ISSN: 2321-8169
04 - 08

Empirical Mode Decomposition based Feature Extraction Method for the Classification of EEG Signal

Anant kulkarni
MTech Communication Engineering
Vellore Institute of Technology
Chennai, India
anant8778@gmail.com

Dr Suchetha M.
Associate Professor
Vellore Institute of Technology
Chennai, India
suchetha.m@vit.ac.in

***Abstract*—** Disease identification is a major task in the field of biomedical. To perform it the analysis of EEG signal is to be performed. The proposed method presents for feature extraction from electroencephalogram (EEG) signals using empirical mode decomposition (EMD). Its use is motivated by the fact that the EMD gives an effective time-frequency analysis of nonstationary signals. The intrinsic mode functions (IMF) obtained as a result of EMD give the decomposition of a signal according to its frequency components. In this present the research of upto third order temporal moments, and spectral features including spectral centroid, coefficient of variation and the spectral skew of the IMFs for feature extraction from EEG signals. Features are physiologically relevant to normal EEG signals. Normal EEG signals have different temporal and spectral centroids, dispersions and symmetries. The performance of the proposed method is studied on a publicly available dataset which is designed to handle various classification problems including the identification of epilepsy patients also detection of seizures and non-seizures. The calculated features are fed into the standard support vector machine (SVM) for classification purposes. The Experimental results show that good classification results are obtained using the proposed methodology for the classification of EEG signals.

Keywords- *Eempirical mode decomposition, intrinsic mode function, feature extraction, classification.*

*****

I. Introduction

Electroencephalogram (EEG) is a set of electric potential differences that contain the information about the human brain activity. It exhibits the data regarding the volume currents that spread from a neural tissue throughout the conductive media of the brain. These measurements can be obtained using sensors placed on the scalp or using the intracranial electrodes. The EEG signals can be effectively used for various applications such as emotion recognition, brain–computer interfaces (BCIs), etc. One of the most important applications of the analysis of EEG signals is its use in neuroscience to diagnose diseases and brain disorders. Epileptic seizure is one of the most common neurological disorders worldwide. Its detection is typically done by the physicians using a visual scanning of the EEG signals which is a time consuming process and may be inaccurate. These inaccuracies are particularly significant for long time duration EEG signals.

More recently, new techniques for analysis of nonlinear and nonstationary EEG signal have been proposed , which are based on the Empirical Mode Decomposition developed especially for nonlinear and nonstationary signal analysis. The mean frequency (MF) measure of intrinsic mode functions has been used as a feature in order to identify the difference between non-seizure and seizure EEG signals[1]. In this work instantaneous frequency has been used as a feature of IMFs for the classification between healthy and epileptic seizure EEG signals.

The parameters extracted from the EEG signals are very useful for diagnostics various. The spectral parameters based on the Fourier transform are useful for analysing the EEG signals and have shown good results on their classification. Such as several methods mentioned as use of short time Fourier transform (STFT) and wavelet transform in the literature. Although good results are obtained using these methods, the STFT does not yield a multiresolution analysis of the signals. This is because of the fact that the STFT uses the filters of the same bandwidth for signal decomposition at all frequencies. This limitation is typically resolved using the wavelet analysis in which a multiresolution time-frequency analysis is facilitated by forming band pass filters with varying bandwidths. Researchers have found the wavelet analysis to be a very useful tool for various signal processing applications and it is performed in frequency domain[2].

The EMD is a time-frequency based method which decomposes a signals into a number of intrinsic mode functions which are oscillatory components. This empirical method is effective for a time-frequency analysis of the nonstationary signals. This characteristic of EMD has motivated the researchers to use it for the analysis of EEG signals. The mean frequency of IMFs has been used for the classification of EEG signals. In

ISSN: 2321-8169
04 - 08

this work, the analytic IMFs apply Hilbert-Huang transform [(HHT)] for seizure classification of EEG signals. Weighted frequencies in the IMFs to identify seizures in the EEG signals. Besides the strengths of feature extraction methods related to instantaneous frequencies (IF), it is important to note that the extraction of IF is more meaningful when the IMFs extracted from the EEG signals are monocomponent.

