International Journal of Information, Control and Computer Sciences
ISSN: 2517-9942
Vol:8, No:8, 2014

Brainwave Classification for Brain Balancing Index (BBI) via 3D EEG Model Using k-NN Technique

N. Fuad, M. N. Taib, R. Jailani, M. E. Marwan

Abstract**—**In this paper, the comparison between k-Nearest Neighbor (kNN) algorithms for classifying the 3D EEG model in brain balancing is presented. The EEG signal recording was conducted on 51 healthy subjects. Development of 3D EEG models involves pre-processing of raw EEG signals and construction of spectrogram images. Then, maximum PSD values were extracted as features from the model. There are three indexes for balanced brain; index 3, index 4 and index 5. There are significant different of the EEG signals due to the brain balancing index (BBI). Alpha-α (8–13 Hz) and beta-β (13–30 Hz) were used as input signals for the classification model. The k-NN classification result is 88.46% accuracy. These results proved that k-NN can be used in order to predict the brain balancing application.

Keywords**—**Brain balancing, kNN, power spectral density, 3D EEG model.

I. Introduction

CLASSIFICATION is the method of finding a set of models that describes and distinguishes data classes for the use of predicting the class of objects whose class labels are unknown [1], [2]. The k-Nearest Neighbor (kNN) is one of the classification techniques using machine learning algorithm. The kNN is known as simple but robust classifier and produced high performance results even for complex applications [3], [4]. The kNN uses a distance of features in a data set to determine the data belongs to which group. Close distance between features mean the features in same group while long distance between features mean that the features in the different group. Therefore kNN is a nonparametric procedure to determinate the appropriate group which close in Euclidian distance [5]. For example, kNN was used to classify epileptic and normal brain activities through EEG signals [6]. Another example, kNN was used to classify ten samples of EEG signals for individual biometric purposes [7] and various applications [8]-[11].

The electroencephalogram (EEG) is a total of different sinusoids with a wide frequency spectrum that is divided into different frequency bands such as alpha, delta, theta and beta bands [12]. An EEG spectral pattern is produced by several spectral components. The power for each spectral power has the frequency bands: theta-θ (4–8 Hz), delta-δ (0.5–4 Hz), alpha-α (8–13 Hz) and beta-β (13–30 Hz) [13]. The EEG oscillations utilize these components and hypothesize it to produce the variation of cyclical in the excitability of neuronal assemblies [14], [15]. The highest frequency band and the lowest amplitude is beta while the lowest frequency band with the highest amplitude is delta. However, it is not limited to brain related diseases but also used for other applications such as Brain-Computer Interfacing (BCI) [16] and Intelligence Quotient (IQ) [17]. In EEG research, kNN is widely used as classifier in to order to classify the EEG signals.

Human brain consists of two parts such as left hemisphere and right hemisphere. The language, arithmetic, analysis and speech are performed at left side of the brain. The right side of hemisphere will dominant in the cognitive tasks such as understanding, emoting, perceiving, remembering and thinking [18]-[21]. When the right and left brain are used for healthy lifestyle, human felt in happiness and good health [22]. Recently, many researchers increase their interest to find the methods for balancing of the brain [23]-[25]. The most popular methods are auditory and visual in brainwave entrainment that results more wave that similar to the frequency following response [24]-[26]. Other methods include Transcranial Magnetic/Electric Stimulation and traditional techniques such as massages, meditation and acupunctures [23]-[25]. From the review there were studies in brainwave balancing application but the number of published papers is too little.

The objective of this paper is to do classification of power spectral density (PSD) features from three dimensional (3D) models for brainwave balancing application using kNN.

II. Methodology

The flow diagram of methodology has been shown in Fig. 1. Initially, EEG signals were collected from 51 volunteers. Then, the EEG signals were pre-processed to produce clean signals and filtering into four band frequencies delta-δ band, theta-θ band, alpha-α band and beta-β band. Next, the 2D image called spectrogram was produced from clean EEG signals and 3D EEG model have been developed from EEG spectrogram using image processing techniques, then classification using k-NN technique.

N. Fuad is a lecturer in Department of Computer Engineering, Faculty of Electrical and Electronic Engineering, Universiti Tun Hussein Onn Malaysia, 86400 Johore, Malaysia. She also a Phd student at Faculty of Electrical Engineering, Universiti Teknologi MARA, 40450 Selangor, Malaysia (e-mail: norfaiza@uthm.edu.my).

