J. Appl. Environ. Biol. Sci., 7(6S)65-71, 2017

ISSN: 2090-4274
Journal of Applied Environmental and Biological Sciences
www.textroad.com

Aesthetics Classification on Rotating 3D Visual Stimuli Using EEG, Wavelet Transform, PSD and KNN

Lin Hou Chew, Jason Teo, James Mountstephens

Faculty of Computing and Informatics,Universiti Malaysia Sabah, Kota Kinabalu, Sabah, Malaysia

Received: May 19, 2017
Accepted: July 18, 2017

ABSTRACT

Aesthetics are an essential element in industrial design whereby it could influence our affect, emotion and feeling. Furthermore, an aesthetically pleasing product would be perceived to have better usability. Aesthetics experience brings us intense mind pleasure through stimuli such as music, visual art or any object that is in contact with us where such an experience leads to preference and judgement towards the stimuli. Neuroaesthetics is the study of neurology on aesthetics experience to explain and understand the underlying structure of aesthetics judgement in the human brain. In this preliminary study, aesthetics preferences on moving 3-dimensional (3D) visual stimuli were studied on 10 young adults as subjects using electroencephalography (EEG). Features including the alpha, beta, gamma, theta and delta waves were extracted using Wavelet Transform and then Power Spectral Density (PSD) estimation methods, namely the Welch and Burg methods were applied to the features. K-nearest neighbor (KNN) was used to classify the extracted information into 2 classes, i.e. like and dislike. The best accuracy obtained was 74% using the Welch method and nearest neighbor of 1 for the KNN classifier.

KEYWORDS: Preference Recognition, Power Spectral Density (PSD), 3-Dimensional (3-D), K-Nearest Neighbors (KNN), Electroencephalography (EEG).

INTRODUCTION

Aesthetics experience is one of the feeling that gives us pleasure and satisfaction through contact with stimuli such as music and visual art, where this feeling has decisive effects on our thought, preference, judgement and perspective on the stimuli unconsciously. Damasio [1], a famous neuroscientist once said, “Humans are not either thinking machines or feeling machines but rather feeling machines that think.” To think by feeling has our thought, judgement, preference and perspective influenced by our affect, emotion and feeling and that is why an aesthetically pleasing product is perceived to have better usability and credibility [2].

Owing to the influence on thought, judgement, preference and perspective brought by aesthetics experience, the relation between human and aesthetics experience is widely explored by neuroscientists and psychologists in order to have a better explanation on interplay between arts and brain either psychologically or neurologically. The study on aesthetics experience through the neuroscientific method is also known as neuroaesthetics and this study not only focuses on understanding and explaining the phenomena, but it also aims to recognize the aesthetics preference using functional neuroimaging technology such as positron emission tomography (PET), functional magnetic resonance imaging (fMRI), electroencephalography (EEG) and magnetoencephalography (MEG). Although many studies have been conducted to understand and explain aesthetics preference in neurological level, yet the recognition on aesthetics preference is not widely studied.

Several studies have been conducted to measure the aesthetics preference through stimuli such as music [3], images [4], video [5] and 3D shape [6-7] using EEG. In [5] measure the preference of video stimuli on 15 subjects using band power as features through Fast Fourier Transform (FFT) technique for four preference classes using the EmotivEpoc headset to obtain accuracies of up to 97.39% (±0.73%). Whereas, in [4] measured the preference of images individually on 11 subjects using frequency band as the feature for 2 preference classes using the EmotivEpoc headset and obtained accuracies of up to 88.54% on average. In [3] measured the preference of music on 9 subjects using frequency band as the feature through time frequency analysis (TFA) for 2 preference classes using the EmotivEpoc headset and obtained accuracies of up to 86.52% (±0.76%). In [6-7] measured the preference of motion 3D shapes on 5 subjects using frequency band as feature through TFA and wavelet transform for 2 preference classes using Advanced Brain Monitoring (ABM) B-alert X10 device and obtained accuracies up to 80% and 82% respectively.

