Comparative Analysis of Spectral Estimation Methods for Brain-Computer Interfaces

Rafik Djemili, Hocine Bourouba, and Mohamed Cherif Amara Korba

***Abstract*—**In this paper, we present a method in order to classify EEG signals for brain-computer interfaces. EEG signals are first processed by means of spectral estimation methods to derive reliable features before classification step. Spectral estimation methods used are standard periodogram and the periodogram calculated by the Welch method, both methods are compared with logarithm of band power (logBP) features. In the method proposed, we apply linear discriminant analysis (LDA) followed by support vector machine (SVM). Classification accuracy reached could be as high as 85%, which proves the effectiveness of classification of EEG signals based BCI using spectral methods.

***Keywords*—**Brain-Computer Interface (BCI) – Motor Imagery – EEG – Linear Discriminant Analysis (LDA) – Support Vector Machine (SVM).

I. Introduction

BRAIN-Computer Interfaces (BCI) is defined as a communication system by direct use of an individual's brain signals [1] without any use of peripheral muscles and nerves. The technology might be promising for people who cannot use their arms or hands normally because they have damaged regions such us amyotrophic lateral sclerosis (ALS), spinal cord injury, brain stream stroke, or quadriplegic patients [2]. These brain signals can be measured noninvasively in humans using electroencephalography (EEG) [3]-[5], or invasively for example electrocorticography (ECoG) [6],[7] where the electrical signal is taken directly inside the human brain, typically in patients being monitored prior to surgery.

Because of its ease of use and low cost, EEG is a practical measurement device for use in engineering applications. Signals measured by EEG have good time resolution, and are the most widely used in BCI systems [8]. EEG based BCI systems utilize many types of brain signals that serve as inputs, among these signals are slow cortical potentials (SCPs) [9], P300 potentials [10], steady state visual evoked potentials (SSVEPs) [11], event-related synchronization/ desynchronization (ERD/ERS) [12], sensor motor rhythms [13], and event-related potentials [14]. These signals are processed to extract specific signal features that reflect the user's intent (e.g. SCPs), sensory motor cortex rhythms, etc … [15].

A typical BCI system involves three main steps:

1. Signal acquisition: by electrodes placed on the scalp.
2. Extraction of EEG features that characterize the type of brain electrical activity, in this work sensor motor rhythms are used. The goal of this step is to transform the initial space to a multidimensional space.
3. EEG features classification, also known as translation algorithm, here linear and non linear classification algorithms could be used.

In the development of a BCI system, a problem may arise from the extraction of EEG features which characterize the brain activity, a fail in this step has a highly impact on the performance of the classifier used forward whatever the ability of this classifier to distinguish between different classes, it could not be possible to overcome limitations due to a bad characterization of classes.

In the work between hand, EEG signals came from somatosensory cortex, called sensorimotor rhythms (SMRs). SMRs are usually divided into two frequency bands, μ band (8-12) Hz and β band (15-30) Hz and are quantified in form of Event-Related Desychronization (ERD) or Event-Related Synchronization (ERS). ERD consists of a power decrease in μ and (or) β rhythms, while ERS consists of a power increase in the same frequency bands related to a reference period prior to the stimuli [16]. Many studies [17],[18] demonstrated that during physical and motor imagery of left and right hand movements, ERD occurs predominately over the contralateral brain hemispheres. The post movement ERS associated with the end of the movement or the imagination period can also be found in the same left and right motor areas [19].

In this paper, a method based on linear discriminant analysis (LDA) classifier followed by support vector machine (SVM) is proposed to differentiate between imagery left and right hand movements, whose EEG signals are characterized by three spectral estimation methods: standard periodogram, Welch periodogram, and logarithm of band powers. These features are calculated over different frequency bands in order to find the most appropriate for each feature and for each subject. The rest of the paper is organized as follows, in section 2 datasets and feature extraction methods are described, we give a brief presentation of the classifiers in section 3, while section 3 deals with the presentation of the results of the method proposed, finally a conclusion is drawn in section 5.

