Interictal Epileptiform Discharges (IEDs) classification in EEG data of epilepsy patients

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Abstract. Interictal Epileptiform Discharges (IEDs), which consists of spike waves and sharp waves, in human electroencephalogram (EEG) are characteristic signatures of epilepsy. Spike waves are characterized by a pointed peak with a duration of 20–70 ms, while sharp wave has a duration of 70–200 ms. The purpose of the study was to classify spike wave and sharp wave of EEG data of epilepsy patients using Backpropagation Neural Network. The proposed method consists of two main stages: feature extraction stage and classification stage. In the feature extraction stage, we use frequency, amplitude and statistical feature, such as mean, standard deviation, and median, of each wave. The frequency values of the IEDs are very sensitive to the selection of the wave baseline. The selected baseline must contain all data of rising and falling slopes of the IEDs. Thus, we have a feature that is able to represent the type of IEDs, appropriately. The results show that the proposed method achieves the best classification results with the recognition rate of 93.75 % for binary sigmoid activation function and learning rate of 0.1.

1. Introduction

Electroencephalography (EEG) is supporting tools for establishing epilepsy diagnosis when the clinical history indicates that the patient has recurrent seizures. Patients with epilepsy will show Interictal Epileptiform Discharges (IEDs) in the EEG recording [1]. Generally, IEDs consist of spike waves or complexes polyspike waves, and sharp waves. Spike waves has duration of 20-70 ms, while sharp waves has duration of 70-200 ms [2]. The two waves have amplitude bigger than 30μV [2]. However, this difference in duration is related to the size of the epileptic zone which would certainly have an impact on clinically significant differences in epilepsy patients [3].

Seizure detection and classification using EEG signal have been widely published [4-10], as well as IEDs. Among such studies, Valenti [11] presented automatic detection of interictal spikes using data mining models. Sharma [12] studied a novel scheme for the validation of an automated classification method for epileptic spikes by comparison with multiple observers. Automated Event Detection of Epileptic Spikes Using Neural Network is proposed by Khanwani [13], while Zacharaki [14] studied a machine learning approach for automated detection of epileptiform discharges in low dimensional embedding space. However, all methods only proposed the classification or detection of IEDs and non-IEDs. Not many studies have discussed the classification of IEDs types. Automatic identification of two types of IEDs, repeated sharp waves and runs of sharp-and-slow-waves, using
support vector machine is proposed by Chang [15]. In 2017, Puspita [16] proposed Bayesian approach to classify spike waves and sharp waves based on the feature resulting from Walsh transformation. Moreover, a simplier method in classifying spike wave, sharp wave and Wicket spike, is also presented by Puspita [17] and Jaya [18]. In contrast to the previous study, in this study, we used frequency feature with correction baseline to improve classification accuracy. The selected baseline must contain all data of rising and falling slopes of the IEDs. We also compute the statistical feature, such as mean, standard deviation, and median, of each wave. Furthermore, Backpropagation Neural Network is applied to classify spike waves and sharp waves based on frequency and statistical feature.

The organization of this paper is organized as follows. Section 2 describes the methods for extraction feature and Backpropagation Neural Network as a classifier. The results and discussion are presented in section 3. Finally, the conclusion is offered in section 4.

2. Methods

In this study, we construct IED profile based on frequency and statistical feature for each wave. Furthermore, the Backpropagation Neural Network is used to classify the IED profile into one of two classes, namely spike wave class or sharp wave class.

2.1. Feature Extraction

A total of 109 EEG recordings used in this study were taken from Hasan Sadikin Bandung hospital. Furthermore, the EEG recordings in European data format (edf), that is localized in time interval containing IEDs based on the observation of an EEGer, are converted into ASCII (American Standard Code for Information Interchange) data using Polyman software.

In this study, we choose two baselines that must contain all data of rising and falling slopes of the IEDs, as illustrated in Figure 1. We compute the amplitude $A_j$, duration $\Delta t_j$ and statistical feature, such as mean $R_j$, standard deviation $S_j$ and median $M_j$, where $j = 1, 2$, based on each baseline of the IEDs, by using the following formula:

$$A_1 = v_n; \quad A_2 = v_n + v_m; \quad \Delta t_1 = t_n - t_1; \quad \Delta t_2 = t_m - t_n; \quad R_1 = \sum_{h=1}^{n} \frac{v_h}{n}; \quad R_2 = \sum_{h=m-n}^{m} \frac{v_h}{m-n}; \quad S_1 = \sqrt{\sum_{h=1}^{n} \frac{(v_h - R_1)^2}{n-1}};$$

$$S_2 = \sqrt{\sum_{h=n}^{m} \frac{(v_h - R_2)^2}{m-n-1}}; \quad M_1 = \frac{1}{2} \left( \frac{v_n + v_{n+1}}{2} \right) \quad \text{and} \quad M_2 = \frac{1}{2} \left( \frac{v_{m-n} + v_{m-n+1}}{2} \right) \quad \text{if} \ n \ \text{and} \ m-n \ \text{are even numbers, while} \ M_1 = \frac{v_{n+1}}{2} \ \text{and} \ M_2 = \frac{v_{m-n+1}}{2} \ \text{if} \ n \ \text{and} \ m-n \ \text{are odd numbers, respectively.}$$

