A Survey of Computer Aided Automatic Detection Techniques for Improving Classification Performance of Epilepsy Disease

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*Abstract— The primary symptom of epilepsy is seizure generation, and it is considered as one of the most prevalent neurological disorders. As per the census, 1 out of every 100 - 200 persons in India is subjected to have epilepsy. The Indian Epilepsy Centre (IEC) provides facilities to analyze the behaviour of the brain during seizures by In-depth evaluation and consultation on an out-patient basis and sophisticated tests like electroencephalogram (EEG) signals. EEG is the most prudential and useful method for detecting seizure generation which is caused by abnormal electrical activity in the brain. With the emerge of data-analytics, a lot of studies are focusing on seizure detection are being conducted. The reason for studies on seizure not only helps for diagnosis purpose, also to provide a new avenue for explaining the underlying causes of seizures and epilepsy. This paper examines current practices, problems, and prospects of computer- aided detection and classification techniques for epilepsy disease. A overview and comparison of the performance of many seizure detection algorithms which are developed earlier is also provided in this paper. The main aim of this paper is to briefly provide all existing developments in the field of computer-aided diagnosis system for epilepsy detection and summarization of major advanced classification approaches and the techniques used for improving classification accuracy.***

Keywords—**Classification, Electroencephalogram (EEG), Epileptic seizure detection, Feature extraction, Pre-processing, PSD (power spectral density).**

I. INTRODUCTION

Epilepsy is a predominant disease among many neurological disorder which is characterized by means of seizures generation that are caused by sudden inappropriate disturbances and unpredictable activities of epileptic patients. As per reports provided by World Health Organization (WHO), Epilepsies are caused by abnormal firing of neurons in the brain which is actually brain disorders that range from disabling to life-threatening ones. Epilepsy patient's conditions are divided into two groups: electrographic and behavioral. The electrographic condition is monitored by means of EEG signal patterns, where else behavioral can be observed with routine observations of patient behavior. Electroencephalogram (EEG), which reveals the temporal and spatial information of brain's electrical activities, which is successfully used for the diagnosing purpose of epilepsy patients [1]. So it is important for differentiating between healthy and seizure affected EEG signals thus detection of seizure is important for immediate treatment [2]. Therefore, automatic classification of EEG signals finds its major contribution in clinical studies for treating epilepsy seizure.

Automatic detection of the seizure using EEG signals is generally done by machine learning approach. There are many machine learning methods have been used for classification of EEG signal [3-5]. The performance of multiclass classification [11] of EEG signals depends mainly on the extraction of feature. The feature extraction methods are divided into four types: time domain, frequency domain, time-frequency domain, and nonlinear analysis [12].

This paper outlines the various techniques which are used for detection and classification of Epilepsy. Various performance comparisons of the seizure detection algorithms are also reviewed.

II. EEG EPILEPTIC SEIZURE DETECTION AND CLASSIFICATION

A generalized framework for detecting and classifying the EEG epileptic seizure activities involve the following steps are observed in Fig 1.

An Epileptic seizure detection and classification system can be divided into three stages: data preprocessing, signal processing and feature extraction, and classification. These sections are described below.

A. EEG Preprocessing

Generally, in biomedical signal processing, it is important to remove the noise and artifacts which are present in the original signals. Especially in recordings of brain signal from EEG have a wide range of artifacts, which may occur during the acquisition of signal [12]. The pre-processing stage tries to remove these artifacts without losing pertinent information. The EEG preprocessing step involves the removal of these unwanted artifacts.

Some preprocessing techniques are done to find out the desired band of frequency, filtering techniques (e.g. band-pass filter), Bayesian denoising [13] and independent component analysis (ICA), are indicatively used for artifact removal.