In this paper, we propose a novel feature extraction methodology for the classification of EEG signals involve it three stages. The first stage of the algorithm involves the calculation of EMD of the EEG signal, thereby giving a set of IMFs. The first three IMFs are selected for further processing. The second stage involves feature extraction which is done by calculating the temporal and spectral characteristics of the IMFs, which is the main contribution of this paper. For the calculation of spectral features, we have used power spectral density (PSD). The temporal and spectral features are obtained from the Hilbert transformed IMFs. Thus, using this transformation can remove the DC offset from the spectral content of the signals which is one of the sources of nonstationarity in the signals. The third stage involves the use of support vector machine (SVM) for the classification of EEG signal.

II. DATASET

In this study, we have used an EEG dataset that is publicly available online[8] (Sample EEG signals are shown in Fig. 1).The dataset consists of five subsets fig. 1(denoted as sets A-E) each containing 100 single channel EEG signals, each one having a duration of 23.6 s. These signals have been selected from continuous multichannel EEG recording after visual inspection of artifacts. The Sets A and B consist of surface EEG segments collected from five healthy volunteers in awaken and relaxed state with their eyes opened and closed respectively. Segments in Sets C, D, and E are obtained from an archive of EEG signals of presurgical diagnosis. Five patients are selected who have achieved complete control of seizure after resection of one of the hippocampal formations. The following fig. 1 shows sample of EEG signals with five different sets A, B, C, D and E respectively. Sample EEG signals from five different sets from rows 1 to 5 (A, B, C, D, and E, respectively) were recorded during seizure free intervals (i.e., interictal) respectively. Set E contains signals corresponding to seizure attacks (i.e., ictal EEG), recorded using all the electrodes. The signals are recorded in a digital format at a sampling rate of 173.61 Hz. Thus, the sample length of each segment is 173.6 × 23.6 ≈ 4097.

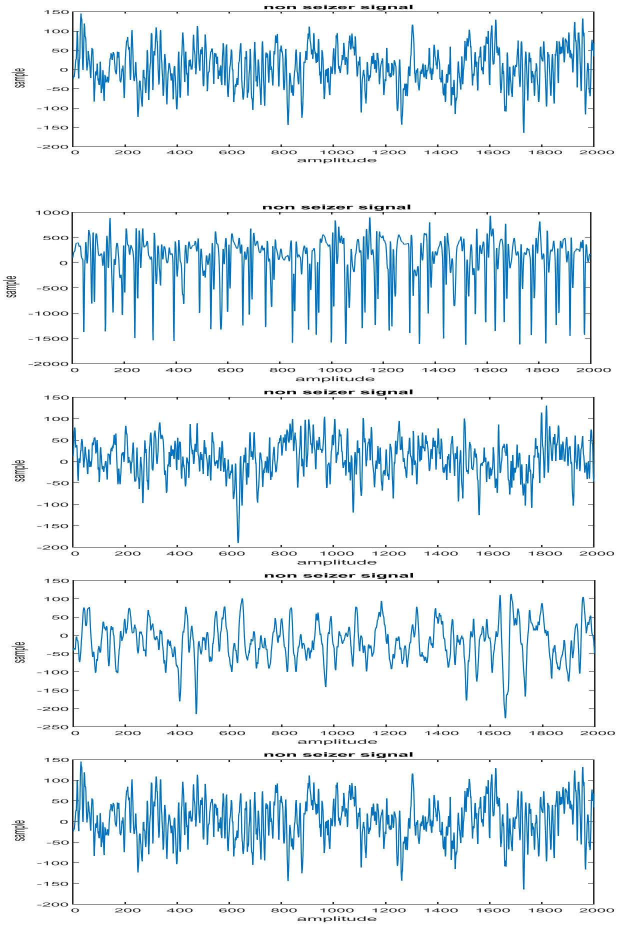


Fig. 1:- Sample of EEG signals from five differents set(A,B,C,D,E)

III. METHODOLOGY

a)Empirical Mode Decomposition:-

The EMD is a data dependent method of decomposing a signal into a number of oscillatory components, known as intrinsic mode functions (IMFs). EMD does not make any assumptions about the stationary or linearity of the data the aim of EMD is to decompose signals into a number of IMFs, each one of them satisfying the two basic conditions:[9]-

- The number of extrema or zero crossings must be the same or differ by at most one.
- At any point, the average value of the envelope defined by local maxima and the envelope defined by the local minima is zero.