In this preliminary study, we explored the preference measurement of 3D shapes using EEG on 10 young adults based on frequency bands to classify 2 preference classes where the 3D shapes were generated using the GielisSuperformula [8]. The EEG signal is collected using a wireless medical grade EEG system, ABM B-alert

Corresponding Author: Lin Hou Chew, Faculty of Computing and Informatics,Universiti Malaysia Sabah, Kota Kinabalu, Malaysia, E-mail: chewqueenie@hotmail.com

X-10. Wavelet transform and different methods in power spectral density (PSD) including Welch and Burg methods are applied to the EEG signal to decompose the signal in to 5 frequency bands (i.e. Delta (0-4 Hz), Theta (4-8 Hz), Alpha (8-16 Hz), Beta (16-32 Hz) and Gamma (32-64 Hz)). K-nearest neighbor (KNN) classifier is then used to classify 2 preference classes and the nearest neighbor of KNN from 1 to 9 is tested to obtain optimum accuracy rate. The flow structure of the study is as shown in Figure 1.

Figure 1: The data flow structure of the study

DATA ACQUISITION

During data acquisition, there are 3 main inseparable elements: (a) stimuli to trigger the brain signals with preference, (b) subjects to view on stimuli and deciding on the preference, and (c) EEG acquisition system to collect the brain signals. Meanwhile, the flow of the data acquisition process is as shown in Figure 2.

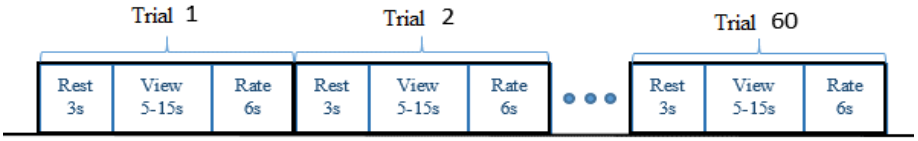


Figure 2: The flow of data acquisition process

There are a total of 60 trials to display all 60 3D visual stimuli where in each trial, there are 3 main states: rest, view and rate states and each of the state takes 3 seconds, 5-15 seconds and 6 seconds respectively. Each trial requires 14 to 24 seconds to complete and the total time taken for each data acquisition process is 14 to 24 minutes.

During the rest state, a blank screen is displayed to subject for 3 seconds to rest the brain and avoid any brain activities related to the previous trial. During the view state, a 3D visual stimulus with rotating motion is displayed to the subject. The shape is rotated to enable subjects to view the shapes from different angles. The subject is required to view for a minimum of 5 seconds to a maximum of 15 seconds, whereby the subject is free to proceed to the next state after a minimum time based on their will by pressing the spacebar. However, at the maximum time of 15 seconds, the system will automatically proceed to the next state. The decision to implement the free will during view state is to reduce the waiting time where complaints on fatigue are received during the pilot study. The subject is required to accomplish a monotonous and repetitive task that takes 14-24 minutes which caused the subject to get bored and fatigue [9]. During the rating state, a 5-point scale (1: like very much, 2: like, 3: undecided, 4: do not like, 5: do not like at all) is displayed for 6 seconds to subject with ticking of the time remains. The 3 states are repeated for 60 times as there are 60 3D visual stimuli.

Subjects

10 subjects (5 females and 5 males) with an age ranged from 20 to 23 (mean=22.4) were involved in the study. The subjects are do not have any known history of psychiatric illnesses and had normal or corrected-to-normal vision. A brief introduction is given to the subjects which includes the purpose and the flow structure of the study. The subjects are advised to minimize their movement, especially not to touch or put their hands on the face during the acquisition to minimize the artifacts on the EEG signals. All the subjects had understood and consented before being involved in the study.

3D Stimuli

60 3D visual stimuli are used as stimuli to elicit the aesthetics preference of the subjects. The 3D visual stimuli were generated by using the Gielissuperformula [8] and the generated shapes are randomly generated to have bracelet-like shape. Bracelets are a type of jewelry where aesthetic value in jewelry is an important factor which leads to preference.