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II. Materials and Methods

A. EEG Datasets

A description of the two datasets used in this work is given below.

A.1. BCI Competition II dataset III

This dataset is provided by Graz BCI group [20], the data was recorded from a normal subject (female 25 years old). The subject sat in a relaxing chair with armrests. The task was to control a feedback bar by means of imagery left and right hand movements. The orders of left and right cues are random. The experiment consists of 7 runs with 40 trials each. Each trial has 9s length as shown in Fig. 1. The first 2s was quite, at t=2s an acoustic stimulus indicates the beginning of the trial, the trigger channel 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 recording was made using a g-tec amplifier and Ag/AgCl electrodes. Three bipolar EEG channels (anterior '+', posterior '-') were measured over C3, Cz and C4. The EEG was sampled with 128 Hz, it was filtered between 0.5 and 30 Hz. In the 280 trials, 140 trials were used to train the classifier, the 140 others to test the performance of the classifier.

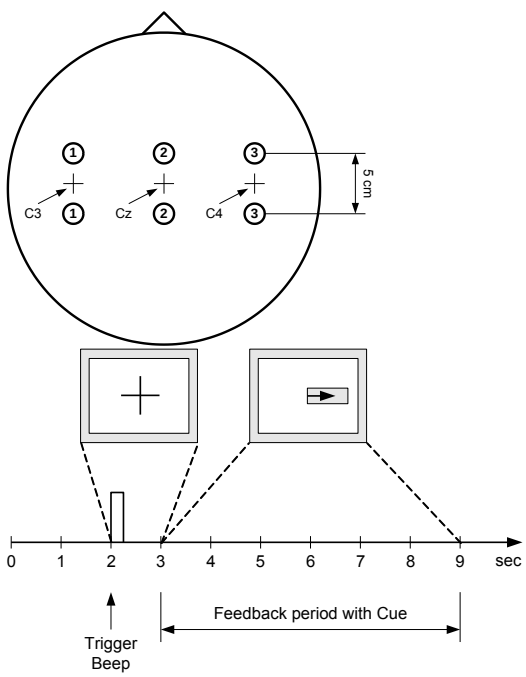

Fig. 1 Electrodes position and timing scheme of a single trial

A.2. BCI Competition III dataset IIIb

This dataset contains three subjects, labeled S4, X11 and O3. It was constituted with the same experimental setup as the previous one. The EEG signals were sampled at 125 Hz. The subjects S4 and X11 have 540 labeled trials for training, whereas the subject O3 has 320 labeled trials. The same number of trials as in training is used for testing the classifiers for each subject. More details of this dataset are found in [21].

B. Spectral Estimation Methods

EEG signals are processed in order to estimate the signal power spectral density (PSD). Two techniques were analyzed in this work: (a) standard periodogram, (b) Welch periodogram, and compared with logarithm of band powers (logBP) usually used in BCI systems [22].

B.1. Standard Periodogram

The periodogram is considered as a non-parametric spectral analysis, and is based on Discrete Time Fourier Transform (DTFT) of a signal x(n), and it is defined by:

$$\breve{S_p}(f) = \frac{T_s}{N}\left[\sum_{n=1}^{N} x(n)e^{-j2\pi f n T_s}\right]^2 \quad (1)$$

Where, $\breve{S_p}(f)$ is the periodogram, T_s is the sampling frequency, N is the number of samples of the signal, and f is the frequency.

B.2. Welch Periodogram

Welch periodogram is a modified version of the periodogram, where the signal x(n) is first split into M segments, the standard periodogram is then calculated on each of the M segments and finally averaged, this has the advantage of reducing the variance of the spectrum.

Welch periodogram could be calculated by:

$$\breve{S_w}(f) = \frac{1}{M}\sum_{m=1}^{M} \breve{S_p}(f) \quad (2)$$

B.3. Log BP

For a signal x(n) of N samples, logBP is given by:

$$logBP = log\left[\frac{1}{N}\sum_{i=1}^{N} x(i)^2\right] \quad (3)$$

Fig. 2 and 3 give the estimation of power spectral density using Welch method for left and right imagined hand movements taken from channels C3 and C4.

