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EEG SIGNAL ANALYSIS FOR EPILEPTIC SEIZURE PREDICTION: A REVIEW STUDY

Tahereh Rashnavadi
Master of Biomedical Engineering, University of British Columbia

INTRODUCTION

Traditionally, the spatiotemporal dynamics of the brain can be measured by EEG. EEG was first invented by Hans Berger in 1929, and since then more research focused on analysis of human brain activity. In fact, the EEG has become one of the most important and widely used quantitative diagnostic tool in analysis of brain signals and patterns [1].

The EEG records the activity of complex neuronal generators predominantly near the surface of the cerebral hemispheres which is known as cortical EEG. This signal is altered as it comes through the skull, and once it arrives at the scalp surface to be transduced by electrodes is at a microvolt level and prone to environmental noise and artifacts. The EEG recording can be performed non-invasively or invasively. Non-invasive EEG is performed by placing electrodes on the scalp, whereas in the invasive technique electrodes are implanting in the intracranial area in the brain during surgery. Typically, a recorded non-invasive EEG signal has an amplitude between 10 μv and 100 μv with a frequency in the range of 1 Hz to about 100 Hz.

One of the key clinical applications of EEG is to record and monitor the brain signals of epileptic patients. Due to apparently unpredictable nature of epileptic seizures, the onset of seizure can cause epileptic patients to hurt themselves or other people. Hence, researchers have conducted an enormous amount of work on the prediction and detection of the onset of epileptic seizures [2].

EEG can detect epileptic activity in the form of prolonged discharges accompanying clinical seizures and interictal spikes. In epileptic patients, it is important to record such events and to find which part of the brain generates them. This information helps classify the type of epilepsy and therefore administer optimal medical treatment [3].

In order to assist epileptic patients to overcome the negative influences of unpredictable seizures, a reliable detective system is required to warn the patient minutes before the seizure occurrence. Therefore, methods capable of seizure prediction through EEG signal analysis have developed to open new therapeutic possibilities [4], however, this prediction is difficult because the onset of a seizure can be hidden, intangible, and dynamic in the complex nervous system.

Recently, digital signal processing techniques have been employed to provide opportunities to unearth the hidden neuron systems behind epilepsy. Because the acquired EEG signal is in the form of time series, from which researchers extract the quantitative features of epilepsy, so its analysis involves a considerable amount of signal processing for signal-to-noise-ratio (SNR) enhancement, feature selection, source localization, and automated classification.

EPILEPSY DISORDER

Epilepsy is a neurological disorder that is characterized by spontaneous seizures that occur when neurons discharge synchronically in the cortical regions of brain and it is one of the most common neurological disorders, second only to stroke, with a prevalence of 0.6–0.8% of the world's population [4]. The form of the seizure depends on the region of the brain that is affected. Seizures can be generated from both synaptic processes, which contribute to triggering and spread of a seizure, and non-synaptic processes, which support seizure activity during states of reduced synaptic transmission. However, the most common hypothesis is an alteration in the balance of excitation and inhibition within neuronal circuits. This can cause from the changes in the synthesis, release, or postsynaptic action of the excitatory and the inhibitory neurotransmitter or from changes in the properties of voltage-sensitive ion channels, ion transporters or changes in the anatomical or functional connections between cells.

To analyze the epilepsy disorder, researchers categorize the EEG signals into three states including interictal (abnormal signals between epileptic seizures), preictal (epileptic background), and ictal (epileptic seizure), illustrated in figure 1. As a preictal state exists just before seizure occurs, the classification of the three states, particularly the detection of the preictal state will help clinicians control epileptic patients in advance. However, the detection of a preictal state is more challenging than the detection of normal and ictal signals [5, 6]. The difficulty in detecting this state can be attributed to the similarity between preictal and ictal signals and the nonlinear complex nervous systems.

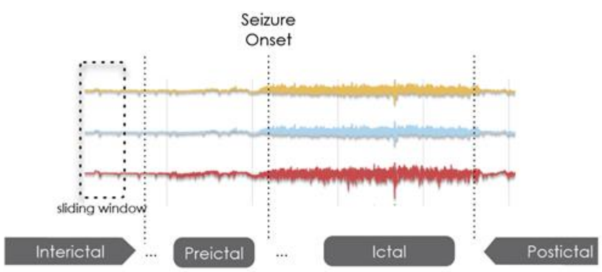

Figure 1: Segmentation of EEG signal for epilepsy disorder

EEG SIGNAL PROCESSING

In EEG signal processing, minimizing the noise and artifacts is a critical issue as the amplitude of signal is very low and sensitive to external noise (the low SNR), and also wide variety of artifacts can closely mimic the brain activity which make them exceedingly difficult to be distinguished. More specifically, there are two main origins for EEG artifacts including physiological origin (e.g. eye movement and blinks), and non-physiological or technical origin (electrodes and equipment). An overview of the most common sources of noise as well as several methods for removal of noise in EEG are discussed in [7].

The traditional method of EEG analysis relies mostly on its visual inspection. Due to the fact that visual inspection in the time domain is very subjective, several advanced signal processing techniques were proposed in order to quantify the extracted information from EEG. Typically, this technique is called “feature extraction” in which a set of measurement or a block of information is considered each time to facilitate the interpretation of the acquired signal [8]. Feature extraction techniques can be applied in time domain, frequency domain, or time-frequency domain to extract the hidden information from the EEG signal.

