Classification of EEG Spectrogram Using ANN for IQ Application

Mahfuzah Mustafa[1,2]
[1]Faculty of Electrical & Electronics Engineering
Universiti Malaysia Pahang, Kampus Pekan,
26600 Pekan, Pahang, Malaysia
mahfuzah@ump.edu.my

Mohd Nasir Taib[2,3], Sahrim Lias[2,3], Zunairah Hj Murat[2,3], Norizam Sulaiman[1,2]
[2]Faculty of Electrical Engineering
[3]Biomedical Research Laboratory for Human Potential
Universiti Teknologi MARA
40450 Shah Alam, Selangor, Malaysia

***Abstract*— The intelligence term can be view in many areas such as linguistic, mathematical, music and art. In this paper, the Intelligence Quotient (IQ) is measured using Electroencephalogram (EEG) from the human brain. The spectrogram images were formed from EEG signals, then the Gray Level Co-occurrence Matrix (GLCM) texture feature were extracted from the images. This texture feature produced big matrix data, thus Principal Component Analysis (PCA) is used to reduce the big matrix. Then, ANN algorithm is employed to classify the EEG spectrogram image in IQ application. The results will be validated based on the concept of Raven's Standard Progressive Matrices (RPM) IQ test. The results showed that the ANN was able to classify the EEG spectrogram image with 88.89% accuracy and 0.0633 MSE.**

Keywords—EEG; spectrogram image; GLCM; ANN

I. INTRODUCTION

Often, the method used by psychologist to evaluate human intelligence is by using the intelligence quotient (IQ) test. Some of popular IQ test modules are Raven's matrices [1-3]. However, recently, many studies evaluate human intelligence using Electroencephalogram (EEG) [4-6]. The EEG is the goodness culture-free test to be employed in IQ test [7]. Culture-free test meant that the system was developed using of little use of language and independent of the area education settings. For example, people who are received education in the urban areas are different from who are received educations in the rural areas. This means that different education settings area will result in different answers when answering an IQ test.

The EEG brainwaves recorded in terms of electric signals which grouped into four brainwaves called Delta, Theta, Alpha and Beta [8].This brainwaves are recorded in the form of amplitude vs time or in other word, time-based. It can also be translated into frequency based, and usually Fourier Transform will be used. The brainwave can also be analyzed with a technique called time-frequency based or also known as spectrogram image. The spectrogram image has been used in the study of heart abnormalities from Electrocardiogram (ECG) signals [9]. The spectrogram image can be generated by using various techniques such as Short Time Fourier Transform (STFT), Wigner-ville, Choi Williams and Gabor.

The spectrogram image can be analyzed using texture analysis in image processing namely Gray Level Co-occurrence Matrix (GLCM). The GLCM technique is popular employ in extracting texture from satellite image [10]. The use of this technique is also popular in biomedical image analysis to detect disease in liver and brain [11, 12].

After successful extraction of GLCM features from spectrogram image, various classifiers can be used for classification purpose. The Artificial Neural Network (ANN) was selected because it is highly suited to process feature rich data [13, 14]. There are studies using extracted EEG signals features to be fed into ANN in various application. For example, the ANN is employed to analyze the epileptic seizure [15] and Parkinson disease [16]. From this findings, it denotes a promising result in biomedical field. However, the use of ANN as classifier in IQ application via GLCM texture feature analysis never has been reported via literature. There is an example of this technique in brainwave balancing application [17]. The aim of this paper is to classify EEG spectrogram image for IQ application using ANN.

II. MATERIALS AND METHODS

The experiment of this study consists of four phases including EEG signals collection, data preprocessing, data analysis and ANN classification (Fig.1). Initially, the EEG signals were collected at Biomedical Research and Development Laboratory for Human Potential, Faculty of Electrical Engineering, Universiti Teknologi MARA (UiTM), Malaysia. The EEG signals samples were collected from 50 volunteers, which are from 21 males and 29 females with a mean age of 23.16. All volunteers were in healthy condition and did not consume of any medication prior to the test. This study was approved by the ethics committee UiTM. Next, the EEG signals were preprocessed in order to produce cleaned EEG signals. The data analysis consisted of several components namely translating the EEG signals into spectrogram image, extracting EEG features using GLCM texture features and reducing the data dimension using PCA. Finally, ANN is used to classify the EEG spectrogram image.

