Prediction and Detection of Epileptic Seizure by Analysing EEG Signals

Mohammad Zavid Parvez  
Charles Sturt University, Australia  
Email: mparvez@csu.edu.au  
Phone/Fax: +61 2 6338 4322

Manoranjan Paul  
Charles Sturt University, Australia  
Email: mpaual@csu.edu.au  
Phone/Fax: +61 2 6338 4260
INTRODUCTION

Epilepsy is one of the common neurological disorders characterized by a sudden and recurrent malfunction of the brain that is termed “seizure”, affecting around 50 million individuals worldwide (WHO, 2013). Epilepsy seizure may lead to many injuries such as fractures, submersion, burns, motor vehicle accidents and even death. It is highly possible to prevent these unwanted situations if we can predict/detect electrical changes in brain that occur prior to onset of actual seizure. When building a prediction model, the goal should be to make a model that accurately classifies preictal period (prior to a seizure onset) from interictal (period between seizures when non-seizure syndrome is observed) period. On the hand, for the detection we need to make a model that can classify ictal (actual seizure period) from non-ictal/interictal period.

In the brain, neurons exploit chemical reaction to generate electricity to control different bodily actions and this ongoing electrical activity can be recorded graphically which is popularly known as Electroencephalogram (EEG). EEG is well accepted tool for epileptic seizure prediction/detection that can measure the voltage fluctuations of the brain. Feature extraction, analysis, and classification of EEG signals are still challenging issues for researchers due to the variations of the brain signals. Variations of EEG signals depend on different brain locations, number of channels, and different patterns of signals from different people. Another challenge for detection/prediction of EEG signals is to get reasonable accuracy for real time applications.

In this chapter we will discuss the fundamental steps (such as artifact removal, feature extractions, feature selections, classifications, regularization of noisy output, and decision function, etc.) of the prediction and detection of epileptic seizure through the analysis of EEG signals. We will also discuss (i) the characteristics of EEG signals for healthy people and epileptic seizure patients, (ii) existing features extraction techniques with their advantages and limitations, (iii) existing classification techniques with their advantages and
disadvantages, (iv) other challenging issues in near future for emerging technologies, and (v) future trend of research for high accuracy in detection and prediction.

BACKGROUND

Human brain processes sensory information received by external and internal stimuli. It controls movement and regulates cognitive functions such as thinking, learning, remembering, speaking, and decision making. The brain consists of perhaps 100 billion or more nerve cells called neurons (Craig et al., 2013). Every neuron has thousands of interconnections among them. Interconnected neurons are responsible for higher order thinking, complex behaviour, and it provides us with the ability to perceive, understand, and react to environmental events. The human brain is an organic electrochemical computer as neurons exploit chemical reactions to generate electricity. The electrochemical nature of neurons gives rise to our actions, our modes, and our behaviour. When a neuron becomes excited it passes electro-chemical impulses incoming from the dendrites along the axon to communicate with other neurons in the brain (Neurology Applied, 2013) (see in Fig 1). EEG is a non-invasive graphical record of ongoing electrical activity, which measures the changes of the electrical activity in terms of voltage fluctuations of the brain through multiple electrodes place on the scalp. In clinical contexts, the main diagnosis of EEG is to discover abnormalities of brain activities such as the epileptic seizure. Other clinical uses of EEG are in diagnosis of coma, brain death, encephalopathies, sleep disorder, etc. Moreover, the analysis of EEG signal has many other applications such as video quality assessment (Scholler et al., 2012), emotion recognition (Soleymani et al., 2012), and alcohol consumption measurement (Di et al., 2010), etc.
Seizure is simply the medical condition or neurological disorder in which too many neurons are excited in the same time caused by brain injury or by an imbalance of chemical in the brain that is characterized predominantly by unpredictable interruptions of normal brain function. Epilepsy is another medical condition characterized by spontaneously recurrent seizures. During the seizure period the brain cannot perform normal task as a result people may experience abnormal activities in movement, sensation, awareness, or behaviour. There are 1% of total population in the worldwide affected by epileptic seizure (Netoff et al., 2009). The detection of epileptic seizure plays important role for medical diagnosis of epilepsy. EEG recordings are very reliable in the diagnosis of epilepsy. EEG signals from an epileptic patient can be divided into five periods or stages (i) non-seizure period– no epileptic syndrome is visible, (ii) ictal period–actual seizure period, normally duration is 1 to 3 minutes (iii) preictal period– 30 minutes to 60 minutes before ictal period, (iv) post-ictal period– 30 – 60 minutes after ictal period, and (v) interictal period– period between post-ictal period to pre-ictal period of the immediate next ictal. Some portion of the interictal period, which does not have any epileptic syndrome, can be defined as a non-seizure period. Prediction and detection of seizures by analysing ictal, pre-ictal, and interictal could alert a patient of the next seizure and also could lead to better treatment and safety.

