# Novel Methods for Stress Features Identification using EEG Signals

Norizam Sulaiman[1,2]
[1]Faculty of Electrical & Electronics Engineering
Universiti Malaysia Pahang
26600 Pekan, Pahang, Malaysia
norizam@ump.edu.my

Mohd Nasir Taib[2], Sahrim Lias[2], Zunairah Hj Murat[2],
Siti Armiza Mohd Aris[2], Noor Hayatee Abdul Hamid[2]
[2]Faculty of Electrical Engineering
Universiti Teknologi MARA
40450 Shah Alam, Selangor, Malaysia
dr.nasir@ieee.org

***Abstract*—This paper introduces new methods to extract stress features from electroencephalogram (EEG) signals during two cognitive states; Closed-Eyes (CE) and Open-Eyes (OE) using Relative Energy Ratio (RER), Shannon Entropy (SE) and Spectral Centroids (SC). The group with the stress features was identified and classified using k-Nearest Neighbor (k-NN). The RER in term of Energy Spectral Density (ESD) for each frequency band (delta, theta, alpha and beta) in four different groups consisted of 180 EEG data were calculated and analyzed. Then, the SE was used to confirm the pattern of stress features. Meanwhile, SC was applied to the RER of each group and then the results were selected as input features to k-Nearest Neighbor (k-NN) for the classification purposes. The training and testing of the classifier were evaluated at 50:50 ratios and 70:30 ratios. The proposed method showed promising results where the combination of RER, SE and SC techniques with the training and testing of k-NN set at 70:30 able to detect and classify the group with the unique stress features at 88.89% accuracy.**

***Keywords-Stress features; EEG; Relative Energy Ratio; Shannon Entropy; Spectral Centroids; k-NN***

## I. INTRODUCTION

Stress is caused by human resistance towards new challenges or stressors (stress factors) emotionally, mentally or physically [1]. In other word, stress caused the imbalance of sympathetic and parasympathetic level in human Autonomous Nervous System (ANS) [2]. Even though stress can be categorized into positive stress ("eustress") such as joy and negative stress ("distress") such as depression, most human suffered negative stress which affects their lifestyle (affective style). Negative stress can make human feel tension, anxious, angry and frustrated [3-5]. Meanwhile, unable to sustain stress may lead human to symptom of burn-out or fatigue [6]. Beside the release of *cortisol* (stress hormone), stress can be quantified from human bio-signals such as EEG, Electrocardiogram (ECG), Electromyogram (EMG), Galvanic Skin Response (GSR), Blood Volume Pulse (BVP), Blood Pressure (BP), Skin Temperature (ST) and Respiration [3-4]. Among these bio-signals, the changes in ANS system due to stressors can be apparently and effectively represented by EEG signals [3, 7]. Stress pattern can be indicated by high Beta power and low Alpha power at anterior side of human brain [3].

Researchers had studied the characteristic of EEG signals from the change of human cognitive state after performing some mental tasks or due to stressors such as noisy working area, high workload, unfinished job, improper sleep and family conflict. The change of human cognitive state affects human emotion where stress belongs to negative emotion [8-11].

## II. LITERATURE SURVEY

Beside the questionnaires based method such as Cohen's Perceived Stress Scale (PSS), Stress Response Inventory (SRI) and Hamilton Depression Rating Scale (HDRS) to determine the level of stress and depression, feature extraction from EEG signals also offers a good alternative. For example, Discrete Wavelet Transform (DWT) was used to extract features from EEG signals before feeding to k-NN to classify human emotion in term of disgust, happy, surprise, fear and natural with classification accuracy of 83.26% [12]. Teplan used slope of EEG linear regression to be a feature to determine the relaxation level of an individual [13-14]. Sulaiman *et al.* [15] used a combination of EEG Asymmetry and Spectral Centroids techniques as a feature to detect unique pattern of human stress. Spectral Centroids feature extraction technique was widely used in speech and audio recognition because of its robustness to recognize the dominant frequency [16-18]. Poulus *et al.* [19] used EEG spectral power and mean frequency of Alpha band to be a feature to NN (Neural Network) in order to identify person characteristic. In addition, k-NN classifier was used to detect and classify human personality and characteristic from the EEG pattern when listening to music [20-23]. Statistical features from EEG signals were used to be an input to Neural Network to classify human emotion at 95% rate after undergone emotion stimuli [24]. Neural Network which was trained using EEG Power Spectral Density and generalization techniques from a subject performed five mental tasks able to improve the discrimination rate of mental tasks with 80-86% accuracy [25-26].

