Modeling Of EEG Signal Sound Frequency Characteristic Using Time Frequency Analysis

R. Sudirman (*IEEE member*)*, A. K. Chee, W. B. Daud
Faculty of Electrical Engineering, Universiti Teknologi Malaysia, 81310 Skudai, Johore, Malaysia
*Corresponding author: rubita@fke.utm.my

Abstract—**This paper presents the study of sound frequency characteristic based on Electroencephalography (EEG) signals. The study includes feature extraction of the EEG signals with respect to different sound frequencies, covering low frequency (40 Hz), mid-range frequency (5000 Hz), and high frequency (15000 Hz). Human brain activities are expected to be different when exposed to different sound frequencies, and can be shown through EEG signals. In this paper, EEG signal characterization is done using Fast Fourier Transform (FFT), moving average filters, and simple artefact filtering with reference EEG data per individual. Based on the characteristics of the EEG signal, the sound frequency can be categorized and identified using the proposed method.**

Keywords – ECG signal; sound frequency; artifact filtering; Fast Fourier Transform; moving average filter

I. INTRODUCTION

Hearing is one of the human five senses. The sense of hearing is performed by human auditory system: vibrations are detected by the ears and transduced into nerve impulses that are perceived by brain, primarily in the temporal lobe of human brain. Ideally, a healthy human can hear sounds within the range of 20 Hz – 20 kHz. Hearing different quality of sound, i.e. loud or soft, high pitch or low pitch, audible or inaudible etc., will have different effects to our brain. The ability to differentiate the quality of a specific sound is due to human brain response to different qualities of sound. The human brain do produces different electrical activity due to the different frequency of sounds.

One of the common methods to measure human brain activity is by using Electroencephalography (EEG) technology. EEG is an electrical waveform that is recorded from the brain by using electrodes appropriately placed on the head/scalp. To visualize this EEG signal, this signal is amplified and displayed through a computer or other suitable instrument. EEG signal consists of a wave that varies in time, much like a sound signal, or a vibration. As such, it contains a great deal of information that can be used to characterize the EEG signals for clinical and research purposes.

The useful information contained in the raw EEG signal cannot be visualized with just bare eyes. On top of that, raw EEG signals usually contain artifacts that will complicate the analysis of EEG signal. These artifacts or noise maybe caused by the instrument or biological response, e.g. eyes movement, certain concentration or distraction etc. In order to analyze and classify the EEG signal correctly, the EEG signals need to be processed, and the artifacts to be filtered. Characteristics of the signals are to be extracted, and classification will be done based on these characteristics or qualities of the EEG signals. The characteristics of these EEG signals may have slight difference as each of us is a unique entity.

A study by [1] demonstrated that the sounds containing enhanced inaudible high-frequency component (HFC) has modulatory effect on human acoustic perception. This study was done by using a multi-disciplinary approach, consisting of behavioral measurements of the comfortable listening level (CLL), psychological measurements of the subjective impression of sound and physiological measurements using EEG. Results from this study had shown that with the increase in the intensity of inaudible HFC leads to a significant increase in CLL, the subjective impression of sound, and greater occipital alpha-EEG signal. However, it was noticed that all these effects had some optimum point, and will not increase further once reached the optimum point. The most prominent effects occurred with an increase of +6 dB in the HFC.

From the study, it is summarized that the effects of inaudible HFC modulates human sound perception in different aspects. The study is concluded by proposing a two-dimensional sound perception model, i.e. the sound frequencies in the audible range as a message carrier, and frequencies above audible range, together with those in the audible range as a modulator of sound perception through human brain system.

Another work by [2] confirmed the characteristic of EEG and the location in brain when a person is exposed to different rhythm music. Music, i.e. combination of waveform with different frequencies, will induce different response from human brain. In this research, the subjects were exposed to different kind of music, i.e. Skating Waltz, Radetzy-March, disco music and finally quietness for few minutes. From this research, it showed that when listening to music, the low frequency spectrum (lower than 10 Hz)

978-0-7695-4062-7/10 $26.00 © 2010 IEEE
DOI 10.1109/AMS.2010.52

was restrained obviously, where as the high-frequency composition of EEG signal had obvious enhancement. The quicker the rhythm, the higher the characteristic frequency emerging was in the EEG signal. The most significant EEG signal enhancement was noticed around the area of Temporal lobe and Parietal lobe.

Similar research was carried out by [3], where subjects were exposed to metal music, sonata music and favorite music of the subjects. Band powers were extracted from the EEG signal of a total of 21 channels (electrodes placed on the scalp). With band powers as the features or characteristic of the EEG signal, the correlation between different situations and subjects was used to show the difference of EEG signals from different channels. The result from this study showed that channel T3 (of temporal lobe) and Pz (of parietal lobe) played an important role in feeling different kind of music/sound wave.

From the work by [2] and [3], it is confirmed that activity of human brain will be affected when listening to different rhythm of music, or in other words, different qualities of sound wave. The location in brain which had obvious enhancement was around temporal lobe, and parietal lobe. This also suggested that brain response to different rhythm of music can be measured through EEG signal at around temporal and parietal lobe of human brain.

