EEG Signal Classification Using Power Spectral Features and linear Discriminant Analysis: A Brain Computer Interface Application

Jaime F. Delgado Saa
UNIVERSIDAD DEL NORTE. Barranquilla – Colombia, jadelgado@uninorte.edu.co

Miguel Sotaquirá Gutierrez
UNIVERSIDAD DEL NORTE. Barranquilla – Colombia, msotaquira@uninorte.edu.co

ABSTRACT

Biological signal processing offers an alternative to improve life quality in handicapped patients. In this sense is possible, to control devices as wheel chairs or computer systems. The signals that are usually used are EMG, EOG and EEG. When the lost of ability is severe the use of EMG signals is not possible because the person had lost, as in the case of ALS patients, the ability to control his body. EOG offers low resolution because the technique depends of many external and uncontrollable variables of the environment. This work shows the design of a set of algorithms capable to classify brain signals related to imaginary motor activities (left and right hand imaginary). First, digital signal processing is used to select and extract discriminant features, using parametrical methods for the estimation of the power spectral density and the Fisher criterion for separability. The signal is then classified, using linear discriminant analysis. The results show that is possible to obtain good performance with error rates as low as 13% and that the use of parametrical methods for Spectral Power Density estimation can improve the accuracy of the Brain Computer Interface.

Keywords: Brain Computer Interface, EEG, Linear Discriminant Analysis, AR modeling, Oscillatory Brain Activity.

1. INTRODUCTION

When a person suffers a disease that compromise the ability to perform motor activity, there is a chance to restitute some control of the environment using biological signals like EOG, EMG or EEG[4]. The first two signals offer a limited use because in the case of EOG the quality of the signal depends of environment characteristics, which are out of control [4]. In the case of EMG, these signals can't be used when the disease is severe and the person can´t control the motor activity of his body. The aim of a brain computer interface is to translate EEG signals into instructions for controlling a computer, which mean a new communication channel.

A general approach to Brain Computer Interface includes a signal acquisition system, preprocessing, selection and extraction of features, classification and feedback. The acquisition signal system must guarantee a good signal to noise ratio through implementation of filters and other techniques of digital signal processing in order to eliminate noise present on the EEG signal. For the selection and extraction of features of the signal, the knowledge of the biological signals characteristics is needed. In this area the ERP´s [5], the oscillatory brain activity, slow cortical potentials and neuronal ensemble activity are of interest and these signals are used as input for the BCI. Finally the classifier selects between the classes represented by the EEG signals, here the neural networks, support vector machines and Linear Discriminant have been used showing god performance [6][7].

2. EXPERIMENTAL DATA

This work made use of the dataset III (Department for Medical Informatics, University of Technology Graz) of the BCI competition II (2003), this dataset is described on [1]. The data consists of 140 trials each of 9 seconds; from second 3 to 9 the subject is asked to perform one of two mental tasks. The signals are recorded from the positions C3, C4 and Cz, according to the 10 – 20 standard [4] and the sample rate is 128Hz. The labels of the required task are given on an array call x_train and other set of data call x_test is provided for test the system. The labels of this data are provided for evaluation and determination of indexes of performance. The figure 1 shows the timing scheme for each trial.

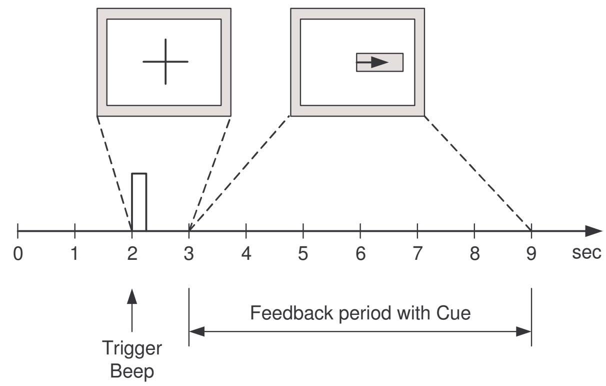

Figure 1. Timing scheme of the dataset III from BCI competition II [1].

