Classification of EEG Signal for Body Earthing Application

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***Abstract*—Stress is the way our body reacts to the threat and any kind of demand. Stress happens when your nervous system releases the stress hormones including adrenaline and cortisol that lead to an emergency response of the body. Body earthing technique is used to resolve this problem. Body earthing is a method that is used to neutralize positive and negative charge in the human body by connecting to the earth. EEG signals can be used to verify the positive effect of body earthing. This project focuses on the classification of EEG signals for body earthing application. First, EEG signals from human brainwaves were recorded by using Emotive EPOC Headset, before and after body earthing for the 30 subjects. The alpha band and the Beta band were filtered by using Band-pass filter 'Butterworth'. After filtering, the threshold of signal amplitude was set in the range of -100 µV to 100 µV in order to remove the noise or artifact. For feature extraction, Short-time Fourier Transform (STFT) and Continuous Wavelet Transform (CWT) were used. Lastly, the Artificial Neural Network (ANN) model is employed to classify EEG signal taken from samples, before and after the body earthing. A number of neurons chosen for this project are 55 with the mean square error 0.0023738. The result showed that Alpha band signals before body earthing are low compared to after body earthing. Whereas, for the Beta band signals, the result before body earthing is high compared to after body earthing. The increased signals of the Alpha band show that subjects are in relax state, while the decreased of Beta band signals shows the sample in stress state. These results imply for both features of STFT and CWT. Based on the confusion matrix, the result for the ANN classification yields 86.7% accuracy.**

***Index Terms*—Body Earthing; Classification; CWT; EEG signal; STFT;**

I. INTRODUCTION

Based on previous studies, the body earthing or grounding can reduce pain and fatigue. The free electrons will be absorbed into the body when they are directly connected to the earth. The function of body earthing is to balance the positive charge produced in the body cell to maintain the neutral state of the body.

Ghaly and Teplitz stated in their paper that the effect of grounding or body earthing when sleeping could result in the change of cortisol level in the human body. For two months, 12 subjects that had sleep dysfunction, pain, and stress slept by using conductive mattress pads, and this method is the same as grounded in the Earth. Further, to analyze the result of cortisol changes, the level of diurnal cortisol secretion was measured and circadian cortisol were profiled. Results from the project indicate that the level of cortisol during sleep at night was reduced while the synchronization of cortisol hormone discharges was more in the arrangement with the normal 24-hour circadian rhythm profile [1].

Chevaler et al. carried out a study to investigate the earthing effects on human physiology. The conductive adhesive patch was placed in the sole of 58 subjects' feet. The parameters of electrophysiological and the physiological were recorded using biofeedback system. Body earthing was carried out for 28 minutes for each sample in two conditions: before and after body earthing. After the earthing, half of the subjects demonstrated an immediate change in RMS of estimations of EEG signal from the left hemisphere, but not the right hemisphere at all frequencies. Earthing the human body indicated significant consequences for electrophysiological properties of the cerebrum and musculature on the BVP of the electrophysiological recordings. The progressions in EEG, EMG, and BVP recommended decreases in the general level of stress and a movement in ANS adjusted upon the body earthing [2].

EEG is an electrophysiological checking technique to record the electrical movement of the cerebrum. EEG is utilized to gauge voltage changes from ionic current inside the neurons of the brains [3]. EEG is additionally the recording of cerebrum unconstrained electrical activity over the time allotment. EEG can recognize the combinations of numerous neurons that transmit signal, while making an immense measure of electrical activity in the brains.

The limit of EEG is to record the neuronal activity in the mind that prompts electric fields to the surface of the head with a high temporal resolution. Along these lines, electroencephalographic perusing is a non-intrusive framework that can be associated with patients, ordinary adults, and adolescents with no hazard or restrictions. EEG signal, which is transmitted by human's cerebrum is a mixture of activities, disposition, and different emotions.