Two epilepsy dataset are publicly available for the experiments; one is Epilepsy small dataset, 2012 and another is Epilepsy large dataset, 2013. Epilepsy small dataset, 2012 consists of five subsets, each containing 100 single-channel EEG signals with 23.6 seconds. Among them two subsets are taken from healthy volunteers (i.e., non-seizure dataset), two subsets are taken from seizure free intervals (i.e., interictal) and one subset is taken during seizure period (i.e., ictal) from five patients captured by 32 electrodes. Epilepsy large dataset, 2013 contains invasive EEG recordings of 21 patients suffering from medically intractable focal epilepsy. The data was obtained by the Neurofile NT digital video EEG system with 128 channels, 256 Hz sampling rate, and 16 bit analogue-to-digital converter (Epilepsy large dataset, 2013).

Epileptic seizure detection technique can be done using different steps such as pre-processing (cleaning the dataset by removing various artifacts, line noise, etc.), features
extraction, features selection and classifications (see detailed explanation in section Main focus of the article and corresponding figure at

Fig 4). A number of seizure detection techniques are already available to classify seizure and non-seizure EEG signals. Panda et al., 2010 computed various features like energy, entropy, and standard deviation by discrete wavelet transform and used support vector machine (SVM) as a classifier. Dastidar et al., 2007 applied wavelet transformation to decompose the EEG signals into different range of frequencies and three features, such as standard deviation, correlation dimension, and the largest Lyapunov exponent (quantifying the non-linear chaotic dynamics of the signals), are employed and different methods applied for classification. Ocak, 2008 proposed fourth level wavelet packet decomposition method to decompose the normal and epileptic EEG epochs to various frequency bands and then used genetic algorithm to find optimal feature subsets which maximize the classification performance. Polat et al., 2007 proposed two stage processes: first was feature extraction using first Fourier transform (FFT) and second was decision making using decision making classifier. The techniques have used Epilepsy small dataset, 2012 and the classification accuracies were 91.2% (Panda et al., 2010), 96.7% (Dastidar et al., 2007), 98.72% (Polat et al., 2007), and 98% (Ocak, 2008).

Recently empirical mode decomposition (EMD) is proved to be an efficient transformation technique for EEG signal classification. Pachori, 2008 decomposed EEG signals into intrinsic mode function (IMF) using EMD and then computed mean frequency for each IMF to differentiate seizure and non-seizure EEG signals. Bajaj et al., 2012 extracted amplitude and frequency modulation bandwidth of IMFs as features using EMD. Among the existing contemporary techniques, Bajaj et al.’s technique is the latest and the best in terms of performance. They used least square SVM (LS-SVM) technique for the classification of seizure and non-seizure EEG signals using the small dataset with 23.6 second duration and obtained 98.0 to 99.5% accuracy using radial basis function (RBF) kernel and also obtained 99.5 to 100% accuracy using Morlet kernel. The small dataset with duration 23.6 second has seizure (i.e., ictal) and non-seizure signals which can be distinguished by their visual phenomena such as amplitude and changing rate of frequency (see in Fig 2) where the non-seizure signal the amplitude is low and the frequency is high while the nature of seizure signal is totally reverse.
Parvez et al., 2013 proposed different feature extraction techniques, based on discrete cosine transformation (DCT), DCT-discrete wavelet transformation (DCT-DWT), and singular value decomposition (SVD), for ictal (seizure period) and interictal (period between seizures) EEG signals classification using large dataset which contains 24 hour signals from each patient. Parvez et al., 2013 applied their techniques on two dataset (Epilepsy small dataset, 2012 and Epilepsy large dataset, 2013) and they got good classification accuracy for their techniques. They also demonstrated the non-abrupt phenomena (i.e., not easily distinguishable between ictal and interictal based on amplitude and frequency) of the ictal and interictal signal for the both cases of Frontal and Temporal lobe compared to the large dataset shown in Fig 3. Parvez et al., 2013 also shown that EEG signals from different locations exhibit different phenomenal activities for an ictal and interictal period. Thus, classification of ictal and interictal EEG signals are challenging compared to that of seizure (i.e., ictal) and non-seizure EEG signals.

