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RESEARCH

Automated epilepsy detection techniques from electroencephalogram signals: a review study

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Abstract

Epilepsy is a serious neurological condition which contemplates as top 5 reasons for avoidable mortality from ages 5–29 in the worldwide. The avoidable deaths due to epilepsy can be reduced by developing efficient automated epilepsy detection or prediction machines or software. To develop an automated epilepsy detection framework, it is essential to properly understand the existing techniques and their benefit as well as detriment also. This paper aims to provide insight on the information about the existing epilepsy detection and classification techniques as they are crucial for supporting clinical-decision in the course of epilepsy treatment. This review study accentuate on the existing epilepsy detection approaches and their drawbacks. This information presented in this article will be helpful to the neuroscientist, researchers as well as to technicians for assisting them in selecting the reliable and appropriate techniques for analyzing epilepsy and developing an automated software system of epilepsy identification.

Keywords: Classification, EEG, Epilepsy, Feature extraction, Machine learning, Time–frequency

Introduction

According to Epilepsy Action Australia, circa 65 million people at the world level has epilepsy, and 80% are living in developing countries [1]. “Seizure” is defined as a paroxysmal malfunction of the neurological activity precipitate due to the immoderate hypersynchronous of the neurons present in the brain [2]. “Epilepsy” is the state of perennial unprovoked seizure attacks [3]. Epilepsy is menacing brain dysfunction, which increases the occurrence risk of other maladies like Dementia, Cardiovascular Disorders, Depression, Sleep Disorder, Migraine, Cognitive Impairment, Mental De-cline (in the chronic condition), Brain tumors, etc. and affect other body parts and Pregnancy as well [4]. Epilepsy can affect anybody irrespective of person’s age, intellect, gender, cultural or social differences whereas it is scrutinized that the prevalence of epilepsy is on the peak during the early stage of childhood and also high in the late stage of life [5]. Sudden Unexpected Death in Epilepsy (SUDEP) is approximately 24 fold more in an epileptic patient as compared to the general [6]. Epilepsy is diagnosed with the help of an Electroencephalogram (EEG), which tracks the electrical activity in the brain and records the brain wave pattern [7–9]. In the cases of having un-certainty in the diagnosis of epilepsy or the reason behind paroxysmal spells is un-clear, then EEG recording is contemplated as the most accurate and promising diagnosis test. Finding traces of epilepsy through the visual marking of long EEG recordings by human experts is a very tedious, time-consuming, and high-cost task [10–12]. It is always a challenging issue for the researcher and neurologist to detect epilepsy disorder from EEG signals, which contains huge fluctuating information about the functional behavior of the brain [13]. For all of the above-mentioned rea-sons, it is always an imploration for the automated epilepsy seizure activity detection techniques that can save and improve the life of epileptic patients.

Despite the fact that numerous anti-epileptic drugs have been developed from the last decade still, one-third of epileptic patients continue to have a seizure attack in spite of treatment. One of the main important difficulties in the treatment of epilepsy syndrome is the

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ability to detect clinical seizures rapidly (time of greater seizure susceptibility) and accurately. The record about epilepsy is present from since 2000 years B.C., whereas, the automatic epilepsy detection or prediction came to start from the 1970s [14, 15]. Over the last few decades, there is remarkable advancement has been perceived in the field of automated epilepsy detection.

This paper carried out a reviewed study about different machine learning epilepsy detection techniques. This research will contribute as a “roadmap” for the researchers and developing technicians that assist epileptic seizure detection. Because in this paper, we have covered mostly the significant techniques for seizure detection as well as highlighted the drawbacks of the existing techniques as a gap which is very crucial for guiding the researchers, clinicians, and technologists during the advance development effort of epilepsy detection. This research study is unique as we critically analyze the extant epilepsy detection and classification techniques in order to determine the certain opportunities for the research and technology that aid in clinical decision-making and benefit to the mainstream seizure diagnosis. The rest of the paper is systematized as: section 2, provide present techniques for epilepsy detection from EEG signals. Section 3 includes literature summary in the field of epilepsy detection from EEG Signals. Drawbacks of the existing techniques are discussed in section 4. Section 5 comprises discussion and future direction. Section 6 draws the conclusion of this paper.

Present techniques for epilepsy detection from EEG signals

EEG analysis and classification is an essential part of the diagnosis of epilepsy disorders as EEG patterns are the real replication of the electrophysiological state of the brain at a particular time frame. This section provides brief information about the various existing epilepsy detection techniques based on the different approaches of EEG signals analysis and classification. Figure 1 represents the overview diagram of epilepsy detection from EEG signals system followed by all the techniques described in the paper. The first step is data acquisition. Most of the researchers has used the online available EEG data. Next step is the feature extraction. Extracting the relevant statistical feature of the network plays a crucial function during the classification of distinct EEG signals [16–19]. In technical term, a feature embodies as a discern-able dimension that can characterize the unique or distinguishable properties of a pattern or configuration [20, 21]. In the process of feature extraction, the vast EEG data is simplified into a feature vector on the principle of least possible loss of information. The third step is the classification. In classification, the set of unidentified observation (testing group) is predicted or classified into the appropriate class by considering some criteria

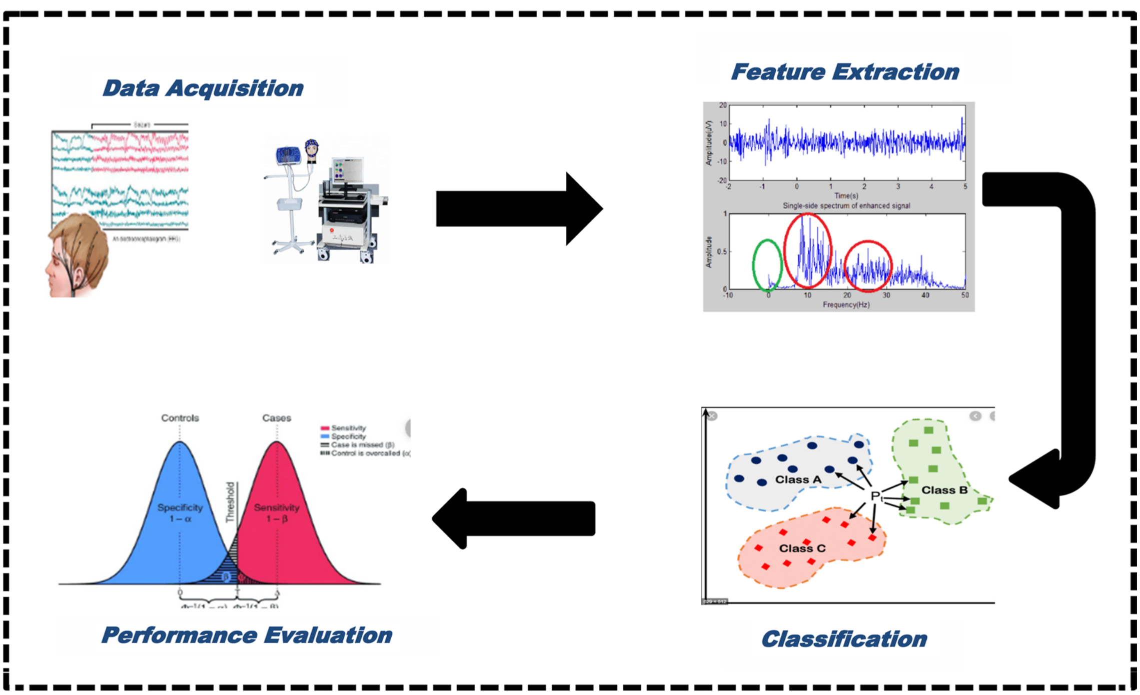

Fig. 1 The overview diagram of epilepsy detection from EEG signals system followed by all the techniques described in the paper

on the set of identified observation (training group) [22–26]. The last step is the performance evaluation which is assessed by employing some defined standard measuring parameters such as accuracy, sensitivity, specificity and area under the roc curve etc.