The superformula used to generate the 3D visual stimuli is as shown in (1). This formula could generate various natural and elegant 2D visual stimuli. To obtain 3D stimuli, multiplication of additional superformula using spherical product as shown in (2), (3) and (4) is applied. The 3D generator is further known as supershape generator.

$$r(\theta) = \frac{1}{\sqrt[n1]{\left(\left|\frac{1}{a}\cos\left(\frac{m}{4}\theta\right)\right|\right)^{n2} + \left(\left|\frac{1}{b}\sin\left(\frac{m}{4}\theta\right)\right|\right)^{n3}}} \tag{1}$$

$$x = r_1(\theta) \times \cos(\theta) \times r_2(\varphi) \times \cos(\varphi) \tag{2}$$

$$y = r_1(\theta) \times \sin(\theta) \times r_2(\varphi) \times \cos(\varphi) \tag{3}$$

$$z = r_2(\varphi) \times \sin(\varphi) \tag{4}$$

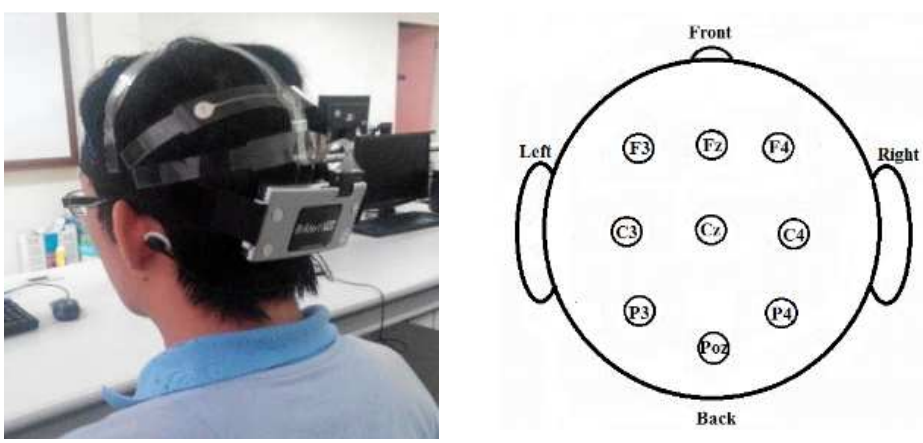
where $-\pi \leq \theta < \pi$ and $-\frac{\pi}{2} \leq \varphi < \frac{\pi}{2}$.

To generate bracelet-like 3D visual stimuli with different features, 10 parameters of the supershape generator are generated randomly within a range to maintain bracelet-like shape. The parameters m1, n11, n13, m2, m21 and m23 are fixed at the range from 0 to 20 while for parameters n12 and n22 are fixed at the range from 15 to 30. The parameter c is fixed at the range from 1 to 10 and the parameter t is fixed at 5.5 to maintain the radius of the shapes.

The 3D visual stimuli are virtually displayed on a computer screen with a rotating motion for the stimuli which enables the subjects to view the shapes at different angles. The motion on the 3D visual stimuli is important as motion is a natural factor in recognizing objects [10].

Acquisition Device

A medical grade wireless EEG device from ABM, B-Alert X10 as shown in Figure 3(a) with a 9-electrode channel interface is used to acquire EEG signals from the subjects. The ABM B-Alert X10 was chosen for the cost-effectiveness, usability and handiness. The sampling rate of B-Alert X10 is 256 Hz with 16 bits. The electrodes positions (i.e. F3, Fz, F4, C3, Cz, C4, P3, POz and P4) are based on the international 10-20 electrode placement system as shown in Figure 3(b) with 2 reference electrodes placed on left and right mastoid bone.



