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Automatic Recognition of Epileptic Seizure from EEG Signal Based on Discrete Wavelet Transform

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Abstract

Background: Automatic Recognition of Epileptic Seizure from EEG Signal based on Discrete Wavelet Transform. In traditional methods such as visual scanning, epilepsy detection is a time-consuming process which requires high accuracy and experience for analyzing the whole length of data. The main objective of this study is automatic diagnosis of epileptic seizures via discrete wavelet transform.

Methods and findings: The data sets used in this work are electroencephalogram (EEG) signals. The classification of EEG signals proposed in this paper for diagnosis of epileptic seizures is based on wavelet transform. The method is composed of three steps: a) wavelet transform based feature extraction, b) feature space dimension reduction based on scatter matrices and c) classification. The proposed approach, applied on EEG data sets, belong to three categories: a) healthy persons, b) persons with epilepsy during a seizure-free period and c) persons with epilepsy during a seizure.

Conclusion: The classification in this work is more accurate than previous studies. Conducted simulation shows the effectiveness of proposed method.

Keywords: Epilepsy diagnosis; Seizure detection; Discrete wavelet; Quadratic classifiers

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Introduction

Epilepsy is the most common chronic neurological disorder, which afflicts about 1-3% of the world's population [1]. A seizure happens when neurons generate uncoordinated electrical discharges that spread all over the brain. Epilepsy is a recurrent seizure disorder caused by abnormal electrical discharges from brain cells, often in the cerebral cortex [2]. EEG is a graphical recording of ongoing electrical activity, which measures the changes of the electrical activity in term of voltage oscillations of brain through multiple electrodes placed in different locations of the brain [3].

In clinical contexts, the main diagnosis of EEG is to discover abnormalities of brain activities referred to the epileptic seizure. Another clinical utilization of EEG includes diagnosis of coma, brain death, encephalopathy, sleep disorder etc. Also, EEG can be used in many applications such as emotion recognition [4], video quality evaluation [5], alcoholic consumption measurement [6], sleep stage detection [7], variation of the brainwaves by smoking [8], mobile phone usages [9], etc.

The detection of epileptic seizures by visual scanning of a patient's EEG data, usually gathered over a few days, is a grueling and time-consuming process. Moreover, it requires an expert to analysis the entire length of the EEG records, in order to detect epileptic activity. Thus many automated epileptic detection systems have been proposed in the recent years [10]. The time taken to off-line review of the long-term EEG recording has been reduced considerably using such automated systems. Also, neurologist can discern and treat more patients in given time.

The entire process of epileptic seizure detection can be generally categorized into two main steps: (1) feature extraction and (2) classification. Selecting an optimal set of significant feature plays a deciding role in developing a good classification system. The methods used for analyzing the EEG signal in recent studies consists of auto correlation function, time domain properties, frequency domain properties, time-frequency analysis, nonlinear time series analysis, wavelet transform, nonlinear time series analysis. Wavelet transform is the most successful method among above methods [11-16].

For epileptic diagnosis, the features of patient EEG signal should be extracted. This features includes the average EEG signal size,

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the average duration of EEG, coefficient of variation, the relative wavelet energy, entropy (Statistical measure of randomness), dominant frequency [17], the relative wavelet energy, the spectrum of the average power as the input of adaptive neural networks, and two EEG time-domain features namely relative spike size and spike rhythmicity.

An automatic classification must be accurate and reliable. High accuracy guarantees a correct diagnosis and facilitates treatment. Several techniques have been proposed for detection of epileptic seizures and this percent accuracy. Chua et al. in [18] for epileptic seizure, fulfilled the calculation of non-linear features derived from higher-order statistics and categorized them by Gaussian mixture classification into two groups with and without seizure. The accuracy of this research is 93%. Orhan et al. [19] achieved the accuracy of 97% using wavelet transform and K-nearest neighbor classifier. Ghosh-Dastidar et al. [20] used the principal component analysis and artificial neural network to detection epileptic seizure. The accuracy of this method is concluded to be 99%. Gajic et al. in [21] used wavelet transform, extracted features with four criteria and classified them by utilizing the square classifier using wavelet transform. The accuracy of this research is 99%.

