Classification of Normal and Epileptic Seizure EEG Signals Based on Empirical Mode Decomposition

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Abstract Epileptic seizure occurs as a result of abnormal transient disturbance in the electrical activities of the brain. The electrical activities of brain fluctuate frequently and can be analyzed using electroencephalogram (EEG) signals. Therefore, the EEG signals are commonly used signals for obtaining the information related to the pathological states of brain. The EEG recordings of an epileptic patient contain a large amount of EEG data which may require time-consuming manual interpretations. Thus, automatic EEG signal analysis using advanced signal processing techniques plays a significant role to recognize epilepsy in EEG recordings. In this work, the empirical mode decomposition (EMD) has been applied for analysis of normal and epileptic seizure EEG signals. The EMD generates the set of amplitude and frequency modulated components known as intrinsic mode functions (IMFs). Two area measures have been computed, one for the graph obtained as the analytic signal representation of IMFs in complex plane and another for second-order difference plot (SODP) of IMFs of EEG signals. Both of these area measures have been computed for first four IMFs of the normal and epileptic seizure EEG signals. These eight features obtained from both area measures of first four IMFs have been used as input feature set for classification of normal and epileptic seizure EEG signals using least square support vector machine (LS-SVM) classifier. Among all three kernel functions namely, linear, polynomial, and radial basis function (RBF) used for classification, the RBF kernel has provided best classification accuracy in the classification of normal and epileptic seizure EEG signals. The proposed method based on the two area measures of IMFs obtained using EMD process, together with

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LS-SVM classifier has been studied on EEG dataset publicly available by the University of Bonn, Germany. Experimental results have been included to show the effectiveness of the proposed method in comparison to other existing methods.

1 Introduction

Human brain is a highly complex system. The epilepsy is a common neurological disorder of human brain. It affects at least 50 million people of the world (Ngugi et al. 2010). The annual occurrence of epilepsy, 48 per 100,000 populations in developed counteries was reported in Hirtz et al. (2007). The prevalence of epilepsy is higher in low and middle income countries than developed countries (Thurman et al. 2011). At least 50 % of the epileptic cases start developing at childhood or adolescence (World Health Organization 2014). Occurrence of epilepsy can also be noticed in elderly people, which may require special considerations in treatment (Ramsay et al. 2004). If the patient with epilepsy are treated properly, then 70–80 % of them can lead to normal lives (World Health Organization 2014). Therefore, study of epilepsy is an important research area in the field of the biomedical engineering.

The electroencephalogram (EEG) signals are very useful to measure the electrical activity of the human brain. The EEG signals are commonly analyzed by experts in order to assess the states of the brain. The EEG based measures are very helpful for diagnosis of neurological disorders specially epilepsy. Presence of spikes in EEG signals is main indication of epileptic seizure activity in the brain (Ray 1994; Mukhopadhyay and Ray 1998). Automatic detection of epileptic seizure by analyzing EEG signals using advanced signal processing techniques is very useful for diagnosis of epilepsy (Iasemidis et al. 2003).

The EEG recording using electrodes from the scalp is the result of firing of neurons within the brain (Schomer and da Silva 2005). The EEG signals recorded from scalp exhibit oscillations of different range of frequencies, corresponding to the electrical activities of the neurons in the brain. These oscillations of different frequency ranges present in the EEG signals are related with the different states of the functioning of human brain. A typical voltage range of the amplitude of EEG signal for a adult human is about 10–100 μV when measured from the scalp (Aurlien et al. 2004).

Conventional scalp EEG signal recording is performed by placing electrodes over the scalp. The conductive gel or paste is utilized in order to make proper electrical connection between scalp and electrode. The electrode cap is generally used for recording of EEG signals. There are some standards that have been defined for electrode placement over the scalp, out of which international 10–20 system (Andrzejak et al. 2001) is commonly used for EEG signal recording of healthy persons. The intracranial EEG signals obtained using intracranial electrodes which also requires depth electrodes for recording of ictal and seizure-free EEG signals for

epilepsy patients can be useful for diagnosis of epilepsy (Andrzejak et al. 2001). The presence of interference or artifacts due to external sources, in the EEG signal recording may create problem in the diagnosis based on these recorded EEG signals. Therefore, filtering is required to remove these artifacts (Senthil et al. 2008).

1.1 Epileptic Seizure EEG Signals

Epilepsy is one of the most common neurological disorders of human brain. As epileptic activity manifests the clear and abnormal transient patterns in a normal EEG signal, therefore EEG signals are widely used in diagnostic application for detection of epilepsy. In epileptic patients, brain exhibits the process known as 'epileptogenesis' (Cross and Cavazos 2007) in which normal neural network abruptly converts into a hyper-excitable network, causing evocation of strange sensations and emotions or sometimes muscle spasms and consciousness loss. In such subjects, the nerve cells in the brain transmit excessive electrical impulses that cause epileptic seizures. Epilepsy is recognized by occurrence of such unprovoked seizures. Evaluation of the epilepsy can be performed by recording and analyzing the epileptic seizure EEG signals from the electrodes which are placed on the affected area on the brain scalp region (Coyle et al. 2010; Ince et al. 2009). The recorded EEG signals are complex, non-linear, and non-stationary in nature (Acharya et al. 2013; Boashash et al. 2003; Pachori and Sircar 2008; Pachori 2008). The epileptic seizures can have severe harmful effect on the brain. Manual process to identify the seizure events, consists of visual inspection and review of the entire recorded EEG signals by trained expert, which is time consuming process and demands considerable skills. Moreover, subjective nature of expert can also affect the judgement of seizure events in EEG records. Therefore, it is appealing to develop computer-aided automatic analysis method that consists of advanced signal processing techniques, for classification between normal and epileptic seizures EEG signals in recorded EEG signals.

1.2 Classification of Epileptic Seizure EEG Signals

Various methods have been developed for automatic classification of the epileptic seizures by extracting parameters from EEG signals. These parameters can be extracted using time-domain, frequency-domain, time-frequency domain and non-linear methods of analysis and serve as the features for classification of EEG signals based on signal processing methods (Acharya et al. 2013).

Many time-domain based techniques have been presented in literature with an objective to detect epileptic seizures from EEG signals. The value of linear prediction error energy has been found to be much higher in seizure EEG signals than

that of seizure-free EEG signals and has been used to detect epileptic seizures in EEG signals (Altunay et al. 2010). The fractional linear prediction (FLP) method has been employed to model seizure and seizure-free EEG signals and prediction error energy along with signal energy with support vector machine (SVM) classifier has been used to classify the epileptic seizure EEG signals from the seizure-free EEG signals (Joshi et al. 2014). Epileptic seizures have been detected in EEG signals using principal component analysis in combination with enhanced cosine radial basis function neural network (Ghosh-Dastidar et al. 2008). Artificial neural network (ANN) based methodology has been developed to detect the epileptic seizure using time-domain as well as the frequency-domain features in Srinivasan et al. (2005). Spectral parameters based on the Fourier transformation of EEG signals have been utilized to detect epileptic seizures in EEG signals (Polat and Güneş 2007).