These features are the fundamental basis for detection, classification and recognition the behavior of the EEG signal. The extracted features can be binary, categorical or continuous, they can also represent the EEG signal specifications such as amplitude, voltage, and frequency. Researchers have applied different feature extraction techniques such as discrete wavelet transform (DWT) [9], principle component analysis (PCA) [10], and high order spectra [2, 5, 11] to analyze the EEG signal.

Figure 2 shows the structure of an EEG-based seizure detector. Following noise reduction, in order to analyze the signal, various digital signal processing techniques can be applied. First, the main features of the signal must be extracted and integrated. This feature selection is also an important stage as the dynamics of nervous systems can be described through these features. Next, these features are used as input for machine-learning systems, known as classifiers, which ultimately allow researchers to detect epileptic seizures with relatively high accuracy.

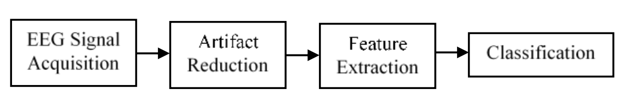

Figure 2: The block diagram of a typical EEG-based seizure detector

CLASSIFICATION: SUPPORT VECTOR MACHINE

Research in automated seizure detection began in the 1970s and since then various classification algorithms have been proposed to address this problem [12]. These automated systems can be divided into two main categories including, interictal spike detection or spike detection analysis, and epileptic seizure analysis [13].

It is crucial for these methods to provide a highly sensitive detection system, even if it results in a large number of false detections which later can be disregarded by the clinicians. The precision of the automatic detection or prediction systems depends on the extracted features and the classifiers which are used to analyze the EEG signal.

Various classifiers have been applied in this area including simple threshold, linear classifiers, artificial neural networks (ANNs) [14], *k*-nearest neighbor and support vector machine (SVM) [6, 11, 15]. However, recent research demonstrates that SVM, proposed by [16], is an effective method for EEG signal classification. SVM's adaptability in stationary and nonstationary environments, as well as its feasibility to analyze the nonlinear signal in high dimensional space makes it more reliable machine learning technique for EEG signal compared to other classifiers [8, 17]. An integrated review of the classification methods used in the literature can be found in [13].

[18] presented an overview of mathematical basics of SVM classifier and its application on EEG signal analysis. As illustrated in the figure 3, SVM classifies data into two classes by constructing an optimal hyperplane with largest margin between the two separated classes. The support vectors which are located on the boundary, the colored data points, are used to calculate the separating hyperplane. For two dimensional data, single hyperplane is sufficient to separate the data into two classes of class 1 with circle data points (or spike signal) and class 2 with square data points (or non-spike signal). Furthermore, in order to provide better discrimination between data from different classes, SVM maps the extracted features to higher dimensional space, and then constructs an optimal hyperplane in the mapped space [19]. Following is the summary of the two methods which used SVM classifier in their experiments.

1- [6] demonstrated an automatic technique on identification of epileptic EEG siganls using non-linear higher-order spectra features and the two Gaussian mixture model (GMM) and SVM classifiers. They used the extracted features to train the classifiers for being able to distinguish between normal, pre-ictal and seizure states as illustrated in figure 4. Based on the classifiers' precision a given EEG signal segment (test data) was then tested and classified in one of the three particular states. Consequently, if a classifier could correctly allocate the test signal to its originated state, then it could be used as a detector of seizure onset.

2- [20] also demonstrated a method to detect the epileptic signal using DWT features and SVM classifier. In order to reduce the features dimension, they have applied PCA technique before signal classification. They claimed that based on the relatively high accuracy of their proposed method (accuracy of 99%) compared to the most published results so far, it is possible to detect epilepsy at an early stage of the illness using their developed method.

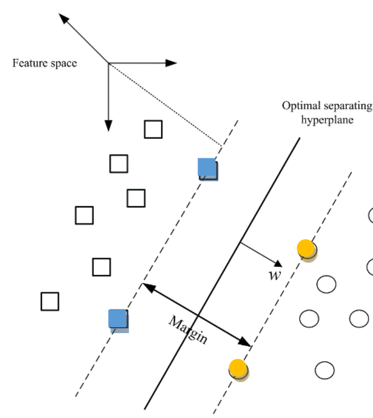

Figure 3: Support vector machine classifier [21]

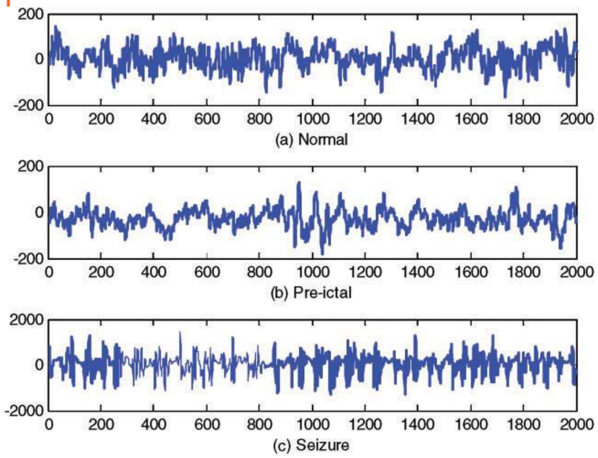

Figure 4: EEG segments for training the classifier [6]

CONCLUSION

This paper briefly reviewed the current literature on the EEG signal processing for epileptic seizure detection. Also, the main signal processing techniques used in the current research were highlighted. In addition, although some promising achievements were reported for prediction or detection of the epileptic seizures, more work is required to enhance the reliability of these systems. This goal can be achieved through improvement of the extracted features, signal analysis and classification techniques.

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