CLASSIFICATION OF EPILEPTIC STATES USING ROOT-MUSIC AND MLPNN

Ahmad R. Naghsh-Nilchi, Mostafa Aghashahi

Computer Engineering Department, University of Isfahan, Isfahan, IRAN
nilchi@eng.ui.ac.ir, mostafa_aghashahi@yahoo.com

ABSTRACT

A new approach based on root-MUSIC frequency estimation method and a Multiple Layer Perceptron neural network is introduced. In this method, a feature vector is formed using power frequency, entropy, standard deviation, as well as the complexity of the time domain Electroencephalography (EEG) signal. The power frequency values are estimated using root-MUSIC algorithm. The resulted feature vector is then classified into three categories namely healthy, inter-ictal (epileptic during seizure-free interval), and ictal (full epileptic condition during seizure interval) states using Multiple Layer Perceptron Neural Network (MLPNN). The experimental results show that EEG states classification maybe achieved with approximately 94.53% accuracy and variance of 0.063% applying the method on an available public database. This is a high speed with high accuracy as well as low misclassification rate method.

1. INTRODUCTION

The seizure mechanism resulted from Epileptic patients is not completely known yet, however, it is generally agreed that the brain's electrical activity transfers from a pre-seizure state called *Pre-ictal* to a final seizure state called *Ictal*. Since the epilepsy is characterized by recurrent unprovoked seizures, the state between two seizures is called *inter-ictal* [1].

However, Ictal electrical activity during a seizure differs significantly from the activity observed from a normal person with respect to both spectral as well as pattern of neuronal firing. Detection of seizure with only superficial observation of EEG signal, even for a trained neurologist, is not simply possible. Existence of muscle artifact, conflict with other brain activity and other existing artifacts as well as very low amplitude and so much noise sensitive EEG signals makes the seizure detection even more difficult. There is a need for an algorithm to overcome these problems in order to diagnosis and treat this disease properly.

Researches on automatic detection and prediction of epileptic seizures were started as early as 1970s [2, 3]. The early methods were primitive and were commonly based on linear analysis. In recent years, nonlinear analysis methods especially Chaos theory [4, 5, 6, 7, 8] and methods based on time-frequency distributions such as Wigner-Ville, Margenau-Hill, Rihaczek, Choi-Williams [9], STFT and wavelet transform [10, 11] has been popular among many researchers. These researches are mainly focused on detecting two ictal and normal states.

In recent years, Dastidar et al. [5, 6, 7] have reported accuracy about 96.67% by using wavelet transform and nonlinear features. Apparently, these researchers are the only group that tried to classify the EEG signals into three states, adding inter-ictal along with Ictal and normal states.

Spectral estimation methods including AR based and pseudo-spectrum based methods is one of the effective methods used for seizure detection. A. Subasi et al. compared subspace-based method with AR spectral estimation for classification of seizure and non-seizure EEG signal [12]. In their work, *AR* methods including *Burg*, *Yule–Walker*, and pseudo-spectrum algorithms such as *MUSIC* were compared with each other in terms of their frequency resolution and the effects on only classification of epileptic seizure.

They implied that the subspace-based methods are extremely valuable for use in epileptic seizure detection. They, however, did not classify inter-ictal states.

The same research group in another study have used *MUSIC*, autoregressive (*AR*) and periodogram methods (such as *FFT*) to obtain power spectrum of EEG signal of epileptic patients [13]. In their study, the power spectrum was used as an input to a classifier. They implied that the *MUSIC* and MLP-based classifier produces accurate classification. Like the previous one, they did not classify inter-ictal state in this study.

MUSIC algorithm was also used successfully for classification of the arrhythmia from Electrocardiography (ECG) [14].

In this article, motivated by works done in [13] and [14], the harmonics of the EEG signal are estimated using root-MUSIC algorithm (a variation of MUSIC algorithm). Adding the entropy of the estimated spectrum, standard deviation, and the complexity measure of the original signal to these harmonics values allows us to create a feature vector necessary for our classification purpose. This feature vector is classified into three states, namely healthy, inter-ictal and ictal states, using Multiple Layer Perceptron (MLP) neural network.

