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A New Approach in Epilepsy Diagnosis using Discrete Wavelet Transformation and Analysis of Variance

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Abstract

Epilepsy is a chronic disorder and outbreak of brain function, caused by the abnormal and intermittent electric discharge of brain neurons. Electroencephalogram signals represent brain activities, and one of the methods of diagnosing epilepsy is using EEG brain signals. In this article, a new method for diagnosing epilepsy using EEG signal processing is presented. At first, the EEG signal is divided into five frequency sub-bands using Discrete Wavelet Transformation (DWT). Then, the features are extracted from five frequency sub-bands, and the best features are selected by the analysis of variance (ANOVA) method. Finally, by using the Support Vector Machine (SVM) algorithm, these features are used to classify seizure and non-seizure EEG signals. The simulation results from the Bonn university dataset affirm the suggested approach's advantage in comparison with some other basic classical methods in terms of accuracy, sensitivity, and specificit.

Keywords: Epileptic Seizure, Features selection, Electroencephalogram signals, Support Vector Machine (SVM).

1. INTRODUCTION

Epilepsy is a neurological disorder; after stroke, it is the second most common neurological disorder in humans and affects about 1% of the world's population [1, 2]. Epilepsy can happen at different ages and affect the sufferers, causing a change in their state, behavior, or lack of consciousness [3, 4]. EEG signals play a vital role in diagnosing this disease [5]. EEG recordings made with mobile recording devices generate a large amount of data, which takes a long time for an expert to analyze in order to diagnose the epileptic region [1, 6]. Recently, learning-based approaches have demonstrated considerable promise in various applications.

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Specifically, computerized automatic diagnosis systems have been designed to help specialists accelerate the diagnosis of epilepsy by automatically recognizing epileptic states from the EEG signal [7-9].

The four steps of automatic epilepsy diagnosis are signal decomposition into frequency bands, feature extraction, feature selection, and classification [1, 10]. Choosing the right algorithms in each of these steps is very important for the accuracy of epilepsy diagnosis [11, 12]. This has caused it to attract the attention of more researchers every day, some of whom will be reviewed below.

In [13], spectral entropy, sample entropy, and phase entropy are extracted as features from the EEG signal, and then the fuzzy classifier is used to classify the diagnosis of epilepsy. In [14], statistical features are used to extract features, and SVM is used to classify the diagnosis of epilepsy. In [15], the characteristics of the power, including the relative power spectrum, the power spectrum ratio, and the cross-correlation coefficients, are extracted, and then the artificial neural network is used for the classification of epilepsy. In [16], the wavelet transform and the energy of the wavelet coefficients are presented as features, and the adaptive neural fuzzy network is used for the classification of epilepsy. In [17], the binary gravity search algorithm is used to select features, and the k-nearest-neighbors algorithm is used to classify epilepsy. In [18], autoregressive analysis is used to extract features from EEG signals, and a multilayer perceptron classifier is used to classify epilepsy. In [5], a combination of time and frequency methods are used to extract features. In [19], multi-wavelet transform and approximate entropy are used to extract and select features, respectively.

The main challenge in the automatic identification algorithms of epileptic seizures is the selection of features that distinguishes different stages of epilepsy from each other. It is essential to choose the distinguishing features of the EEG signal; if the appropriate features are not selected, sufficient information may not be obtained from the EEG signal to diagnose epilepsy. Finally, it can cause a disturbance in the accuracy of the diagnosis of epilepsy. Therefore, it is necessary to propose a suitable method to select the desired features of the EEG signal.

In this article, the EEG signal is decomposed into five frequency sub-bands using DWT, and then the features are extracted from the EEG frequency sub-bands using time-based, frequency-based, and time-frequency-based methods. Then, the ANOVA method is used to select the desired features. Finally, the SVM algorithm is used to classify the EEG signal. The organization of the rest of the article is as follows: in the second part, the proposed method for the diagnosis of epilepsy is described, and in the third and fourth parts, the experimental results and conclusions are discussed, respectively.

