EEG Signal Classification Using Empirical Mode Decomposition and Support Vector Machine

Varun Bajaj and Ram Bilas Pachori

School of Engineering, Indian Institute of Technology Indore, 452017 Indore, India
{varun,pachori}@iiti.ac.in

Abstract. In this paper, we present a new method based on empirical mode decomposition (EMD) for classification of seizure and seizure-free EEG signals. The EMD method decomposes the EEG signal into a set of narrow-band amplitude and frequency modulated (AM-FM) components known as intrinsic mode functions (IMFs). The method proposes the use of the area parameter and mean frequency estimation of IMFs in the classification of the seizure and seizure-free EEG signals. These parameters have been used as an input in least squares support vector machine (LS-SVM), which provides classification of seizure EEG signals from seizure-free EEG signals. The classification accuracy for classification of seizure and seizure-free EEG signals obtained by using proposed method is 98.33% for second IMF with radial basis function kernel of LS-SVM.

Keywords: Epileptic seizure EEG signal, Empirical mode decomposition, Support vector machine, EEG signal classification.

1 Introduction

The electroencephalogram (EEG) is a representative signal containing information about the condition of the human brain. The disorder in the human brain creates a lot of physiopathological diseases, especially the epileptic seizure. The epileptic seizure disorder is characterized by recurrent electrical discharge of the cerebral cortex. The epileptic seizure results in irregular disturbance of brain function [1]. Detection of epilepsy or epileptic seizure by visual scanning of EEG signal is a very time consuming and may be inaccurate, particularly for long recording data set; therefore the parameters extracted from EEG signals are highly useful in diagnostics.

Most of the methods developed in the literature for EEG signal analysis and classification are based on time domain, frequency domain, and time-frequency domain. The spikes detection methods for EEG signal analysis have been proposed in [2, 3]. The measures namely, dominant frequency,

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average power in the main energy zone, normalized spectral entropy, spike rhythmicity, and relative spike amplitude together with artificial neural network (ANN) have been used for normal and epileptic EEG signal analysis [4]. Earlier studies have shown that the EEG signal is a non-stationary signal [5-9]. The nonlinear measures like correlation dimension, Lyapunov exponent and fractal dimension quantify the degree of complexity of a EEG signal [10-13]. The correlation integral measure is sensitive to wide variety of nonlinearity and has been used to characterize the epileptogenic regions of the brain during the interictal period [14]. The sample entropy has been used as a feature for the classification of different classes of EEG signals [15]. The entropy measure quantify the irregularity and complexity in time series. The entropy and Lyapunov exponent together with wavelet transform have been proposed for seizure detection by analyzing the complexity of some specific EEG sub-bands [16, 17]. The author has proposed a novel scheme based on the discrete wavelet transform (DWT) and approximation entropy for epilepsy detection in [18]. The proposed method for epileptic seizure detection in [19] is based on the multiwavelet transform and approximation entropy.

Recently, new techniques for analysis of nonlinear and non-stationary EEG signals have been proposed in [20-22], which are based on the empirical mode decomposition (EMD) developed especially for nonlinear and non-stationary signal analysis [23]. The mean frequency (MF) measure of intrinsic mode functions (IMFs) has been used as a feature in order to identify the difference between ictal and seizure-free EEG signals [20]. In [21], the weighted frequency of IMFs has been used as a feature for the classification between healthy and seizure EEG signals. Moreover, it has been shown that the EMD method has more classification accuracy and low computational complexity in comparison to multivariate EMD for EEG signal classification. The area measured from the trace of the analytic signal representation of IMFs has been used as a feature in order to discriminate normal (or healthy) EEG signals from the epileptic seizure EEG signals [22].

The main purpose of this paper is to propose the use of the area parameter and mean frequency of IMFs for classification of EEG signals. The area of analytic IMFs and mean frequency of the IMFs have been used as an input feature set to least squares support vector machine (LS-SVM) for classification of seizure and seizure-free EEG signals. The rest of the paper is organized as follows: In section 2, EEG signal dataset, the EMD method, area and mean frequency parameters, and LS-SVM classifier are presented. The results and discussion for the classification of EEG signals based on area and mean frequency features of IMFs are presented in section 3. Finally, the section 4 concludes the paper.

