American Journal of Computer Science and Engineering
2015; 2(4): 26-31
Published online July 20, 2015 (http://www.openscienceonline.com/journal/ajcse)

Epilepsy Seizure Detection Using Autoregressive Modelling and Multiple Layer Perceptron Neural Network

Abdelhaq Ouelli*, Benachir Elhadadi, Hicham Aissaoui, Belaid Bouikhalene

Sustainable Development Laboratory, University Sultan Moulay Slimane, Beni Mellal, Morocco

Email address

ouelli2000@yahoo.fr (A. Ouelli)

To cite this article

Abdelhaq Ouelli, Benachir Elhadadi, Hicham Aissaoui, Belaid Bouikhalene. Epilepsy Seizure Detection Using Autoregressive Modelling and Multiple Layer Perceptron Neural Network. *American Journal of Computer Science and Engineering.* Vol. 2, No. 4, 2015, pp. 26-31.

Abstract

In this paper, we present a new method for epilepsy seizure detection based on autoregressive modelling. The method, termed linear prediction coding (LPC), is used to model ictal and seizure-free EEG signals. It is found that the modeling error energy is substantially higher for ictal EEG signals compared to seizure-free EEG signals. Moreover, it is known that ictal EEG signals have higher energy than seizure-free EEG signals. These two parameters are then given as inputs to train a Multiple Layer Perceptron (MLP). The trained MLP is then used to classify a set of EEG signals into ictal and seizure-free categories. It is found that the proposed method gives a classification accuracy of 94.67% when the MLP is trained with the Levenberg–Marquardt (LM) algorithm.

Keywords

Electroencephalogram (EEG) Signal, Linear Prediction Coding (LPC), Multiple Layer Perceptron (MLP), Epileptic Seizure Classification

1. Introduction

Epilepsy is a neurological disorder that affects approximately 1% of the world's population (about 50 million people). Epileptic seizures are the result of abnormally excessive or synchronous neural activity in the brain. One of the widely used methods to assess brain activity is through the Electroencephalogram (EEG) signals. Detection of epileptic seizures using the EEG signals is important for the diagnosis of epilepsy [1].

During epileptic seizures major changes occur in a patient's EEG signal due to synchronous electrical activity of the neurons. One of the definite characteristics of seizure EEG signal is the occurrence of spikes and sharp waves [2]. Detection of seizures using EEG signals is required in both diagnostics and therapy. The parameters extracted from EEG signals can be used as valuable diagnostic features for automatic detection of epileptic seizure [3]. Spectral parameters based on the Fourier transform are commonly used features for detection and classification of epileptic seizure EEG signals [4]–[5]. However, the underlying assumption of the Fourier transform based analysis is that the signal being analyzed is stationary. Previous studies have shown that the frequency components of EEG signal change over time i.e., the EEG signal is a non-stationary process [6]–[10]. Several time–frequency domain based methods have been developed for detection of epileptic seizure from EEG signals. These methods include the short time Fourier transform [11], the wavelet transform [12]–[13], the multi-wavelet transform [14], the smoothed pseudo-Wigner–Ville distribution [15], and the multifractal analysis and wavelet transform [16]–[17]. The improved generalized fractal dimension has been used for discriminating ictal EEG signals [18]. Recently, empirical mode decomposition (EMD) based methods for the classification of ictal EEG signals have also been reported in literature [19]–[24].

The purpose of this paper is to classify a given set of EEG signals into ictal and seizure-free categories. A new technique for EEG signal classification is presented which is based on Autoregressive Modelling and Multiple Layer Perceptron Neural Network. The EEG signal is passed through a linear prediction (LPC) filter. Coefficients of the filter are calculated by the Burg method to get the best possible model of the signal. A prediction error is defined as the difference between the modeled signal and the actual signal. Since the linear prediction filter has a low-pass nature, it cannot accurately model the sharp changes that occur in ictal EEG signals thus increasing the prediction error. The prediction error energy for a set having both ictal and seizure-free EEG signals is calculated. The prediction error energy and the signal energy of each signal are given as parameters to train a Multiple Layer Perceptron (MLP). Then a new set of error and signal energy values is given as input to the MLP. The MLP subsequently classifies the points of the new set into ictal and seizure-free categories.

