EEG Classification and Short-Term Epilepsy Prognosis using Brain Computer Interface Software

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***Abstract*—The recent advances of Brain Computer Interfaces (BCI) systems, can provide effective assistance for real time prognosis systems for patients who suffered from epileptic seizures. This paper presents an EEG classification strategy for short-term epilepsy prognosis, using software for Brain-Computer Interface (BCI) systems. A training scenario is presented, where significant features are extracted and a classification algorithm is trained. The training procedure extracts knowledge in terms of a classification model, which is employed in a real-time testing. For the training of the classification scenario a five-classes dataset of EEG signals is employed in which two-classes have been recorded extracranially and the rest three intracranially including one class with epileptic seizure activity and two classes with seizure-free signals. Promising quantitative results are reported.**

Keywords-component; EEG classification; Brain Computer Interface systems; BCIs; Epilepsy diagnosis;

I. Introduction

Epilepsy is a chronic neurological disorder of the human brain that affects people of all ages and worldwide [1,2]. It is characterized by recurrent seizures, which are brief episodes of involuntary movement that may involve a part of the body (partial) or the entire body (generalized), and are sometimes accompanied by loss of consciousness [1-6]. These seizures are recorded and analyzed using the electroencephalogram (EEG) which measures the brain electrical activity. Currently, such analysis is mainly done through long-term monitoring by expert neurologists and is very time-consuming, subjective and require considerable skills [1-6]. Thus, computer-aided analysis has a tremendous potential in practice since the automation can shorten this time-consuming process by identifying and extracting EEG periods of particular interest to expert neurologists [1,2].

Computer-aided analysis of EEG signals is a developing field that has gained much attention in past years [1,2]. It usually includes a three-step algorithm which includes: a feature extraction stage, a feature reduction or selection stage, and a feature classification stage [1,3-12]. In addition, recent advances of the hardware and software communications EEG systems that permits cerebral activity alone to control computers or external devices known as brain-computer interface (BCI) systems, enable more diverse research [13]. The BCI field quickly identified the necessity for computer-aided systems that makes BCI more user-friendly, real-time, easy to use and appropriate for people that are not able to use them [13].

In case of epilepsy, a BCI system that relies on the above algorithm schema can help an expert neurologist by highlighting the epileptic patterns in the EEG recordings up to a significant level [13]. Obviously, the task of diagnosis should be left to the expert. However, this becomes effectiveness as it decreases the amount of data to be analyzed and reduces the workload. Along with classification stage, BCI systems can also provide simultaneous visualization of multiple channels, which aids the expert neurologist in discriminating between generalized and partial epileptic seizure activities. In addition, real-time detection of epileptic seizure activities is crucial and can assist on improving the patients' quality of life. Accurate assessment, pre-surgery evaluations, epileptic seizure prognosis, and emergency alerts for clinical help, all rely on

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the quick and accurate detection of the onset of epileptic seizures [13].

There is a crucial need to develop new approaches using advanced technologies in order to assist in the processing of EEG data and apply computer-aided analysis for real-time EEG classification and short-term epilepsy prognosis. Thus, this study is an effort to explore such progresses, having a novel, free, and open source BCI tool to experiment with a well-known public available EEG dataset [14]. The rest of this paper is organized as follows: in Section II the proposed EEG classification approach using the open source BCI tool is outlined in detail. In Section II the results from the application of this approach on a benchmark EEG dataset is presented. Finally, in Section IV a discussion is made about future extensions of this approach.

II. METHODS

The proposed approach is developed using the OpenViBE BCI software [15], which is an open-source tool for signal processing, focusing mostly in BCIs. OpenVibe provides both a Scenario Designer and an Acquisition Server. Scenario Designer consists of a user-friendly interface, where the user can develop their data flows in a tree view environment. "Box algorithms" implement a list of existing algorithms, which are the building blocks of OpenVibe scenarios. Acquisition Server provides drivers for direct communication between software and mostly used BCI devices. The flowchart of the proposed approach is presented in Fig. 1.

