International Journal of Engineering Research and Technology. ISSN 0974-3154 Volume 10, Number 1 (2017)

Application of Intrinsic Mode Function Based Features and Artificial Neural Network for the Classification of Normal and Epileptic EEG Signals

Dattaprasad A. Torse
Research Scholar, Department of Electronics and Communication Engineering,
KLS Gogte Institute of Technology, Udyambag, Belagavi, Karnataka, India.

Veena Desai
Professor, Department of Electronics and Communication Engineering,
KLS Gogte Institute of Technology, Udyambag, Belagavi, Karnataka, India.

Rajashri Khanai
Professor, Department of Electronics and Communication Engineering,
KLE's Dr. M.S.S.C.E.T., Udyambag, Belagavi, Karnataka, India.

Abstract

A seizure is defined as 'a transient occurrence of signs and/or symptoms due to abnormal excessive neuronal activity in the brain'. A subsequent advancement made in epilepsy and neuroscience research defines that the clinical diagnosis of a seizure is experimental and it depends on groups of certain signs and symptoms. This paper on electroencephalogram (EEG) signal analysis focuses on seizure signalsorting byeliminatingsomepossiblesimilar signals to seizures. Seizures have been classified in time and the borders of signals during a seizure, signals between seizures and after a seizure are separated. In this paper a feature extraction method based on EmpiricalMode Decomposition (EMD) is proposed. The sifting process decomposes the EEG signal into Intrinsic Mode Functions (IMFs) by the EMD algorithm and five statistical parameters are computed using these IMFs whichforms the input to a classifiers. Experimental results of two class classifiercarried out on the clinicaldataset show that an accurate classification rate of 96.3% is achieved in the discriminationbetween normal and ictal EEG, and an accuracy of 95% is reached in the classification ofinterictal and ictal EEG signals. The results are comparable or have done better thancurrentresearchpublished.

Keywords: Empirical Mode Decomposition, Intrinsic Mode Function, Adaptive Data Analysis, Information Transfer Rate, Neurofeedback, Neural Networks

Introduction

TheEEG is a time varying non-stationary signalgenerated by brain electrical activity recordedfromscalpelectrodes on the surface of the head [1]. The study of theEEG plays a vital role in the analysis ofneurological diseases. Epilepsy is one of the most commonneurological disorder affecting more than 50 million individualsover the world [2]. Traditionally, neurologists utilize a visualinspection of the EEG recordings in order to detect epilepticseizures, and this is a cumbersome and subjective process with many errors in diagnosis. The methods aretime consumingespecially with large duration EEG recordings. Hence, an automatic method of diagnosis is proposed and implemented effectively by many researchers. Since EEG monitoring and analysis in patients isa continuous process, in order to make it fully automated with indication of seizure occurrence, many signal processing algorithms need to be considered. A neurofeedback technique is an effective way to treat brain disorders in which faster algorithms improve the Information Transfer Rate (ITR) to improve system response.

In the last two decades, many researchers addressed theproblem of automatic seizure detection. It has been shown [3,4]that all the methods fall into four categories: (i) time domain, (ii) frequency domain, (iii) joint time–frequency domain, and (iv)nonlinear methods. Using Principal and Independent Component Analysis (PCA and ICA) the classification of epileptic EEG signals is achieved in [5]. The spectral analysis by Fourier methods is a common technique used in EEG analysis in the frequency domain. A system for two-class epilepsy detection using the nonparametric Welch method is presented in [6]. Many researchers have tried joint time-frequency domain feature extraction method due to the fact that Fourier method are not suitable for non-stationary EEG signals [7,8]. The joint time–frequency methods like the Wavelet Transform (WT), Discrete Wavelet Transform (DWT) [9] for automated detection of epilepsy and Acharya et al.[10] used wavelet packet decomposition (WPD) for detecting epileptic stages using Higher Order Spectra (HOS) cumulants. The Recurrence Quantification Analysis as nonlinear method has been used to show nonlinearity characteristics of the EEG signals in [11].

