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Detection of epileptic seizures from EEG signals with Hilbert Huang Transformation

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Abstract

Epilepsy is a significant neurological disease that occurs due to abnormal activities of a particular portion of brain neurons. Electroencephalography (EEG) signals are mainly used to detect this disease. Epilepsy can be diagnosed automatically by measuring and analyzing the non-linearity and non-stationary properties of EEG signals. In this study, the Hilbert Huang Transformation (HHT) is proposed to extract the distinctive features from EEG signals for epileptic seizure detection. Research work, firstly, the mean Instantaneous Amplitude (IA) and mean Instantaneous Frequency (IF) data were extracted from EEG signals with Hilbert Huang Transformation (HHT) as a feature. Then, these features were classified with Extreme Learning Machine (ELM). Classification results indicated that epileptic seizures are detected with high accuracy. In addition, the performance evaluation of the proposed method was compared with some other techniques studied by using the same dataset recently. According to the experimental results, HHT based approach has 0.5-1% better classification accuracy than current studies and higher accuracy in detecting epileptic seizures than similar studies.

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1. Introduction

Biomedical signals are crucial for both diagnosis and treatment of diseases and for displaying health conditions. Although biomedical signals are examined in two groups as electrical and non-electrical signals, electrical biomedical signals are widely used in scientific studies. One of the electrical biomedical signals commonly used in biomedical studies is the Electroencephalography (EEG) signal. EEG is a method that can measure and record the electrical activities of the brain and capture temporary events that cause recurrent functional disorders in the human brain [1]. EEG signals are obtained through electrodes placed at specific points on the head. These signals can be defined as voltage changes caused by ionic current occurring in neurons in the brain. Observing these changes is very significant in disease diagnosis. One of the essential purposes of using EEG signals is to be preferred for the detection of epilepsy disease [2]. Epilepsy is a clinical condition caused by the disruption of abnormal electrical activities that occur temporarily in part of the brain cells. It is a neurological disease known as a temporary recurrent and unpredictable epileptic seizure that can be seen in approximately 50 million people worldwide [3]. Physiological effects such as changes in mental state, lack of attention, empty gaze and inability to remember are primarily observed in patients [4]. In addition, during sudden and unpredictable seizures, due to the loss of consciousness, the person is unable to protect himself at that moment so that the person may be exposed to the risks of injury, suffocation and death [2, 4]. These seizures can be detected and diagnosed by monitoring long-term EEG recordings. Monitoring of EEG signals requires a lot of attention. Although the expert does the monitoring and interpretation of the EEG recordings, sometimes reading error may occur. Systems that can automatically detect epilepsy disorders have been developed to assist specialists in the diagnosis and treatment process. Recently, many EEG signal processing analysis methods have been studied for automated epilepsy detection systems. These methods generally aimed to obtain specific features from the EEG signal and classifying these features [3]. Feature extraction from EEG signals is usually located in the time, frequency, or time-frequency domain (TFD). In the time domain, methods

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such as basic component analysis-based radial-based artificial neural networks (ANN) are used [5].