## III. PROPOSED STRESS DETECTION TECHNIQUES

From previous studies, researchers had developed various feature extraction and classification techniques including various stress inducement methods to relate human physiological signals with stress but yet to come out with a reliable stress index.

This paper proposes a new technique to recognize stress unique features from the healthy subjects by using k-NN classifier and parameters such as RER, SE and SC. The function of each parameter that was used in this study is described below.

### A. Relative Energy Ratio (RER)

RER is used to observe the changes in EEG frequency bands due to the stressors. When stress occurred, energy of Alpha band will be reduced. Meanwhile, energy of Beta band will be increased.

### B. Shannon Entropy (SE)

SE is used to quantify the energy distribution from the Power Spectrum of EEG signals. It is another method to translate the change in EEG Power Spectrum due to stressors [27].

### C. Spectral Centroid s (SC)

SC finds the dominant energy from the group with stress features. It is widely used in audio and speech recognition system to detect the dominant frequency from the audio or speech signals

### D. k-NN Classifier

k-NN is a robust supervised classifier which is trained with the features obtained from RER and SC to classify the group with a unique stress features from two difference cognitive states (CE and OE).

## IV. MATERIALS AND METHODS

### A. Subjects and Data Re-generation

The study employed 185 EEG data from different experiments which were categorized into 4 groups. All data were taken from healthy subjects. Group 1 consisted of 51 EEG data represent Closed-eyes (CE) state with psychoanalysis test [28]. Group 2 consisted of 50 data which represent EEG data during Open-eyes (OE) state (performed IQ test) [29]. Meanwhile, Group 3 and 4 consisted of 42 data each which represent EEG data during CE state (before performing Horizontal Rotation and after performing Horizontal Rotation) [31]. However, due to data corruption, 37 data were removed; 8 EEG data from Group 1, 3 EEG data from Group 2, 13 EEG data from Group 3 and 4 respectively. Hence, data re-generation technique in equation (1) and (2) was used to replace the corrupted data to each group yielding 180 EEG data; 50 EEG data for Group 1, 50 EEG data for Group 2, 40 EEG data each for Group 3 and 4. The data re-generation was implemented by adding acceptable noise to the raw data in each group as shown in (2). The maximum difference between raw data and re-generated data was checked not to exceed 10% difference by comparing the maximum and minimum values of the original data with re-generated data. Otherwise, the noise factor needs to be adjusted to appropriate scale as shown in (3). F in (1) serves as a noise factor which can be adjusted to produce a required data.

The data were re-generated using normally distributed pseudorandom numbers which can generate negative and positive data and can be added to the EEG original data.

