Fractal Based Feature Extraction Method for Epileptic Seizure Detection in Long-Term EEG Recording

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Abstract. One of the most common brain disorders is epilepsy. A person who has epilepsy is not able to have normal days like the others. It’s characterized by more than two unprovoked seizures. However, the faster detection and treatment of epileptic seizures, the quicker reduction of the disease abnormal level. Neurologists are still diagnosing, detecting, and testing a seizure manually by observing the Electroencephalogram (EEG) signals. This takes a very long time because of the irregularity of EEG signals. Hence, a Computer-Aided Diagnosis (CAD) is developed by many scientists to help neurologists in detecting seizures automatically. In this research, a CAD system was developed at CHB-MIT dataset. The EEG signals were processed at several stages through this system, namely pre-processing, decomposition, feature extraction, and classification. In pre-processing, the EEG signals were uniformed by selecting the most appropriate channels and filtered using Butterworth Bandpass Filter (BPF) to remove noise. The process continued to the decomposition and feature extraction stage using Empirical Mode Decomposition (EMD) and fractal dimension-based methods, i.e. Higuchi, Katz, and Sevcik, respectively. Then, the features were classified by Support Vector Machine (SVM). The proposed method achieved the highest accuracy at 94.72% on the Chb07 record. Meanwhile, the average accuracy was 81.2% for all records. The proposed study is expected to be applied for the detection of seizure onset in a real-time system.

1. Introduction

Epilepsy is a neurological disorder in certain brain areas, characterized by abnormal electrical activity in the brain [1]. In this condition, it is important in early detection of seizure events in epilepsy patients to determine the type and management of treatment. However, continuous use of the drug for a long time can be more debilitating than the seizure itself. About 10% to 30% of cases cannot be controlled using drugs. In some serious cases, special medical personnel are needed to avoid sudden unexplained death in epilepsy (SUDEP) or death caused by disturbed heart rhythm and injury caused by seizures [2]. According to WHO, around 50 million people suffer from epilepsy which makes epilepsy a serious neurological disease. About 80% of sufferers who suffer from epilepsy come from developing countries [3]. In developing countries, epilepsy affects many people starting in young adults and adolescents [4].

Some popular medical modalities for detecting and locating the source of seizures, including Magnetic Resonance Imaging (MRI), Computed Tomography (CT) and Electroencephalogram (EEG) [5], [6]. However, MRI and CT scans are cost sensitive, complex, and limited in terms of usage time which refers to they cannot be used continuously in a short span of time. Therefore, EEG is preferred
in seizure analysis. Numerous studies have been carried out for the purpose of classification/detection and prediction of seizures based on EEG wave analysis. Studies related to the classification of seizure and non-seizure events have been reported in [7–9]. Several approaches to feature extraction including entropy and principal component analysis have been applied to the Bonn EEG dataset containing both seizure and non-seizure EEGs. Another study proposes a simulated epileptic EEG classification method on a Hauz Khas EEG dataset containing ictal, inter-ictal and pre-ictal events [10], [11]. Some studies focus on classifying the EEG seizure type as reported in the study [12], [13].

The methods proposed in these studies generate high accuracy in classification (generally > 90%, some of them generate 100% accuracy), however simulations are still performed on framed EEG signals. Moreover, the simulations have not been implemented in the long-term EEG recordings which contain normal and ictal conditions. Analysis of the continuous EEG recordings is very important in detecting seizure onset and predicting seizures. Since CHB-MIT provided the long-term epileptic EEG recordings, several studies have been starting to simulate the detection of seizure onset along the EEG recordings. Research by Solaija et al. [14] proposed a seizure detection method using Dynamic Mode Decomposition (DMD) and curve-length. The accuracy generated in the study was 87.32%. A study by Alotaiby et al. [15], proposed the Common Spatial Pattern (CSP) method and the Linear Discriminant Analysis (LDA) classifier, yielding an accuracy of 89%. Meanwhile in the study conducted by Khan et al. [16], reported the seizure detection method using Discrete Wavelet Transform (DWT), LDA, and wavelet-based feature extraction. The simulation results provide a detection accuracy of 92%. All the studies that have been carried out have aimed at providing the best detection accuracy with an efficient method.