In the studies carried out in the frequency domain, with the assumption that EEG signals are stationary signals, attributes extracted using the Fourier Transform (FT) and Wavelet Transform (WT) are classified by using classification methods such as decision trees, ANN and support vector machines (SVM) [6]. In addition to all these studies, non-stationary EEG signals have been widely used in many scientific studies in this field. Epileptic seizures detections were performed by using the properties of non-stationary EEG signals in the time-frequency region. Siuly et al. [7] calculated the permutation entropy, histogram and statistical properties with the transformation of Hermite transformation EEG signals into a new form. Afterwards, they identified these features by least squares and SVM to classify EEG signals to detect epileptic seizures. Recent studies have benefited from the HHT conversion, a new method proposed by Norden E. Huang in 1998 to analyze both non-linear and non-stationary high-dimensional EEG signals [8]. For detecting epileptic seizures, Hilbert Vibration Decomposition (HVD) was performed by extracting single component attributes of momentary amplitude and frequency changes of EEG signals [9]. Fu et al.[10] detected epileptic seizures with the SVM classifier using features such as mean, variance, skewness and pixel density in the HHT-segmented grayscale time-frequency image histogram. Matris et al. [11] used spectral entropy and spectral energy properties of spectral peaks calculated from the Intrinsic Mode Functions (IMF) for epileptic seizure detection. Shuren ve Zhong have performed epileptic seizure detection using different threshold levels of IMF signals again for their properties obtained by Empirical Mode Decomposition (EMD) to separate EEG signals into several IMFs [12]. Feldman detected epileptic seizures by decomposing HVD, a newer signal decomposition technique, by separating non-stationary time series and suggesting harmonic extraction with reduced energy content [13]. Ghayab et al. [14] sequential feature selection (SFS) features were reduced in size after feature extraction from multi-channel EEG signals with simple random sampling (SRS). Later, these features were classified with the least-square support vector machine (LS_SVM) classifier. In experimental studies, they achieved an accuracy rate of 99.90%. Zhu et al. [15] proposed feature extraction with the Fast Weighted Horizontal Visibility (FWHV) algorithm for seizure detection of EEG signals. They obtained by comparing the extracted features with fast FT and sample entropy. Supriya et al. [16] used statistical methods for feature extraction after converting the weight visibility graph and EEG signals into a complex network. These features were classified with k-NN and SVM and detected seizures. Kumar et al. [17] proposed feature extraction by dividing WT and EEG signals into different sub-bands for seizure detection. Afterwards, they classified these features with the SVM classifier types. Demir at al. [18] Convolution Neural Network (CNN) based efficient approach was proposed for emotion recognition with EEG. After EEG signals were converted to EEG rhythm images with Continuous Wavelet Transform (CWT), feature extraction was performed with CNN. Deep features are classified with SVM.

In this research, average instantaneous amplitude and mean instantaneous frequency values were obtained as features by the HHT method from stationary and non-linear EEG signals. Epileptic seizures are detected automatically by classifying these features with ELM. In experimental studies, 10-fold cross-validation was performed to evaluate the validity of the method. Results present that the proposed method appears to have achieved a classification accuracy of 0.5-1% better than current studies. The rest of the research work, HHT method and feature extraction are introduced in EEG dataset part 2. In chapter 3, experimental studies are mentioned. Finally, in section 4, evaluations regarding the results of the study are presented.

2. Material and Method

In this section, the methods used for the dataset, feature extraction, and classification are described in detail.

2.1. EEG dataset

EEG is a recording of the electrical activity of the brain from the scalp. These electrical activities have variable frequencies and magnitudes. The magnitude of the EEG signals is in the microvolt levels. EEG signals are divided into four groups according to their frequency: delta (1-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), beta (13-30 Hz), and gamma (30- 80 Hz) [18], [19].

Bonn EEG dataset is utilized to test the method proposed in this research work [20]. The dataset contains five separate EEG sub-datasets, Set A, Set B, Set C, Set D, Set E. Each subset includes 100 EEG signals recorded for 23.6 seconds, and each signal consists of 4097 samples. Datasets A and B are recorded EEG signals from five healthy participants with eyes open and eyes closed, respectively. The C and D dataset contains EEG signals from opposite episodes of the head, respectively, from processes without seizures from five epileptic patients.