EEG analysis can be categorized into four domains: time based analysis; frequency based analysis; time–frequency based analysis, and analysis by non-linear methods. Below is the brief introduction about the above four EEG analysis domains.

EEG analysis based upon time domain

A time-domain approach based upon the analysis of EEG signals on particular time window by considering time as the variable of EEG signal. The time domain analysis comprises two main technique named linear prediction (LP) and component analysis (CA).

Linear prediction

The linear prediction is a technique is used to compute the set of coefficients that will define the behavior of EEG signal by linear time-invariant [27]. The linear prediction is a technique where the imminent outputs $\widehat{y}(i)$ is the linear combination of input $x(i)$ and previous outputs $y(i-1), y(i-2), \ldots.., y(i-p)$

$$\widehat{y}(i) = \sum_{j=1}^{p} n(j)y(i-j) + \sum_{j=0}^{N} j(j)x(i-j) \quad (1)$$

In the Eq. (1), n and k symbolizes the predictor coefficients. In EEG signal processing, the n predictor coefficients are generally considered zero and the imminent outputs $\widehat{y}(i)$ is completely depend upon previous output i.e.:

$$\widehat{y}(i) = \sum_{j=0}^{N} j(j)x(i-j) \quad (2)$$

Component analysis

Component analysis technique (CA) is an unsupervised method that reduces the high dimensional data into feature sets. Principal component analysis (PCA), independent component analysis (ICA) and linear discriminant analysis (LDA) are the approaches based upon CA.

Principal component analysis Karl Pearson developed PCA in 1901. Principal component analysis is a dimension–reduction technique which is based upon orthogonal transformation and reduces the high dimensional data into Eigenvector and also very successful in the EEG signal analysis [28, 29]. The principal components decomposition of Y can be defined as:

$$T = YW \quad (3)$$

In the Eq. (3), Y denotes the data matrix with zero empirical mean and W is the matrix of the principal component of Y and the columns of W are the eigenvectors of Y^TY. Figure 2 illustrates how three-dimensional gene expression data are reduced to two-dimensional subspace with the help of Principal Component Analysis [30].

Independent component analysis In ICA, the multivariate signal is disintegrated into sub-constituent whereas these sub-constituent are non-Gaussian signals and not dependent on each other. ICA is used to find the hidden features presents in the EEG signals. The ICA transform is defined as:

$$h = Wx \quad (4)$$

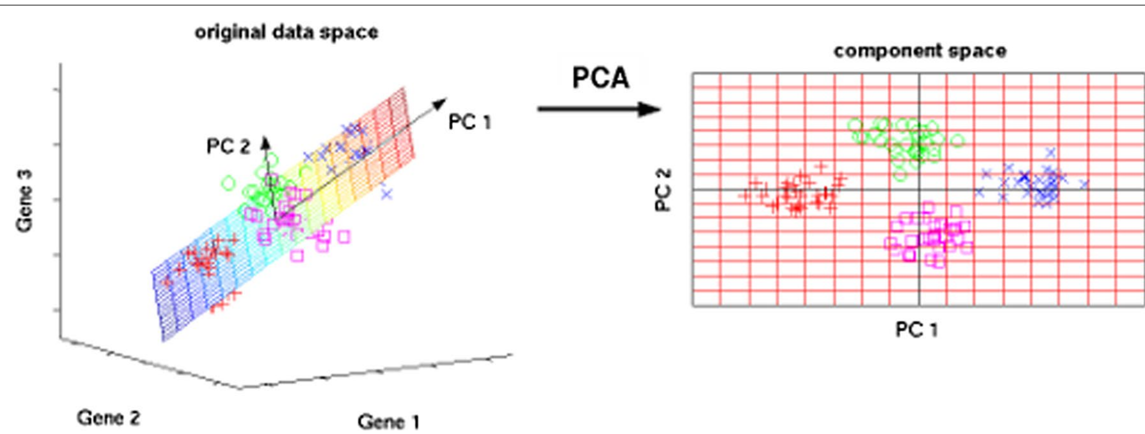

Fig. 2 Illustrates principal component analysis [30]

In the Eq. (4), h denotes the sets of hidden components, or independent constituent and x signify the set of the observed data or original signal. W is missing matrix [31].

Figure 3 illustrates the ICA has been implemented on data set X for the identification of original factors s and the dependencies specified by the matrix A [30].

Linear discriminant analysis Similar to PCA, LDA is also used for dimensional reduction. LDA method is supervised in nature. It is based upon the linear combination of parameters that describe the data adequately. LDA is used in the case when the dimensions are based on independent variables for each and every observation.

EEG analysis based upon frequency-domain

In the frequency domain, the hidden information of the EEG signals can be elaborated by decomposing the signals into pure sinusoidal waves with different frequency ranges. A frequency-domain approach based upon the analysis of EEG signals on frequency spectral estimation of statistical and Fourier Transform (FT) methods. The Spectral analysis is further classified into two parts named: Non-Parametric approach and the parametric approach.

Non-parametric approach

In this approach, firstly the auto-correlation from the EEG signals are computed. Afterward, the Fourier Transform is applied to the extracted auto-correlated data in order to extract the power spectrum density. The Welch method [32] is considered as one of the best methods for extraction the power spectrum density. Welch method include the decomposition of EEG signals into overlapping epoch sections. Afterward, the data window is applied to each section for calculation periodogram, and then the averaged of the periodogram is used to evaluate the Power Spectral Density. Figure 4 illustrates the Power Spectral Density estimate of one epoch EEG signal [33].