2. Methodology

2.1. Autoregressive Modelling

Autoregressive (AR) methods have been used in a number of studies to model EEG data by representing the signal at each channel as a linear combination of the signal at previous time points.

Based on autoregressive (AR) or all-pole model of the EEG signal, an EEG signal dataset can be characterized as an output of a causal, stable, linear time-invariant stationary AR (P^{th} order) system given by

$$y(\mathrm{n}) = -\sum_{i=1}^{\mathrm{p}} a_i\, y(n-i) + e(n) \quad (1)$$

where (a_i) are the AR parameters, commonly known as the linear prediction coefficient (LPC) and $e(n)$, is assumed to be white Gaussian noise excitation with zero mean and variance σ^2. The AR parameters (a_i) can be estimated using the Burg method.

AR models provide a compact, computationally efficient representation of EEG signals. Furthermore, AR model parameters are invariant to scaling changes in the data that can arise from inter-subject variations, such as scalp and skull thickness. Due to these properties, AR modeling has been extensively used in EEG for different analyses such as feature extraction and classification tasks.

2.2. Multiple Layer Perceptron (MLP)

An artificial neural network (ANN) is usually a classifier made up of large number of simple, highly interconnected elements called nodes or neurons which perform a simple numerical computation task. Although each neuron does a simple processing job, mutual effect of all the neurons on each other makes them a powerful classifier.

There are different neural network topologies as well as different neurons types that make any specific ANNs. Learning ANNs is accomplished through special training algorithms developed according to some special learning rules based on selected topology and neuron. The training algorithms are designed such that a particular ANN gives the best possible results in a specific network. In this paper, the MLP neural network is used for classifying the EEG signals.

The architecture of MLP neural network may contain two or more layers. Input layer is the first layer which its number of neurons is equal to the number of selected specific features. Output layer is the last layer which determines the desired output classes.

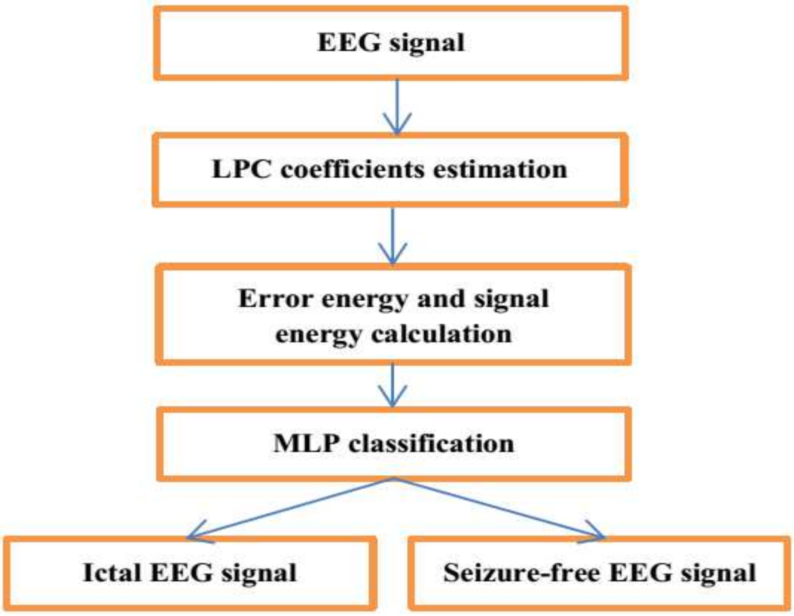

Fig. 1. *Flow chart of the proposed method.*

The number of neuron in the output layer depends on the number of desired classes and design. The intermediate layers may be added to increase the ability of the network and it mostly is useful for nonlinear systems. Although each MLP network could include multiple hidden layers, it is typical to use just one hidden layer with a try-and-error based number of neurons.

Unlike the input and output layers, we have no prior knowledge of the number of neurons needed in the hidden layer. Large number of neurons in the hidden layer would definitely increase the computational complexity and processing time. On the other hand, small amount of neurons would increase the classification errors.