Signal intensity of the EEG signal is quite small and measured in microvolts (µV). The main frequency of human EEG signal waves is delta, theta, alpha and beta [4]. Delta waves have a recurrence of 3 Hz or underneath. It has a tendency to be the most elevated inadequacy and the slowest waves. It is ordinary as the predominant mood in babies up to one year and in stages 3 and 4 for the rest. Next, theta has a recurrence of 3.5 to 7.5 Hz and moderate action is delegated. It is flawlessly typical in children up to 13 years and during resting period, but an unusual occurrence for grown-ups during their alert condition. Besides, alpha has a frequency around 7.5 and 13 Hz, and generally the best found are is in the back areas of the head on every side. Lastly, a normal rhythm is during beta waves frequency at 14 Hz and above. It is the dominant rhythm in patients who are alert or anxious or have their eyes open.

During the research, it is important to choose a suitable equipment for capturing the human brain waves signal and transmitted it to the PC. Emotiv EPOC Headset is an EEG sensor headset that reads the signals and a computer-based system capable of processing the readings. The raw EEG data can be collected by using Emotiv EPOC Headset. The placing of several electrodes on the scalp is to measure the variety of the electric potential created by neuronal action. Emotiv EPOC Headset is also a low-cost brain PC interface for human PC connection created by Emotiv Corporation. It is a high-resolution device mounted on the head, which consists of 16 electrodes, while 2 electrodes are used for reference and have Bluetooth USB adapter [5].

EEG recordings were taken for both left and right hemispheres at points Fp1 (AF3) and Fp2 (AF4) in the international 10-20 system of electrode placement. The 10/20 system is an internationally recognized method to describe the location of scalp electrodes. In this project, placement of electrodes is based on 10/20 system. The number of '10' and '20' refers to the distances between the adjacent electrodes, in which the distance are either 10% or 20% of the total front back or right left from the skull. These electrodes are labelled with letters, whereas the right hemisphere with even numbers and left hemisphere with the odd numbers. A high power of Alpha power shows the relax state of brain activity, while the low power indicates the active state of brain activities.

A. Zabidi et al. mentioned that the technique to study the characteristics of EEG signal in frequency and time domain simultaneously is by using time-frequency analysis [6,7] The most basic form of time-frequency analysis is STFT that describes the imperative of frequency and spectral content of signal at each point. Spectrogram was used to do the analysis of the signal in time-frequency domain by applying the STFT on the signal. Then, the signal is mapped into the 2D function of time and frequency.

Based on the studies conducted by Tzallas et al., several time-frequency analyses were used to classify EEG signal for epileptic seizures. All of the methods will be compared to the EEG signal analysis. STFT and 12 different time-frequency distributions will be used to calculate the PSD of each partition and the results were compared. STFT gives a good result on the classification of the problem [8].

Research done by M.Akin is to investigate the wavelet whether the transform is good for the spectral analysis. Wavelet transform has been compared with FFT to see which one is better as the spectral analysis tool of EEG signal. It was found that the WT is more suitable to analyze the EEG signal depends on the scaling and shifting of the mother wavelet [9].

M. Kemal Kiymik applied the STFT and CWT to the EEG signals from normal person and child who are having an epileptic seizure. Both outcomes were analyzed, and it was resolved that the STFT was more relevant for the constant handling of EEG signs due to its short procedure time. In any case, the CWT still had a good resolution and the execution is sufficiently high to be used in clinical and research settings [10].

Based on a research done by Abdul Hamit Subasi and Ergun Ercelebi, they used ANN and LR to classify the EEG signal. In the study, two different classification models were introduced. One of the methods is the conventional statistical technique that used LR. Another technique is the rising computationally capable systems based on ANN [11-13]. The comparison between the created classifiers was essentially in view of the investigation of the ROC curves and also various scalar performance measures relating to the grouping. The MLPNN based classifier was more accurate compared to the LR based classifier [11].

Belakhdar et al. contemplated and assessed the performances of two classifiers, which are the ANN and SVM. The project goal is to dive deep into the examination and to direct the suitable enhancement prompting an expansion in the accuracy. In computing the components vector, FFT was utilized. The vector contains 9 highlights, in which these elements were then inputted to ANN and SVM classifier to choose the most fitting one. ANN classifier was the best compared to the SVM [14,15].

II. Research Method

First, EEG signals from human brainwaves were recorded using Emotive EPOC Headset, before and after body earthing. The alpha band and the Beta band were filtered by using Band-pass filter 'Butterworth'. After filtering, the threshold of signal amplitude was set in the range of -100 μV to 100 μV in order to remove the noise or artefact. For feature extraction, STFT and CWT were used. Lastly, the ANN model is employed to classify EEG signal taken from the samples, before and after the body earthing process.

