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Classification of EEG Signal for Epileptic Seizure DetectionusingEMD and ELM

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Abstract—This paper proposes the classification of EEG signal for epilepsy diagnosis. Epilepsy is a neurological disorder which occurs due to synchronous neuronal activity in brain. Empirical Mode Decomposition (EMD), Extreme Learning Machine (ELM) are the techniquedelivered in the proposed method.Input EEG signal, which is available in online as Bonn Database is decomposed into five Intrinsic Mode Functions (IMFs) using EMD.Higher Order Statistical moments such as Variance, Skewness and Kurtosis are drawn out as features from the decomposed signals. Extreme Learning Machine is used as a classifier to classify the EEG signals with the taken features, under various categories that include healthy and ictal, interictal and ictal, Non seizure and seizure, healthy, interictal and ictal. The proposed method gives 100%accuracy, 100%sensitivity in discriminating interictal and ictal, non seizure and seizure, healthy and ictal, healthy, interictal and ictal, 100% specificity in classifying healthy and ictal, interictal and ictal and 100% and 99%accuracy in case of discriminating interictal and ictal, non seizure and seizure.

Index Terms—Electroencephalogram(EEG), Empirical Mode Decomposition (EMD), Extreme Learning Machine (ELM), Feature Extraction, seizure detection.

1 INTRODUCTION

Epilepsy is a disorder which happens due to unusual dischargesin brain.The intense electrical activity causes a temporary disruption to normal brain making the brain's messages get mixed up. This results in recurrent seizures. About60 million people are suffered with epilepsy in the world. Epileptic seizures fall into two types namely Partial seizures and Generalized seizures. Partial seizures impact only a portion of the brain which leads to temporal paralysis and generalized seizures involve electrical discharges that occur all over the brain which cause loss of consciousness.

Electroencephalogram (EEG), being a non-invasive tool evaluates the patient with epilepsy. It examines the brain patterns and assists in epilepsy diagnosis, if any unusual activity takes place in the brain. Extracranial EEG measurements are obtained by keeping electrodes on the scalp whereas Intracranial EEG (iEEG) recordings are examined by keeping electrodes on the cortex of the brain or deep within the structure of the brain. For a normal brain activity, the firing of neuron occurs about 80 times per second and neurons fires about 500 times per second for an epileptic brain activity.

Various approaches have been integrated for the seizure detection. Shafiul Alam et al. proposed seizure detection using Artificial Neural Network (ANN).Empirical Mode Decomposition is used for decomposition purpose [1].Shufang Li et al. used EMD to extract coefficient of variation and fluctuation index as features. Support Vector Machine (SVM) classifier is utilized for the classification of interictal and ictal subjects [2].Complexity based features are taken using Wavelet Transform and the features are selected using Genetic Algorithm. Extreme Learning Machine is used as the classifier for recognizing the epileptic activities. The method proposed by Yuedong Song et al. gives less accuracy without the use of Genetic Algorithm [3].Bandwidth features namely Amplitude Modulation Bandwidth and Frequency Modulation Bandwidth is computed using EMD techniques and these features were fed to the Least Square Support Vector Machine (LS-SVM) for classification purpose [4].Nandish et al. used Average method and Max-Min method for taking the features. Among the two methods Max-min with Neural Network gave better accuracy[6].Fuzzy classifier could able to discriminate healthy, interictal and ictal subjects with good accuracy by the usage of entropy features [7].Multiwavelet Transform along with ANN technique had been used by Ling Guo et al. Entropy based features are extracted for classifying healthy and epileptic subjects. Computation cost increases due to the excessive number of features [11]. EEG signal is analysed with time-frequency methods and Artificial

Neural Network (ANN)[16].Usage of ANN makes high computational complexity and takes huge training time.

EMD delivered by Huang is widely adaptable to non-stationary and nonlinear signals.It is used in the case of reducing noise and providing information. In this paper, classification of EEG signal for epileptic seizure detection is done with EMD and ELM. Variance, Skewness and Kurtosis are taken as features,which describes the shape of EEG signals. The features are then trained and tested using ELM classifier to discriminate healthy, interictal and ictal subjects underdifferent cases. ELM classifier requires no iterate tuning and classifies signal with good accuracy.

