CLASSIFICATION OF SPIKE-WAVE DISCHARGE WITH STFT APPROACH

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ABSTRACT

Spike-Wave Discharge (STD) is an abnormal brainwave pattern in the brain area that has possibility of generating an epilepsy seizure. The brainwaves can be recorded by using Electroencephalogram (EEG) device. The purpose of this paper is to classify STD that occurred in epilepsy patient using k-Nearest Neighbor (kNN) with Short-Time Fourier Transform (STFT) approach. The EEG signals were downloaded from an established website that consisted of epilepsy and non-epilepsy samples. The process of artifact removal was done to ensure that the generated EEG signals and STFT were clean. Then, energy is extracted from STFT for four bands, namely Delta-band, Theta-band, Alpha-band and Beta-band. The experimental result showed that the kNN was able to classify the STD waves with 100% accuracy for the tested ratio training of 80:20.

***KEYWORDS**: Spike-Wave discharge; Epilepsy; Brainwave; EEG signals; STFT; kNN*

1.0 INTRODUCTION

Epilepsy is a disorder of the normal brain function by the existence of abnormal synchronous discharges in large groups of neurons in brain structures. It was estimated about 1% of the world's population suffers from this disease (Tzalla et al., 2009). It is also known as brain pathology that affects about 40 million people in the world (Martinez-Vargas et al., 2011). The epileptic can be in different condition whether in absence or presence. In presence cases, it will confirm in the Electroencephalogram (EEG) signals which sometimes will be confused with other disorders because of similar seizures like activity were produced (Chaovalitwongse et al., 2007). It often leads to very long, even up to one week continuous EEG recording in detecting seizures when traditional methods were applied. Therefore, many diagnostic systems have been introduced and applied (Chaovalitwongse et al.,

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2007). In absence seizures, the EEG offers a great chance to measure and compare the quantity of seizure activity during a limited period of time before and during interventional therapy. A typical absence is characterized by a generalized synchronous 3Hz spike and wave discharges 5 to 20 seconds long in duration (Niedermeyer & Silva, 2005). Epilepsy is a disease that attacks human due to some condition existed in the brain. The epilepsy detection was used the EEG signals and the result of normal and abnormal conditions were indicated the signals (Chaovalitwongse et al., 2007). The epileptic seizures can be detected when it massed with high frequency activity (Martinez-Vargas et al., 2011).

Brainwave is about electrical activity that had been generated by brain signals. The tools for recording electrical activity generated by brain signals are called EEG. It has been reported that the brainwave of epilepsy patient mostly in sharp, spike and complex wave pattern (Tzalla et al., 2009). In addition, epilepsy brainwaves pattern lies in wide variety of EEG signals in forming of low-amplitude and polyspikes activity (Martinez-Vargas et al., 2011). Generally, the disease was examined through the brainwaves or EEG signals by clinical neurologists. The wave shapes of the brain patterns were commonly sinusoidal and measured from peak to peak in the amplitude range of 0.5 μV to 100 μV. The frequency of brainwave is below one Hz to up 100 Hz (Anusha, et al., 2012). The brainwaves have been categorized into four frequency bands namely Beta (>13 Hz), Alpha (8-13 Hz), Theta (4-8 Hz) and Delta (0.5-4 Hz). All these frequency bands will be used to characterize the epilepsy brainwave in terms of amplitude (voltage) and frequency (Mustafa et al., 2013).

There are many techniques that can be used to detect this disease notably using in time analysis, frequency analysis or time-frequency analysis. The time-frequency image processing techniques is defined as spectrogram. The time-frequency domain can be used to detect this spike using, for example Short-Time Fourier Transform (STFT). The sinusoidal frequency and phase content of local sections of a signal as it changes over time can be determined using the STFT (Tzallas, Tsipouras & Fotiadis, 2009). In performance terms, using the STFT and the Time-varying autoregressive (STTVAR) compared to the Smoothed Pseudo Wigner-Ville (SPWV) and the Continuous Wavelet Transform (CWT) techniques, the STFT and the STTVAR performed better for the time-frequency analysis as the classifier performance with the lower quantity of relevant features (Martinez-Vargas et al., 2011). The parameters used in STFT were able to focus on the information in a well localized region in the time-frequency representations, while in the CWT and SPWV the information remains discrete along the whole time-frequency plane, possibly because of the representations may not fit accurately the analyzed signal. In time-frequency analysis the STFT is used and other twelve (12) Time-Frequency Distributions (TFD). Some of the TFDs employed a frequency and/or a time smoothing window. The Margenau-Hill (MH), Wigner-Ville (WV), and Rihaczek (RIH) distributions do not employ smoothing window, while the pseudo-MH (PMH) and pseudo-WV (PWV) employ frequency smoothing windows. All other methods discussed above employed both frequency and time smoothing windows (Tzallas, Tsipouras & Fotiadis, 2009). If one is to compare using the STFT technique with other techniques, the STFT would give better accuracy and excellent result (Tzallas et al., 2009). The epileptic brainwave seizures contain high frequency activity when the frequency bands in the range of Hz to 20 Hz and over 30 Hz. In the case of the STFT technique, the frequency bands up to 50 Hz is observed (Martinez-Vargas et al., 2011).