The EEG signals exhibit non-stationary nature (Boashash et al. 2003). In literature, many time-frequency domain based methods have been proposed to detect epileptic seizure EEG signals, these methods include time-frequency distribution (Tzallas et al. 2007, 2009), wavelet transform (Ghosh-Dastidar et al. 2007; Uthayakumar and Easwaramoorthy 2013; Ocak 2009; Subasi 2007; Subasi and Gursoy 2010; Adeli et al. 2007; Acharya et al. 2012), multi-wavelet transform (Guo et al. 2010), and empirical mode decomposition (EMD) (Pachori 2008; Oweis and Abdulhay 2011; Pachori and Patidar 2014; Li et al. 2013; Bajaj and Pachori 2012). The Fourier-Bessel (FB) series expansion of intrinsic mode functions (IMFs) extracted from EMD, has been used to compute mean frequency of IMFs and these mean frequencies have been used as features to discriminate ictal and seizure-free EEG signals (Pachori 2008). In Oweis and Abdulhay (2011), weighted mean frequency of IMFs has been proposed to detect epileptic seizures from EEG signals. Ellipse area of second-order difference plot (SODP) of different IMFs with 95 % confidence limit has been proposed as a feature to classify epileptic seizure and seizure-free EEG signals (Pachori and Patidar 2014). The coefficient of variation and fluctuation index computed from IMFs of EEG signals have been proposed to recognize patterns of ictal EEG signals (Li et al. 2013). The amplitude modulation (AM) and frequency modulation (FM) bandwidths computed from the IMFs together with least square support vector machine (LS-SVM) classifier have been used for classification of seizure and nonseizure EEG signals (Bajaj and Pachori 2012).

Various non-linear parameters have been proposed as features for classification of epileptic seizure EEG signals. The Lyapunov exponent parameter with probabilistic neural network (PNN) in Übeyli (2010) and Güler et al. (2005), correlation integral in Casdagli et al. (1997), fractal dimension parameters in Easwaramoorthy and Uthayakumar (2011) and Accardo et al. (1997), multistage nonlinear pre-processing filter combined with a diagnostic neural network in Nigam and Graupe (2004), entropy based measures with adaptive neuro-fuzzy inference system in Kannathal et al. (2005), and approximate entropy (ApEn) with ANN in Srinivasan et al. (2007) have been proposed for discrimination of epileptic seizure EEG signals.

In this work, we propose a method based on the EMD process for classification of normal and epileptic seizure EEG signals. The area measures namely area of analytic signal representation of IMFs and area of ellipse from SODP of IMFs have been used as an input feature set for LS-SVM classifier.

The rest of the chapter has been organized as follows. In Sect. 2, proposed methodology has been described which includes dataset, EMD method, feature extraction and LS-SVM classifier. Feature extraction section consists of two further subsections: one of which is analytic signal representation and area computation of circular region and other is second-order difference plot and area computation of elliptical region. Results of experimental analysis and comparison with other methods have been discussed in Sect. 3. Finally, conclusion has been provided in Sect. 4.

2 Methodology

2.1 Dataset

In this work, the online publicly available EEG dataset as described in Andrzejak et al. (2001) has been used. Recordings in this dataset include EEG signals which have been acquired for both healthy and epileptic subjects. This dataset contains five subsets denoted as Z, O, N, F, and S, each of which having 100 single-channel EEG signals of duration 23.6 s. The first two subsets Z and O are surface EEG recordings of five healthy volunteers. These subsets contain EEG recordings with eyes open and closed, respectively. The subset F have been recorded in seizure-free intervals from five patients in the epileptogenic zone and the subset N has been acquired from the hippocampal formation of the opposite hemisphere of the brain. The subset S contains seizure activity selected from all recording sites exhibiting ictal activity. The subsets Z and O have been recorded extracranially using standard electrode placement scheme (according to the international 10–20 system (Andrzejak et al. 2001), whereas the subsets N, F, and S have been recorded intracranially using depth electrodes implanted symmetrically into the hippocampal formations. Subsets N and F have EEG signals which were taken from all contacts of the relevant depth electrode (Andrzejak et al. 2001). The strip electrodes were implanted onto the lateral and basal regions (middle and bottom) of the neocortex. The EEG signals of the subset S contains segments taken from contacts of all electrodes (depth and strip). Set N and F contain only activity measured during seizure free intervals, while set S only contains seizure activity. The data were digitized at a sampling rate of 173.61 Hz using 12-bit analog-to-digital (A/D) converter. Bandwidth range of bandpass filter were 0.53–40 Hz. More detail about this dataset can be found in Andrzejak et al. (2001). In this study, we have used subsets Z and S of the dataset to evaluate performance of, proposed method which consists of EMD, feature extraction and classification using LS-SVM classifier.

2.2 Empirical Mode Decomposition

The main idea of empirical mode decomposition (EMD) is based on the assumption that any signal comprises of different simple mode of oscillations (Huang et al. 1998). It is a data dependant signal processing technique that represents any temporal signal into a finite set of amplitude and frequency modulated (AM-FM) oscillating components termed as intrinsic mode functions (IMFs). It is noteworthy that this method of decomposition does not require any prior assumption about the stationarity and linearity of signal. The EMD method decomposes a complicated signal $x(t)$ iteratively into a set of the band-limited IMFs, $I_m(t)$, where $m = 1, 2, \ldots, M$ (Huang et al. 1998). Each of these IMFs satisfies the following two basic conditions:

1. The number of extrema and the number of zero crossings must be either equal or differ at most by one,
2. The mean value of the envelopes defined by the local maxima and that of defined by the local minima must be zero.

The EMD algorithm to extract IMFs from a signal $x(t)$ can be explained in following steps (Huang et al. 1998):

1. Find all the local maxima and local minima in the signal $x(t)$.
2. Connect all the maxima and all the minima separately in order to get the envelopes $E_{\max}(t)$ and $E_{\min}(t)$ respectively.
3. Compute the mean value of the envelopes by using the following formula:

$$m(t) = \frac{E_{\max}(t) + E_{\min}(t)}{2} \tag{1}$$

4. Subtract $m(t)$ from signal $x(t)$ as:

$$g_1(t) = x(t) - m(t) \tag{2}$$

5. Check if the $g_1(t)$ satisfies the conditions for IMF as mentioned above or not.
6. Repeat the steps 2–5 until IMF is obtained.

After obtaining first IMF define $I_1(t) = g_1(t)$ which is smallest temporal scale in $x(t)$. Next IMF can be derived by generating a residue $r_1(t) = x(t) - I_1(t)$ which can be used as the new signal for above algorithm. The process is repeated until the residue obtained becomes a constant or monotonic function from which no more IMF can be generated. The obtained IMFs are a set of narrow-band symmetric waveforms. After the decomposition, the signal $x(t)$ can be represented as follows (Huang et al. 1998):