The EEG signals were collected and processed using intelligent signal processing technique developed in SIMULINK and MATLAB.

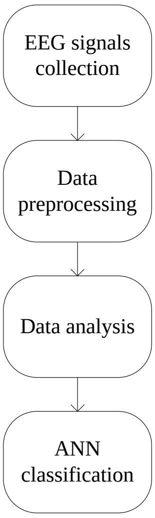

Fig. 1. Experiment methodology

A. *EEG Signals Collection*

The EEG data were collected with bipolar electrodes by using standard gold disc electrodes, with 2-channels Fp1 and Fp2 and reference to earlobes A1, A2 and Fpz. The electrode connections are in accordance to 10-20 International system with 256 Hz sampling rate. EEG signals are taken from volunteers using a device called g.MOBIlab. The EEG signals were recorded in two states, 3 minutes with eyes closed and 10 minutes with eyes opened while volunteers answer the 20 questions of IQ test (Fig. 2). After volunteers finish answering the IQ questions, the score will be recorded. The score collected will determine the level of volunteers IQ. In this experiment, there are seven levels or indices of IQ. The lowest index refers to the extremely low IQ index, while the highest index refers to the very superior IQ. The IQ test questions were developed based on Raven Progressive Matrices test and were designed specifically to test mathematical-logical intelligence.

B. *Data preprocessing*

The EEG signal preprocessing consists of two stages; artefact removal and band pass filter. Artefacts occur when the volunteers blink his or her eyes. These artefacts were removed by the means of programming designed using MATLAB tools by setting a threshold value. The threshold was set to eliminate data when the values are less than -100 μV and more than 100 μV. The band pass filter was set for the frequency from 0.5 Hz to 30 Hz using Hamming window with 50% overlapping.

C. *Data analysis*

In data analysis, the cleaned EEG signals were formed into spectrogram images by using Short Time Fourier Transform (STFT). The STFT was calculated by multiplying the Fourier Transform of the EEG signal by window function. The spectrogram image formed is based on the frequency bands. The Beta band is set from 13 Hz to 30 Hz, Alpha band is set from 8 Hz to 13 Hz, Theta band is set from 4 Hz to 8 Hz and Delta band is set from 0.5 Hz to 4 Hz.

Then, the resulting spectrogram image will be processed by means of GLCM texture analysis. In this experiment, GLCM will be produced by four orientations (0^0, 45^0, 90^0 and 135^0), 32 grey levels and one displacement. The 20 texture features were extracted by using Haralick [10], Soh [18] and Clausi [19] techniques.

As the experiment was conducted with two conditions, i.e. eyes closed and eyes opened, then there should be the relationship for the two conditions. Therefore, features derived from GLCM texture feature from both conditions were correlated by using alpha and beta ratio. The equations for alpha and beta ratio shown in (1) and (2)

$$\text{alpha ratio} = (\alpha_{CE}/\Sigma \text{ all freq band}) - (\alpha_{OE}/\Sigma \text{ all freq band}) \quad (1)$$

$$\text{beta ratio} = (\beta_{CE}/\Sigma \text{ all freq band}) - (\beta_{OE}/\Sigma \text{ all freq band}) \quad (2)$$

where

α is an extracted GLCM texture from alpha band spectrogram.

β is an extracted GLCM texture from beta band spectrogram.

CE in subscript letters is for closed eyes condition.

OE in subscript letters is for opened eyes condition.

The results from the GLCM texture feature and ratios produce very large data matrix. Therefore, PCA was employed to reduce the data matrix and select the significant principal component to represent this matrix data.

