Characterization of Mental States from EEG Signals

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Abstract:- The main purpose of this research is using Brain Computer Interfaces (BCI) in the development of a model to characterize mental states using EEG signals, by implementing an automatic classification algorithm, and also by extracting features using the Fast Fourier Transform (FFT). Some experiments were carried out with 35 people. In the experiments, the relaxation and concentration states were classified using the SMO algorithm. The best result was an accuracy of 94.11%.

Keywords:- *EEG; BCI; OpenViBE; SMO; Mental States.*

I. INTRODUCTION

Brain Computer Interface (BCI) is linking the brain activity to a computer, which allows a person to directly control devices with his brain waves without using his muscles. This kind of systems brings the possibility to people with severe motor disabilities to send commands to electronic devices through their brain waves. The brain waves are electric signals, which need to be identified, processed, and classified in order to execute a specific command or trigger a specific action [1].

Hence, the use of Electroencephalogram (EEG) in the field of BCI has obtained great interest with diverse applications ranging from medicine to entertainment [2]. EEG is a technique to measure the electric signals produced by the brain activity. From EEG measurements, it may be possible to extract information and decipher the internal thought, and deliver in direct way information about physiological functions, thus resulting in some form of synthetic telepathy [2, 3]. The EEG may provide the information about the underlying neural activities in the brain, and the EEG signals exhibit no stationary and extremely complex behavior [4].The first step of BCI systems is the data collection and filtering, the filters are designed in such a way that they do not introduce any change or distortion to the signals [2]. In order to extract useful information from the EEG data, pattern recognition algorithms may be employed. Most schemes are based on statistical probability evaluation, neural networks, SVM, or other similar techniques [5]. However, dealing with EEG classification, an important problem is the large number of features. Thus, a feature selection must be computed [2]. Furthermore, the filtering task is not trivial, fore some reasons: only a mean value of the brain in some zones of the outer part is known; the electrical activity, depending on the task a person is performing, could involves the whole brain; there is always a lot of electrical activity, also when we are just thinking or doing "nothing". This kind of activity, including breathing and all involuntary movements, are always present and represent noise that is often bigger than the signal we need to detect [6].

There are five major brain waves distinguished by their different frequency ranges [7]: Delta waves lie within the range of 0.5 to 4 Hz, Theta waves lie within the range of 4 to 7 Hz, with an amplitude usually greater than 20 μ V, Alpha with a rate of change lies between 8 and 13 Hz, with 30-50 μV amplitude, Beta, the rate of change lies between 13 and 30 Hz, and usually has a low voltage between 5-30 μV. Beta is the brain wave usually associated with active thinking, active attention, focus on the outside world or solving concrete problems and finally the Gamma waves which lie within the range of 35Hz and up. It is thought that this band reflects the mechanism of consciousness [7]. Alpha, beta, theta and delta frequencies are used in our work to classify the mental tasks. The purpose of this work is the development of a model to characterize mental states, by implementing the SMO algorithm, and also by extracting features using the FFT. The classification model was implemented through the development of a visual tool. This tool allows adding EEG signals to a set of training data. The experiments were carried out with 35 people. The relaxation and concentration mental states were classified in the experiments. The best result was an accuracy of 94.11% in a controlled environment with digital signal processing. The paper is organized as follows: Section 2 presents some related works, section 3 describes the methodology, section 4 details the architecture of the tool developed, section 5 describes the experiments and results, and finally section 6 presents the conclusions and future works.