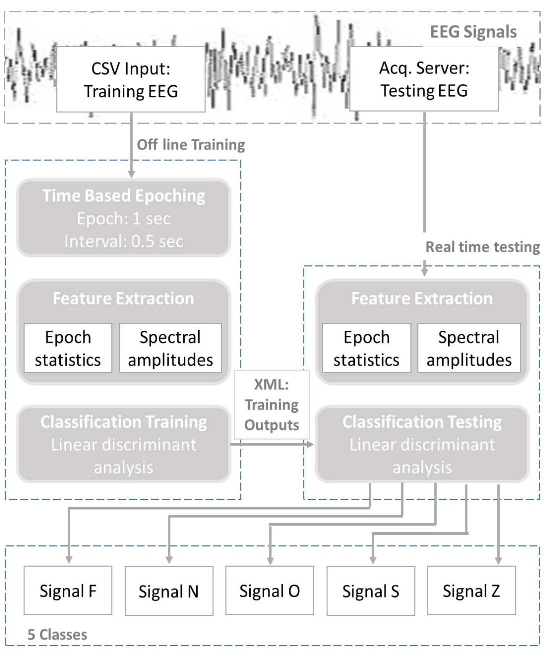

Figure 1. Flowchart of the proposed EEG classification approach.

As it is shown in Fig.1 the training phase and the testing phase performs individually. According to the OpenVibe architecture the training phase take place in off-line mode, employing the training dataset. Indeed, in most of the cases, the classification procedure need computation effort, and it is extremely time consuming to operate in real time. Thus, training scenario is employed off-line producing an XML structured file, which contains training parameters. During the testing "classification processor" box deploy the knowledge of XML for real time EEG signal classification. Testing EEG signal is imported to the testing scenario using the Acquisition Server.

A. *Training Phase*

During the training phase training dataset, well known EEG signals denoted as Z, O, N, F and S (see Section III for the description of EEG dataset) are employed to train the classification algorithm. Next, EEG signal epochs are extracted to compute features of each one of them. Both time-based and spectral features are computed for the classification problem. Finally, the classifier is used to extract knowledge for the testing phase.

1) *Input Signal*

For training signal importing the "CSV file reader" box is used. Already retrieved EEG signal could be used as training dataset. In our case, five different EEG signals (one for each class) should be imported. The features for each one EEG signal will be inserted in different inputs of the classifier. Thus, all EEG signal which belong to the same class should be merge into one. Although the procedure is off-line executed, the input of EEG dataset is utilized in a real-time simulation. As a result, duration of training phase will be equal to the duration of the whole input EEG signal plus the duration of classification algorithm execution.

2) *Time Epoching*

Time epoching is commonly used method instead of extracting simple fragment of EEG signal. Using epoching discontinuity of EEG signal fragment are avoided. Actually, epochs are EEG signal 'slices' which length is configurable, as is the time offset between two consecutive epochs. The proposed approach employs a "Time Based Epoching" box, where each epoch last for 1 sec, while the interval offset is 0.5 sec.

3) *Feature Extraction*

To feed the classification algorithm several features have been extracted from each epoch of the EEG signal. In total 11 features, have been used for the proposed approach. Six of them are statistic values of the EEG signal epoch such as: mean value of epoch, variance of epoch etc. provided directly by the "Univariate Statistics" box of the designer. The six output of "Univariate Statistics" box is directly input to a "Feature Aggregator", which put all the feature together (In the output of "Feature Aggregator" each feature are the columns and epochs are the rows). Apart from time based feature, spectral features are also extracted. In current work a "Spectral Analysis" box, which is based on Fast Fourier Transform (FFT), is used in the whole image. Then, the amplitude of FFT, inputs to "Frequency Band Selectors" where the EEG signal spectrum is split into five bands.