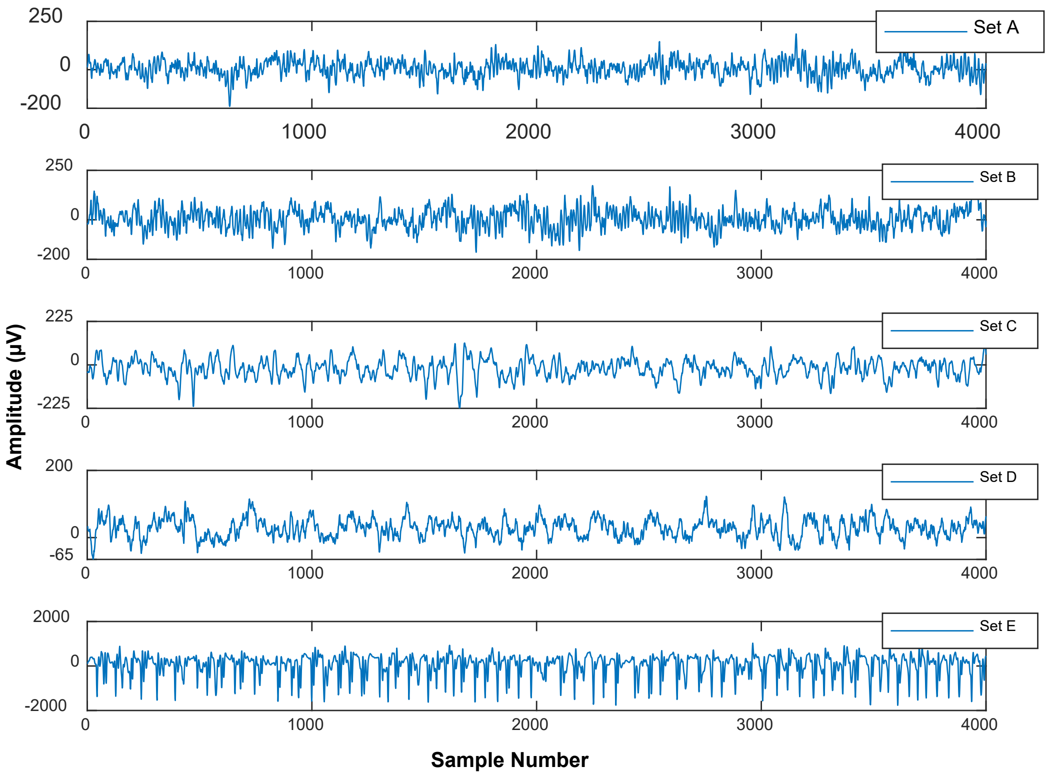


Figure 1. Sample EEG signals of the five subsets A, B, C, D and E.

The E dataset contains EEG signals taken at the time of seizures from five epileptic patients. Figure 1 shows sample EEG signals of the five subsets in the Bonn Dataset.

2.2. Method

In this study, a new time frequency-based method is presented to detect epileptic seizures from EEG signals. The technique, the block diagram of which is given in Figure 2, consists of two separate sections: obtaining attributes and classification. For feature extraction, instantaneous amplitude and instantaneous frequency variations of stationary and non-linear EEG signals were obtained with HHT. Averages of instantaneous amplitude and frequency changes were taken separately, and their attributes dataset was created.

At the last stage, epileptic seizures were detected automatically by classifying these attribute data with the ELM classifier. ELM was preferred as the classifier due to its successful classification and high performance in classification and regression applications. More detailed information for ELM can be viewed from Huang's [8] article.

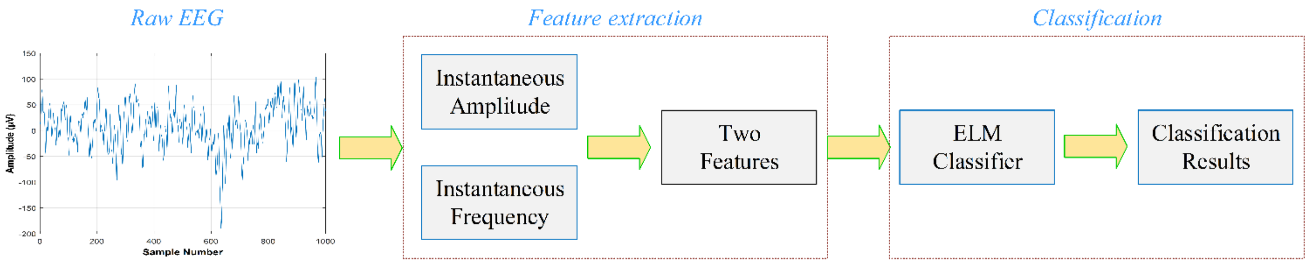


Figure 2. Block diagram of the proposed method.

