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Assessment of EEG Signals Using Chaos Analysis Methods

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Abstract: *Electroencephalogram (EEG) signals carry information about the dynamics of the brain. A nonlinear method development is of great significance objective or goal because of the brain signals are nonlinear. Epilepsy is a neurological disorder which can be seen all over the world. It can be diagnosed by brain's electrical activity. The determination of epileptic attacks or seizures by EEG signals is quite common in both clinical and research fields. During epileptic seizures, brain dynamics that make up the graph consists of abnormalities in EEG signals. Therefore, both time and frequency bands of the signals as well as need to go to review and determination of the pattern. Preictal and ictal EEG epochs were evaluated by wavelet-entropy and artificial neural networks (ANN) methods in this study. One hour EEG signals from different patients were used for wavelet-entropy method. One-hour epileptic EEG signals divided into two states (preictal and ictal) for this study. Then preictal end ictal states divided into 20 second segments. All of EEG segments have been separated into the standard subbands. Shannon entropies of the EEG subbands are calculated; and finally the feature vectors are classified with ANN. As a result, preictal and ictal EEG subbands'entropy values distinguish preictal and ictal segments from each other and the distinctiveness of gamma subbands' entropy values are more robust. The composite system that was proposed using performance evaluation criteria showed a 97,5 % success rate in classification.*

Keywords: *EEG, Epilepsy, Wavelet-entropy, ANN.*

1. Introduction

Electrical signals derived from dynamics of biological organs are used in many areas of medicine, diagnosis and treatment. EEG, ECG and other biological signals directly or indirectly provides information about the condition of the organ involved. Biological signals are processed by different signal processing methods such as time, frequency, time-frequency and phase. In the light of these new strategies are being developed in the medical field. In the context, EEG signals were examined by chaos analysis methods to obtain the information about the dynamics and the state of the brain. Also, considered will gain a new dimension to the pathological EEG signals.

A negativity of the brain affects the brain and the body with synchronized between the brain and all of the organs in the body due to the interactive structure with the body. Similarly, a negativity of the body affects the body together with the brain. EEG signals carry information about the dynamics of the brain. The accuracy of this information as possible to understand of the development of methods that can be used is very important. A nonlinear method development is of great significance objective or goal because of the brain signals are nonlinear.

Epilepsy is a neurological disorder which can be seen all over the world. It can be diagnosed by the brain's electrical activity. The determination of epileptic attacks or seizures by EEG signals is quite common in both clinical and research fields. Because EEG signals are non-stationary signals, they must be examined with the nonlinear analysis methods.

During epileptic seizures, brain dynamics that make up the graph consists of abnormalities in EEG signals. Because of the dynamics of these signals are due to several factors are not easy to put the required informations. Therefore, both time and frequency bands of the signals as well as need to go to the review and determination of the pattern. Identifying patterns of the signals depends on the extraction of the characteristics. Defining the degree of a property of an event is about separation in the event of sharp lines from others. Therefore, the incident event clearly must could be characterize the detected property.

In this study, the dynamics of the brain contribute to the development of detection and early diagnosis systems and EEG signals in order to achieve the results form the basis for the determination of pathological conditions, epileptic signals, chaos analysis methods are used. Preictal(prior to the actual seizure) and ictal(actual seizure period) EEG epochs were evaluated by wavelet-entropy method. Wavelet entropy is derived from combination of the wavelet and entropy terms that is considered as a measure of irregularity of the signals(systems). Wavelet analysis is of great importance when the property is removed from non-stationary signals. It is a method that giving the information of time-frequency of the signal. Wavelet analysis is preferred to seperate the signal to the spectral bands and to focus on spesific subbands. Entropy is a concept of thermodynamics is a measure of the disorder of the system. Pincus initially used the entropy in 1991[1]. Later, many researchers have applied entropy to epileptic EEG signals[2-9]. And also, many researchers have applied entropy, HOS, RQA and similar methods to epileptic EEG signals[10-17].

Each quantity obtained from the system defines a different feature vector. The excessive number of feature vectors means better recognition of the system. Since that means more parameters, the processing load also increases.

EEG data have been acquired from the database of Universities of Dicle and Inonu, Department of Neurology. To apply chaotic methods to these segments, phase spaces have primarily been created, then wavelet of EEG signals have been calculated and then entropy of each subbands are calculated.