M. N. Taib and R.Jailani are senior lecturers with Faculty of Electrical Engineering, Universiti Teknologi MARA, 40450 Selangor, Malaysia. (e-mail: nasir@uitm.edu.my, rozita@uitm.edu.my).

M. E. Marwan are with Kolej Poly-Tech MARA Batu Pahat, 83000 Johor, Malaysia (e-mail: erwandy@gapps.kptm.edu.my).

International Journal of Information, Control and Computer Sciences
ISSN: 2517-9942
Vol:8, No:8, 2014

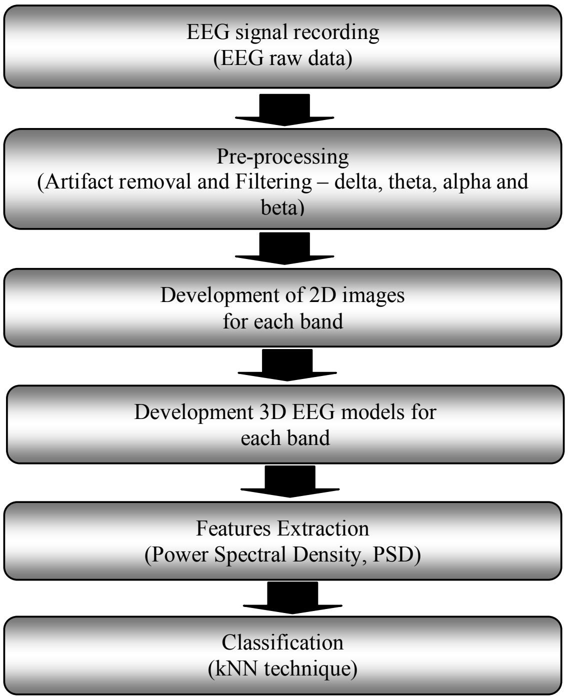

Fig. 1 Flow diagram of methodology

The experimental setup for EEG signal recording has been displayed in Fig. 2. There were two channels and one reference to two earlobes used to collect or record EEG signal. These channels connected to gold disk bipolar electrode that complied with 10/20 International System. The sampling rate is 256Hz. Channel 1 positive was connected to the right hand side (RHS), Fp_2. The left hand side (LHS), Fp_1 was connected to channel 2 positive. Fp_Z is the point at the center of forehead declared as reference point. MOBIlab was used in wireless EEG equipment and the EEG signal was monitored for five minutes. The Z-checker equipment was used to maintain the impedance to below than 5kΩ. The MATLAB and SIMULINK are used to process the data with the intelligent signal processing technique.

A. Data Collection

This research involved volunteers of samples which are students and lecturers. The data are collected from Biomedical Research and Development Laboratory for Human Potential, Faculty of Electrical Engineering, Universiti Teknologi MARA Malaysia (UiTM). All volunteers are healthy and not on any medication before the tests. These are performed and have fulfilled the requirement provided by the ethics committee from UiTM. Table I showed the number of sample for each index.

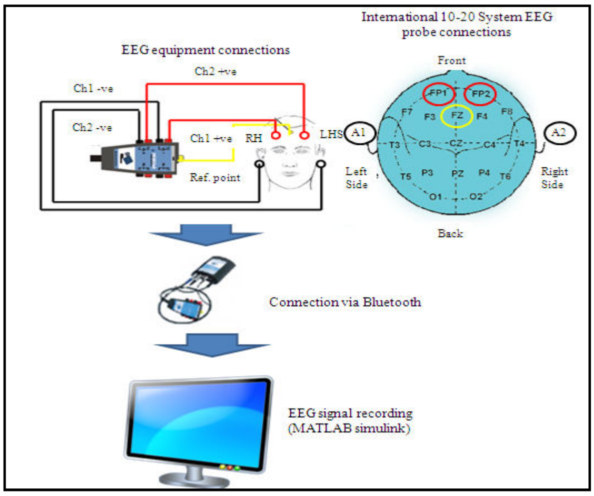

Fig. 2 Experimental setup

TABLE I
BRAIN BALANCING GROUP WITH RANGE OF BALANCE SCORE

Index level	Percentage difference between left and right	Samples
Index level 3	40.0%-59.9%	9
Index level 4	20.0%-39.9%	37
Index level 5	0.0%-19.9%	5

B. Data Preprocessing for Development 3D model

The EEG signals were pre-processed to produce clean signals and filtering into four band frequencies delta-δ band, theta-θ band, alpha-α band and beta-β band using signal processing technique. Next, the two dimensional (2D) images or spectrogram was produced from clean EEG signals and three dimensional (3D) EEG model have been developed from EEG spectrogram using image processing techniques. These techniques have been explained previously in detail [27], [28]. Although after 3D model development, some features has been extracted from the model.