A. Data Collection

The 30 subjects were randomly chosen from the students in *Universiti Malaysia Pahang* (UMP), who were between 19 to 23 years old. For the EEG signals recording for 6 minutes per subject, students must be free from consuming any types of medicine or drug. It is to make sure that the accuracy of the data will not be affected. Subjects also not wear hair gel or spray before collecting the data because the electrode cannot attach to the scalp if the spray and gel were used. In addition, subjects must be alert during the data collection session.

The raw EEG data can be collected using Emotiv EPOC Headset. The purpose of placing of several electrodes on the scalp is to measure the variety of the electric potential created by neuronal action. Emotiv EPOC Headset is also a low-cost brain PC interface for human PC connection created by Emotiv Corporation. It is a high-resolution device that mounted on the head, which consisted of 16 electrodes, while 2 electrodes were used for reference and have Bluetooth USB adapter.

The 10/20 system is an internationally recognized method to describe the location of the scalp electrodes. In this project, placement of electrodes is based on 10/20 system. The number of '10' and '20' refers to the distances between adjacent electrodes, which are either 10% or 20% of the total front back or right left from the distance of the skull. These electrodes are labelled with a letter, whereas the right hemisphere with even numbers and left hemisphere with odd numbers. A high power of Alpha power shows the relax state of brain activity, while the low power indicates the active state of brain activities.

B. EEG Signal Pre-processing

All EEG data were pre-processed by using MATLAB software. The Alpha and Beta band in EEG signals were filtered using the Bandpass filter. The Band-pass filter "Butterworth" is chosen because it has the flattest and there is no ripple passband. The EEG raw data were filtered in the frequency range of 8 Hz to 13 Hz in order to get the Alpha band signals. However, the EEG raw data were filtered in the frequency range of 13 Hz to 30 Hz to get the Beta band signals, so the frequency outside the range will be filtered.

After filtering, the threshold of signal amplitude was set in the range of -100 µV to 100 µV to remove the noise or artefact that will affect the accuracy of the result.

C. EEG Signal Processing

In signal processing, the time-frequency based analysis was used. Variety of the time-frequency analysis methods can be used such as STFT, WV, IPS and CWT [16]. In this project, STFT and CWT were used as the methods for the time-frequency based analysis.

a. Short-Time Fourier Transform

STFT permits observing the changes in the frequency spectra with reliance on the time. The sampled data are partitioned into fragments by windowing function [17]. The time and the frequency resolution are specifically identified with the window size. The shorter window implies better time resolution yet the frequency resolution will be worse. The time resolution can be expanded by window overlapping.

b. Continuous Wavelet Transform

The CWT gives an option signal representation with an adaptable time-frequency resolution. For the development of non-stationary signals, the mathematical functions that can be used are Wavelets [18]. The wavelet transform performs a decomposition of the analyzed signal, x(t) into a group that is localised in time and frequency.

D. Artificial Neural Network

ANN consists of a simple processing unit, which is neurons or cells that are communicated by transmitting signals to each other over a large number of weighted connections. Inputs for the processing units are received from an external source or neighboring unit and it is used to compute output signal to send to other unit.

There are three types of units in neural network systems, which are the input layers, hidden layers and output layers. Two layers of Feed-Forward Neural Network were used in this project. The network was trained using scaled conjugate gradient backpropagation. The input vector is represented by features arranged in 4 x 120 matrix. The information vector is combined with a 2 x 120 target grid for training. The 120 sections were acquired from the number of sections multiplied by the number of subjects. The components were partitioned into 80% for training set, 5% for validation set and 15% for testing set. The analysis was performed using Neural Network Toolbox in MATLAB. The ANN performances were evaluated by means of MSE and Confusion Matrix.

III. Result and Discussion

Figure 1(a) and Figure 1(b) show the spectrogram representation of the Alpha band and Beta band for AF3 respectively. Figure 1(c) and Figure 1(d) are the spectrogram representation for AF4 channel. Based on Figure 1(a) to Figure 1(d), the highest energy is represented by the red color. The figure shows that the highest energy which is between the frequencies of the band. For Alpha band, the signals are between 8 Hz to 13 Hz, while for the Beta band the signals are between 13 Hz and 30 Hz.