Given that we have a signal, the calculation of its IMFs involves the following steps.

1) Identify all extrema (maxima and minima) in x(t).

2)Interpolate between minima and maxima, generating \the envelopes $E_l(t)$ and $E_m(t)$.

3) Determine the local mean as a (t) $=E_m(t) +E_l(t)/2$.

4) Extract the detail $h_1(t) =x(t)-a(t)$ i.e.

5) Decide whether $h_1(t)$ is an IMF or not based on two basic conditions for IMFs mentioned above.

6) Repeat step 1 to 4 until an IMF is obtained.

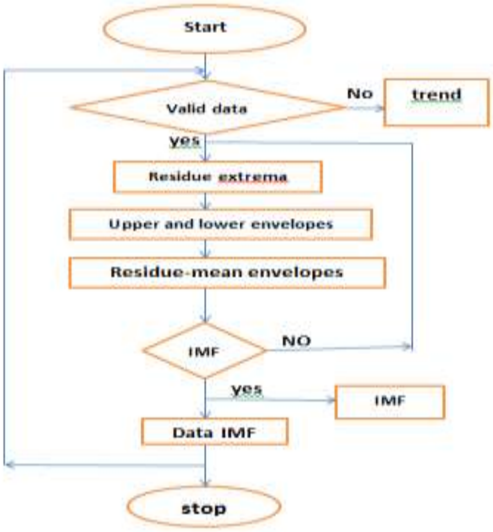
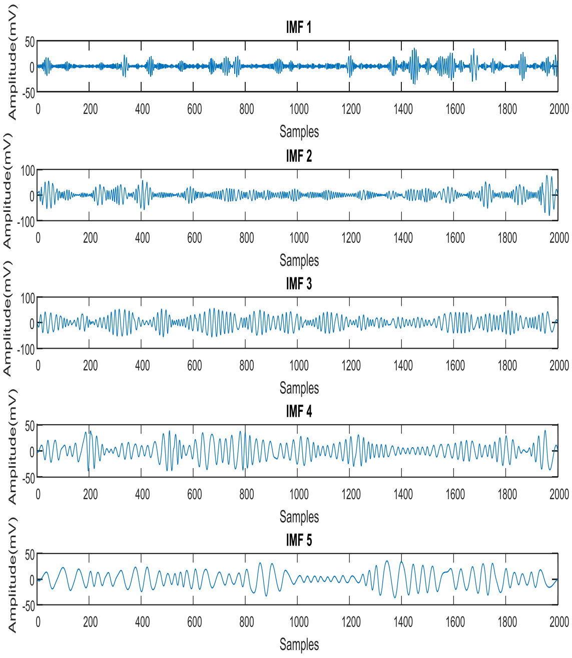


Fig. 2:-Flow chart of EMD algorithm

b) Intrinsic mode Function(IMF) Levels:-

Once the first IMF is obtained, define c1(t)=h1(t), which is the smallest temporal scale in x(t). A residual signal is obtained as r1(t)=x(t)-c1(t). The residue is treated as the next signal and the above mentioned process is repeated until the final residue is a constant (having no more IMFs) fig. 3 at the end of the decomposition [4].