C. Features Extraction

Feature extraction is a process after 3D development because of the process involves simplifying the amount of resources required to describe a large set of data accurately. When performing analysis of complex data one of the major problems stems from the number of variables involved. Therefore, after development of 3D EEG model, the power spectral density (PSD) has been extracted as features. Only maximum PSD values are chosen as parameters. These features were analyzed using statistical analysis for recognizing the pattern in brain balancing application in [29].

D. Classification Algorithm

In this paper, KNN algorithm is used for classification. The ratio used for training and testing process was 80:20. The ratio 80:20 means that 80% of the data is selected for training process, while 20% of the data is selected for testing process.

The outputs of classifiers were verified together with brain dominance questionnaire [30]. The best model for both classifiers is selected based on the highest accuracy. In kNN algorithm, the k variable is varied and the distance is fixed. The distance is used Euclidean. The k variable is varied from 1 to 8. Equation (1) is implemented for Euclidean distance,

$$d(X_i, X_j) = \sqrt{\sum_{k=1}^{n} (X_{ik} - X_{jk})^2} \quad (1)$$

where;

X_i or X_j are the training and testing data.

i and *j* are the index of the data

k is the counter for the length of the training data (n).

In order to produce the best classification performance, the classifier must be tested for accuracy, sensitivity and specificity. Accuracy is defined as the closeness of the measurement to its value, sensitivity is described as the true positive that is correctly, and specificity indicates the true negative that is correctly identified. Accuracy, sensitivity and specificity can be calculated using (2) to (4), respectively. In order to make proper computation of accuracy, sensitivity and specificity in the classification process, s confusion matrix need to be built.

$$Accuracy = \frac{(TP + TN)}{TP + TN + FP + FN} \quad (2)$$

$$Sensitivit\ y = \frac{(TP)}{TP + TN} \quad (3)$$

$$Specificity = \frac{(TN)}{TN + FP} \quad (4)$$

The confusion matrix for 2 x 2 matrices of the datasets is shown in Table II.

TABLE II
CONFUSION MATRIX FOR 2 X 2 MATRICES TARGET CLASS

Output	TP	FP
	FN	TN

The error from classifier is calculated negative which is correctly by using the Mean-Square Error (MSE). The MSE is calculated using (5).

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \quad (5)$$

where N is the number of data point, $\hat{y}_i$ is the predicted value for case i, and y_i is the expected value for case i.

III. RESULTS AND DISCUSSION

3D EEG models were produced using optimization; gradient and mesh algorithms as depict in Figs. 3 (a)-(h). The 3D signal is spectral of PSD and a different maximum PSD produced by each frequency band. Eight 3D signals for channels Fp1 and Fp2 are produced by EEG sample. The 3D EEG model produced as depicted in Table III.