In the Literature, wavelet and entropy methods are widely used for analysis of the chaotic time series or systems. In addition, time-frequency techniques can be used to analyze this kind of signals and systems.

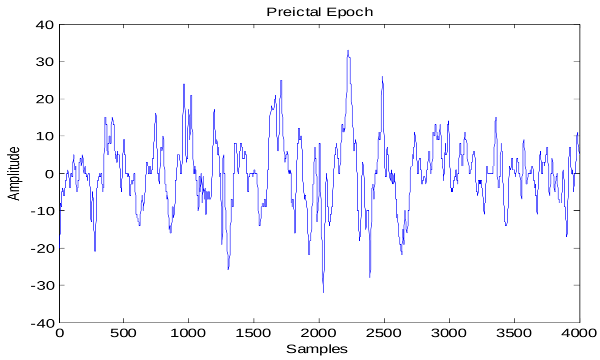

Fig1. *Preictal segment of epileptic EEG signal*

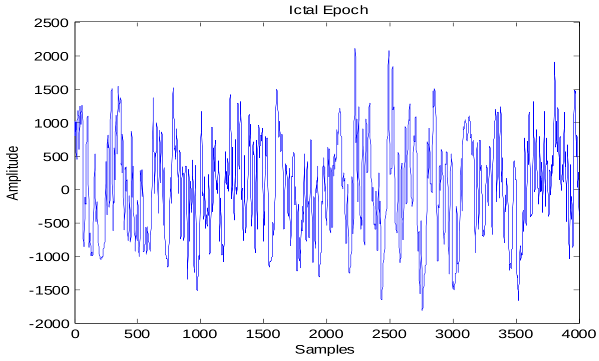

Fig2. *Ictal segment of epileptic EEG signal*

In this study, preictal (Figure 1) and ictal (Figure 2) EEG epochs were examined. One hour EEG signals from different patients were used for wavelet-entropy analysis method. One-hour epileptic EEG signals divided into two states as preictal and ictal for this study. Then preictal end ictal states divided into 20 second segments. All of the EEG signals have been separated into the standard subbands which are: delta=(0-4Hz), theta=(4-8Hz), alpha=(8-12Hz), beta=(12-30Hz) and gamma=(30-60Hz). Then, the Shannon entropies of the EEG subbands are calculated; and finally the feature vectors are classified with ANN. ANN was trained with 60 EEG segments in total, composed of preictal and ictal segments, and a test was conducted with the remaining 40 segments. The measured wavelet entropies of EEG segments were detected to be distinctive in classification. The composite system that was proposed using performance evaluation criteria showed a 97,5% success rate in classification.

2. MATERIALS AND METHODS

This section composed of information about EEG, epilepsy, wavelet entropy and ANN. Schematic diagram of Proposed system is shown in Figure 3.

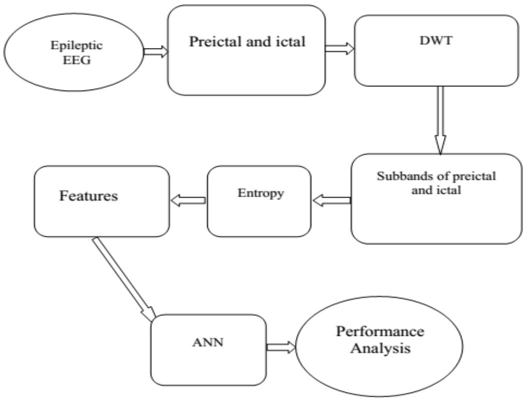

Fig3. *Schematic diagram of the proposed system*

2.1. Electroencephalogram

Studies in 1870s with the brain of rabbit by Caton spontaneous and continuous activity in the brain was discovered. The earliest records of the human brain the electrical field in the 1920s was carried out by Hans Berger. This is called EEG recording and suggested that some diseases have changed the character of the EEG.

Electrical recordings obtained from surface of the brain(cortex) and the outer surface of the head(scalp) show that a continuous electrical activity of the brain. Patterns of electrical activity that are included as well as a large extent and the severity of the sleep-wake states and brain diseases such as epilepsy and changes in the level of arousal, resulting in some of the brain is determined by psychoses. These electrical potentials oscillations are called as “brain waves” and the whole recordings are called Electrencephalogram[18]. The signals which produced by the human brain are called EEG signals. These signals include very specific information about the state of the brain. Even now, many scientists mapped to the human brain, how to decide and how the human brain thinks making many efforts on issues such as and this studies are in progress. Frequencies of the EEG signals, brain EEG signals from varies points of the phase differences with each other, provides important information about human brain.