2.2.1. Hilbert Huang transformation

Norden E. Huang proposed the HHT method in 1998 for the time-frequency analysis of both non linearity and non-stationary signals, in particular. Unlike traditional time frequency analysis methods such as Fast Fourier Transformation (FFT) and WT, it is used to analyze non-stationary and non-linear signals. HHT consists of two essential components; EMD and IMF [21]. It is particularly suitable for the display of time-frequency-energy systems. The most meaningful way to physically define such a system is instantaneous frequency information that reveals in-wave frequency modulation. The easiest way to calculate the instantaneous frequency is to use HDD. HHT is a method mainly used to express one-dimensional time series to analytical form in biomedical signal processing and power systems applications [22],[23].

HHT process for a sample x(t) signal could be defined as in (1):

$$H[x(t)] = F^{-1}\{F\{x(t)\}u(t)\} \qquad (1)$$

where *F{.}* and $F^{-1}\{.\}$ is FFT and Inverse FFT, respectively, here u*(t)* expression in equation (1) is presented in equation (2):

$$u(t) = \begin{cases} 1 & n = 0, (N/2) \\ 2 & n = 1,2,\dots,(N/2)-1 \\ 0 & n = (N/2)+1,\dots,N-1 \end{cases} \qquad (2)$$

Here *N* is the sample length of *x(t)*. HHT uses both FFT and inverse FFT processes. Moreover, using a time series, it is possible to define an analytical signal generated by the imaginary part of the HHT. The HHT result of the time series is an analytical time series, a complex value signal. The amplitude and phase of the signal are time-dependent. This signal contains instantaneous amplitude, instantaneous phase and instantaneous frequency information. In this context, an analytic signal of a real-time *x(t)* signal *z(t)* could be defined as in equation (3). The instantaneous amplitude *a(t)* and instantaneous phase *φ(t)* defined in equation 3 could be found with equation (4).

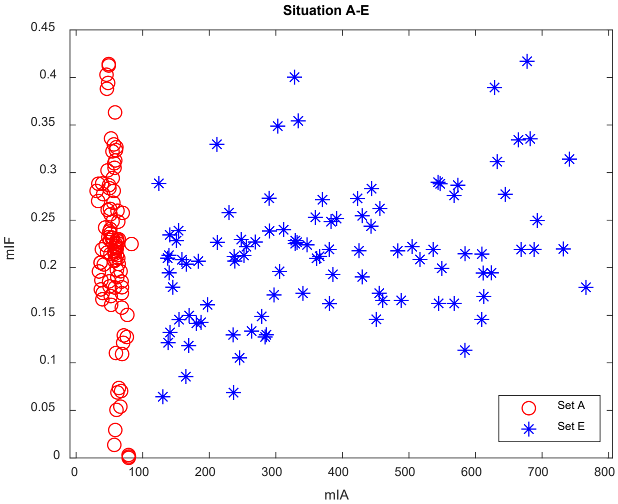
$$z(t) = x(t) + iy(t) = a(t)e^{i\varphi t} \qquad (3)$$

$$a(t) = \sqrt{[x^2(t) + y^2(t)]}\,, \varphi(t) = arctan\frac{y(t)}{x(t)} \qquad (4)$$

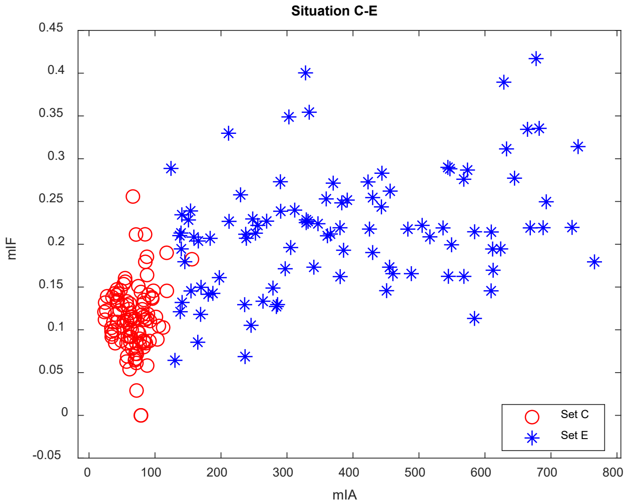
Moreover, the instantaneous frequency could be calculated with the help of $\omega(t) = \frac{d\varphi(t)}{dt}$ relation.