It has been reported that energy was used to extract features from the spectrogram (Tzallas, et al., 2009). This technique was successful and give promising result. The Energy should shows a different pattern in Delta, Theta, Alpha and Beta frequency bands (Hua et al., 2009).

The classification of spectrogram image is done using the k-Nearest Neighbor (kNN). The kNN is selected because it is simple, forceful and produced better performance even though the applications were complex (Mustafa et al., 2012). This technique can be implemented by MATLAB programming tools. The kNN algorithm is described as the purpose of the space between the feature in one set of data, the nearest space between the features fitting to the same class, while the furthest between the features show the feature fitting to another class (Mustafa et al., 2012). In the EEG research, kNN is used as a classifier to catergorize the EEG signals. Chaovalitwongse et al., (2007) reported that the epileptic and normal brain activities were classified using the EEG signals. In this algorithm, the distance and k variable were to be varied. For k variable, the value can be varied with the same simulation value. The accuracy percentage (Tzallas et al., 2009) of this algorithm defined as the number of correctly classified patterns over with the total number of patterns. In the kNN, the use of Euclidean distance will show the highest accuracy than other distances. It proved that by using this method its results were better due to better accuracy (Mustafa et al., 2012).

The aim of this paper is to classify the STD using kNN with STFT approach. The proposed method, discussion of the results and the conclusion were described next.

2.0 EXPERIMENTAL PROCEDURES

The method of this paper will be described from Section 2.1 To Section 2.6, which covered the raw EEG signals, generation of EEG signals, signal pre-processing, spectrogram image, feature extraction and classification.

2.1 EEG signals

The EEG signals were downloaded from website Vis Caltech, which contained the EEG signal from rats. Although these recorded data were from rat and not human, the main features found in the recorded rat data are common to human EEG (Quiroga et al., 2002). These signals contained brainwaves from epilepsy and non-epilepsy sample. The EEG signals are collected from Fp1 and Fp2 channels.

2.2 EEG signals generation

The downloaded data is small, so the noises were added to this EEG signal in order to increase the number of samples. The noises were added randomly by using MATLAB software. The frequency for both channels were set with the highest amplitude of the signals. The size of both channels will be multiplied by the value of frequency and the generated random signals. From the value, the signals for each channel were added with noise. As a result, 60 samples were generated which consisted of 30 samples for epilepsy and 30 samples for non-epilepsy.

2.3 EEG signal pre-processing

EEG signal pre-processing comprised of the artifact removal and band pass filter. The artifacts occurred when a person moved or blink his eyes and will be removed by setting to its threshold value. The threshold value setting is important to be removed from this artifact when the MATLAB tools were used. The values of threshold were set higher than 100μV and smaller than 100 μV in order to eliminate the irrelevant data. Lastly, the frequency range of 0.5Hz to 30Hz with 50% intersecting in Hamming window is intended with band pass filter.

2.4 Spectrogram image

By using both Fp1 and Fp2 channels in the STFT technique, the spectrogram images were produced. The STFT was created by multiplying Fourier Transform (FT) of the EEG signal with window function. According to the frequency bands, the spectrogram will be produced. The frequency bands of Beta are set from 13 Hz to 30 Hz, Alpha is set from 8 Hz to 13 Hz, Theta is set from 4 Hz to 8 Hz and lastly Delta is set from 0.5 Hz to 4 Hz.