$$x(t) = \sum_{m=1}^{M} I_m(t) + r_M(t) \tag{3}$$

where, M is the number of IMFs, $I_m(t)$ is the mth IMF and $r_M(t)$ is the final residue.
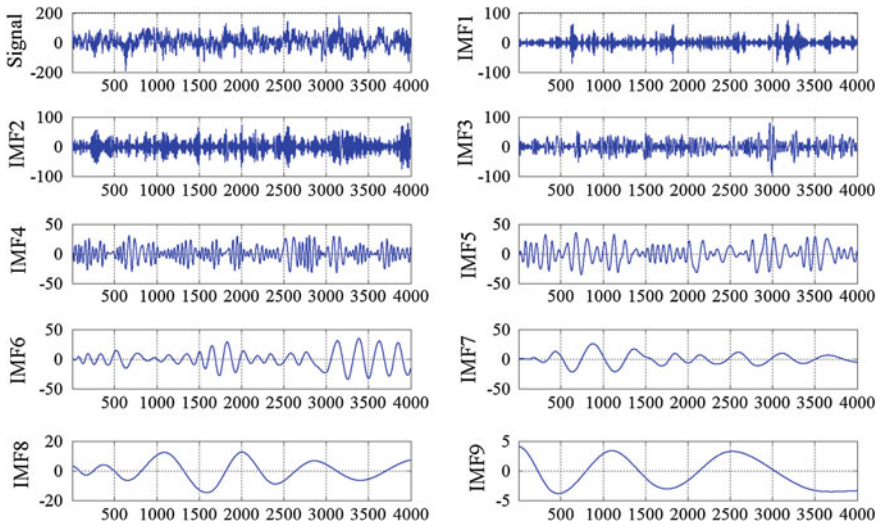
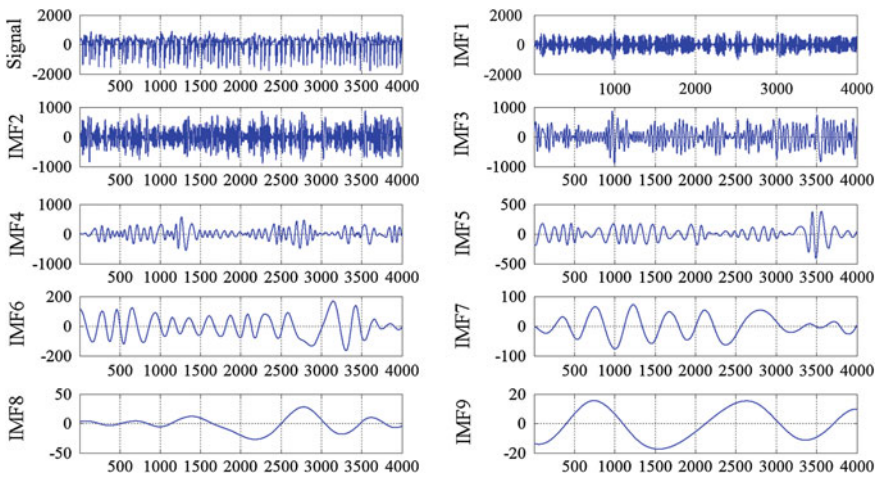**Fig. 1** Normal EEG signal and its first nine IMFs

Fig. 2 Seizure EEG signal and its first nine IMFs

The empirical mode decomposition of the normal and epileptic seizure EEG signals are shown in Figs. 1 and 2 respectively. It should be noted that only first nine IMFs of the signals are shown in each figure for EEG signal.

2.3 Feature Extraction

Feature extraction is an important step in pattern recognition and plays a vital role in detection and classification of EEG signals by extracting relevant information. Feature extraction can be understood as finding a set of parameters which effectively represent the information content of an observation while reducing the dimensionality. These parameters explore the property of two classes which has separate range of values for different classes. Two different area measures which are related with the variability of the signal are used here as a feature set. These area measures are computed for first four IMFs to create feature vector space. Final feature set consists of eight features for classification of normal and epileptic seizure EEG signals. The computation of these area measures have been described in detail as follows:

2.3.1 Analytic Signal Representation and Area Computation of Circular Region

The IMFs that have been obtained using EMD method on EEG signals are real signals. These IMFs can be converted to analytic signals by applying the Hilbert transform.

Analytic signal of $x(t)$ can be defined as (Huang et al. 1998; Lai and Ye 2003):

$$z(t) = x(t) + jy(t) \tag{4}$$

where, $y(t)$ represents the Hilbert transform of the real signal $x(t)$, defined as follows:

$$
\begin{aligned}
y(t) &= x(t) * \frac{1}{\pi t} \\
&= \frac{1}{\pi} \text{p.v.} \int_{-\infty}^{\infty} \frac{x(\tau)}{t - \tau} d\tau
\end{aligned}
\tag{5}
$$

with Fourier transform

$$Y(\omega) = -j \, \text{sgn}(\omega) X(\omega) \tag{6}$$

where p.v. indicates the Cauchy principle value, and $X(\omega)$ is Fourier transform of signal $x(t)$.

The signal $z(t)$ can also be expressed as:

$$z(t) = A(t) e^{j\phi(t)} \tag{7}$$

where, $A(t)$ is the amplitude envelope of $z(t)$, defined as:

$$A(t) = \sqrt{x^2(t) + y^2(t)} \tag{8}$$

and $\phi(t)$ is the instantaneous phase of $z(t)$, defined as:

$$\phi(t) = \tan^{-1}\left(\frac{y(t)}{x(t)}\right) \tag{9}$$

The instantaneous frequency of the analytic signal can be obtained by differentiating (9) as:

$$
\begin{aligned}
\omega(t) &= \frac{d\phi(t)}{dt} \\
&= \frac{x(t)\frac{dy(t)}{dt} - y(t)\frac{dx(t)}{dt}}{A^2(t)}.
\end{aligned}
\tag{10}
$$

The instantaneous frequency $\omega(t)$ of the analytic signal $z(t)$ is a measurement of the rate of rotation in the complex plane. The Hilbert transform can be applied on all IMFs obtained by EMD method. The IMFs are mono-component signals and exhibit property of locally symmetry. Therefore, the instantaneous frequency is well localized in the time-frequency domain and reveals a meaningful feature of the signal (Huang et al. 1998).

The analytic signal can be obtained for all the IMFs using the Hilbert transform. A complex signal can be represented as a sum of proper rotational components using EMD method which makes it possible to compute the area in a complex plane (Amoud et al. 2007). Since each IMF is a proper rotational component and has its own rotation frequency, the plot of the analytic IMF follows circular geometry in complex plane. The complex plane representation can be obtained by tracing the real part against the imaginary part of the analytic signal. The analytic signal representations in complex plane corresponding to the normal and epileptic seizure EEG signals and their first four intrinsic mode functions are depicted in Figs. 3 and 4, respectively. These figures present the traces of entire signals in the complex plane, as well as those of each IMF for both signals. It can be observed that the shape of this trace is similar to a rotating curve. The analytic signal representation of IMFs in complex plane possess a proper structure of rotation with a unique center (Lai and Ye 2003).