$$\text{Noise} = \text{randn}(\text{EEG raw data}) \times F \quad (1)$$

$$\text{Re-generated data} = \text{EEG raw data} + \text{Noise} \quad (2)$$

$$F = \text{Noise Factor} = 1.5 \quad (3)$$

### B. EEG Measurement and Protocol

The EEG signals were recorded using EEG Data Acquisition instrument (g.MOBILab). Bipolar EEG gold-plated EEG electrodes were placed at prefrontal area of brain region, Fp1, Fp2, Fpz (ground) and references to earlobes A1 and A2 as shown in Fig. 1. This montage followed the International 10-20 system [30]. The impedance for EEG electrodes was checked below 5 kΩ. The sampling rate for EEG measurement was set to 256 Hz. Prior to EEG measurement, subjects were asked to sit on a chair quietly, relax and close their eyes. In addition, the EEG waveforms conditions were checked for any errors. The recording period was 3 minutes for CE state and 10 minutes for OE state which requires more time since subjects needed to answer IQ test while their brain activities were recorded at the same time. For OE state, subjects were asked to answer 20 IQ test questions with maximum time of 10 minutes using GUI (Graphical User Interface) software based on Excel Visual Basic (VB). The captured EEG signals were sent to a Personal Computer or Laptop through Bluetooth. The data were processed and analysed using intelligent signal processing technique developed in SIMULINK and MATLAB. The Bioinformatics Toolbox, FIR Filter Design and Spectral Analysis were used to analyse EEG signals.

The questions for IQ test were developed based on the modified Raven's Standard Progressive Method (SPM) [28]. During IQ test, subjects were required to minimize their movement in order to reduce noise on EEG recording. All the research activities were performed with the ethical approval from local ethical committee.

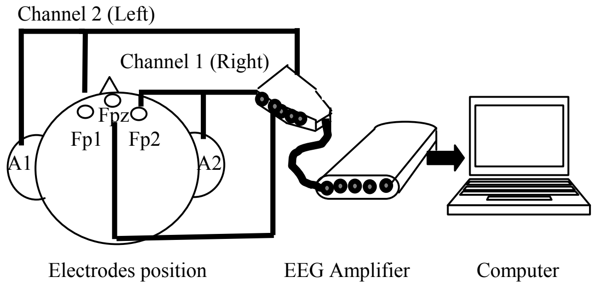


Figure 1. EEG measurement set-up.

### C. *EEG Signals Analysis*

The EEG data from channel 1 brain Right Hemisphere and channel 2 brain Left Hemisphere were analysed in off-line manner. The artifacts caused by eye-movements, eye blinks, muscle movement and power line were removed by setting threshold values of 100 µV where any data above the threshold values were rejected. This data can be considered as an addition of noises [30]. The EEG data were filtered using band pass filter set from 0.5 Hz to 30 Hz to produce Delta band, δ (0.5 – 4 Hz), Theta band, θ (4 – 8 Hz), Alpha band, α (8 – 13 Hz) and Beta, β band (13 – 30 Hz). The power for EEG frequency band was calculated by performing Fast Fourier Transform (FFT) with Hamming window. The window was set to 256 with 50% overlapping. The FFT length was set to 1024. Then, the Energy Spectral Density (ESD) was calculated by dividing the area of Power Spectral Density (PSD) curve with frequency range of the band as shown in Fig. 2 below. ESD is selected for feature calculation instead of PSD because it covers overall energy distribution for each frequency band (range of frequency). Meanwhile, PSD selects the highest power or energy at peak frequency. Thus, the ESD value will be lower than PSD value.

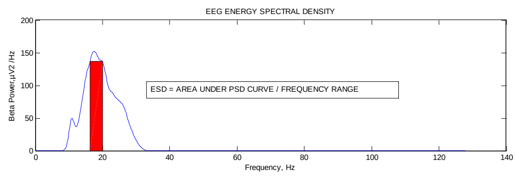



Figure 2. PSD plot of Beta band.

### D. *Experiment Flow Chart*

The flow chart of experiment methodology is shown in Fig. 3. SE and SC were applied to the RER for each group after EEG raw data for all frequency bands were converted to ESD using Fast Fourier Transform (FFT). Then, all the selected features were put into k-NN classifier to classify the potential group that might have stress features. K-NN was evaluated for two sets of training and testing ratios; 50:50 and 70:30 in order to know whether the training and testing ratios affect the classifier performance or not. The classifier was also evaluated at different k-value, distance and rule setting in order to determine whether the distance and rule have affected the classifier accuracy besides the training and testing ratio. Here, the classifier was trained with EEG features (RER and SC) to identify the group that might have stress features. In classification process, Spectral Centroids across the frequency bands for each group were calculated and selected as a class. Here, there will be four values of Spectral Centroids for four groups which representing four classes for classification process.