Frequency waves in the EEG contains critical information which is extremely important. EEG signals contain information about the functions of the brain. In order to use this information, signal machinists have a variety of researching. Some pathological symptoms go unnoticed in the time domain. Neurologists usually diagnosed based on the time domain. Recently, computers to register these signals and the improvement of the spectral analysis methods that finding the frequency components of these pathological conditions have made it possible to benefit[19].

There are cases that need to be considered when EEG recording. Human brain, when people are awake, asleep or in which people feel a wide variety of situations depending on the frequency and amplitude of the signals produced. EEG signals from the surface of the head are between 1-100 µV peak to peak amplitude and between 0.5 to 100 Hz in the frequency bands[20].

It is required along-term measurement and registration in order to obtain meaningful information from EEG signals. Because, EEG signals changes according to the activity of the brain frequency, phase and amplitude information.

2.2. Epilepsy

Epilepsy is a disease which popularly known as “seizure” focused on the brain. In the general population is not known many real associated with this disease. Seizure is a fenomena for recognizing epilepsy and may be in different forms. Epileptic seizure means some of the neurons in the central nervous system due to different causes increased excitability of the brain caused by a sudden focal or generalized paroxysmal character of a reactions[21]. Epilepsy is a chronic disorder characterized by recurrent unprovoked seizures.

A large collection of neurons synchronous and abnormally discharge caused epileptic seizures. Synchronous discharge stereotyped, involuntary and suddenly appeared and these changes cause transient epileptic seizure behavior deeply affects the patient’s life. Abnormal cell discharge may ocur for reasons such as trauma, oxygen unsufficient, tumors, infections and metabolic disorders. However, it is not possible to find any reason half of epileptic patients[22].

Despite it is called epilepsy as “seizure disease” but it is not true the seizures to be mentioned as “epilepsy”. Seizures are symptom but epilepsy is a disease that characterized by recurrent seizure[23].

2.3. Chaos Analysis

The signals were recorded in the form a one-dimensional time series provide information on the dynamic properties of a system. In order to understand the behavior of the dynamic system, especially with an irregular status variables derived from specific time intervals the temporal evolution of the system to be drawn from measurements is very important. Dynamics of the system that defines the temporal evolution of the system is recreated by the independent variables which represented by trajectories in the phase space attractor[24-27].

One dimensional disordered system at regular intervals in the form of time series represent a function of the measurement data of the experimental record. The purpose of predicting of function’s attractor and topological properties is to re-establish the phase space of the system. The first recommendation on this issue in 1980 by Packard. Packard observed turbelent or chaotic flow measurements to obtain a number of trailers in the phase space structure of the re-established[28].

2.3.1. Phase Space Reconstruction

In order to chaos analysis firstly, the phase space of time series is created.

Space that consisting of state variables and their derivatives is called phase space. When time evolving, a point of state space follows a path which is called trajectory[29]. Often, two or three dimensional space are studied and a point is determined by Cartesian coordinates x, y and z directions of the state. This customization is inadequate when dealing with a dynamical system, because it will not stay fixed to place points in the dynamical systems, ie, the point position depends on the time in motion. This is written as [x(t), y(t), z(t)]. Dynamics or motion is indicated by a set following equations(1).

$$\begin{aligned} dx/dt &= f_1(x,y,z) \\ dy/dt &= f_2(x,y,z) \\ dz/dt &= f_3(x,y,z) \end{aligned} \tag{1}$$

Phase space transforms the numbers to the images. The smallest piece of the basic information are pulled a system of mechanical or fluid in motion for all releases. A flexible roadmap is drawn on its own means [27]. Time information is illustrated in the form of coordinates in the phase space. Coordinates are the parameters which lead to change in the time series. The image formed in the phase space is called “attractor”. If the dimension of the phase space is fractal, the attractor is called “strange attractor”.

Attractors may occur in different ways depending on the dynamic behavior of the system. If a dynamic system having any initial condition and the system is stable, attractor in the phase space to reach the point that represents a temporary situation at that point and then remains stable state. These attractors which consist of a point are called “point attractors”. The attractors which showing the periodic behavior of a dynamical systems in the phase space are called as “periodic attractors”. Periodic attractors in the phase space trajectories corresponding to all initial values follow by a closed path. One of the most important features of the point and periodic attractors has a fixed ratio of the distances between the orbits is that it has drawn. Through changing variables in the system has connected to the next state of the system can be determined with the help of prior states. Thus, long term prediction can be made.