Selection of the appropriate features is one of the most important tasks in the design of proper classifiers; since, if the features are not selected well, even the best classifier will perform very poorly [21]. It should be noted that the two important reasons can be cited for achieving imperfect result in above research. On the one hand, the criteria for feature extraction are selected incorrectly. On the other hand, there is incomplete extraction of features as a result of underutilization of appropriate indicators. In other words, the EEG signal features of the patient persons should be extracted as correctly and completely as possible. This is because a classifier needs to the characteristics of signals in order for it can separate them from one another.

In this paper, with suitable indicators, wavelet transform method and square classifier is used for correct and quite accurate epileptic seizure detection and the characteristics of each signal are extracted as the best possible way. In other words, the classifier can be separate different signals by using five appropriate features. The separation of different signals will result in more accurate sickness diagnosis and treatment facilitation.

Research Methodology

The utilized EEG data are a subset of EEG data corresponding to both normal and epileptic persons presented by Dr. Ralph and rzejak from the Epilepsy Centre at the University of Bonn, Germany [22]. As can be seen from **Figure 1**, three EEG data sets from three different groups have been analyzed in this paper:

- Healthy persons with normal EEG data
- Epileptic persons during a seizure-free interval with interictal EEG data
- Epileptic persons during a seizure with ictal (epileptic) EEG data

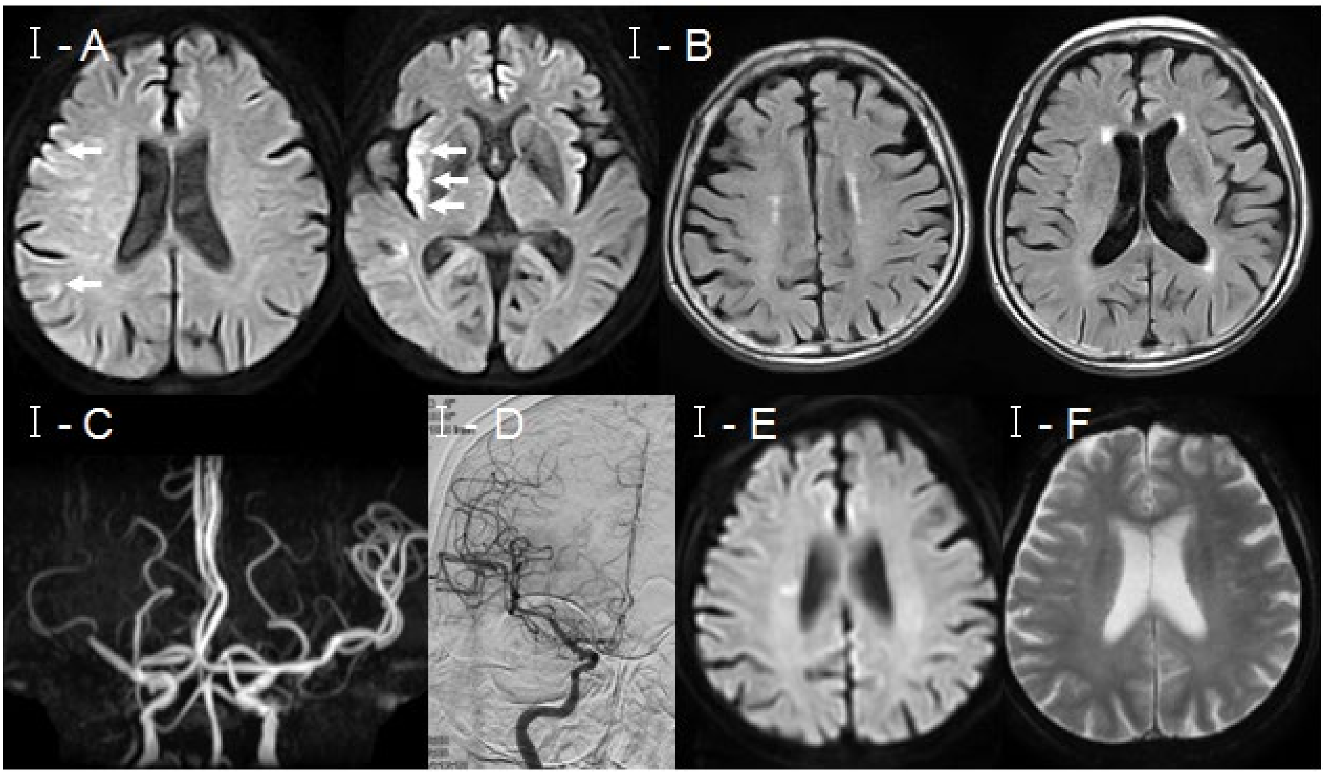

Figure 1 Three EEG data sets from three different groups (the first five seconds of EEG data), A: Normal, B: Interictal, C: Ictal.