2 Methodology

2.1 Dataset

An EEG dataset, which is available online in [24] and includes recordings for both healthy and epileptic subjects, is used. The dataset includes five subsets (denoted as Z, O, N, F, and S) each containing 100 single-channel EEG signals, each one having 23.6 second duration. The subsets Z and O have been recorded extracranially, whereas sets N, F, and S have been recorded intracranially. These subsets are linked with the conditions, recording regions, and activities of the brain as: subset Z (healthy eyes open), subset O (healthy eyes closed), subset F (epileptogenic zone), N (hippocampal formation of opposite hemisphere), and subset S (epileptic seizure). The EEG signals of subsets N and F were taken from all contacts of the relevant depth electrode [24]. The

Table 1. Summary of the EEG dataset

	SF class (N, F)	S class (S)
Number of epileptic subjects	Five	Five
Electrode type	Intercranial	Intercranial
Electrode placement	Epileptogenic zone	Epileptogenic zone
Subject's state	Seizure-free (Intericatal)	Seizure (Ictal)
Number of EEG signals	200	100
Signal duration	23.6 second	23.6 second

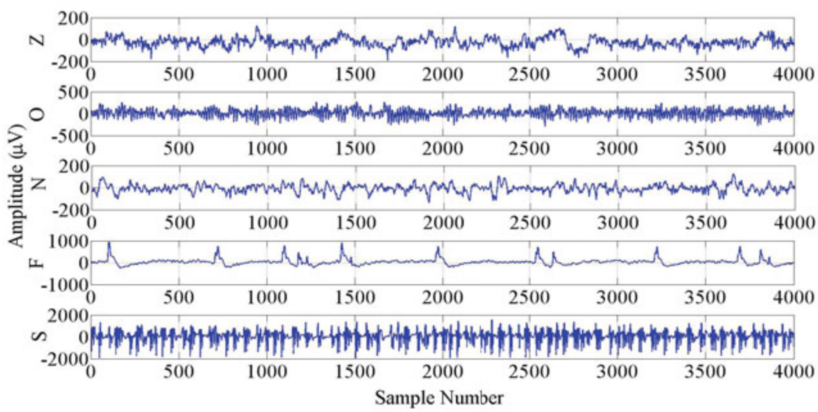

Fig. 1. An example of EEG signals from each of the five subsets (Z, O, N, F, and S).

strip electrodes were implanted onto the lateral and basal regions (middle and bottom) of the neocortex. The EEG signals of the subset S were taken from contacts of all electrodes (depth and strip). Sampling frequency of the data is 173.61 Hz. Typical EEG signals (one from each subset) are shown in Figure 1. In this paper, the subsets N and F are combined to form seizure-free (SF) class and subset S forms the seizure (S) class. The summary of the EEG signals in these two classes are shown in Table 1.

2.2 Empirical Mode Decomposition

The empirical mode decomposition method is an adaptive and data-dependent method. The EMD method does not require any condition about the stationarity and linearity of the signal. The aim of the EMD method is to decompose the nonlinear and nonstationary signal $x(t)$ into a sum of intrinsic mode functions (IMFs). Each IMF satisfies two basic conditions: (I) the number of extrema and the number of zero crossings must be the same or differ at most by one, (II) at any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero.

The EMD algorithm for the signal $x(t)$ can be summarized as follows [25]:

(a) Detect the extrema (both maxima and minima) of the data set $x(t)$.
(b) Generate the upper and lower envelopes $e_{max}(t)$ and $e_{min}(t)$, respectively by connecting the maxima and minima separately with cubic spline interpolation.
(c) Determine the local mean as $a(t) = \frac{[e_{max}(t)+e_{min}(t)]}{2}$.
(d) Extract the detail $h_1(t) = x(t) - a(t)$.
(e) Decide whether $h_1(t)$ is an IMF or not by checking the two basic conditions as described above.
(f) Repeat steps (a) to (e) and end when an IMF $h_1(t)$ is obtained.