Since the Epilepsy small dataset, 2012 is small and perfectly cleaned, well defined seizure and non-seizure EEG signals, the accuracy of the above mentioned detection techniques
perform very well that close to 100%. However, in real scenario, we do not get cleaned signals; the signals might have different stages such as interictal, preictal, postictal, and ictal (i.e., seizure). Thus, when the above mentioned detection techniques are applied on the EEG signals with different stages, their performance is well below from the perfection e.g., 85% or less. Thus, detection of seizure with great accuracy is still a challenging issue.

Fig 3: Ictal (Patient one, 7th datablock, channel one) and interictal (Patient one, 95th datablock, channel one) of Frontal lobe dataset from (Epilepsy large dataset, 2013) Epilepsy Center of the University Hospital of Freiburg.

Prediction of seizure is a difficult problem to provide a good trade-off between a high (close to 100%) predictive capability of seizures (i.e., ictal) and a low (close to zero) false-positive rate (fpr) by analysing interictal and preictal signals assuming that ictal period will start immediate after preictal period. To predict an ictal signal we need to go through all steps of detection techniques (between interictal and preictal signals) and then we need to regularise the classification output using various techniques such as Kalman filter (Lefebvre et al., 2001), particle filter (Driessen et al., 2005), window-based filtering (Netoff et al., 2009) and finally we need to apply a decision function for ultimate predicted output. Many methods have been proposed to predict epileptic seizure by classifying preictal and interictal EEG signals. They have employed univariate techniques (Rasekhi et al., 2013), eigenspectra of space delay correlation and covariance matrices (Williamsona et al., 2012), Hilbert-Huang transform (Duman et al., 2012), and autoregressive modelling and least-squares parameter estimator (Chisci et al., 2010). According to classification results of preictal and interictal EEG signals with respect to sensitivity, Chisci et al., 2010 proposed technique carries good
sensitivity compared to above mentioned techniques using large dataset. However, Rasekhi et al., 2013 got 79.3% sensitivity for their own dataset.

**MAIN FOCUS OF THE ARTICLE**

The mechanism of producing epileptic seizure is still mysterious. The mechanism can be identified by combining features including firing rate, power spectral density and complexity analysis of the electrical signals of the human brain. Seizures (i.e. ictal) are characterized by large fluctuations of firing rate which is referring to dysfunctional regulation of neuronal activity.

Lots of research work has already made to the prediction of epileptic seizure based on real time analysis of EEG signals. Despite of remarkable advantage, results thus obtained are not sufficient for the realization of the real time signal analysis for the patient and cannot timely and reliably predict an oncoming epileptic seizure (Schelter et al., 2008). A major limitation of many proposed prediction techniques is their wide resort to demonstration of EEG signals that need offline processing. It is difficult for online processing to provide good prediction capability of seizure and low false positive rates due to increase number of EEG channels, and to introduce different artifacts.

The term “Seizure Detection” and “Seizure Prediction” are significantly difference on the basis of characteristics of signals. In the case of detection, the seizure detection technique is not expected to identify the presence of a seizure until the characteristics of the seizure have appeared in the biologic signals being monitored. In the case of seizure prediction, the technique is expected to estimate seizures onset before they start. The difference can become confused when there is uncertainty about when the seizure starts and if the prediction technique is based on detecting a signal pattern that is consistently followed by a seizure. In this case the “prediction” method may be actually just “detecting” the seizure before its seizure onset.