2 METHODOLOGY

This section has three steps.
i) Decomposition of input signal
ii) Feature Extraction
iii) Classification of EEG signal

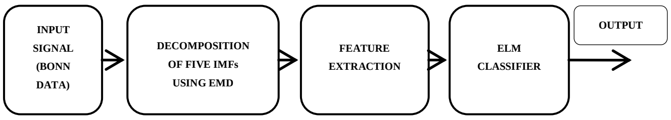

Fig. 1. Block diagram of Seizure detection using EMD- ELM

2.1 DatabaseDescription

Bonn Database [18] from the Department of Epileptology is used. The dataset is possessed with five sets namely Z, O, N, F, S. The dataset Z and O have EEG recordings that were obtained from healthy subjects with their eyes opened and closed respectively. The measurements for the set Z and O were carried out using extracranial electrodes. The dataset N, F, S have recordings from epileptic patients. Sets F and N have EEG measurements that were observed, intracranially during seizure free interval, from epileptogenic zone and from hippocampal formation of opposite hemisphere of the brain. The dataset S has ictal EEG recordings from the epileptogenic zone. The 100 single channel EEG signals from each person are recorded in 23.6s with the sampling rate of 173.6Hz.

2.2 EmpiricalModeDecomposition

An adaptive, nonlinear technique referred as Empirical Mode Decomposition (EMD) fragments the nonstationary signal into Amplitude-Frequency modulated components namely Intrinsic Mode Function (IMF).

The block diagram of seizure detection using EMD with ELM is given in Fig.1.The steps involved in EMD Algorithm is given below
i) Take an input signal s andconsider it to be s=h, n=0
ii) Local maxima and Local minima of input signals are found
iii) Upper envelope (e_{max}) and lower envelope (e_{min}) are found by connecting the local maximum and local minimum respectively, through cubic spline function
iv) Mean of upper envelope and lower envelope are determined

$$m=(e_{max}+e_{min})/2 \qquad (1)$$

v) The value of mean should be subtracted from the input signal

$$H=h-m \qquad (2)$$

vi)Check whether the stopping criterion(α) lies in the range 0.2-0.3, in the calculation of standard deviation given in (3). If the condition is satisfied then take imf_n=H, n=n+1 and go to the step vii, elseconsider the input signal s as H i.e. s=H and repeat the process from i to vi

$$sd=\frac{\sum|H-h|^2}{\sum h^2}< \alpha \qquad (3)$$

vii)Calculate residue signal r=h-imf_n, if r is a function of monotonicity end the process else consider s=r and repeat from (i)

Empirical mode decomposition is more adaptable to nonlinear and nonstationary signals. The frequency component decreases, as the number of intrinsic mode function level increases. The information does not get lost when the frequency decreases. Flow chart of EMD algorithm is given in Fig.2.

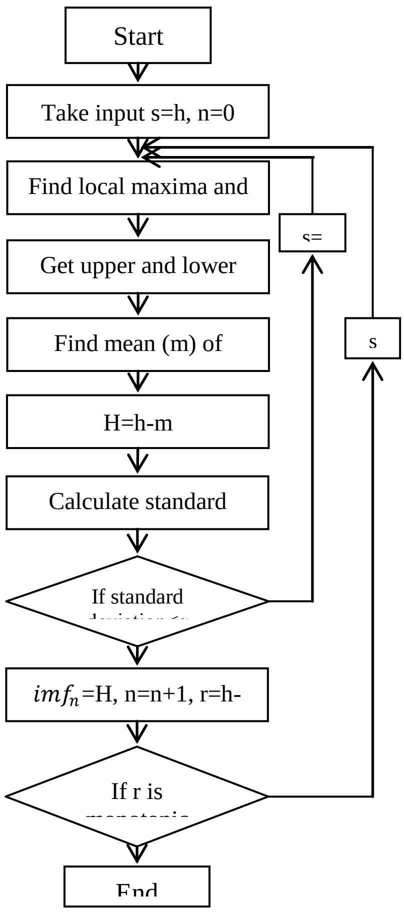

Fig. 2. EMD Algorithm

The original signal(s) can be regained by adding IMFs level and residue signal(r) that have the lowest frequency. The representation of original signal is given by (4)