Chaotic behavior is characterized by the separation of the state space’s orbits close. As a function of time, the separation between the two closest trajectory increases exponentially. Generating chaotic behavior of the state space of three or more dimensions an important feature of the trajectory without intersecting each other without repeating themselves by coiling and stay within a limited region capabilities. This type of the dynamic movements is called as “strange attractor”. If the behavior of the attractor is chaotic, it is called “chaotic attractor”[30].

When it is examined the values of the single system variable, it is not possible to draw just a phase space multivariable systems. So Takens[30], uses the same variable as the coordinate values of the pseudo-phase space at different time revealed. This space usually is consist of the original time series and delayed time series values. At this stage, it is important that to find the most convenient delay parameter and the number of coordinates.

For calculation of the chaotic dynamics it is required that time series reconstruction in the phase space. The same time in the phase space is made comparison of two or more functions. It is required at least two functions for reconsruction of a state space. According to Takens theorem[31], if we have only one time series we use time series and its derivatives to construct phase space as shown in the equation(2).

$$y(n) = \left[x(n),\ x(n+\tau),\ x(n+2\tau),..\ x(n+(m-1)\tau)\right] \tag{2}$$

Because the creation of the time series in the phase space and thus create a larger Euclidean space without any ambiguity situation presenting the structure of the attractor. “m” is embedding dimension and “τ” is time delay which is used in the equation(2).

2.3.2. Embedding Dimension and Time Delay Parameter

Embedding dimension must be selected optimum value for the best form of attractor in the phase space. Embedding dimension “m” is calculated by false nearest neighbors (FNN) method.

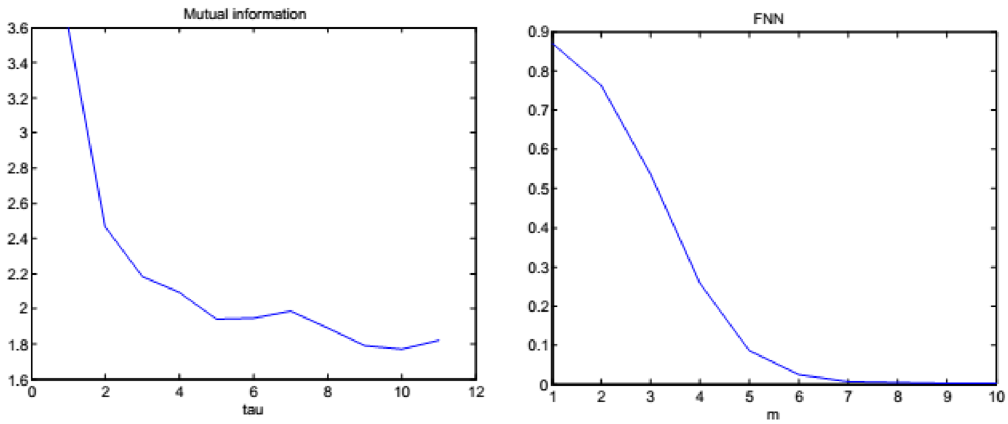

Fig4. *FNN and mutual information of epileptic EEG signal. “tau” indicates time delay parameter and “m” shows embedding dimension*

It is shown embedding dimension “m” by FNN method for epileptic EEG signal in Figure 4.

The value that intersects the horizantal axsis shows the embedding dimension “m=7” in Figure 4.

If embedding dimensions were choosen a small value the attractor loose its natural appearence because of mixing of dimensions. The performans of process drops if we select unneccesary great dimensions.

Delay parameter “τ” is calculated by the first local mimimum of the mutual information function. Time delay “τ” value should be selected optimum. When time delay parameter “τ” is small value the attractor would be linear. When “τ” value is great the attractor disperse in the phase space and lose its properties.

$$x = A\sin(wt + \theta) + B \tag{3}$$

We take a sine function as shown in equation(3). Here, A is amplitude and B is a dc component of the wave. w=2πf is angular frequancy and θ=wτ is a phase angular. A “τ” shift in the time domain leads to a “θ” phase shift. This corresponds to the distance between the two components in the phase space. That means Euclidean distance between a(t) and a(t+ τ).