2. MATERIALS AND METHOD

2.1 Data

The data used in this research are a subset of the EEG data for both healthy and epileptic subjects made available online by Dr. Ralph Andrzejak of the Epilepsy Center at the University of Bonn [15]. In fact, the EEG data is selected from three groups, each containing 100 single-channel EEG segments and each has duration of 23.6 seconds. The selected groups are:

- group Z (Healthy group): signal segments from healthy subjects
- group N (inter-ictal group):signal segments from epileptic subjects during a seizure-free interval
- group S (Ictal group): signal segments from epileptic subjects during a seizure interval

All EEG signals are recorded with the same 128-channel amplifier system, using an average common reference. The data were digitized at 173.61 samples per second using 12 bit resolution and they have the spectral bandwidth of the acquisition system, which varies from 0.5 Hz-85 Hz.

2.2 Root-MUSIC algorithm

Subspace-based spectrum estimations such as MUSIC are used for estimating frequencies and powers of signals from noisy measurements [16]. These methods are based on an eigen-decomposition of the correlation matrix of the noisy signal. Signal is partitioned into signal subspace and signal-plus-noise subspace such that noise subspace is orthogonal to the signal-plus-noise subspace. Even when the signal-to-noise ratio (SNR) is low, the subspace-based methods give frequency spectra of high resolution. These methods are best suited for narrow-band signals that can be assumed to be composed of several special sinusoids buried in noise.

In MUSIC method, it is supposed that signal is produced from P source with different angles with an additive white noise. The MUSIC pseudo-spectrum is calculated via the following formula:

$$\begin{aligned}\overline{R}_{music}(e^{j2\pi f}) &= \frac{1}{\sum_{m=P+1}^{M} |v^H(f)q_m|^2} \\ &= \frac{1}{\sum_{m=P+1}^{M} |Q_m(e^{j2\pi f})|^2}\end{aligned} \tag{14}$$

where $v^H(f)$ is the conjugate transpose of time-window frequency vector given as:

$$v(f) = [1 \;\; e^{j2\pi f} \ldots e^{j2\pi(M-1)f}]^T \tag{15}$$

that is simply a length-M DFT vector at frequency f. q_m are noise eigen-vectors. Roots of the denominator of Eq.14 correspond to the frequencies of the complex exponentials. These roots produce P peaks in the pseudo-spectrum. Therefore, we might want to consider the Z-transform of this denominator:

$$\overline{P}_{MUSIC}(z) = \sum_{m=P+1}^{M} Q_m(z) Q_m^*(\frac{1}{z^*}) \tag{16}$$

which is the sum of the z-transforms of the pseudo-spectrum due to each noise eigenvector. This $(2M-1)^{th}$-order polynomial has $M-1$ pairs of roots with one inside and one outside the unit circle. Since we assume that the complex exponentials are not damped, their corresponding roots must lie on the unit circle. Thus, if we have found the $M-1$ roots of Eq.16 the P closest roots to the unit circle will correspond to the complex exponentials. The phases of these roots may be computed and are equivalent to the estimated frequencies.

This method of rooting the polynomial corresponding to the *MUSIC* pseudo-spectrum is known as *root-MUSIC*. Note that in many cases, a rooting method is more efficient than computing a pseudo-spectrum at a very fine frequency resolution that may require a very large FFT [16].

In order to calculate the *root-MUSIC* from Eq.16, the number of harmonics that compose the signal and is represented by the number of signal eigenvectors (i.e. P in Eq.16) should be known or selected based on proper experiments. We select various values for this parameter as reported in section 3.

Note that EEG signal has low amplitude that make it very sensitive to noise; Therefore, using super-resolution eigen-based pseudo-spectral estimation method such as *root-MUSIC* can significantly improve accuracy of detection and reduce incorrect classifications percentage.

2.3 Methodology

The proposed method is composed of three steps: pre-processing, feature extraction and signal classification. As the first step, the pre-processing includes a low pass filter which is used to limit the frequency band of EEG signals such that it can eliminate the involved noise in the received signal to some extent. In the second step, the feature vector is formed using the discussed features extracted from the time-domain EEG signal and its root-MUSIC pseudo-spectral estimation. The final step includes the classification of the feature vector using an MLP neural network. A brief description of the method is as follow.

From physiological standpoint, frequencies greater than 60 Hz can be classified as noise and could be discarded [5]. Therefore, we used a finite impulse response (FIR) low pass filter to discard the frequencies over 60Hz. Note that, the energy of the frequency band eliminated by the filter is negligible compared with that of the retained band in the 0–60 Hz range.