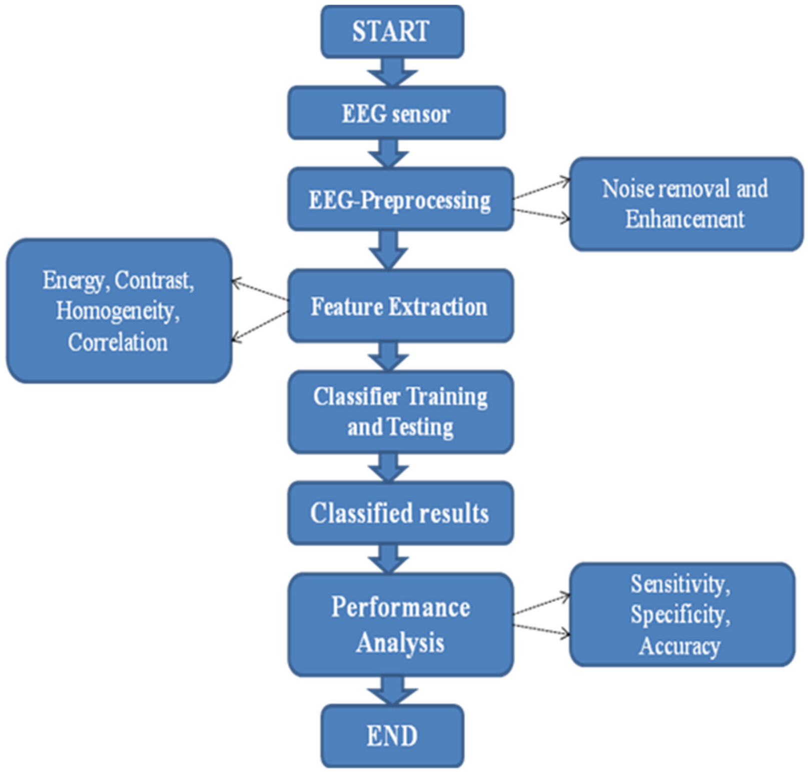

Fig. 1 Block diagram of EEG epileptic seizure detection and classification

B. EEG Signal Processing and Feature Extraction

In an automatic seizure detection method, the predominant steps involved for examining the EEG data is done by selection of optimal signal representation method and feature extraction which will aid for determining and evaluating the characteristics of the EEG signals during all phase of seizure. Features that are used for EEG representation may be analyzed in time, frequency or t-f domain [13].

An example of EEG during a seizure and non-seizure activity in various domains such as time domain [14], [15], frequency domain [16], [17], and time-frequency analysis [18] are provided below.

1) *Time-domain analysis*: The features which are estimated directly as a function of time in EEG signals so called as time domain analysis. These features include amplitude [19-20], entropy [19-21] and statistical moments of EEG signal [22], which will provide the change in the brain signal during epileptic activities. Fig 2 provides the time domain analysis of EEG signal.

Fig. 2 EEG signal time domain analysis for non-seizure and seizure activity

2) *Frequency-domain analysis:* Usually, there will a change in the frequency component when EEG signal is affected during an epileptic seizure. Therefore frequency component of the affected EEG signal has to be extracted which can be done Fourier transform. Different Frequencies which may occur due to change in the activity of the brain can be observed by frequency feature. Some commonly used features such as average band frequency, power spectrum, maximum power [23], central, mean, spectral roll- off and dominant frequency [21]. Fig. 3 provides the PSD (power spectral density) of three different EEG signals in which there is a variation in peaks of the frequency band which varies 25-35 Hz as minimum and 10-15 Hz as maximum and that will occur only during the presence of the seizure.

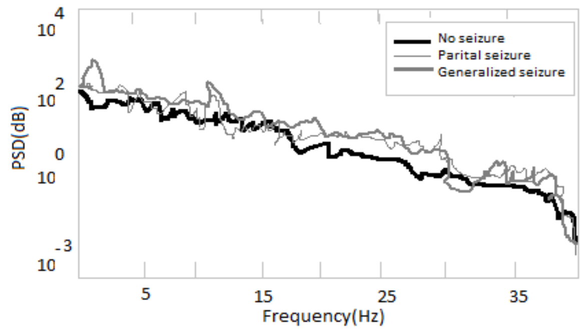

Fig. 3 PSD of three different EEG signals

3) *Time-frequency analysis:* As a well-known drawback of time and frequency domain analysis such as time domain provides only the correct location of the signal change but fails to provide the frequency range and frequency analysis provides only the frequency components but fails to provide the time moment occurrence at that frequency. These limitations can be overcome by means of time-frequency analysis as shown in Fig 4. Gabor et al [24] used a standard method, like the spectrographic methodology for finding the wavelet transform. The features of time-frequency domain of EEG signal have been extracted by Quadratic time-frequency domain TFD (QTFD), Wigner-Ville distribution (WVD) [25], and wavelet analysis.