It is shown delay parameter “τ” by the mutual information method for a one-hour EEG signal in Figure 1. The first local minimum shows the time delay parameter “τ=5” in Figure 4.

2.3.3. Wavelet-Entropy Method

Wavelet-entropy is consist of wavelet and entropy terms. It is determined irregularity of signal time-frequency content with wavelet-entropy analysis.

Fourier analysis is preferred in stationary signals but wavelet analysis is preferred in nonstationary signals. Because of EEG is nonstationary signal it was analyzed by wavelet analysis. We see a time-frequency picture of the signal by wavelet analysis. In addition, it was reflected states of subbands of the signals.

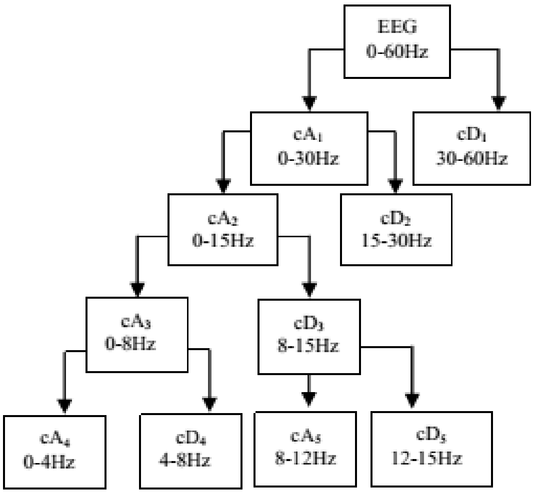

Fig5. *Wavelet analysis scheme of approximate and detail coefficients of EEG segments*

Wavelet analysis is of great importance when the property is removed from non-stationary signals. It is a method that giving the information of time-frequency of the signal. Wavelet analysis is preferred to seperate the signal to the spectral bands and to focus on spesific subbands. As shown schematically in Figure 5, signal is passed through a low-pass and a high-pass filter repeatedly. Subbands are filtrated by low-pass filter are known as “approximate coefficients” and sub-bands are filtrated by high-pass filter are known as “detail coefficients”.

Wavelet analysis scheme which is given in Scheme1 designed specifically for EEG subbands. Approximate coefficients of EEG signals are expressed as “cA” and detail coefficients as “cD”. Approximate and detail coefficients of EEG segments are calculated by wavelet analysis.

Approximate and detail coefficients of EEG segment are calculated by wavelet analysis. Then the energy of each band is calculated and it is normalized as given in equation(4).

$$P_j = \frac{E_j}{E_{top}} \tag{4}$$

Here, P_j refers to the normalized energy, E_j refers to the subbands energy and E_t refers to the total energy of EEG segment, where j=1, 2, 3, 4, 5 refer to the subbands of EEG segment. These normalized subband energies are the nature of the distribution of EEG generating system presence in different situations to be considered. Comparision of these distributions are calculated by Shannon entropy in equation(5).

$$S = -\sum_j P_j \ln P_j \tag{5}$$

Here, the obtained value of entropy is a measure of disorder of a system. This criterion is considered to offer an overview of the system. This information describes a feature vector of the system to another point of view.

2.4. Artificial Neural Networks

Artificial neural networks inspired by biological neural networks were uncovered. ANN is an information processing system that have some performance characteristics similar to biological neural networks[31]. There are information processing function that required intelligence on the basis of

ANN. This systems consists of processing element interconnected by a one-way point channels. There is a similarity between the functions of the human brain and ANN. Therefore, ANN can be called the human brain model. ANN behaviors can be changed by environment. If inputs and desired outputs are given the system, ANN can adjust itself so as to give different answers. A typical neural network is a combination of layers of processing elements. The most commonly used type of ANN is a multilayer feedback learning perceptron. Multilayer perceptron consists of the input layer that receives data from outside, output layer that gives the data of network to the output and one or sometimes more than one hidden layers between the input and output layers[33].

In this study, 50 preictal and 50 ictal, a total of 100 EEG segments have been used for classification. While 60 segments were used for training ANN and 40 segments for testing. The segments have been separated five sub-bands by wavelet analysis. It was applied entropy to the sub-bands of each segment and thus it was calculated wavelet entropy values. ANN inputs consists of these five subband entropies. These wavelet entropy values constitude the feature of preictal and ictal segments.