3. Experimental Studies

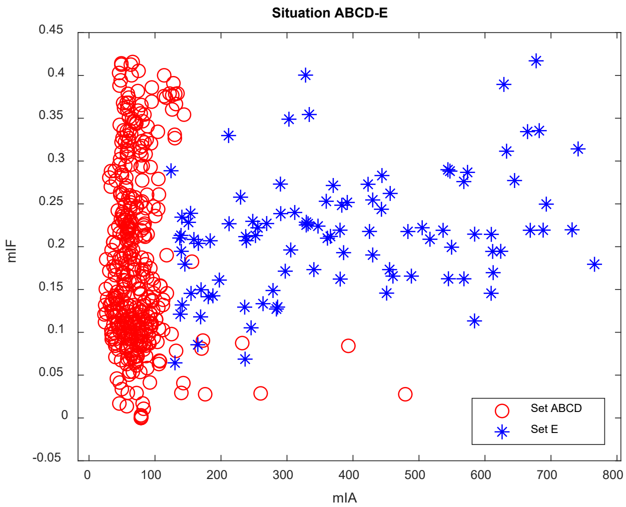
Feature extraction from raw EEG data is crucial in detecting epileptic seizures. The extracted features should both provide maximum discrimination from raw EEG data and have low computational complexity. In this respect, the method suggested in Fig. 2 was used to extract the features from the raw EEG signals. In the experimental studies, the EEG data from healthy, disease-diagnosed but non-epileptic seizure participants and EEG data for participants who had seizures in the Bonn EEG dataset were classified as such (A-E, B-E, C-E, D-E and ABCD-E).



(a)



(b)



(c)

Figure 2. Scattering curves of (a) A-E, (b) C-E and (c) ABCD-E.

Instantaneous amplitude and instantaneous frequency values of EEG signals in each group were obtained with HDD. Then, the average of each signal's instantaneous amplitude and frequency changes was used as an attribute. The scatter curves shown in Figure 3 a-c are created for A-E, C-E and ABCD-E situations better to understand the efficiency of mean IA (mIA) and mean IA (mIF) attributes after they are obtained with HHT. As can be seen in the scatter curves in Fig. 3 (a-c), it shows that it has the potential to extract distinctive features from the attributes obtained from the EEG signals of different datasets.

The obtained attributes are applied to the input of the ELM. The number of hidden layer neurons 1000 in ELM was determined empirically as activation function sigmoid. In the performance evaluation of the proposed method, 10-fold cross-validation is taken into consideration. As the classification criteria, as shown in equations 5, 6 and 7, the accuracy (ACC), sensitivity (SEN) and specificity (SPC) criteria are respectively taken as reference.

$$ACC = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \quad (5)$$

$$\boldsymbol{SEN = \frac{TP}{TP+FN} \times 100} \quad (6)$$

$$SPC = \frac{TN}{TN+FP} \times 100 \quad (7)$$

Where TP represents the total number of true positive, TN represents the total number of true negative, FP represents the total number of false positive, and FN represents the total number of false negative.

Table 1. HHD method and ELM Classification Performance

Situation	Accuracy (%)	Sensivity (%)	Specificity (%)
A-E	100	100	100
B-E	99.50	100	99.09
C-E	99.50	99.09	100
D-E	96.50	98.18	99.75
ABCD-E	98.2	93.94	99.50

Table 1 shows the classification results of the proposed method for five different conditions to detect epileptic seizures from EEG signals. The table contains the evaluations of accuracy, sensitivity and specificity performances. As can be seen in Table 1, A-E and B-E appear to achieve 100% and 99.5% accuracy in distinguishing healthy individuals and individuals with epileptic seizures, respectively. Similarly, C-E and D-E achieved 99.5% and 96.5% accuracy in detecting individuals with epileptic seizures, respectively. In another experimental study (case ABCD-E), a success rate of 98.2% was achieved in distinguishing between healthy (A, B) and disease-diagnosed (C, D) participants and patients with seizures (E).