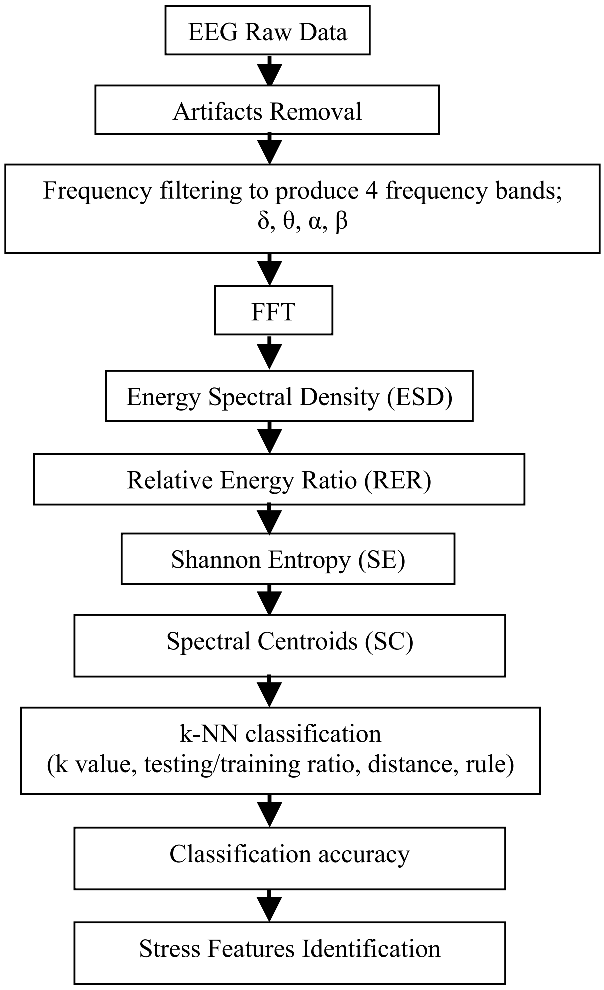



Figure 3. Experiment methodology.

### E. *Formula of Relative Energy Ratio (RER)*

The power spectrum for each bands and groups are calculated in term of Energy Spectral Density as shown in (4).

$$\text{Total power} = (\text{ESD } \delta + \text{ESD } \theta + \text{ESD } \alpha + \text{ESD } \beta) \quad (4)$$

Power Spectrum ratio for each frequency bands are calculated using equations in (5), (6), (7) and (8).

$$\delta \text{ power ratio} = |(\log_{10}(\text{ESD } \delta/\text{Total Power}))| \quad (5)$$

$$\theta \text{ power ratio} = |(\log_{10}(\text{ESD } \theta/\text{Total Power}))| \quad (6)$$

$$\alpha \text{ power ratio} = |(\log_{10}(\text{ESD } \alpha/\text{Total Power}))| \quad (7)$$

$$\beta \text{ power ratio} = |(\log_{10}(\text{ESD } \beta/\text{Total Power}))| \quad (8)$$

### F. Shannon Entropy (SE)

The SE can be expressed as shown in (9). Here, index *i* represents the subject and index *n* represents the total number of subjects. *RER* is a relative energy ratio per frequency band. For example, β power ratio represents the *RER* at β band.

$$SE = -\sum_{i=1}^{n} RER_i \times \log_{10} RER_i \tag{9}$$

### G. Spectral Centroids (SC)

The Spectral Centroids are calculated using formula in (10).

$$C_i = \sum_{i=1}^{n} F_i \times |S_i| / \sum_{i=1}^{n} |S_i| \tag{10}$$

Here, $S_i$ is an energy obtained from the spectrogram of the *RER*. $F_i$ is the average frequency weighted by the amplitude of $S_i$ where *i* is an index represents the subject and index *n* represent the total number of sample in the group [16-18].