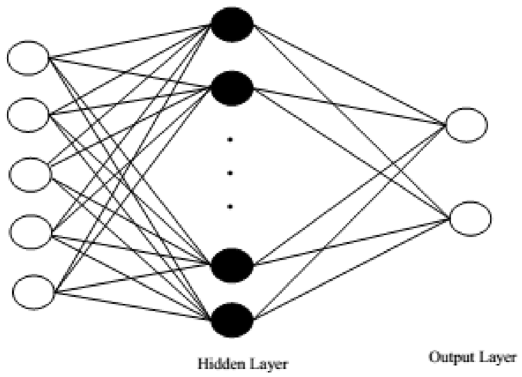

Fig6. *Multi-layer artificial neural networks model*

It was tested in different situations and obtained the most successful ANN shown in Figure 6. This model has 5 input layers, one hidden layer which consists of 10 neurons and 2 output layers. Output layer is composed of two neurons, including preictal and ictal states. Log sigmoid transfer function is used for hidden and output layers. Also, Levenberg-Marquart algorithm is used for learning algorithm. Tuning parameters of classifiers are randomly selected and 2-fold cross validation is used.

3. Results

3.1. Feature Extraction

In this section, first of all it was reconstructed phase space of epileptic EEG signals.

The data used in this study was taken from the EEG laboratory archives of the Neurology Department at Medicine Faculty of Dicle and Inonu Universities. The data had been recorded from 7 adult patients between 2001-2013 years during clinical studies. It had also been reported that 5 of patients were man and other 2 were woman whose ages were ranging from 25 to 45. The recording period had been varied from 3 to 48 hours. All of patients have partial seizures. The records were noninvasively taken from 16 standard sites of 10-20 system on scalp of patients at 200 Hz sampling rate using a digital video EEG recording system.

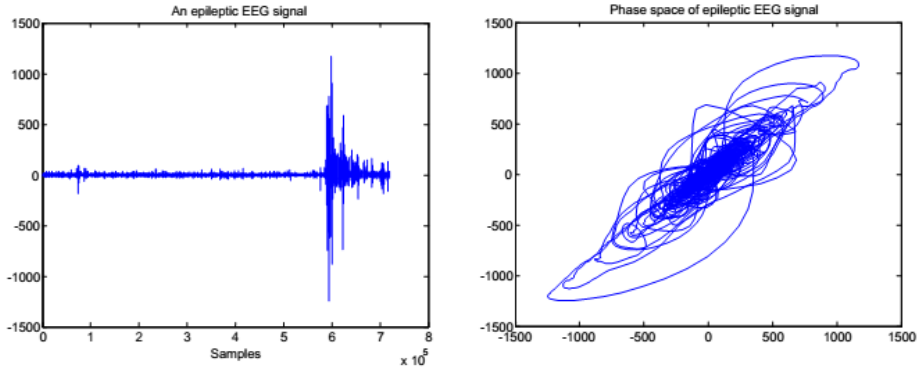

Fig7. *An epileptic EEG signal and its phase space plot*

The time series graph of an epileptic EEG signal is shown in Figure 7. When we analyze epileptic EEG signal, there is an increase in amplitude during epileptic attacks. However, it is difficult by visual determination before and after attack. In addition any excessive increase in amplitude of the signal is not mean an epileptic attack. Therefore, these signals would be better disscused in another domain. The dark parts in the center of phase space in Figure 4 show preictal state and the lines outside of the center show the ictal state.

In Figure 8, the entropy values of delta, theta, alpha, beta and gamma subbands of epileptic EEG signals have been shown. All of subbands' entropy values are distinctive properties, but gamma subband's entropy values are the best distinctive properties.

One of the feature vector of preictal and ictal segments is shown in Table 1.

Table1. *A feature Vector of Preictal and Ictal Segments*

Features	Preictal	Ictal
Entropy (Delta)	0,0070	0,0091
Entropy (Theta)	0,0065	0,0098
Entropy (Alpha)	0,0067	0,0105
Entropy (Beta)	0,0069	0,0104
Entropy (Gamma)	0,0064	0,0113

3.2. Performance Analysis

The performance analysis criterian are used to assess the performance of the system by using equations 6-10.