II. RELATED WORK

In this section, some works related with classification of EEG signals are described. In [2] EEG signals are recorded from 16 channels and studied during mental and motor tasks. Features are extracted from those signals using time analysis, frequency analysis and time-frequency-space analysis. Extracted features are classified using an artificial neural network trained with the back propagation algorithm. In [3] the potential use of EEG as a means for silent communication by decoding imagined speech is explored. The goal of this work is to classify imagined syllables. In this research, the EEG data are preprocessed to reduce the artifacts and noise by using a subspace-based Wiener filter and for the classification the k-Nearest Neighbor classifier is used. In [4] the EEG signal is decomposed into 6 levels by using Daubechies' wavelet, and also the DWT is used for feature extraction. The Fourier transform is used to observe the frequency of the components of each EEG band, and for the classification, KNN and SVM classifiers were used. In [6] a system capable of recognizing and classifying four tasks is developed. The data is formed by time series subsequently transformed to the frequency domain, in order to obtain the power spectrum, and the classification algorithm used is SVM. In [8] an experiment to extract out the information related to imagination concealed in EEG signal is performed. The EEG signals are recorded from 8 channels and processed to extract the features using AR model and then classified using KNN. In [9] the implementation of a snake game, controlled by the user is brainwaves using NeuroSky is described. The prototype incorporates acquiring the EEG signals, processing and classifying the EEG signals, and using the signal classification to control a game. In [10] an extraction method to extract brain waves features from EEG for the purpose of person identification is proposed. The method was evaluated with Shannon Entropy. In [11] the brain waves of a person, recorded in real time are used as a password to unlock the screen.

III. METHODOLOGY

The methodology designed in this work, for the classification of mental states, consists of four phases. In the Fig. 1 this methodology is presented, and the phases are explained below.