RER of δ, θ, α, β as shown in (5), (6), (7) and (8) were used as input features to k-NN classifier. In addition, Spectral Centroids for each group as shown in (10) was used as classification's class. Since there are four groups, there will be four Spectral Centroids values and four classes. The Spectral Centroids are used to find the centre value of the groups for each frequency bands. The accuracy of the classifier will be calculated based on input features and classes. Hence, RER and Spectral Centroids are the important parameters in classification process. The classifier cannot run without these parameters. Meanwhile, SE as shown in (9) is not used in classification process. Instead, it is used to find the abnormality or uncertainty in the data that might be related to stress. Basically, the data that contain abnormality features will have smaller value of SE compared to normal data [6]. Thus, SE is used to indicate which groups might have stress features before starting the classification process.

### H. k-NN Classification

k-NN is a supervised, simple and robust learning algorithm [5, 12]. It is a powerful technique for pattern classification of non-parametric analysis [5]. The classifier works by comparing a new sample (testing data) with the baseline data (training data). The classifier finds the k neighborhood in the training data and assign class which appear more frequently in the neighborhood of k. The value of k needs to be varied in order to find the match class between training and testing data. In this research, the k values are varied from 1 to 10. The value of k is typically small [5]. The default value of k is 1. For example, if k=1, the testing data will be assigned to the class of its nearest neighbors where k must be positive integer [5].

In order to identify neighbors, the distance and rule of k-NN classifier must be chosen. There are 5 types of k-NN distance; "Euclidean", "Cityblok", "Cosine", "Correlation" and "Hamming". Meanwhile, there are 3 types of k-NN rule; "Nearest", "Random" and "Consensus". The default neighborhood setting is "Euclidean" and "Nearest". In this study, only k-NN distance of "Euclidean", "Cityblock" and "Cosine" along with all types of rule are used to find the object similarity in the k neighborhood as shown in equation (11), (12) and (13).

$$d(X_i, X_j) = \sqrt{\sum_k (X_i - X_j)} \tag{11}$$

Equation (11) defines the formula for "Euclidean" distance. Here, $X_i$ or $X_j$ is either testing or training data where *i* and *j* represent the index of the data.

$$d_{ij} = \sum_{k=1}^{n} |(X_{ik} - X_{jk})| \tag{12}$$

Equation (12) defines the formula for "Cityblock" distance. Here, $X_{ik}$ or $X_{jk}$ is either testing or training data where *i* and *k* is the index of the data. Here, the "Cityblock" distance is the summation of the difference between the data and then the results are assigned to the class that come out most frequently in the neighborhood of k.

$$d_{ij} = 1 - \sum_{k=1}^{n} (X_{ik} \times X_{jk}) / \left( \sqrt{(X_{ik})^2} \times \sqrt{(X_{jk})^2} \right) \tag{13}$$

Equation (13) defines the formula for "Cosine" distance. Here, $X_{ik}$ or $X_{jk}$ is either testing or training data where *i* and *j* is the index of the data. Meanwhile, *k* is the index of the subject and *n* is the total number of sample. Here, "Cosine" distance involve the summation of the multiplication of the data over square root of the data that assigned to the class that come out most frequently in the neighborhood of k.

Beside the k value and training and testing ratio, the classifier default settings are changed in order to find the best setting that is able to produce high accuracy of classification. The k-NN classifier was also evaluated by changing the default setting of distance from "Euclidean" to "Cityblock" and "Cosine". The k-NN classifier rule was changed from the default setting of "nearest" to "random" and "consensus".

## V. RESULTS AND DISCUSSION

EEG power spectrum obtained from the Fourier Transform of EEG raw data were verified and tested for normality using statistical software (SPSS). Then, the EEG power spectrum in term of ESD was plotted against frequency band in order to verify the characteristic of the EEG power as shown in Fig. 4.