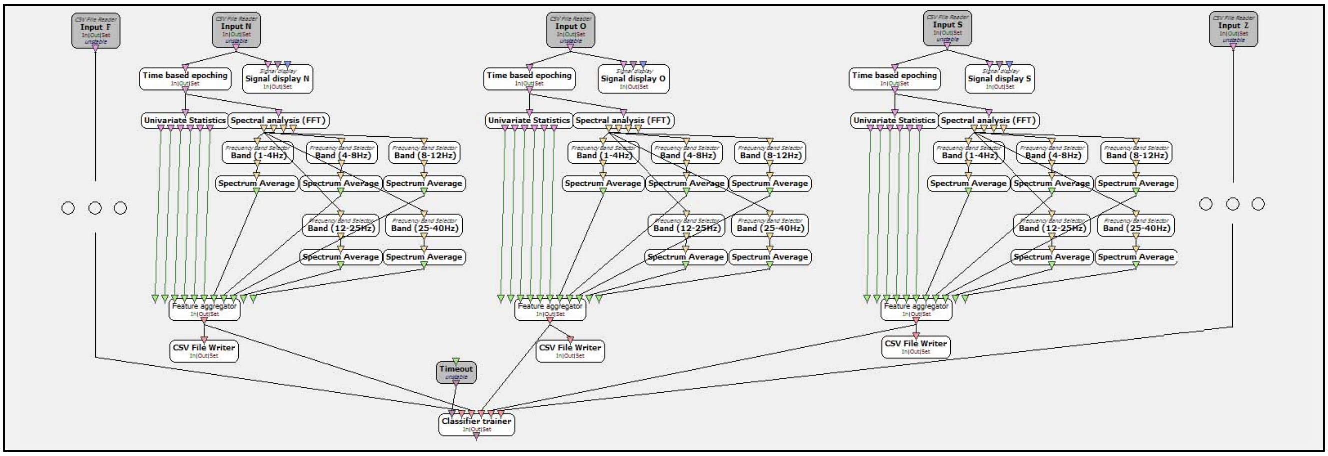

Figure 2. Training Scenario for 5-classes EEG classification problem.

These bands have been defined according to brain wave frequencies which are recorded with an EEG:

- Alpha (a) waves frequency: 8-12 Hz.
- Beta (b) waves frequency: 12-25 Hz.
- Theta (g) waves frequency: 4-8 Hz.
- Delta (d) waves frequency 1-4 Hz.

Finally, a “Spectrum Average” box calculates the average of spectral amplitude per band and lead to the feature to “Feature Aggregator”. Details of extracted features are presented in Table I.

TABLE I. TIME AND SPECTRAL -BASED FEATURE FOR EEG CLASSIFICATION.

	Features Details	
	Feature Type	***Feature Description***
1	**Time Based Features**	Mean value of EEG signal epoch
2		Variance of EEG signal epoch
3		Range of EEG signal epoch
4		Median value of EEG signal epoch
5		Inter- Quantile-Range
6		Percentiles (30%)
7	**Spectral Features**	Spectrum Amplitude for Band (1-4 Hz)
8		Spectrum Amplitude for Band (4-8 Hz)
9		Spectrum Amplitude for Band (8-12 Hz)
10		Spectrum Amplitude for Band (12-25 Hz)
11		Spectrum Amplitude for Band (25-40 Hz)

4) Classification

For the classification, the linear discriminant analysis (LDA) algorithm is employed [12,13,15]. The aim of LDA is to use hyperplanes to separate the data representing the different classes. The strategy generally used for multiclass BCI is the “One Versus the Rest" strategy which consists in separating each class from all the others [13].

Training Scenario is detailed presented in Fig. 2. In case of 5-classes problem for the classification of the current dataset, “Classifier Trainer” box requires one input for each class. As a result, five different blocks for feature extraction are need. As it is shown in Fig.2 “CSV File writers” have been also used to extract the features of each class into csv format for further processing.

B. Testing Phase

Since the training phase has been off-line completed and the XML has been generated, new signal can be imported in the testing scenario via the Acquisition Server. In case of the testing, epoching is not required, so that the features must be extracted directly from the EEG signal per each second. All the boxes for feature extraction of the training scenario are also employed, however only one block of these boxes is enough to calculate the features of one input EEG signal.

Fig. 3 illustrates the Testing Scenario, where an Acquisition Server feeds a new input (EEG signal) for classification in one of the five classes. Each epoch of the new signal is classified according to the extracted knowledge of the training phase.

Fig. 4 and 5 show two examples of what the Testing Scenario offers for real-time visualization of EEG signal and spectrum.

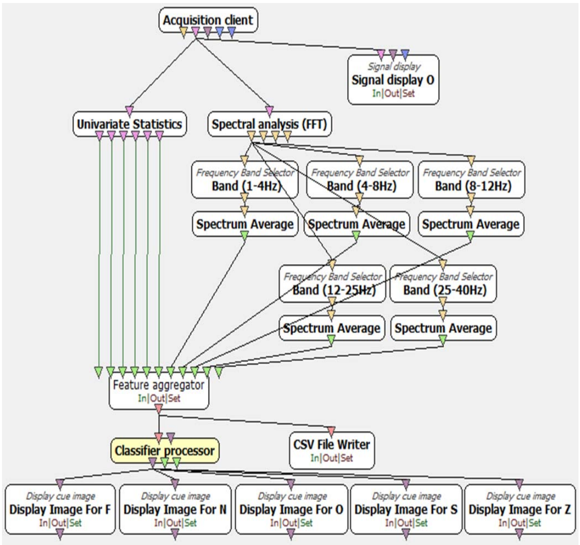

Figure 3. Testing Scenario for EEG signal classification.