$$s= \sum_{n=1}^{N} imf_n + r \qquad (4)$$

2.3Feature Extraction

Variance, Skewness and Kurtosis are taken as features from the decomposed signals of EMD. Variance (σ^2), Skewness (sk) and Kurtosis (ku)are given by

$$\sigma^2 = \frac{1}{N}\sum_{i=1}^{N}(x_i - ⍰)^2 \qquad (5)$$

$$Sk=\frac{1}{N}\sum_{i=1}^{N}\left(\frac{x_i-\mu}{\sigma}\right)^3 \qquad (6)$$

$$Ku=\frac{1}{N}\sum_{i=1}^{N}\left(\frac{x_i-\mu}{\sigma}\right)^4 \qquad (7)$$

where the mean (μ) is $\mu=\frac{1}{N}\sum_{i=1}^{N} x_i$, N is the length of imf (N=1024),x_i is the imf of signal for ith sample and standard deviation (σ) is $\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i-\mu)^2}$

Variance, Skewness and Kurtosis describes the dispersion, asymmetry and peakness of the dataset.

2.4Extreme Learning Machine

Extreme Learning Machine makes use of Single hidden layer feed forward neural network (SLFN).Architecture of ELM is given in Fig.3.Single hidden layer feed forward neural network (SLFN) possessing L-hidden node with additive and Radial Basis Function (RBF) is given by

$$\beta_j \, g\,(w_j , b_j , x_i)) = o_j \,(8)$$

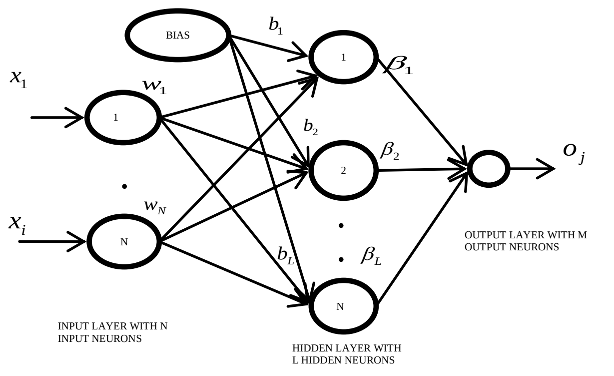

Fig. 3. ELM Architecture

The activation function for additive hidden node and Radial Basis Function hidden node is given (9) and (10)

$$g\,(w_j , b_j , x_i)=g\,(w_j .x_i+b_j)(9)$$

$$g\,(w_j , b_j , x_i)=g\,(b_j \|x_i\text{-}w_j\|)(10)$$

w_j is the weight vector connecting the input layer to the jth hidden nodeand b_j isthe bias of the jth hidden node.For N samples with L hidden nodes that has zero error can be given as T=βH whereβ is the weight between hidden and output layer and T is the target.Unipolar sigmoidal activation function is given by

$$G(w_j , x_i , b_j) = 1\big/ 1+e^{(-((w_j * x_i)+b_j)*\lambda)} \qquad (11)$$

where λ is the learning parameter that ranges between 0 to1.

ELM is carried out three steps that require no tuning. It involves

i) Assigning randomly input weights (w) and bias (b)
ii) Calculating the hidden layer output matrix H
iii)Determining the output weights $\beta^{\wedge} = H^{-1}T$ where H^{-1} is the Moore Penrose generalized inverse of H. The steps are summarized and given in Fig.4.

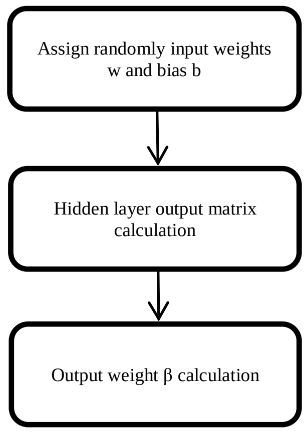

Fig. 4. Steps for ELM

3 PERFORMANCE MEASURES

The performance analysis is carried out by finding Sensitivity, Specificity and Accuracy.