A network with too few neurons in this layer would make it incapable of differentiating between complex patterns leading to only a linear estimation of the actual trend. In contrast, if the network has too many neurons in such a layer, not only training time excessively increases but also the over-fitting may be occurred on training data, which leads to poor generalization of untrained data. Therefore, determining the appropriate number of neurons in the hidden layer is one of the most critical tasks in a neural network design.

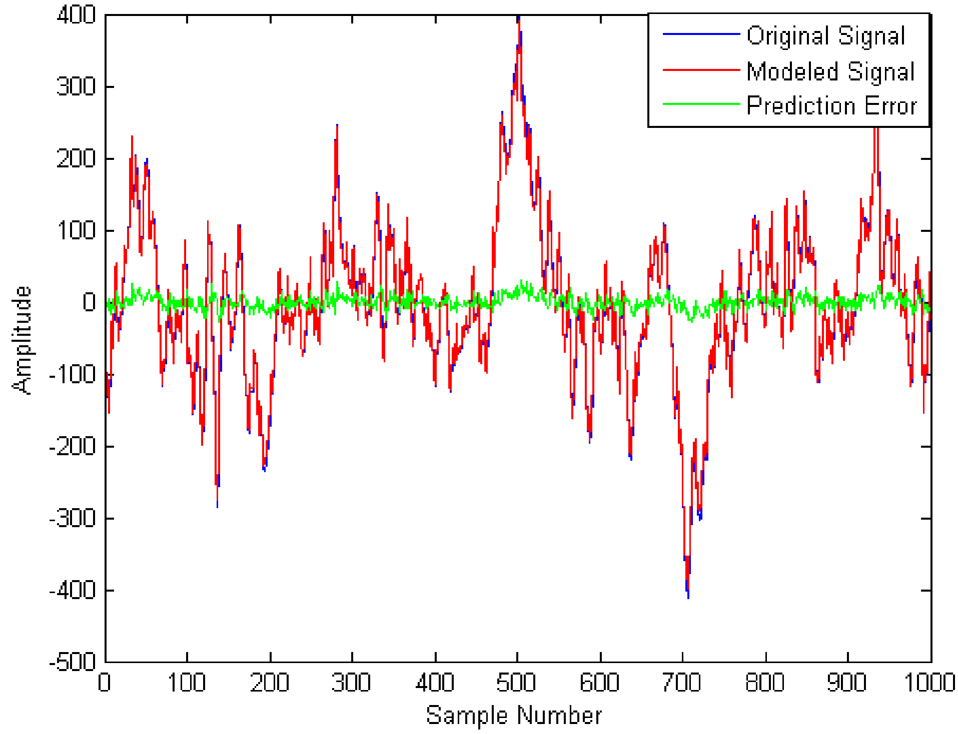

Fig. 2. *Autoregressive modelling of seizure-free EEG signal.*

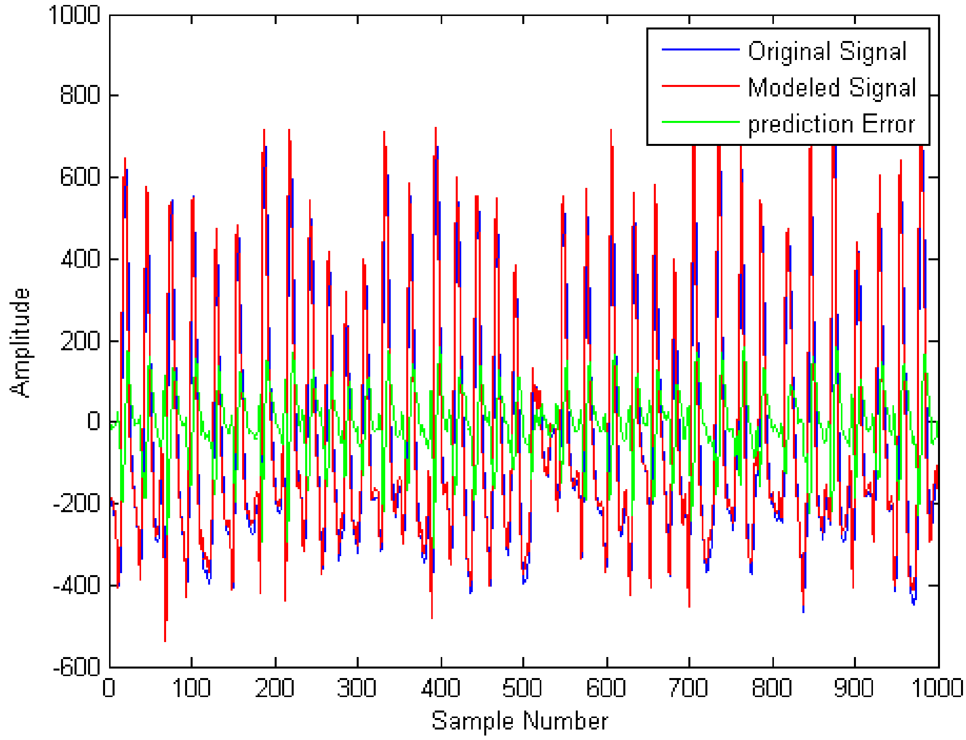

Fig. 3. *Autoregressive modelling of ictal EEG signal.*

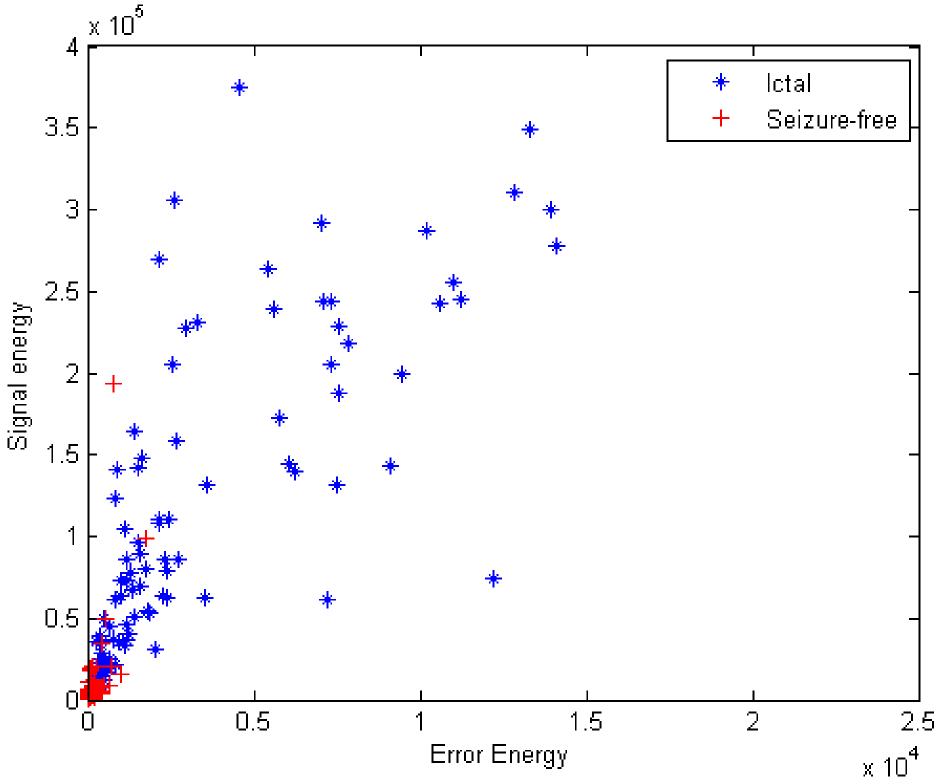

Fig. 4. *Classification plot.*

The most popular approach to find the optimal number of hidden layers is by try-and-error [25]–[27]. In this research, we choose this approach, as well. After numerous experiments, the best result is achieved when 30 neurons are selected in the hidden layer.