Each data set is sampled at 173.61 Hz and within 23.6 s, by a 128-channel amplifier system, containing 100 single-channel EEG segments. The EEG data collection is achieved from the skull and recorded signal, using the standardized electrode placement technique **(Figure 2).**

The EEG sections are selected from all of the recorder sections which show seizure activity. Each EEG section is considered as a separate EEG signal which contributes to obtaining 300 parts data. The first five seconds of EEG data is shown in **Figure 1**.

Five sub-band of spread spectrum EEG signal that generally used in clinical research contain: delta (0–4 Hz), theta (4–8 Hz), alpha (8–16 Hz), beta (16–32 Hz), and gamma waves (32–64 Hz). Higher frequencies are often used for abnormal brain states such as epilepsy.

Diagnosis of epileptic seizures is proposed based on wavelet transform and statistical pattern recognition by an automated classification of EEG signals.

1) The first step of this method is to obtain a set of features after wavelet transform of EEG data, containing energy, dominant frequency, average EEG duration, entropy, and standard deviation of both wavelet coefficients and the EEG signal in five sub-bands of clinical research. In the following, the index is defined as a brief:

Entropy (S) is a thermodynamic quantity, which measure the degree of disorder in any system. The higher degree of disorder causes the higher entropy. The unit of entropy is joule per kelvin (J/K) in the international System of Units (SI). It is essential to note that entropy is a state function and independent of route.

Frequency (ƒ) is a criterion to measure the number of occurrences of an event in a given time. Dominant frequency, the frequency at which the largest energy between the frequencies of spectrum. The unit of dominant (HZ) in the international system of units (SI).

The average a sample of size n, X_1, $X_2 \dots X_n$, is the quotient of the sum of the size on n.

$$X' = \sum \frac{X_i}{n},\ i = 0,1,2,\dots n \tag{1}$$

Energy means the activity of a fundamental physical quantity, in physics and other sciences. Energy is a quantity used to describe the state of a particle, object, or system attributed to it.

Signal Energy:

A) Time-continuous signal energy

$$E = \int_{t1}^{t2} \left| x(t)^2 \right| dt \tag{2}$$

B) Time-discrete signal energy

$$E = \sum_{n=n1}^{n2} \left| x[n] \right|^2 \tag{3}$$

In statistics, the standard deviation (shown with the symbol σ) is one of the dispersion indices which shows how much data are away from the average value.

If X is a random variable with mean μ:

$$E[X] = \mu \tag{4}$$

Operator E shows the mathematical expectation of X. Thus, the standard deviation can be defined using the expectation operator characteristics, as follows:

$$\begin{aligned}
\sigma &= \sqrt{E\left[(X-\mu)^2\right]} \\
\sigma &= \sqrt{E\left[X^2\right] + E\left[(-2\mu X)\right] + E\left[X^2\right]} = \sqrt{E\left[X^2\right] - 2\mu E\left[X\right] + \mu^2} \\
\sigma &= \sqrt{E\left[X^2\right] - 2\mu^2 + \mu^2} = \sqrt{E\left[X^2\right] - \mu^2} \\
\sigma &= \sqrt{E\left[X^2\right] - \left(E\left[X\right]\right)^2}
\end{aligned} \tag{5}$$

2) The second step is reducing dimension of the feature space using scatter matrices. Eventually, two quadratic classifiers are designed, which are able to recognize all three groups of the discussed EEG signals from each other. **Figure 3** shows the entire structure of the algorithm.

