Review article

Review on diverse approaches used for epileptic seizure detection using EEG signals

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Abstract

Epileptic seizure detection is a common diagnosis practiced by the expert clinicians through direct visual observation from the electroencephalography (EEG) signal. This detection by the expert clinicians is considered sensitive to bias and time consuming. Further, it suffers from various problems like unsustainability in larger dataset processing and low power detection. Hence, many computerized detection approaches are highly preferred to eliminate the aforementioned problems and to expedite the research in epilepsy seizure detection for aiding the medical professionals. Many such automated epilepsy diagnosis framework has been designed by various researches, which is made to operate in a single or in a combined manner with other domains. This study reviews different approaches, which is been designed to aid the human diagnosis using new avenues that explains the causes of epilepsy and seizures. Further, this study summarizes various methods used previously to analyze the epilepsy and seizures based on its state of art approach. Also, investigations are carried out in terms of performance evaluation to find the best suitable epileptic seizure detection technique in the application of Neuro-informatics.

Keywords: Epileptic seizure detection; Electroencephalography; Automated epilepsy diagnosis; Neuro-informatics

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Introduction

EEG is progressively increasing its vital diagnosis and treatment of neuro-degenerative ailments and brain signal abnormalities. The EEG assists doctors for setting up an exact diagnosis. In neurology, a primary need to diagnose EEGs is to find epilepsy, as epileptic action which makes anomalies on an EEG signal[1]. EEG is additionally utilized as a first-line technique for diagnosing numerous neurological issues. Besides, EEG can likewise be utilized as a part of the finding of unconsciousness, brain death and encephalopathies. EEG has turned out to be extremely well known in the application of brain computer interface (BCI).

Numerous procedures utilized as a part of research are not adequately standardized to be utilized as a part of the clinical setting. As EEG records contain huge information, the improvement of BCI is fundamental for classifying unusual EEG signals from normal EEGs. This supports mainly in determining the brain sicknesses and contributes better understanding of the BCI applications. The primary motivation behind a classification is to isolate EEG segments and to choose whether individuals are healthy, or to evaluate the mental condition of patients identified with a performed operation.

In this paper, we provide a brief overview of epilepsy and the diagnosis of epileptic disease in human brain. This method provides a brief discussion of electroencephalogram (EEG) in Epilepsy Diagnosis and classification of EEG signal using various techniques. The signal classification includes supervised, unsupervised and semi-supervised.

The outline of the paper is represented as follows:

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Section 2 discusses the EEG in Epilepsy Diagnosis. Section 3 provides the fundamentals of EEG Signal Classification and Section 4 provides various techniques on signal classification. Finally, section 5 concludes the paper.

EEG in epilepsy diagnosis

Seizures are characterized as sudden changes in the brain with electrical impulses that results in adjustments over the behaviors like jerks, losing consciousness and temporary memory loss and loss of breath.This occurs usually in the brain cortex and may create abnormality in brain and instability of neurotransmitters.

Neurons ordinarily create electrochemical impulses that follow up on different glands, neuronsand muscles to deliver human emotions, thoughtsand actions. In epilepsy, the normal neuronal movement behavior is noticeably disturbed, strange sensations, feelings and behaviors, or at times muscle spasms, consciousness loss and convulsions. A brief electrical signal emerging from neurons are insecure characteristically, in light of a genetic defect or from unstable neurons through metabolic anomalies. On the other hand, the unusual release may originate from a localized area of the cerebrum caused by head damage. Amid seizures, neurons fires 500 times each second, substantially quicker than a normal firing (1–100 μV).

EEG is a basic component examination of and conclusion epilepsy[4]. EEG plays a major role in diagnosis and monitoring seizure disorders of a patient. One of the fundamental explanations for this is it is an advantageous and generally cheap approach to show the physiological manifestations of irregular cortical excitability with epilepsy. The main indication of EEG is the epileptic seizure. The seizures can incorporate a discrete part of the complete or partial brain mass. The recorded EEG signal generally represents the electrical activity of brain caused by neuron firing along the scalp.At the point when epilepsy is available, seizure activity will show up as rapid spiking on the EEG. Epileptic movement makes abnormalities in EEG and creates a mark in EEG signals[5].

EEG decides seizures and epilepsy disorder in epilepsy patients, in this way deciding antiepileptic medication choice and the prognosis prediction. Another essential commitment of EEG discoveries is to decide the multi-axial diagnosis of epilepsy, as far as whether the seizure issue is generalized or focal, symptomatic or idiopathic or part of an epilepsy disorder[6]. The EEG gives critical data about EEG and epileptiform releases and is required for the analysis of particular electroclinical disorders[7]. Such analyses convey critical prognostic data, direct determination of antiepileptic drug, and recommend when to stop the medication. Neurologic imaging and examination in the fundamental idiopathic is genetic hereditary, where the epilepsies are normal [8]. Behind a seizure, the EEG foundation might be moderate. Conversely, interictal EEG frequencies suggest symptomatic epilepsy, which are slower than normal.Epileptiform releases help clinicians to isolate partial seizures.

