Epileptic Seizure Detection using Spike Information of Intrinsic Mode Functions with Neural Network

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***Abstract*— The epilepsy is serious neurological disorder which disturb the common activities of person with recurret seizures. The electroencephalogram (EEG) signal is used to analyze for the detection of epilepsy seizure. This paper presents new spike based feature as it is one of main characteristics of epilepsy prone EEG. The IMFs (Intrinsic Mode Decomposition) of the EEG is calculated by employing EMD (Empirical Mode Decomposition) and first five IMFs are used in proposed study. Since the presence of spikes increases the amplitude of signal, maximum value of each IMF is used as feature to train the classifier. The classification of EEG signal into seizure or no-seizure is done by using ANN (Artificial neural networks). The results of the each IMF is recorded individually and concluded the third IMF shows the best presence of spikes. The results of proposed method is also compare with other existing techniques for the validation.**

Keywords—Epilepsy; Seizures; Electroencephalogram; Intrinsic Mode Functions; Empirical Mode Decomposition; Artificial Neural Network.

I. INTRODUCTION

The neurological activities of the human define the status of the brain as well as body. These activities are recorded in the form of signals and analysis of which requires tools pertaining the digital signal processing. One of the disorder for which brain activities are analyzed is for the detection of epileptic seizure. It is unprovoked abnormal activities of the brain which disturb the daily life of person in which person experience seizure which also result into the death in some cases [1]. The activities are generally produced due to the generation of extra electrical charge by the neurons in brain [2]. Total 1% of the world population is suffering from this disease [3]. Electroencephalogram (EEG) signal is measurement of the brain activities in the form of electrical signal which cover the wide range of information of the brain activity. The patient is put under the analysis for long time which results into large data of EEGs and the EEG is studied by the trained experts for abnormality. The whole process is expensive and time consuming [4].

The analysis of an EEG is done by the decomposition or preprocessing of a signal which is followed by the parametric extraction. The parameters must be related to the abnormality for which the signal is analyzed. Discrimination of ECG signal into seizure or no-seizure by using supervised learning mechanism. Different authors have used the different approaches for each step.In [5, 6] an EEG signal is considered as stationary signal, time and frequency related components are extracted from a signal for detection of epileptic EEG signal. The signal is also considered as non-stationary signal in which methods based on time-frequency is employed for EEG signal analysis [7, 8]. The other studies in which signal is considered as non stationary employed multiwavelet [1519] and wavelet [3,9-14] for epilepsy classification.The different parameters extracted related to the epilepsy are frequency based, amplitude based, mean and standard deviation after employing wavelet transformation on the signal and independent component analysis [16-18]. The coefficients of sub-bands, average of coefficients, entropy of the sub-bands after wavelet decomposition are also used as parameters for epilepsy classification [19, 20]. The modeling and prediction error after employing Linear Prediction Filter, Equal Frequency Discretization and Fractional Linear Prediction is also used as parameters for epilepsy classification [21-23].The Empirical Mode Decomposition (EMD) based methods for epilepsy seizure detection has also been developed recently which analyze the signal on the basis of non linear and non-stationary signal [24-28]. The weighted frequency of Intrinsic Mode Functions (IMFs) is considered as discriminating parameters of epileptic and non epileptic EEG signal [24]. In other study related to EMD, the area from the analytic representation of the IMFs is used for classification [25]. The Second Order Difference plots of the IMFs are also proposed for seizure detection [26]. Instantaneous area, amplitude modulation and frequency modulation bandwidth of IMFs is also used for classification in seizure classification [27-28].