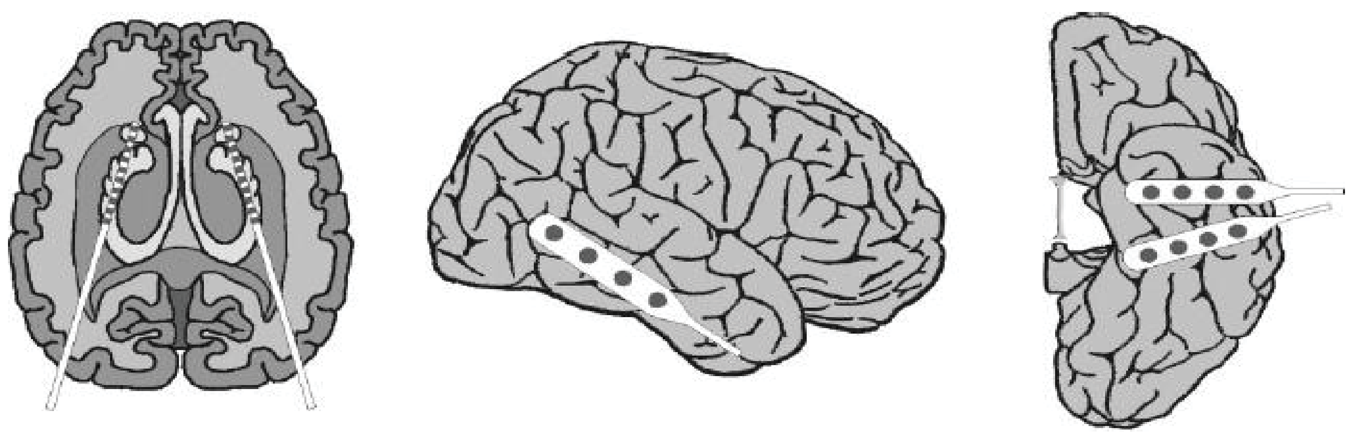

Figure 2 Implanted intracranial electrodes for pre-surgical evaluation of epilepsy patients. Depth electrodes were implanted symmetrically into the hippocampal formations (top).