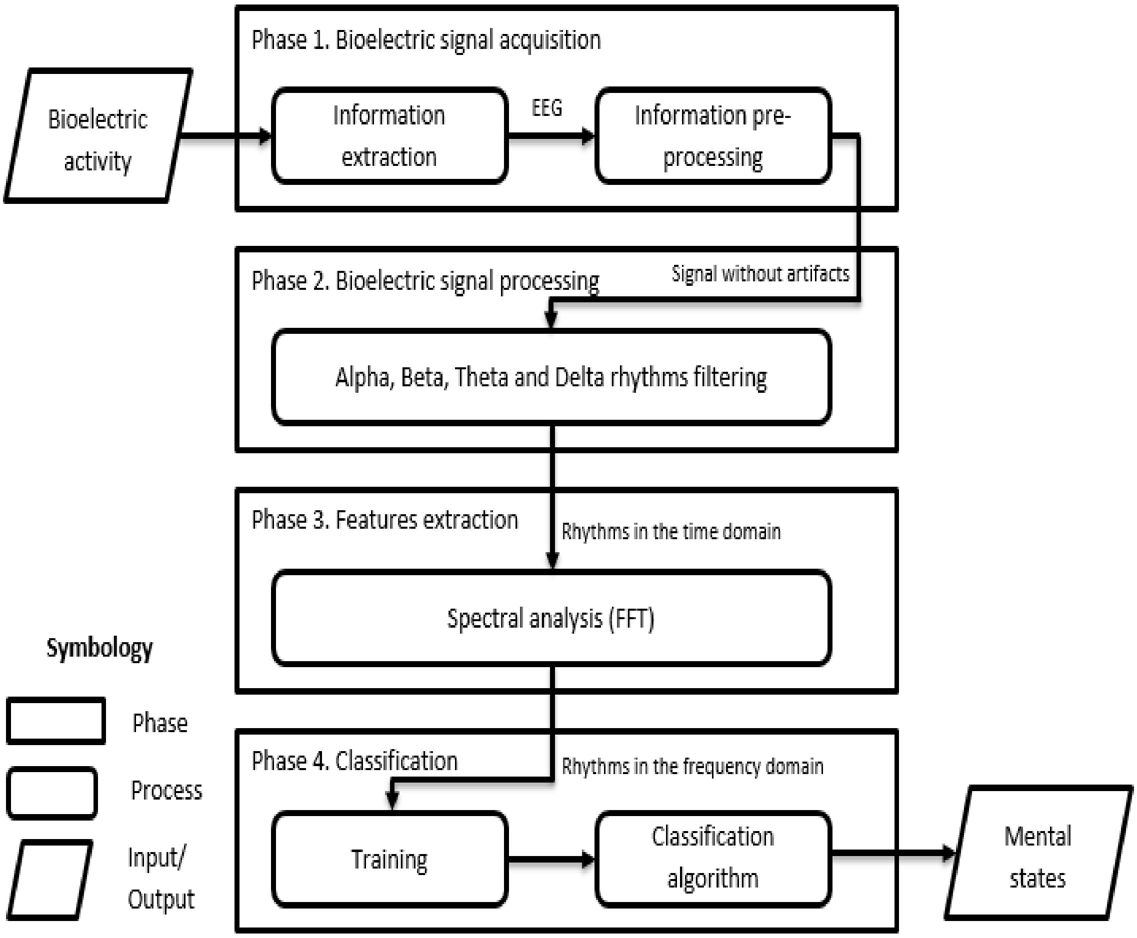

Fig 1:- Methodology for mental states classification

A. Phase 1: Bioelectric Signals Acquisition

In this phase, the EEG signals are acquired in a digital way, and then the signals are pre-processed in order to eliminate artifacts, and also to obtain the alpha, beta, theta and delta rhythms. These processes are briefly explained in the next subsections.

➢ *Information Extraction*

For the process of information extraction, the Emotiv[1] BCI device was used. Emotiv provides the necessary libraries to obtain the signals from itself. The Emotiv libraries can be implemented in some programming languages, like C#, C++, Java or Python. However, the open source software called OpenViBE[2], allows to obtain EEG signals from the Emotiv, and also allows to process and analyze the signals. Because of this, OpenViBE was implemented in our methodology.

➢ *Information Pre-Processing*

The recording of the brain signals are called EEG. This kind of signals contain valuable information, but difficult to separate. The information can represents the

[1] https://emotiv.com/

[2] http://openvibe.inria.fr/

physical movements that we perform, our feelings, our moods, and so on. Hence, the signals must be processed in order to remove non relevant information for the specific purpose. The noise, also called artifact, is an unwanted signal that causes erroneous results in the analysis of EEG signals. Some artifacts could be eye blinking, signals associated with cardiac movements, breathing, facial movements and noise caused by the BCI device itself. The pre-processing process is performed by removing noise, and unnecessary signals at some frequencies. The filter used for removing noise was a high pass filter with a cutoff frequency of 0.16 Hz.

B. Phase 2: Bioelectric Signal Processing

The signal needs to be processed, in order to obtain the alpha, beta, theta and delta rhythms. Thus, it is necessary to apply a filter to the signal. These rhythms belong to the following frequency ranges:

- Delta → 1 to 4 Hz.
- Theta → 4 to 7 Hz.
- Alpha → 7 to 13 Hz.
- Beta → 13 to 30 Hz.

The filter used for obtaining the rhythms, was a band pass with a cutoff frequency of 0.5 Hz. and 40 Hz.

C. Phase 3: Features Extraction

In this phase, the Power Spectral Density (PSD) is calculated, based on the FFT of the signal. The PSD describes the distribution of the content in the signal power, with respect to the frequency.

D. Phase 4: Classification

In this phase, the classification of the signals is performed through two processes: training and classification. These processes are described below.

➢ *Training*

For the process of information extraction, the Emotiv BCI device was used. In the training phase, the behavior patterns based on the four main waves: alpha, beta, theta and delta, are obtained from certain activities executed by different test subjects. These activities propitiate the concentration and relaxation mental states. The signals obtained in this process are labeled with the concentration or relaxation labels, according to the behavior patterns. Then, the signals are stored in a training data set, and finally with the training data set a classification model is generated.

➢ *Classification Algorithm*

The classification is executed with the Weka libraries, using the SMO algorithm. The entry of this module are new signals of alpha, beta, theta and delta. These signals are classified as a concentration or relaxation mental states, from the classification model generated in the previous process.

IV. ARCHITECTURE OF THE SYSTEM

In this section, the architecture of the system developed, by following our methodology is presented. The Fig. 2 presents the architecture of the prototype.