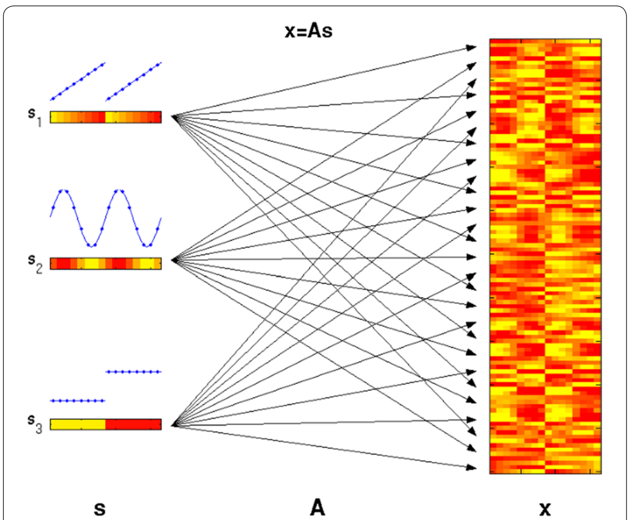

Fig. 3 Illustrates the ICA

Parametric approach

The parametric approach provides improved frequency resolution in comparison to the non-parametric approach. The parametric approach assumes apriori information about some parameters can help to characterize the EEG signals properly. The prior information can be useful to calculate the desired Power Spectral Density. During the parametric approach, it is supposed that the EEG signals are a stationary and random process. These stationary signal are considered as the output of a filter with white noise as input. After that, the parameters correspond to that filter are evaluated. There are various techniques to compute the filter parameters on the basis of the model used as a filter. The three best model are the Moving Average model, the Auto-Regressive model, and the Auto-Regressive Moving Average model [34]. Figure 5 represents the Auto-Regressive model estimation of EEG signals [35].

EEG analysis based upon time–frequency domain

The time–frequency domain provides information about both the time and frequency mechanisms of the signal concurrently [16]. This technique is based upon the stationary principle and as a result window process is essential in the pre-processing stage. The time–frequency domain can be categorized as (1) Wavelet transform and (2) Hilbert–Huang Transform (HHT).

Wavelet transform

Wavelet transform (WT) is a spectral estimation method in which a function is represented as an infinite sequence of wavelets. A wavelet is defined as a small waveform with determinate energy and duration. In Wavelet transform, the primary function named mother wavelet is evaluated continuously along the time scale to achieve the wavelet coefficients. The wavelet coefficients provide information about the signal in both the time and frequency frame. In the Wavelet transform, the signal is decomposed into sub-bands, and relevant features are extracted from that sub bands [36]. The procedure is continued for the number of levels until the required results not achieved. The wavelet transform is of three kinds: Discrete Wavelet Transform, Continuous Wavelet Transform and Wavelet Packet Decomposition (WPD). Figure 6 illustrates the wavelet packet decomposition up to level 2. In the Fig. 1,

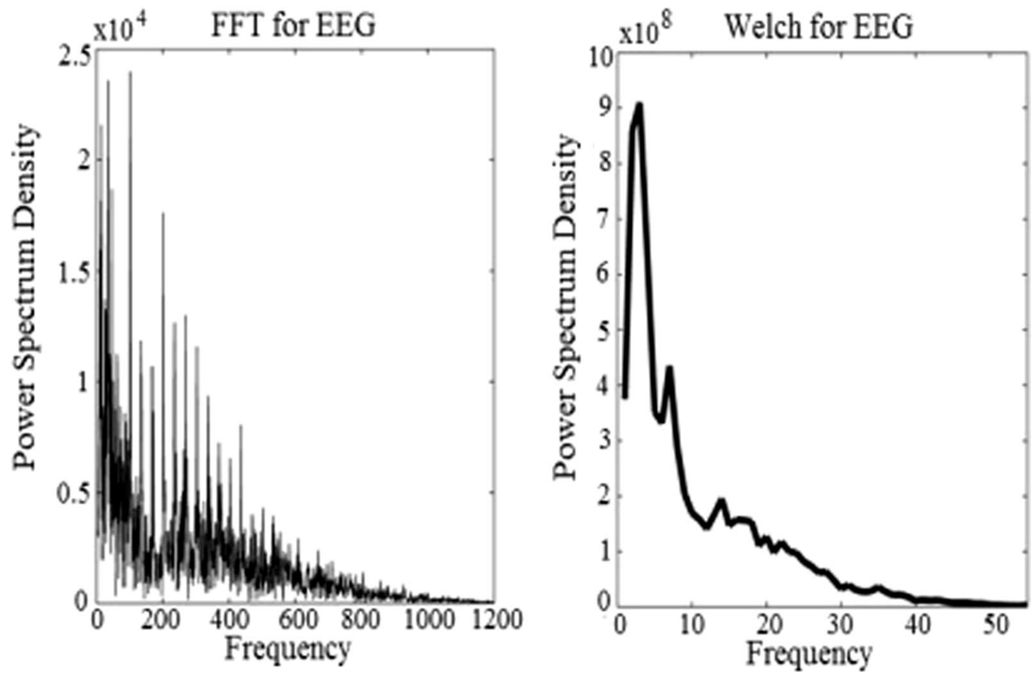

Fig. 4 Illustrates the power spectral density of one epoch EEG signal [33]

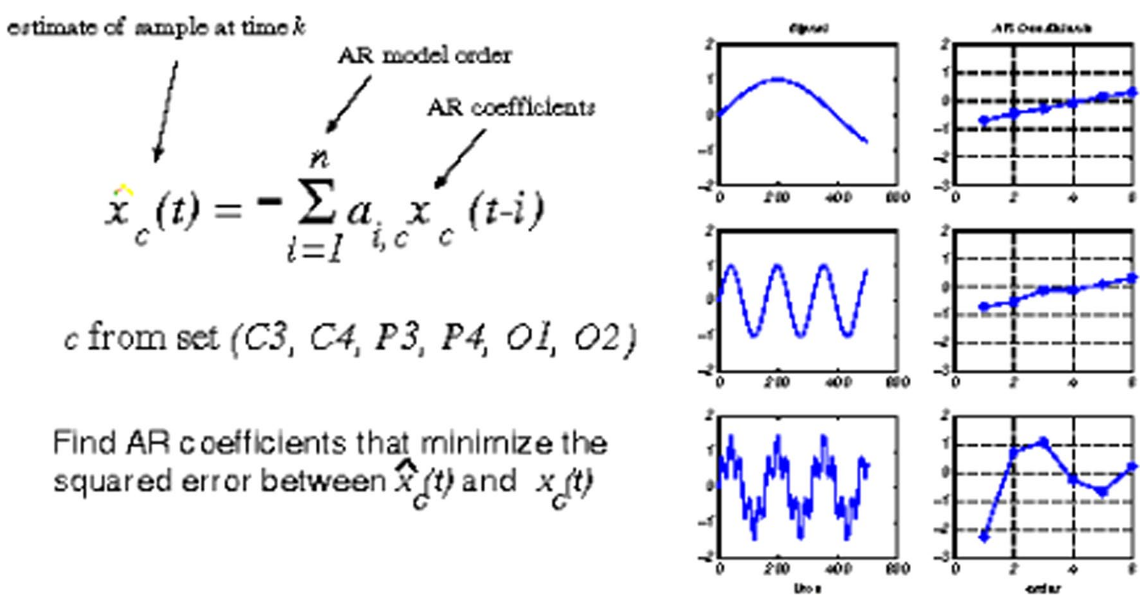

Fig. 5 Represents the Auto-Regressive model estimation of EEG signals [35]

a_1 denotes the approximation coefficients, and d_1 symbolizes the detail coefficients at level 1 of WPD. Similarly, aa_2, da_2, ad_2, and dd_2 signifies level 2 WPD. Figure 7 illustrates the Lifting Wavelet Transform (LWT) [37].

