Detecting Ictal and Interictal Condition of EEG Signal using Higuchi Fractal Dimension and Support Vector Machine

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Abstract. Ictal and interictal periods are the most important condition which needed to find for detecting and predicting seizure condition in epileptic patients. Neurologist spends hours to analyze electroencephalogram (EEG) signals in order to find a certain pattern for diagnosing epilepsy. This manual interpretation has a high chance of error and very time consuming. In order to minimize mistakes, various studies have proposed a computer-based detection system to support the detection of ictal and interictal conditions. In this study, we extract the EEG signal pattern by using the Higuchi fractal dimension to classify the ictal and interictal conditions of EEG signals. The features are extracted from five EEG sub-bands, delta, theta, alpha, beta, and gamma band. Those features are then fed to support vector machine as the classifier using 10-cross folds validation. The experiment shows that the use of HFD and the quadratic kernel is suitable for ictal detection. While the use of cubic kernel and HFD is suitable for detecting interictal conditions.

1. Introduction

Epilepsy is a worldwide neurological disease which identified as a syndrome rather than as one condition [1]. Epilepsy is known as an abnormality that occurs because the abnormal pattern activities in the brain [2]. Based on the data from the World Health Organization (WHO), there are more than 50 million people worldwide are diagnosed as people with epilepsy. This number is increasing every year, especially in low-and middle-income countries, which is 139 per 100.000 persons per year [3]. Epilepsy is ranked in the top 50 of the highest causes of morbidity and mortality worldwide [4].

There are several medical device that can be used for helping neurologist in diagnosing epilepsy, one of them is electroencephalogram (EEG) [5]. This analysis can be done by reading the EEG signal manually. EEG signal is one type of biological signals which has a high complexity and it is vary among individuals. That is, an analysis through visual observation on a large EEG signal recording is often difficult [6].

Some studies proposed mathematical computation-based automation methods for the detection of epilepsy. There are several reviews about previous studies in epileptic seizure in EEG signal which can be found in [7–9]. All of these studies are very useful for neurologist and even for patients in facing the effects of epileptic seizure. Researchers are continuously develop the computer aided diagnose system for detecting seizure in EEG signals in order to achieve highest accuracy.
The interpretation of the epileptic EEG signals is not an easy task. This is due to the nature of the EEG signal which are chaotic, non-stationary, and non-linear [10]. For example, processing epileptic-EEG signals in the frequency domain are deemed to be inappropriate because it refers to these properties [8]. Another approach that has recently received much attention is complexity analysis. In biological signals, complexity is associated with the adaptation ability of human in the experience impaired bodily functions, the complexity of the system in the body will decrease [11].

One method of complexity analysis is entropy that used in the case of Alzheimer's/dementia detection studies [12–15]. The use of complexity measurement can provide a consistent conclusion, that in patients with dementia, the complexity of EEG signals is decreases while it is compared with patients in normal condition. There are several studies which used entropy analysis for analyzing the epileptic EEG signals, such as reported in [16–18]. From that study, the entropy method produced a good performance in the detection of epilepsy. The purpose of implementing and developing this method is to get high performance and high validity. Therefore, in this study, we propose a complexity analysis for EEG epileptic detection system applying the Higuchi Fractal Dimension (HFD) for feature extraction. The system is combined with Support Vector Machine (SVM) for the classification of seizure signals. Eventually, this proposed method can be used to predict seizures. The proposed research is expected to become new knowledge and references, the possibility that the method used can be further developed.

The rest of the paper organized as follows. The second section describes the Bonn University dataset, HFD, and SVM classifier. The third section describes the result obtained in this work. The last section described the conclusion of this work.

2. Material and Method
This work used secondary EEG recording data obtained from Bonn University. The EEG signals is processed based on the frequency bands. We used five frequency bands, which are the delta, theta, alpha, beta, and gamma band. HFD is calculated from each sub-band, then we used it as the features. The process is shown in Figure 1.