Sensitivity= TP/ (TP + FN)(12)

Specificity= TN/ (TN +FP)(13)

Accuracy=(TP+TN) / (TP+FN+TN+FP)(14)

Where TP, FN, TN, FN represents True Positive,False Negative,True Negative,False Positive respectively.

4 RESULTS AND DISCUSSIONS

Feature extraction and classification of EEG signal is presented using Empirical Mode Decomposition (EMD)with Extreme Learning Machine (ELM) classifier. Bonn dataset being sampled at 173.6 Hz is band limited to 86.8Hz. When decomposition is analysed with EMD, the frequency ranges of first five IMF are given: IMF1 (0–44 Hz), IMF2 (0–30

Hz), IMF3 (0–20Hz), IMF4 (0–9Hz),IMF5 (0–7 Hz).The frequency range gets decreased to the range 0-3 Hz for the 6th IMF.

The epileptic EEG signal deals with the frequency range of 3-29 Hz.So First Five IMF of the signal is used when the decomposition is carried out using EMD. Fig. 5, Fig. 6, Fig.7 shows healthy EEG signal with five imfs, interictal EEG signal with five imfs, ictal EEG signal with five imfs respectively. Theamplitude and frequency modulated oscillatory patterns are well noticed from the generated imfs.

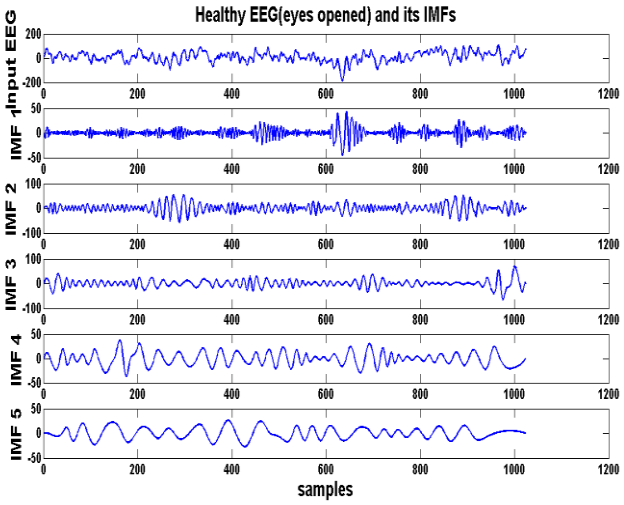

Fig. 5. Healthy EEG (eyes opened) and its five imfs using EMD

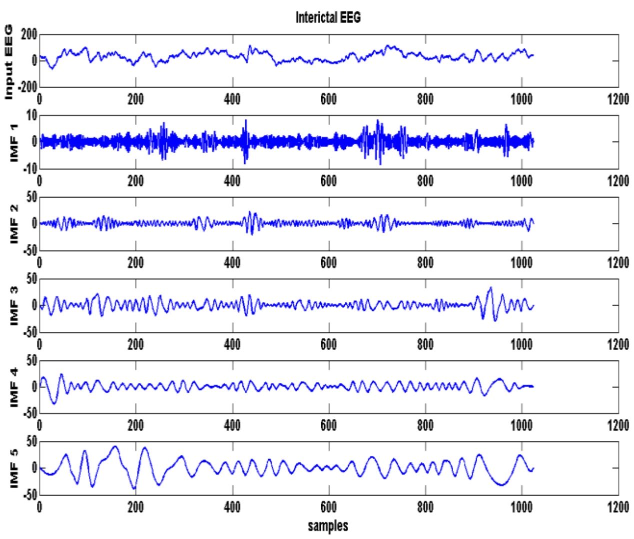

Fig. 6. Interictal EEG and its five imfs using EMD

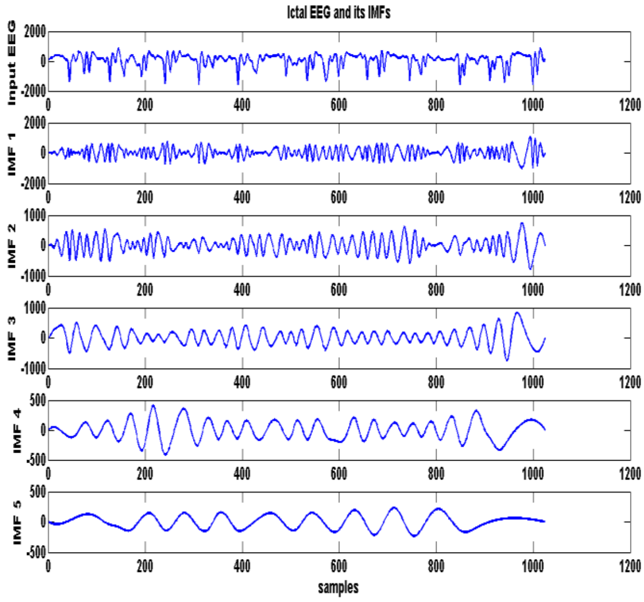

Fig. 7. Ictal EEG and its five imfs using EMD

The extracted featuresnamely variance, skewness and kurtosis are shown in histogram to define the shape of healthy,interictal and ictal EEG signals.Histogram of healthy, interictal and ictal EEG signals are shown in Fig. 8. (a), Fig. 8. (b),Fig. 8. (c) respectively.Mean value of ictal EEG signal is high when compared to interictal and healthy EEG signals.From the histogram diagram, it is seen that the EEG signal's shape differs with the seizure occurrence and nonseizure occurrence

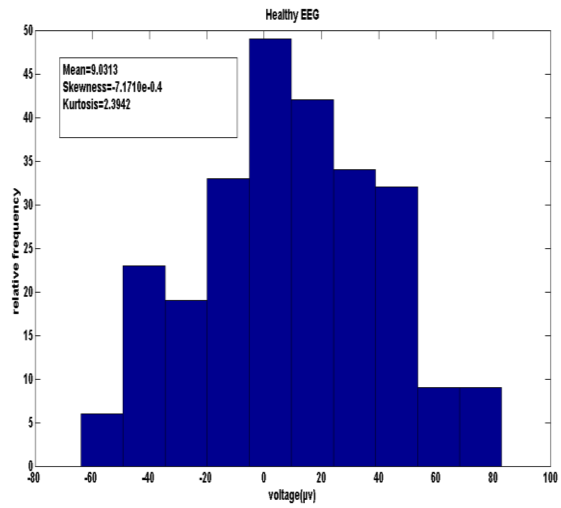

Fig. 8. (a) Histogram of healthy EEG

Fig. 9. (a),Fig. 9. (b),Fig. 9. (c) depicts the histogram of IMF2 of healthy, interictal and ictal EEG signals respectively.