(a) **(b)**

Figure 3: (a) ABM B-Alert X10 headset. (b) Electrode positions of ABM b-alert X10 based on international 10-20 electrode placement system

DATA PROCESSING AND FEATURE EXTRACTION

ABM provides a Software Development Kit (SDK) for B-Alert X10 in Matlab. EEG signals are decontaminated internally from 5 different artifacts by the SDK in real-time where the artifacts include EMG (electromyography), eye blinks, excursions, saturations and spikes. The decontamination algorithm removes environmental artifacts by applying a 60 Hz notch filter and artifacts such as excursions, saturations and spikes are analyzed in the time domain. The EEG signals are then deconstructed using wavelet transformation to remove EMG and eye blink activities [11]. Meanwhile, part of the signals which are contaminated by artifacts are removed, the interpolation method using penalized least square regression based on 3D discrete cosine transform (DCT-PLS) [12] is applied to reconstruct the EEG signals.

The EEG signals are decomposed over 5 levels into approximation coefficients and detailed coefficients using Wavelet Transform as shown in Table 1.

Table 1: Decomposition of EEG signals

Frequency Range (Hz)	Decomposition Level	Frequency Bands	Frequency Bandwidth (Hz)
1-4	A5	Delta	4
4-8	D5	Theta	4
8-16	D4	Alpha	6
16-32	D3	Beta	18
32-64	D2	Gamma	32
64-128	D1	Noises	64

Daubechies' 4 discrete wavelet (db4) wavelet function is used to decomposing EEG signals to obtain Delta (0-4 Hz), Theta (4-8 Hz), Alpha (8-16 Hz), Beta (16-32 Hz) and Gamma (32-64 Hz) rhythms. Wavelet function db4 is typically chosen for its near optimal time-frequency localization properties [13]. After the decomposition, the method in estimating PSD such as Welch and Burg methods are applied to the signal and a total of 45 features (9 channels X 5 frequency bands) are obtained.

FEATURE SELECTION AND CLASSIFICATION

KNN [14] classifier is used to classify 2 preference classes and the nearest neighbor from 1 to 9 are tested. The Like class refers to trials rated at 4: Like and 5: Like very much. Meanwhile, the Dislike class correspond to the trials rated as 1: do not like at all and 2: do not like. The neutral class corresponding to rating at 3: Undecided, where neutral is not included in the training and testing in classifiers. The ratio of training to testing cases of the data is 3:1. Table 2 shows the number of samples in the training and testing dataset where 364 samples were used to train the classifier and 150 samples were used to test the classifier.

Table 2: Train and test dataset

Class	Like	Dislike	Total
Train set	217	147	364
Test set	67	83	150
Total	284	230	514

A brute-force search is applied to the classifier to test all the combinations of the obtained features. However, to search through all the combinations would require a long period of time to complete, so the combinations of the features are tested for 1 to 5 features and Table 3 shows the accuracies at 68.67% and above on either method of PSD and number of nearest neighbor. The features in Table 3 with occurrence higher than 1 are used to train and test the classifier.

Table 3: Classification accuracy obtained using brute force search based on 1-5 features combination

Set of Features	Accuracy
Fzbeta,C3beta,C4gamma,P3alpha	68.67%
Czgamma,C3beta,F3delta,P3delta	
POztheta,Fzbeta,C4gamma,F3delta,P3delta	
POzdelta,C3beta,F4alpha,F4beta,F4gamma	
Fzalpha,Czalpha,F3beta,F3delta,F4beta	
Fzbeta,C4gamma,C4theta,F3delta,F4alpha	
Fzgamma,Fzdelta,C3alpha,C3beta,C4theta	
Fztheta,Fzdelta,F3beta,F4alpha,F4beta	
C4gamma,F3gamma,F3delta,F4gamma	69.33%
C4gamma,F3delta,F4gamma,P3theta	
POztheta,Czbeta,C4gamma,F3delta,P3delta	
POztheta,C3gamma,C3theta,F3delta,F4alpha	

Fzbeta,Czgamma,C3beta,C4gamma,P3alpha	
Fzbeta,C3beta,C4gamma,P3alpha,P4gamma	
Fzdelta,C4gamma,F4alpha,F4gamma,F4theta	
Fzdelta,F3beta,F4alpha,F4beta,P3alpha	
Czalpha,C3gamma,C4theta,F3delta,F4gamma	
Cztheta,C4gamma,F4gamma,P3alpha,P3beta	
Fztheta,Fzdelta,F3beta,F4alpha,F4beta	70.00%
POztheta,Fzbeta,C3gamma,F3delta,P3delta	70.67%
C3gamma,C4gamma,F3gamma,F3delta,F4gamma	72.67%

The features with occurrence higher than 1 is used as features to run another brute force search on the classifier to minimize the search time and so a total of 17 features are selected which include F3delta, C4gamma, F4gamma, F4alpha, Fzbeta, C3beta, Fzdelta, P3alpha, C3gamma, F4beta, F3beta, Poztheta, P3delta, C4theta, F3gamma, Czgamma and Fztheta which believed to be more information among all the 45 features.