EEG signal processing technique plays a significant role in prediction and detection of epileptic seizures. Recently, lots of research work has been devoted to the prediction and detection of epileptic seizures based on analysis of EEG signals. Properly prediction and detection of Epilepsy puts away the patients from fractures, submersion injuries, burns,
vehicle accidents, etc. Therefore, it is significant to prevent epilepsy through correctly predict/detect preictal, ictal, and interictal stage to get accurate prediction/detection results. Feature extraction and classification of seizure detection can be processed offline but seizure prediction should be processed in real time. Basic block diagram of seizure detection and prediction are presented in Fig 4 and Fig 5 respectively.

The main objective to seizure prediction/detection is able to timely identify the arrival of epileptic seizure in a fully automated way. The system architecture adopted such prediction/detection purposes are schematized in Fig 4 and Fig 5. Note that the detection technique follows the stages that are pre-processing, feature extraction, feature selection, and classification whereas prediction has more two stages that are regularization and decision function. The concise description of the process diagram of detection and prediction are as follows:

![Fig 4: The basic seizure detection block diagram.](image)

In the next sub-sections will explain the basic steps of the detection and prediction techniques such as pre-processing, feature extraction, feature selection, classification, regularization and decision function.

**Pre-processing**

A pre-processing step is exploited in order to eliminate the influence of disturbance (i.e. artifact) of EEG signals. The artifact can be divided into two parts; one is physiological
artifact that raised from the body and another is non-physiological artifact that comes from environment and instruments. There is several type of physiological artifact such as muscle artifact, pulse artifact and eye blinking artifact. The non-physiological artifact is power line artifact and sweat artifact (i.e. water, minerals, and lactate so on).

Notch filter can be used to remove line noise interference. Wavelet transform is an efficient denoising technique that is introduced the non-linear and non-stationary EEG signals (Krishnaveni et al., 2006). Adaptive filter is another technique to remove noise from EEG signals (Olguin et al., 2005). Blind signal separation techniques based on principle component analysis (PCA) and independent component analysis (ICA) approach can separate unknown mixture of the signals (Nait-Ali, 2009). EMD has powerful nature to analysis non-stationary and non-liner EEG signals that achieve an effective approach to remove power line interference noise and other high frequency noise (Molla et al., 2010).

![Fig 5: The basic seizure prediction block diagram.](image)

**Feature Extraction**

For the sake of classification, relevant features needed to be extracted from EEG signals. It is important to use real time classification techniques for prediction and detection purposes for actual applications. Moreover, computational burden should be reduced and false positive rate should be lowered for sensitivity while preserving high prediction ability. EMD, singular value decomposition (SVD), and discrete wavelet transformation (DWT) may be good
techniques for the feature extraction of EEG signals as EEG signals has non-linear nature. The fundamental part of the Hilbert–Huang transformation (HHT) (Huang et al., 2006) is EMD method in which any linear/non-linear dataset is represented as a finite and small number of components called intrinsic mode functions (IMFs). This decomposition technique depends on local characteristics of dataset instead of pre-defined basis functions. Therefore, it is highly efficient and adaptive. In general, SVD is a powerful tool in linear algebra and has been extensively applied to signal processing, statistical analysis and mathematical modelling. Nonlinear SVD is an extension of SVD for both the qualitative detection and quantitative determination of nonlinearity in a time series. SVD can be considered as a generalization of the spectral decomposition of square matrices, to analyze rectangular matrices. SVD decomposes a rectangular matrix into three simple matrices: two orthogonal matrices and one diagonal matrix (non-zero singular value). The non-zero-singular values of SVD are the square roots of the non-zero eigenvalues. Non-zero-singular values can be used for distinguish features for EEG classification as they have distributed frequencies in higher order to lower order. In DWT, it is a wavelet transform for which the wavelets are discretely sampled. A key advantage is that it captures both frequency and location information (location in time). DWT works based on multi-level where each signal is decomposed into several scales and each scale provides a particular coarseness of signal. Each phase of decomposition of a signal is composed of two down samplers by 2 and two digital filters. In each phase, high pass filter which serves as the discrete mother wavelet, and low pass filter which acts as the mirror version of the corresponding. The down-sampled outputs of the first low-pass and high-pass filters supply the approximation and detail information respectively. The first approximation is further decomposed and the procedure is continued. H. Adeli et al. mentioned that the Daubechies order 4-wavelet (db4) is the most suitable for EEG signal analysis (Adeli et al., 2003). A EEG signal can be decomposed into different frequency bands such as gamma (30-60Hz), beta (13-30Hz), alpha (8-12Hz), theta (4-8Hz), and delta (0-4Hz) through DWT. Among the frequency bands, the gamma band is related to seizure as it carries more information than the other bands see in Fig 6.
Feature selection