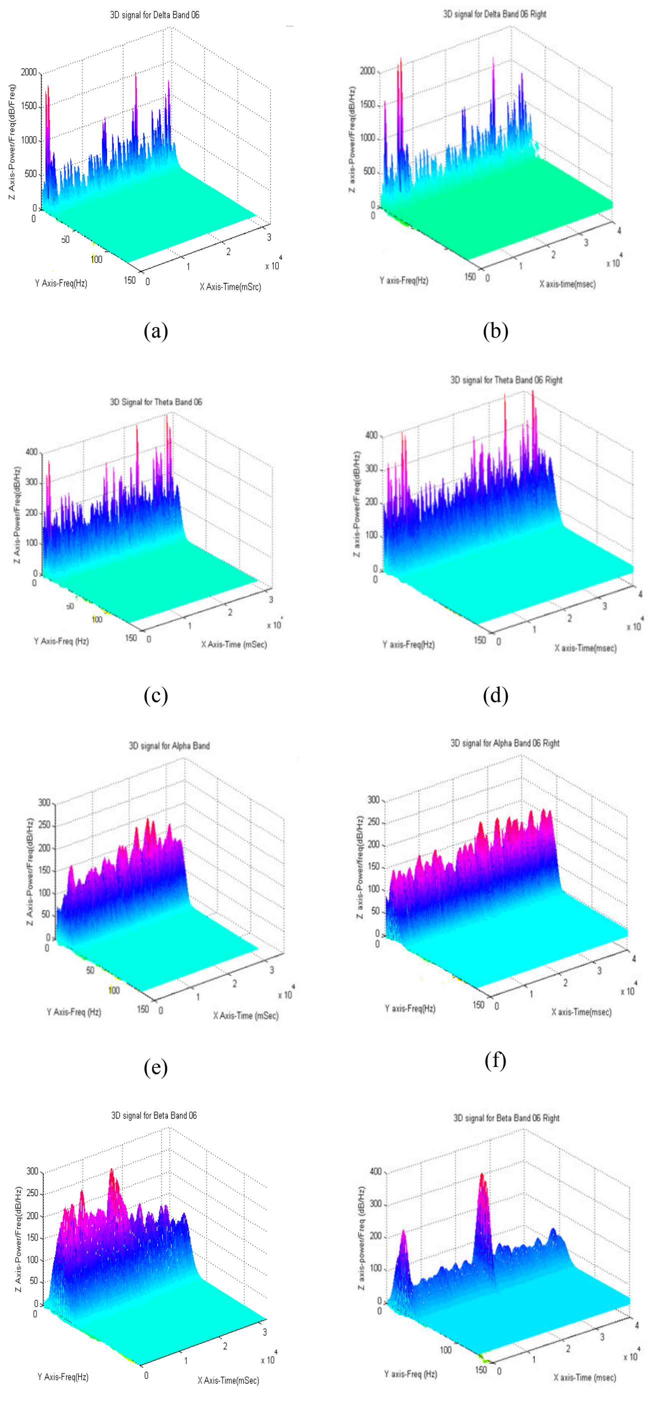

Fig. 3 3D EEG model for (a) Delta band from LF (b) Delta band from RF (c) Theta band from LF (d) Theta band from RF (e) Alpha band from LF (f) Alpha band from RF (g) Beta band from LF (h) Beta band from RF

TABLE III
DATA SAMPLE PER INDEX

Index level	Samples	3D EEG model
Index level 3	9	72
Index level 4	37	296
Index level 5	5	40

The kNN algorithm consists of two stages. The first is training stage and the second is classification or testing stage. From Fig. 4, the highest accuracy is 100% for training and 86.1% for testing. The k value was set to 8. The training and testing accuracy were consistent at k equal to 6, 7 and for testing.

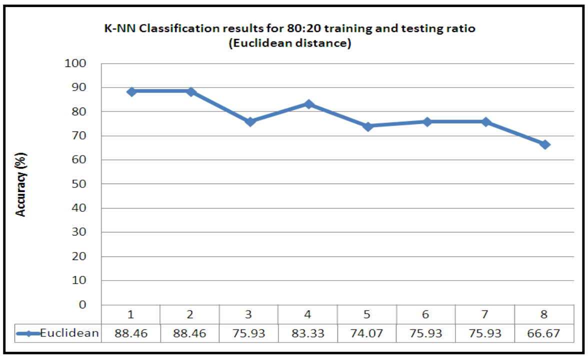

Fig. 4 kNN accuracy for different k value

In order to support the classifier performance, the classifier is also tested for sensitivity and specificity, and the classification results obtained when k is varied from 1 to 8 are shown in Table IV.

TABLE IV
THE SUMMARY OF CLASSIFICATION ACCURACY, SENSITIVITY AND SPECIFICITY AT 80:20 TRAINING TO TESTING RATIO

k	Accuracy (%)	Sensitivity (%)	Specificity (%)
1	88.46	89.09	91.61
2	88.46	90.00	91.67
3	75.93	89.23	90.53
4	83.33	90.00	89.56
5	74.07	89.33	90.26
6	75.93	88.75	90.38
7	75.93	89.41	90.50
8	66.67	88.89	91.03

Figs. 5 and 6 show result for 80:20 training to testing ratio; it is observed that at the highest classification accuracy rate (88.46%), the classification error is 0.14% (0.0014). And the total classification error is 2% (0.02) when the value of k is varied from 1 to 10. The classification error increases the value of classifier neighborhood k increase, as can be observed in the rapid increase in the classification error when k = 5 and above.