2.5 Feature extraction

The energy is used to extract features from the spectrogram for all the frequency bands (Delta, Theta, Alpha and Beta). The energy was calculated from the spectrogram of each Fp1 and Fp2 channels. The frequency on which the peaks located were composed was to recognize the most energy was focused in frequency bands. The energy for epilepsy and non-epilepsy were determined in both channels.

2.6 Classification

The features from energy were substituted into the kNN to classify whether the brainwaves were the epilepsy or non-epilepsy samples. The data were split into training and testing with two ratios which were 70:30 and 80: 20. The k variable ranging from 1 to 48, and the accuracy of each experiment was recorded.

3.0 RESULT AND DISCUSSION

There were five downloaded samples which were coded with sample A, B, C, D and E. Sample A represented a normal case person (non-epilepsy) and the next four samples of B, C, D and E were person with epilepsy disease. Since the number of samples was small samples, the noises were added to produce larger samples. As a result, the experiment would have a total of 60 samples of which 30 from the non-epilepsy samples and another 30 from the epilepsy samples. Figure 1 and Figure 2 showed the original epilepsy EEG signal of Fp2 channel and the generated signal respectively. The difference between epilepsy and non-epilepsy EEG signals were shown in Figure 1 and Figure 3.

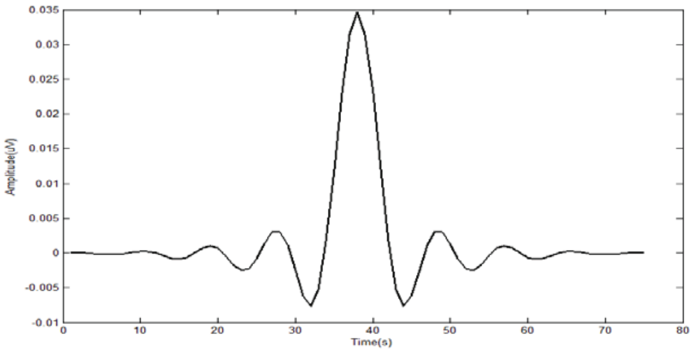

Figure 1. A sample of Epilepsy EEG signal from Fp2 channel.

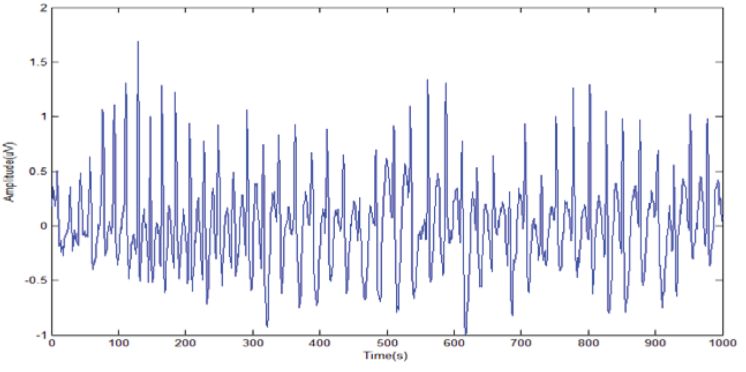

Figure 2. A sample of generated Epilepsy EEG signal from Fp2 channel.

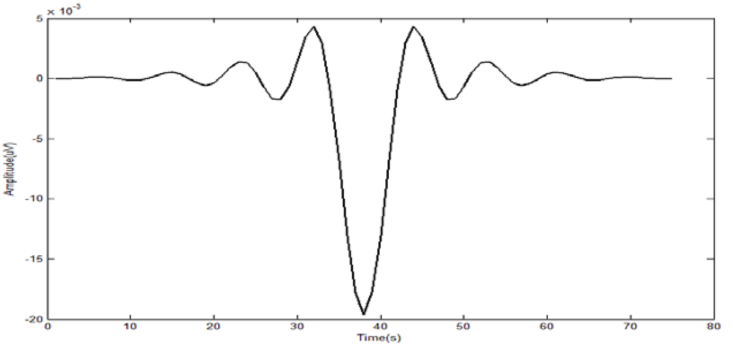

Figure 3. A sample of non-epilepsy EEG signals from Fp1 channel.

Spectrogram images generated by STFT for both Fp1 and Fp2 were shown in Figure 4 (a)-(h). These are Delta-band, Theta-band, Alpha-band and Beta-band. The number of spectrogram generated for epilepsy and non-epilepsy samples were both 240 from both channels. Hence the total for spectrogram images were 480. The resulting energy feature extractions from the spectrogram images were shown in Figure 4 (a) - (h).