EEG signal classification

Recently, the EEG signal classification plays a major role in biomedical research, specifically in diagnosing the diseases in brain. It also provides a better perception of cognitive process, specifically in reading the signals.The efficient classification technique segments well the EEG signal, which is used for good decision making while monitoring the patients' health.The key problem in EEG recordings is the representation of its analysed pattern for classification, since it contains substantial data. The most important process is the extraction of related feature from the EEG signal and then the extracted feature is used for further classification.

The classification involves the usage of certain mechanical process for sorting letters, updated financial and personal information is assigned to an individuals and diagnosis of disease forthe instant treatment while anticipating authoritative test outcomes [9].Classification also plays a major role in pattern recognition and in machine learning process, which assigns the input data to a give category[9,10]. For example, classifying a malicious or non-malicious segment from an email or classifying the observed attributes for diagnosing the disease. The main aim of classification task is to relegate class labels based on the extracted features from the observed datasets in relation with a particular problem. The classification process is executed by the algorithm, specifically a classifier, which is a mathematical function that maps the given set of input data to a specific category. Such algorithms can figure out how to recognize the classes of feature vector, on account of training sets, which is made of labelled feature vectors along with the classes to which it belongs.

The EEG signal analysis and classification process measures the activity of the brain through the EEG leads that procureslarge data acquisition. Keeping in mind, the end goal to get the most possible execution, it is important to work with small values that depict some applicable signal properties, which are termed as features. Such features are aggregated to feature vectors[11]. Hence, the feature extraction can be characterized as an operation which transforms the EEG signal into a feature vector, which represents the pattern with reduced dimensional space. Signal classification intends to break down various characteristic features and choose class to which the signal has to be placed. The subsequent choice of classification can be mapped with the user interface to uncover data about the physical process, where the signal is created.

Types of classification: The EEG signals are classified into supervised[13-25] and unsupervised classification[12]. Major biomedical researches uses supervised classification to manage large data with information related to the dataset or the obtaining the information of class labels by training the classifier. The supervised learning involves the instruction of classifier by the supervisor while developing the classifier model. Supervised methodology expect that the training set has been given, comprising of instances, which are labelled appropriately with the correct output[9,10]. For instance, if the problem is spam filtration, at that point x_i(email) and y_i(spam or non-spam) makes the perceptions to be any vector, whose elements are chosen from feature set.

In this manner, in supervised classification, the point is to discover the transformation between the class label and feature space. In the event that the class label has limited elements, at that point the problem is regarded as aclassification process. For instance, the issue with binary classification involves the separation of classes into two category, for example, the target and non-target classes. Classification algorithms rely mostly on labelled output, where the learning is supervised or unsupervised based on statistical or non-statistical data.The supervised classification algorithms foreseescategorical labels as: support vector machine (SVM)[26-35], Global modular PCA with SVM[36-41], linear discriminant analysis (LDA), Naive Bayes, decision trees, K-nearest-neighbour (kNN), logistic regression, neural networks, Kernel estimation, linear regression, Kalman filters, Gaussian process regression, fractional linear prediction[2] etc. The aim of these algorithms is to amplify the precision of testing over testing dataset and hence, the supervised algorithms are used mostly in classifying the EEG signals.

The unsupervised classification groups the given dataset into classes based on the measures. The training data are not been inbuilt with labelled items and the correct output pattern is determined for the new data instances by discovering inherent data patterns[9,10]. Even for smaller dataset, the class label information for unsupervised learning is not available.The most common unsupervised learning algorithms are hierarchical clustering, k-means clustering, principal component analysis (PCA), kernel PCA, independent component analysis (ICA), hidden Markov models, categorical mixture model, etc.

The mix of supervised and unsupervised classification algorithms is recently investigated as semi-supervised learning, which makes use of unlabeled(large sets) and labelled information data (small sets).

EEG signal classification methods

To attain better classification of the EEG signal in epilepsy detection, a precise feature extraction is required to extract the relevant features from the original EEG signal. Indeed, if the features separated from EEGs are not significant and do not precisely portray the EEG signals utilized; a classification algorithm utilizing such features will experience difficulty while distinguishing the feature classes. Thus, the correct classification rate will be low. It is seen that various techniques have been utilized for feature extraction in epileptic EEG information. The feature extraction techniques can be ordered into four classes: parametric, non-parametric, eigenvector and time-frequency[3,28] methods.