Central tendency measure (CTM) provides a rapid way to summarize the visual information related to a graph or plot (Cohen et al. 1996). The modified CTM can be used to measure the degree of variability from analytic signal representation of the signal. CTM can be used to determine the area of the complex plane representation (Pachori and Bajaj 2011). The radius corresponding to 95 % modified CTM can be used to compute the area of analytic signal representation of the IMF in complex plane. The modified CTM provides the ratio of points falling inside the circular region of specified radius to the total number of points in analytic signal
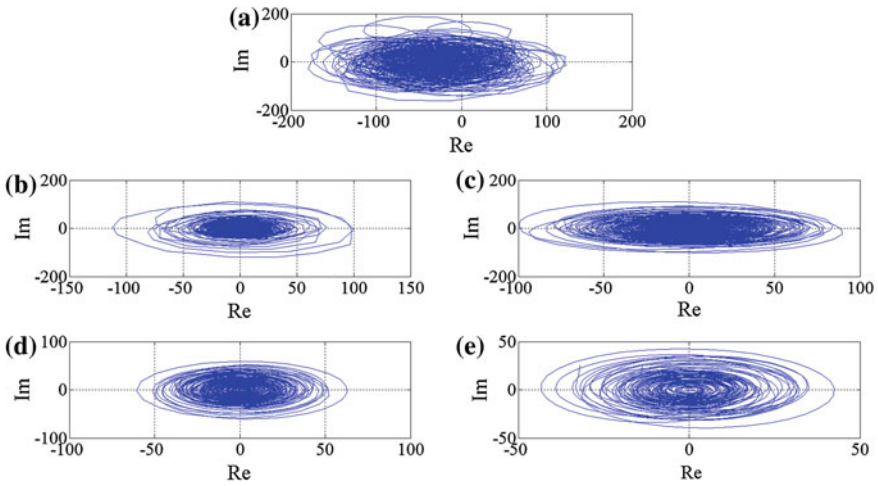
Fig. 3 Analytic signal representation in the complex plane for window size of 4,000 samples: **a** Normal EEG signal, **b** IMF1, **c** IMF2, **d** IMF3 and **e** IMF4
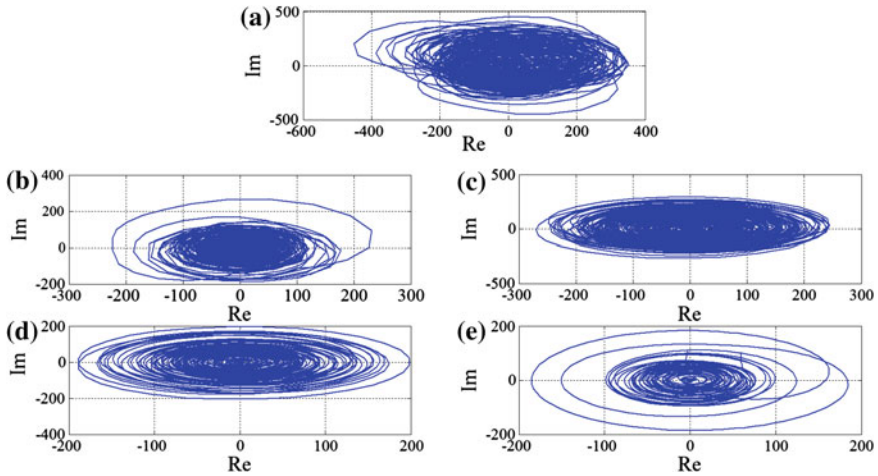

Fig. 4 Analytic signal representation in the complex plane for window size of 4,000 samples: **a** Seizure EEG signal, **b** IMF1, **c** IMF2, **d** IMF3 and **e** IMF4

representation. Let, the total number of points are N and the specified radius of central area is r, then modified CTM can be defined as (Pachori and Bajaj 2011):

$$\text{CTM} = \frac{\sum_{k=1}^{N} \rho(d_k)}{N} \tag{11}$$

$$\rho(d_k) = \begin{cases} 1 & \text{if } ([\Re\{z[n]\}]^2 + [\Im\{z[n]\}]^2)^{0.5} < r \\ 0 & \text{otherwise} \end{cases} \quad (12)$$

where, $1 \le k \le N$. If r_{CTM95} is the radius corresponding to 95 % CTM, then area of analytic signal can be defined as:

$$A_{\text{analytic}} = \pi r_{\text{CTM95}}^2 \quad (13)$$

2.3.2 Second-Order Difference Plot and Area Computation of Elliptical Region

The second-order difference plot (SODP) provides a graph of successive rates against each other and has been used to measure the variability present in EEG and center of pressure (COP) signals (Thuraisingham et al. 2007; Pachori et al. 2009). Useful diagnostic information can be extracted from SODP of the IMFs of EEG signals. The area of SODP of IMFs of EEG signals can be used as features for classification of normal and epileptic seizure EEG signals. The SODP of signal $x[n]$ can be obtained by plotting $X[n]$ against $Y[n]$ which are defined as (Cohen et al. 1996),

$$X[n] = x[n+1] - x[n] \quad (14)$$

$$Y[n] = x[n+2] - x[n+1] \quad (15)$$

In SODP above mentioned successive rates are plotted against each other, consequently provides rate of variability of data. The 95 % confidence ellipse area can be used to determine the confidence area of SODP of IMFs which covers around 95 % of the points. SODP corresponding to the normal and epileptic seizure EEG signals and their first four intrinsic mode functions are shown in Figs. 5 and 6, respectively. These figures represent trace of two successive rates, $X[n]$ and $Y[n]$ of different IMFs of EEG signals. The SODP of IMFs of EEG signals exhibit elliptical patterns, the area of ellipse in SODP of IMFs has been used as a feature for classification of epileptic seizure and seizure-free EEG signals (Pachori and Patidar 2014). In this work, we have used the area parameter computed from the SODP of IMFs as a feature for classification of normal and epilpetic seizure EEG signals. The procedure to compute the 95 % confidence ellipse area from the SODP can be given as (Prieto et al. 1996; Cavalheiro et al. 2009):

The μ_X and μ_Y are mean values of $X[n]$ and $Y[n]$ as defined in Prieto et al. (1996), Cavalheiro et al. (2009) and μ_{XY} can be defined as,

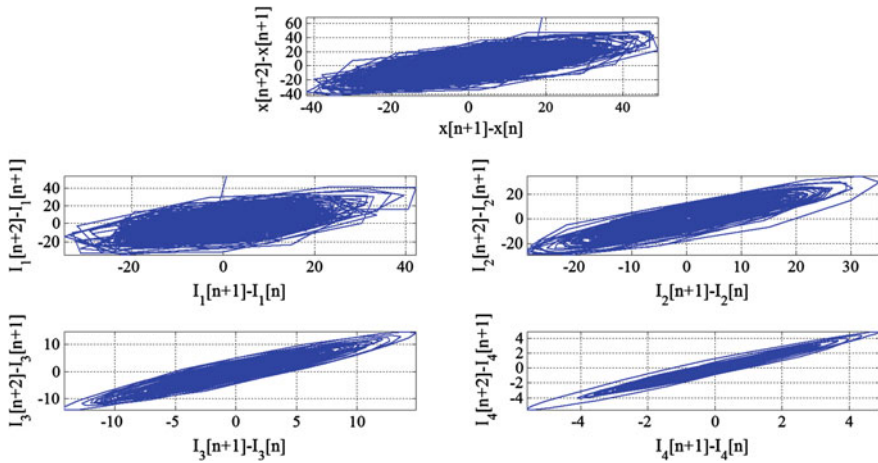$$\mu_{XY} = \sqrt{\frac{1}{N}\sum X[n]Y[n]} \quad (16)$$