Therefore, this paper proposes a seizure onset detection system for long-term EEG recording of epilepsy patients. This system consists of feature extraction and automatic classifier to provide a decision whether a seizure or non-seizure signal. Simulations were carried out on EEG records sourced from the CHB-MIT dataset. We propose a fractal dimension-based feature extraction method which is calculated on the decomposed signal resulting from Empirical Mode Decomposition (EMD). The feature vectors were then classified using the Support Vector Machine (SVM) as normal or seizure onset.

2. Material and Method

Our proposed method is shown in the figure 1. We started the process with pre-processing stage using Band Pass Filter (BPF) to filter the EEG raw signals from 0.3-60 Hz. The filtered signals were windowed to several 10-minute windows. For each window, we calculated the features resulted from EMD in three fractal analysis calculation which are Katz, Higuchi, and Sevcik Fractal. In the final stage, we classified the features with linear SVM. Every step of the proposed method is explained in the next subsection.

![Figure 1. General process of the proposed method.](image)

2.1. CHB-MIT EEG Dataset

This study used EEG dataset which legally published by CHB-MIT. In this dataset, there are two classes, i.e. seizure conditions (S) and normal conditions (N). The dataset, a set of data consists of various recordings from 24 patients aged below 22 years old, was recorded using 256 Hz sampling frequency and 18-32 channels [17]. There are a lot of sessions in the recordings with the length of 1 to 4 hours on average. More detailed information for each patient can be seen in Table 1. However, this study only used 8 patients, specifically Chb01 to Chb08, since the electrode montage used was the same.
Table 1. Summary of the CHB-MIT data used in this study.

| Patient | Number of channels | Number of sessions | Recording time (h) | Number of seizures |
|---------|--------------------|--------------------|--------------------|--------------------|
| Chb01   | 23                 | 42                 | 40.55              | 7                  |
| Chb02   | 23                 | 36                 | 35.3               | 3                  |
| Chb03   | 23                 | 38                 | 38                 | 7                  |
| Chb04   | 23-24              | 42                 | 155.9              | 4                  |
| Chb05   | 23                 | 39                 | 39                 | 5                  |
| Chb06   | 23                 | 18                 | 66.7               | 10                 |
| Chb07   | 23                 | 19                 | 68.1               | 3                  |
| Chb08   | 23                 | 20                 | 20                 | 5                  |

2.2. Pre-processing

Pre-processing stage is a step to make all of the information uniform, plus to erase the noise [14]. Each patient’s EEG signal recording was recorded using 23 channels on various configurations. Those channels had to be eliminated to get the uniform information in one dataset. The eliminated channels were the least used and different configuration channels.

Besides channels, there was some noise including blinking eyes and other external circumstances while recording the brain signals using EEG. In this research, the BPF filter was done at the fourth-order in frequency of 0.3-60 Hz and 256 Hz of sampling frequency to reduce noise. In addition, the filtered signals were windowed into 10-minute windows.

2.3. Empirical Mode Decomposition (EMD)

EMD is a well-known method to handle the nonstationary and nonlinear property of EEG signals. As a signal decomposition method, EMD is an intuitive and adaptive method that could recognize the mode intrinsic oscillator in time domain for empirical data [18]. EMD has several requirements, e.g. the signal must have at least two values of extrema, one minimum ($e_{\text{min}}(t)$) and one maximum ($e_{\text{max}}(t)$).

By that, the characteristic of time series depends on the time delay between the values of extrema. If there are no values of extrema inside the dataset, but only their turning point, differentiating the turning point once or several times will be able to bring out the values of extrema [19].

EMD’s principal is decomposing an input EEG signal, $x(t)$, into some frequency bands, namely Intrinsic Mode Function (IMF) [20]. IMF was calculated in equation (1):

$$ x(t) = \sum_{n=1}^{N} c_{n}(t) + r_{n}(t) $$

where $c_{n}(t)$ is the value of n IMFs and $r_{n}(t)$ is the IMF residue.

Other function of IMF is to analyse a signal by increasing IMF index and decreasing IMF frequency. The point of IMF states that all of the data, which is represented with IMF, are composed in several simple mode intrinsic oscillator. IMF treats the mode intrinsic oscillator as the harmonic function and make it possible to do frequency and amplitude modulation [18]. IMF itself has two conditions. The first condition is the extrema amount and zero-crossing of the displayed data must be equal or leastwise had one point in difference. The second condition is the mean value of local maxima and minima needs to be zero [21]. Figure 2 shows a complete procedure of EMD process [18], [22].
Figure 2. EMD decomposition process.