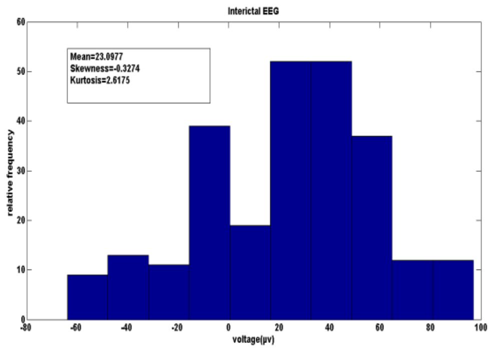

Fig. 8. (b) Histogram of interictal EEG

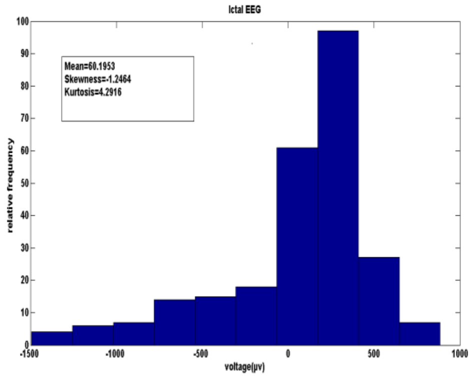

Fig. 8. (c) Histogram of ictal EEG

Classification is done underdifferent case using Extreme Learning with unipolar sigmoidal activation function. Table-I gives the performance analysis of EEG signal classification using single imfs. Classifiers namely C-1, C-2, C-3, C-3 are formed using three features from the five single IMFs. In Case I, sets Z, O, N and F together forms the non-seizure class and sets S form the seizure class. 100% specificity with 99% accuracy is got in C-3 where 100% sensitivity is obtained in C-1 and C-2 while discriminating non seizure from seizure ones.Case-II delivers the classification of EEG signal for healthy subjects (Z) and ictal subjects (S) with accuracy of 96.88%,100% sensitivity and 94%specificity.Perfect classification is achieved in Case-III which depicts the discrimination of interictal and ictal EEG signals.100% sensitivity,100% specificity and 100% accuracy is accomplished in this case.

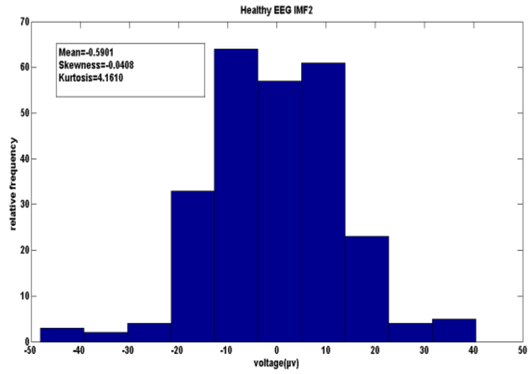

Fig. 9. (a) Histogram of IMF 2 of healthy EEG

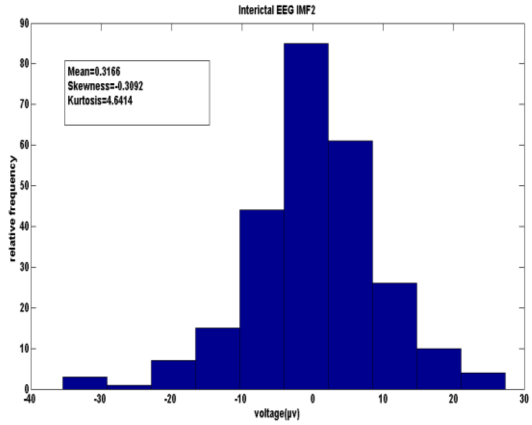

Fig. 9. (b) Histogram of IMF 2 of interictal EEG

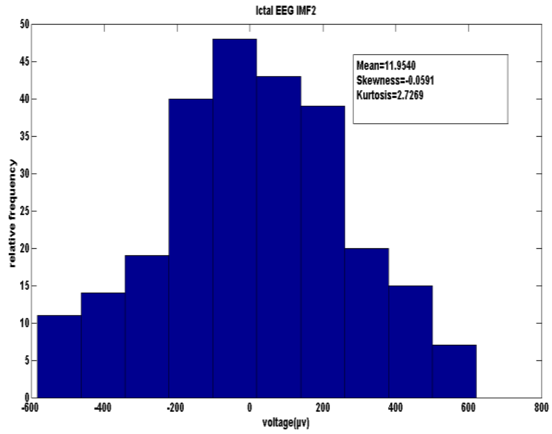

Fig. 9. (c) Histogram of IMF 2 of ictal EEG

Case-IV deals in distinguishing healthy, interictal and ictal class. Accuracy of 98% is got in discriminating ictal from interictal and healthy subjects. In Case-V, sets Z and O are grouped to healthy subjects, sets N and F are tagged to interictal subjects and set E forms the ictal class.100% sensitivity,100% specificity and 100% accuracy is obtained in distinguishing ictal class from healthy and interictal class. Table-II exhibits the classification performance of EEG signal using multiple IMFs. Features from five IMFs are combined and they are given to the classifier C-6.