II. MATERIAL AND METHOD

A. EEG Dataset

The proposed method is implemented on the publically available dataset by Bonn University, Germany [29]. The whole dataset consist five sets; A, B, C, D and E where each set contains 100 single channel EEG signals of duration 23.6 second. The dataset is recorded by placing the electrodes according to 10-20 international system with with 128 channel amplifier system at 173.61 Hz sampling frequency. The first two set A and B contains the signal of five healthy volunteers by using surface EEG recording system with their eyes open and closed. The set C and D contains the signal from the five patients suffering from epileptic seizure during seizure free stage. The set C contains the signal from epileptogenic zone and set D contains the signal from hippocampal formation of the brain which is opposite to the hemisphere. The last set E contains the signal during the active seizure stage from all the recording sites. To verify the proposed algorithm for seizure detection, two set A and E is considered where set A belong to seizure free class and set E belong to seizure class. The Fig. 1 and 2 shows the signal from Set A and E.

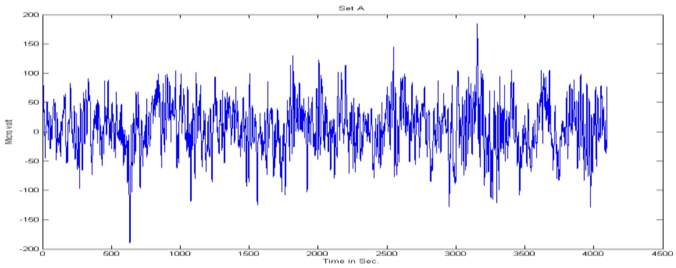

Fig. 1 Signal from Set A (Non-Seizure)

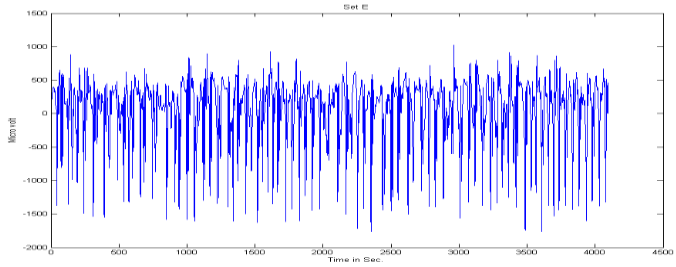

Fig 2. Signal from Set E (Seizure)

B. Empirical Mode Decomposition

The basis of decomposition by EMD is time and frequency oscillation components with assumptions that a signal composed of different intrinsic oscillations. EMD decomposes the signal into the sub-bands which are known as Intrinsic Mode functions (IMF) without providing any condition and information related to the signal linearity [30]. In decomposition of the signal $s(t)$ by EMD can be represented as sum of IMFs and residue which is shown by equation 1, where N is number of IMFs and $r_n(t)$ is residue function.

$$s(t) = \sum_{n=1}^{N} I_n(t) + r_n(t) \qquad (1)$$

The decomposition of the signal into IMFs by EMD must satisfy two conditions. The first condition is in all the dataset number of zero crossing and number of extrema must be either same or differ by one atmost and the second condition, at each point envelope defined by local maxima and local minima must be zero. The algorithm of decomposition of signal $s(t)$ into IMFs by EMD is summarized into following steps:-

1) Extract the extrema value of signal $s(t)$.
2) Connect the maxima and minima by cubic spline interpolation and generate lower envelope $e_1(t)$and upper envelope $e_m(t)$.
3) Find the mean value $m(t) = (e_1(t)+ e_m(t))/2$.
4) Calculate the sample signal: $I(t)=s(t)-m(t)$.
5) Check that the calculated $I(t)$ falls under two conditions which is specified for IMF.
6) Repeat the above steps until the residue is left from which no further IMF can be extracted.

When the first IMF $I(t)$ is found, calculate the residue by subtracting the $I(t)$ from the original signal; $r(t)=s(t)-I(t)$. This process is continue until the residue is left from which no further IMF can be extracted. In proposed study we have considered the first five IMF sub-bands only and the efficiency of IMFs in detection of epilepsy are compared. The decomposition of the one EEG signal from Set A and E by EMD into IMFs is shown in Fig 3-4.