In the second step, which is the feature extraction to form the feature vector, root-MUSIC pseudo-spectrum of band limited EEG signal resulted from pre-processing is computed. Then, the *standard deviation (Std)* and *complexity* of the time-domain EEG signal, after passing it through a low-pass FIR filter with a cut-off frequency of 60Hz, is computed.

Complexity is one of Hjorth parameters [17] and is calculated using another Hjorth parameter named *Mobility*. It is given by:

$$Mobility(s) = \frac{\delta_{s'}}{\delta_s} \tag{18}$$

In this equation, δ_s is the standard deviation of the signal, s, and $\delta_{s'}$ is the standard deviation of the derivative of s. Derivative of the signal, s', is calculated using:

$$s'(j) = s(j+1) - s(j) \tag{19}$$

Now the complexity is calculated using Eq.18 via following equation:

$$Complexity(s) = \frac{Mobility(s)}{Mobility(s')} \tag{20}$$

Another variable used as a feature, is the Log-Entropy, which is calculated using the following relation:

$$Entropy(s) = \sum_i \log(s_i^{\,2}) \qquad (21)$$

where s_i is ith input data sample.

The required feature vector is then formed from combination of *Std, Complexity and entropy* parameters as well as the frequencies that is estimated via *root-MUSIC* algorithm mentioned above, according to the following relation:

$$\begin{aligned} FeatureVector(s) = [&Freq1, Freq2, ..., Std(s),\\ &Complexity(s), entropy(Freq1, Freq2, ...)] \end{aligned} \qquad (22)$$

which *freq1*, *freq2*, ... are estimated frequencies resulted from root-MUSIC algorithm.

The feature vector is then normalized such that each of its values is fall into the range of [-0.5, 0.5]. The normalized values help the feature vector be more adapted to the Neural Network classifier. Finally, the resulted normalized feature vector is applied as the input to the neural network classifier.

2.4 MLP Neural Network

One of the most common Neural Networks is Multiple Layer Perceptron Neural Network (MLPNN). The architecture of MLPNN 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. 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 MLPNN mostly useful for nonlinear systems. Although each MLPNN 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 the processing time, however, small amount would increase the classification errors. Therefore, determining the appropriate number of neurons in the hidden layer is one of the most critical tasks in a neural network design.

The most popular approach to find the optimal number of hidden layers is by try-and-error [18]. In this research, we choose this approach, as well. The best result is achieved when 50 neurons are used in the hidden layer.

Another important and integral part of ANN model is to select a suitable training algorithm. An optimal training algorithm is the one that shorten the training time most while achieves the best possible accuracy. As there are number of training algorithms for MLPNN, we used the Feed-Forward back propagation training algorithm in our study [18].

3. EXPERIMENTAL RESULTS

The problem of improving the classification accuracy is tackled from two different angles: 1) designing an appropriate feature space by identifying the parameters that increase the interclass separation of *root-MUSIC* algorithm used in this research; and 2) designing a classifier that can accurately model the classification problem based on the selected feature space.

The EEG classification problem is approached using a supervised learning technique, namely Feed-Forward back-propagation training algorithm. Usually, for supervised learning, the available input data set is divided into training input set and testing input set.

For obtaining a sound result, we used *k-fold cross validation* (with *k=3*) for testing and training data [19]. In this study, the training input consists of *100* training instances out of *300* available EEG signals. The remaining instances are used for testing input. Each instance is represented by the aforementioned *FeatureVector* calculated using Eq.22. In addition, each *3-folding* is done *20* times and their averages and variances are obtained.

Root-MUSIC order selection

As we mentioned earlier, *root-MUSIC* is a parametric frequency estimation algorithm. The number of harmonics (i.e. complex exponentials) composing signal is required (i.e. *P* in Eq.16) in the *root-MUSIC* spectral estimation.

From our past experiments and other literatures [12, 13], we predict that the number of harmonics may lie down in the range of 2 to 20. We select all the numbers in the range separately. Fig.5 and Fig.6 illustrates overall accuracy and variance percentage of classification in terms of various numbers of selected harmonics.