The modelbased strategies accept that the signal fulfills a generation model with function form, and continues the assessment of parameters in the model. Some prevalent parametric strategies are, moving average (MA) model, autoregressive (AR) model, lapaunov exponents and autoregressive-moving average (ARMA) model. The AR show is appropriate for spectral representation with narrow crests. The MA demonstratesa decent estimate to those spectra which are described by wide and sharp peaks. Such wideband spectra are experienced less in applications than narrowband spectra, so that some constrained interests for utilizing the MA for the estimation of estimation. Spectra with both sharp and deep peaks are displayed by ARMA model. The ARMA estimators are computationally straightforward and very dependable; however their precision might be poor at times[18-21].

The non-parametric strategies depend completely on the power spectral density (PSD), which provides the spectral estimates.This non-parametric strategies constitute the PSD estimation using classical means. Two non-parametric techniques, periodogram and the correlogram, give a sensibly high resolution to adequately long data lengths, however poor the spectral estimators on the grounds, where variance is high and causes a constant data length increment. The high variance in correlogram and periodogram techniques persuades the improvement of changed strategies that have reduced the variance in terms of decreasing variance.

Mappings between the frequency and time spaces are utilized generally as a part of signal investigation and handling. The strategies in time-frequency domain uses Fast Fourier change (FFT), wavelet transform (WT)[43], Tunable-Q Wavelet Transform[40], short time Fourier transform (STFT), wavelet entropy[29], wavelet energy function[30], multi domain wavelet threshold[44], harmonic wavelet packet transform[36], Stockwell transform[38], ensemble empirical mode decomposition[37], Multivariate Empirical Mode Decomposition[14], Bootstrap Aggregating[45], visibility graph[2,27], Cohen class kernel functions[33] and other entropy based methods[17]. Since, Fourier strategies may not be suitablefor non-stationary signal or stationary signals with short-lived segments. From the prior works, Gabortransform over short-time Fourier change (STFT) is a better technique for perfect classification. The wavelet change (WT) provides signal representation in a cross section of building blocks, with high time and frequency time restriction. The wavelets, in discrete and continuous forms, and in addition as far as a multi- resolution approximation.

Eigenvector strategies are utilized for assessing frequencies and signal powerfrom noise-corrupted estimations. These techniques depends mainly on an Eigen decomposition of the correlation matrix from noise-corrupted signal. Lower the signal-to-noise ratio (SNR) is, the eigenvector strategies delivershigh resolution frequency spectra. The eigenvector strategies, for example, minimum-norm and multiple signal classification (MUSIC) are most appropriate to the signals that can be made of few sinusoids covered in noise[21].

Recently, the feature extraction techniques are combined with various classifiers like: adaptive neuro-fuzzy inference system[39], support vector machine (SVM)[35], Global modular PCA with SVM[41], least square support vector machine (LS-SVM)[45] and artificial neural network (ANN)[31,39], ANN with Fuzzy relations[32], multilayer perceptron neural network (MLPNN)[42], recurrent neural network (RNN)[39], relevance vector machine (RVM), probabilistic neural network (PNN), mixture of experts (MEs), modified mixture of experts (MMEs), k-NN[15,34], Genetic algorithm[38], nonlinear sparse extreme learning machine[43], Wavelet based envelope analysis (EA) with neural network ensemble[20], random forest classifier[22, 16], Bayesian classifier[23], fuzzy entropy model[24], rule based classifier[26], weighted extreme learning[13] and logistic tree model.

The execution of a classifier depends on the qualities of the classified data. There is no single classifier that works best on every given issue. Different observational tests have been performed to compare the execution of classifier and to distinguish the data qualities that decides the performance of classifier. The accuracy measures and confusion matrix are extremely prevalent strategies for assessing the nature of classification system. All the more as of late, receiver operating characteristic (ROC) curve have been utilized to assess the trade-off in classification algorithms between false and true positive rates. This basically utilizes accuracy to evaluate the execution of proposed strategies. The ROC curves and confusion matrix are additionally used to assess the execution of classification performance.

Conclusion

This paper provides a detailed survey on various techniques utilized to classify the epilepsy signal from the ECG signal. The paper presents numerous signal process methods to extract the features from the EEG signal and various classification methods. However, there are some limitations associated with these methods. Such limitations are mainly due to inaccuracy in extracting the features from the signal and it is not accurate with large data, since it requires lengthy training time. Such limitations can be avoided by improving the classification methods with certain future enhancements.

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