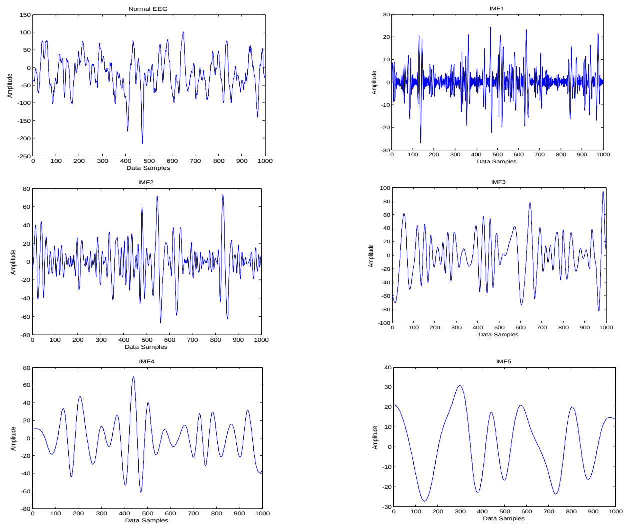
For nonlinear and non-stationary signal analysis Huang et al. [12-15] developed a data driven technique known as Empirical mode decomposition (EMD). In EMD, EEG signal is decomposed adaptively into a finite number of Intrinsic Mode Functions (IMFs). Research on effectiveness of IMF features such as entropy, inter-quartile range, mean absolute deviation and standard deviation has been done [16]. More advanced statistical examination of the resulting IMFs has revealed that the energy evaluation of IMFs [17], the weighted frequency of each IMF [17], the direct area of analytic IMFs [18], the coefficient of variation and fluctuation index of IMFs

International Journal of Engineering Research and Technology. ISSN 0974-3154 Volume 10, Number 1 (2017)

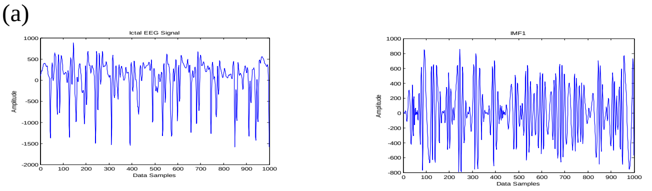
[19] all calculated after applying EMD to preprocessed EEG signals have been used as features for epileptic seizure detection. In this paper, we propose five statistical parameters for the classification of non-seizure (normal, interictal) and seizure (ictal) EEG signals. These statistical parameters calculated using IMFs obtained from the decomposition of EEG raw signals by the EMD method, have been used as feature inputs to a Multilayer Perceptron Neural Network (MLPNN). The MLPNN is used due to its capability to classify non-stationary signals with optimum learning algorithm [20].

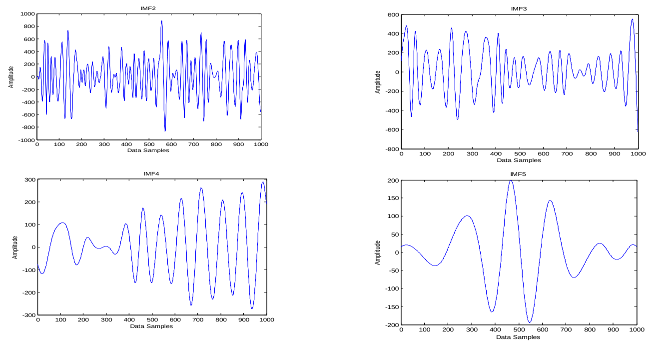
Dataset

The paper utilizes EEG dataset obtained from Dr. Mohire's Clinic and Research center, Kolhapur, India recorded using RMS EEG machine. Another dataset used in our experiments is from the department ofepileptology at the University of Bonn, which is publiclyavailable in [21]. The datasetconsists offive sets (denoted Z–E), each containing 100 singlechannelEEG signals of 23.6 s. For every single channel recording each data is represented for 4096 samples out of which 1000 data points have been considered in this work. These signals have been sampled at frequency of 173.61 Hzwith bandpassfilter settings at 0.5–40 Hz. Sets Zand O have been taken from surface EEG recordings offivehealthy volunteers, while sets N and F have been measured inseizure-free intervals fromfive patients. Set Srecording exhibit ictal activity.Therefore, in the present work three dataset Z, F, and Scorresponding respectively to normal EEG signals, interictal action and seizure activity was classified. Note that the signals of set E are taken frompatients during a seizure activity, while the signals of set F arefrom the same patients in seizure-free intervals.