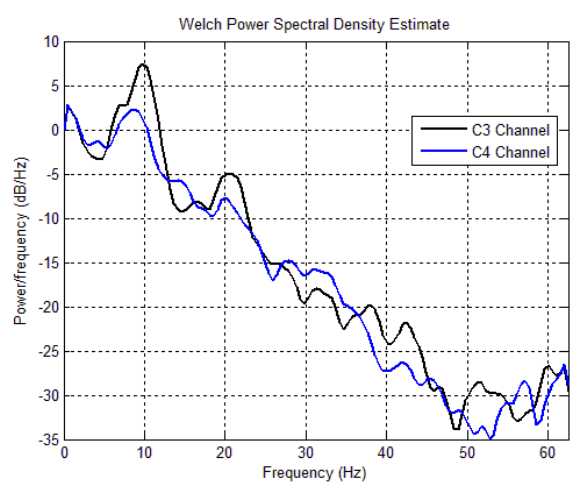

Fig. 2 Welch periodogram computed with 256 points FFT over a time window of 1s for the subject S4, trial # 5 for left hand imagined movement

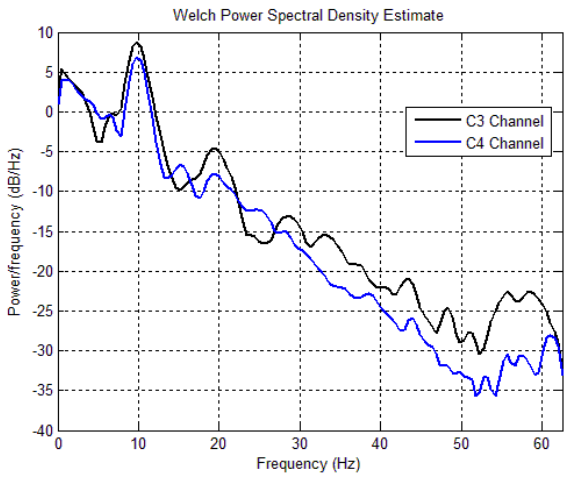

Fig. 3 Welch periodogram computed with 256 points FFT over a time window of 1s for the subject S4, trial # 5 for right hand imagined movement

It is shown from figures 2 and 3, a relatively power decrease occurring in event-related desynchronization (ERD) with peaks around 10 Hz (μ) and 20 Hz (β), whenever the imagined movement is.

III. Classifiers

In the field of the classification of EEG signals for brain-computer interface applications, it is well known that linear classifiers can yield a higher performance compared to more complex non linear classifiers [15],[23]; thus in this study linear discriminant analysis and linear support vector machine classifiers will be used, a brief introduction of these two classifiers is given below.

A. Linear Discriminant Analysis (LDA)

LDA is a type of a classifier widely used in the BCI community; it assumes that different classes of features are linearly separable. LDA constructs a decision function represented mathematically as:

$$g(x) = w^T x + w_0 \tag{4}$$

Where x is the input vector, w is a weight vector and w_0 is a threshold. The input feature vector is assigned to one class or the other on the basis of the sign of g(x). w may be calculated as [24]:

$$w = \Sigma_c^{-1}(\mu_2 - \mu_1) \tag{5}$$

Where μ_i is the estimated mean of class i, and Σ_c is the estimated common covariance matrix.

B. Support Vector Machine (SVM)

SVM is another widely used tool for BCI. The SVM maps input vectors in to a higher dimensional space where the classification can be easily done; then the SVM finds a linear separating hyperplane with the maximal margin in this higher dimensional space. The optimal hyperplane can be obtained by solving a constrained optimization problem [25] stated as:

$$\underset{w,b,\xi}{Min} \ \frac{1}{2}w^T w + c \sum_{i=1}^{n} \xi_i \tag{6}$$

Subject to:

$$\xi_i \geq 0; \ \ y_i(w^T \phi(x_i) + b) \geq 1 - \xi_i \tag{7}$$

Where ξ_i are called slack variables, c>0 is a regularization parameter determining the tradeoff between the complexity and the empirical error.