Feature selection is a technique that removes the irrelevant feature from the feature set and selects the most relevant one. PCA and ICA can be used for dimensionality reduction of the features (Naeem et al., 2009).

Classification

The goal of a classifier is to find patients states such as preictal/ictal (Class 1) and interictal (Class 2) using machine learning approaches with cross-validation. The challenge is to find the mapping that generalized from training sets and unseen test sets. For the cross-validation, data are partitioned into training set and test set. SVM) (Vapnik, 1995) is a good classifier for EEG signals classification. It can minimize the operational error and maximize the margin hyperplane, as a result it will maximize the classification performance.

Let us consider binary classification problem with the training set \( \{x_i, y_i\}_{i=1}^N \), along with corresponding targets \( \{y_i\}_{i=1}^N \) where \( x_i \in \mathbb{R}^n \) and \( y_i = \{1, -1\}_{i=1}^N \). Assume there exists a linear separable hyperplane \( f(w, b) = \|w\| \sqrt{2} \) such that
\[ w^T x_i + b \geq 1 \quad \forall i : y_i = 1 \]
\[ w^T x_i + b \leq -1 \quad \forall i : y_i = -1 \]

where the decision function is:
\[ f(x) = \text{sign}(w^T g(x) + b) \]  

(1)

where \( w \) is the weight vector and \( g(x) \) is the mapping function of \( x \) and \( b \) is a bias.

The optimization problem of LS-SVM can be solved in the following way:
\[
\min_{w, b, c} \frac{1}{2} \|w\|^2 + \frac{C}{2} \sum_{i=1}^{N} z_i^2 \\
\text{subject to } y_i ((w^T x_i) + b) = 1 - z_i, i = 1...N.
\]

(2)

where \( z_i \) are the slack variables, it represents the upper bound training error and \( C > 0 \) trades off margin size and training error.

Lagrange multipliers \( \alpha_i \) can be introducing:
\[
\min_{w, b, c, \alpha} \frac{1}{2} \|w\|^2 + \frac{C}{2} \sum_{i=1}^{N} z_i^2 - \sum_{i=1}^{N} \alpha_i \left( y_i (w^T g(x_i) + b) - z_i \right) \\
\text{subject to } \alpha_i \geq 0; i = 1...N.
\]

(3)

For non-linear problem the kernel function is introduced in the above problem. Therefore, the decision function can be defined:
\[ f(x) = \text{sign} \left[ \sum_{j=1}^{N} \alpha_j y_j K(x_j, x) + b \right] \]  

(4)

where \( K(x, x_j) \) is a kernel function.

Parvez et al., 2013 has classified ictal and interictal EEG signals. The classification performance is evaluated using the receiver operating curve (ROC) shown in Fig 7 and it visual classification result shown in Fig 8.

**Regularization of Classification Outcome for Prediction**

Pre-processing, feature extraction, feature selection, and classification are the steps for detection. For prediction we need more steps such as regularization and decision function. Regularization is dealing with real classification data that is noisy. The noisy classification data is negatively affecting the seizure prediction techniques. Therefore, we need some regularization approach to overcome this problem. According to the non-linear nature of EEG
signals, extended kalman filter (Lefebvre et al., 2001) or particle filter (Driessen et al., 2005) could be good practise to properly use of regularization approach as both filters are widely used for solving non-linear state estimation problems. In seizure prediction, we can apply kalman and particle filter for regularization of the over-fitting classification models for better classification results and eventually they reduce the false positive rate.

![Receiver Operating Characteristic curve](image)

Fig 7: The receiver operating characteristics (ROC) curve of third subset of training and testing EEG signals using LS-SVM with RBF kernel from Frontal lobe (Parvez et al., 2013).