The process is started by calculating the upper \( e_{\text{max}}(t) \) and lower envelope \( e_{\text{min}}(t) \) followed by finding the local mean \( m(t) \). The detail \( d(t) \) of the signal then obtained by reducing the original signal \( s(t) \) with \( m(t) \). If the detail matches the IMF criteria, it will be used as the selected IMF. Otherwise, the \( d(t) \) is used as the next \( s(t) \) and the process is repeated from calculating the upper and lower envelope. The selected IMF then removed from the original signal to obtain the temporary residue \( r(t) \). The \( r(t) \) is used as the next input if it does not meet the monotonic function criteria. This process is stopped when the \( r(t) \) is monotonic function.

2.4. Fractal Dimension (FD) Analysis

Fractal dimension (FD) is a common method in biomedical waveform analysis and was first introduced by Mandelbrot in 1982 [23]. The purpose of FD in this study was to measure the complexity of signals produced by EEG due to fractal's key features which are self-similarity and irregularity [24].

The FD waveform is defined as \( D \) in Equation (2):

\[
D = \frac{\log_{10}(L)}{\log_{10}(d)}
\]

where \( L \) is the wavelength and \( d \) estimates the Euclidean distance of the first and the furthest wave point. Moreover, \( D \) is also be written in Equation (3):

\[
D = \max\{d \cdot c(1, i)\}
\]

where \( d \cdot c \) stands for distance and \( i \) is the maximum range that is started from the first point [25].

2.4.1. Higuchi FD

Higuchi is used in order to calculate the fractal dimension \( D \) to be used as an input of measurement built upon a discrete time series [26]. For certain time, the Equation (4) is defined as follows [27]:

\[
X_i^n = y(m), y(m+k), y(m+2k), y(m+3k), ... , y (m + \left[\frac{N-m}{k}\right]k)
\]

where \( m = 1, 2, 3, ... , k \) and \( \frac{N-m}{k} \) defines Gauss notation, also \( k \) and \( m \) are integers. The role of \( k \) here is to identify each start and interval time. More than that, the length of \( X_i^n \) of every time is in Equation (5):
\[ L_m(k) = \frac{1}{k} \sum_{j=1}^{[N-m/k]} \left| X(m+ik) - X(m+(i-1)k) \right| \frac{N-1}{[N-m/k]} / k \]  

(5)

where the term (6)

\[ \frac{N-1}{[N-m/k]} \]  

(6)

represents a normalization factor at the FD’s length. \( L(k) \) is the average value over \( k \) sets of \( L_m(k) \) as illustrated in the Equation (7) [27]:

\[ L(k) = \frac{1}{k} \sum_{m=1}^{k} L_m(k) \]  

(7)

Using all these equations, fractal dimension \( D \) of Higuchi was calculated as a slope of the plot’s linear regression [28].

2.4.2. Katz FD

Katz FD solves a problem with general units-making technique, called yardstick. It uses the variable \( a \) to reflect the average distance between successive points [29]. It is obtained from the Euclidean distances in the successive points [30]. Therefore, the mathematical equation shall be written as Equation (8) below:

\[ D = \frac{\log_{10} \left( \frac{L}{a} \right)}{\log_{10} \left( \frac{d}{a} \right)} = \frac{\log_{10}(n)}{\log_{10} \left( \frac{d}{L} \right) + \log_{10}(n)} \]  

(8)

where \( a \) is the mean distance between successive points, so that \( n \) is \( L \) divided by \( a \) states the number of successive points in waveforms [31].

2.4.3. Sevcik’s FD

In Sevcik’s method [32], the approximate value of FD can be estimated from a set of \( N \) which is sampled at a waveform. Here the FD approximation is received from Hausdorff \( D_h \) dimension explanation [33]. From there, the \( D_h \) value in a metric group is represented in Equation (9):

\[ D_h = \lim_{\varepsilon \to 0} \frac{-\log \left( N(\varepsilon) \right)}{\log(\varepsilon)} \]  

(9)

where \( N(\varepsilon) \) is the total of \( \varepsilon \) radius needed for FD. On the other hand, a waveform of length \( L \) can be defined as \( N(\varepsilon) = L / 2\varepsilon \), so that the Equation (9) becomes Equation (10) as follows:

\[ D = \lim_{\varepsilon \to 0} \left[ \frac{-\log(L) - \log(2\varepsilon)}{\log(\varepsilon)} \right] \]  