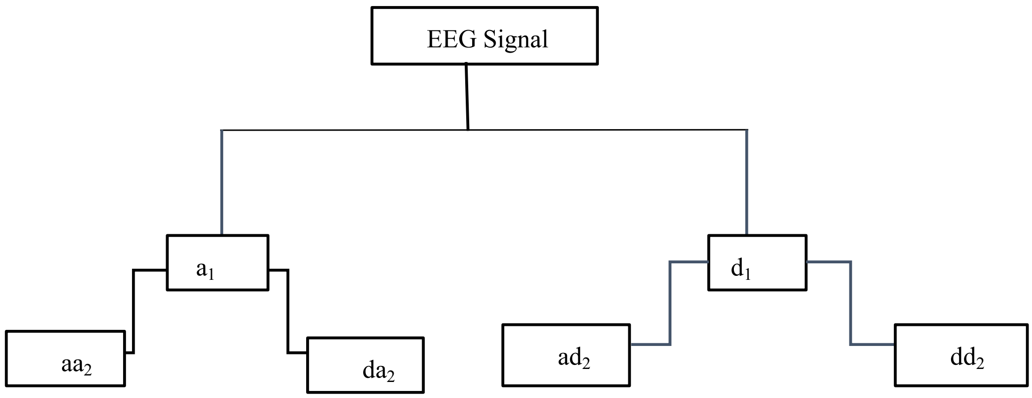

Fig. 6 Wavelet packet decomposition upto level 2

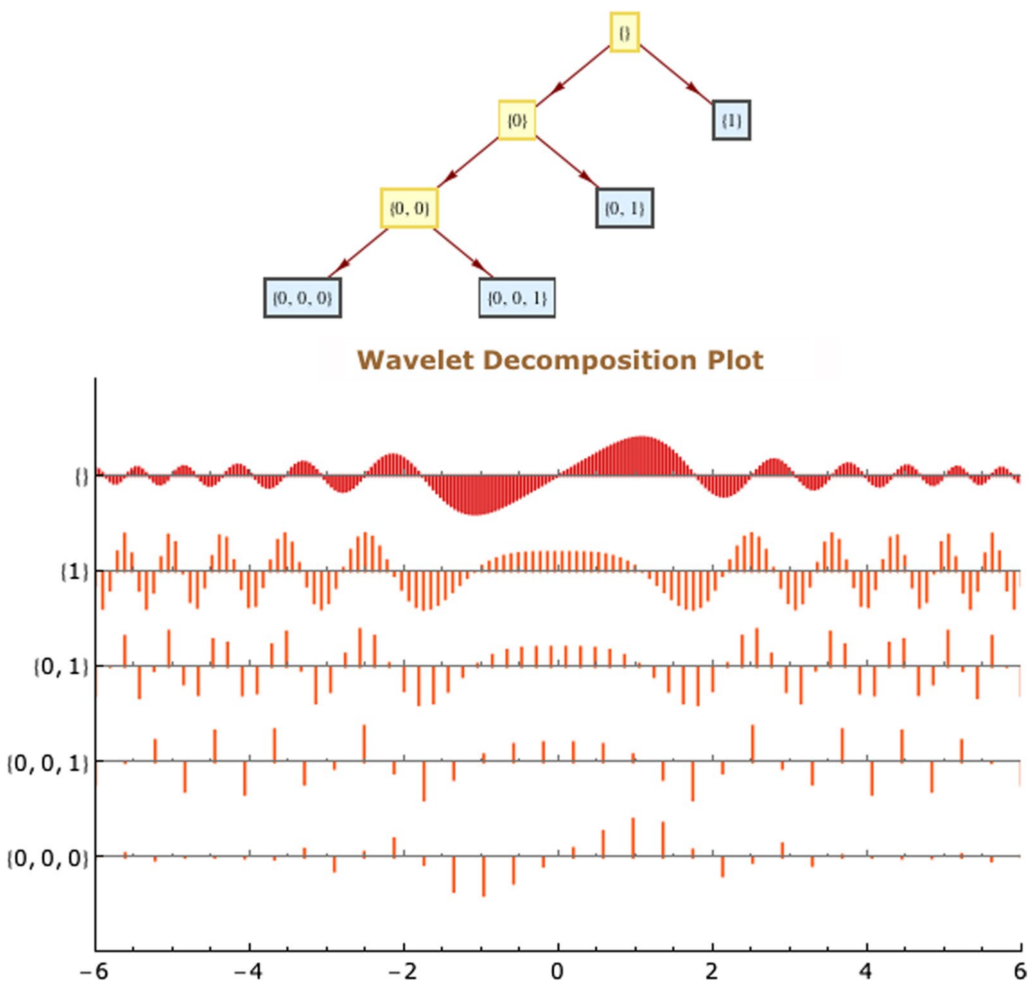

Fig. 7 Illustrates the Lifting Wavelet Transform [37]

Hilbert–Huang transform (HHT)

In Hilbert–Huang Transformation, there is decomposition of EEG signals into Intrinsic Mode Functions (IMFs) so that instantaneous frequency of the data can be achieved. In EEG signal analysis, IMFs is firstly extracted with the help of Empirical Mode Decomposition (EMD) afterward, Hilbert Transform is executed to every IMFs in order to achieve the instantaneous frequencies and amplitudes. Then, with the help of Hilbert-weighted frequency, the EEG signals are classified. EMD is the vital part of HHT as EMD can decompose the complex EEG signals into a fixed and small number of sub-parts [38]. Figure 8 represents the Hilbert–Huang Transform of a signal [39].

Non-linear methods of EEG analysis

Non-linear approaches are used in the analysis of EEG in order to characterize the complexity and fractal nature of EEG signals which cannot be described by the linear analysis [40]. Nonlinear methods are the more promising approach for describing the EEG signals as it can identify the non-linear coupling and phase locking within the harmonic of the same scale of frequencies. Below is the brief information about various non-linear parameters that are used in the analysis of EEG signals.

Higher order spectra

Higher Order Spectra (HOS) is one of the promising non-linear technique for EEG signals analysis. HOS is basically a higher orders measures of the EEG signals. HOS can detect anomalies form EEG signals by identifying the non-linearity, nonstationary, non-Gaussian nature and phase locking among the harmonic constituents of the EEG signal. HOS is also termed as polyspectra. It can provide the spectral information about the higher order statistics. The Higher Order Spectra of Gaussian signals has zero statistical value [41]. Therefore, HOS is a powerful noise immunity tool in the case of Gaussian noise. In addition to this, HOS is also preserving the phase characteristics of the EEG signals. Normalized bispectral entropy, normalized bispectral squared entropy, Mean bispectrum magnitude, and bispectrum phase entropy are the name of some HOS based parameters which can be extracted from bispectral for EEG signal analysis.