3. FEATURE SELECTION AND EXTRACTION

In order to select the correct features of the EEG signal related to the mental activity, here is proposed the use of parametric methods for power spectral density estimation. The power spectral density of the signal, using parametric methods, is computed as the frequency response of an autoregressive model of the signal, based on previous values of the signal. In [8] was found that the order of this model is very important to obtain an accurate estimation of the spectrum. The order of the model is selected based on several criteria. The Akaike's final prediction error (FPE) criterion was use in [8] and the results show that orders as low as five can be used to model shorts segments of the EEG signal, however an order ten is suggested because it shows better results. The parametric method selected was the one proposed by Burg; this method always produce a stable model that minimizes the error on backward and forward directions and has a good resolution for large datasets. Figure 2 shows the PSD for one trial from 0s to 9s over the electrodes C3, C4 and Cz.

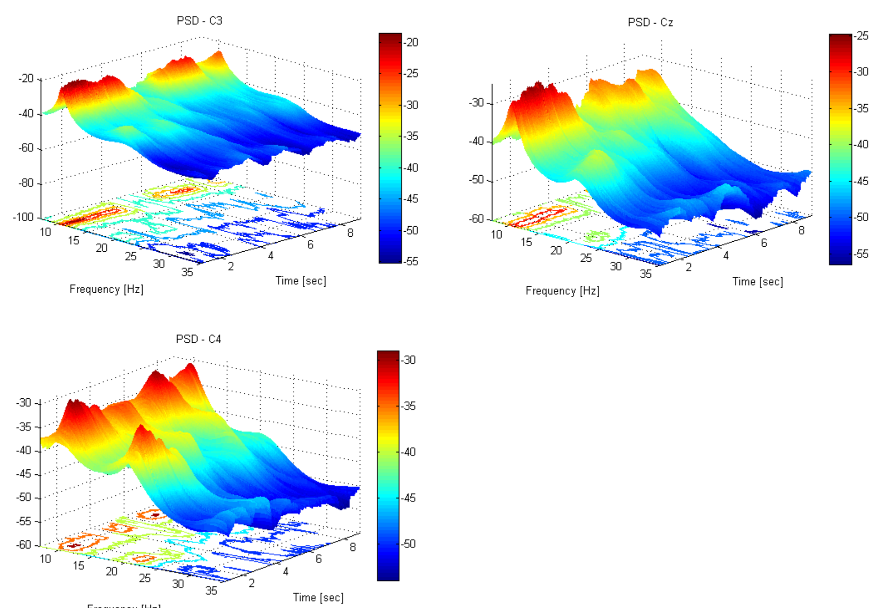

Figure 2. Power Spectral Density for 9 seconds signal during imaginary right hand movement.

Figure 2 shows that the PSD of the signal has frequency bands where peaks are found, this peaks correspond to alpha and beta signals in band of 8Hz-12Hz for alpha and 16Hz – 24 Hz for beta [2][11]. The average of the power for each class and each frequency component as time run for the 140 trials are depicted in Figure 3. This figure shows the differences between power in alpha and beta bands during imaginary right – class 2 – and left – class 1 – hand movement.