Once the first IMF is derived, define $c_1(t) = h_1(t)$, which is the smallest temporal scale in $x(t)$. To find the rest of the IMFs, generate the residue $r_1(t)$ of the data by subtracting $c_1(t)$ from the signal as $r_1(t) = x(t) - c_1(t)$. The above illustrated sifting process will be continued until the final residue is a constant, a monotonic function, or a function from which no more IMFs can be derived. At the end of the decomposition the original signal $x(t)$ is represented as:

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

Where M is the number of IMFs, $c_m(t)$ is the m^{th} IMF, and $r_M(t)$ is the final residue. Each IMF in the equation (1) is assumed to yield a meaningful local frequency, and different IMFs do not exhibit the same frequency at the same time. Then, the equation (1) can be written as:

$$x(t) \approx \sum_{m=1}^{M} A_m(t) \cos[\phi_m(t)] \tag{2}$$

Matlab codes are available at http://perso.ens-lyon.fr/patrick.flandrin/emd.html. The IMFs generated by EMD method on the 23.6 second seizure-free EEG signal and seizure EEG signal are shown in Fig. 2 and Fig. 3 respectively.

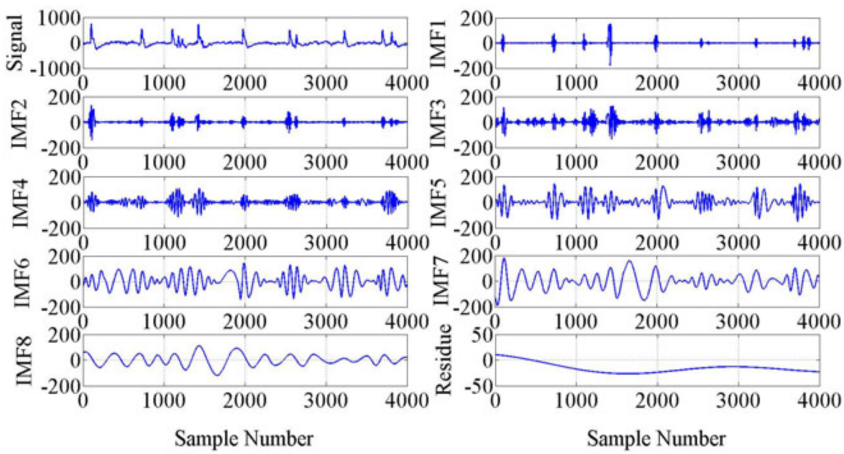

Fig. 2. Empirical mode decomposition of the 23.6 second seizure-free EEG signal.

2.3 Area Computation of Analytic Intrinsic Mode Functions

The analytic signal $z(t)$ of a signal $c(t)$ can be defined as [23]:

$$z(t) = c(t) + j\widehat{c}(t) \tag{3}$$

Where $c(t)$ is a real signal and the Hilbert transform of $c(t)$ is given by:

$$\widehat{c}(t) = c(t) * \frac{1}{\pi t}$$

The equation (3) can be written as:

$$z(t) = A(t)e^{j\phi(t)} \tag{4}$$

The analytic signal amplitude $A(t)$ and instantaneous phase $\phi(t)$ can be defined as follows:

$$A(t) = \sqrt{c^2(t) + \widehat{c}^2(t)}, \phi(t) = \arctan\left[\frac{\widehat{c}(t)}{c(t)}\right] \tag{5}$$

The analytic signal representation for m^{th} IMF, $c_m(t) = A_m(t)\cos[\phi_m(t)]$ in equation (2), is given by:

$$z_m(t) = A_m(t)e^{j\phi_m(t)} \tag{6}$$

In the analytic signal representation of the discrete-time signal $z[n]$, the imaginary part of the signal $z[n]$ is plotted against the real part of the signal $z[n]$. The nonlinear and non-stationary signal does not have direction of rotation with unique center in the complex plane. The analytic signal representation of IMFs provides the direction of rotation and unique center of the plot, and also make possible to compute surface area of analytic IMFs in the complex plane [22]. It should be noted that the EMD method is such a method which represents the nonlinear and non-stationary signal by a sum of proper rotations. This makes possible to compute surface area in the complex plane. The central tendency measure (CTM) is an automatic method for summarize the visual information in the plot. The CTM has been used to measure the degree of variability from a second-order difference plot of biomedical signals [26]. We have used modified CTM to determine the radius of the analytic signal representation of IMFs in the complex plane [22]. The CTM is computed by selecting a circular region of radius r, around the origin, counting the number of points that fall within the radius, and dividing by the total number of points. Let N be the total number of points and r the radius of the central area. Then, the modified CTM for analytic signal $z[n]$ is given by the following expression:

$$\mathrm{CTM} = \frac{\sum_{n=1}^{N} \delta(d_n)}{N} \tag{7}$$

$$\delta(d_n) = \begin{cases} 1 \text{ if } \left([\Re\{z[n]\}]^2 + [\Im\{z[n]\}]^2\right)^{0.5} < r \\ 0 \text{ otherwise} \end{cases} \tag{8}$$

The radius (r_{CTM}) corresponding to 95% CTM has been used to compute the area of analytic IMF in complex plane. The area (A) is computed by using the following equation:

$$A = \pi r_{CTM}^2 \tag{9}$$

For radius (r_{CTM}), the CTM provides the 95% points of the total data points lie in the circle corresponding to r_{CTM}.

2.4 Mean Frequency Computation of Intrinsic Mode Functions

The zero-order Fourier-Bessel (FB) series expansion of a signal $y(t)$ considered over some arbitrary interval $(0, a)$ is expressed as [27]:

$$y(t) = \sum_{p=1}^{P} D_p J_0 \left(\frac{\lambda_p}{a} t \right) \tag{10}$$

Where $J_0(.)$ are zero-order Bessel functions, and $\{\lambda_p; p = 1, 2, 3, ..., P\}$ are the ascending order positive roots of $J_0(\lambda)$ =0. The sequence of Bessel functions $\left\{ J_0 \left(\frac{\lambda_p}{a} t \right) \right\}$ forms an orthogonal set on the interval $0 \leq t \leq a$ with respect to the weight t, that is,

$$\int_0^a t J_0 \left(\frac{\lambda_p}{a} t \right) J_0 \left(\frac{\lambda_q}{a} t \right) dt = 0 \qquad \text{for } p \neq q \tag{11}$$

Using the orthogonality of the set $\left\{ J_0 \left(\frac{\lambda_p}{a} t \right) \right\}$, the FB coefficient D_p are computed by using the following equation:

$$D_p = \frac{2 \int_0^a t y(t) J_0 \left(\frac{\lambda_p}{a} t \right) dt}{a^2 [J_1(\lambda_p)]^2} \tag{12}$$

with $1 \leq p \leq P$, Where P is the order of the FB expansion, and $J_1(\lambda_p)$ are the first-order Bessel functions. It should be noted that the FB series coefficients D_p are unique for a given signal, similarly as the Fourier series coefficients are unique for a given signal. However, unlike the sinusoidal basis functions in the Fourier series, the Bessel functions decay over time. This feature of the Bessel functions makes the FB series expansion suitable for non-stationary signals [28-30]. The mean frequency of signal $y(t)$ can be computed by the following equation [20]:

$$f\text{mean} = \frac{\sum_{p=1}^{P} f_p E_p}{\sum_{p=1}^{P} E_p} \tag{13}$$

Where

$$E_p = D_p^2 \frac{a^2}{2} [J_1(\lambda_p)]^2 = \text{ (energy at order } p) \tag{14}$$

$$f_p = \frac{\lambda_p}{2\pi a} = \text{ (frequency at order } p) \tag{15}$$

Mean frequency represents the centroid of the spectrum, and thus characterizes the frequency components of the intrinsic mode functions of the EEG signal.

2.5 Least-Squares Support Vector Machine

The effectiveness of the parameters (area and mean frequency of IMFs) in classifying the seizure and seizure-free EEG signals is evaluated using a least