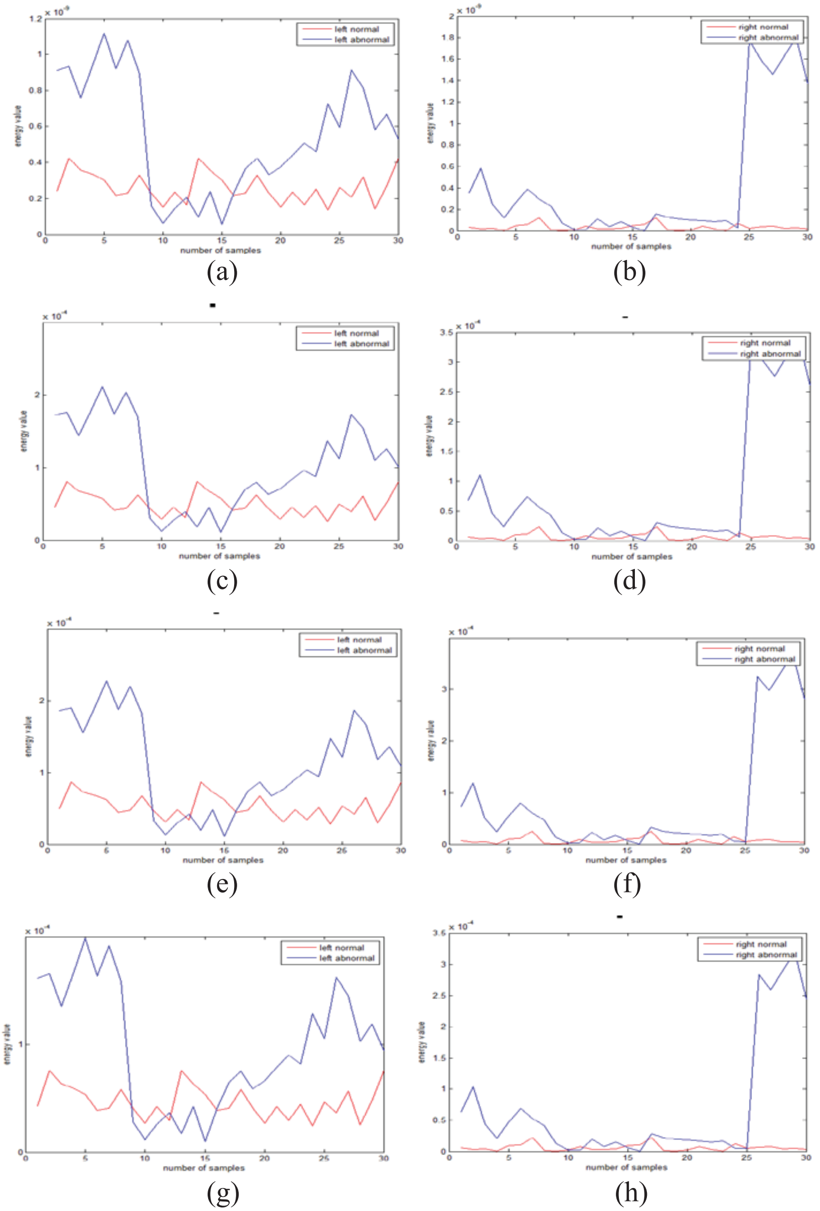

Figure 4. The Energy features value (a) Delta-band from Fp1 (b) Delta-band from Fp2 (c) Theta-band from Fp1 (d) Theta-band from Fp2 (e) Alpha-band from Fp1 (f) Alpha-band from Fp2 (g) Beta-band from Fp1 and (h) Beta-band from Fp2.

Based on Figure 4 above, the significant difference can be seen in non-epilepsy (normal) and epilepsy (abnormal) energy features. It was observed that the value of energy for the epilepsy case was at its highest compared to the non-epilepsy case in two channels. These results were used as input to the kNN classifier.

Figure 5 below showed the result of kNN after varying the k value. The k value is varied from 1 to 48. The results were presented the in terms of percentage in both 70:30 and 80:20 ratio. It was shown that the ratio 80:20 gave good results with 100% accuracy. However the ratio 70:30 would result with 100% accuracy for values of k = 9. The best result was in a situation where the 80:20 ratio was applied to the value of k = 3 and giving 100% accuracy.