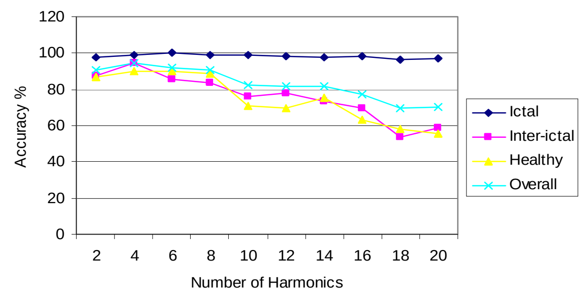

Fig.5) Accuracy vs. the selected number of root-MUSIC harmonics.

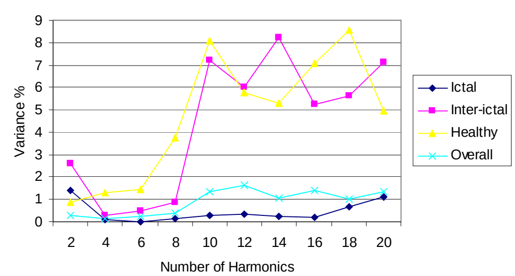

Fig.6) The effect of number of root-MUSIC harmonics vs. variance

Fig.5 and Fig.6 illustrates that the best accuracy is achieved when the number of harmonics is selected to be 4 considering both the accuracy and variance of simulation results.

MLPNN Parameter

The effect of 5 to 80 number of hidden layer neurons in MLPNN for sound classification is studied. Fig. 7 and 8 show the average accuracy and the variance, respectively, of classifying the three epileptic states, and the overall performance, employing the selected signals in the database, using our method.

Since the weight initialization is random, each experiment setup has been repeated 20 times using *3-folding* and the average of the results are taken. The variances depicted in Fig.8 are, in fact, the overall variation for the accuracies of different number of hidden layer neurons.

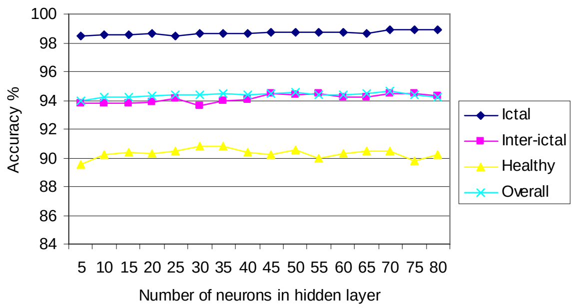

Fig.7) Accuracy vs. the number of hidden neurons in MLPNN

The results obtained in Fig.7 illustrate that there are low variations in ictal, inter-ictal and overall accuracy for the number of neurons in the hidden layer over five. This implies that there is a low sensitivity to the number of hidden layer neurons, and that it is not necessary to select a large number of neurons which complicate the complexity.

It also shows that the accuracy for ictal state detection is the highest while the accuracy for determining the healthy state is the least one among all cases.

The effect of number of hidden neurons in MLPNN using root-MUSIC in terms of the variance of accuracy is shown in Fig.8. It shows that the classification of the healthy and iter-ictal states have large variances while a least amount of variation appears for the case of ictal state classification. Considering the results in both Fig.7 and Fig.8, we selected 35 neurons in the hidden layer of MLPNN. This number of neurons generates a very good accuracy as well as a very low variance to classify all the three states.

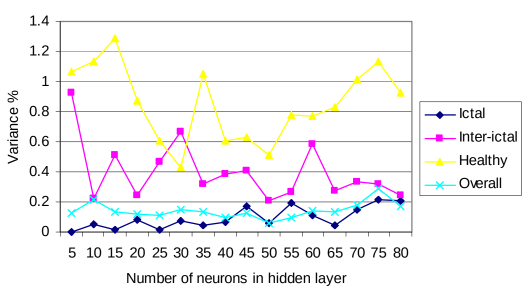

Fig.10) The computed variance for repeating the experiments 20 times at different number of hidden neurons in MLPNN.

Furthermore, the performance of our method for seizure detection is evaluated in terms of sensitivity, specificity and overall accuracy. Sensitivity and specificity are used to evaluate the ability of the classifier to discriminate one class against another. The sensitivity is calculated as the proportion of positive samples correctly assigned to the positive class. The specificity is the proportion of negative samples correctly assigned to the negative class. The overall accuracy is the fraction of the total number of signals correctly classified.

Table 1 shows the results using 35 neurons in the hidden layer and selecting 4 harmonics for *root-MUSIC* algorithm.