The dual formulation of (6) and (7) is:

$$\underset{\alpha}{Max.} \ \sum_{i=1}^{n} \alpha_i - \frac{1}{2}\sum_{i,j} \alpha_i \alpha_j y_i y_j K(x_i, x_j) \tag{8}$$

Subject to:

$$0 \leq \alpha_i \leq c, i = 1 \ldots n; \ \ and \ \ \sum_{i=1}^{n} \alpha_i y_i = 0 \tag{9}$$

Where α_i is the Lagrange multiplier. The training input vectors for which Lagrange multipliers are not zero are called support vectors. By using different types of kernel functions in (8), one can obtain different discriminant decision functions. The kernel function used in this work is linear.

IV. Experimental Results

A. Experimental Setup

For the experiments carried out in this study and prior to feature extraction step, EEG signals are first filtered in some frequency band in order to carry ERD and ERS patterns. Various frequency bands are tested, in addition of standard μ [8-12] Hz and β [16-24] Hz rhythms, we also used the broadband [8-30] Hz containing both μ and β rhythms, and the frequency band [0-30] Hz including μ, β, α, δ, and θ EEG rhythms. Filtering EEG signals is accomplished by three types of filters, finite impulse response (FIR) filter, and infinite impulse response (IIR) filter using the well known Butterworth and Chebychev filters. After filtering the EEG signals by the appropriate filter in the fixed frequency band, EEG signals are divided into 1s epoch time interval every 500ms during the presentation period, namely from 4 to 9s for BCI competition II data III [20], and from 4 to 7s for BCI competition III data IIIb [21]. For each 1s time interval, one of the following spectral estimation methods is applied: standard periodogram, Welch periodogram, and logarithm of band powers (logBP). All the features are calculated on C3 and C4 channels, concatenated and fed to the classifier.

B. Simulation Results

Tables 1 to 4 give the performance of LDA classifier for each subject; note that we have as many as 4 frequency bands X 3 types of filters X 3 spectral estimation method of simulation results.

TABLE I
PERFORMANCE ACCURACY (%) OF LDA CLASSIFIER FOR BCI2DATA3 SUBJECT

Frequency Band	[0-30] Hz			[8-30] Hz			μ [8-12] Hz			β [16-24] Hz		
	FIR	Butterworth	Chebychev	FIR	Butterworth	Chebychev	FIR	Butterworth	Chebychev	FIR	Butterworth	Chebychev
Standard Periodogram	58.6	62.8	57.1	64.3	62.8	60.0	66.4	62.1	64.3	60.0	59.3	57.8
Welch Periodogram	64.3	64.3	64.3	64.3	65.7	65.0	65.7	66.4	**69.3**	59.3	58.6	60.0
logBP	62.1	64.3	63.6	67.1	67.8	67.1	66.4	65.7	65.7	60.7	61.4	58.6

Table II
PERFORMANCE ACCURACY (%) OF LDA CLASSIFIER FOR SUBJECT S4

Frequency Band	[0-30] Hz			[8-30] Hz			μ [8-12] Hz			β [16-24] Hz		
	FIR	Butterworth	Chebychev	FIR	Butterworth	Chebychev	FIR	Butterworth	Chebychev	FIR	Butterworth	Chebychev
Standard Periodogram	59.1	62.4	64.8	65.9	61.8	61.6	55.9	55.4	55.9	71.7	62.0	63.0
Welch Periodogram	63.0	63.0	62.0	60.7	62.4	63.7	53.0	55.2	55.9	**75.5**	68.5	67.8
logBP	64.1	61.1	58.1	55.4	58.0	57.8	55.2	54.1	55.4	69.6	65.0	63.3