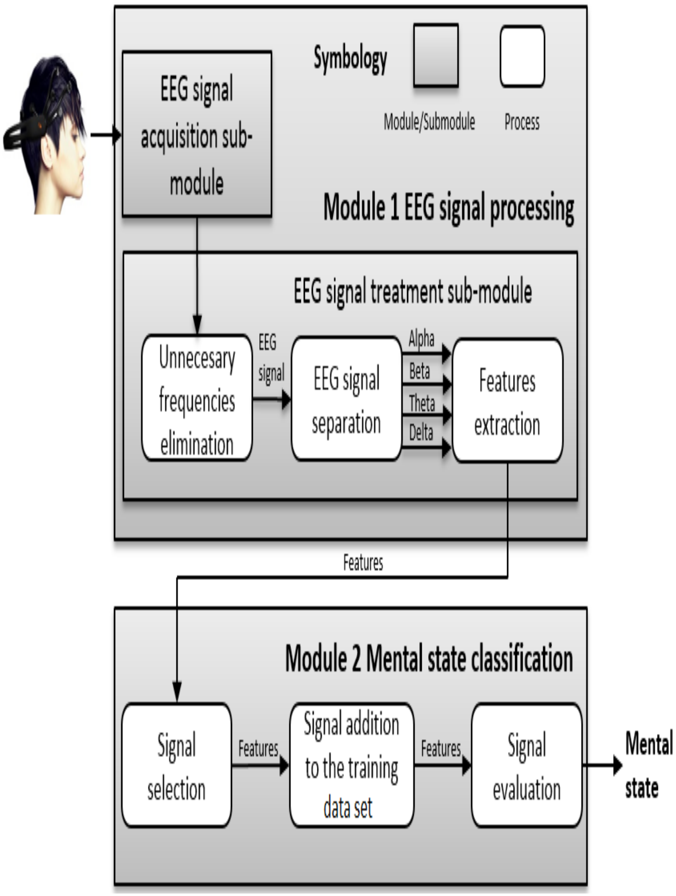

Fig 2:- Architecture of the Mental States Classification System

A. Module 1 EEG Signal Processing

This module was developed with the OpenViBE software, and implements the phases 1, 2 and 3 of our methodology. In the first module, the EEG signals are obtained through the Emotiv device. Then, in the second module, the unnecessary frequencies are eliminated with a band pass filter, also the alpha, beta, theta and delta rhythms are separated, and finally the characteristics are obtained through the FFT.

➢ *EEG Signal Acquisition Submodule*

Open ViBE has a submodule for acquiring signals from several BCI devices. The acquisition submodule communicates with BCI devices via proprietary drivers of each BCI device and then, the OpenViBE acquires the digital signals.

➢ *EEG Signal Treatment Submodule*

Open ViBE has a submodule for the programmed scenarios creation, these scenarios are used for the EEG signals treatment. The programmed scenarios communicate with the acquisition submodule in order to obtain the signals and then, the signals are processed.

B. Module 2 Mental States Classification

This module was developed with Java and the Weka library. And, the module implements the phase 4 of our methodology. The input of this module is the signal processed in the previous module. Also, a visual tool for the mental state classification was developed.