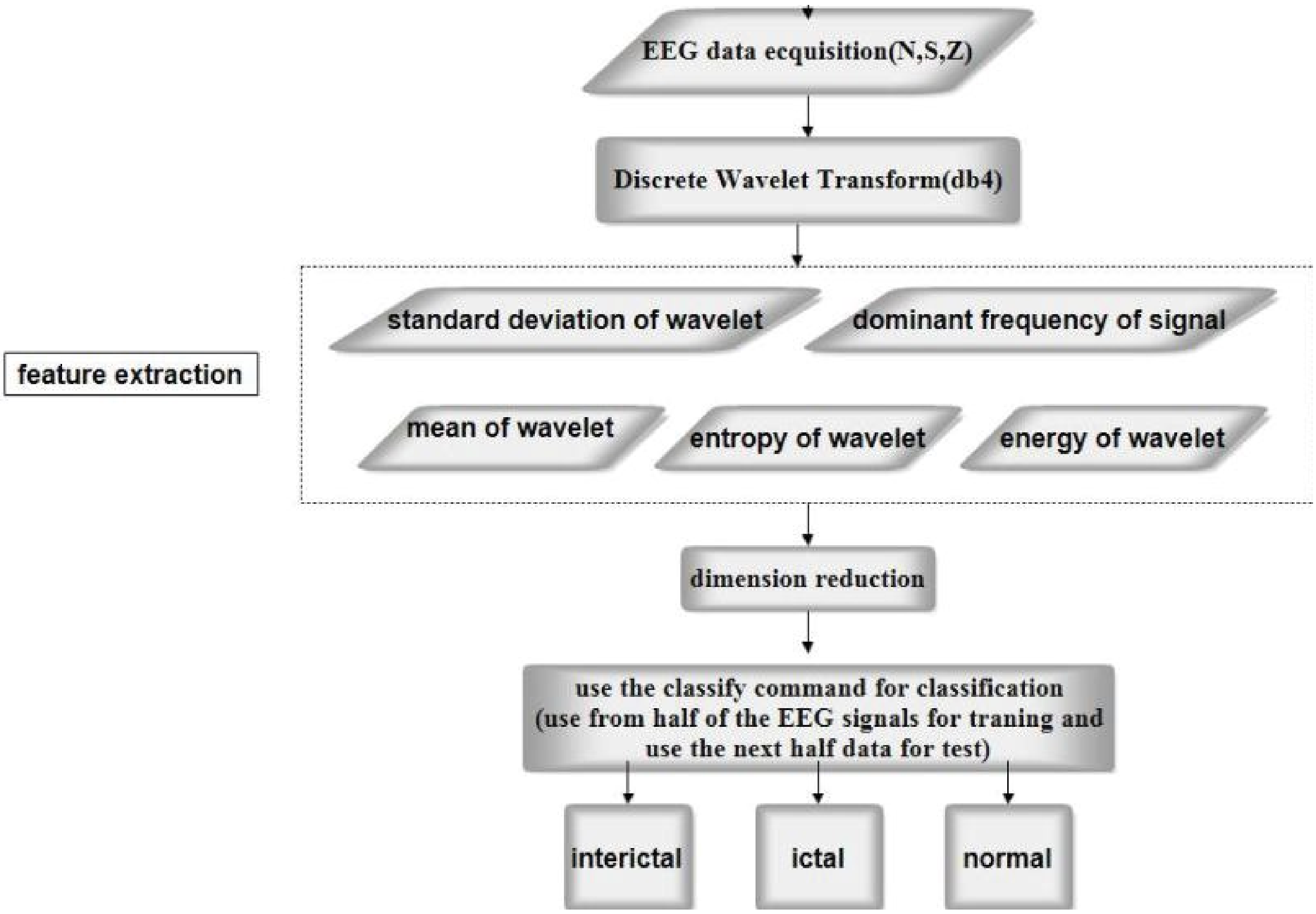

Figure 3 Entire structure of the algorithm.

Wavelet transform as a linear frequency-time transformation is an effective analytical tool for signal analysis, pattern recognition, and classification. It is also appropriate for analysis of transient, non-static phenomenon, and noise reduction. As a category of functions, it has the capability to localize information in both time and frequency [23]. Therefore, the wavelet transform has been used widely in biomedical signal processing [24-26]. In discrete wavelet analysis, a multi-resolution explanation is utilized to decompose a given signal X (t) into increasingly finer/ delicate details. This explanation is based on two sets of basic functions [27], i.e., the wavelets and the scaling functions, in accordance with the following formula:

$$x(t)=\sum_{k}2^{j0/2}a_{j0}(k)\varphi\left(2^{j0}-k\right)+\sum_{j=j0}^{\infty}\sum_{k}2^{j/2}d_{j}(k)\psi\left(2^{j}t-k\right) \quad (6)$$

Where ϕ (t) is the basic scaling and ψ (t) is the mother wavelet. In this expansion, the first term indicates an approximation of X (t) based on the scale index of j0, while the second term appends more detail utilizing larger j, which is the better scale. These coefficients in above expansion are called the discrete wavelet transform (DWT) of the signal X (t). Also, these coefficients can be obtained as follows, in orthogonal wavelets:

$$a_{j}(k)=\int_{-\infty}^{\infty}2^{j/2}x(t)\varphi\left(2^{j}t-k\right)dt \quad (7)$$

$$d_{j}(k)=\int_{-\infty}^{\infty}2^{j/2}x(t)\psi\left(2^{j}t-k\right)dt \quad (8)$$

In which αj (k) is the wavelet approximation coefficients and dj (k) is detail coefficients. In the DWT, the frequency axis is divided into two intervals toward the lower frequencies. It should be mentioned that the bandwidth length reduces exponentially.

Results

The wavelet transform is able to decomposition the signal to different frequency sub-bands. In This manner, this method is effective and without the computational burden. In each of the previously derived sub-bands the signal can be reconstructed and its time-domain features in different sub-bands can be studied separately, based on wavelet coefficients achieved after the wavelet transform.

Among variety of wavelet, the fourth-order Daubechies wavelet was selected according to their performance comparison in this process. It should be noted that in the signal analysis using wavelet transform, choosing the appropriate type of wavelet and number of decomposition levels are very important.

After analyzing the signal using wavelet transform and extraction of the features, formation of the feature vector $Y = [y_1, y_2, \ldots, y_n]$ is formed which has very large dimensions. Designing the classifiers in large scale it is very difficult and working with such matrix associated with numerical problems. Therefore the matrix size must be reduced, despite the loss of a part of data.

The most usual method, among different methods of determining the matrix reduction feature is the Karhunen-Loeve method. It depends on the area of operation. Also this method as a principle component analysis (PCA) referred. In these methods, the greatest extent random scattering vector is determined and this is done via an analysis of covariance matrix.