Another important and integral part of ANN model is to select a suitable training algorithm. This process is highly dependent on selected topology and neuron type. An optimal training algorithm is the one that shortens the training time most while achieves the best possible accuracy. As there are a number of training algorithms for MLP neural network, we used the Resilient back propagation (RBP), the Scaled conjugate gradient (SCG), and the Levenberg–Marquardt training algorithms in our study [26]–[27].

2.3. Proposed Method

The EEG signal is passed through an LPC filter. The filter then calculates the autoregressive coefficients of the signal using the Burg method. The LPC coefficients are used to model the signal according to Eq. (1). The difference between the actual signal and the modelled signal is defined as the prediction error. The energy of prediction error is estimated once the signal modelling is complete. The energy of the signal is also calculated and this procedure is repeated for the entire set of EEG signals. It should be noted that the impulsive nature or sharp changes in the ictal EEG signals will require high order of LPC in order to model the signal. The requirement of LPC order will be low for seizure-free EEG signals due to absence of impulses or sharp changes. For the same order modelling error in the seizure-free EEG signals will be less compared to ictal EEG signals. The modelling error together with signal energy helps us to develop a classification system in order to classify the ictal and seizure-free EEG signals. Next, we choose 50% of the signals each from the ictal category and the seizure-free category and use their prediction error energy and signal energy as features to train a MLP classifier. Finally, the rest of the prediction error energy and signal energy data is used for classification of the EEG signals into ictal and seizure-free categories. We vary the training algorithms and the activation functions types used for training the MLP classifier to get the highest accuracy. The performance of the method is evaluated through MLP classification plots and by calculating accuracy (ACC), sensitivity (SEN), and specificity (SPE) values for the set of classified data. The flow chart of the proposed method is shown in Figure 1.

3. Results

To verify our proposition we did simulations on the EEG dataset available publicly in [28]. The dataset consists of five subsets (denoted as Z, O, N, F, and S) each containing 100 EEG signals, each one having 23.6 s duration. In this study, we have used only the subsets F, N, and S to perform simulations. The signals in the subset F and N have been measured in seizure-free intervals from five patients. Subset F is measured from the epileptogenic zone and N from the hippocampal formation of the opposite hemisphere of the brain. The subset S contains seizure activity, selected from all recording sites exhibiting ictal activity. The sampling frequency of the EEG signals in the dataset is 173.61 Hz.

In this work, we have performed the autoregressive modelling on each signal. First, each of the signals was passed through a linear prediction filter and the optimal coefficients were estimated. Next, using these coefficients the prediction error energy for each signal was calculated. The error energy and signal energy were given as inputs to train a MLP classifier. For training 50% of the data was used, the remaining 50% data was kept for classification. The MLP can be trained using different training algorithms and after trial and error it was found that the maximum classification accuracy of 94.67% was obtained for the Levenberg-Marquardt (LM) algorithm. The classification accuracy results for different training algorithms for each set of data are summarized in Table 1.

The classification test performance of the MLP-classifier can be determined by computation of sensitivity (SEN) and specificity (SPE) along with accuracy (ACC). They are defined as:

$$SEN = \frac{true\ positives}{total\ positives} \times 100 \quad (2)$$

$$SPE = \frac{true\ negatives}{total\ negatives} \times 100 \quad (3)$$

$$ACC = \frac{correctly\ classified}{total} \times 100 \quad (4)$$

These values were calculated for different training algorithms and are presented in Table 2. The modeling of seizure-free and ictal EEG data for a sample signal is shown in Fig. 2 and Fig. 3 respectively, we can see clearly that both the modeling error energy and the signal energy are substantially higher for ictal EEG signals compared to seizure-free EEG signals The classification of data into ictal and seizure-free classes using the two proposed features is shown in Fig. 4. It is clear from the Fig. 4 that the proposed method can be used as a diagnostic tool for detecting ictal EEG signals.