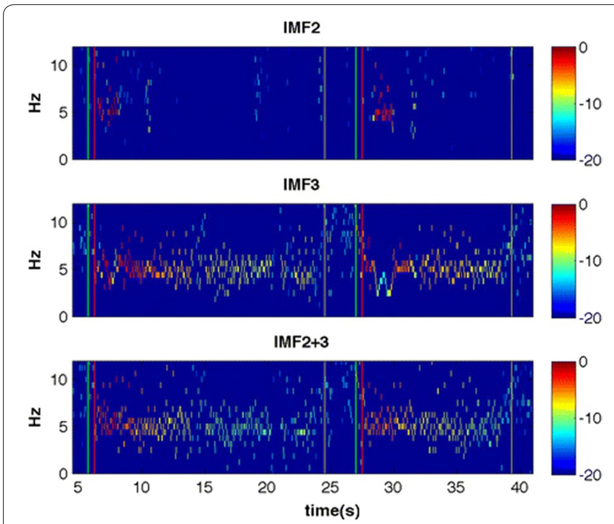

Fig. 8 Represents the Hilbert spectrum [39]

Higher-order cumulants

The cumulants are a set of measures that are the alternative to the moment's distribution. The third order cumulant (third central moment) and higher order cumulants play a vital role in the analysis of the EEG signal [42].

Recurrence plot

Recurrence plot (RP) is a graphical representation of the recurrences of the phase states in two-dimensional space. RP is useful in the analysis of EEG signals by identifying the hidden periodicities which are difficult to recognize in the different domains of EEG signals. It also helps to depict the non-stationary and non-linear character of EEG signals by visualizing the periodic behavior of EEG signals in the phase space trajectory. The RP illustrates the sets of pairs of times at which the EEG signal trajectory is at a similar place [43]. Figure 9 represents RP produced from 2 s of EEG data [44].

Recurrence period density entropy

In order to determine the periodicity of the EEG signal, the recurrence period density entropy (RPDE) technique is advantageous. It is used to measure the periodicity of the EEG signal in the phase space without requiring any prior information about linear, Gaussian and dynamical aspects of EEG signals. RPDE is the illustration of non-linearity, non-Gaussianity and non-deterministic nature of the EEG signal [45].

Recurrence Quantification Analysis

This technique is used to evaluate that how many times and how long the recurrences of EEG signals takes place in its phase-space. It is used to measure the complexity of the system. The Recurrence Quantification Analysis (RQA) is basically used to illustrate and measure the small-scale structural presentation of recurrence plots of EEG signals [46]. Mean diagonal line length, recurrence rate, longest diagonal line, determinism, longest vertical line, entropy, recurrence time, laminarity, and trapping time are the names of few parameters which are used to

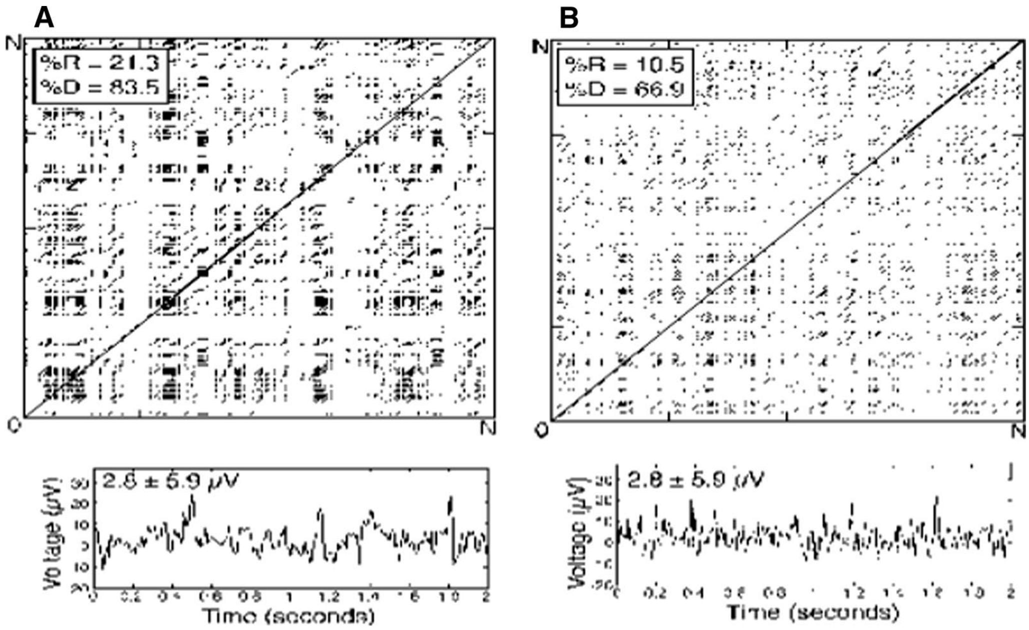

Fig. 9 Represents RP produced from 2 s of EEG data [44]

evaluates the Recurrence Quantification Analysis of EEG signals. Figure 10 represents RQA of 2 s EEG epoch [47].

Approximate entropy

Steven Pincus developed the idea of Approximate Entropy (ApEn) [48]. It is a measure which is used to determine how regular and complex is the EEG signal are. For irregular and complex EEG signals, the ApEn measure high value. ApEn is an efficient tool for noisy and short data sample length with low computational cost. If X_N is a sequence consisting of N dimensions and C_l (r) represents the occurrence of repetitive patterns with length l. Then approximate entropy of X_N, for a pattern of length l and similarity measure r is defined as:

$$ApEn(X_N, l, r) = \ln\left[\frac{C_l(r)}{C_{l+1}(r)}\right] \tag{5}$$

Sample entropy

Sample entropy is the extension and modified version of ApEn. It is a regularity or complexity measurement. It is used to measure the complexity of EEG signals [49]. Sample Entropy includes the observation of patterns in EEG signals to check the degree of complexity in that. It does not count the measurement of the self-similar pattern. It has the main advantage over ApEn is that it is not restricted to sample length. During seizure activity, the sample entropy of EEG signals starts decreases.

Multiscale entropy

Multiscale entropy method is used to measure the complexity of EEG signals of finite length [50]. Multiscale entropy proved that the original data is more complicated than surrogate data. It is used to determine the complexity dynamics of EEG signals at multiple time scales.

Fractal dimension

Fractal dimension (FD) is used as a parameter to detect and differentiate certain states of the physiological function of EEG signals. Fractal dimension is one of the promising means for modeling the EEG signals which is highly complex and irregular in nature [51]. It is used to analyze the non-linearity as well as the chaotic aspects and behavior of the EEG signals. In the case of the information dimension, the fractal dimension is described as:

$$\mathrm{FD} = \lim_{\epsilon \to 0} \frac{-\langle \log p_\epsilon \rangle}{\log \frac{1}{\epsilon}} \tag{6}$$

In the above equation, p signifies the probability and ϵ denotes the scaling factor. Figure 11 illustrates Fractal Dimension [52].