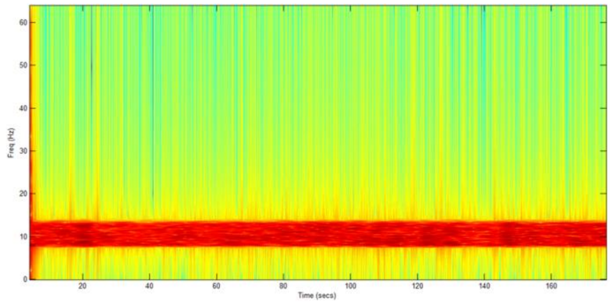

Figure 1(a): STFT spectrogram for Alpha Band in AF.

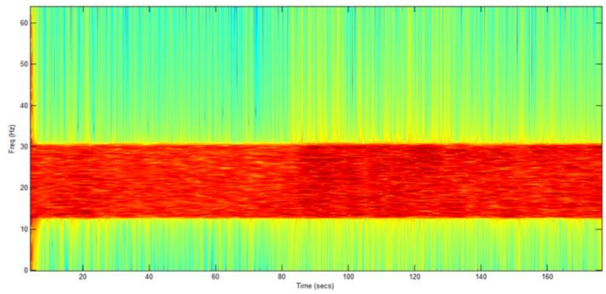

Figure 1(b): STFT spectrogram for Beta Band in AF3.

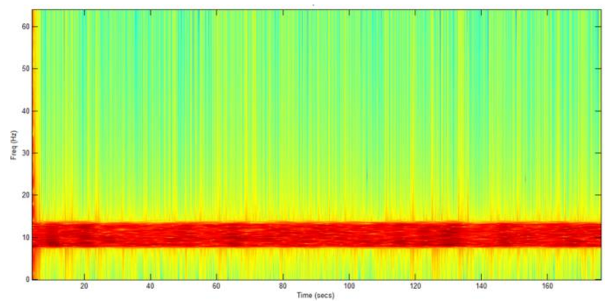

Figure 1(c): STFT spectrogram for Alpha Band Signal in AF4.

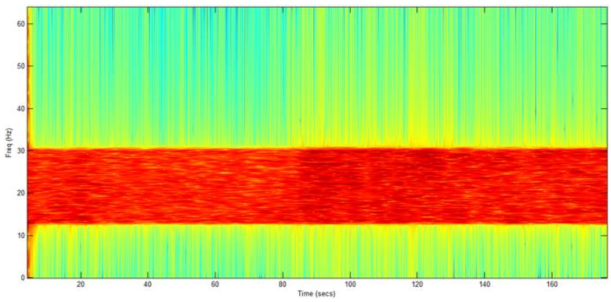

Figure 1(d): STFT spectrogram for Beta Band Signal in AF4.

Figure 2(a) and Figure 2(b) show the scalogram representation of the Alpha band and Beta band for AF3 respectively. Figure 2(c) and Figure 2(d) are the scalogram representation for AF4 channel. Based on Figure 2(a) to Figure 2(d), the highest energy is represented by the red color. The figure shows that the highest energy is between the frequencies of the band. For Alpha band signals are between 8 Hz to 13 Hz, while for the Beta band is 13 Hz to 30 Hz. The time range is from 100ms to 200ms.

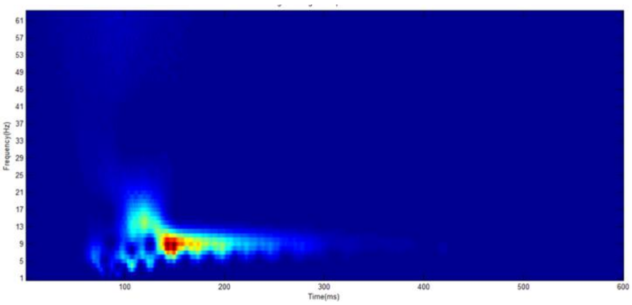

Figure 2(a): CWT scalogram image for Alpha Band in AF3.