TABLE 1
CLASSIFICATION PERFORMANCE USING SINGLE IMFs

CLASSIFIERS		C-1	C-2	C-3	C-4	C-5
Case I (Z,O,N, F),S	Sensitivity	**100**	**100**	**93.33**	**93.3**	**100**
	Specificity	82.9	**97.14**	**100**	**94.29**	81.86
	Accuracy	85.88	**97.65**	**99**	**94.12**	84.52
Case II Z,S	Sensitivity	**93.33**	**100**	**93.33**	**93.33**	**100**
	Specificity	**100**	**94.12**	**100**	82.35	70.59
	Accuracy	**96.88**	**96.88**	**96.88**	87.50	84.38
Case III N,S	Sensitivity	**100**	**100**	**100**	**100**	**100**
	Specificity	**100**	82.35	88.24	52.94	82.35
	Accuracy	**100**	**90.6**	**93.75**	75.00	**90.63**
Case IV O,F,S	Sensitivity(O)	**97**	87.88	81.82	**100**	**100**
	Specificity(O)	80	47.06	72.22	66.67	48
	Accuracy(O)	**91.67**	74	79	88.24	78.43
	Sensitivity(F)	**94.44**	84.85	61.11	83.33	44.64
	Specificity(F)	**90**	76.47	78.79	78.79	**90.91**
	Accuracy(F)	**92.11**	82	72	80.39	74.51
	Sensitivity(S)	**100**	**100**	86.67	86.67	**100**
	Specificity(S)	**97.22**	82.86	**97.22**	88.89	50
	Accuracy(S)	**98.04**	88	**94**	88.24	64.71
Case V (Z,O), (N,F),S	Sensitivity(ZO)	88	70	70	80	**92**
	Specificity(ZO)	51.43	60	85.71	35	25
	Accuracy(ZO)	73	65	76.19	61.18	63.10
	Sensitivity(NF)	84.62	60	57.14	53	40
	Specificity(NF)	63	84	**90**	55.10	76
	Accuracy(NF)	73	74.12	76.19	54.12	61.
	Sensitivity(S)	80	**100**	**100**	**100**	**100**
	Specificity(S)	**95.71**	88.57	**100**	88.73	53.62
	Accuracy(S)	**93**	**90.59**	**100**	**90.59**	62

TABLE 2
CLASSIFICATION PERFORMANCE USING MULTIPLE IMFs

CLASSIFIER		C-6
Case I (Z,O,N,F),S	Sensitivity	88.71
	Specificity	34.71
	Accuracy	74.12
Case II Z,S	Sensitivity	80
	Specificity	**100**
	Accuracy	90.63
Case III N,S	Sensitivity	60
	Specificity	52.94
	Accuracy	57
Case IV O,F,S	Sensitivity(O)	61.76
	Specificity(O)	39
	Accuracy(O)	54
	Sensitivity(F)	63.16
	Specificity(F)	73
	Accuracy(F)	69.23
	Sensitivity(S)	20
	Specificity(S)	75.68
	Accuracy(S)	58
Case V (Z,O),(N,F),S	Sensitivity(ZO)	82
	Specificity(ZO)	88.57
	Accuracy(ZO)	84
	Sensitivity(NF)	65.71
	Specificity(NF)	**96**
	Accuracy(NF)	83.53
	Sensitivity(S)	80
	Specificity(S)	88.5
	Accuracy(S)	87

From the Table-I and Table-II, it is expressed that classification using single IMF gives good performance when compared to multiple IMF in most of the cases. Three features are taken when using with single IMF whereas fifteen features are used when dealing with multiple IMFs. Thecomputational time gets reduced when performing with single IMF.

5 CONCLUSION

In this paper, classification of EEG signal for seizure detection under various cases that includes healthy and ictal, interictal and ictal, non seizure and seizure, healthy, interictal an ictal is proposed. EMD is applied to decompose the input signal into five IMFs. Higher order statistical features like variance, skewness and kurtosis are extracted from the decomposed signals to distinguish healthy, interictal and ictal subjects. The taken features aretrained and tested using the ELM classifier. It has been exhibited that the proposed method shows 100% sensitivity, 100% specificity and 100% accuracy in most of the cases when discriminating with single IMF rather than multiple IMFs. Future enhancement can be done by including the case of classifying the EEG signal into sets Z, O, N, F, and S for epilepsy detection.

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