(10)
Sevcik FD concatenates double linear transformation from FD waveforms to a metric space that has been normalized. Through the normalization process, a unit square is able to be visualized in $N \times N$ cells. Then, the final equation gained is shown in Equation (11):

$$D = \lim_{N \to \infty} \left[ 1 + \frac{\log(L) - \log(2)}{\log(2(N-1))} \right]$$

(11)

where $D$ equals to fractal dimension and the approximation is enhanced as $N \to \infty$ [28].

2.5. Support Vector Machine (SVM)

SVM performs linear and non-linear classification by easily changing the kernel function. It is one of the most popular classification method since the results are relatively high [34]. The principle of SVM is finding an imaginary plane called hyperplane to apply the concept of classes separation [35]. Vapnik shows that if the distance of the margin is maximum, SVM will get the optimal hyperplane [36]. Hence, the hyperplane discriminant value is achieved using Equation (12) below:

$$f(x) = \sum_{i=1}^{M} y_i a_i k(x, x_i) + b$$

(12)

where $M$ is total of training samples, $x_i \in \mathbb{R}^d$, $y_i \in \{-1,1\}$, $k(x, x_i)$ is kernel function, and $a_i \neq 0$.

This research used only the linear kernel of SVM to classify the features from FD because it was better in the decision function to know about the effects of training samples selection on the final classifier’s performance [30]. The equation of Linear SVM [37] is represented in the Equation (13):

$$\min \frac{1}{m} \sum_{i=1}^{m} \xi_i + \frac{1}{C} \sum_{i=1}^{m} a_i$$

(13)

where $\xi_i \geq 0$, $i = 1, \ldots, m$ are stack variables.

3. Result

First of all, this study chose 18 channels in pre-processing stage, i.e. C3-P3, C4-P4, CZ-PZ, F3-C3, F4-C4, F7-T7, F8-T8, FP1-F3, FP1-F7, FP2-F4, FP2-F8, FZ-CZ, P3-O1, P4-O2, P7-O1, P8-O2, T7-P7, and T8-P8. These channels must be selected further in the channel selection process. A channel selection was done by calculating the energy in the channels. The mean technique was utilized to select temporary channels with energy value higher than the average channel energy [22], [23]. Then, temporary channels were reviewed to see the most-used channels, named final selected channels, which are shown in Table 2. There were 3 channels at least in Chb03 and Chb08, also 5 channels at most in Chb02. After getting most-used channels, the process continued to next stages.

The dataset has 174 and 9,031 of S and N conditions respectively at chosen patients. These were a significant difference number of S and N conditions. This situation predisposed the classification stage and caused unbalanced class data. Unbalanced class data is a condition where classes in a dataset are not equally distributed. Not only decreasing the accuracy, but also increasing the possibility of undetected errors [38], [39]. So, the majority samples were eliminated following the under-sampling method. In this study, the training data consisted of more than or equal to 50% of the total number of S and N conditions in every channel which were randomly chosen. Meanwhile, the testing data is the rest of them.
Table 2. Final selected channels.

| Patient ID | 1       | 2       | 3       | 4       | 5       |
|------------|---------|---------|---------|---------|---------|
| Chb01      | FP1-F3  | FP2-F4  | P4-O2   | P8-O2   |         |
| Chb02      | T7-P7   | FP1-F3  | P3-O1   | FP2-F4  | CZ-PZ   |
| Chb03      | F7-T7   | FP1-F3  | FP2-F4  |         |         |
| Chb04      | FP1-F7  | F7-T7   | FP1-F3  | FP2-F8  |         |
| Chb05      | F7-T7   | P7-O1   | FP1-F3  | F3-C3   |         |
| Chb06      | FP1-F3  | C4-P4   | FZ-CZ   | CZ-PZ   |         |
| Chb07      | FP1-F7  | FP1-F3  | FP2-F4  | FP2-F8  |         |
| Chb08      | F7-T7   | P7-O1   | P8-O2   |         |         |

Figure 3 shows the average system accuracy value of 8 patients. The highest and lowest accuracy was obtained by Chb07 and Chb06 in 94.72% and 63.45% respectively. Meanwhile, the system achieved 81.2% of average accuracy value from 8 patients with all durations of the recordings included.