2. METHOD

According to Figure (1), the process of diagnosing epilepsy includes two steps: training and testing. Both processes are discussed in this part. The training phase extracts rules from EEG signals, and the test phase uses generated rules to classify the new signal. The DWT for EEG signal analysis,

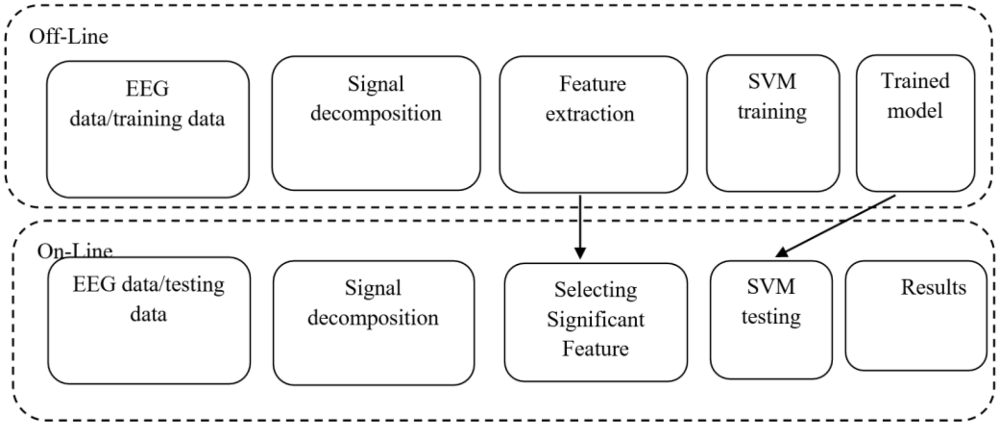

Fig1. Diagram of the proposed method.

Table 1. ***Frequency bands of EEG signals with four-level DWT decomposition.***

Frequency band (Hz)	Decomposed signal
86.8-43.4	D1
43.4-21.7	D2
21.7-10.8	D3
10.8-5.4	D4
5.4-0	A4

extraction, and selection of features and classification is made separately in each of the training and testing stages, which will be explained in the following.

2.1. Discrete Wavelet Transform

In this section, the DWT method is used to analyze the EEG signal into different frequency bands of delta, theta, alpha, beta, and gamma of the brain signal. Discrete wavelet functions are defined by pairs of high-pass and low-pass filters. These filters separate the high- and low-frequency components of the input signal. In the first stage, the output of the high-pass filter is the detail coefficients (D1), and the output of the low-pass filter is the approximation coefficients (A1). The coefficients of A1 are decomposed again, and this process is repeated four times. A 3-level Daubechies wavelet decomposition of EEG signal is utilized to obtain four frequency bands. The frequency sub-bands in each of which the wavelet coefficients have been extracted are listed in Table (1).

2.2. Feature Extraction

In this section, after analyzing the frequency spectrum of the EEG signal, time-based, frequency-based, and time-frequency-based features are used. In Table (2), a list of the combinations of all three methods of features used in this article is introduced.

Fifteen features are extracted from both EEG signals (the raw signal and five sub-bands analyzed by the DWT algorithm). Some of these features may be redundant and not suitable for classification. Removing redundant features is very important. In this article, the feature ranking method is used, and the extracted features are classified according to their importance for an epilepsy diagnosis. Here, ANOVA is applied for choosing the most relevant features based on ranking feature vector by computing F-value for each feature. For instance, the F-values of all features are depicted in Figure (2).

Table 2. ***A list of features extracted from the time domain and sub-bands.***

Sr. No	Feature	Formula Eq. No
1	Mean	$\mu_a = \frac{1}{N}\sum_{i=1}^{N} a_i$
2	Standard deviation	$\sigma_a = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\left\|a_i - \mu_a\right\|^2}$
3	Variance	$V_a = \frac{1}{N-1}\sum_{i=1}^{N}\left\|a_i - \mu_a\right\|^2$
4	Skewness	$S_a = \frac{R_3}{R_2\sqrt{R_2}}, R_k = \frac{1}{N}\sum_{i=1}^{N}\left\|a_i - \mu_a\right\|^k$
5	Kurtosis	$K_a = \frac{R_4}{R_2 R_2}, R_k = \frac{1}{N}\sum_{i=1}^{N}\left\|a_i - \mu_a\right\|^k$
6	Line length	$L_a = \sum_{i=1}^{N-1}\left\|a_i - a_{i-1}\right\|$
7	Non-linear energy	$NE_a = \sum_{i=2}^{N-1}\left\|a_i^2 - a_{i+1}a_{i-1}\right\|$
8	SampEn	$SEn(a,m,r) = \log\phi^m(\mathrm{r}) - \log\phi^{m+1}(\mathrm{r})$ $\phi^m(\mathrm{r}) = \sum_{j=0}^{N-m}\sum_{i=0}^{N-m}\Theta\left(r - \left\Vert a_i - a_j\right\Vert_\infty\right)$ where $\Theta(.)$ is Heaviside step function
9	Permutation Entropy	$PEn(a) = -\sum_{k=1}^{m!} p(\pi_k)\log p(\pi_k).$ $p(\pi_k) = \frac{1}{N-m+1}\sum_{i=0}^{N-m}\delta[a_i - \pi_k]$ where $\delta(.)$ is Dirac function
10	Shannon Entropy	$ShEn(a) = -\sum_{i=1}^{N} p_i \log p_i.$
11	Spectral Entropy	$SpEn(a) = -\sum_{i=1}^{N} p_f \log p_f.$
12	mobility	$M_a = \frac{\sigma_{a'}}{\sigma_a},\ a_i' = a_{i+1} - a_i$
13	complexity	$C_a = \frac{\sigma_{a''}/\sigma_{a'}}{\sigma_{a'}/\sigma_a},\ a_i'' = a_{i+1}' - a_i'$
14	Number of zero-crossings	NZ_a
15	Number of local extrema	NX_a