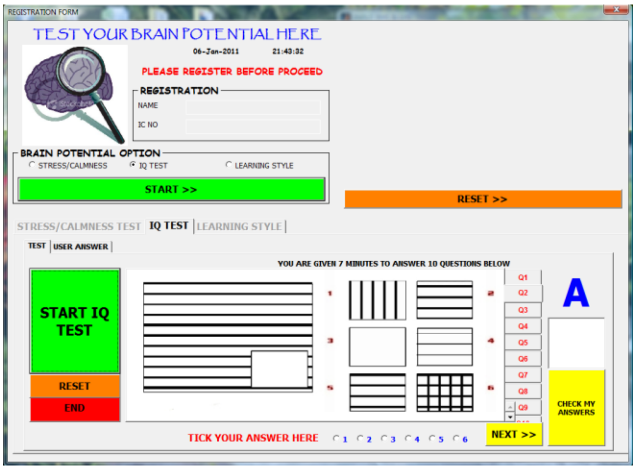

Fig. 2. Sample of IQ test.

D. *Artificial Neural Network(ANN) Classification*

This experiment using feed-forward ANN with 8 inputs and 1 output to classify the EEG spectrogram image. The sigmoid was selected for the ANN activation function. The best ANN model can be obtained by optimizing three parameters, namely the number of neurons in the hidden layer, learning rate and momentum rate. The parameters to be optimized vary while the two parameters were fixed and MSE were observed and collected. The optimum parameters can be achieved by finding the lowest mean square error (MSE). Many studies refer to MSE as the error goal [20-22]. Finally, the best model for the experiment was selected for the final application. The data were divided into two parts for training and testing purposes. The 80% of the data were used for training while the remaining 20% is used for the testing.

III. RESULTS AND DISCUSSION

As discussed, the artefacts were removed using threshold value. After the artefact removal process, the EEG signals has peak less than 100µVand more than -100µV, as seen in Fig. 3.

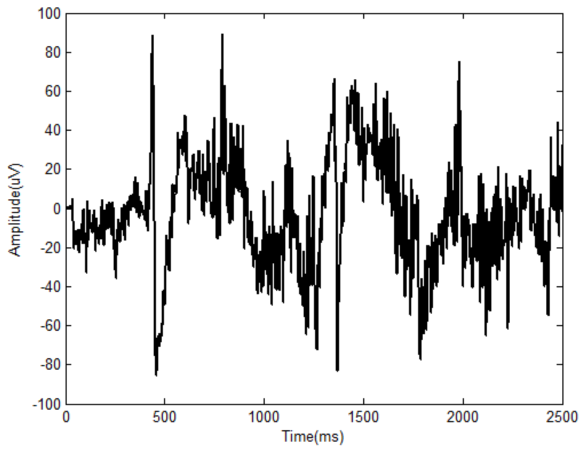

Fig. 3. A sample of EEG signals after artifact removal process.

Band pass filtering process was done to ensure that the frequency of 0.5 Hz to 30 Hz will be used for the purpose of analysis. This frequency limit was set based on four frequency bands namely Delta, Theta, Alpha and Beta. After done band pass filter, the EEG signals have frequency maximum 30 Hz as seen in Fig. 4.

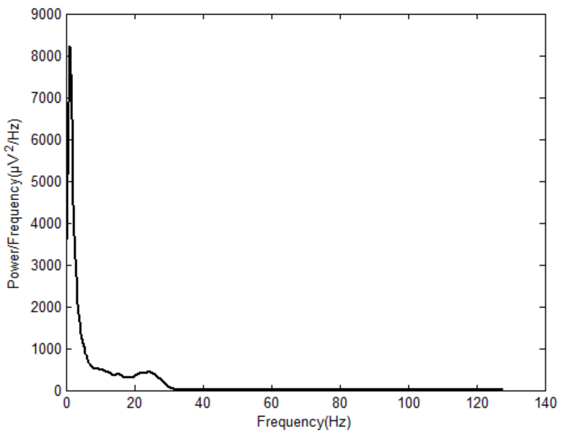

Fig. 4. A sample of EEG signals after band pass filtering process.