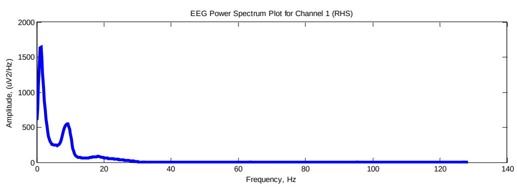



Figure 4. A plot of Power Spectrum versus Frequency.

The graph in Fig. 4 indicates that Delta and Theta band have high amplitude at lower frequency. However, Alpha and Beta band have low amplitude at higher frequency. It is vital to inspect the characteristic of EEG power after filtering process per respective frequencies. It can be used to validate the filter setting. The normality of EEG data and their characteristics will assist classifier in producing a good classification results.

Since the purpose of the study is to identify the stress features, there is compulsory to observe the change of amplitude of RER of Alpha and Beta bands. For a clearer view of the changes in the energy, the relative energy ratios of both bands are plotted as shown in Fig. 5. It is difficult to see the stress features in RER of Delta and Theta band since these bands represent the brain in deep sleep and light sleep activity respectively [30-31]. Hence, the pattern of stress can be seen well in the change of RER of Alpha and Beta band. The Alpha band represents the relaxation state of the brain activity [30-31]. Meanwhile, Beta band represents the alertness state of the brain activity [30-31]. Average RER of Alpha and Beta band in Group 2 will serve as benchmark to RER of Alpha and Beta band in other groups since it represents change of brain activity due to stress. When the stress occurred, the amplitude of Alpha band will decrease and the amplitude of Beta band will increase. RER of Beta band in Group 2 is higher than RER of Beta band in Group 1, Group 3 and Group 4. Conversely, RER of Alpha band in Group 2 is lower than RER of Alpha band in Group 1, Group 3 and Group 4. This scenario indicates that subjects in Group 2 might experience stress during answering IQ test questions.

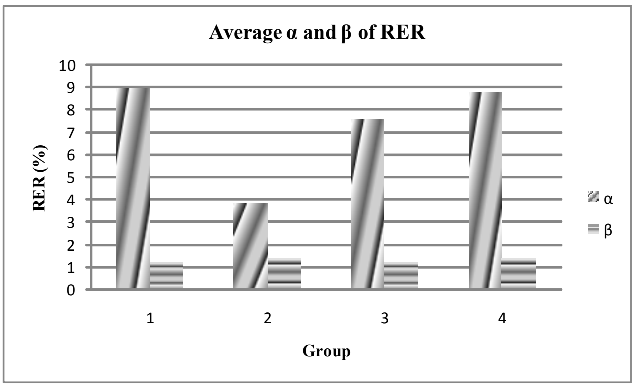



Figure 5. Histogram plot of average RER of Alpha and Beta bands.

The result of SE for all groups as shown in Fig. 6 depicts a significant decrease in SE values for Group 2. This observation tallies with the results shown in Fig. 5. Thus, it confirms that change in energy distribution was due to stressors.

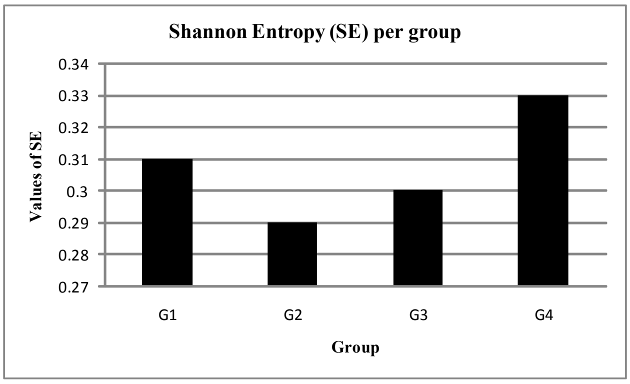



Figure 6. Histogram plot of SE per group.