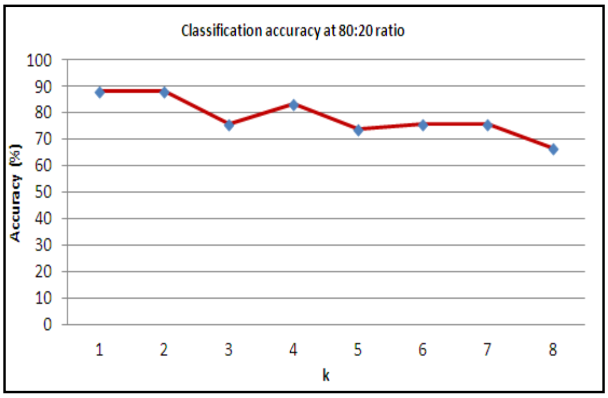

Fig. 5 The classification accuracy versus k at 80:20

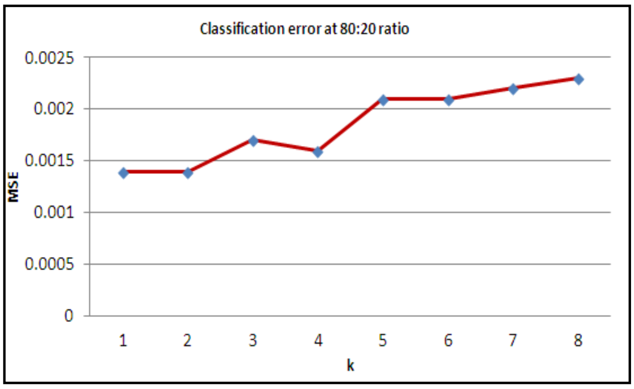

Fig. 6 The classification error versus k at 80:20

IV. CONCLUSION

The kNN classifier is successfully described the behavior of the different brain balancing index with classification accuracy 100% for training and 88.46% for testing. In the experiment, when the value of k increased, it will produce low percentage in classification. Actually, the correct classification for large samples will be high while the small samples will be low. The observation showed kNN was able to correctly classify features extraction (maximum PSD) from 3D EEG model with the highest success rate when k=1 and 2.

ACKNOWLEDGMENT

N.Fuad would like to thank the members of Biomedical Research Laboratory for Human Potential, FKE, UiTM for their cooperation and kindness and Advanced Signal Processing Research Group (ASPRG) for their supportive.

REFERENCES

[1] M. Khan, Q. Ding, and W. Perrizo, *k-nearest neighbor classification on spatial data streams using P-trees*: Springer Berlin Heidelberg, 2002.
[2] J. Han and M. Kamber, *Data Mining Concepts and Techniques*, second ed. San Francisco, CA: Morgan Kaufmann 2006.
[3] R. Polikar, "Pattern Recognition," in *Wiley Encyclopedia of Biomedical Engineering*, M. Akay, Ed., ed. New York: John Wiley & Sons, 2006.
[4] D. M. Dzuida, *Data Mining for Genomics and Proteomics: Analysis of Gene and Protein Expression Data*: John Wiley & Sons, 2010.