Figs. 5 (a) - (h) are the results of the spectrogram images for the eyes closed state. The spectrogram images produced for all frequencies band (Delta, Theta, Alpha and Beta). Each frequency bands produced different texture pattern. The EEG spectrogram images were produced in size 435 x 343 pixels.

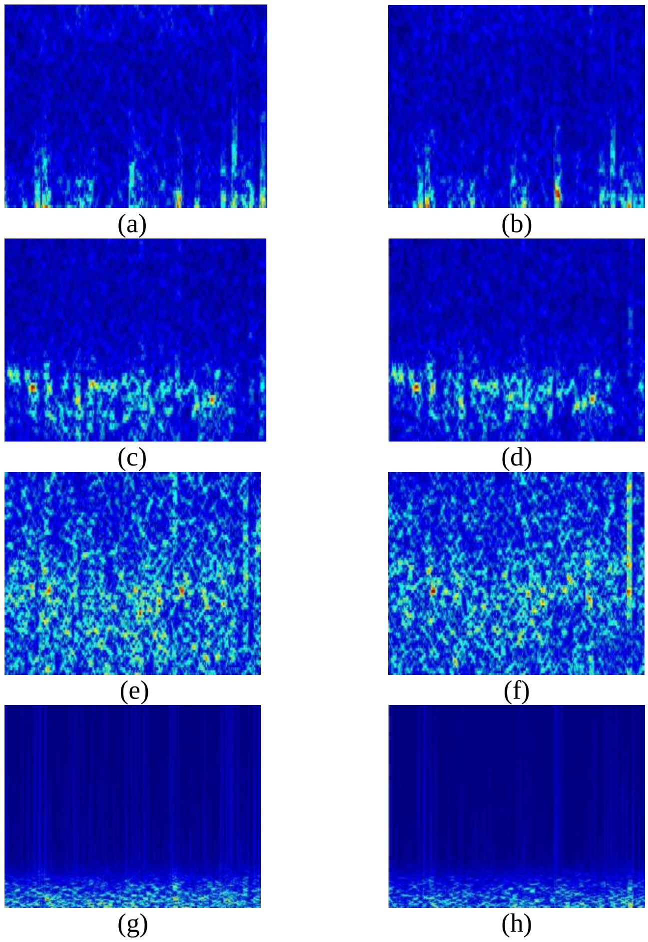

Fig. 5. Spectrogram images in eyes close state for (a) Delta band from left channel, (b) Delta band from right channel, (c) Theta band from left channel, (d) Theta band from right channel, (e) Alpha band from left channel, (f) Alpha band from right, (g) Beta band from left channel, and (h) Beta band from right channel.

From the GLCM texture analysis and ratios produced 80 features for each spectrogram image. PCA is used to reduce the large dimension features. The PCA selects 8 principal components out of 80 because it produced high percentage of eigenvalue.

Performance of optimization of the ANN was presented in Figs. 6, 7, and 8. The legend 'solid' line and 'dot' line represents mean squared error and accuracy percentage. Fig. 6 illustrates the result for optimizing the number of neurons in the hidden layer size. It was found that the hidden layer 14, 20 and 21 may produce good prediction outcome. In this experiment, the network with hidden layer size 20 with accuracy rate 92.68% with MSE 0.0852 was selected.

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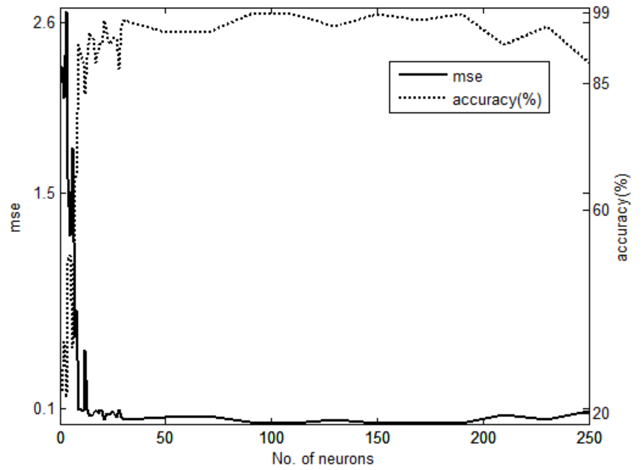

Fig. 6. Training performance and prediction accuracy with varying hidden layer size.