Table 1: performance of Root-MUSIC (4 harmonics)
(Using 35 neuron in hidden layer of MLPNN)

	Groups	**Root-MUSIC** *(with 4 harmonics)*
Sensitivity (%)	Healthy	90.19900
	Inter-ictal	94.27861
	Ictal (seizure)	98.68159
Specificity (%)	Healthy	95.09950
	Inter-ictal	97.13930
	Ictal (seizure)	99.34080
Overall accuracy (%)		**94.527363** *(var=0.058)*

As illustrates in Table 1, our method recognizes the *seizure* state about 98.68% (sensitivity) and specificity of 99.34%. That is, the method misclassifies *Healthy* or *inter-ictal* class as seizure only 0.66% of the times. This is a significant achievement compare to the reported results by other researches mentioned earlier in the introduction.

4. DISCUSSION

Although there are many studies dealing with seizure detection in the literature, a strict comparison between our method and the results reported by other researches are somewhat difficult. The reason behind this is that these researches are considered different number of epileptic states and well ass using non-standard and different databases, some of them not even available in the public domain.

In some papers only two states are considered: *seizure* and *non-seizure*. In some others, including our approach, discrimination between healthy and *inter-ictal* states for non-seizure situation are also considered. In this case, since *Ictal* and *inter-ictal* states are very similar, classification procedure is much more complicated.

In addition, the EEG signal samples used in most reports are created individually and therefore there are not available for further comparison, making the comparison between our method and theirs practically impossible.

As we mentioned earlier, we selected data from a public database available online [15]. This allows us to compare our method with the methods reported in [6, 7] where they considered the same problem of classifying three epileptic states as well as using the same public database. Table 2 is created with the aforementioned considerations.

Note that, although the research done in [13], where MUSIC algorithm was employed, could not be considered for full comparison since the classification for only two states was studied and reported, we provided a vague comparison between our method and [13] as reported in the table. A very important note is that in their implementation, they used an entire window of MUSIC spectrum values usually in order of 128 or 256 values (they did not report their window size), as features on MLPNN, while we employed four values resulted from four harmonics of root-MUSIC added to two other features (total of 6 feature values). That is, the learning process for their MLPNN involved a tremendous amount of computations compare to our implementation. That makes our algorithm in a sharp advantage in terms of processing time.

Table 2: Comparing the results obtained from the new method with that of [13], [6], and [7]

Methods	Accuracy (%)	Variance (%)
Proposed (root-MUSIC-MLP)	**94.53**	**0.06**
MUSIC-MLP [13] used for 2 states	77.39	15.3
PCA-WAVELET-CHOAS [6]	96.66	1.4
MIX-BAND-WAVELET-CHAOS [7]	96.67	-

Based on the results reported in this table, the proposed *root-MUSIC* based method is proved to be a powerful approach with suitable results, although it seems to have a somehow less accuracy. However, the advantage of our method is its lower computational complexity. Another clear advantage of our method is that it produces a very low variance. This implies that the proposed algorithm is much more robust.

5. CONCLUSION

In this paper, we propose an efficient new method based on *root-MUSIC* frequency estimation algorithm and MLPNN for the classification of EEG signals into three states namely *healthy*, *inter-ictal* and *ictal* or *seizure*. In our method, *root-MUSIC* spectral estimation is employed to estimate the frequencies of the obtained signal and MLPNN is employed for classification of the root-MUSIC estimated frequencies picking different number of harmonics as well as the standard deviation and the complexity of the time-domain EEG signal. The simulation results show that only four harmonics are good enough to give acceptable accurate results.

In order to assess the clinical applicability of the proposed method for epilepsy diagnosis and seizure detection, the classification sensitivity and specificity and the overall accuracies for each state (healthy, inter-ictal, or ictal) are tabulated in Table 1 (standard deviations of overall accuracy are noted in parentheses). It shows that the classification accuracy of about 94.53% and standard deviation of 0.06% is obtained.

As the proposed system is based on features that have a low computational burden, it is suited for the real-time detection of epileptic seizures from ambulatory recordings. The comprehensiveness (since three states are considered), real-time, high accuracy as well as a low misclassifying rate of our method make the detection of this chronic disease feasible.

REFERENCES

[1] F. H. Lopes da Silva, J. P. Pijn, and W. J. Wadman, “Dynamics of local neuronal networks: Control parameters and state bifurcations in epileptogenesis,” Prog. Brain Res., vol.102, pp. 359–370, 1994.