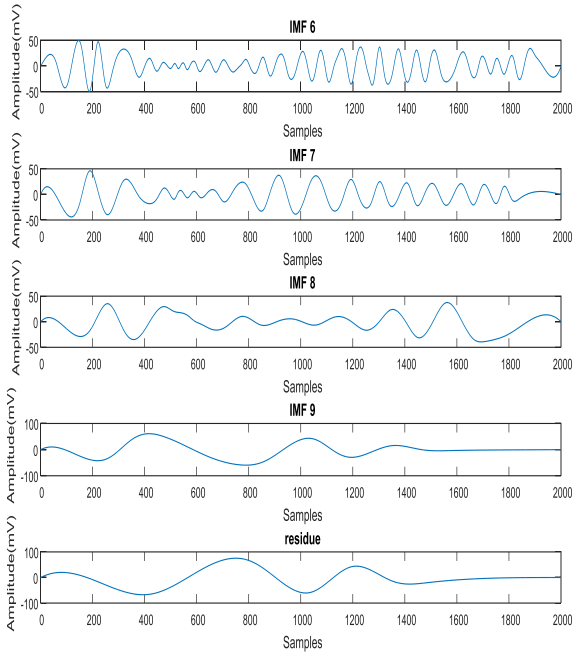


Fig. 3:- Decomposed Normal EEG signal using EMD

C) Features:-

Thus the original signal can be represented as follow:-

$$X(t) = \frac{1}{N}\sum_{i-1}^{N} Cm(t) + Rm(t).$$

Where m is the number of IMFs, $C_m(t)$ is the nth IMF and $R_m(t)$ is the final residue. Thus any signal can be implemented as sum of IMFs and a residue.

i. *Temporal Statistics of analytic IMFs*:-

Statistical features of IMFs are useful for discriminating between normal and pathological EEG signals. The decomposed signals obtained are shown in fig. 4. A visual analysis of the IMFs obtained from healthy and epilepsy patients during interictal and ictal periods after Hilbert transform reveals that they are quite different from one another [7]. Interestingly, these differences are appropriately captured using the statistics of the IMFs for an IMF [6], these statistics can be obtained by the following quantities:

Mean (μ(t)):= $1/N \sum_{i=1}^{N} y(i)$

Variance (σ(t)):= $\sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(y(i) - \mu(t)\right)^2}$

Skewness(β(t)):-$\frac{1}{N}\sum_{i=1}^{N}\left(\frac{y(i)-\mu(t)}{\sigma(t)}\right)^3$

ISSN: 2321-8169
04 - 08

Where N is the number of samples in the IMF.

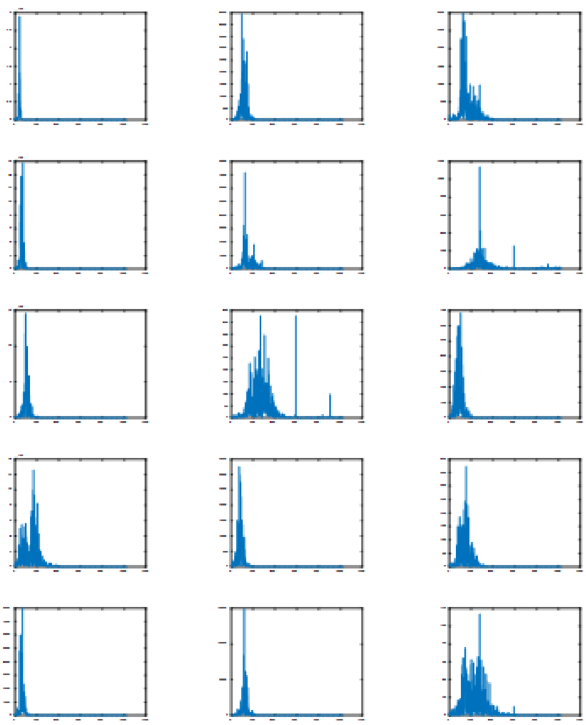


Fig. 4:-plots of temporal signals obtained from the IMFs after EMD decomposition

ii. *Spectral statistics of Analytic IMFs*:-

Strength of EMD is that it has the ability to perform a spectral analysis of the signals. A frequency based analysis can therefore be useful for feature extraction from EEG signals. The spectral features obtained from IMFs can thus give a rich clue about the physiology of the EEG signals. Normally, using EMD, this spectral analysis is done using the calculation of instantaneous frequencies (IF). As an alternative, we have resorted to the calculation of PSD for feature extraction purposes [7]. The discrimination power of the PSD features can be visually analyzed by their respective plots for three IMFs from the normal and pathological EEG signals. The PSD can be calculated as follows:-

$$P(w) = \sum_{-\infty}^{\infty} Ry(n) e^{-jwn}$$

Where Ry(n) represents the autocorrelation of y(n), defined as Ry(n) = E(y(m)y*(m)).