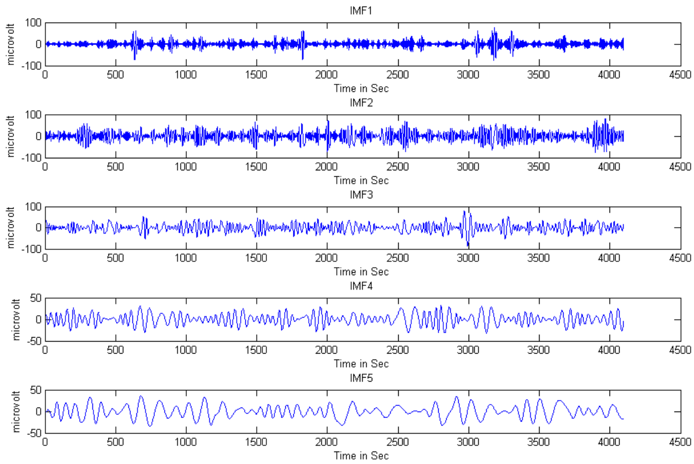

Fig 3 The IMFs of Set A

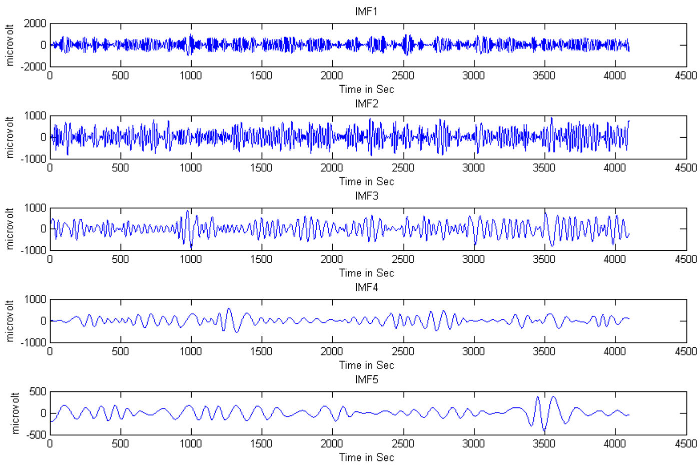

Fig 4 The IMFs of Set E

C. Paramters Extraction

In this stage, parameters from both the classes (Non-Seizure and Seizure) are extracted from the decomposed IMFs of an EEG signal which are further used to train the classifiers. The parameters are chosen in such a way that it must be discriminate the both classes with large margin in their values. The values of the parameters of both classes are desired to be non-overlapping in nature. The spikes are one of the main characteristics of the EEG with epilepsy as compare to normal EEG signal [31, 32]. Now as signal with epilepsy have spikes in its pattern so it is obvious to predict that the amplitude of the epilepsy prone EEG signal would be much higher as compare to the normal EEG signal. For the validation of the above statement, the value of the maximum amplitude is extracted of decomposed IMFs of each signal from the both Set A and E which are graphically plot for each IMF individually. For the better understanding and visibility, only 30 signals are considered for the validation of the above statement. The comparisons of extracted parameters from both classes are shown in Fig. 5-9.