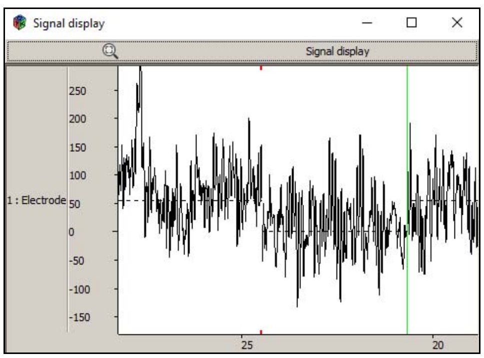

Figure 4. Example of visualization of EEG signal in real-time.

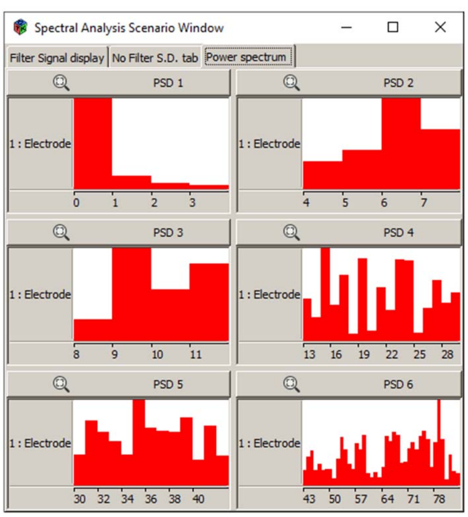

Figure 5. Example of visualization of EEG spectrum in real-time.

III. DATASETS AND RESULT

For the evaluation of the proposed approach a well-known dataset with EEG signals is employed [14]. The signal is categorized as Z, O, F, N and S, where each one consists of 100 single channel segments of signals of 23.6-sec duration. All the signals were recorded with the same 128-channel amplifier system using a sampling rate of 173.61 Hz. The signals were selected and cut out from continuous multichannel EEG recordings after visual inspection for artifacts. Signals Z (eyes open) and O (eyes closed) have been recorded from healthy volunteers, which were relaxed in an awake state. Signals N, F, and S have been recorded during a pre-surgical diagnosis. Only signals from S contains seizure activity, while N and F were recorded from within the epileptogenic zone, and from the hippocampal formation of the opposite hemisphere, respectively.

For the evaluation of the proposed approach standard classification performance metrics have been used including for each class: True Positive Rate (*TPR*) and Positive Predictive Value (*PPV*).

$$TPR_i = \frac{\#\ of\ \ samples\ of\ \ class\ i\ classified\ in\ class\ i}{total\ \#\ of\ \ samples\ in\ class\ i}. \tag{1}$$

$$PPV_i = \frac{\#\ of\ \ samples\ of\ \ class\ i\ classified\ in\ class\ i}{total\ \#\ of\ \ samples\ classified\ in\ class\ i}. \tag{2}$$

Results are obtained during the training phase, using the 10-fold cross validation technique. Table II shows the confusion matrix for 5-classes problem, as well as the TPR and the PPV for each class.

TABLE II. RESULTS FOR 5-CLASSES PROBLEM

		Classification					
		Z	***O***	***N***	***F***	***S***	***TPR %***
EEG Signals	***Z***	3502	559	314	173	0	**77.00**
	O	964	3411	23	155	0	**74.93**
	N	323	114	2865	1237	9	**63.00**
	F	191	64	2333	1819	141	**40.00**
	S	86	114	136	300	3911	**86.00**
	PPV %	**69.12**	**80.04**	**50.52**	**49.38**	**96.30**	

Furthermore, the overall classification accuracy (*ACC*) was also calculated:

$$ACC = \frac{\#\ of\ \ correctly\ classified\ samples}{total\ \#\ of\ \ samples}. \tag{3}$$

IV. DISCUSSION

In this paper, we have explored the capability of the OpenViBE platform to develop an EEG classification approach for short-term epilepsy prognosis. The obtained results indicated that the proposed approach can address the problem of classification of EEG signals related to epileptic activity. This approach offers all the required tools for real-time EEG signal acquisition, processing and visualization. The main merits of the proposed approach are: the modularity, the tools for visualization of the EEG signal and spectrum as well as the various tools provide to the different types of user, such as the acquisition server or the pre-configured scenarios.

An extension of the proposed approach to automatically detect epileptic seizures in long-term EEG signals, and subsequently, classify them into different epileptic categories will be of high clinical value. In addition, other existing EEG classification techniques for epileptic seizure detection or prediction, not presently utilized for BCI purposes, could be investigated and may prove to be worthwhile [13]. Finally, it should be pointed out that once BCI will be more extensively used in daily clinical practice, new properties will have to be thought carefully, such as the availability of large EEG datasets or long term variability of EEG signals related to epilepsy.

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