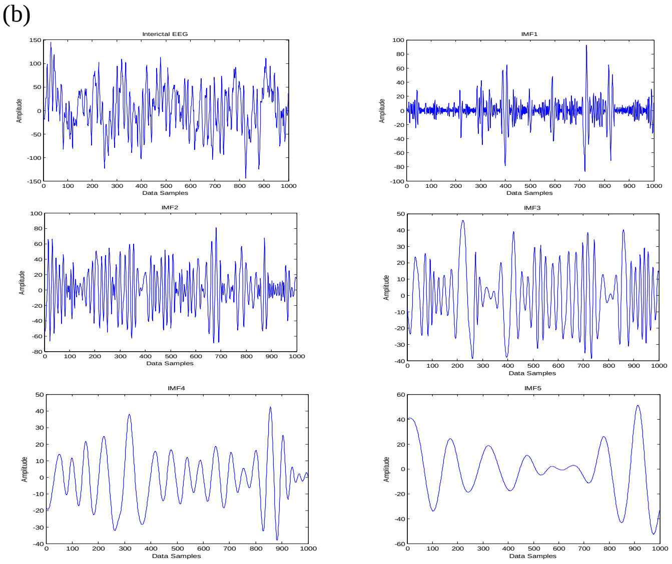


(a)





(b)



(c)

Figure 1: (a)Normal EEG signal, its first four IMFs and residual, (b)Interictal EEG signal, its first four IMFs and residual, (c) Ictal EEG signal, its first four IMFs and residual

Empirical Mode Decomposition (EMD)

A purely adaptive data driven analysis toolEmpirical Mode Decomposition (EMD) method decomposes any nonlinear and non-stationary signal $x(t)$ into a finite number of intrinsic mode functions (IMFs). In order to decompose the signal each IMF satisfies two fundamental conditions [22]: (1) the number of extrema and the number of zero crossings must be the same or differ by at most one; (2) at every point, the mean value of the envelope defined by the local minima and the envelope defined by the local maxima is zero. A signal $x(t)$ can be expressed in terms of its M IMFs as:

$$x(t) = \sum_{m=1}^{M} imf_m(t) + r_m(t) \quad (1)$$

Where$M$ is the number of IMFs, $imf_m(t)$ is the m^{th} IMF, and $r_m(t)$is thefinal remainder.

The complete procedure for getting IMFs for the signal $x(t)$ areexplained as follows [19,23]:

Initialization: $m = 0; r(t) = x(t)$

(1) Find the local minima and the local maxima of $x(t)$.

(2) Get the lower and upper envelopes $e_l(t)$ and $e_u(t)$ bylinking the minima and the maxima respectively witchcubic spline interpolation.

(3) Determine the mean $M_n(t)$ as:

$$M_n(t) = \frac{e_{l(t)} + e_{u(t)}}{2} \quad (2)$$

(4) Extract $h(t)$ as:

$$h(t) = x(t) - M_n(t) \quad (3)$$

if $h(t)$ satisfies the IMF conditions, $m = m + 1$, $imf_m(t) = h(t)$,go to (5) else x(t) = h(t) and repeat (1)–(4).

(5) Define:

$$r(t) = r(t) - imf_m(t) \quad (4)$$

if r(t) is a monotonic function, terminate the procedure,else, $x(t) = r(t)$ and go to (1).

Artificial neural network (ANN)

The Artificial Neural Network (ANN) is mainly employed in pattern recognition. An ANN is formed by a massively neural units fully connected to each other. The neural network has to be trained (in supervised manner) to optimally adjust weights and biases in order to produce a desired output. Artificial neural networks (ANN) were successfully used in a wide variety of medical applications [24–28]. The Multilayer Perceptron Neural Network (MLPNN) is apparently the most commonly employed neural network construction due to its ability to classify unobserved dataand simplicity of use on test data. A MLPNN, with a three layer structure namely: an input layer, a hidden layer and an output layer,is majorly used in classification problems. In major classification problems, the desired output vector has its components 1's and 0's, with 1 indicates the class to which belongs the corresponding input vector. The input layer's size is decided by the input feature vector, a hidden layer has number of nodes decided by cross validation, and an output layer is designed by the desired output vector. In this work the MLPNN has been trained with backpropagation algorithm [20].

