Tonic Clonic Seizure Classification Based on EEG Signal Using Artificial Neural Network Method

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***Abstract*—An instrument to record the activity of brainwave in specific time called Electroencephalography (EEG). EEG signal can be used to analyze the epilepsy disease. One of a signal that appears when a seizure happens called Tonic Clonic Seizure (TCSZ) signal. Brainwave of seizure patient has a low frequency with a tighter pattern than brainwave of normal people. The purpose of this research is to classify between the tonic clonic seizure signal and normal EEG signal using Artificial Neural Network (ANN) Backpropagation method. At first, the features of signals will be extracted by using Mel Frequency Cepstral Coefficients (MFCC). The output of MFCC will be the input for ANN Backpropagation classifier. The result of this research has reached 100% of accuracy value with 13-MFCCs features and 25-MFCCs features.**

Keywords—TCSZ, ANN Backpropagation, MFCC, Epilepsy

I. Introduction

Epilepsy is one of a disease that is caused by brain dysfunction. EEG is used as an instrument to record the activity of the human brain in a specific time [1]. Analyzing computed EEG signal can help to obtain information that can be used to diagnose normal brain wave activity or epilepsy. One of a signal that appears in EEG signal during epilepsy is tonic clonic seizure signal [2]. TCSZ has two steps of event, at first stiffening or tonic phase then jerking of the body or clonic phase [2]. Mel Frequency Cepstral Coefficients (MFCC) will be the features extraction and Artificial Neural Network Backpropagation will be the classifier. MFCC can process quasi-stationary signals which are forms of sound signals and EEG signals [3][4]. This method has been widely used in EEG signal processing with high accuracy [5]. The output of this research is system reliability in classifying between TCSZ and normal EEG signal.

II. Method

A. *EEG Data*

The dataset is available at Temple University Hospital [2]. Data is recorded by using 250 Hz sampling frequency each second from each data [2]. Electrode placement on the scalp using the standard of 10/20 system, data is only taken at one part in the frontal cortex. The number of training dataset is 30 data (15 TCSZ and 15 normal) and the number of evaluation dataset is 30 data (15 TCSZ and 15 normal). Each length of data is cut according to the duration of seizure time in millisecond. After cutting the length of data, each of it will be extracted by using MFCC and classified by using ANN-BP.

B. *Preprocessing*

The steps of preprocessing are:

1) Fill missing value : the process of filling the data value with the closest value of it.

2) Normalization : the process of diving total raw data value with maximum raw data value. The purpose of this step is to change the range of amplitude value from 0 untul 1.

C. *Mel Frequency Cepstral Coefficients (MFCC)*

The MFCC features extraction process consists of five major steps performed in the following order [6][7][8] :

1) Framing : It's a process to split the signal into short-time frames with frame length range from 20 until 40 ms. The signal can be assumed to be stationary in that range. Frame size is set to 30 ms, and 20 ms for the overlap.

2) Windowing : Applying a window function to each frame to reduce discontinuities.

3) Fast Fourier Trasnform : It's a process to convert on each frame from time domain to frequency domain. The output of this process called Spectrum.

4) Mel Frequency Wrapping : Calculating the log amplitude at spectrum into mel scale by using 40 triangle filter bank [7]. The output of this process is log energy for each filter.

5) Discrete Cosine Transform : Transforming mel spectrum coefficient by using DCT. The output of this process called Mel Frequency Cepstral Coefficients (MFCC)

Data is divided into some frames. 13 cepstral coefficients, 25 cepstral coefficients and 35 cepstral coefficients are used for each frame where the zeroth coefficient is replaced with log energy value.

D. *Artificial Neural Network*

Artificial Neural Network with Backpropagation algorithm is a supervised neural network that is used for EEG signal classification. The backpropagation algorithm can generate complex decision boundaries and the weights of each neuron can be modified at iteration [4]. The architecture of Artificial Neural Network with Backpropagation algorithm is shown in figure 1.

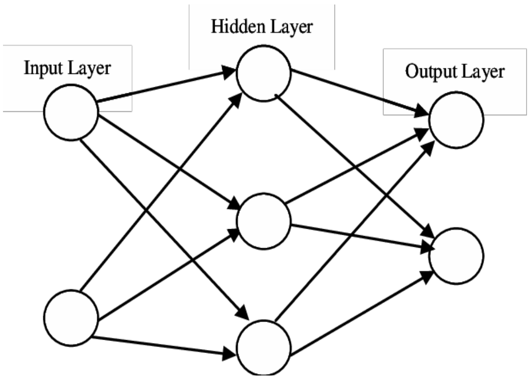

Fig. 1. Backpropgation Architecture.

The input layer is features of signal that has been extracted using MFCC while the number of hidden layer is at least 1 hidden layer of neurons. The function of neurons are to compute the weighted sum of the incoming features of signals, to yield net inputs, and pass these values through an activation function to yield the neurons' activation values [9].

In this research, the input layer consists of 13 neurons, 25 neurons, or 35 neurons. The number of hidden layer is set to 2 layers with 10 neurons for each layer. Training goal is set to 0.01. the training iterations are fixed at 100 epochs. The output will be normal or TCSZ [9].

III. Result and Discussion

In this research, 13-MFCCs, 25-MFCCs, and 35-MFCCs features are tested for getting accuracy value. The system is tested with 30 dataset (15 TCSZ and 15 normal).

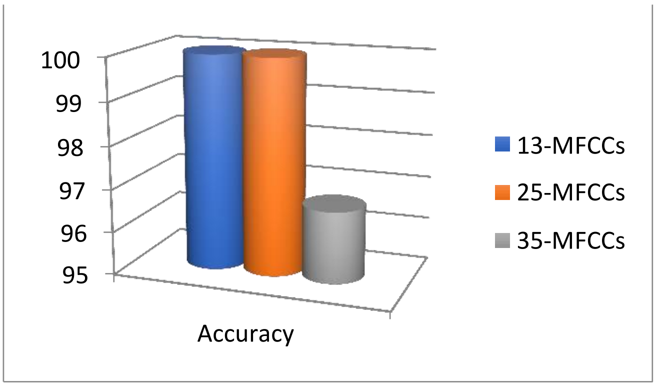

Fig. 2. The accuracy performance of MFCC features.

.Figure 2 shows the value of accuracy each setups. 13-MFCCs and 25-MFCCs have reached the highest value of accuracy. When increasing the features from 25-MFCCs to 35-MFCCs, the value of accuracy decreases to 96,67%.

IV. Conclusion

In this paper, the brainwave of tonic clonic seizure are detected by using MFCC as features extraction and ANN Backpropagation algorithm as classifier. Backpropagation algorithm can compute the error contribution of each neuron. Three different setups are tested for getting better accuracy with 13-MFCCs, 25-MFCCs and 35-MFCCs. The 13-MFCCs and 25-MFCCs setups have reached the maximum value with 100% accuracy. Other measures of performance may also be analyzed in the future such as sensitivity and specificity and also feature selection could be used to reduce the feature dimension by selecting best MFCCs.

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