Fig. 5 SODP of the normal EEG signal and its first four IMFs
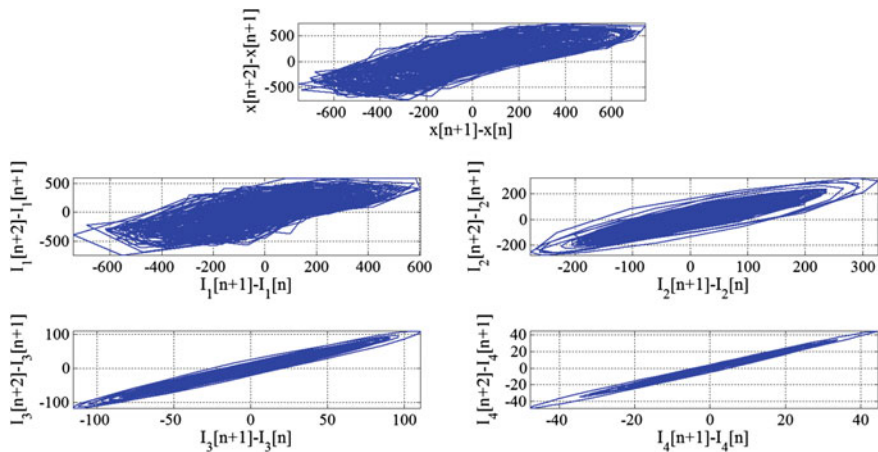

Fig. 6 SODP of the seizure EEG signal and its first four IMFs

The D parameter can be computed as:

$$D = \sqrt{(\mu_X^2 + \mu_Y^2) - 4(\mu_X^2\mu_Y^2 - \mu_{XY}^2)} \qquad (17)$$

and,

$$a = 1.7321\sqrt{(\mu_X^2 + \mu_Y^2 + D)} \qquad (18)$$

$$b = 1.7321 \sqrt{(\mu_X^2 + \mu_Y^2 - D)} \tag{19}$$

The ellipse area can be computed from the parameters a and b as:

$$A_{\text{ellipse}} = \pi ab. \tag{20}$$

2.4 Least Square Support Vector Machine

Classification is a problem of finding out the particular category of data to which the new upcoming observed sample can belong. The decision is made on the basis of the observed samples of data whose category is already known, these sets of observed samples are known as training sets. Support vector machine (SVM) is a machine learning technique used to classify samples belongs to different classes. SVM is a very useful tool for pattern classification problem (Cortes and Vapnik 1995). SVM is trained to search for an optimal separating hyperplane that can provide superior generalization, particularly when dimension of input data is large. Hyper planes are determined to create decision boundaries between two different classes of data in SVM. The effectiveness of the features in classifying normal and epileptic seizure EEG signals has been evaluated using a least square support vector machine (LS-SVM) a least square version of SVM (Suykens and Vandewalle 1999).

Consider a training set of N data points (x_i, y_i), $i = 1, \ldots, N$, where x_i is input data and $y_i = +1$ or -1, class label for two different classes. The SVM approach aims at constructing a discriminant function of the form:

$$f(x) = \text{sign}\left[\omega^T g(x) + b\right] \tag{21}$$

where, ω is the d-dimensional weight vector and b is a bias, and $g(x)$ is a mapping function that maps x into d-dimensional space. The goal of SVM algorithm is to identify optimum separating hyper plane which is able to maximize the distance from either class to the hyperplane. This problem of optimization can be formulated as a quadratic programming problem considering inequality constraints (Suykens and Vandewalle 1999). The LS-SVM is the least square variant of SVM for classification of two class problem. The statement of the problem can be written as in following way:

$$\text{Minimize } J(\omega, b, e) = \frac{1}{2}\omega^T\omega + \frac{\gamma}{2}\sum_{i=1}^{N} e_i^2 \tag{22}$$

subjected to following equality constraints:

$$y_i\left[\omega^T g(x_i) + b\right] = 1 - e_i, \ i = 1, 2, 3, \ldots, N \tag{23}$$

where, $e = (e_1, e_2, \ldots, e_N)^T$. The Lagrangian multiplier α_i can be defined for (22) as:

$$L(\omega, b, e; \alpha) = J(\omega, b, e) - \sum_{i=1}^{N} \alpha_i\{y_i[\omega^T g(x_i) + b] - 1 + e_i\} \tag{24}$$

On solving (24), the LS-SVM classifier can be expressed as:

$$f(x) = \text{sign}\left[\sum_{i=1}^{N} \alpha_i y_i K(x, x_i) + b\right] \tag{25}$$

where, $K(x, x_i)$ is a kernel function. The following kernel functions are used in this work, which have been defined in Khandoker et al. (2007):

1. Linear kernel: The linear kernel can be defined as:

$$K(x, x_i) = x^T x_i \tag{26}$$

2. Polynomial kernel: The polynomial kernel can be defined as:

$$K(x, x_i) = (x^T x_i + 1)^d \tag{27}$$

where d is the degree of polynomial.
3. Radial basis function (RBF) kernel: The RBF kernel can be defined as:

$$K(x, x_i) = e^{\frac{-||x-x_i||^2}{2\sigma^2}} \tag{28}$$

where, width of RBF kernel can be controlled by varying scaling factor σ. The performance evaluation parameters of the LS-SVM classifier depends on the selection of the kernel parameters. In this work, we have used trial and error method in order to determine the suitable kernel parameters for classification of normal and epilpetic seizure EEG signals.

2.4.1 Performance Evaluation Parameters

The classification performance of the LS-SVM classifier for classification of normal and epileptic seizure EEG signals can be evaluated by computing the sensitivity, specificity, and accuracy. Sensitivity measures the ability of test to identify proportion of actual positives as such. Considering an example where percentage of epileptic seizure signals from test set, correctly falls in the category of epileptic seizure signals after classification. Specificity measures the ability of test to exclude

the actual negatives correctly. For example, percentage of normal EEG signals correctly identified as not having seizures. A perfect classification would result in 100 % sensitivity by detecting all epileptic seizure EEG signals correctly. It also exhibits 100 % specificity by not recognizing any normal EEG signal as epileptic seizure signal. Positive predictive value is, the fraction of total positive patterns, which represents the actual positive patterns (Azar and El-Said 2014). Accuracy of classification is proportion of number of patterns which are correctly classified. Similarly, negative predictive value is, the fraction of total identified negative patterns, which represent actual negative patterns. Considering, *TP* and *TN* represent the total number of correctly identified true positive patterns and true negative patterns respectively, along with *FP* and *FN* represents total number of false positive patterns and false negative patterns, respectively. The sensitivity (*SEN*), specificity (*SPF*), accuracy (*ACC*), positive prediction value (*PPV*), negative prediction value (*NPV*) of classifier can be defined as (Azar and El-Said 2014):

$$SEN = \frac{TP}{TP + FN} \times 100 \ (\%) \tag{29}$$

$$SPF = \frac{TN}{TN + FP} \times 100 \ (\%) \tag{30}$$

$$ACC = \frac{TP + TN}{TP + TN + FP + FN} \times 100 \ (\%) \tag{31}$$

$$PPV = \frac{TP}{TP + FP} \times 100 \ (\%) \tag{32}$$

$$NPV = \frac{TN}{TN + FN} \times 100 \ (\%) \tag{33}$$

Matthews correlation coefficient (*MCC*) is another parameter to measure classification performance, which is the indication of classification accuracy of imbalanced positive and negative patterns in dataset (Azar and El-Said 2014). Higher the value of *MCC* parameter, the better the classifier performance (Yuan et al. 2007). The *MCC* parameter can be defined as follows (Yuan et al. 2007):

$$MCC = \frac{TP \cdot TN - FN \cdot FP}{\sqrt{(TP + FN)(TP + FP)(TN + FN)(TN + FP)}}. \tag{34}$$

3 Experimental Results and Discussion

Main steps of proposed method include applying EMD on EEG signals to obtain IMFs, computation of both area measures for first four IMFs, extraction and formation of feature set, training and testing of LS-SVM classifier. The proposed

method has been implemented using Matlab. The Matlab codes for EMD method are available at http://perso.enslyon.fr/patrick.flandrin/emd.html. In this study, the proposed methodology has been validated with one online freely available EEG dataset (Andrzejak et al. 2001). As discussed in Sect. 2.1, this dataset includes EEG signals which have been recorded from both healthy and epileptic subjects. It contains five subsets denoted as Z, O, N, F, and S. Data subsets Z and S have been used to evaluate the performance of the proposed method for classification of normal and epileptic seizure EEG signals. Data subset Z consists of normal EEG recordings taken from 5 healthy volunteers and subset S consists of the EEG recordings of seizure activities. Each of these subsets have 100 single-channel EEG signals of duration 23.6 s.