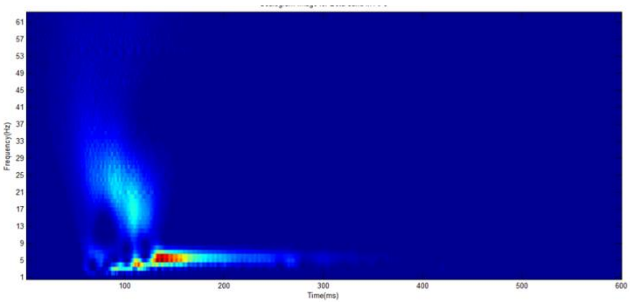

Figure 2(b): CWT scalogram image for Beta Band in AF3.

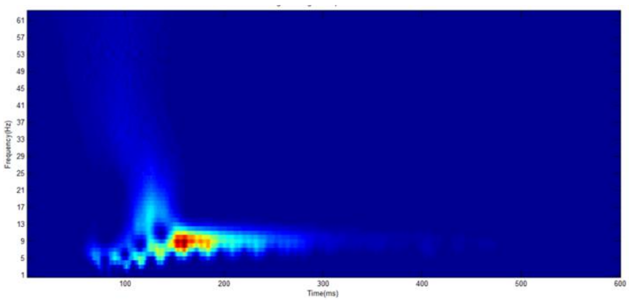

Figure 2(c): CWT scalogram image for Alpha Band in AF4.

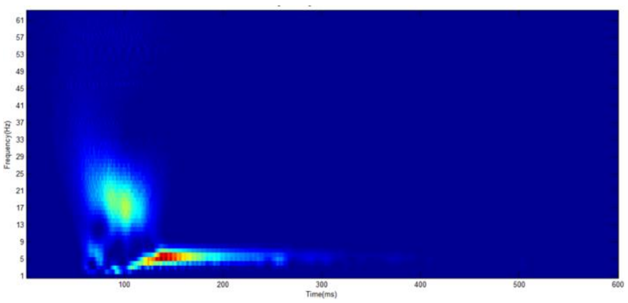

Figure 2(d): CWT scalogram image for Beta Band in AF4.

Figure 3 shows the comparison of CWT and STFT based on the energy extracted. The result shows the value of energy extracted from the CWT is high compared to the STFT. This is because CWT can extract the wavelet coefficients at certain frequency, and this is very useful to monitor the critical frequency components to the performance of the structure. In terms of releasing the stress, CWT and STFT have shown the same result.

Figure 4 shows the training performance and prediction accuracy with varying numbers of neurons in hidden layers. The variation number of neurons used between 5 and 150. The number of neurons with the lowest MSE of AF4 channel is chosen for this project. From ROC Curve in Figure 5, class 1 is the stress state, while class 2 is for the non-stress state.

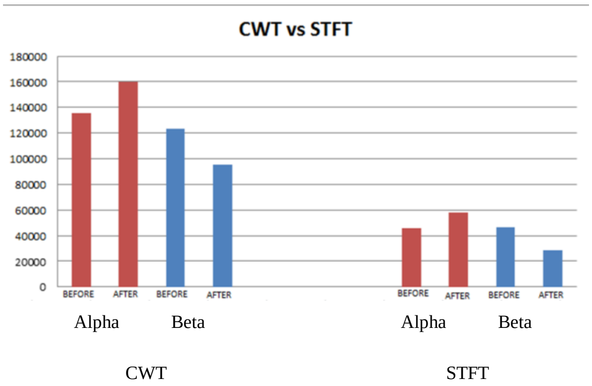

Figure 3: Comparison between CWT and STFT in terms of Alpha-band and Beta-band.

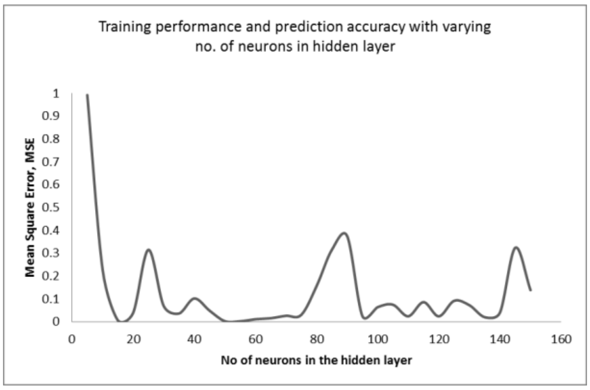

Figure 4: Training performance and prediction accuracy with varying no of neurons in hidden layers.