2.1. Bonn University Dataset
The dataset used in this work is a public dataset from Bonn University, Germany. This dataset recorded from five patients and has five classes of EEG recording named Set A-E. Each set has 100 records with 23.6 seconds in length. Set A and set B was recorded from healthy patients with eyes open and closed, respectively, and called as a normal condition. The electrodes used to record these sets were the scalp EEG method (sEEG). On the other hand, the three other sets were recorded using the intracranial method (iEEG). EEG signals in Set C were recorded in the hippocampal formation of the brain, while set D was in the epileptogenic zone. These two sets are called as an interictal condition. The last set, Set E, was recorded from patients in seizure condition and called as an ictal
condition. The data was pre-processed using a bandpass filter at 0.53-40 Hz with 173.61 Hz of sampling rate [19]. An example of the five classes is shown in Figure 2.

Figure 2 Examples of EEG signal from Bonn University Dataset: (a) Set A – normal open eyes; (b) Set B – normal closed eyes; (c) Set C – interictal hippocampal formation; (d) Set D – interictal epileptogenic zone; (e) Set E – ictal (seizure condition).

2.2. Higuchi Fractal Dimension

This work used the Higuchi Fractal Dimension as the feature extraction method. This method was developed by Higuchi et al. in 1988 [20]. For a finite set of time series data obtained from a regular interval \( S(1), S(2), S(3), \ldots, S(N) \), a new time series can be made as equation 1.

\[
S'_m; S(m), S(m+k), S(m+2k), \ldots, S\left( m + \left\lfloor \frac{N-m}{k} \right\rfloor k \right)
\]  

(1)

The \( m \) and \( k \) are integers, which showed the initial and the interval time, respectively. Furthermore, the curve length is defined using equation 2.

\[
L_m(k) = \frac{1}{k} \left\{ \sum_{i=1}^{N-m} \left| X(m+ik) - X(m+(i-1)k) \right| \cdot \left\lfloor \frac{N-m}{k} \right\rfloor / k \right\}
\]

(2)

The \( L_m(k) \) average value is calculated using equation 3.

\[
L(k) = \sum_m L_m(k)
\]

(3)

The Higuchi fractal dimension value is obtained in the slope between \( \ln(L(k)) \) and \( \ln(1/k) \). That is when the value of \( L(k) \propto k^{-D} \) is fulfilled, the curve is said fractal with \( D \) as the dimension.

2.3. Support Vector Machine

SVM often used because it aims to find the best hyperplane as part of the Structural Risk Minimization principle to separate between two classes in a region so that this algorithm is suitable to be implemented as a classification [21–24]. Several types of SVM are Linear, Cubic, Quadratic, Medium Gaussian, Coarse Gaussian, and Fine Quadratic Gaussian [25–27]. Generally, the basic principle of support vector is a linear classifier [28,29], then continued on nonlinear to solve the
problems by combining with the kernel concept in high-dimensional workspaces. Hyperplane design on SVM to classify all the data into two classes, as seen in Figure 1a, showing a number of patterns (circle and square) that represent members of two classes [30] and various alternative discrimination boundaries are shown in Figure 3a showing a number of patterns (circle and square) that represent members of two classes [30] and various alternative discrimination boundaries are shown in Figure 3b.

![Figure 3 Classification of two classes with a hyperplane](image)

The purpose of calculating the hyperplane margin is to find the maximum point to be referenced as the best hyperplane. In the same way, the support vector can be called the closest pattern of each class as shown in Figure 2, and the distance between the hyperplane is called the boundary or margin.

![Figure 4 The differences between hyperplane and support vector](image)

The core of the learning process in SVM is finding the best hyperplane. The thick red line and the thick green line in Figure 4 shows the best hyperplane flanked by the support vector line. The function of the hyperplane line is determined by equation 4:

\[ f(x) = w \cdot x + b = 0 \]  

(4)

Where \( w \) is the weight of the hyperplane vector [31], and \( b \) defines the bias. For maximum margins, the SVM optimization in equation 5 is used for the case of linear classification in primal space:

\[ \min \frac{1}{2} ||w||^2 \]  

(5)

Whereas the non-linear case is separated by the soft margin concept to minimize misclassification errors by introducing slack variables which are symbolized by \( \varepsilon \), where \( \varepsilon_i \geq 0 \).

\[ \varepsilon_i \geq 0, i = 1, ..., n. \]  

(6)

As shown in Figure 5, the value of the slack variable for the correct classification data is \( \varepsilon_i = 0 \). The value of the slack variable for data is between the margins \( 0 \leq \varepsilon_i \leq 1 \). For incorrect classification data, the value of the slack variable is \( \varepsilon_i = 1 \). The number of error values (slack variable) multiplied
by C. C values is based on trade-offs between maximum margins and tolerable errors. With the soft margin SVM optimization concept, the following equation 7 is made:

\[
\tau(w) = \frac{1}{2} \|w\|^2 + C \sum_{i=1}^{n} \varepsilon_i 
\]