The decomposition of EEG signals using EMD method results into IMFs that are in decreasing order of frequency, in which first component is associated with highest frequency. As the IMFs can help to compute the area of analytic signal representation of the IMFs in the complex plane and ellipse area parameter obtained from SODP of IMFs, therefore the EMD has been used to decompose the EEG signals into a set of IMFs. These above mentioned two area parameters have been used to create the feature space for classification between normal and epileptic seizure EEG signals.

Recently in Pachori and Bajaj (2011), the ability of the analytic signal representation of IMFs to discriminate EEG signals which contains normal and epileptic seizure EEG signals has been explored. It comes out of this study that the analytic signal representation of IMFs provides a set of proper rotations which facilitates accurate identification of the centers and estimation of surface areas in the complex plane. It has been shown that the area parameter of the analytic IMFs has significant potential to differentiate between epileptic seizure and normal EEG signals. The experimental results of the above mentioned method reveals that the epileptic seizure EEG signals had evidently greater surface area in comparison to that of the normal EEG signals. The increased surface area in the complex plane for IMFs of the epileptic seizure EEG signals could be attributed to large amplitude of EEG signals for seizure subjects. It should be noted that the use of EMD enabled the extraction of individual centers of rotation for each IMF. Furthermore, as discussed in this study, it is evident from experimental analysis, that window size of 2,000 samples has provided better results, therefore the same window size has been used to compute the area parameters in this work. As the analytic signal representation has circular geometry, therefore modified CTM has been measured to compute the area of the analytic signal representation of the IMFs of EEG signals in the complex plane. The radius of the circular region which covers the 95 % of the CTM has been used to determine the area parameter for first four IMFs of EEG signals. In Pachori and Patidar (2014), the efficacy of the ellipse area parameters of SODP of IMFs for classification of seizure-free and ictal EEG signals has been examined. This study has employed the 95 % confidence ellipse area as a feature for discrimination of ictal EEG signals from the seizure-free EEG signals, and the classification performance of the ellipse area parameter have been evaluated for various window sizes (500, 1,000, 2,000, 4,000 samples) of seizure-free and ictal EEG signals.

Table 1 Classification performance of the proposed method for different kernel functions

Performance parameters	Linear	Polynomial ($d = 2$)	RBF ($\sigma = 1$)
SEN (%)	100	100	100
SPF (%)	97.00	90.00	100
ACC (%)	98.50	99.00	100
PPV (%)	97.69	90.91	100
NPV (%)	100	100	100
MCC	0.97	0.98	1

Along with area parameter of analytic IMFs, we have also computed 95 % confidence ellipse area of SODP for first four IMFs of EEG signals which covers around 95 % points in SODP. By considering both area measures for first four IMFs, lead to eight features that forms the final input feature set for LS-SVM based classification of normal and epileptic seizure EEG signals.

SVM is a supervise machine learning approach, suitable for small-sample dataset (Azar and El-Said 2014). LS-SVM is the least square reformulation of the SVM problem (Suykens and Vandewalle 1999) which uses equality constraints, instead of inequality constraint used in standard SVM. Consequently, solution follows from set of linear equations instead of quadratic programming problem. Hence, LS-SVM offers less computational complexity with excellent generalised performance (Suykens and Vandewalle 1999). In this work, the area parameters computed from the IMFs has been used as input feature set for LS-SVM classifier for classification of normal and epileptic seizure EEG signals. In order to evaluate the classification performance, different kernel functions have been utilized and their performance parameter values have been shown in Table 1. Various performance parameters discussed in previous section have been computed for three kernel functions which are linear kernel, polynomial kernel, and radial basis function (RBF) kernel. It can be observed that performance parameter values for RBF kernel are best among three kernel functions. The value of scaling factor associated with RBF kernel has been set empirically as 1. The ten-fold cross validation procedure is suitable for evaluating classification accuracy of a classifier for classification of biomedical signals (Sharma et al. 2014; Pachori and Patidar 2014). In this study, ten-fold cross validation procedure has been employed to evaluate the classification performance of LS-SVM classifier.

The classification accuracy achieved using proposed method with RBF kernel is 100 % which suggests successful identification of all, normal and epileptic seizure EEG signals. The resulting 100 % sensitivity shows the correct identification of all epileptic seizure EEG signals and 100 % specificity shows adequate classification by not recognizing any normal EEG signal as epileptic seizure EEG signal. Moreover, Table 2 shows the results obtained with proposed method and some other existing methods using the same dataset. Different parameters analysed for classification in other compared methods have also been mentioned in Table 2. It should be noted that the performance of the proposed method in terms of classification accuracy is same as that of discussed in Tzallas et al. (2007), in which time-frequency analysis based parameters have been used for classification. The area

Table 2 Comparison of the proposed method for classification of normal and epileptic seizure EEG signals with the existing methods studied on same dataset

Authors	Method	Accuracy (%)
Nigam and Graupe (2004)	Nonlinear pre-processing filter and diagnostic neural network	97.2
Srinivasan et al. (2005)	Time and frequency domain based features and recurrent neural network	99.6
Kannathal et al. (2005)	Entropy based measures and adaptive neuro-fuzzy inference system	about 90
Polat and Güneş (2007)	Fast Fourier transform based features and decision tree	98.72
Subasi (2007)	Discrete wavelet transform based features and mixture of expert model	94.5
Tzallas et al. (2007)	Time-frequency analysis based features and artificial neural network	100
This work	Proposed method	100

measures used in this work are the simple and can be used as indicators for diagnosis of epilepsy. Moreover, these parameters are defined in time domain which can help us to implement the proposed methodology for epileptic seizure detection with low computational complexity. It can be observed that performance of the proposed method in terms of accuracy is better than that of the other compared methods. The experimental analysis of the proposed method shows that features based on area measures are very effective to represent the behavior of epileptic seizure EEG signals giving excellent classification performance.