Furthermore, frequency of the waveforms can be extracted by using the following formula [17]:

$$f = \frac{\text{the number of data in 1 second}}{\text{time duration of 1 waveform}} = \frac{500}{\Delta t}$$

with $\Delta t = \Delta t_1 + \Delta t_2$. The features are represented as a $9 \times 1$ vector in the following form:

$$x_i = \begin{pmatrix} f_i \\ A_1 \\ A_2 \\ R_1 \\ S_1 \\ S_2 \\ M_1 \\ M_2 \end{pmatrix}, \quad i = 1, \ldots, k.$$
where $k$ is the number of data. Before the Backpropagation Neural Network is applied to distinguish spike waves and sharp waves, we re-scale the profile data in scale of $[0,1]$ to improve the accuracy by using the following formula:

$$
\hat{X} = \frac{X - \min(X)}{\max(X) - \min(X)}
$$

where $X = (x_1, x_2, ..., x_k)^T$ [11].

2.2. Backpropagation Neural Network as a Classifier

The algorithm of the Backpropagation Neural Network (BNN) is discussed in detail in [17]. In this study, the architecture of BNN consists of 1 input layer with nine neurons, 1 hidden layer with 2 and 3 neurons, and 1 output layer with 1 neuron. The IEDs data, that has been extracted in the previous subsection, are divided into training and testing data. Furthermore, spike wave is represented as number 0, while sharp wave is represented as number 1.

Let $\hat{x}^*$ be the testing data. $\hat{x}^*$ is classified into spike wave or sharp wave by following classification rules:

- if the output value $\leq 0.5$ then $\hat{x}^*$ is spike wave, and
- if the output value $> 0.5$ then $\hat{x}^*$ is sharp wave.

3. Results and Discussion

In this study, we use 60 data of Spike waves and Sharp waves, respectively, as training data, and 80 data as testing data consisting of 35 data of spike waves and 45 data of sharp waves. Then the classification results using BNN are compared by the EEGer’s expertise.

| No. | Learning Rate ($\alpha$) | MSE  | Correct classification of Testing Data | Recognition Rate (%) |
|-----|--------------------------|------|----------------------------------------|----------------------|
|     |                          |      | Spikes | Sharp |                          |                      |
| 1.  | 0.05                     | 0.0141 | 33     | 34    | 83.75                    |                      |
| 2.  | 0.1                      | 0.0072 | 33     | 42    | 93.75                    |                      |
| 3.  | 0.3                      | 0.0089 | 34     | 39    | 91.25                    |                      |
| 4.  | 0.5                      | 0.0089 | 34     | 39    | 91.25                    |                      |
| 5.  | 0.7                      | 0.0118 | 34     | 38    | 90                       |                      |
| 6.  | 0.9                      | 0.0145 | 32     | 36    | 85                       |                      |
Table 2. Classification Results for Binary Sigmoid activation function with 3 neurons in the hidden layer.

| No. | Learning Rate ($\alpha$) | MSE   | Correct classification of Testing Data | Recognition Rate (%) |
|-----|--------------------------|-------|----------------------------------------|----------------------|
| 1.  | 0.05                     | 0.0075| 32                                     | 41                   | 91.25                |
| 2.  | 0.1                      | 0.0064| 32                                     | 41                   | 91.25                |
| 3.  | 0.3                      | 0.0043| 31                                     | 36                   | 83.75                |
| 4.  | 0.5                      | 0.0048| 31                                     | 34                   | 81.25                |
| 5.  | 0.7                      | 0.0042| 34                                     | 37                   | 88.75                |
| 6.  | 0.9                      | 0.0049| 32                                     | 34                   | 82.5                 |

Table 1 and table 2 show the classification results using Binary sigmoid activation function in hidden and output layers for some variations of learning rate. The best classification results is achieved by the BNN model using 2 neurons in the hidden layer with a learning rate of 0.1. The recognition rate of this result, i.e. 93.75%, is better than the previous result in [18] which only achieved 88%. Figure 2(a) and 2(b) show the testing results for learning rate of 0.1 using the optimum weight values that minimize the network performance function, namely Mean Square Error (MSE), in the training process.

In this study, we also use others activation function, such as Hyperbolic tangent and Bipolar sigmoid, but the operation in the training process produces undefined numerical results. Moreover, the MSE values for every epoch tend to infinity and sometimes unstable, as shown in figure 3(a) and 3(b).

![Figure 2](image)

**Figure 2.** (a) Testing results for binary sigmoid activation function with $\alpha = 0.1$, (b) The Mean Square Error every epoch.
4. Conclusion
In this study, we proposed a simpler model to classify the type of IEDs using Backpropagation Neural Network (BNN) based on frequency and statistical feature, such as mean, standard deviation, and median. The selection of two different baselines for the raising and falling slope of the IEDs affects the frequency feature. The selection features may improve the accuracy. The results show that the hidden layer with 2 neurons for learning rate of 0.1 and binary sigmoid activation function gives the best classification result, where the recognition rate is 93.75%. According to the recognition rate, this result is better than the result of the previous study [18].

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