Classification of Epileptiform Waves Based on Frequency by Using Backpropagation Neural Network

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Abstract: Epilepsy is an abnormal condition of brain activity that can be recorded by using Electroencephalography (EEG). On epilepsy patient, most of the recording is interictal wave that in form of spike wave and sharp wave. This study has goal to classify whether the interictal waves are spike wave or sharp wave. The study was conducted in two stages Identification and Classification. Firstly, The epileptogenik wave were identified by shifting the baseline of each wave to select the best baseline that contain all data of the wave, then doing normalization of it to get the features of frequency, amplitude 1 and amplitude 2. Secondly, Backpropagation Neural Network method is applied to classify it. Classification is done by using 200 data consisting of 120 training data and 80 testing data. The results show that classification using binary sigmoid activation function give same recognition rate of 91.25 % for all variation of learning rate.

1. Introduction

Epilepsy is a brain disorder that most often occurs[1]. It is approximated that 2.4 million people worldwide are diagnosed with epilepsy each year. In developed countries, yearly new patients epilepsyare about 0.03 % to 0.05% of the population the population. In developing countries, the number could be twice as high [1].

Elektroencefalografi (EEG) is a recording of electrical signa[l of a brain neuron [2] EEG instrument is fistly used by Hans Berger to record the human brain in 1924 [3]. By using the developed instrument, Gibbs, Davis and Lennoxs found interiktal spike, 3 Hz spike and wavecomplex on absence seizure, then Gibs and Jasper found spike interictal wave as indicated of focal epilepsy in 1935. Since that invention, the EEG has been used to diagnose and to take care epilepsy [4].

EEG recordings in people with epilepsy can be ictal waves (recording with the seizure) and interictal wave (records outside of seizure). However, interictal waves are the most EEGs at the time of recording [5].

Several studies have been conducted to detect epileptogenic wave by extracting features such as walsh transformation [6], wavelet transform [7]-[9]. Previous researches have been classified spike waves and sharp waves [10] and epileptiform and wicket spike [11] by using the frequency and gain recognition rate of approximately 80%. However, the proposed classification model still has shortcomings in choosing the baseline [10,11]. Waves in the frequency feature extraction process leads to loss of information and data for a specific time duration. This led to misclassification, especially on sharpwaves.
Epileptics have interictal typical waveform, which is referred to as a wave epileptogenic. Epileptogenic wave consists of spikewaves and sharp waves. The difference between the spike wave and sharp wave only in its duration, whereas spike wave duration 20-70 ms while sharp waves duration 70-200 ms[5]. However, the difference is related to the duration of the epileptic zone size that will have an impact on clinically significant differences in epilepsy[12].

2. Methods
In this section we explain the feature extraction, feature normalization and data classification using Backpropagation neural network to classify the waves based on frequency.

2.1. Feature Extraction
In this research, the data of EEG recording is taken from the previous research [10]. The initial step in this process is to choose the baseline of the wave epileptogenic by simulation as follows:

![Figure 1 Simulation of selection of epileptogenic waves](image)

If \(v_1, v_2, \ldots, v_n\) are the discrete signal / data from one wave epileptogenic, then the frequency of the wave can be obtained by using the following formula:

\[
f_i = \frac{500}{(\Delta T_1_i + \Delta T_2_i) \cdot i = 1, \ldots, p}
\]

with \(T_1 = t_n - t_1\), \(\Delta T_2 = t_m - t_n\)

where:

- \(p\) = the numbers of epileptogenic waves
- \(f_i\) = frequency of the \(i^{th}\) epileptogenic waves

Amplitude \(A_1\) and \(A_2\) can be calculated by using the following formula:

\[
A_{1i} = v_n, A_{2i} = v_n + v_m
\]

where:

- \(A_{1i}\) = amplitude 1 of the \(i^{th}\) epileptogenic waves
- \(A_{2i}\) = Amplitude 2 of the \(i^{th}\) epileptogenic waves

It aims to make the data of epileptogenic wave become uniform. Then, the shifting simulation of baseline can be seen in Figure 3 and Figure 4.
Figure 2. Shifting Simulation of left baseline
\[ V_i = v_i + v_1, i = 1, \ldots, n \]

Figure 3. Shifting simulation of right baseline
\[ V_i = v_i - v_1, i = 1, \ldots, n \]

where:
- \( V_i \) is shifting baselines for each wave left epileptogenic.
- \( v_i \) is the data on each wave epileptogenic.
- \( t_1 \) is the time of each wave epileptogenic.