4 Conclusion

This book chapter has developed a novel approach for classification of the normal and epileptic seizure EEG signals using empirical mode decomposition and computing two area parameters for IMFs. Since the EEG signal is non-linear and non-stationary in nature, the EMD which is data dependent approach and suitable for analysis of nonlinear and non-stationary signals, efficaciously decompose the EEG signals into IMFs which are oscillatory components. In this work, we have explored the capability of two area parameters as the features for classification of normal and epileptic seizure EEG signals. It is noteworthy that the symmetric nature of IMFs, makes it possible to compute these two area measures and justifies the application of EMD before feature extraction from EEG signals. Computation of area measures uses the analytic signal representation of IMFs and SODP of IMFs. The IMFs have single center of rotation with circular geometry in analytic signal representation. Similarly, IMFs also exhibit elliptical patterns in SODP. Consequently, these

obtained geometrical patterns help to compute the area of analytic signal representation in complex plane with 95 % CTM and 95 % confidence area of ellipse in SODP. It has been found that these two area parameters have significantly higher values for seizure EEG signals as compared to normal EEG signals. The performance of LS-SVM classifier is best when RBF kernel has been employed to create decision boundary between two classes (normal and seizure) and consequently have provided 100 % classification accuracy. The features of the proposed method are suitable for real time implementation of an expert system for detection of the epileptic seizure in EEG signals. This system can act as an important diagnostic tool for clinician to detect the epilpesy automatically by analysing EEG signals.

In future, performance of the proposed methodology can be evaluated for classification between different classes of EEG signals like normal, inter-ictal and ictal EEG signals. The future direction of research may also include the application of the proposed methodology for identification of different psychological states of brain from EEG signals. Moreover, it would be of interest to study the expert system based on the proposed methodology for classification of other signals like electromyogram (EMG) signals, center of pressure (COP) signals, electrocardiogram (ECG), and speech signals corresponding to normal and abnormal conditions.

References

Accardo, A., Affinito, M., Carrozzi, M., & Bouquet, F. (1997). Use of the fractal dimension for the analysis of electroencephalographic time series. *Biological Cybernetics, 77*, 339–350.

Acharya, U. R., Sree, S. V., Alvin, A. P. C., & Suri, J. S. (2012). Use of principal component analysis for automatic classification of epileptic EEG activities in wavelet framework. *Expert Systems with Applications, 39*(10), 9072–9078.

Acharya, U. R., Sree, S. V., Swapna, G., Martis, R. J., & Suri, J. S. (2013). Automated EEG analysis of epilepsy: A review. *Knowledge-Based Systems, 45*, 147–165.

Adeli, H., Ghosh-Dastidar, S., & Dadmehr, N. (2007). A wavelet-chaos methodology for analysis of EEGs and EEG sub-bands to detect seizure and epilepsy. *IEEE Transactions on Biomedical Engineering, 54*(2), 205–211.

Altunay, S., Telatar, Z., & Erogul, O. (2010). Epileptic EEG detection using the linear prediction error energy. *Expert Systems with Applications, 37*(8), 5661–5665.

Amoud, H., Snoussi, H., Hewson, D. J., and Duchêne, J. (2007). Hilbert-Huang transformation: Application to postural stability analysis. In: *29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society* (pp. 1562–1565), Lyon, France , 29–23 Aug 2007.

Andrzejak, R. G., et al. (2001). Indications of nonlinear deterministics and finite-dimensional structures in time series of brain electrical activity: Dependence on recording region and brain state. *Physical Review E, 64*(6), 061907.

Aurlien, H., et al. (2004). EEG background activity described by a large computerized database. *Clinical Neurophysiology, 115*(3), 665–673.

Azar, A. T., & El-Said, S. A. (2014). Performance analysis of support vector machines classifier in breast cancer mammography recognition. *Neural Computings and Applications. 24*(5), 1163–1177. doi:10.1007/S00521-012-1324-4.

Bajaj, V., & Pachori, R. B. (2012). Classification of seizure and nonseizure EEG signals using empirical mode decomposition. *IEEE Transactions on Information Technology in Biomedicine, 16*(6), 1135–1142.

Boashash, B., Mesbah, M., & Colditz, P. (2003). Time–frequency detection of EEG abnormalities. In B. Boashash (Ed.), *Time-frequency signal analysis and processing: A comprehensive reference* (pp. 663–670). Oxford: Elsevier.

Casdagli, M. C., et al. (1997). Non-linearity in invasive EEG recordings from patients with temporal lobe epilepsy. *Electroencephalography and Clinical Neurophysiology, 102*(2), 98–105.

Cavalheiro, G. L., Almeida, M. F. S., Pereira, A., & Andrade, A. O. (2009). Study of age-related changes in postural control during quiet standing through linear discriminant analysis. *BioMedical Engineering Online, 8*(35), 10–1186.

Cohen, M. E., Hudson, D. L., & Deedwania, P. C. (1996). Applying continuous chaotic modeling to cardic signal analysis. *IEEE Engineering in Medicine and Biology Magazine, 15*(5), 97–102.

Cortes, C., & Vapnik, V. (1995). Support-vector networks. *Machine Learning, 20*(3), 273–297.

Coyle, D., McGinnity, T. M., & Prasad, G. (2010). Improving the separability of multiple EEG features for a BCI by neural-time-series-prediction-preprocessing. *Biomedical Signal Processing and Control, 5*(3), 196–204.

Cross, D. J., & Cavazos, J. E. (2007). The role of sprouting and plasticity in epileptogenesis and behavior. In S. Schachter, G. L. Holmes, & D. G. Trenite (Eds.), *Behavioural Aspects of Epilepsy* (pp. 51–57). New York: Demos Medical Publishing.

Easwaramoorthy, D., & Uthayakumar, R. (2011). Improved generalized fractal dimensions in the discrimination between healthy and epileptic EEG signals. *Journal of Computational Science, 2*(1), 31–38.

Ghosh-Dastidar, S., Adeli, H., & Dadmehr, N. (2007). Mixed-band wavelet-chaos neural network methodology for epilepsy and epileptic seizure detection. *IEEE Transactions on Biomedical Engineering, 54*(9), 1545–1551.

Ghosh-Dastidar, S., Adeli, H., & Dadmehr, N. (2008). Principal component analysis enhanced cosine radial basis function neural network for robust epilepsy and seizure detection. *IEEE Transactions on Biomedical Engineering, 55*(2), 512–518.

Güler, N. F., Übeyli, E. D., & Güler, I. (2005). Recurrent neural networks employing Lyapunov exponents for EEG signals classification. *Expert Systems with Applications, 29*(3), 506–514.

Guo, L., Rivero, D., & Pazos, A. (2010). Epileptic seizure detection using multiwavelet transform based approximate entropy and artificial neural networks. *Journal of Neuroscience Methods, 193*(1), 156–163.

Hirtz, D., Thurman, D. J., Gwinn-Hardy, K., Mohamed, M., Chaudhuri, A. R., & Zalutsky, R. (2007). How common are the "common" neurologic disorders? *Neurology, 68*(5), 326–337.

Huang, N. E., et al. (1998). The empirical mode decomposition and Hilbert spectrum for nonlinear and non-stationary time series analysis. *Proceedings of the Royal Society of London Series A: Mathematical, Physical and Engineering Sciences, 454*(1971), 903–995.

Iasemidis, L. D., et al. (2003). Adaptive epileptic seizure prediction system. *IEEE Transactions on Biomedical Engineering, 50*(5), 616–627.

Ince, N. F., Goksu, F., Tewfik, A. H., & Arica, S. (2009). Adapting subject specific motor imagery EEG patterns in space–time–frequency for a brain computer interface. *Biomedical Signal Processing and Control, 4*(3), 236–246.