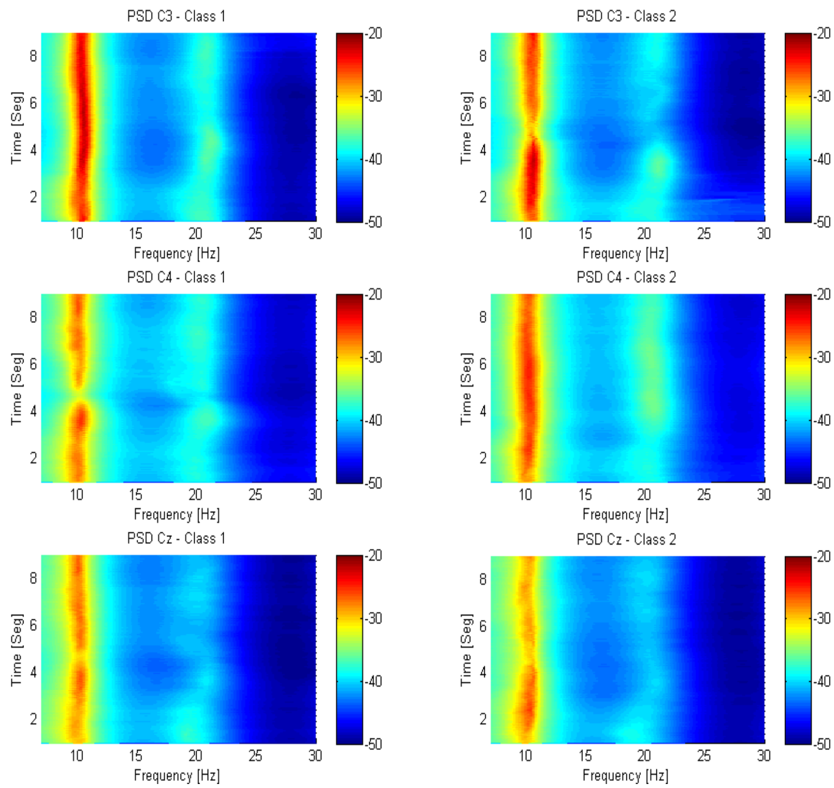

Figure 3. Average power for class 1 and class 2 trials.

To select the band of frequency that carries more information about the oscillatory brain activity related to the two mental task realized by the user (Class 1, Class2), the train dataset is analyzed by the grade of separability of the frequency components during the realization of imaginary motor activity [12]. For this purpose the Fisher criterion, which is a measure of class separability it's introduced as is propose in [13]:

$$Fr_i = \frac{(m_{1i} - m_{2i})^2}{{\sigma_{1i}}^2 + {\sigma_{1i}}^2}$$

Where m_{1i} and m_{2i} correspond to the mean of the feature *i* (frequency component) for Class 1 and Class 2 respectively.

${\sigma_{1i}}^2$ and ${\sigma_{2i}}^2$ are the variances of the feature I for Class 1 and Class 2 respectively. This gives a matrix where the Fisher ratio can be selected for a specific frequency and time. The figure 3 shows the Fisher ratio matrix values for the EEG signal over C3, C4 and Cz.

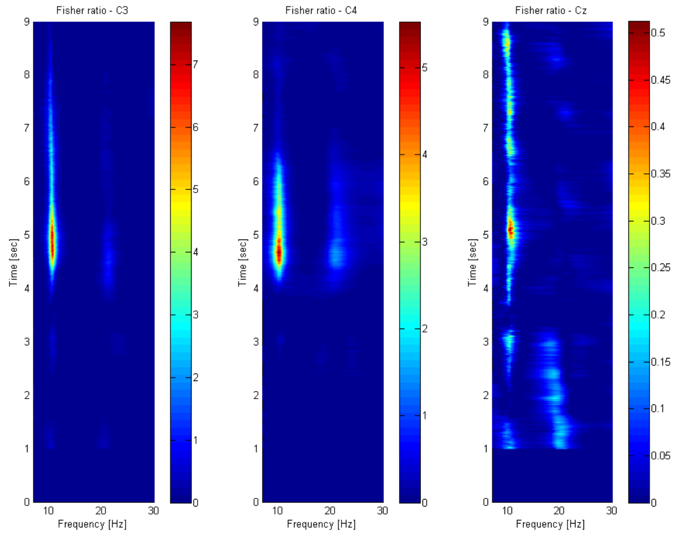

Figure 4. Fisher ratio for EEG signal over C3, Cz and C4

Figure 3 shows that components around 10 (mu) and 20Hz (beta) are the ones with more separability indicated for the higher values of the fisher ratio; based on this information it´s possible to build a feature vector which elements are the power over the frequencies with higher values for the fisher ratio over C3, C4 and Cz. This results in a 5 elements feature vector, that correspond to the alpha and beta bands limited to the frequencies that show high separability en C3, C4 and Cz (the beta band over Cz don't provide any information), that conform a feature vector which will be the input to the Linear Discriminant Analysis classifier.

4. CLASSIFICATION

The Linear Discriminant Analysis (LDA) groups objects into mutually exclusive groups based on their features. The aim of this analysis is to select the best discriminant function that differentiates the groups (or classes)
If the number of classes is 2 then the function is a line, if the number of classes is 3 the function is a plane, for more than 3 classes the discriminant function is a hyper-plane. Using the training set, the parameters of the discriminant Function are obtained. Figure 5 shows how error rate (in the classifier) varies when the number of features (used for training the classifier) increases.