Furthermore, the features of each wave can be expressed in the vector epileptogenic measuring 3 \( \times \) 1 as follows:
\[ v_i = (\text{Frequency}(i)) = (f_i A_1, A_2) \]

where:
- \( f_i \) = frequency of the \( i^{th} \) epileptogenic waves
- \( A_1 \) = amplitude of the \( i^{th} \) epileptogenic waves
- \( A_2 \) = Amplitude 2 of the \( i^{th} \) epileptogenic waves

2.2. Feature Normalization

The aims of feature normalization is to make all of the feature in the same range that can improve the accuracy. The process can be done by re-scale the feature data in [0,1] scale by the formula:
\[ X_{\text{new}} = \frac{(X - \text{min}(X))}{\text{max}(X) - \text{min}(X)} \]

where, \( X = (X_1, X_2, \ldots, X_n)^T \) [13]
2.3. **Backpropagation Neural Network**

This process is done to classify the EEG waveforms. The process is conducted in two stages: training process and testing process. In the training process, a Backpropagation algorithm is applied into a multilayer perceptron (MLP). The architecture of the process can be seen in the Figure (2).

![Figure 4 Architecture of Backpropagation Neural Network](image)

The activation function of binary sigmoid is used to activate neuron become output layer $y$. The formula is:

$$ y = f(x) = \frac{1}{1+e^{-x}} $$

with $f'(x) = f(x)(1-f(x))$

Then, the algorithm of the Backpropagation is started by initializing weights and biases with random values, learning rate, error tolerance ($\varepsilon_T$), and epoch maximum ($E_{max}$). The second step is input the profile of EEG waveforms, then calculate the output values. After that, calculate the Mean Square Error (MSE), then compare the result with Error tolerance. If $MSE \leq (\varepsilon_T)$, then stop the training network, else comparing the Epoch with epoch maximum. If epoch maximum $\geq E_{max}$ then stop training network, else update weights and biases. Then the process will begin from the second step again until we obtain the optimum values that minimize the Mean Square Error.

3. **Result and Discussion**

The feature data extraction results in previous section which consists of three parameters, namely the frequency, amplitude 1 and amplitude 2 are divided into two groups, namely training data consists of 120 data and testing data consists of 80 data. Training data are used to build the model, while testing data are used to measure the accuracy of the model. After the training data and testing data is normalized, the BNN is applied with various learning rate to classify epileptogenic waves into spike waves or sharp waves.

Classification results can be seen in Table 1.

| No. | Learning Rate ($\alpha$) | MSE   | Correct classification of Testing Data | Recognition Rate (%) |
|-----|--------------------------|-------|----------------------------------------|-----------------------|
|     |                          |       | Spike | Sharp             |                       |
| 1.  | 0.1                      | 0.0123| 32    | 41                | 91.25                 |
| 2.  | 0.3                      | 0.0123| 32    | 41                | 91.25                 |
| 3.  | 0.5                      | 0.0122| 32    | 41                | 91.25                 |
| 4.  | 0.7                      | 0.0123| 32    | 41                | 91.25                 |
| 5.  | 0.9                      | 0.0121| 32    | 41                | 91.25                 |

From Table 1, we can see that binary sigmoid activation function gave the same recognition rate of classification result for all various of learning rate. The recognition rate is 91.25%. The shifting of the
baseline make less of the loss information then the previous research[10,11]. It result in better recognition rate.

![Training result for α = 0](image1.png)

**Figure 5.** Training result for $\alpha = 0$

![Testing result for α = 0, 9](image2.png)

**Figure 6.** Testing result for $\alpha = 0.9$

![The Mean Square Error every epoch](image3.png)

**Figure 7.** The Mean Square Error every epoch
4. Conclusion
From the result of the study it can be concluded that by shifting the baseline for each waves from previous research[5] resulted in better recognition rate. It is because the loss information of each waves are decreased.

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