Joshi, V., Pachori, R. B., & Vijesh, A. (2014). Classification of ictal and seizure-free EEG signals using fractional linear prediction. *Biomedical Signal Processing and Control, 9*, 1–5.

Kannathal, N., Choo, M. L., Acharya, U. R., & Sadasivan, P. K. (2005). Entropies for detection of epilepsy in EEG. *Computer Methods and Programs in Biomedicine, 80*(3), 187–194.

Khandoker, A. H., Lai, D. T. H., Begg, R. K., & Palaniswami, M. (2007). Wavelet-based feature extraction for support vector machines for screening balance impairments in the elderly. *IEEE Transactions on Neural Systems and Rehabilitation Engineering, 15*(4), 587–597.

Lai, Y. C., & Ye, N. (2003). Recent developments in chaotic time series analysis. *International Journal of Bifurcation and Chaos, 13*(6), 1383–1422.

Li, S., Zhou, W., Yuan, Q., Geng, S., & Cai, D. (2013). Feature extraction & recognition of ictal EEG using EMD and SVM. *Computers in Biology and Medicine, 43*(7), 807–816.

Mukhopadhyay, S., & Ray, G. C. (1998). A new interpretation of nonlinear energy operator and its efficacy in spike detection. *IEEE Transactions on Biomedical Engineering, 45*(2), 180–187.

Ngugi, A. K., Bottomley, C., Kleinschmidt, I., Sander, J. W., & Newton, C. R. (2010). Estimation of the burden of active and life-time epilepsy: A meta-analytic approach. *Epilepsia, 51*, 883–890.

Nigam, V. P., & Graupe, D. (2004). A neural-network-based detection of epilepsy. *Neurological Research, 26*, 55–60.

Ocak, H. (2009). Automatic detection of epileptic seizures in EEG using discrete wavelet transform and approximate entropy. *Expert Systems with Applications, 36*(2), 2017–2036.

Oweis, R. J., & Abdulhay, E. W. (2011). Seizure classification in EEG signals utilizing Hilbert-Huang transform. *BioMedical Engineering Online, 10*, 38.

Pachori, R. B. (2008). Discrimination between ictal and seizure-free EEG signals using empirical mode decomposition. *Research Letters in Signal Processing*, *293056*, 5 p.

Pachori, R. B., & Bajaj, V. (2011). Analysis of normal and epileptic seizure EEG signals using empirical mode decomposition. *Computer Methods and Programs in Biomedicine, 104*(3), 373–381.

Pachori, R. B., Hewson, D., Snoussi, H., & Duchêne, J. (2009). Postural time-series analysis using empirical mode decomposition and second-order difference plots. In *IEEE International Conference on Acoustics, Speech and Signal Processing* (pp. 537–540), Taipei, Taiwan, 19–24 Apr 2009.

Pachori, R. B., & Patidar, S. (2014). Epileptic seizure classification in EEG signals using second-order difference plot of intrinsic mode functions. *Computer Methods and Programs in Biomedicine, 113*(2), 494–502.

Pachori, R. B., & Sircar, P. (2008). EEG signal analysis using FB expansion and second-order linear TVAR process. *Signal Processing, 88*(2), 415–420.

Polat, K., & Güneş, S. (2007). Classification of epileptiform EEG using a hybrid system based on decision tree classifier and fast Fourier transform. *Applied Mathematics and Computation, 187* (2), 1017–1026.

Prieto, T. E., Myklebust, J. B., Hoffmann, R. G., Lovett, E. G., & Mykelbust, B. M. (1996). Measures of postural steadiness: Differences between healthy young and elderly adults. *IEEE Transactions on Biomedical Engineering, 43*(9), 956–966.

Ramsay, R. E., Rowan, A. J., & Pryor, F. M. (2004). Special considerations in treating the elderly patient with epilepsy. *Neurology, 62*(5 suppl 2), S24–S29.

Ray, G. C. (1994). An algorithm to separate nonstationary part of a signal using mid-prediction filter. *IEEE Transactions on Signal Processing, 42*(9), 2276–2279.

Schomer, D. L., & da Silva, F. L. (Eds.) (2005). *Electroencephalography*: *Basic Principles, Clinical Applications, and Related Fields*. Philadelphia: Lippincot Williams & Wilkins.

Senthil, P. K., Arumuganathan, R., Sivakumar, K., & Vimal, C. (2008). Removal of artifacts from EEG signals using adaptive filter through wavelet transform. In *9th IEEE International Conference on Signal Processing*, 2008 (pp. 2138–2141).

Sharma, R., Pachori, R. B., & Gautam, S. (2014). Empirical mode decomposition based classification of focal and non-focal EEG signals. In *IEEE International Conference on Medical Biometrics* (pp. 135–140), Shenzhen, China, 30 May–01 June 2014.

Srinivasan, V., Eswaran, C., & Sriram, N. (2005). Artificial neural network based epileptic detection using time–domain and frequency–domain features. *Journal of Medical Systems, 29* (6), 647–660.

Srinivasan, V., Eswaran, C., & Sriraam, N. (2007). Approximate entropy-based epileptic EEG detection using artificial neural networks. *IEEE Transactions on Information Technology in Biomedicine, 11*(3), 288–295.

Subasi, A. (2007). EEG signal classification using wavelet feature extraction and a mixture of expert model. *Expert Systems with Applications, 32*(4), 1084–1093.

Subasi, A., & Gursoy, M. I. (2010). EEG signal classification using PCA, ICA, LDA and support vector machine. *Expert Systems with Applications, 37*(12), 8659–8666.

Suykens, J. A. K., & Vandewalle, J. (1999). Least squares support vector machine classifiers. *Neural Processing Letters, 9*(3), 293–300.

Thuraisingham, R. A., Tran, Y., Boord, P., & Craig, A. (2007). Analysis of eyes open, eye closed EEG signals using second-order difference plot. *Medical & Biological Engineering & Computing, 45*(12), 1243–1249.

Thurman, D. J., et al. (2011). Standards for epidemiologic studies and surveillance of epilepsy. *Epilepsia, 52*(s7), 2–26.

Tzallas, A. T., Tsipouras, M. G., & Fotiadis, D. I. (2007). The use of time–frequency distributions for epileptic seizure detection in EEG recordings. In *Proceedings of 29th Annual International Conference of the IEEE on Engineering in Medicine and Biology Society* (pp. 3–6), August 2007.

Tzallas, A. T., Tsipouras, M. G., & Fotiadis, D. I. (2009). Epileptic seizure detection in EEGs using time–frequency analysis. *IEEE Transactions on Information Technology in Biomedicine, 13*(5), 703–710.

Übeyli, E. D. (2010). Lyapunov exponents/probabilistic neural networks for analysis of EEG signals. *Expert Systems with Applications, 37*(2), 985–992.

Uthayakumar, R. & Easwaramoorthy, D. (2013). Epileptic seizure detection in EEG signals using multifractal analysis and wavelet transform. *Fractals, 21*(2).

World Health Organization. (2014). *Neurological disorders, including epilepsy*. Retrieved from http://www.who.int/mental_health/management/neurological/en/. Accessed 8 Apr 2014.

Yuan, Q., Cai, C., Xiao, H., Liu, X., & Wen, Y. (2007). Diagnosis of breast tumours and evaluation of prognostic risk by using machine learning approaches. *Communications in Computer and Information Science, 2*, 1250–1260.