Spectral Centroid:-

The centroid frequencies of the IMFs extracted from EEG signals form distinct groups when supervised clustering is applied on the EEG signals. The centroid frequency is therefore a distinctive feature that can be used for the characterization of EEG signals. It is defined as:-

$$C_s = \frac{\sum_w w P(w)}{\sum_w P(w)}$$

Where P(w) is the amplitude of wth frequency.

Variation Coefficient:-

It gives information about spectral variation in the IMFs. It is different for normal and pathological EEG signals. This variation can be calculated as follows:

$$\sigma^2_s = \frac{\sum_w (w - Cs)^2 P(w)}{\sum_w P(w)}$$

Spectral Skew:-

Skewness is the third order moment and it measures the symmetry/asymmetry of a distribution. Visual inspection of the plot of PSD of IMFs shows that the skewness of the power of IMFs for the normal and pathological EEG signals differs thus potentially yielding a useful feature for the classification of EEG signals. Skewness of the PSD can be calculated a:

$$B_s = \frac{\sum_w \left(\frac{w - Cs}{\sigma s}\right)^3 P(w)}{\sum_w P(w)}$$

Its feature vector can be obtained by their concatenation as follows:-

$$F = [\ \mu(t)\ \sigma(t)\ \beta(t)\ C_s\ \sigma^2_s\ B_s\ ].$$

IV. CLASSIFIACTION

Feature extraction is followed by the classification of EEG signals using support vector machines (SVM). The SVM, originally proposed by Vapnik et al. Mainly consists of constructing an optimum hyperplane that maximizes the margin of separation margin between two different classes. It uses a kernel to transform the input data to a higher dimensional space followed by an optimization step for the construction of an optimum hyperplane [5]. This approach builds the classification models having excellent generalization capability and thus is used in a very wide range of pattern recognition applications. The decision function of SVM is as follows:

$$D(x) = \sum_i \alpha i\, K(Xi, F) + b$$

Where K(.) is the kernel function and F is the input vector. For our implementation, we have used liner kernel for SVM classification.

V. SIMULATION RESULTS

The performance of the proposed methodology for feature extraction from EEG signals is studied using standard measures such as overall accuracy and area under receiver operating characteristics (ROC) curve. In addition to the analysis of results produced by the\ methodology proposed in this paper, we have implemented several other descriptors of EEG signals. These methods

ISSN: 2321-8169
04 - 08

include temporal statistics of IMFs from EMD [8], instantaneous frequency (IF) features, the frequency modulation (FM) and amplitude modulation (AM) bandwidth features [10] and wavelets. This selection has been done based on a high degree of accuracy achieved by these methods in the classification of EEG signals. The features obtained using all the descriptors are classified using four different classifiers i.e., 1-nearest neighbor (1NN), decision trees, artificial neural networks (ANN), and support vector machine (SVM) based classifiers for a rich analysis. The test bench is kept consistent for all these methods to ensure a fair comparison of their performance. According to experimental results we calculate the statistical parameter of seizure and non-seizure. Which is given below. Statistical parameter for non-seizure signal given below:

statistical parameter	imf1	imf2	imf3	imf4	imf5	imf6	imf7	imf8	imf9
mean	-0.03074	-0.04457	0.087518	-0.1015	0.025631	0.220189	-0.25231	0.581286	2.084131
variance	3.897988	16.53824	30.74322	57.30674	98.81519	156.3765	148.7804	138.6543	301.1271
skewness	0.055057	-0.18944	-0.04159	-0.22685	0.185288	0.122848	-0.02109	-0.35402	0.031714
autocorrelation	1	-0.17747	-0.02816	-0.25909	-0.10483	0.067859	0.086789	0.101296	-0.05081
power spectral density	0.300719	0.632448	2.438035	3.278997	0.209109	15.4327	20.26397	107.555	1382.611
stdandard deviation	1.974332	4.066724	5.544657	7.570121	9.940583	12.50506	12.19756	11.77516	17.35301
Instantaneous Frequency	310.7551	215.5773	234.8645	224.8956	182.4685	223.997	301.3318	-456.834	353.3534
spectral centriod	10	10	10	10	10	10	10	10	10
variation coefficient	6.72E-33	9.26E-33	7.68E-34	3.46E-31	8.20E-35	2.76E-31	1.32E-33	9.07E-31	7.01E-31