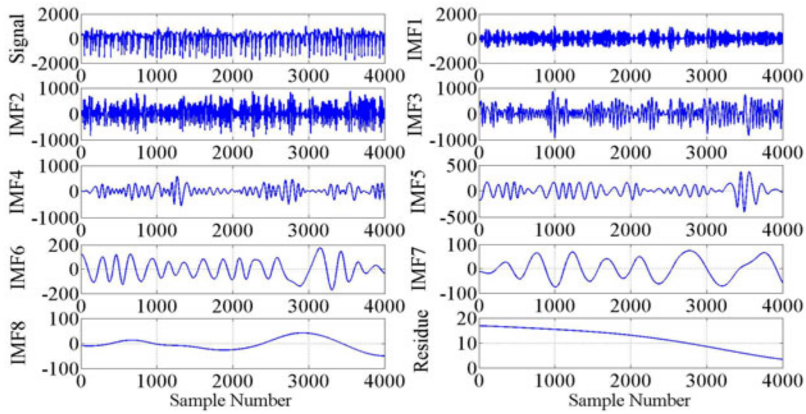

Fig. 3. Empirical mode decomposition of the 23.6 second seizure EEG signal.

squares support vector machine (LS-SVM). For two-class support vector machine, we consider the following decision function [31, 32]:

$$f(x) = \text{sign}\left[w^T g(x) + b\right] \tag{16}$$

where w is the l dimensional weight vector and b is a bias, and $g(x)$ is a mapping function that maps x into the l dimensional space. In order to obtain w and b, the optimization problem can be formulated in the following way:

$$\text{Minimize} \qquad J(w, b, e) = \frac{1}{2} w^T w + \frac{\gamma}{2} \sum_{i=1}^{N} e_i^2 \tag{17}$$

subject to equality constraints

$$y_i[w^T g(x_i) + b] = 1 - e_i, \qquad i = 1, 2, ..., N \tag{18}$$

where $\{x_i, y_i\}_{i=1}^{N}$ are N training input-output pairs, y_i=1 or -1 if x_i belongs to class 1 or 2, respectively and $e = (e_1, e_2, ..., e_N)^T$. The Lagrangian multipliers α_i can be defined for equation (17) as:

$$L(w, b, e; \alpha) = J(w, b, e) - \sum_{i=1}^{N} \alpha_i \{y_i[w^T g(x_i) + b] - 1 + e_i\} \tag{19}$$

where α_i are Lagrange multipliers and $\alpha = (\alpha_1, \alpha_2, ..., \alpha_N)^T$. After solving equation (19), the LS-SVM classifier is obtained as:

$$f(x) = \text{sign}\left[\sum_{i=1}^{N} \alpha_i y_i K(x, x_i) + b\right] \tag{20}$$

where $K(x, x_i)$ is a kernel function. In this work following kernel functions were used:

(1) Linear kernel: The linear kernel can be defined as [33],

$$K(x, x_i) = x^T x_i \tag{21}$$

(2) Polynomial kernel: The polynomial kernel can be defined as [33],

$$K(x, x_i) = (x^T x_i + 1)^d \tag{22}$$

where d is the degree of polynomial.
(3) Radial basis function (RBF) kernel: The RBF kernel can be defined as [33],

$$K(x, x_i) = e^{\frac{-||x - x_i||^2}{2\sigma^2}} \tag{23}$$

where σ controls the width of RBF kernel. The choice of value for kernel parameter influences the classification outcome. Please refer to [32] for detailed information about the LS-SVM.

3 Results and Discussion

The analytic signal representation of EEG signals in the complex plane do not have a specific geometry, makes it difficult to define the circle that encloses 95% data points of the total data points. The EMD process makes possible to cover more than 95% points of the total data points that lie within the circle due to having circular form of analytic IMFs in the complex plane. The value of estimated area is large in seizure EEG signals when compared with that seizure-free EEG signals. The increased surface area observed from the seizure EEG signals possibly due to greater amplitude of the high frequency IMFs of EEG signals for seizure EEG signal class.

The EMD method decomposes a signal into narrow-band AM-FM components (IMFs), which facilitates computation of mean frequency of IMFs. Mean frequency estimation was performed using the Fourier-Bessel expansion method. The coefficients of the FB expansion have been used to compute the mean frequency of the IMFs. The class discrimination ability of area and mean frequency parameters of IMFs is quantified using Kruskal-Wallis statistical test. The results are shown in Fig. 4 and Fig. 5. As it can be easily observed, although the area and mean frequency features of first four IMFs are statistically significant (small p-values), the EEG signals may not be classified correctly by simple threshold method. This motivates us to use area and mean frequency parameters of IMFs as input features in the LS-SVM classifier in order to obtain more accurate classification of seizure and seizure-free EEG signals. We have randomly selected 60% of the features of the dataset for training and the remaining used for testing.