Fig. 7 shows the result of the finding of the optimum learning rate. From this figure, both accuracy and MSE show fluctuating trend. The lowest MSE shows at point 0.2 and 0.3, the highest accuracy shows at point 0.2 and 0.3, therefore 0.2 and 0.3 may produce a good result. It has been found learning rate values of 0.2 gives optimum accuracy 93.90% with MSE 0.0704.

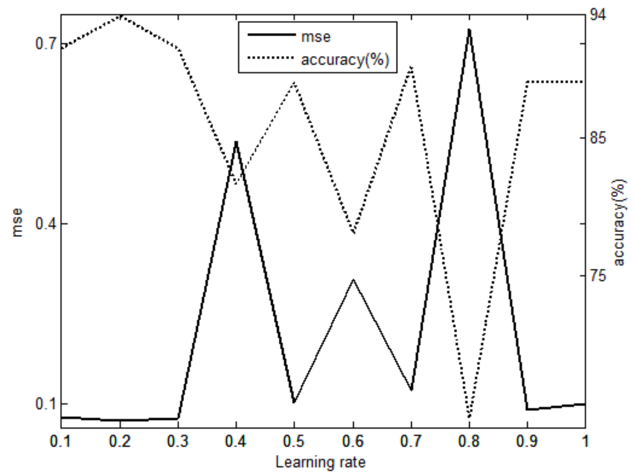

Fig. 7. Training performance and prediction accuracy with varying learning rate.

Fig. 8 illustrates the result of the finding of the momentum rate. From the figure, 'solid' line shows fluctuating trend and it reaches the lowest point at 0.2 and 0.9. The 'dot' line shows fluctuate trend and it reach the highest point at 0.2 and 0.9. Therefore, a momentum rate at 0.2 and 0.9 may produce a good prediction outcome. The momentum rate 0.9 was found to be the optimum accuracy 97.56% with MSE 0.0538. Finally, the best network is defined by the 20 hidden neurons, 0.2 learning rate and 0.9 momentum rate.

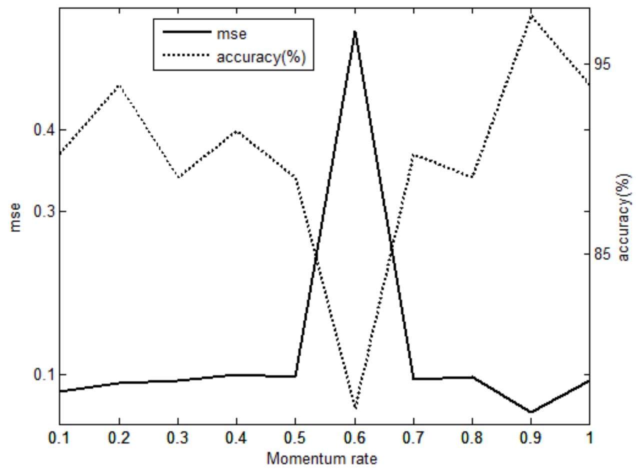

Fig. 8. Training performance and prediction accuracy with varying momentum rate.

Table I illustrates the result of accuracy and MSE after testing using the ANN with the optimized parameters. From the table, this ANN model gives 88.89% of accuracy and 0.0633 of MSE.

TABLE I. ACCURACY, MSE ON TESTING PERFORMANCE FOR ANN ALGORITHM

Accuracy (%)	**MSE**	**Optimized parameters**
88.89	0.0633	Hidden neurons - 20 Learning rate - 0.2 Momentum rate - 0.9

IV. CONCLUSION

In this paper, the classification using the ANN algorithm is presented with the aim to classify the EEG spectrogram for IQ application. In order to achieve good results, the ANN model was optimized in training phase by varying the neurons in the hidden layer, learning rate and momentum rate. The experimental result showed that the ANN was able to classify EEG spectrogram image with an accuracy 88.89% and MSE 0.0633

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