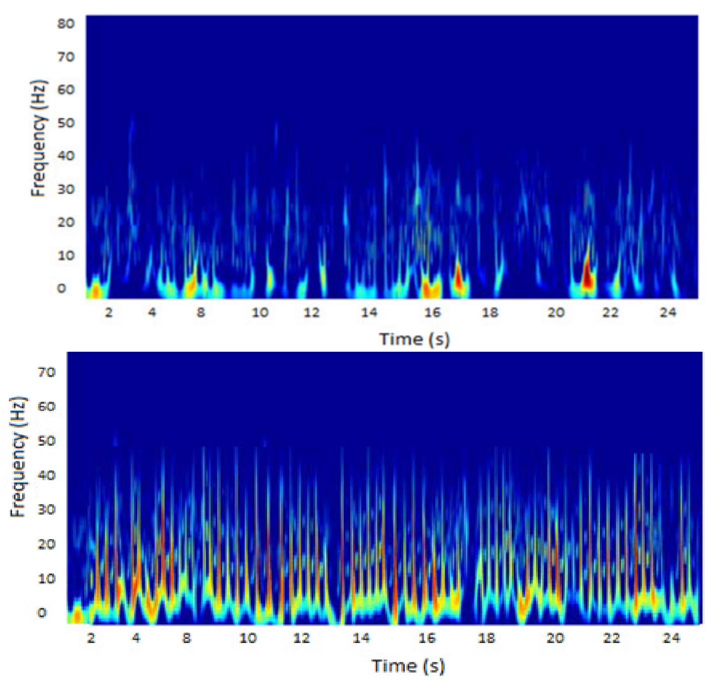

Fig. 4 EEG signal time–frequency domain analysis for non-seizure and seizure activity

C. Feature selection:

For improving the performance of the classifier it is important to select the needed feature. For instances, when two or more combination of the features have same correlations then there may be chances for the redundant feature which will result in high dimensional feature spaces. This condition is known as the curse of dimensionality [26].Many studies are being conducted to reduce or transform the higher dimensionality into smaller ones, which are jointly known as dimensionality reduction technique. The mostly used methods for the dimensionality reduction technique are the linear-discriminate analysis (LDA) [31], singular-value decomposition (SVD) [32], principal component analysis (PCA) [33] and factor analysis [33].

The dimensionality of the feature vector could also be reduced by applying the statistics methods like average power, mean, entropy, standard deviation and analysis of variance (ANOVA) [34] to the wavelet coefficients of each band [27-29]. Mihandoost et al. Proposed a methodology called class separate ability to select the best feature by utilizing the Markov random field (MRF) such as the between-class distance is maximized whereas the within-class distance is minimized. This method aid the nonlinear mapping [35].

Minasayan et al. utilized measure of mutual information between features [36]. In machine learning works, parallel class of feature-selection methods has been utilized for improving the performance .some of such algorithms are quadratic approximation function step-wise regression [37], least-squared regression [38] and multi-variant linear regression [39] which find its application in seizure detection.