Classifier assessment performance

The performance of the MLPNN classifier is evaluated using three parameters, namely sensitivity (SE), specificity (SP) and classification accuracy (CA) defined as [28]:

$$SE(\%) = \frac{NP}{TNP} \times 100 \quad (5)$$

where NP represents the number of correctly detected positive patterns andTNP represents the total number of actual positive patterns. A positive pattern indicates a detected seizure (ictal).

$$SP(\%) = \frac{NN}{TNN} \times 100 \quad (6)$$

where NN represents the number of correctly negative pat-terns and TNN the total number of actual negative patterns.

$$CA(\%) = \frac{NC}{TNP} \times 100 \quad (7)$$

whereNCC represents the number of correctly detected pat-terns and TNP represents the total number of patterns.

Methods

The automated seizure detection algorithm is shown in Fig.1. The algorithm is applied to every epoch of EEG signal considered for the datasets.

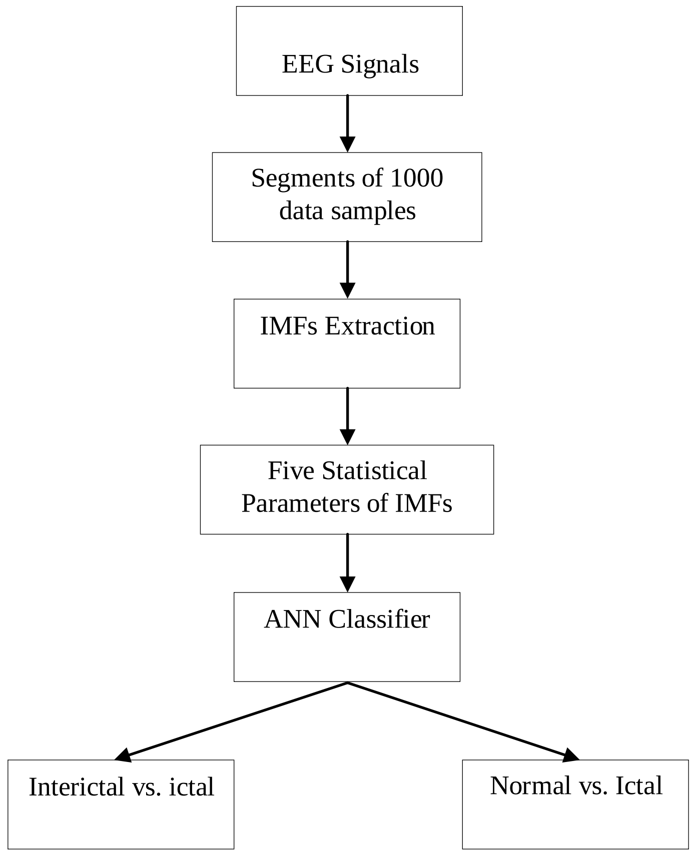


Figure 2: Flow chart of the proposed seizure detection technique.

Results

To authenticate the algorithm proposed in this paper, EMD is applied on all types of EEG signals and IMFs are obtained. The statistical parameters of these IMFs are applied to MLPNN for classifications. The detailed results are discussed in the following section.

Feature Extraction

In this study five statistical parameters are calculated on each IMF obtained after the decomposition of an EEG segment by the EMD algorithm. These statistical parameters are used as a single input vector to the MLPNN classifier.

The statistics employed in this study are as follows [29]:

1. Mean value in each IMF
2. Minimum value in each IMF.
3. Maximum value in each IMF.
4. Standard deviation in each IMF.
5. Variance in each IMF.