RESULTS AND DISCUSSION

The classification accuracy of different combinations on features is as shown in Table 4 and Table 5 through Burg method and Welch method respectively. The accuracy of 72% and above using Burg method is as shown in Table 4 while Welch method is shown in Table 5. The highest accuracy for Burg methods is 73% with nearest neighbor set to 2 along with features Czgamma, C3beta, C3gamma, C4gamma, C4 theta, F3beta, F3gamma, F3delta, F4beta and P3alpha whereas the highest accuracy for the Welch methods is 74% with nearest neighbor set to 1 along with features Fzdelta, C3beta, C3gamma, C4gamma, C4theta, F3beta, F3delta, F4alpha, F4beta, F4gamma, and P3alpha, also with Fzdelta, Czgamma, C3beta, C3gamma, C4gamma, C4theta, F3beta, F3delta, F4alpha, F4beta, F4gamma and P3alpha.

Table 4: Accuracy of different combinations of features using the burg method

Set of Features	K	Accuracy
Czγ,C3β,C3γ,C4γ,C4θ,F3β,F3γ,F3δ,F4β,P3α	2	73%

Table 5: Accuracy of different combinations of features using the welch method

Set of Features	K	Accuracy
Fzδ,C3β,C3γ,C4γ,C4θ,F3β,F3δ,F4α,F4β,F4γ,P3α	1	74%
Fzδ,Czγ,C3β,C3γ,C4γ,C4θ,F3β,F3δ,F4α,F4β,F4γ,P3α	1	74%
Fzδ,Czγ,C3β,C3γ,C4γ,C4θ,F3β,F3δ,F4α,F4β,P3α	1	73%
Fzδ,Czγ,C3β,C4γ,C4θ,F3β,F3δ,F4α,F4β,P3α	1	73%
Fzδ,C3β,C3γ,C4γ,C4θ,F3β,F3δ,F4α,F4β,P3α	1	73%
Fzδ,C3β,C4γ,C4θ,F3β,F3δ,F4α,F4β,F4γ,P3α	1	73%
Fzβ,Fzδ,C3β,C4γ,C4θ,F3β,F3δ,F4α,F4β,F4γ,P3α	1	73%
Fzδ,C3β,C3γ,C4γ,C4θ,F3β,F3γ,F3δ,F4α,F4β,P3α	1	73%
Fzβ,Fzδ,Czγ,C3β,C3γ,C4γ,C4θ,F3β,F3δ,F4α,F4β,F4γ,P3α	1	73%
Fzβ,Fzδ,C3β,C4γ,C4θ,F3β,F3δ,F4α,F4β,P3α	1	72%
Fzβ,Fzδ,C3β,C4θ,F3β,F3γ,F3δ,F4α,F4β,P3α	2	72%
Fzβ,Fzδ,C3β,C3γ,C4γ,C4θ,F3β,F3δ,F4α,F4β,P3α	1	72%
Fzδ,Czγ,C3β,C3γ,C4γ,F3β,F3γ,F3δ,F4α,F4β,P3α	2	72%
Fzδ,Czγ,C3β,C4γ,C4θ,F3β,F3γ,F3δ,F4α,F4β,P3α	2	72%
Fzδ,C3γ,C4γ,C4θ,F3β,F3γ,F3δ,F4α,F4β,F4γ,P3α	1	72%
Fzβ,Fzδ,Czγ,C3β,C3γ,C4γ,C4θ,F3β,F3δ,F4α,F4β,P3α	1	72%
Fzβ,Fzδ,Czγ,C3β,C4γ,C4θ,F3β,F3γ,F3δ,F4α,F4β,P3α	2	72%
Fzδ,Czγ,C3β,C3γ,C4γ,C4θ,F3β,F3γ,F3δ,F4α,F4β,P3α	1	72%
Fzβ,Fzδ,C3β,C3γ,C4γ,C4θ,F3β,F3γ,F3δ,F4α,F4β,F4γ,P3α	1	72%