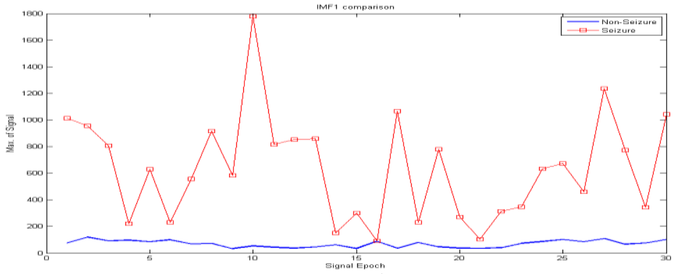

Fig 5 Comparison of IMF1

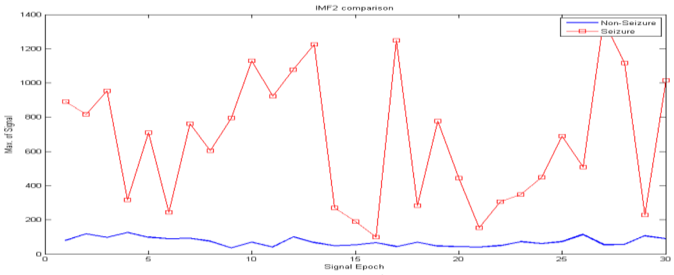

Fig 6 Comparison of IMF2

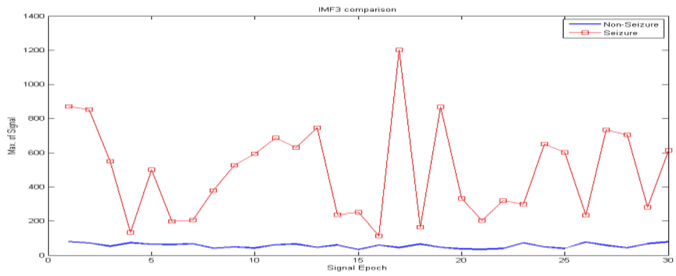

Fig 7 Comparison of IMF3

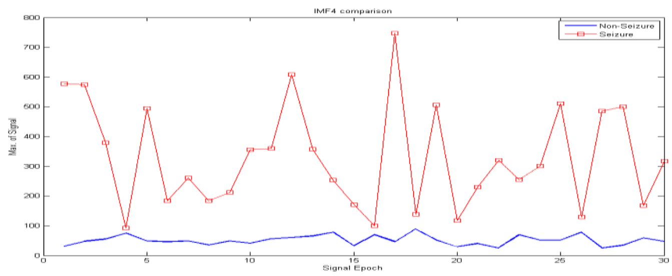

Fig 8 Comparison of IMF4

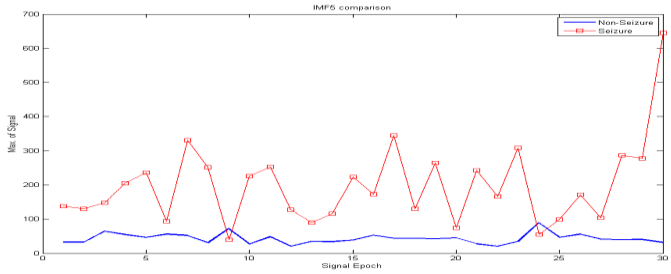

Fig 9 Comparison of IMF5

The Fig 1-4 makes clear that there is least overlapping of the values of maximum amplitude of both classes but in Fig 5 shows that there is little overlapping in the values of parameters of two classes. The average values of the proposed parameters of IMF1 of Set A and E are 74.25 and 555.5, IMF2 of Set A and E are 75.78 and 591.01, IMF3 of Set A and E are 56.01 and 444.85, IMF4 of Set A and E are 49.5 and 303.37 and IMF5 of Set A and E are 43.87 and 197.85. So the Fig 1-5 and average values of parameter from all IMFs shows that EEG with epilepsy activity have spikes as compare normal EEG signal. From the discussion it is clear that spikes are characteristics of epileptic prone EEG signal and are worth for training the classifiers as they are non-overlapping in their nature, so maximum amplitude of the decomposed IMFs are used in proposed study.

D. Classification

ANN has been the choice of classification in many of the different fields due to adaptability and robustness [13, 33]. It consists of the neurons which are arranged in multiple layers named Input layer, Hidden layer and output layers which are arranged in same order. Neurons of the adjacent layers are connected to each other with some associated weights and bias. The weights are adjusted during the training phase to produce the desired results. The back propagation algorithm is used for the classification in two phases. In first phase, the ANN is provided with the training data along with labels to which the training data belongs. Each layer of network receives the training data and propagates it to next layers by applying the transfer function to it except the input layer. The output layer produce the vector which is compared with label of the training data and error is calculated. The weights of the network are updated according the error which is propagated back to network. In second phase, network is tested for the classification of the problem. The test vector is feed to the network and on the basis of output of the network system notifies the presence of abnormality (Epilepsy) in signal. In proposed study, ANN has three layers; first is input layer, second hidden layer and then output layer where output function for hidden and output layers is log sigmoid. The Mean Square Error is used as the performance function.