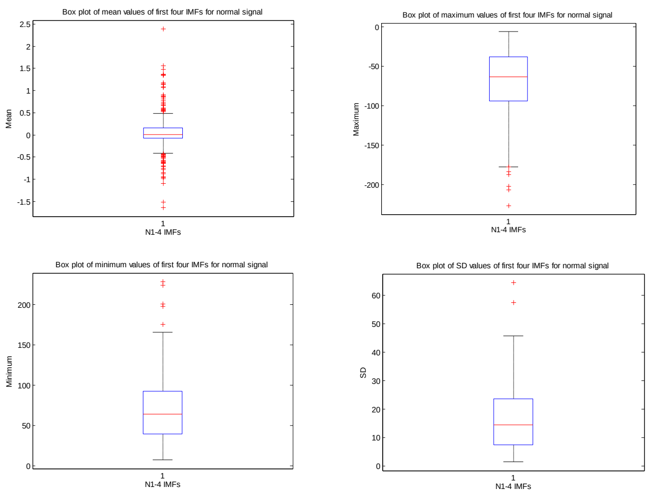
The statistical parameters of combination of first three IMFs have been considered for producing a strong feature vector.

Classification using MLPNN

All the 300epochs of normal, epileptic and interictal EEG signals are of segments of 1000 data samples and each segment is decomposed into four IMFs and residual. Selection of the appropriate number of IMFs is of great importance in the analysis of signals using EMD. The EMD method is purely data driven and the length of the signal being processed plays an important role in deciding the feature values for classification.For long size signalssufficient number of the IMFs are extracted. For the same reason a data sample value of 1000 is selected in this work as compared to smaller data samples [30]. The theory of EMD suggests that first few IMFs can contain the higher frequency components and subsequent IMFs represent lower average frequencies [31]. Therefore, the first four IMFs of each EEG segment are considered in this study.

The box plots for the mean, minimum, maximum, standard deviation and variance of the values of the four IMFs are plotted in Fig. 3-5. These values have been calculated for calculated for normal, interictal and ictal EEG segments respectively. It is shown that the regions for ictal, normal and interictal features are different for these EEG segments. To obtain this variation a complex nonlinear classifier has been used. The multilayer perceptron neural network (MLPNN) with 25 hidden layer is set to 20, while in the output layer it is set to 2 and equals the number of the distinct classes.

Selection of 75%, 50% and 40% of the features of each set (Z, F, S) is done and used for training, validation and testing the MLPNN. In this work, this feature extraction and classification algorithms have been developed usingMATLAB [32]. The support set is used as an early stopping criterion to avoid over-fitting. The sensitivity, specificity and classification accuracy of the classifier is shown in Tables 1 and 2. For first four IMFs i.e. IMF1, IMF2, IMF3 and IMF4 the classifier has inputs vectors taken only from these IMFs statistical parameters. For testing the efficacy of combination of IMF parameters IMF 1–2, 1-3 and 1-4 are considered which means that the statistical parameters are from the combined IMFs: 4 parameters for 3 IMFs and a total number of 12 parameters are considered.



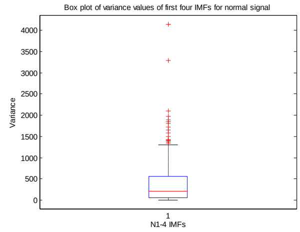


Figure 3: Box Plots for first four IMFs ofnormal signal.

When features are computed with the first four IMFs that is IMF 1–4, a correct performance of the classifier in terms of Sensitivity (SE), Specificity (SP) and Classification Accuracy (CA) is obtained. The Table 2 depictsthe role of combining the IMFs for improvement in the accuracy. But due to lack of correlation between the features there is no significant improvement is seen. The best performance reached in the classification on EEG signals between the seizure and seizures is with values of 96.5% of sensitivity, 96.3% of specificity and 95% of classification accuracy.