Statistical parameter for non-seizure signal given below:-

statistical parameter	imf1	imf2	imf3	imf4	imf5	imf6	imf7	imf8	imf9
mean	9.434779	7.716412	5.491209	2.38973	-0.07229	6.177517	-1.15301	-3.63838	-1.93148
variance	124897.3	62937.98	47526.46	43768.23	22504.55	7631.689	2572.267	4319.178	1445.276
skewness	-0.05152	-0.0688	-0.02749	0.085695	0.012142	0.092552	0.067623	0.114994	0.174252
autocorrelation	1	0.881769	0.579875	0.203951	-0.12786	-0.33954	-0.40794	-0.35112	-0.21435
power spectral density	28334.37	18953.13	9598.119	1817.807	1.663226	12147.25	423.1722	4213.72	1187.495
stdandard deviation	353.4081	250.8744	218.0056	209.2086	150.0152	87.35954	50.71752	65.72046	38.01679
instantaneous Frequency	0.027936	1.669903	4.525657	-1.64388	-24.7024	-39.808	14.22582	31.72948	42.37548
spectral centriod	10	10	10	10	10	10	10	10	10
variation coefficient	7.90E-32	1.97E-30	7.04E-32	1.01E-32	4.84E-34	3.01E-30	1.59E-33	3.77E-32	0
spectral skew	1.96E+43	-2.63E+40	4.84E+41	-2.20E+40	-9.27E+35	6.33E+40	-2.26E+42	2.88E+41	0

REFERENCES

[1] V. Srinivasan, C. Eswaran, and N. Sriraam, “Artificial neural network based epileptic detection using time-domain and frequency-domain features,” J. Med. Syst., vol. 29, no. 6, pp. 647–660, 2005.

[2] K. Polat and S. Günes, “Classification of epileptiform EEG using a hybrid system based on decision tree classifier and fast Fourier transform,” Appl. Math. Comput, vol. 187, no. 2, pp. 1017–1026, 2007.

[3] A. Tzallas, M. Tsipouras, and D. Fotiadis, “Epileptic seizure detection in EEGs using time-frequency analysis,” IEEE Trans. Inf. Technol. Biomed., vol. 13, no. 5, pp. 703–710, Sep. 2009.

[4] N. Robinson, A. Vinod, K. K. Ang, K. P. Tee, and C. Guan, “EEG-based classification of fast and slow hand movements using wavelet-CSP algorithm,” IEEE Trans. Biomed. Eng., vol. 60, no. 8, pp. 2123–2132, Aug. 2013.

[5] N. Mammone, F. La Foresta, and F. C. Morabito, “Automatic artifact rejection from multichannel scalp EEG by wavelet ICA,” IEEE Sensors J., vol. 12, no. 3, pp. 533–542, Mar. 2012.

[6] R. B. Pachori and P. Sircar, “EEG signal analysis using FB expansion and second-order linear TVAR process,” Signal Process, vol. 88, no. 2, pp. 415–420, 2008.

[7] S. F. Liang, H. C. Wang, and W. L. Chang, “Combination of EEG complexity and spectral analysis for epilepsy diagnosis and seizure detection,” EURASIP J. Adv. Signal Process, vol. 2010, p. 853434, 2010.

[8] EEG Time Series Download Page 2012 [Online]. Available:http://epileptologiebonn.de/cms/front_content.php?idca=193&lang3

[9] V. Bajaj and R. Pachori, “Classification of seizure and non-seizure EEG signals using empirical mode decomposition,” *IEEE Trans. Inf. Technol. Biomed.*, vol. 16, no. 6, pp. 1135–1142, Nov. 2012.