The classification test performance of the LS-SVM classifier can be determined by the computation of sensitivity, specificity, and accuracy. The sensitivity (SEN), specificity (SPE), and accuracy (Acc) are defined as:

$$SEN = \frac{TP}{TP + FN} \times 100 \tag{24}$$

$$SPE = \frac{TN}{TN + FP} \times 100 \tag{25}$$

$$Acc = \frac{TP + TN}{TP + TN + FP + FN} \times 100 \tag{26}$$

Where TP and TN represent the total number of correctly detected true positive events and true negative events respectively. FP and FN represent the total number of erroneously positive events and erroneously negative events respectively. Table 2 shows the classification performance [sensitivity (SEN), specificity (SPE), and accuracy (Acc)] of the LS-SVM classifier using different kernels for first four IMFs of EEG signals. The classification accuracy for classification of seizure and seizure-free EEG signals obtained by proposed method is 98.33% for second IMF with RBF kernel of the LS-SVM classifier.

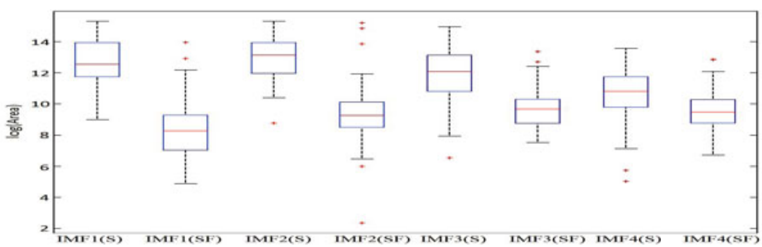

Fig. 4. Comparison of area parameter for seizure and seizure-free EEG signals for first four IMFs.

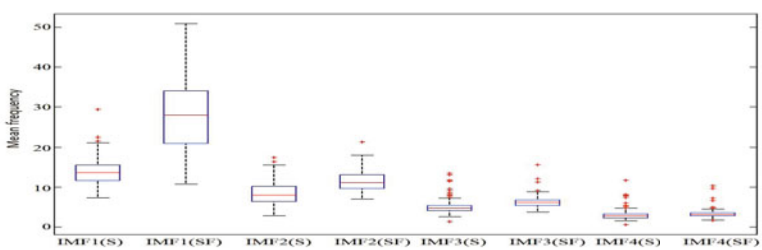

Fig. 5. Comparison of mean frequency estimation for seizure and seizure-free EEG signals for first four IMFs.

Table 2. Sensitivity, specificity, and accuracy of IMFs with different kernels of LS-SVM classifier for classification between seizure-free (SF) and seizure (S) EEG signals

Kernel function	Kernel parameter	Statistical parameter	IMF1	IMF2	IMF3	IMF4
Linear	-	SEN	82.93	82.76	94.12	72.22
		SPE	92.41	82.42	76.70	73.53
		Acc	89.16	82.50	79.16	73.33
Polynomial	d=3	SEN	90.48	86.83	90.32	80.95
		SPE	97.44	91.46	86.52	76.77
		Acc	95.00	90.00	87.50	77.50
RBF	σ=5	SEN	90.48	**100.00**	88.57	80.00
		SPE	97.44	**97.56**	89.41	78.95
		Acc	95.00	**98.33**	89.16	79.1

4 Conclusion

The empirical mode decomposition process is a useful and powerful method to decompose EEG signal into a set of IMFs. The parameters (area and mean frequency) extracted from the IMFs of EEG signals have been found useful in discrimination of seizure and seizure-free EEG signals. Finally, we conclude that the area and mean frequency parameters of IMFs are effective for classification of seizure and seizure-free EEG signals. The classification results indicated that the RBF kernel of LS-SVM had provided 98.33% accuracy in classification of seizure and seizure-free EEG signals. Future direction of research may include application of area and mean frequency parameters of IMFs to identify different behavioral/psychological states from EEG signals. In addition, the problem of automatic kernel selection for EEG signal classification in different brain conditions is needed to research further.

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