TABLE III
PERFORMANCE ACCURACY (%) OF LDA CLASSIFIER FOR SUBJECT X11

Frequency Band	[0-30] Hz			[8-30] Hz			μ [8-12] Hz			β [16-24] Hz		
	FIR	Butterworth	Chebychev	FIR	Butterworth	Chebychev	FIR	Butterworth	Chebychev	FIR	Butterworth	Chebychev
Standard Periodogram	72.2	76.6	75.9	71.8	73.7	73.0	51.6	55.5	56.8	70.0	68.0	71.3
Welch Periodogram	74.8	**78.9**	77.6	77.6	77.6	76.8	61.1	62.0	62.2	77.8	75.9	74.8
logBP	57.6	61.5	61.6	65.7	69.1	71.1	54.4	58.7	58.9	73.9	73.5	72.0

TABLE IV
PERFORMANCE ACCURACY (%) OF LDA CLASSIFIER FOR SUBJECT O3

Frequency Band	[0-30] Hz			[8-30] Hz			μ [8-12] Hz			β [16-24] Hz		
	FIR	Butterworth	Chebychev	FIR	Butterworth	Chebychev	FIR	Butterworth	Chebychev	FIR	Butterworth	Chebychev
Standard Periodogram	57.2	55.3	54.4	63.4	49.7	56.9	70.6	35.0	40.9	72.2	65.6	77.2
Welch Periodogram	79.1	75.6	77.2	51.9	54.4	50.6	50.9	33.4	34.4	68.4	55.6	59.4
logBP	75.6	75.0	75.9	52.5	51.6	56.2	50.0	52.8	52.2	59.7	60.0	57.8

From tables 1 to 4, it is shown that there are no trends towards neither a specific frequency band nor a type of a filter. The best testing accuracy is achieved in the μ and β rhythms respectively for bci2data3 and S4 subjects, while for the other two subjects X11 and O3, the low frequency band of 0-30 Hz appears relevant. This confirms the fact that classification of EEG signals for brain-computer interface applications is mostly subject specific; for example for S4 and X11 subjects, the classification results in the μ rhythm are the lowest when compared to the rest of the frequency bands involved in this study. It is worthnoting that all the best results were given only by the Welch method for estimating the power spectral density.

As a second step in this work, we chose the best systems given by the LDA classifier and we would further to analyze these results by a linear SVM. Figure 4 represents the classification accuracy for all the subjects used in the present study for LDA and SVM classifiers.

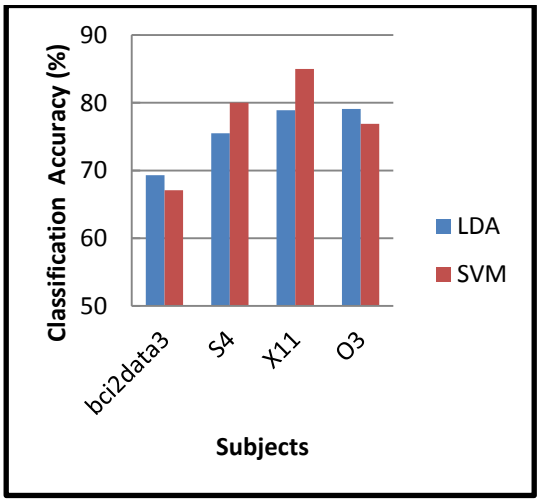

Fig. 4 LDA and SVM classification accuracy for all the subjects

From the Fig.4, the SVM classifier outperforms LDA for the subjects S4 and X11 for which the performance attained respectively 80 and 85%, while for the subjects bci2data3 and S4, results of the SVM classifier were slightly inferior to those of the LDA classifier.

V. CONCLUSION

In this work, spectral estimation methods were used in order to classify EEG signals for brain-computer interfaces. Spectral estimation methods are standard periodogram and Welch periodogram which were compared to the logarithm of band powers (logBP). We used two commonly linear classifiers, LDA and SVM. Our results show that the Welch method can effectively classify EEG signals for BCIs applications.

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