Correlation dimension

Correlation dimension is a measure which quantifies the complexity of EEG signals [53]. Correlation dimension is one of the categories of the fractal dimension. It is also

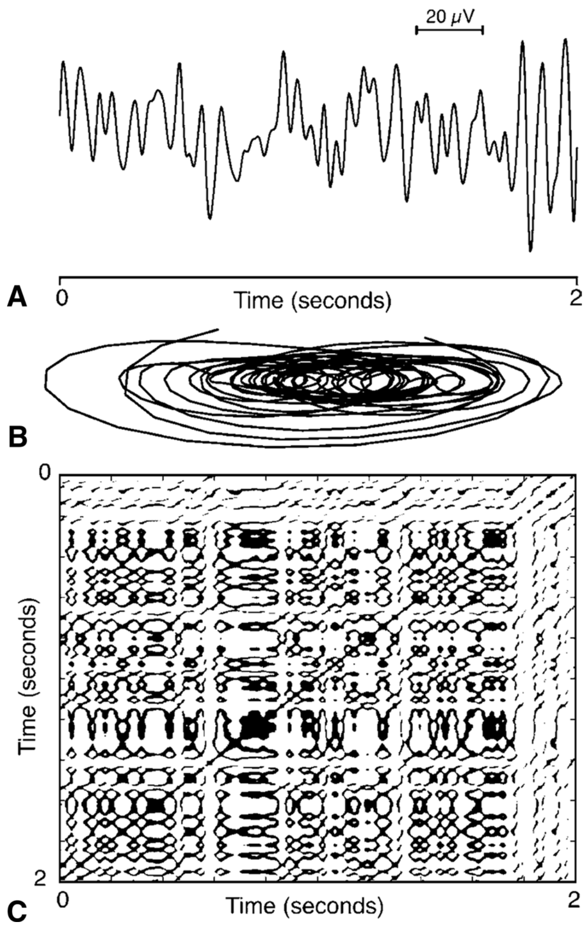

Fig. 10 Illustrates RQA of 2 s EEG epoch [47]

used to differentiate among the deterministic chaos and random noise in order to identify the potential faults [54]. Correlation dimension is generally computed by the GP algorithm which was developed by the Grassberger and Procassia [53]. Correlation dimension is described as:

$$D_2 = \lim_{\epsilon \to 0} \frac{\ln \sum_{j=1}^{K(\epsilon)} p_j^2}{\ln \epsilon} \tag{7}$$

In the above Eq. (7), $K(\epsilon)$ symbolize the total numeral of hypercube with side length ϵ and covered the attractor, p_j denotes the probability of identifying a point in the hypercube j.

Hurst exponent

Hurts describe an empirical descriptor an, the Hurst exponent (H) is used to define the natural phenomena related to the temporal nature of EEG signals [55]. It is also applied for evaluating the randomness of a process. In addition to this, the fractal dimension is also correlated with the Hurst exponent. Hurst exponent is used to quantifying the self-similar, the amount of long-range dependency and also for the prediction of EEG signals. Hurst exponent H is described as:

$$H = \frac{\log(D|S)}{\log(T)} \tag{8}$$

In the Eq. (8), T signifies the duration of the EEG signals and $(D|S)$ defines the rescaled range value. D denotes the difference among the maximum and minimum deviation from the mean. S symbolizes the standard deviation. After plotting the $(D|S)$) versus T in the axes of log, the slope of the regression line estimates the H [55].

Largest Lyapunov exponent

Largest Lyapunov exponent (LLE) is used as a measuring unit to check the dependency of the process on its initial conditions. It is used in the analysis of EEG signals to quantify the chaoticity in that. It defines the rate of deviation of nearby trajectories. A positive value of Largest Lyapunov Exponent demonstrates the presence of chaos nature. LLE is defined as [56]:

$$d(t) = Ke^{c_1 t} \tag{9}$$

In the above equation, $d(t)$ denotes the average divergence at time t, K symbolize the constant that used for the normalization of initial separation and c_1 represents the exponential divergence of nearest neighbors.

Literature summary in the field of epilepsy detection from EEG signals

Automated EEG based seizure detection for assistance in epilepsy syndrome was started in the early 1970s. Prior et al. [57] introduce a device named as Cerebral Function Monitor (CFM) that monitor the long-term EEG without any supervisor. The device was able to detect tonic clonic seizures on the basis of the high increase in the amplitude of the EEG signal. Latter on Babb et al. [58] designed an electronic circuit based seizure detection. Gotman et al. [14] in 1976 tried to identify and quantify the inter-ictal activity during a seizure with the help of the small computerized system.

In 1982, Gotman individually developed a computerized automated epilepsy detection technique [59]. Afterward, has been recognized as an avant-gardist who

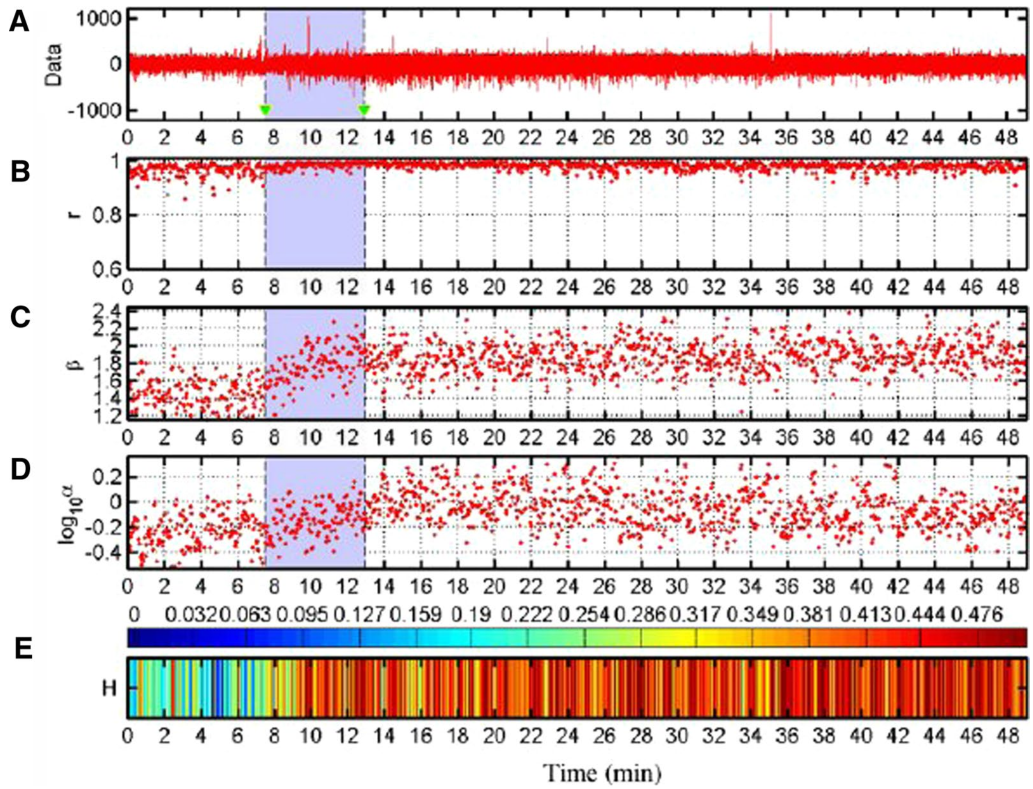

Fig. 11 Illustrates fractal dimension [52]

instigate the idea of the automated computerized based epilepsy detection system. The proposed technique was not patient-specific in nature (i.e., not specific to an individual). The method was based upon the discovery of sudden fluctuation in the rhythmic bustle of EEG signals within the frequency range of 3–20 Hz. For seizure detection, some experiments had been performed in which the amplitude of EEG signals is measured with respect to the background, the period of time, and the periodicity of EEG signals. But the proposed algorithm was unsuccessful in detecting epileptic seizure from that EEG signals in which the frequency bustle is high, and amplitude is low. In addition to this, it was not to detect epilepsy from that EEG signals in which the various frequency ranges exist. It was only able to detect the epileptic seizure with a frequency less than 20 Hz. Latterly [60], this technique was modified and used on the larger EEG database with 5303 h recording. The main aim of these new methods was to consider the large temporal context of EEG data and to increase the specificity of the technique. The technique suffered from the detection delay drawback and therefore was not successful in implementing in a real-time application.