![Average System Accuracy Values](image)

**Figure 3.** Average system accuracy values.

4. Discussion
Classification results shows that the proposed system achieved low seizure detection accuracy in average. The average value is affected by the low accuracy in Chb01, Chb03, Chb04, and the lowest in Chb06. The reason for the poor performance in Chb01, Chb03, Chb04, and Chb06 is the poor EEG recording quality. Specifically in Chb06, according to [40], the amplitude and frequency have slightly difference which make the system harder to detect seizures. However, some attempts in optimizing the accuracy by changing the training data repeatedly gave higher results.

The seizure detection on CHB-MIT dataset has been done in some previous studies. Tanu et al. [41] proposed a seizure detection using Wavelet Packet Decomposition (WPD), Sample Entropy (SampEn), and Linear Discriminant Classifier (LDC) of 171 recordings. However, they didn’t state the number of patients, yet they set the record length to 25 seconds for each recording. On the other hand, Das et al. [42] successfully detected seizures on 24 patients, but the recording length taken was only 10 seconds from the seizure and non-seizure conditions of each patient. The average accuracy achieved was 72.92% which considered low by applying Principal Component Analysis (PCA), Variational Mode Decomposition (VMD), SampEn, Spectral Entropy (SpecEn), and event detection rule for the classification stage. Khan et al. [16] detected seizure using DWT, wavelet-based feature extraction, and LDA. They achieved an average system accuracy of 92% only for patient 1 to patient 5.
Raghu et al. [43] gained an average system accuracy of 94.38% with DWT, Sigmoid Entropy, and SVM for merely 58 hours duration of EEG recordings. Then, M. Tăuţan et al. [44] got a highest accuracy of 94% over all patients, but they just selected 20 seconds of S conditions and 20 seconds of N conditions. They detected seizure with many feature extraction methods, one of them is Shannon Entropy (ShEN), and a classification method, namely Random Forest (RF). The comparison has been summarized in Table 3.

Table 3. Performance comparison on previous studies.

| Authors         | Methods                                      | Number of patients | Duration of EEG recordings (h) | Average system accuracy (%) |
|-----------------|----------------------------------------------|--------------------|-------------------------------|-----------------------------|
| Tanu et al.     | WPD, SampEn, and LDC.                       | Not stated         | 1.2                           | 81.65                       |
| Das et al.      | PCA, VMD, SampEn, SpecEn, and event detection rule. | 24                 | 3.8                           | 72.92                       |
| Khan et al.     | DWT, wavelet-based feature extraction, and LDA. | 5                  | 308.75                        | 92                          |
| Raghu et al.    | DWT, Sigmoid Entropy, and SVM.               | 2                  | 58                            | 94.38                       |
| M. Tăuţan et al.| ShEN and RF.                                 | 24                 | 16                            | 94                          |
| **This study**  | EMD, Katz FD, Higuchi FD, Sevcik FD, and SVM. | 8                  | 463.55                        | 81.2                        |

The use of fractal dimension measurement in seizure detection systems in this study shows a promising result compared to the aforementioned studies. The proposed method is more efficient in detecting more EEG recordings with only three features. However, it still needs improvement, such as adding the analysis in the time-frequency domain. Since there is a frequency shifting in the seizure condition, the time domain analysis cannot give adequate information. Thus, for future development, a multi-domain analysis can be observed to obtain better signal resolution.

5. Conclusion

This study presents a fractal dimension-based feature extraction method for seizure detection. The process starts in pre-processing stage where the CHB-MIT dataset are uniformed by a channel selection method and the EEG signals are filtered using BPF. After that, the process moves to decomposition stage using EMD to calculate the features in feature extraction stage with Katz, Higuchi, and Sevcik algorithms. As a decomposition method, EMD, along with these fractal dimension-based methods are tested to be a very helpful system in handling the characteristics of EEG signals. Finally, we classify the feature vectors using SVM as seizure and non-seizure conditions. The highest system accuracy is 94.72% for Chb07 and the average system accuracy is 81.2% for Chb01 to Chb08. The proposed method in this study can be considered for application in real-time detection of seizure onset of long-term EEG recordings. In future research, we try to improve the pre-processing stage to get better accuracy detection.

6. References

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