![Classification of Ictal and Interictal signals from Frontal lobe using SVD method](image)

Fig 8: Classification of Ictal and Interictal signals from Frontal lobe for the third subset of training and testing using the proposed method based on SVD (Parvez et al., 2013).

**Decision Function**
More accurate classification output can be obtained after regularization of classification results. However, a stand-alone classification output of an EEG signal (or a part of an EEG signal) might not provide accurate predicted results; thus, sometimes a decision function can be formulated based on the combined classification output of different time-window of an EEG signal or a number of EEG signals in different channels. For the seizure prediction a number of criteria (such as accuracy, sensitivity, and specificity) are used to verify the classification outcome. Accuracy is determined as an overall performance measurement; however, sensitivity is determined from preictal signals and specificity from interictal signals. The accuracy, sensitivity and specificity are defined as follows where TP is true positive, TN is true negative, FP is false positive, and FN is false negative:

\[
\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \times 100
\]

\[
\text{Sensitivity} = \frac{TP}{TP + FN} \times 100
\]

\[
\text{Specificity} = \frac{TN}{TN + FP} \times 100
\]

In the window system decision function formulation, sensitivity and specificity are computed based on seizure prediction threshold with a seizure prediction window. Whenever, summation of all classification output in a given window is greater than seizure prediction threshold then the seizure prediction is triggered. If a seizure takes place during the specific time interval as indicated by the decision function then the seizure is correctly predicted.

FUTURE RESEARCH DIRECTIONS

We need an automated system to predict and detect EEG signals for different reasons:

- Detecting sophisticated changes in EEG signals correctly through manual process is a difficult task.
- Continuous monitoring of EEG signals for day to day is impossible by a person or a number of people.
- Having a qualified person who can diagnose the signals about a probable seizure is very costly.

Therefore, we have to analyse sophisticated changes of EEG signals for different dataset for more accuracy through automated or semi-automated system.

In the near future the following issues need to be addressed for correctly seizure detection and prediction:
• EEG capture machines may have more channels in future: we may need modern techniques which can exploit inter-channel correlation for better detection and prediction.

• Interferences of other signals on captured EEG signals: EEG signals may have interferences from other signals generated from portable electronics devices. For this, we may expect different line noise and artifacts. We may need different techniques to eliminate those unwanted noise through investigating the characteristics of those noises.

• Wireless signals and wired signals: EEG signals can be captured through wired and wireless devices. We may need to investigate whether the characteristics or noise are different in those signals.

CONCLUSION

A reliable seizure prediction and detection system could lead to better treatment and safety for epileptic patients. Therefore, it is very important to detect seizure onset not only for treatment but also for preventing the seizure. Prediction and detection of seizures, by analysing preictal/ictal, and interictal EEG signals with good sensitivity and specificity, could put away a patient from the next seizure. Automatic prediction is necessary due to three reasons; correctly detection, continuous monitoring and reduce operational cost. In this chapter we have explained the current state of the arts on the different steps of the seizure detection and predictions with their limitations and advantages. We have also indicated futures challenges of the prediction and detection. The accuracy of the prediction and detection in real time EEG signals are below the expected level, thus, more research should be conducted for better accuracy.

REFERENCES


Epilepsy large dataset. (2013). Epilepsy Center of the University Hospital of Freiburg, Retrieved July 20,2013 from http://epilepsie.uni-freiburg.de/freiburg-seizure-prediction-project/eeg-database.


KEY TERMS

Seizure: It is simply the medical condition or neurological disorder in which too many neurons are excited in the same time.

Epilepsy: It is a medical condition having spontaneously recurrent seizure.

Electroencephalogram (EEG): It is a record of electrical signal to represent the human brain activity.

Support Vector Machine (SVM): It is a potential methodology for solving problem in linear and nonlinear classification, function estimation, and kernel based learning methods.

Empirical Mode Decomposition (EMD): It can decompose a signals finite number of intrinsic mode functions (IMFs), which are ordered from higher frequency component to lower frequency component.

Ictal: Actual seizure period.

Interictal: Period between two adjacent seizures.

Preictal: Prior to the actual seizure.