After verification of RER pattern from each group by SE, the Spectral Centroids were applied to the RER for all frequency bands. The results of the Spectral Centroids calculation per bands and group are shown in Fig. 7. Here, only centroids values of Alpha and Beta was shown since these frequency bands were reliable indicator for existence of stress. A Centroids value of Beta band in group 2 was higher than Centroids value of Alpha band. For the rest of the groups, Centroids values of Beta band were lower than Centroids values of Alpha band.

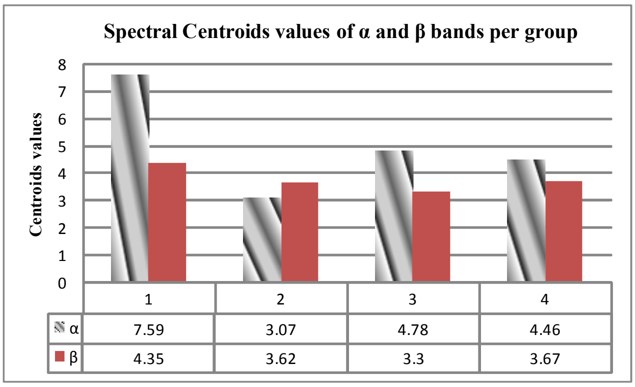



Figure 7. Histogram plot of Centroids of Alpha & Beta Energy Ratio per band

However, the overall or average Centroids values per frequency bands in group 2 were smaller than the average value of Centroids for other groups as shown in Fig. 8. The results for Centroids confirmed the stress pattern shown in Fig. 5 and Fig. 6. The results of the experiments indicate that the Centroids values can be used as unique features to indicate the pattern of human stress. The overall Centroids values for all groups were used as target or class in training the k-NN classifier. The stress pattern was confirmed by k-NN classifier.

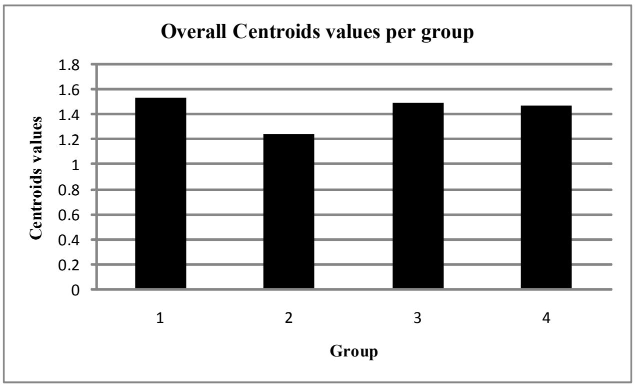
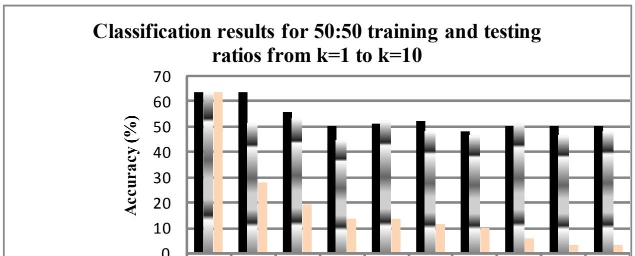



Figure 8. Histogram plot of Overall Centroids values per group.

The values of Spectral Centroids together with EEG power band ratio were used as features in the k-NN classifier. The results of the classification are shown in Fig. 9 and Fig. 10. In Fig. 9, the training and testing ratio was set to 50:50. The classification produced the highest accuracy, 63.33% where the distance was set to "cosine" and rule was set to nearest, "random" and "consensus" respectively. The highest classification was obtained at k = 1 and k = 2 for the combination of "cosine" and "nearest". In addition, the highest classification was also obtained at k = 1 for the combination of "cosine" with "random" and "consensus". The classification results indicate that the default value of k (k = 1) is enough to determine the highest classification accuracy.