Sensitivity =TP/(TP+FN) (6)

Specificity =TN/(TN+FP) (7)

PPV=TP/(TP+FP) (8)

NPV=TN/(TN+FN) (9)

Accuracy=(TP+TN)/(TP+TN+FP+FN) (10)

The performance analysis criterian is known as "Sensitivity", "Specificity", "Positive Predictive Value", Negative Predictive Value" and "Accuracy". These criterian is calculated for each EEG segments.

Sensitivity is used to determine the ability of the separation ictals from actual ictals. Specificity is used to determine the ability of the separation preictals from actual preictals. PPV is used to determine really the possible presence ictal when classifier gives ictal results. NPV is used to determine really the possible presence preictal when classifier gives preictal results. Accuracy is used to determine the ratio of correctly classified samples to all samples.

Preictal and Ictal Truth-Predictive Matrix is shown in Table 2.

Table2. *Preictal and Ictal Truth-Predictive Matrix*

<table>
<tr><td colspan="2" rowspan="2"></td><td colspan="2">PREDICTIVE</td></tr>
<tr><td>Ictal(+1)</td><td>Preictal(-1)</td></tr>
<tr><td rowspan="2">TRUTH</td><td>Ictal (+1)</td><td>TP
(19)</td><td>FN
(0)</td></tr>
<tr><td>Preictal (-1)</td><td>FP
(1)</td><td>TN
(20)</td></tr>
</table>

The values obtained from these measurements are given in Table 2. It is coded as TP(True Positive), FP(False Positive), TN(True Negative), and FN(False Negative). These criterian is labeled (-1) for preictal and (+1) for ictal EEG segments.

The final result of performance analysis criterian is shown in Table 3.

Table3. *Performance Analysis Criterian*

	Sensitivity	Specificity	PPV	NPV	Accuracy
Performance %	100	95	95	100	97,5

ANN classifier perform with an accuracy of 97.5%, sensitivity and specificity of 100% and 95% respectively.

4. Discussion

Objective of this study is to determine the differences between preictal and ictal EEG segments. For this purpose, this study composed of wavelet-entropy and ANN methods.

The advantage of this study, preictal and ictal states is determined with high accuracy by only one feature (wavelet-entropy).

First of all, one-hour epileptic EEG signals divided into five subbands for wavelet analysis. All of EEG segments have been separated into standard subbands. Then entropy of each subbands are calculated. And then, Shannon entropies of EEG subbands are calculated; and finally the feature vectors are formed by combining the values obtained with this method. In this study, 50 preictal and 50 ictal, a total of 100 EEG segments have been used for classification. While 60 segments were used for training ANN and 40 segments for testing. ANN inputs consists of these five subband entropies. These wavelet entropy values constitude the feature of preictal and ictal segments. These features were found to be distinctive values. Preictal and ictal segments which used for classification are shown in Table 4.

Table4. *Number of 20 Seconds Preictal and Ictal Segments Analyzed per Patient*

Patient	Number of Preictal Segments	Number of Ictal Segments
A	10	5
B	5	10
C	5	10
D	10	5
E	10	5
F	5	10
G	5	5

Summary of previous works for classification of preictal and ictal states are shown in Table 5.

Table5. *Summary of Previous Works for Classification of Preictal and Ictal StateS*

Year(Ref.)	Authors	Features	Classifier	Accuracy (%)
2006(2)	WA Chaovalitwongse, OA Prokopyev, PM Pardalos	Lyapunov Exponents, Angular Frequency, and Entropy	Support Vector Machine (SVM)	Close to 90
2008(13)	KC Chua, V Chandran, R Acharya, CM Lim	Higher Order Spectra (HOS) Power Spectrum and the Bispectrum(PSD)	Gaussian Mixture Model (GMM)	93.11(HOS) 88.78(PSD)
2012(5)	UR Acharya, F Molinari, SV Sree, S Chattopadhyay, Kwan-Hoong Ng, JS. Suri	Aproximate Entropy (ApEn), Sample Entropy (SampEn), Phase Entropy(S)	Fuzzy Sugeno Classifier (FSC), SVM, KNN, Probabilistic Neural Network (PNN), Decision Tree (DT), GMM, and Naive Bayes Classifier (NBC).	98.1
2012(15)	L Chen, J Zou, J Zhang	Recurrence Quantification Analysis (RQA)		-

Pincus [1] tried to measure complexity of Rossler, Logistic and Henon chaotic systems by applying approximate entropy method. Acharya and et al. [5] have applied approximate entropy, sample entropy and phase entropy to epileptic EEG signals in their studies. They used normal, preictal and ictal EEG segments. The classification performance of their method was 98.1% by using Support Vector Machines, Probabilistic Neural Networks and K-Nearest Neigbours (KNN). Kumar and et al. [11] have extracted features of epileptic EEG signals by using discrete wavelet and approximate entropy methods. ANN was used as classifier and has 100% performance rate in classification.