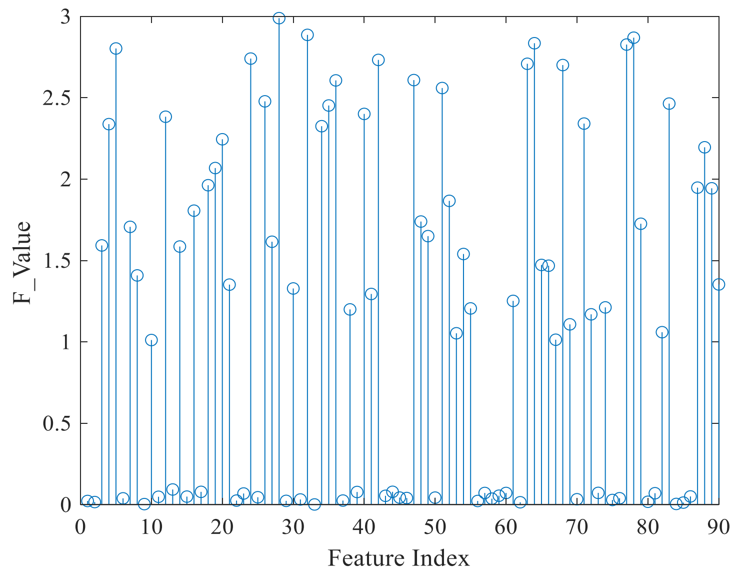

Fig. 2. F-value for all 90 features by using analysis of variance.

2.3. Classification

Support vector machine classification was presented in 1963 by Vepnik. In this method, geometric parameters are used instead of statistical parameters, so it is part of the non-parametric classification category[20]. SVM is an advanced pattern classifier that properly separates two classes, and it was developed based on statistical learning. It distinctly classifies data points by finding the best hyperplane with the maximum margin, and it is also capable of disregarding outliers. For linearly non-separable data points, the sample space is mapped to the high-dimensional feature space through a non-linear kernel function in SVM. Thus, the kernel function converts not separable data into separable data. Hence in the present study, different linear and non-linear kernels such as linear, quadratic, cubic, and Gaussian (radial basis) were applied to determine the best hyperplane, and the results related to the highest accuracy are shown.

3. RESULTS

In this section, the performance of the proposed method is compared with other classical methods [11, 21-26]. All experiments were performed on a personal computer with MATLAB 2020. In the following, the evaluation criteria, database, and test results will be discussed.

3.1. Evaluation Criteria

To evaluate the effectiveness of epilepsy diagnosis methods, classic evaluation criteria such as accuracy according to (1), the sensitivity of features according to (2), and specificity rate (specificity) according to (3) are used.

$$ACC = \frac{TP + TN}{TP + FP + TN + FN} \tag{1}$$

$$Sensivity = \frac{TP}{TP + FN} \tag{2}$$

$$Specificity = \frac{TN}{TN + FP} \tag{3}$$

In (1-3), TP is the number of correctly predicted EEG signals. TN is the number of correctly predicted no-seizure. Also, FN and FP are the number of EEG signals that are incorrectly predicted as not seizures and the number of non-ES that are incorrectly predicted as seizures, respectively.