[2] S. S. Viglione, V. A. Ordon, and F. Risch, "A Methodology for Detecting Ongoing Changes in the EEG Prior to Clinical Seizures.", 21st Western Institute on Epilepsy, 1970.

[3] S. Liss, "Apparatus for Monitoring and Counteracting Excess Brain Electrical Energy to Prevent Epileptic Seizures and the Like”, US patent #3850161, 1973.

[4] R. Esteller, G. Vachtsevanos, J. Echauz, T. Henryt, P. Pennellt, C. Epsteint,R. Bakayt, C. Bowen and B. Litt, "Fractal Dimension Characterizes Seizure Onset In Epileptic Patients", IEEE, 1999.

[5] H. Adeli, S. Ghosh-Dastidar, N. Dadmehr, "A Wavelet-Chaos Methodology for Analysis of EEGs and EEG Subband s to Detect Seizure and Epilepsy", IEEE Trans. on Biomed. Eng., vol.54, no.2, Feb 2007.

[6] S. Ghosh-Dastidar, H. Adeli, N. Dadmehr, "Principal Component Analysis-Enhanced Cosine Radial Basis Function Neural Network for Robust Epilepsy and Seizure Detection " TBME-00845-2006.R1.

[7] S. Ghosh-Dastidar, H. Adeli, N. Dadmehr, "Mixed-Band Wavelet-Chaos-Neural Network Methodology for Epilepsy and Epileptic Seizure Detection", IEEE Trans. on Biomed. Eng., Vol.54, No.9, Sep 2007.

[8] A. He, X. Yang, X. Yang, X. Ning, “Multifractal Analysis of Epilepsy in Electroencephalogram”, IEEE/ICME intern. Conf. on complex med. eng., 2007.

[9] A.T. Tzallas, M.G. Tsipouras, and D.I. Fotiadis, "The Use of Time-Frequency Distributions for Epileptic Seizure Detection in EEG Recordings", Proc. of the 29th Annual Intern. Conf. of the IEEE EMBS, Lyon, France Aug 23-26, 2007.

[10] T. Nijsen, P. Cluitmans, P. Griep, R. Aarts, “Short Time Fourier and Wavelet Transform for Accelerometric Detection of Myoclonic Seizures”, Belgian Day on Biomed. Eng. IEEE/EMBS Benelux Symp., Dec. 7-8, 2006.

[11] R. Schuyler, A. White, K. Staley, K. J. Cios, “Epileptic Seizure Detection”, IEEE Eng. in Med. and Biol. Mag., March/April 2007.

[12] A. Subasi, E. Erçelebi, A. Alkan and E. Koklukaya, "Comparison of subspace-based methods with AR parametric methods in epileptic seizure detection", Elsevier, Computers in Bio. & Med., Vol.36, Issue 2, pp. 195-208, Feb. 2006.

[13] A. Alkan, E. Koklukaya and A. Subasi, "Automatic seizure detection in EEG using logistic regression and artificial neural network", Elsevier, J. of Neuroscience Methods, Vol.148, Issue 2, pp. 167-176 , 30 Oct. 2005.

[14] A. R. Naghsh-Nilchi, and A. Kadkhodamohammadi, “Cardiac Arrhythmias Classification Method based on Multiple Signal Classification (MUSIC), Morphological Descriptors and Neural Network”, EURASIP Journal on Advances in Signal Processing, Vol. 2008, Article ID 935907.

[15] R. G. Andrzejak, K. Lehnertz, F. Mormann, C. Rieke, P. David, and C. E. Elger, “Indications of Nonlinear Deterministic and Finite-dimensional Structures in Time Series of Brain Electrical Activity", Phys. Rev. E, Stat. Nonlinear SoftMatter Phys., vol.64, pp. 1–8, 2001. (Data Available Online at (www.meb.unibonn.de/epileptologie/science/physik/eegdata.html).

[16] D.G. Manolakis, V.K. Ingle, S.M. Kogon , “Statistical and Adaptive Signal Processing”, McGraw-Hill , pp. 491-506, 2005.

[17] R.M. Rangayyan, “Biomedical Signal Analysis: A Case-Study Approach”, IEEE Press Series on Biomed. Eng., New York, 2002.

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

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