[5] P. Anbeek, K. L. Vincken, M. J. van Osch, R. H. Bisschops, and J. van der Grond, "Probabilistic segmentation of white matter lesions in MR imaging," *Neuroimage,* vol. 21, pp. 1037-44, Mar 2004.
[6] A. A. Petrosian, D. V. Prokhorov, W. Lajara-Nanson, and R. B. Schiffer, "Recurrent neural network-based approach for early recognition of Alzheimer's disease in EEG," *Clinical Neurophysiology,* vol. 112, pp. 1378-1387, 2001.
[7] K. Ansari-Asl, J. J. Bellanger, F. Bartolomei, F. Wendling, and L. Senhadji, "Time-frequency characterization of interdependencies in nonstationary signals: application to epileptic EEG," *Biomedical Engineering, IEEE Transactions on,* vol. 52, pp. 1218-1226, 2005.
[8] Mangai, J. , Wagle, S. , Kumar, V. (2013). 'An Improved k Nearest Neighbor Classifier Using Interestingness Measures for Medical Image Mining'. World Academy of Science, Engineering and Technology, International Science Index 81, International Journal of Medical, Pharmaceutical Science and Engineering, 7(9), 33 - 37.
[9] Tufail, A. , Abidi, A. , Siddiqui, A. , Younis, M. (2012). 'Automatic Classification of Initial Categories of Alzheimer's Disease from Structural MRI Phase Images: A Comparison of PSVM, KNN and ANN Methods'. World Academy of Science, Engineering and Technology, International Science Index 72, 6(12), 1570 - 1574.
[10] Chuang, L. , Hou, Y. , Jr., J. , Yang, C. (2009). 'A Novel Prediction Method for Tag SNP Selection using Genetic Algorithm based on KNN'. World Academy of Science, Engineering and Technology, International Science Index 29, 3(5), 1173 - 1178.
[11] Analoui, M. , Amiri, M. (2008). 'Feature Reduction of Nearest Neighbor Classifiers using Genetic Algorithm'. World Academy of Science, Engineering and Technology, International Science Index 17, 2(5), 785 - 788.
[12] Jansen BH, Cheng W-K. "Structural EEG analysis: an explorative study.", Int J Biomed Comput 1988; 23: 221-37.
[13] L. Sornmo, and P. Laguna, Bioelectrical Signal Processing in Cardiac and Neurological Applications. Burlington, MA: Elsevier Academic Press, 2005.
[14] Y.M. Randall and C. O'Reilly, Computational Exploration in Cognitive Neuroscience: Understanding the Mind by Simulating the Brain, MIT Press London, 2000.
[15] N. Hosaka, J. Tanaka, A. Koyama, K. Magatani, "The EEG measurement technique under exercising", Proceedings of the 28th IEEE EMBS Annual International Conference, New York City, USA, Sept 2006, pp. 1307-1310.
[16] C. Guger, G. Edlinger, W. Harkam, I. Niedermayer, and G. Pfurtscheller, "How many people are able to operate an EEG-based brain-computer interface (BCI)?," *IEEE Transactions on Neural Systems and Rehabilitation Engineering,* vol. 11, pp. 145-147, 2003.
[17] R. W. Thatcher, D. North, and C. Biver, "EEG and intelligence: Relations between EEG coherence, EEG phase delay and power," *Clinical Neurophysiology,* vol. 116, pp. 2129-2141, 2005.
[18] E. Hoffmann, "Brain Training Against Stress: Theory, Methods and Results from an Outcome Study", version 4.2, October 2005.
[19] R. W. Sperry, "Left -Brain, Right Brain," in Saturday Review:speech upon receiving the twenty-ninth annual Passano Foundation Award, 1975, pp. 30-33.
[20] R. W. Sperry, "Some Effects of Disconnecting The Cerebral Hemispheres," in Division of Biology, California Institute of Technology, Pasadena. California, 1981, pp. 1-9.
[21] Zunairah Haji Murat, Mohd Nasir Taib, Sahrim Lias, Ros Shilawani S.Abdul Kadir, Norizam Sulaiman, and Mahfuzah Mustafa. "Establishing the fundamental of brainwave balancing index (BBI) using EEG," presented at the 2nd Int. Conf. on Computional Intelligence, Communication Systems and Networks (CICSyN2010), Liverpool, United Kingdom, 2010.
[22] P. J. Sorgi, The 7 Systems of Balance: A Natural Prescription.
[23] Z. Liu, L. Ding, "Integration of EEG/MEG with MRI and fMRI in Functional Neuroimaging," *IEEE Eng Med Biological Magazine*, vol. 25, pp. 46-53, 2006.
[24] U. Will and E. Berg, "Brain Wave Synchronization and Entrainment to Periodic Acoustic Stimuli," *Neuroscience Letters*, vol. 424, pp. 55-60, 2007.
[25] B.-S. Shim, S.-W. Lee, "Implementation of a 3 –Dimensional Game for Developing Balanced Brainwave," presented at 5th International Conference on Software Engineering Research, Management & Applications, 2007.
[26] Rosihan M. Ali and Liew Kee Kor, "Association Between Brain Hemisphericity, Learning Styles and Confidence in Using Graphics Calculator for Mathematics", Eurasia Journal of Mathematics, Science and Technology Education,vol. 3(2), pp127 -131, 2007.
[27] N.Fuad, R.Jailani, W.R.W.Omar, A.H.Sahidin, M.N.Taib, "Three Dimension 3D signal for EEG .", IEEE Control & System Graduate Research Colloquium 2012 (ICSGRC2012), pp. 262-266,UITM, July 2012.
[28] N. Fuad ,M.N.Taib, "The Three Dimensional Electroencephalogram Model for Brainwave Sub band of Power Spectral.", International Journal of Scientific Knowledge (IJSK) in Computing and Information Technology, Vol. 3, No.1, pp 8-18, 2013.
[29] N.Fuad, M.N.Taib , R.M.Isa, A.H.Jahidin, W.R.W.Omar, 'Brain balancing pattern between left and right frontal using mean relative power ratio via three dimensional EEG model.', Procedia - Social and Behavioral Sciences (2013), Vol.97, pp. 38-45, 2013
[30] L. Mariani. (1996, 1 May 2010). *Brain-dominance questionnaire*. Available:http://www.learningpaths.org/questionnaires/lrquest/lrquest.htm