3.2. Database

The EEG signal dataset of Bonn University has been used to evaluate the performance of the proposed method [27]. These data include five categories: A, B, C, D, and E. Each batch contains 100 EEG signals, and the length of each is 23.6 seconds. Each category includes 4097 number samples. The signal recording system has a bandwidth of 0.5 to 85 Hz. In this dataset, the A and B sets of the EEG signals of five individuals are normal, where the A set of EEG signals is pertinent to the case of eyes open, and the B set is pertinent to the case of eyes closed. The C and D sets consist of the EEG signals of five patients at pre-ictal time. Ultimately, the E set includes the seizure times of five patients with epilepsy with ictal times. In this dataset, the EEG signals of the A and B sets are recorded from the scalp, and the D, C, and E sets are recorded in an invasive way. The ictal time in EEG signal refers to the period of abnormal electrical discharges in the brain that are characteristic of a seizure. During a seizure, the neurons in the brain start firing in an abnormal and synchronized manner, which can be detected by an EEG signal. This abnormal electrical activity is known as the ictal state. The ictal time in EEG signal starts at the onset of the abnormal electrical activity and ends when the activity returns to normal. The duration of the ictal time can vary depending on the type and severity of the seizure. In some cases, the ictal time may be very brief, lasting only a few seconds, while in other cases, it may last several minutes. This database, which consists of five subsets, can be considered different classifications. The most common classification for this database is shown in Table (3).

3.3. Results and Tests

To evaluate the performance of the proposed method, two sets of tests are performed with other classical methods. In the first test set, the effect of the number of different features is evaluated. In the second test set, the performance of the proposed method is compared with other methods [11, 21-26].

3.3.1. The effect of the number of different features in the diagnosis of epilepsy

In this experiment, the effect of the number of different features on the accuracy of epilepsy diagnosis is evaluated. For this purpose, we consider three different attitudes. In the first attitude, we just use the 15 features listed in Table (2) and extract them from the original signal and perform classification on them. In the second attitude, the signal is decomposed using DWT to 5 sub-band and 90 features are extracted on the total, and these features are sent to the classifier for evaluation. In the third attitude, we choose the top 30 most informative features from 90 features and study the classification results. The classification performance for different feature dimensions and three scenarios are shown in Table (4).

Table 3. ***Types of classes considered for this database in the article.***

Case	Classes	Description	Type
1	A and E	Non-seizure and ictal	**Two class**
2	E and B		
3	E and AB		
4	E and C	Inter-ictal and ictal	**Two class**
5	E and D		
6	E and CD		
7	E and CAB	Non- ictal and ictal	**Two class**
8	E and DAB		
9	E and ABCD		
10	E and C, and A	Non-seizure, inter-ictal and ictal	**Three class**
11			
12	A and B and C and D and E		**Five class**

Table 4. ***Performance results of the number of features on the diagnosis of epilepsy.***

# Features	Case	Accuracy (%)	Sensitivity (%)	Specificity (%)
15	1	95.41	94.33	93.25
	9	85.22	89.72	81.55
	11	92.15	94.46	90.65
	12	82.72	86.32	80.25
90	1	80.03	77.42	84.55
	9	78.25	82.65	72.15
	11	65.82	61.90	69.33
	12	58.85	50.15	62.32
30	1	`100	100	100
	9	97.31	95.41	98.05
	11	98.33	98.98	97.95
	12	95.15	93.85	96.75

Table 5. ***Performance results of the proposed method with other methods.***

Methods	Accuracy	Sensitivity	Specificity
Method[21]	79.8	81.5	77.2
Method[22]	93	97	92
Method[23]	98.40	98.22	98.31
Method [11]	94.81	92.63	99.43
Method [24]	99.0	-	-
Method [25]	92.50	-	-
Method [26]	93.62	-	-
Proposed method	99.30	99.64	99.12

As can be seen in Table (4), 30 features have been selected by the method proposed, which has a better performance in diagnosing epilepsy.

3.3.2. Evaluation of the performance of the proposed method compared to other recent works

In this section, the performance of the proposed techniques was compared with other existing new methods using the same dataset, which is shown in Table (V). The proposed method performs better than other methods in terms of accuracy, sensitivity, and specificity (Table V). In general, it can be concluded that the proposed method is very effective in diagnosing epilepsy. It should be mentioned that all approaches were evaluated on the same dataset.

4. CONCLUSION

In this article, a new method is proposed for the automatic classification of brain signals, including epileptic attacks. In this method, the EEG signal is analyzed by DWT into five frequency sub-bands, and time-based features, amplitude-based features, and amplitude- and time-based features are extracted from each spectrum. The importance of analyzing the signal in the spectrum related to its different frequency sub-bands is that the changes created in the EEG signal may not be easily visible in the main signal, while in the sub-bands, changes appear with higher accuracy. Finally, using the extracted features and SVM classification, the parts of the signal with epileptic attacks are distinguished from the parts without attacks. The review of previous studies on this dataset shows that the method proposed in this article has the highest percentage of accuracy in classification.

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