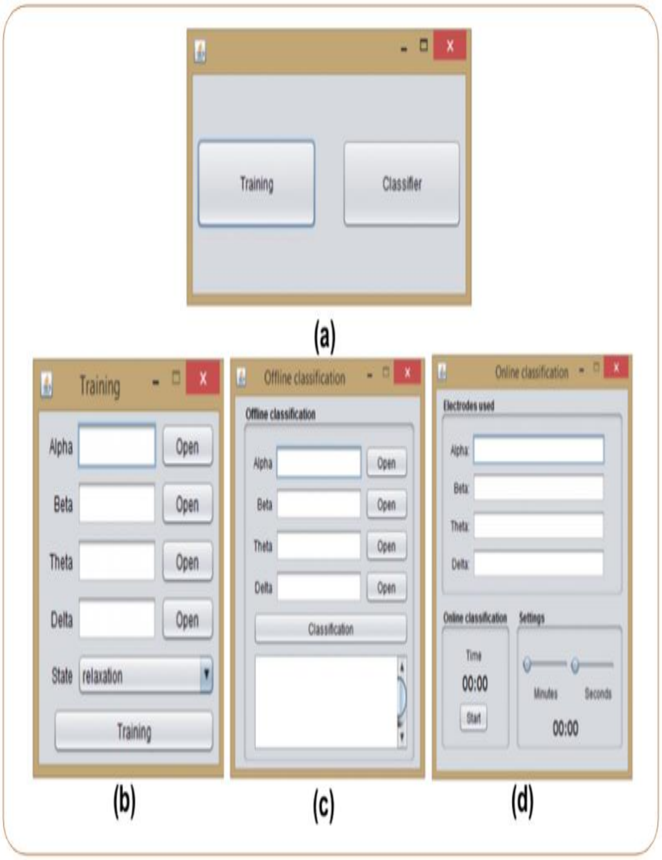

Fig 3:- (a) Principal interfaces of the visual tool, (b) The training interface, (c) The offline classification interface, (d) The interface of the classification online.

The principal interface of the visual tool is composed by two buttons: Training and Classifier (See Fig. 3 (a)). The user can add a signal to the training data set with the first button or classify a new signal with the second button. If the user chooses the Training button, the user must select the files of the EEG signals, and also the user must specify if the signals belong to the relaxation or concentration states, (See Fig. 3(b)). The classifier needs a classification model; this model is generated through the training data set. If the user chooses the Classifier button, the classification could be executed in two different ways: online and offline. In the classification offline, the user must obtain the signals before the classification and save them into files. Then, the user must select the files of the signals, (See Fig. 3(c)). Finally, in the classification online, the signals are classified during the process of signal acquisition, and the user must specify a period of time (See Fig. 3(d)).

V. EXPERIMENTS AND RESULTS

In this section, the experiments for evaluating the method for the characterization of mental states are presented. The mental states classified in the experiments are relaxation and concentration.

➢ *Testing Protocol*

The training data set was generated with the alpha, beta, theta and delta rhythms samples, these samples were obtained from 35 subjects. All the samples were evaluated before adding them to the data set. In the testing protocol for the relaxation mental state, the subject should sleep at least eight hours the previous night for the test. The climate, noise and lighting of the place in which the tests were executed were controlled. In the case of the concentration mental state, two tests were applied in order to identify if the subjects were concentrated or not. The first test was the Trail Making Test, which evaluates the subject concentration; if the subject passed the test, the brain rhythms could be added to the training data set. And, in the second test, the Toulouse test was applied, also with the purpose of evaluating the subject concentration. This test lasted ten minutes, for every subject. The experiments were evaluated with the ten-fold cross validation technique and with the SMO algorithm. The accuracy obtained in the experiments are presented in the Table 1.

	Environment Uncontrolled	**Environment Controlled**
With Signal Processing	73.03%	94.11%
Without Signal Processing	52.45%	55.88%

Table 1:- Results of the Experiments

VI. CONCLUSIONS AND FUTURE WORKS

In this project, a model for the characterization of mental states was developed. The model was implemented through the development of a visual tool. This tool allows the model training generation, and also the EEG signals classification based on the model training. The carried out experiments, allowed us to observe that the EEG signals were contaminated with noise and lighting. By controlling these environmental variables, the EEG signals offered clearer information for digital processing. In the experiments, the features obtained from the brain rhythms shows in the frequency spectrum, that the alpha wave amplitude is inversely proportional to the beta wave during the relaxation and concentration mental states. While in the relaxation state the alpha wave amplitude exceeds the beta wave amplitude; in the concentration state, the alpha wave amplitude is lower than the beta wave amplitude. In the Fig. 4 and Fig. 5 the frequency spectral amplitude of the brain waves in the relaxation and concentration states are shown.