Rosso and et al. [34] have applied orthogonal discrete wavelet transform to EEG signals. They have defined relative wavelet energy, the wavelet-entropy and the relative wavelet entropy. It has been stated that wavelet-entropy has advantages over relative wavelet energy and relative wavelet entropy. Song and Zhang [35] have applied wavelet, sample entropy and genetic algorithms to the epileptic EEG signals. The accuracy of their classifier was 94.2 %.

5. Conclusions

First of all, it is important that early identification of epileptic seizures in terms of doctors and epileptic patients. In terms of epileptic patients, it is required for prevention of accidents determining seizures early. And also, in terms of doctors, it is required for diagnosis determining seizures early. In this context, the discovery of the obvious differences between preictal and ictal states is of great importance. In our study it is determined preictal and ictal states by wavelet-entropy and ANN methods.

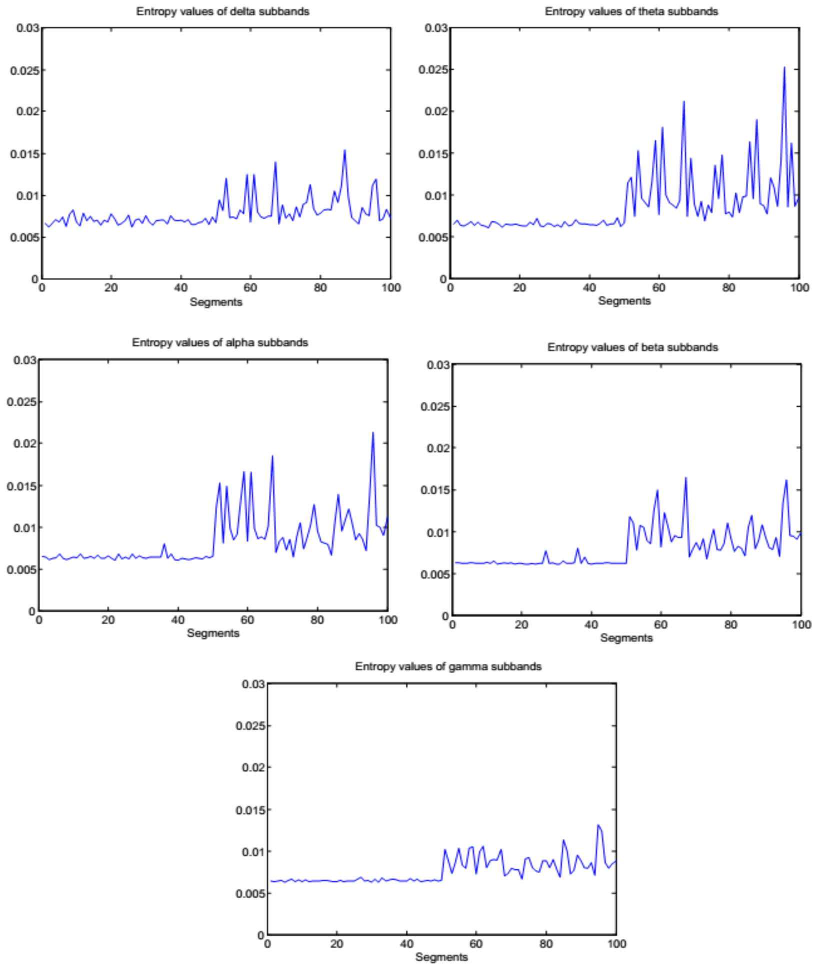

Fig8. *Preictal and ictal subband entropies The first 50 values show subband entropies of preictal and the final 50 values show subband entropies of ictal segments.*

As a result, preictal and ictal EEG subbands'entropy values distinguish preictal and ictal segments from each other and the distinctiveness of gamma subbands' entropy values are more robust(Figure 8). It is important for early detection of ictal state to distinguish between preictal and ictal EEG segments. The composite system that was proposed using performance evaluation criteria showed a 97, 5 % success rate in classification.

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