Table 1. *Classification accuracy for different training algorithms and EEG data sets.*

Training algorithm	Set	Description	Accuracy	Average accuracy
	Set F	Seizure-free	90%	
SCG	Set N	Seizure-free	98%	92.67%
	Set S	Ictal	90%	
	Set F	Seizure free	90%	
RBP	Set N	Seizure free	98%	93.33%
	Set S	Ictal	92%	
	Set F	Seizure free	94%	
LM	Set N	Seizure free	98%	94.67%
	Set S	Ictal	92%	

Table 2. *Sensitivity, specificity, and accuracy values for different training algorithms.*

Training Algorithms	Sensitivity	Specificity	Accuracy
SCG	90%	94%	92.67%
RBP	92%	94%	93.33%
LM	92%	96%	94.67%

In order to evaluate the performance of the proposed method for classification of ictal and seizure-free EEG signals, a comparison with the proposed method in [2] is done. The method proposed in [2] has provided average classification accuracy of 94% for classification of ictal and seizure-free EEG signals, whereas our proposed method provides higher classification accuracy which is 94.67% for classification of ictal and seizure-free EEG signals. We have compared our method for classification of ictal and seizure-free EEG signals with the method proposed in Ref. [2] with same number of EEG signals of the same dataset.

4. Conclusion

Autoregressive modelling is a powerful and effective method for modelling EEG signals. The prediction error energy arising out of this modelling and the energy of the signal are used as features to classify ictal and seizure-free EEG signals. The classification of EEG data using error energy and signal energy as inputs to the MLP classifier has proved to be successful with a maximum classification accuracy of 94.67%. Hence, Autoregressive modelling promises to become an important tool for biomedical signal processing applications. Improvements in classification accuracy may be possible by exploring other features extraction techniques and other classifiers.

Acknowledgements

The authors would like to thank the Epilepsy Center at the University of Bonn, Germany, for making their data available to the epilepsy research community. They also appreciate the anonymous reviewers for the valuable comments.

References

[1] T. Sunil Kumar, Vivek Kanhangad, Ram Bilas Pachori, "Classification of seizure and seizure-free EEG signals using local binary patterns," Biomedical Signal Processing and Control, Volume 15, (January) (2015), pp. 33–40.

[2] S. Altunay, Z. Telatar, O. Erogul, "Epileptic EEG detection using the linear prediction error energy," Expert Systems with Applications, 37 (August (8)) (2010), pp. 5661–5665

[3] U. R. Acharya, S.V. Sree, G. Swapna, R.J. Martis, J.S. Suri, "Automated EEG analysis of epilepsy: a review," Knowledge-Based Systems, 45 (June) (2013), pp. 147–165

[4] Kai Fu, Jianfeng Qu, Yi Chai, Tao Zou, "Hilbert marginal spectrum analysis for automatic seizure detection in EEG signals," Biomedical Signal Processing and Control, Volume 18, (April) (2015), pp. 179–185

[5] Jae-Hwan Kang, Yoon Gi Chung, Sung-Phil Kim, "An efficient detection of epileptic seizure by differentiation and spectral analysis of electroencephalograms," Computers in Biology and Medicine, (May) (2015), In Press

[6] Kai Fu, Jianfeng Qu, Yi Chai, Yong Dong, "Classification of seizure based on the time-frequency image of EEG signals using HHT and SVM," Biomedical Signal Processing and Control, Volume 13, (September) (2014), pp. 15–22

[7] R. B. Pachori, P. Sircar, " EEG signal analysis using FB expansion and second-order linear TVAR process," Signal Processing, 88 (February (2)) (2008), pp. 415–420

[8] Lan-Lan Chen, Jian Zhang, Jun-Zhong Zou, Chen-Jie Zhao, Gui-Song Wang, "A framework on wavelet-based nonlinear features and extreme learning machine for epileptic seizure detection," Biomedical Signal Processing and Control, Volume 10, (March) (2014), pp. 1–10

[9] Y. Liu, W. Zhou, Q. Yuan, S. Chen, "Automatic seizure detection using wavelet transform and SVM in long-term intracranial EEG," IEEE Trans Neural Syst Rehabil Eng, 20 (6) (2012), pp. 749–755

[10] A. T. Tzallas, M. G. Tsipouras, D. I. Fotiadis, "Automatic seizure detection based on time-frequency analysis and artificial neural networks," Computational Intelligence and Neuroscience, 2007 (2007), p. 13 Article ID 80510