The design of Graphical User-Interface (GUI) of this experiment is shown in Figure 6. The GUI is constructed for both the epilepsy and non-epilepsy samples. It was clear that the user can notice the difference image of spectrogram for epilepsy and non-epilepsy in this GUI. Consequently, the user can realize the energy extraction and kNN classification in this GUI. The GUI is built to help with the explanation for the user.

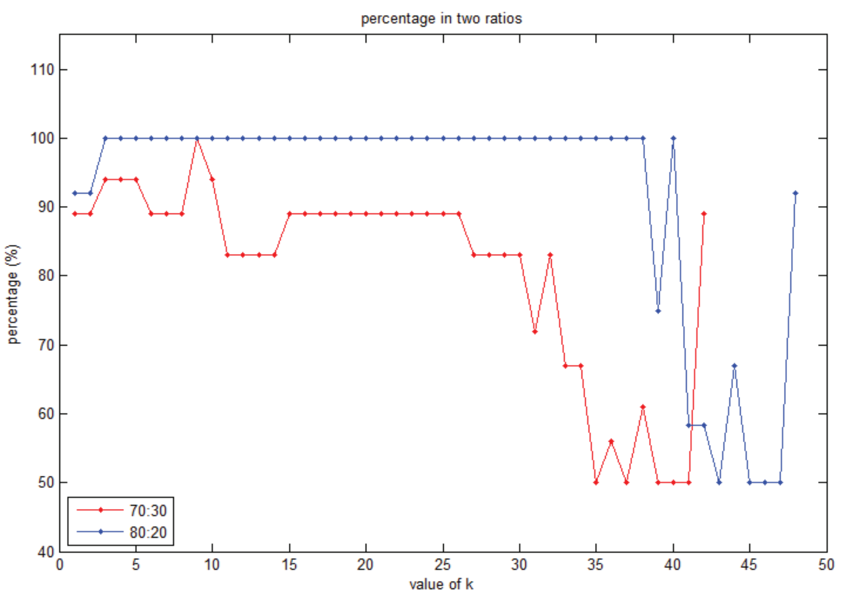

Figure 5. kNN result with varying the k value.

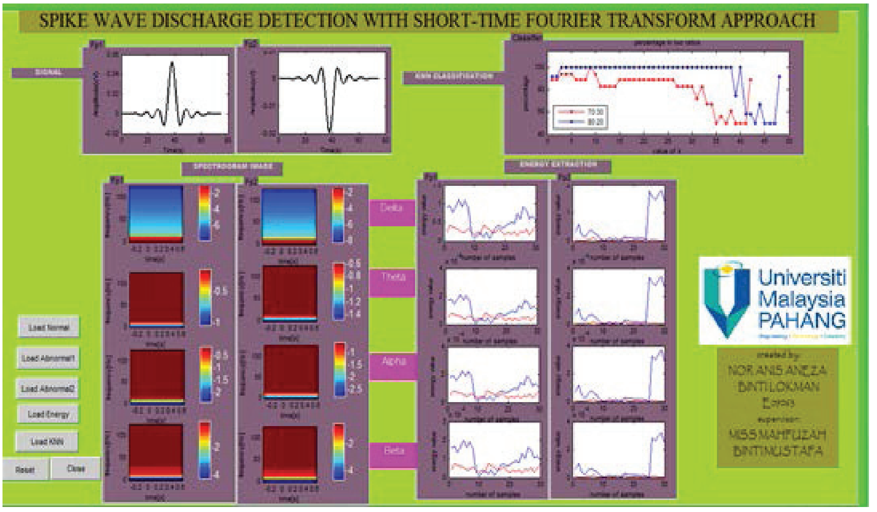

Figure 6. The GUI of STD with STFT approach

4.0 CONCLUSION

Based on the result above, epilepsy brainwave was successful classified by using kNN. This was done by generating the spectrogram image from which the energy was being extracted. From the energy extraction, the epilepsy brainwave showed the higher pattern value, compare with non - epilepsy brainwave. This pattern was consistent for all the four frequency bands (Delta, Theta, Alpha and Beta). These features the important pattern input to kNN classifier. The kNN best result showed the accuracy 100% with the ratio 80 to 20 and k = 3.

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