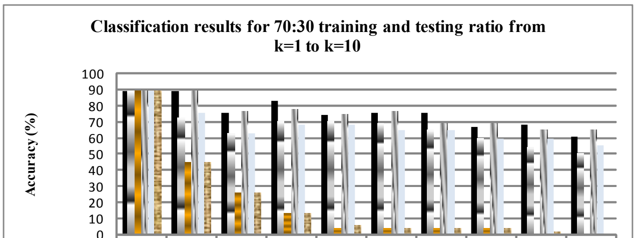



| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| cosine & nearest | 63.3 | 63.3 | 55.5 | 50 | 51.1 | 52.2 | 47.7 | 50 | 50 | 50 |
| cosine & random | 63.3 | 51.1 | 53.3 | 44.4 | 52.2 | 47.7 | 46.6 | 51.1 | 46.6 | 47.7 |
| cosine & consensus | 63.3 | 27.7 | 18.8 | 13.3 | 13.3 | 11.1 | 10 | 5.56 | 3.33 | 3.33 |

Figure 9. k-NN classification accuracy for 50:50 ratio and k from 1 to 10.

From the experiment results, besides the features used to train the classifier, the classifier setting in term of training and testing ratio, distance and rule, also play a vital role in deciding the similarity of testing data in the k neighborhood. The highest classification accuracy occurred at k=1 and k=2. In addition, the highest classification accuracy does not always occurred at the default setting of distance and rule ("Euclidean" and "nearest"). Hence, it is extremely important to evaluate k-NN at all settings. However, it is obvious that it is not necessary to vary k neighborhood values more than 2.

In Fig. 10, the training and testing ratio was changed to 70:30. It improves the classification accuracy from 63.33 % to 88.89 %. The highest classification was obtained at k= 1 and 2 from the default setting and from the combination setting of "Euclidean" and "random", "Euclidean" and "consensus". The combination setting of "cityblock" with "nearest", "cityblock" with "random" and "cityblock" with "consensus" also produced good classification accuracy (88.89%).




| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| Euc & Near | 88.89 | 88.89 | 75.93 | 83.33 | 74.07 | 75.93 | 75.93 | 66.67 | 68.52 | 61.11 |
| Euc & Rand | 88.89 | 72.22 | 62.96 | 70.37 | 70.37 | 68.52 | 64.81 | 59.26 | 53.7 | 50 |
| Euc & Con | 88.89 | 44.44 | 25.93 | 12.96 | 3.7 | 3.7 | 3.7 | 3.7 | 0 | 0 |
| City & Near | 88.89 | 88.89 | 75.93 | 77.78 | 74.07 | 75.93 | 68.52 | 68.52 | 64.81 | 64.81 |
| City & Rand | 88.89 | 75.93 | 62.96 | 68.52 | 68.52 | 64.81 | 64.81 | 59.26 | 59.26 | 55.56 |
| City & Con | 88.89 | 44.44 | 25.93 | 12.96 | 5.56 | 3.7 | 3.7 | 3.7 | 1.85 | 0 |

Figure 10. k-NN classification accuracy for 70:30 ratio and k from 1 to 10.

From the experiment results, besides the features used to train the classifier, the classifier setting in term of training and testing ratio, distance and rule, also play a vital role in deciding the similarity of testing data in the k neighborhood. The highest classification accuracy occurred at k=1 and k=2. In addition, the highest classification accuracy does not always occurred at the default setting of distance and rule ("Euclidean" and "nearest"). Hence, it is extremely important to evaluate k-NN at all settings. However, it is obvious that it is not necessary to vary k neighborhood values more than 2.

## VI. CONCLUSION AND FUTURE WORK

The combination of RER and SC as features to k-NN classifier have enabled the classifier to detect and classify the group with the stress features. The stress features in the group is confirmed by SE. The classifier settings in term of training ratio, testing ratio, distance and rule affects the classifier performance, the major effect came from the feature selection to train the classifier. If the features are reliable, classifier will produce high accuracy of classification result. Hence, it is important to ensure only the correct features are selected for the k-NN classifier. It is also observed that the highest accuracy of k-NN classification is obtained from a lower value of k.

The future work is to use the classification results, RER and SC to assign stress indexes to each group.

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