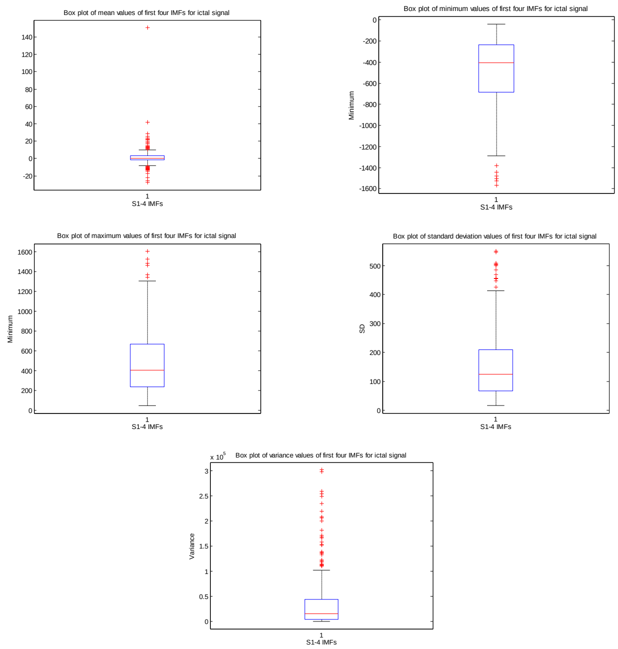


Figure 4: Box Plots for first four IMFs ofseizure signal.

For the classification ofseizure-free and seizure signals (Z–S), the accuracy obtained by the method explained is equivalent to the published results. In the case of the classification of between seizure and seizure signals (F–S), the accuracy obtained by the proposed method is 95 % and performs better than the other methods presented in the literature.

The classification between interictal and ictal EEG signals, the best classification accuracy was attained by the first IMF, afterwards the performance decreased as the levels of the IMFs increased; the combination of the statistical parameters from the pooled IMFs did not yield better accuracies.

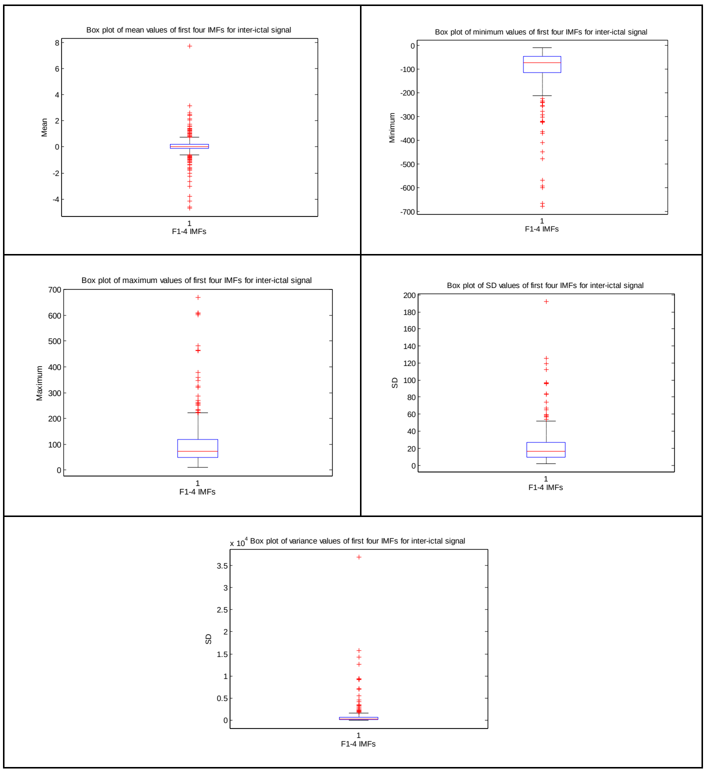


Figure 5: Box Plots for first four IMFs ofseizure signal.

The classification performance of normal and epileptic EEG signals is obtained by employing the statistical parameters obtained from IMFs. The EEG being a nonlinear and non-stationary signal the EMD is an effective tool to the decompose the signalinto a set of symmetric, amplitude and frequency modulated (AM-FM) components [33]. The lower level IMFs contain more frequency components and fast oscillations than the higher order IMFs. This property of analysis helps analysis of non-stationary signals by considering statistical parameters.

Table1: Classification performance for normal and ictal EEG signals.

IMF features	SE(%)	SP(%)	CA(%)
IMF1	92.7	92.5	93.7
IMF2	92.5	92.1	94.1
IMF3	81.3	82.2	88.3
IMF4	79.3	81.2	85.2
IMF1-2	95.8	89.3	95.7
IMF1-3	96.3	92.8	96.1
IMF1-4	97.5	97.3	96.3

Table2: Classification performance for interictal and ictal EEG signals.