In 1993, Qu et al. [61] developed a new technique with the help of K Nearest Neighbor classifier for the automatic detection of seizure activity. The proposed method was patient-specific in nature. It helped to enhance the performance of the seizure detection as the EEG recording of individual-patient shows less inconsistency for the seizure and non-seizure activity but has the limitation on the detection of latency. They modernized this technique a number of times [62–64]. The major limitation of these above patient-specific methods was when it is tested on different types of epileptic patients; it did not provide good results. In addition to this, in case of multiple seizures present in one person, the favorable results in the sensitivity can be achieved by combining different classifiers. Later on, different researcher's pro-posed different types of epileptic seizure detection techniques. Below is the brief in-formation about various epileptic seizure detection methods.

Jahankhani et al. [65] applied a wavelet transform method to extract the parameters and neural network-based classifier for classifying the EEG signals. Subasi et al. [36] detected epilepsy from EEG signals with the help of wavelet transform based feature extraction method in the combination of expert model and observed that combination of expert's model attained higher accuracy as compared to the individual neural network-based model. Ocak et al. [66] applied a discrete wavelet trans-form for the epilepsy detection from EEG by computing approximation and detail coefficients as the features. The proposed method was able to differentiate the seizure activity with 96% classification results. The study results also demonstrated that EEG signals with ictal activity exhibit non-linear behavior while normal EEG behaved like Gaussian linear stochastic system and also the approximate entropy decreases during an epileptic seizure. Kannathal et al. [67] implemented spectral entropy, renyi entropy, kolmogorovsinai entropy, and ApEn in order to detect epilepsy and observed that in the period of epileptic discharge, the four entropy measures decreases.

Polat et al. [68] used Fast Fourier Transformation based Welch technique with decision tree as a classifier to detect epileptic EEG signals and attained the classification performance results with 98.72% accuracy, 99.4% sensitivity, and 99.31% specificity. Later on, Polat et al. [69] proposed a novel hybrid system for classifying the epileptic EEG signals by using Welch FFT technique for parameter extraction and Principal Component Analysis for dimension reduction. The proposed method was built upon an artificial immune recognition system and reported 100% classification accuracy. Kabir et al. [70] developed a seizure detection system with the help of logistic model trees. Siuly et al. [71] reported optimum allocation scheme based upon principal component analysis to distinguish epileptic EEG signals from normal. The motive of using PCA in the proposed study was to develop independent components and to diminish the dimensionality of the data set Ö. F. Alcin et al. [72] introduced a time–frequency (T–F) image-based algorithm to identify epilepsy from EEG signals by using Grey Level Co-occurrence Matrix as a descriptor with Fisher Vector as an encoder and reported high-quality results.

Siuly et al. [73] proposed an optimum allocation based technique for the multi-category EEG signals for epileptic seizure detection. High classification results had been achieved using multiclass least square support vector machine. Afterward, Siuly et al. [74] proposed clustering based innovative technique for epilepsy detection which achieved 94.18% classification accuracy. Later on Siuly et al. [75] proposed a novel framework for epilepsy detection based upon random sampling and optimal allocation sampling. The framework achieved 100% classification accuracy and also proved that random sampling is more efficient for seizure detection as compared to the optimal allocation sampling.

Chua et al. [76] proposed higher order spectra (HOS) based framework for seizure detection and reported 93.11% accuracy for distinguishing different categories of EEG signals. Pravin et al. [77] presented the significance of entropy parameter for distinguishing the normal and epileptic as well as inter-ictal activity EEG signals. The parameters named wavelet entropy, sample entropy, and spectral entropy were extracted in the feature extraction phase. The two neural network-based models (named recurrent Elman network and radial basis) were used for classifying the Epileptic EEG signals. Non-linear features named correlation dimension, Largest Lyapunov Exponent, Hurst Exponent, and entropy were applied to characterize the epileptic EEG signal as well as to differentiate epileptic signals from normal. The more than 90% classification accuracy depicts the significance of the algorithm [78]. Srinivasan et al. [79] applied approximate entropy as a parameter in Elman neural networks and probabilistic neural networks for classifying the epileptic EEG database. The 100% classification accuracy with Elman neural network revealed its importance in the seizure detection field.

Belhadj et al. [80] introduced the clustering method, which was unsupervised in nature for epilepsy detection. Potential-based hierarchical agglomerative clustering method was implemented in combination with empirical mode decomposition. Euclidian distance as well as kolmogorov distance with Bhattacharya distance were calculated among the IMFs and used as input to the Potential-based hierarchical agglomerative clustering system. After applying the proposed methodology to the CHB-MIT epileptic database, they reported 98.84% classification performance results. Shoaib et al. [81] used wavelet energy as a parameter for the development of seizure detection processor with the help of SVM classifier. Aslan et al. [82] considered two different types of epileptic seizure named partial epilepsy and primary general epileptic disorder for analysis under the supervision of two expert neurologists. The radial basis function neural network classifier attained 95.2% accuracy, and a multilayer perceptron neural network classifier perform with 89.2% classification. Guler et al. [83] applied Largest Lyapunov Exponent parameter for the feed-forward neural network as well as for the recurrent neural network for classifying three kinds of EEG signals with normal, interictal and ictal conditions of epilepsy. The recurrent neural network provided more promising results with 96%, classification sensitivity, 97.38% for specificity, and accuracy result was 96%.

Sheykhivand et al. [84] proposed novel framework based on sparse representation-based classification (SRC) theory and proposed dictionary learning. The framework achieved 100% classification accuracy for eight different scenarios of seizure and non-seizure activity. Fasil et al. [85] introduce a method based upon exponential energy feature in order to detect the abnormalities in the amplitude epileptic EEG signals. Lahmiri et al. [86] used generalized Hurst exponent (GHE) for epilepsy detection.

The KNN classifier provides 100% detection rate. Hassan et al. [87] proposed ensemble empirical mode decomposition technique with adaptive noise along with normal inverse Gaussian has been implemented for epileptic seizure detection. This technique achieved higher classification performance with adaptive boosting classifier.