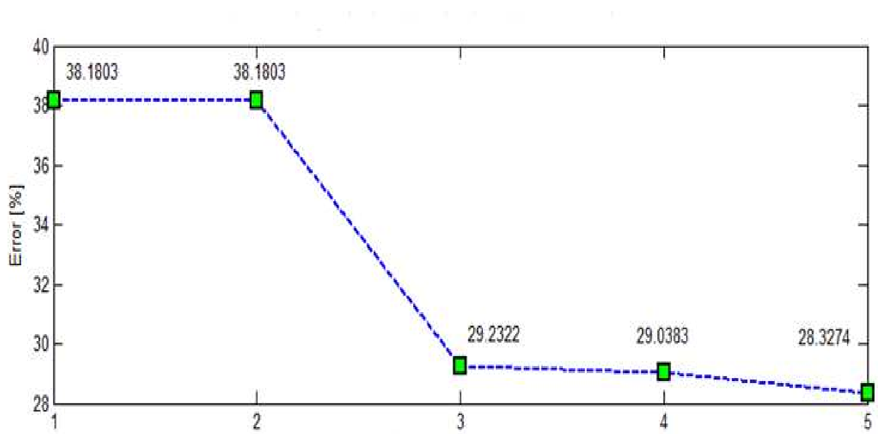

Figure 5. Miss-classification rates as discriminant features are added to the LDA classifier

The figure shows that when the 5 features are added the misclassification rate is 28.32%. Once the feature vector is obtained, is used as input of the LDA classifier.

5. RESULTS

As shown in section III the information from brain signals was extracted using parametric methods for PSD estimation. The Fisher criterion shows the most relevant frequency components which were used to obtain the feature vector. Here is necessary to define a metric to evaluate the performance of the BCI. For this purpose several indexes can be used: Overall accuracy, specific accuracy, mutual information, Cohen's Kappa coefficient [14]. In this work the performance parameters of a communication channel are used to evaluate the performance of the BCI as proposed in [15] as well as the Kappa coefficient which is an indicator of agreement between two estimators. This indicator is considered a robust indicator because it takes into account the probability agreement by chance. Figure 6 shows the course of the mutual information (MI) and the course of the accuracy of the design system for which the maximums are show in the table 1 as well as the time of occurrence.

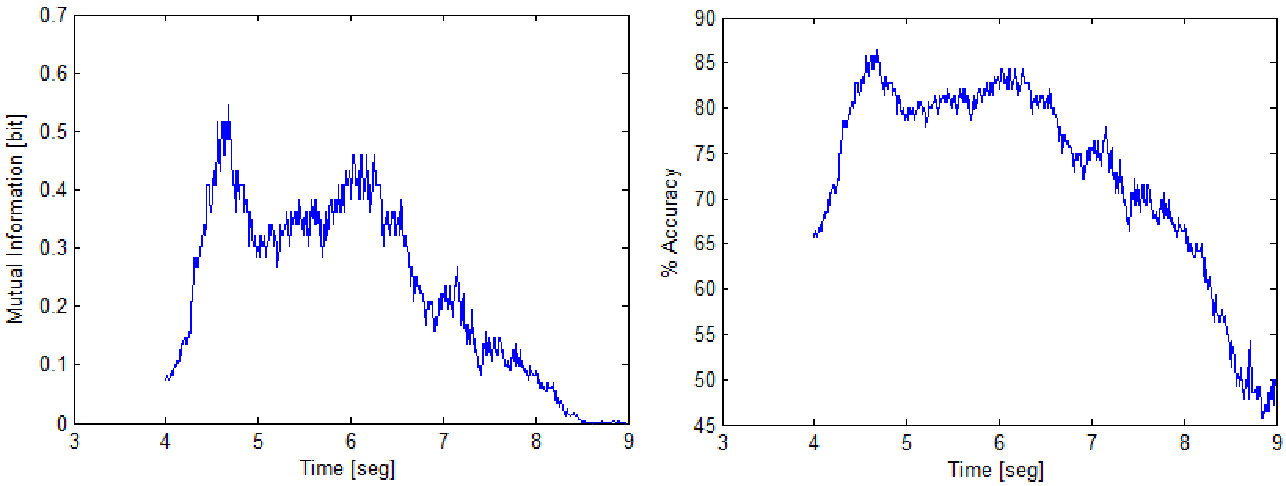

Figure 6. Time course of MI and time course of Accuracy.

Table1. Maximum values for time course of MI and time course of Accuracy.

Method	MI Max	Accuracy Max	Time [s]
LDA	0.5459	86.43%	4.6719

From Table 1and Figure 4 it can be seen that the maximum of the MI occurs when the fisher index shows maximum separability between classes, before that, between seconds 7 and 9 the Fisher index is low causing low MI and low accuracy values .