IMF features	SE(%)	SP(%)	CA(%)
IMF1	92.7	92.5	94.1
IMF2	92.5	92.1	94.2
IMF3	80.3	81.2	82.7
IMF4	78.3	79.2	80.2
IMF1-2	92.8	89.3	94.2
IMF1-3	92.3	91.8	94.7
IMF1-4	96.5	96.3	95.0

Table 3 presents the comparison of the performance between the proposed method and other methods reported in the literature. The techniques developed using the same dataset are considered for the performance comparison.

Table3: Comparison of Classification algorithms

Reference	Technique	CA(%)
Georgion et al.	Permutation Entropy, Support Vector Machine	79.94
Acharya etal.	Entropy, ANN	92.22
Kumar et al.	Wavelets, ApEn, ANN	95
Kumar et al.	Wavelets, ApEn, SVM	95.85
Tzallas et al.	Time-frequency, ANN	100
RamBilas Pachori	EMD, SVM (LS-SVM)	100
This work	EMD, ANN	96.3

Conclusion

In this paper an optimum feature extraction method is proposed for classification of in two class seizure detection. The proposed method utilizes five statistical parameters calculated for IMFs obtained on decomposed EEG signals by the EMD algorithm. A MLPNN is used for the two class classification. Most of the frequency variation is obtained through the first IMFs whichcontain pertinent fundamental properties of EEG signals and result in consistent features in automatic seizure detection settings. An accurate classification performance for normal and ictal EEG signals with accuracy of 96.3% is obtainedand withinterictal and ictal EEG datasets this value is 95%. These results are reliable and are better than few results from other literature on same datasets.Although the dataset used in this paper is commonly used by various researchers for the classification of epileptic and non-epileptic EEG signals, the study presented in this paper is on the long duration EEG recordings. This results in development of an alarm system to alert a seizure onset for patients affecting from epilepsy.

References

[1] Van Veen, Barry D., et al. , "Localization of brain electrical activity via linearly constrained minimum variance spatial filtering", IEEE Transactions on biomedical engineering 44.9 pp. 867-880, 1997.

[2] Gooch, Clifton L., Etienne Pracht, and Amy R. Borenstein, "The Burden of Neurological Disease in the United States: A Summary Report and Call to Action", Annals of Neurology, 2017.

[3] Carney PR, Myers S, Geyer JD. Seizure prediction: methods. Epilepsy Behav, 22:pp.94–101, 2011.

[4] Acharya UR, Tree SV, Swapna G, Martis RJ, Suri JS., "Automated EEG analysis of epilepsy: a review", Knowledge Based Syst, 45, pp.147–65, 2013.

[5] Subasi A, Gursoy MI. "EEG signal classification using PCA, ICA LDA and support vector machines", Expert SystAppl, 37(12):8659–86, 2013.