[11] R. Schuyler, A. White, K. Staley, K. J. Cios, "Epileptic seizure detection," IEEE Engineering in Medicine and Biology Magazine, 26 (March/April (2)) (2007), pp. 74–81

[12] S. Ghosh-Dastidar, H. Adeli, N. Dadmehr, "Mixed-band wavelet-chaos-neural network methodology for epilepsy and epileptic seizure detection," IEEE Transactions on Biomedical Engineering, 54 (September (9)) (2007), pp. 1545–1551

[13] H. Ocak, "Optimal classification of epileptic seizures in EEG using wavelet analysis and genetic algorithm," Signal Processing, 7 (July) (2008), pp. 1858–1867

[14] L. Guo, D. Rivero, A. Pazos, "Epileptic seizure detection using multiwavelet transform based approximate entropy and artificial neural networks," Journal of Neuroscience Methods, 193 (October (1)) (2010), pp. 156–163

[15] A. T. Tzallas, M.G. Tsipouras, D. I. Fotiadis, "Epileptic seizure detection in EEGs using time–frequency analysis," IEEE Transactions on Information Technology in Biomedicine, 13 (September (5)) (2009), pp. 703–710

[16] R. Uthayakumar, D. Easwaramoorthy, "Epileptic seizure detection in EEG signals using multifractal analysis and wavelet transform," Fractals, 21 (June (2)) (2013)

[17] R. Uthayakumar, D. Easwaramoorthy, "Multifractal-wavelet based denoising in the classification of healthy and epileptic EEG signals," Fluctuation and Noise Letters, 11 (December (4)) (2012)

[18] D. Easwaramoorthy, R. Uthayakumar, "Improved generalized fractal dimensions in the discrimination between healthy and epileptic EEG signals," Journal of Computational Science, 01 (March) (2011), pp. 31–38

[19] V. Bajaj, R.B. Pachori, "Classification of seizure and nonseizure EEG signals using empirical mode decomposition," IEEE Transactions on Information Technology in Biomedicine, 6 (November) (2012), pp. 1135–1142

[20] R. B. Pachori, V. Bajaj, "Analysis of normal and epileptic seizure EEG signals using empirical mode decomposition," Computer Methods and Programs in Biomedicine, 3 (December) (2011), pp. 373–381

[21] R. B. Pachori, "Discrimination between ictal and seizure-free EEG signals using empirical mode decomposition," Research Letters in Signal Processing, 2008 (2008), p. 5 Article ID 293056

[22] R. J. Oweis, E.W. Abdulhay, "Seizure classification in EEG signals utilizing Hilbert-Huang transform," BioMedical Engineering OnLine, 10 (May) (2011).

[23] R. J. Martis, U. R. Acharya, J. H. Tan, A. Petznick, R. Yanti, C. K. Chua, E. Y. Ng, L. Tong, "Application of empirical mode decomposition (EMD) for automated detection of epilepsy using EEG signals," International Journal of Neural Systems, 22 (December (6)) (2012)

[24] V. Bajaj, R. B. Pachori, "Epileptic seizure detection based on the instantaneous area of analytic intrinsic mode functions of EEG signals," Biomedical Engineering Letters, 1 (March) (2013), pp. 17–21

[25] L. V. Fausett, Fundamentals of Neural Networks Architectures, Algorithms, and Applications, Prentice-Hall, 1994.

[26] B. B. Chaudhuri, U. Bhattacharya, "Efficient training and improved performance of multilayer perceptron in pattern classification," Neurocomputing 34 (September (1)) (2000) 11–27.

[27] T. M. Mitchell, Machine Learning, McGraw-Hill, 1997, pp. 108–112.

[28] R. G. Andrzejak, K. Lehnertz, F. Mormann, C. Rieke, P. David, C. E. Elger, "Indications of nonlinear deterministic and finite-dimensional structures in time series of brain electrical activity: dependence on recording region and brain state," Physical Review E, 64 (6) (2001) Article ID 061907.