Table 2 shows the values of the kappa, Overall accuracy and specific accuracy.

Table2. Performance indexes for the BCI system.

	Cohen's Kappa	Overall Accuracy	Specific Accuracy	
			Class 1	Class 2
LDA	0.4572	72.86%	72.79%	72.93%

In order to establish if the use of parametric methods for the power spectral density contribute to a better performance of the system, the PSD was computed again using the Short Time Fourier Transform (STFT) which is a non-parametric method. Figure 7 shows the comparison of the course time of MI and accuracy using the Burg method and STFT method. In Tables 3 and 4 the performance indexes are summarized for the two methods.

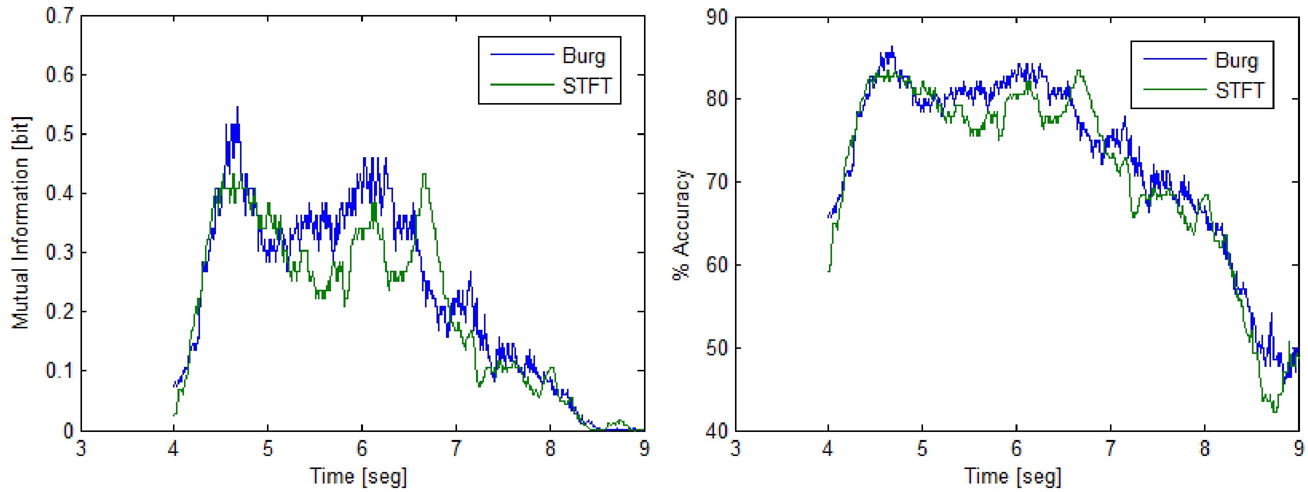

Figure 7. Time course of MI and time course of Accuracy using Burg and STFT methods for Power Spectral Density estimation.

Table 3. Performance indexes using Burg and STFT methods for Power Spectral Density estimation.

	MI Max	Accuracy Max	SNR Max
Burg	0.5459	13.57%	1.1314
STFT	0.4323	16.43%	0.8209

Table 4. Performance indexes using Burg and STFT methods for Power Spectral Density estimation.

	Cohen's Kappa	Overall Accuracy	Specific Accuracy	
			Class 1	Class2
Burg	0.4572	72.86%	72.79%	72.93%
STFT	0.4277	71.39%	71.23%	71.54%

The results show that the best performance is reached using the Burg method; however the differences on the magnitude of the values are not considerable. Here it's clear that the two metrics used show concordance because the burg method has a better performance indicated by the maximum value of mutual information, accuracy, signal to noise ratio, kappa, Overall accuracy and specific accuracy.

6. CONCLUSIONS

This work shows that parametric methods provide a better performance over non- parametric methods (based on DFT). Here the use of Fisher criterion was use to select frequency components that provide more information about the Brain Oscillatory Motor Activity. The results are consistent with the literature [3] showing that beta and alpha frequency bands contain useful information about the execution of imaginary motor activity. Using LDA classifier it was possible to reach accuracy rates as high as 86%.

ACKNOWLEDGMENT

Thanks to the Professors Christian Quintero, for this collaboration on the development of the Brain Computer Interface project from which the present work is part.

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