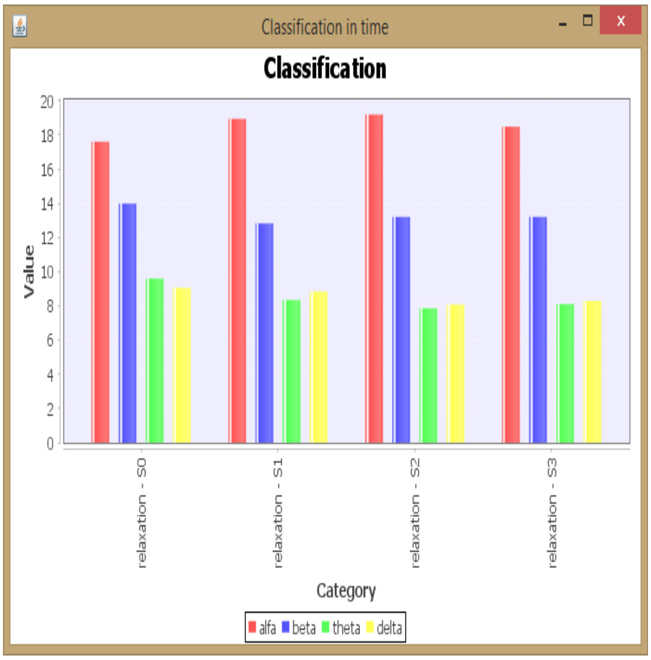

Fig 4:- Frequency espectral amplitude of the brain waves in the relaxation mental state.

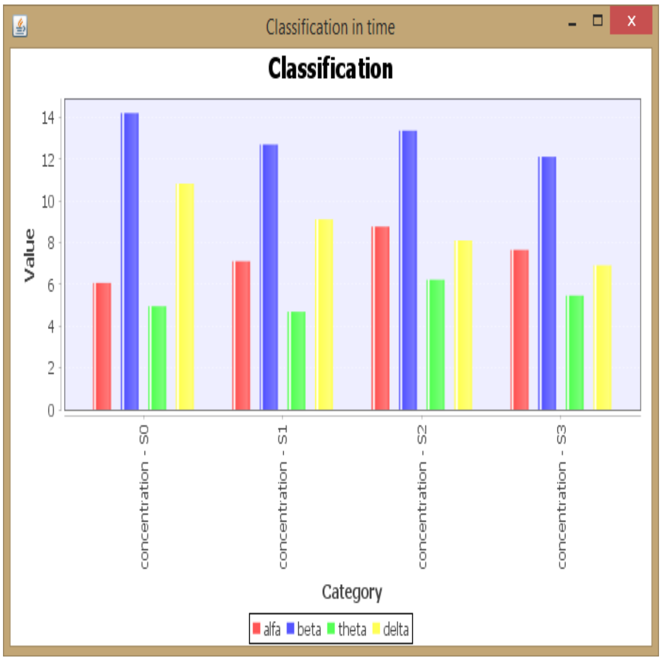

Fig 5:- Frequency espectral amplitude of the brain waves in the concentration mental state.

In the Table 2, a briefly comparison with the state of the art is presented. The results show that our method is better than some other methods.

Work	Device used	Num. of Subjects	Feature Extraction method	Algorithm	Accuracy	Rhythms
[2]	10-20 EEG electrode	24	FFT STFT Space time- frequency analysis	MLP neural network	96.0%	Alpha Beta Theta
[3]	128 channel sensor	7	AR model PSD	KNN	61.0%	Non specified
[4]	10-20 EEG electrode	7	DWT	KNN LDA SVM	60.0% 80.0% 98.0%	Alpha Beta Theta Delta Gamma
[6]	61 electrodes	5	FFT	SVM	68.0%	Alpha
[8]	10-20 EEG electrode	2	AR model	KNN	96.48%	Beta
Ours	Emotiv EEG	35	FFT	SMO	94.11%	Alpha Beta Theta Delta

Table 2:- Briefly Comparison with the State of the Art

The proposed future works are listed below:

- Addition of a phase of elimination of noise, in order to eliminate the noise of the body movement during the EEG signals processing.
- Use of other algorithms to obtain EEG signal features.
- Increase the size of the training data set.
- Model training in uncontrolled scenarios.
- Add other mental states, like meditation, somnolence, and boredom

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