Zarei et al. [88] proposed a framework for epilepsy detection from EEG signals based upon Douglas–Peucker algorithm (DP). In order to find the uncorrelated variables and for reducing the dimensionality, principal component analysis (PCA) has been used. The whole experiments were implemented on Bonn University epileptic EEG data base and four machine learning classifiers has been used to evaluate the performance: random forest classifier (RF), k-NN, SVM and decision tree classifier. The framework provides 99.85% overall classification accuracy with random forest classifier. The drawback of the proposed framework is that computational complexity increases with the increase in data size of EEG signals.

Al Ghayab et al. [89] developed an innovative epilepsy detection technique with the help of tunable Q-factor wavelet transform (TQWT) by decomposing the Epileptic EEG signals into five sub bands as well as Q, R and J levels. Ten statistical signals were extracted from each epoch and evaluated with the help of bagging tree (BT), k-NN), and SVM classifiers. The developed technique archived 100% accuracy with Bonn University Epileptic EEG data and also 100% accuracy with 3750 data size of Born University focal and non-focal Epileptic data set. The main advantage of this technique is its ability of data reduction as well as less computational cost. The draw-back is that it is hard to implement it on real time applications. Al Ghayab et al. [90] presented a method to detect epilepsy seizure using Information Gain (InfoGain) algorithm on fast Fourier transform (FFT) and discrete wavelet transform (DWT) separately. The presented method outperformed with 100% classification accuracy results for different pais of epileptic Bonn data set with (LS-SVM) classifier. The high performance accuracy confirm that FFT when combined with InfoGain can effectively detect seizure activity.

Mahjoub et al. [91] used mixed approach: tunable-Q wavelet transform (TQWT), intrinsic mode functions (IMFs) from multivariate empirical mode decomposition for epilepsy detection. Six binary classification cases are evaluated with SVM classifier and achieved higher classification performance. Wang et al. [92] introduce a multiple time–frequency analysis model in which a novel random forest model is trained and combined with grid search optimization. In order to reduce the dimensionality of features, principal component analysis has been used. The proposed model has been tested on three-class differentiating as healthy subjects, seizure-free intervals, and seizure activity for one time with 96.7% accuracy. The limitation of this model is that it is affected by the presence of noise.

Garcés et al. [93] introduce an adaptive filters and signal averaging based method for epileptic seizure detection. The method has been evaluating on 425 h recording of epileptic CHB-MIT EEG database and achieved sensitivity of 90.3% and specificity of 73.7%. Aung et al. [94] proposed a modified-Distribution entropy (mDistEn) technique for epileptic seizure detection. The modified distribution entropy is evaluated and compared with fuzzy entropy and distribution entropy. The mDistEn based technique achieved 92.5% sensitivity, 85% specificity and 91% accuracy which is quiet low as compared to fuzzy entropy with 90% specificity and 92% accuracy.

Chen et al. [95] introduced entropy-based method for nonlinear dynamics features detection from epileptic EEG seizure. The method used DWT approach and extracting eight different entropies: Approximate Entropy, Spectral Entropy, Fuzzy Entropy, Sample Entropy, Permutation Entropy, Shannon Entropy, Conditional Entropy, and Corrected Conditional Entropy. Six different classifiers has been applied to evaluate the performance of feature sets. LS-SVM classifier provides 100% sensitivity, 99.40% specificity and 99.5% accuracy as compared to other classifiers.

Selvakumari et al. [96] proposed a Patient-Specific epilepsy detection framework with High dimensional Phase Space by using Principal Component Analysis. The classification is executed in two layer such as the first layer encompasses the SVM classifier and the second layer includes the Naive classifier. The framework provides high classification performance with 95.63% accuracy. The framework can recognize the seizure region but cannot recognize the percentage of seizure location in the brain.

Wu et al. [97] introduced an innovative epilepsy detection technique based upon Complementary Ensemble Empirical Mode Decomposition using Extreme Gradient Boosting. Different features were extracted from four distinct domain: time domain; frequency domain; time-frequency domain and entropy-based. The techniques achieved around 100% classification accuracy for the 12 different category of cases based upon seizure and non-seizure activity on Bonn Epileptic data and around 95% accuracy for CHB-MIT database.

Jang et al. [98] developed Euclidean distances based methodology for epilepsy detection in which wavelet transform, peak extraction and phase–space reconstruction has been applied. Sixteen features were extracted and used as input to Neural Networks with Weighted Fuzzy Membership (NEWFM). The method achieved 97.5% classification accuracy.

Drawbacks of the existing techniques

From the above state of the art in the field of automated detection of the epileptic syndrome, it is clear that there are several techniques are available for the analysis and classification of EEG signals in order to detect epilepsy from EEG. But the above-described literature has some restriction and limitations. This section discusses the general drawbacks of the existing methods based on different approaches.

The time-domain based techniques do not provide any information regarding the frequency-based component. It only provides information about the time and magnitude components of the signal of the EEG signals. The non-parametric approach based techniques provided low-frequency resolution and suffered from great noise sensitivity. The parametric approach based techniques have the drawback of the absence of time mechanism of EEG signals. The Fourier transformation based techniques have not enough information about what frequency occur at which time-interval. Time–frequency distribution based methods have the limitations of slow in speed as the time for computing the gradient ascent is high, and extracted measures are inter-dependent. Wavelet Transform based techniques have the drawback of the selection of an appropriate mother wavelet, the number of decomposition levels and the selection of appropriate features from specific sub-bands. Approximate Entropy based methods suffer from the limitations of lacking in relative consistency for the choice of parameters and dependability on the EEG signal length. In the case of Lyapunov Exponent based techniques, the major problem is the remodeled phase spaces which have additional dimensions in comparison to the actual phase space.

Discussion and future direction

The above-mentioned drawbacks of the existing methods clearly demonstrate that there is an obligatory of reliable automated seizure detection techniques that assist the clinicians for the diagnosis of epilepsy and also reduce cost and time. Nowadays, the graph-theory mechanism has provided innovative sights in epilepsy detection from EEG signals with the help of specific graph parameters [99–105]. The graph-theory based techniques characterize a hidden sight of brain activity and brain-behavior mapping. The graph theory not even helps to understand the underlying dynamics of EEG signals at the microscopic, mesoscopic, and macroscopic level but also provides the correlation among them. The graph theory assists in determining the gap present in the EEG patterns. Graph theory harvests important information about the underlying brain connectome with the help of certain topological properties of the EEG signals network. The statistical features of the network build from EEG signals provide critical knowledge about dysfunction related to the structure and function of the brain with epilepsy.

Conclusion

The main motive of this research paper is to provide knowledge to the researchers about the existing methods for epilepsy detection from EEG. This paper presents a brief review about the existing techniques in the field of automated epilepsy detection based on different domains of EEG signals analysis named time domain, frequency domain, time–frequency domain, and analysis on the basis of a non-linear approach. In addition to that, the limitations of the existing methods are also discussed. The limitations of the present methods clearly demonstrate that there are necessities of automated seizure detection techniques that assist the clinicians for the diagnosis of epilepsy by computer-based analysis of EEG and also reduce high cost, fallacy and long haul of examination.

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