[6] Liu A, Hahn JS, Heldt GP, Coen RW., "Detection of neonatal seizures through computerized EEG analysis.ElectroencephalogrClin Neurophysiol, vol82, pp. 30–7, 1992.
[7] Polat K, Gunes S. Classification of epileptiform EEG using a hybrid systems based on decision tree classifier and fast Fourier transform. Appl Math Comput., vol. 187(2), pp.1017–26, 2007.
[8] Adeli H, Zhou Z, Dadmehr N. Analysis of EEG records in an epileptic patient using wavelet transform. J Neurosci Methods, vol. 123(1), pp.69–87, 2003.
[9] Bhattacharyya, Abhijit, et al. "A novel approach for automated detection of focal EEG signals using empirical wavelet transform", Neural Computing and Applications, pp.1-11, 2016.
[10] Acharya, U. Rajendra, et al. "Use of principal component analysis for automatic classification of epileptic EEG activities in wavelet framework." Expert Systems with Applications 39.10 (2012): 9072-9078.
[11] Dattaprasad A. Torse, Veena Desai, Rajashri Khanai, "Classification of Epileptic Seizures using Recurrence Plots and Support Vector Machine", IEEE International Conference on Engineering and Technology (ICET), 2016.
[12] Li, Xinyang, et al., "Discriminative Ocular Artifact Correction for Feature Learning in EEG Analysis", IEEE Transactions on Biomedical Engineering, 2016.
[13] Li, Shufang, et al. "Feature extraction and recognition of ictal EEG using EMD and SVM", Computers in biology and medicine 43.7 (2013): 807-816.
[14] Riaz, Farhan, et al., "EMD-based temporal and spectral features for the classification of EEG signals using supervised learning", IEEE Transactions on Neural Systems and Rehabilitation Engineering 24.1, pp. 28-35, 2016.
[15] Lehnertz K, Elger CE. Spatio-temporal dynamics of the primary epileptogenic area in temporal lobe epilepsy characterized by neural complexity loss. ElectroencephalogrClinNeurophysiol 1995;95(2):108–17.
[16] Biju, K. S., Hara Abdul Hakkim, and M. G. Jibukumar., "Ictal EEG classification based on amplitude and frequency contours of IMFs", Biocybernetics and Biomedical Engineering 37.1, pp.172-183, 2017.
[17] Huang NE, Shen Z, Long SR, Wu MC, Shih HH, Zheng Q, et al., "The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis", Proc R SocLond, 454: pp.903–95, 1998.
[18] Orosco L, Laciar E, Correa AG, Torres A, Graffigna JP.,"An epileptic seizures detection algorithm based on the empirical mode decomposition of EEG", Conf. Proc. IEEE Eng. Med. Biol. Soc.; 2009.
[19] Pachori, Ram Bilas, and Shivnarayan Patidar, "Epileptic seizure classification in EEG signals using second-order difference plot of intrinsic mode function", Computer methods and programs in biomedicine 113.2, pp. 494-502, 2014.
[20] Bishop CM. Neural networks for pattern recognition. Oxford: Oxford University Press; 1995.
[21] Andrzejak RG, Lehnertz K, Monmann F, Rieke C, David P, Elger CE. "Indications of nonlinear deterministic and finitedimensional structures in time series of brain electrical activity: dependence on recording region and brain state", Phys Rev 64(6): pp.061-907, 2001.
[22] Bajaj V, Pachori RB., "Epileptic seizure detection based on the instantaneous area of analytic mode functions of EEG signals", Biomed EngLett,vol. 3:pp. 17–21, 2013.
[23] Li S, Zhou W, Yuan Q, Geng S, Cai D., "Feature extraction and recognition of ictal EEG using EMD and SVM", ComputBiol Med, 43: pp.807–16, 2013.
[24] Bajaj V, Pachori RB., "Classification of seizure and non-seizure EEG signals using empirical mode decomposition", IEEE Trans InfTechnol Biomed, 16(6): pp. 1135–42, 2012.
[25] Flandrin P, Rilling G, Goncalves P. "Empirical mode decomposition as a filter bank", IEEE Signal Process Lett, 11(2):112–4, 2004.
[26] Lin H. "Identification of spinal deformity classification with total curvature analysis and artificial neural network", IEEE Trans Biomed Eng, 55(1): pp. 376–82, 2008.
[27] Srinivasan V, Eswaran C, Sriraam N. "Approximate entropybased epileptic EEG detection using artificial neural networks", IEEE Trans InfTechnol Biomed 11(3): pp.288–95, 2007.
[28] Acharya UR, Faust O, Kadri NA, Suri JJ, Yu W. "Automated identification of normal and diabetes heart rate signals using nonlinear measures", ComputBiol Med 43 (10):1523–9, 2013.
[29] Brownlee, Kenneth Alexander, and Kenneth Alexander Brownlee. Statistical theory and methodology in science and engineering. Vol. 150. New York: Wiley, 1965.
[30] Guo L, Riveero D, Pazaos A. "Epileptic seizure detection using multiwavelet transform based approximate entropy and artificial neural networks", J Neurosci Methods, 193:156–63, 2010.
[31] Djemili, Rafik, Hocine Bourouba, and MC Amara Korba. "Application of empirical mode decomposition and artificial neural network for the classification of normal and epileptic EEG signals." Biocybernetics and Biomedical Engineering 36.1, pp. 285-291, 2016.
[32] Neural Network Toolbox; 2010, Available from: http://www.mathworks.com/help/toolbox/nnet/nnet_product_page.html.
[33] Sharma R, Pachori RB. "Classification of epileptic seizures in EEG signals based on phase space representation of intrinsic mode functions", Expert Syst. Appl, vol.42, pp.1106–17, 2015.