TABLE I
SEIZURE DETECTION ALGORITHM PERFORMANCE COMPARISON

Name of researchers	Year	Processing techniques	Classifier	Performance metrics
Christopher et al.[50]	1999	Self-organizing, Feature map	ANN	Sensitivity: 55.3% Selectivity:82%
He LS et al.[51]	2002	Wavelet transform, Integrated adaptive filtering	ANN	Accuracy : 90.0%, FDR : 6.1%
Alexandros et al.[52]	2009	Time–frequency analysis	ANN	Accuracy :99.28%
Pradipta et al.[53]	2013	DWT	ANN	Specificity:99.19% Selectivity:91.14%,
Zainab et al.[54]	2011	Wavelet transform	Genetic algorithm	Sensitivity ≥ 90% Selectivity ≥ 90%
Petros et al.[55]	2010	Wavelet-based algorithm	ANN	Accuracy :97.25%
Saadat et al.[56]	2013	Seizure onset detection Algorithm DFT , DWT,	IPSONN	Specificity : 84% Sensitivity : 98%,
Dhande et al.[58]	2015	Back propagation Algorithm	ANN	Accuracy :100%
Sharmila et al.[59]	2016	DWT ,Naïve Bayes	K-nearest neighbor	Accuracy :100%
Asha et al.[49]	2013	Wavelet-based algorithm	SVM , ANN	Accuracy :75%
Pega et al.[60]	2003	Mutual information evaluation function (MIEF)	ANN	SDR : 96.35%, FAR : 6.2%.
Samanway et al.[61]	2008	PCA	Enhanced cosine RBFNN	Accuracy :99.3%
Akshata et al.[62]	2016	DWT ,Multi resolution analysis	ANN	Accuracy :96%
Meenakshi et al.[63]	2014	Radial basis function	ANN + SVM + K-means Classifier	Sensitivity : 100%, Accuracy : 100%
Kemal et al.[64]	2007	FFT	Decision-tree classifier+ k-fold cross validation (CV) process	At 5 fold CV accuracy : 98.68%, for 10 fold CV accuracy : 98.72%
Maryann et al. [69]	2005	Time-domain features, Frequency-domain features	ANFIS	Accuracy :92.22%
Subasi et al.[48]	2007	Time-frequency domain, Wavelet-based features	ANN	Accuracy :95%
Boubchir et al. [72]	2014	T-f signal , t-f image related-features	SVM	Accuracy :97.5%
Boubchir et al. [71]	2015	Image texture descriptor-based features	SVM	Accuracy :98%
Boubchir et al.[70]	2013	LBP descriptor-based features	SVM	Accuracy :99.33%
Runarsson et al.[74]	2005	Time domain, Histogram bin amplitudes features	SVM	Sensitivity: 90%
Yoo et al. [14][75]	2013	Time domain, Energies of sub-bands	SVM	Accuracy: 84.4%
Dalton et al.[76]	2012	Time domain. Signature of seizures	SVM	Sensitivity: 91 %, Specificity:84%
Panda et al[77]	2010	Wavelet domain, Energy, entropy standard deviation	SVM	Accuracy: 91.2%
Shoaib et al.[78]	2014	Wavelet features	SVM	Sensitivity: 91%
Tafreshi et al.[79]	2008	EMD detection Wavelet features	Neural network	Accuracy: 95%

D. Classification algorithms

In the field of medical image processing, classification helps for categorizing the given data to its needed group for pattern recognition and machine learning process[40].After the process of feature selection, it is important to classify the EEG signals based on its features variation as seizure affected person or a healthy person.

In order to provide the difference between the classes based on their calculated features by simply giving a threshold and to label them, classification is used. Some simple thresholding methods have been proposed for detecting the seizure; Schad *et al*. [45] used the threshold of local slopes in EEG signals. Gotman used a method called Monitor algorithm [43, 44], for thresholding of time features like amplitude, duration, and coefficient of variation of amplitude.

Many automated clustering and classification techniques are needed if the correlation among features is similar. For the epileptic seizure detection techniques like association rules, LDA [46], hidden Markov modeling (HMM), fuzzy logic [47], and k-means clustering [47] have been used by many researchers.

In last few decades, the use of ANN(Artificial Neural Network) has been increased due to its classification accuracy level. Particularly ANN provides a novelty in finding the relationship between the input and output by the meaning of proper training of variable parameter by means of finding its weights and biases[48].

Like ANN, most commonly used method in machine learning process for finding the multidimensional feature classification is SVM (Support Vector Machine) technique[41]. When the features are so large then it will be classified to its groups based on its separating hyperplane. For transforming the desired feature into linearly separable class, Kernel methods were proposed [42]. For multichannel detection of seizure generated EEG signal, Asha et al. [49] trained ANN/SVM classifier.

Various methods for epilepsy detection and classification are summarized in Table I with its performance metrics which may help the researchers for their works.

III. CONCLUSIONS

Traditionally for diagnosing, monitoring and managing the epilepsy clinical tool namely, EEG is used. EEG signals are obtained from brain scalp and it is visually inspected using strip charts. Due to the production of a large amount of data from EEG recording it became tedious and time consuming for observing it manually. Moreover, they fail to provide the detailed interpretation of EEG traces which may contain some more detailed information about the seizure. Thus a need for automatic detection and classification of epilepsy has been increasingly popular among the researchers. This paper a provides a literature survey of the various important and recent researches which are effectively utilized for detection and classification of Epileptic seizures using EEG signals from a machine learning perspective.

In this paper, various feature extraction techniques for EEG signal such as time domain analysis, frequency domain analysis and time-frequency domain analysis were discussed and also some of the classification methods along with its performance accuracy were also provided for improving the classification accuracy. For reducing the lengthy training time some more enhancement methods are needed.

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