E. Evaluation Paramters

The performance of the proposed method is measured on basis of merits Classification Accuracy, Sensitivity and Specificity. The definitions of these merits are:

Classification Accuracy: - Number of correctly classified by number of total patterns.

Sensitivity: - Number of correct classification of positive patterns by total number of positive patterns.

Specificity: - Number of correct classification of negative patterns by total number of negative patterns.

III. RESULTS AND DISCUSSION

The proposed method is implemented in MATLAB® 2010b on Core 2 Duo (2.93 GHz) with 2.00 GB memory. Each signal from the Set A (Non-Seizure) and Set E (Seizure) is decomposed into IMFs by employing EMD. The parameters are extracted from the first five IMFs and ANN is trained separately for each IMFs for epilepsy classification. The 70% of dataset considered for implementation of proposed method is used for training classifier and 30% used for validation and testing. The Table 1 shows the results in the form of parameters used for performance measure of proposed method which clearly states that IMF3 shows the best results of the proposed method and IMF5 shows the worst results. The reason for the worst results by IMF5 is because there is overlapping of the values of the parameters of both classes. The graphical plot of the results of proposed method is also shown in Fig 10.

The proposed method is compared with other state of art techniques for epilepsy detection from an EEG signal in Table 2. Only those studies are considered for the comparison which have used the same dataset and same problem set (Set A and E). The proposed method performs better than most of the techniques and hence the proposed parameter for spike representation in epileptic EEG signals is acceptable for classification.

TABLE 1. The results proposed method with each IMFs

S.no.	IMF	Classification Accuracy (%)	Sensitivity (%)	Specificity (%)
1	IMF1	97	96	98
2	IMF2	97.5	96	99
3	IMF3	99	98	100
4	IMF4	98	96	100
5	IMF5	91.5	86	97

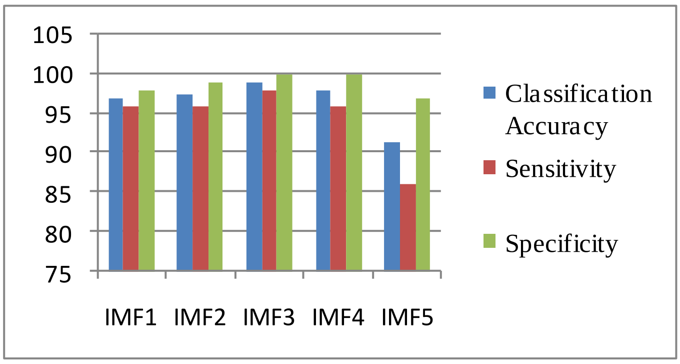

Fig. 10 The results with each IMFs

TABLE 2. Comparison of proposed method

S. no.	Reference	Year	Accuracy(%)
1	[34]	2004	97.2
2	[35]	2005	92.22
3	[5]	2005	99.6
4	[13]	2007	95
5	[6]	2007	98.72
6	[20]	2010	95.2
7	[18]	2011	(PCA + Neural Network) 96.75. (ICA with Neural Network) 93.63
8	[36]	2012	100
9	[23]	2014	93.55
10	proposed	2015	99

IV. CONCLUSION

The visual analysis of an EEG signal for epilepsy is time consuming and expensive. The decomposition of an EEG signal into IMF and using spikes related components of these IMFs for classification reveal that third IMF have better information related to spikes as it gives best results. The graphical plot of the proposed parameters shows the presence of spikes and average values of parameters are also discriminating in nature. The proposed method is designed and tested on publically available dataset and results shows the acceptable nature of parameter for epilepsy classification. The comparison is also made with other techniques for same problem which have used same dataset which shows that proposed spike related parameters are promising in seizure classification.

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The authors declare that there is no conflict of interest.

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