(7)

3. Result and Discussion

We process the EEG signal from the Bonn University database, which has five classes. The classes then grouped into three general conditions. The first is the normal condition, which consists of Set A and Set B. Set C and Set D are grouped as interictal conditions. While Set E is representing an ictal condition. These signals are decomposed into five sub-bands, then calculated the fractal dimension using HFD. Each signal has five features, which are then fed into SVM as the classifier. Three SVM kernels are used in the classification process. They are linear, quadratic, cubic kernels.

There are two main scenarios to evaluate the detection system. The scenarios are based on the approach of seizure detection and prediction system. According to Binder et al. [32], seizure detection is done by finding the ictal period from EEG recording. While seizure prediction needs to find the preictal condition, in this case, it is represented by the interictal condition. Each scenario has several classification tasks (CT), which described in Table 1.

| Scenarios                | Classification Task (CT) | Set Pairs       |
|-------------------------|--------------------------|-----------------|
| Normal vs. Ictal        | CT-A1                    | Set A vs. Set E |
|                         | CT-A2                    | Set B vs. Set E |
|                         | CT-A3                    | Set AB vs. Set E|
| Normal vs. Interictal   | CT-B1                    | Set A vs. Set C |
|                         | CT-B2                    | Set A vs. Set D |
|                         | CT-B3                    | Set B vs. Set C |
|                         | CT-B4                    | Set B vs. Set D |
|                         | CT-B5                    | Set A vs. Set CD|
|                         | CT-B6                    | Set B vs. Set CD|
|                         | CT-B7                    | Set AB vs. Set C|
|                         | CT-B8                    | Set AB vs. Set D|
|                         | CT-B9                    | Set AB vs. Set CD|

The accuracy results for normal vs. ictal scenarios are shown in Table 2. From the result, it can be seen that the quadratic kernel has better results compared with the other two kernels. The highest result is obtained in CT-A2 with 95.5% of accuracy. Table 3 showed the normal vs. interictal vs. interictal scenario. Even though the highest accuracy is obtained in CT-B9 by using the quadratic kernel, the highest average accuracy is obtained with the cubic kernel.
### Table 2 Accuracy result for normal vs. ictal scenario

| Kernel  | CT-A1 | CT-A2 | CT-A3 | Average Acc. |
|---------|-------|-------|-------|--------------|
| Linear  | 83.0% | 93.0% | 86.7% | 87.6%        |
| Quadratic | 87.0% | 95.5% | 90.7% | 91.1%        |
| Cubic   | 86.5% | 93.5% | 86.0% | 88.7%        |

### Table 3 Accuracy result for normal vs. interictal scenario

| Kernel  | CT-B1 | CT-B2 | CT-B3 | CT-B4 | CT-B5 | CT-B6 | CT-B7 | CT-B8 | CT-B9 | Average Acc. |
|---------|-------|-------|-------|-------|-------|-------|-------|-------|-------|--------------|
| Linear  | 90.5% | 79.0% | 92.5% | 82.5% | 93.0% | 84.0% | 92.5% | 92.3% | 94.3% | 89.0%        |
| Quadratic | 92.5% | 88.0% | 95.5% | 95.0% | 93.0% | 87.0% | 93.8% | 92.3% | 96.3% | 92.6%        |
| Cubic   | 94.0% | 91.0% | 95.5% | 96.0% | 93.7% | 93.7% | 94.5% | 92.3% | 96.0% | 94.1%        |

### 4. Conclusion

This work demonstrates a fractal-based method for detecting ictal and interictal conditions from the EEG signal. The EEG signal is decomposed into five sub-bands called delta, theta, alpha, beta, and gamma. The fractal dimensions from each band are then calculated by using Higuchi fractal dimension. The use of fractal dimension calculation is based on the chaotic characteristic of EEG signals. The extracted features are then fed to the SVM with 10 cross-fold validation as the classifier using three types of kernels. The quadratic kernel is suitable for ictal detection, while the cubic kernel is suitable for interictal detection. For future development, we will be adding other non-stationary calculations to extract the features of EEG signals.

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