Table 6 shows the confusion matrix for the best accuracy (74%) obtained via Welch method. Through the use of features Fzdelta, C3beta, C3gamma, C4gamma, C4theta, F3beta, F3delta, F4alpha, F4beta, F4gamma and P3alpha, the true positive (TP), true negative (TN), false positive (FP) and false negative (FN) were 52, 59, 24 and 15 respectively. Meanwhile for the features with Fzdelta, Czgamma, C3beta, C3gamme, C4gamma, C4theta, F3beta, F3delta, F4alpha, F4beta, F4gamma and P3alpha, the TP, TN, FP and FN were 53, 58, 24 and 14 respectively. The total testing data were 150. The confusion matrix for both combinations of features which obtained 74% accuracy are similar since there is only one feature difference between both combinations of features.

Table 6: Confusion matrix for the best accuracy

Features	Actual/Predicted	Like	Dislike
Fzδ, C3β, C3γ, C4γ, C4θ, F3β, F3δ, F4α, F4β, F4γ, P3α	Like	52	15
	Dislike	24	59
Fzδ, Czγ, C3β, C3γ, C4γ, C4θ, F3β, F3δ, F4α, F4β, F4γ, P3α	Like	53	14
	Dislike	25	58

Moreover, the Welch method performed better than the Burg method especially using a nearest neighbor of one and two. Meanwhile, the features in the combination obtained accuracy of 71% and above are mostly from channels Fz, C3, C4, F3, F4 and P3.

Left parietal (P3) is believed to be involved in mental rotation [15], which corresponds to the subjects mentally observing the rotating objects being shown on the screen. Meanwhile, the left and right central strip (C3 and C4) are believed to be active during visualization of movements [16]. Additionally, the frontal lobe (Fz, F3 and F4) is believed to be involved in decision making, memory processing and attention [17-18]. Dorsolateral prefrontal cortex (F3) in the frontal lobe is also related to aesthetic perception [19].

CONCLUSION

This study explored methods to recognize human preference on 3D shapes through physiological signals acquired from 10 young adults using a 9-channel EEG system, ABM B Alert X10 system during perceiving of 3D visual stimuli. Wavelet Transform of wavelet function db4 was applied to the EEG signals and 5 frequency rhythms were obtained for each channel. The PSD estimation methods include Welch and Burg were applied to the frequency rhythms and KNN with nearest neighbors from 1 to 9 were tested. 74% classification accuracy was obtained using KNN with nearest neighbor set to one with Burg processed features Fzdelta, Czgamma, C3beta, C3gamma, C4gamma, C4theta, F3beta, F3delta, F4alpha, F4beta, F4gamma and P3alpha, also Fzdelta, C3beta, C3gamma, C4gamma, C4theta, F3beta, F3delta, F4alpha, F4beta, F4gamma and P3alpha. The set of features obtained high accuracy were mostly from channels Fz, C3, C4, F3, F4 and P3.

ACKNOWLEDGMENT

This project is supported through the research grant ref: FRGS/2/2013/ICT02/UMS/02/1 from the Ministry of Education, Malaysia.