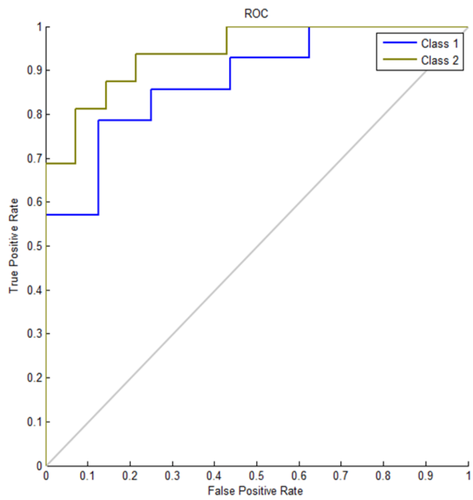

Figure 5: Condition when wheel zigzag gets over block.

Based on Figure 6, the first two diagonal cells show the number and correct percentage classifications by the trained network. As showed in Figure 6, 13 subjects are correctly classified as stress condition. This corresponds to 43.3% of all the 30 subjects. As for the non-stress condition, 13 subjects are correctly classified as non-stress condition and the percentage of correct classifications is 43.3%.

Three subjects are incorrectly classified as stress and it corresponds to 10% of all the 30 subjects, while 1 subject which is incorrectly classified as non-stress corresponds to 3.3% of all data. Out of 14 stress predictions, 81.3% are correct and 18.8% are wrong and out of the 16 non-stress predictions, 92.2% are correct and 7.1% are wrong.

From the 14 of the stress cases, 92.9% are correctly predicted as stress and 7.1% are predicted as non-stress. Out of 16 non-stress cases, 81.3% are correctly classified as non-stress and 18.8% are classified as stress.

Based on the confusion matrix, the overall result of classification yields 86.7% of predictions are correct and 13.3% are wrong classifications.

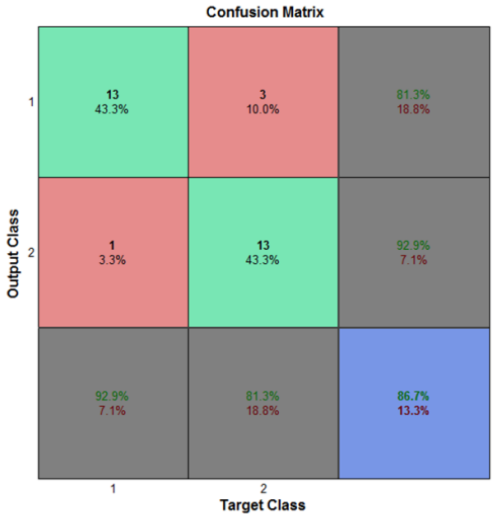

Figure 6: Condition when wheel zigzag gets over block.

IV. Conclusion

This project is to observe the effect of the body earthing to the human brainwaves and emotions. The frequency band of Alpha and Beta band were being analyzed before and after the body earthing by implementing the MATLAB. The objectives of this project are achieved through 4 stages that are the pre-processing of EEG signals, analysis of EEG signal by using Short Time Fourier Transform, Continuous Wavelet Transform and classification using Artificial Neural Network.

The result shows that the objectives, which are to compare the time-frequency analysis of STFT and CWT for EEG signal in body earthing applications and to classify EEG signal for body earthing applications are achieved. Based on the result, before body earthing the Alpha band signal is high and the Beta band signal is low. Alpha band signals are gradually increased and Beta band signals are decreased. The increased Alpha band signal activities show that the subjects feel more relaxed. The decreased of Beta band signal activities show that subjects are in alert and stress state.

For the recommendation, the different technique for EEG signals analysis. There are many types of time-frequency based analysis that can be used. For the classification of EEG signal, another intelligent classification can be used, such as CBR and fuzzy method. In data acquisition, the protocol for EEG signal data acquisition must be followed in order to obtain the accurate result. This is because if all the protocol followed the noise or artefact in the signal, it can be reduced.

Acknowledgment

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