 7: Electrode C1: imaginary and spontaneous signals.

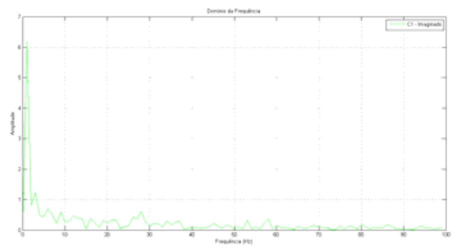

Figure 8: Fourier Transform imaginary movement signals drawn from C1.

2) **Classification with MLP -** The MLP neural network was trained with the Levenberg Marquardt algorithm. The best network topology was selected via k-fold cross-validation and has one hidden layer with 3 neurons. The training stop criteria were a error tolerance of 10^{-3} or 100 training epochs. For each trial, the dataset was divided in two groups: 70% training and 30% test. The results achieved for this methodology setting are presented in the Table I of Section Comparison of Proposed Methodologies.

Methodological Setting II - In this section we propose a different methodology for classification of EGG signals. Our methodology has two steps: 1) Feature selection using discrete wavelet transform (DWT); 2) Signal Classification using a Support Vector Machine (SVM).In the first step, Discrete Wavelet Transform (DWT) is applied on each sample in order to select the most relevant features present in the signal. In the second step, samples presenting the smaller number of features extracted in step 1 were used in the training of a SVM.

1) **Feature Selection with DWT:** In this experiment each sample was processed by the Daubechie-*l* wavelet using the following set of levels *l*={8,7,6,4}. Each level of DWT has a number of different details and features which can be used as input for the classifier. After applying DWT, the level of the each set *l* generates a number of different details {2,4,7,28}.It is known that most classifiers work better with a smaller number of inputs (features). Figure 9 shows the signal after decomposition at level 2. One can notice that although L_1 signal has half of the coefficients of the original signal S, it shows similar characteristics to the signal S. This shows that Wavelet approximation can be used to find a lower resolution that preserves characteristics of similarity of the original signal.

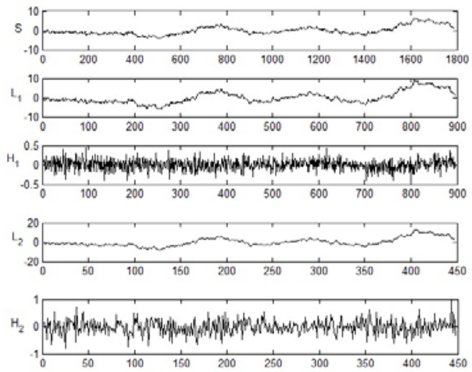

Figure 9: Wavelet – Decomposition at level 2.

2) **Classification with SVMs** - The SVM classifier was used with the RBF kernel. The parameters *gamma* of the RBF kernel were found using 10-fold cross-validation.

Comparison of the Proposed Methodologies

In order to validate our approaches, this section presents the experimental results performed for the two proposed methodologies. The values, presented in this Section, represent the average, for each classifier, of ten runs for each configuration (training/test).

In Table 1 (Proposal I), the majority (about 90%) of the misclassified cases were due to Spontaneous signals classified, erroneously, as Movement Imagination. In such cases may have occurred that the volunteers somehow produced responses near to the Movement Imagination, probably due to some external stimulation. This analysis is just a conjecture, a deeper analysis is needed to provide a better answer for the misclassified cases, and this could be a good future work to develop.

Table 1: Results for Methodological Setting I

Input	% Accuracy
02	91.57
10	89.29
20	90.53
40	94.34

In Table 2 (Proposal II) the best average, in this experiment, were obtained with 7 and 28 features. In this experiment we observed that by reducing the number of inputs of SVM classifier accuracy increased. On the other hand, the decrease much signal resolution accuracy decreased. Must then find a threshold level of decomposition, which is the best resolution.

Table 2: Results for Methodological Setting II

Input	% Accuracy
02	89.04
04	91.90
07	93.17
28	93.65

Although some results in both methods are very close, is important point out that the first method obtained good results using only two features. These slightly fewer features can be very handy with real time application, where decision must be done very quickly.

Also is worth to mention that the second method, using only 07 features obtained very good result, very close to the methodology I, using 40 features (Table 1).

Conclusion

This paper presented the results of two methodologies for detection of imagination and spontaneous movement by signals obtained through an EEG. The signals used were obtained from electrodes C1, C2, C3, C4 and Cz. It is interesting to note that the aim of this work was to employ different pattern recognition techniques to try to reduce the dimension of the problem and the computational complexity of the classifiers. No statistical comparison was performed to show the best method. In all experiments, the results showed that the process of selection and feature extraction before classification signal increased the generalization capability of both classifiers used. In future work the methodologies could be combined, analyzed and compared statistically.

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