The direction which has the largest information should be preserved in both case of before and after dimensions reduction. In the Karhunen-Loeve Expansion method, the main components z1 and z2 are determined based on the calculation of eigenvectors and eigenvalues. After dimension reduction, the dimension of the components z1 is maintained and the dimension of the components z2 will be deleted, because eigenvalues corresponding to z1 are greater than those of the z2.

It is important to note that dimension reduction should have the separation property of the created categories

Even if more than 10 percent of data is lost while reducing the feature matrix, it is possible for the classification using the remaining amount of information to be successful because the perfect dimension reduction (with the property separation).

Several methods have been used for classification of data that includes: artificial neural network, Square classifier, Bayesian classifier and linear classifier, etc. The classifier in this paper is square classifier. In this method half of the data used for training and the rest is used for testing. The purpose is to assign input patterns to one of the categories, according to the selected features for its category. Performance Categories are defined by using sensitivity, specificity and overall classification accuracy.

Sensitivity is the total number of correctly classified positive pattern models divided by the total number of real positive patterns. A positive pattern model of a section of the brain identifies one of these three categories.

Specificity is resulted from dividing real negatives by the sum of true negatives and false positives. Overall classification accuracy is equal to the total number of correctly classified patterns divided by the total number of applied patterns. A template defines an EEG data segment of all three categories. The sorting results contributed from confusion matrix are shown in **Table 1**. Based on the confusion matrix, all 50 of the data of normal EEG, ictalEEG and interictal EEG are classified correctly by the algorithm. By calculating the sensitivity, specialty and accuracy of **Table 2** is obtained, which represents the precise result without error. According to the simulation result, the full separation of categories is possible, and no data has been in the wrong category **(Figure 4)**.

Table 1 Confusion matrix.

Output/Desired	Normal EEG	Interictal EEG	Ictal EEG
Normal EEG	50	0	0
Interictal EEG	0	50	0
Ictal EEG	0	0	50

Table 2 Statistical parameters.

EEG data sets	Sensitivity (%)	Specificity (%)	Accuracy (%)
Normal EEG	100	100	100
Interictal EEG	100	100	-
Ictal EEG	100	100	-

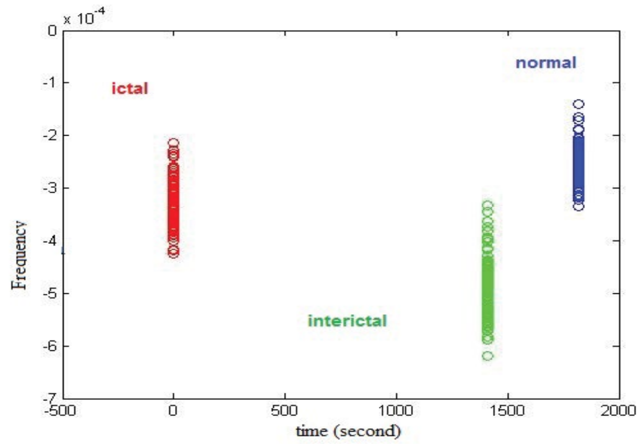

Figure 4 The simulation result.

Discussion

Automatic bio potential detectors have been proposed for real-time detection [24]. The wavelets transform was considered only recently as a relevant pre-processing method in the context of neural signal processing [25]. It has since been successfully used in biomedical applications [26-32]. The EEG always results from a huge number of individual neurons, each interacting with its neighboring neurons as well as with remote neurons whose electric potentials are not included in the measurement. This study aimed to present a method of automatic detection of epilepsy based on EEG, since accurate and in-time diagnosis of the disease has significant impact on the treatment and prevention of long-term effects of taking antiepileptic.

Conclusion

In this study, in order to the automatic detection of epilepsy and EEG data analysis with high accuracy, after processing the data using discrete wavelet transform, extracting more features with more indicators were discussed. Some indicators such as energy, entropy, standard deviation, mean and dominant frequencies were used. According to performed calculations, tables and simulation using MATLAB software, it can be confidently said that the general classification algorithm is able to identify normal, ictal and interictal subjects. It is worthy to note that the accuracy of the proposed method is 100%. Also this method can be used in the clinics in practice. The limitation of this study is the practical so that the results were not applied on group of subjects and the results were theoretically mentioned.

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