REFERENCES

1. A. Damasio, 2010. Self comes to mind: Constructing the conscious brain. Pantheon Books.
2. Chawda, B., B. Craft, P.Cairns, S.Rüger and D.Heesch, 2005. Do Attractive Things Work Better? An Exploration of Search Tool Visualisations. In the Proceedings of the 2005 19th British HCI Group Annual Conference, pp: 1-4.
3. Hadjidimitriou,S.K. and L.J.Hadjileontiadis, 2013. EEG-Based Classification of Music Appraisal Responses Using Time-Frequency Analysis and Familiarity Ratings. IEEE Transactions on Affective Computing, 4(2): 161-172.
4. Kim, Y.,K. Kang, H. Lee and C. Bae, 2015.Preference Measurement Using User Response Electroencephalogram. In: Computer Science and its Applications (eds J. Park, I. Stojmenovic, H. Jeong, G. Yi) pp: 1315-1324.Springer Berlin, Heidelberg
5. Moon, J., Y. Kim, H.Lee, C.Bae and W.C.Yoon, 2013. Extraction of User Preference for Video Stimuli Using EEG-Based User Responses. ETRI Journal, 35(6): 1105-1114.
6. Chew, L.H., J. Teo and J. Mountstephens, 2016. Aesthetic Preference Recognition of 3D Shapes Using EEG. Cognitive Neurodynamics, 10(2):165-173.
7. Chew, L.H., J. Teo and J. Mountstephens, 2015.EEG-Based Aesthetics Preference Measurement with 3D Stimuli Using Wavelet Transform. ARPN Journal of Engineering and Applied Sciences, 10(22): 10745-10751.
8. Gielis, J., 2003. A Generic Geometric Transformation That Unifies a Wide Range of Natural And Abstract Shapes. American Journal of Botany, 90(3): 333-338.
9. Hawkins, W., N. Heffernan and R.S. Baker., 2013. Which is More Responsible for Boredom in Intelligent Tutoring Systems: Students (Trait) or Problems (State)?In the Proceedings of the 2013IEEE Humaine Association Conference on Affective Computing and Intelligent Interaction, pp: 618-623.
10. Vuong, Q.C. andM.J. Tarr, 2004. Rotation Direction Affects Object Recognition. Vision Research,44(14): 1717-1730.
11. Berka, C., D.J. Levendowski,M.N.Lumicao,A. Yau, G.Davis,V.T. Zivkovic,R..E.Olmstead, P.D.Tremouletand P.L.Craven, 2007. EEG Correlates of Task Engagement and Mental Workload in Vigilance, Learning, and Memory Tasks. Aviation, Space, and Environmental Medicine, 78(Supplement 1): B231-B244.

12. Garcia, D., 2010. Robust Smoothing of Gridded Data in One and Higher Dimensions with Missing Values. Computational Statistics and Data Analysis, 54(4): 1167-1178.
13. Murugappan, M., N. Ramachandran and Y. Sazali,2010. Classification of Human Emotion from EEG using Discrete Wavelet Transform. Journal of Biomedical Science and Engineering, 3(4):390-396.
14. Song, Y.,J. Huang, D. Zhou, H. Zha and C.L.Giles, 2007. IKNN: Informative K-Nearest Neighbor Pattern Classification.In the Proceedings of the 2007European Conference on Principles of Data Mining and Knowledge Discovery, pp. 248-264.
15. Alivisatos, B. and P. Michael,1997. Functional Activation of the Human Brain during Mental Rotation. Neuropsychologia, 35(2): 111-118.
16. Beisteiner, R.P.,P. Höllinger,G.Lindinger,W. Lang and A. Berthoz, 1995. Mental Representations of Movements. Brain Potentials Associated with Imagination of Hand Movements. Electroencephalography and Clinical Neurophysiology/Evoked Potentials Section, 96(2): 183-193.
17. Chayer, C. and M. Freedman, 2001. Frontal Lobe Functions. Current Neurology and Neuroscience Reports, 1(6):547-552.
18. Volz, K.G., I.S. Ricardaand D.Y. von Cramon, 2006. Decision-Making and the Frontal Lobes. Current Opinion in Neurology, 19(4): 401-406.
19. Conde, C.J.C., G. Marty, F.Maestú, T. Ortiz, E. Munar, A. Fernández, M. Roca, J. Rosselló and F. Quesney, 2004. Activation of the Prefrontal Cortex in the Human Visual Aesthetic Perception. Proceedings of the National Academy of Sciences of the United States of America, 101(16): 6321-6325.