In addition, the results are shown in Table 2, where the same dataset was used to evaluate better the proposed HHT-based feature extraction and the classification performance with ELM, and some other recent studies and general accuracy rates were compared.

According to our findings in Table 2, for B-E situation, Siuly et al. [7] 0.5% higher accuracy was achieved. In addition, 1% and 0.6% higher accuracy scores were obtained for the C-E and ABCD-E situation, respectively. In the D-E situation, the highest performance is 97.5% accuracy. Our method lagged behind the higher performance with a 1% score. To summarize, it can be seen that the HHT method proposed in four of the experimental studies for 5 different situations has a higher accuracy rate than the other methods.

4. Conclusion and Suggestions

In this research work, a new method based on HHT-based feature extraction is proposed for the detection of epileptic seizures from EEG signals. In this study, the epileptic seizure detection Bonn EEG dataset is used. mIA and mIF attributes obtained from the dataset with HHT are classified with ELM. According to experimental results, 100% accuracy for A-E case, 99.5% for B-E and C-E, 96.5% for D-E and 98.2% for ABCD-E case are achieved. Our proposed method has a more straightforward distinctive feature extraction than the existing methods in the literature; in addition, its better performance in detecting epileptic seizures indicates the superiority of our approach. As a result, it has been put forward that the HHT-based ELM method will contribute to the establishment of a computer-aided medical diagnosis system that enables medical professionals and technicians to make the right decision on patients.

The proposed HHT and ELM based feature extraction method has low computational complexity compared to the state art methods. so the proposed epilepsy detection approach is appropriate for offline real-time and embedded applications.

Table 2. Comparison of the proposed method with the existing methods

Situation	Authors	Methods	Accuracy (%)
A-E	Siuly et al. (2018) [7]	Hermite Transformation LS-SVM	99.5
	Ghayab et al. (2016) [14]	Simple Random Sampling+ Sequential Feature Selection LS-SVM	99.9
	Zhu et al. (2014) [15]	Fast Weighted Horizontal Visibility Graph Constructing Algorithm K-NN	99
	Proposed Method	HHT+ ELM	100
B-E	Siuly et al. (2018) [7]	Hermite Transformation LS-SVM	99
	Zhu et al. (2014) [15]	Fast Weighted Horizontal Visibility Graph Constructing Algorithm K-NN	97
	Supriya et al.(2016) [15]	Complex Network, Modularity and Average weight degree SVM	97.25
	Proposed Method	HHT+ ELM	99.5
C-E	Siuly et al. (2018) [6]	Hermite Transformation LS-SVM	98.5
	Zhu et al. (2014) [15]	Fast Weighted Horizontal Visibility Graph Constructing Algorithm K-NN	98
	Supriya et al.(2016) [15]	Complex Network, Modularity and Average weight degree SVM	98.25
	Proposed Method	HHT+ELM	99.5
D-E	Siuly et al. (2018) [6]	Hermite Transformation LS-SVM	97,5
	Zhu et al. (2014) [15]	Fast Weighted Horizontal Visibility Graph Constructing Algorithm K-NN	93
	Supriya et al.(2016) [15]	Complex Network, Modularity and Average weight degree SVM	93.25
	Proposed Method	HHT+ELM	96,5
ABCD-E	Siuly et al. (2018) [7]	Hermite Transformation LS-SVM	97.6
	Kumar et al. (2014) [20]	DWT-based fuzzy entropy and SVM	92.4
	Proposed Method	HHT+ELM	98.2

Conflicts of interest

The authors state that did not have conflict of interests

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