II. METHODOLOGY

A. EEG Data Collection

EEG data collection is essentially important for the whole project. Without the good quality EEG signals, the analysis and classification in the later stage of this project will be inaccurate. As this project involves artificial intelligent technique for EEG signal classification, it is desirable to have as much data as possible.

Subjects of for the EEG data collection are healthy adults with good hearing ability. The subjects are then exposed to sound waves of different frequencies. The subjects are required to wear the electro-cap connected to the EEG machine located in Medical Electronic Laboratory. The electro-cap is with International 10/20 placements. The 10/20 placements cover all the 4 lobes of our human brain, i.e. frontal, temporal, parietal, and occipital lobes. Fig. 1 shows the 10/20 placement on the electro-cap.

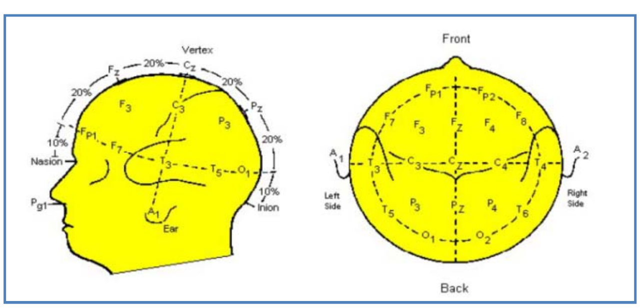


Fig. 1 International 10/20 placement on the electro-cap

The letter F, T, C, P and O stands for Frontal, Temporal, Centre, Parietal and Occipital. "Central lobe" is just for identification purposes, there is no centre lobe in reality. The electrode board adapter is connected to a laptop with Neurofax EEG-9000 software, where the EEG signals from 20 channels are recorded and outputted by Neurofax in ASCII format.

Subjects are exposed to tones with same frequency for at least 10 seconds for EEG data recording. The same process is repeated for various frequencies, from low to high. Neurofax outputs EEG data for all 20 channels. However, only the channels from Temporal lobes are of interest (T3, T5, T4, T6), as the project is focusing on human auditory perception or human brain response towards different sound wave frequencies.

B. EEG Signal Processing

EEG signals are captured by multiple-electrode EEG machines either from inside the brain, over the cortex under the skull, or certain locations over the scalp, and can be recorded in different formats. Normally the EEG signals are presented in time-domain, but some of the EEG machines are capable to perform simple time-domain to frequency-domain transformation and perform frequency analysis and for imaging tools to visualize EEG topographies. There have been many researches on EEG signal processing, and many algorithms were developed for processing EEG signals. The algorithms developed by researchers mainly include time-domain analysis, frequency-domain analysis, spatial-domain analysis and multi processing.

Raw EEG signals collected using EEG machines are often corrupted by artifacts. Artifacts are signals in the EEG that are non-cerebral origin. The most common types of artifacts can be categorized into biological and external artifacts. Biological artifacts include eye blinking/eye movement artifact, cardiac artifact (EKG), muscle activation artifact (EMG) and glotto kinetic artifacts. External artifacts can be originated by the movement of the subjects, momentary change in the impedance of the given electrode, and power line interferences noise (significant 50 or 60 Hz artifacts depending on local power system's frequency). These artifacts strongly influence the quality of the recorded EEG signals and need to be removed for better EEG signal analysis and classification. There are several methodologies for artifact filtering as well as EEG signal processing as discussed in the following subsections.

(i) Artifact Filtering using Empirical Mode Decomposition

Unlike traditional signal analysis methods, i.e. Fourier Transform or wave-based methods which require basic representation of the signals, Empirical mode decomposition (EMD) is a fully data-driven method that does not require any predefined basic signal. EMD methods will generate a collection of intrinsic mode functions, based on direct extraction of the energy associated with various intrinsic time scales, which is the most important parameters of the system, and calculate the instantaneous frequencies. [4] had demonstrated power interference noise removal using EMD. Experiment was done based on the fact that power interference noise usually located at high frequency band (50Hz or 60Hz). In the study, multiple simulations were performed for several different cases to evaluate the performance of the proposed EMD-based method. In order to remove the power interference noise and at the same time preserves the original EEG signal information, low pass filter is designed to preserve important low-frequency component rather than removing the full IMF. Fig. 2 showed second IMF and filtered IMF (based on the original input with noise) by using EMD method.

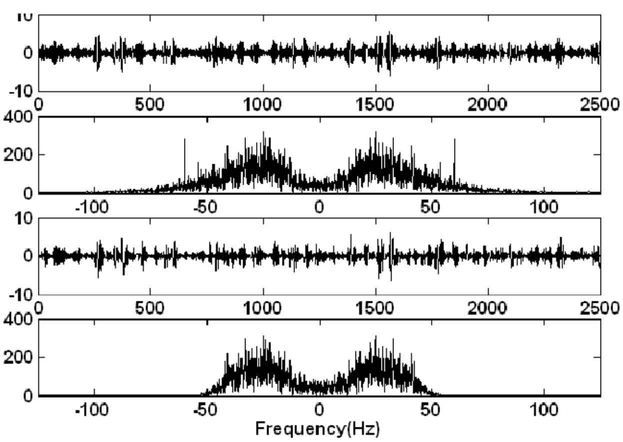


Fig. 2 The second IMF and Fourier spectrum, filtered IMF and Fourier spectrum [4]

(ii) Artifact filtering by using Independent Component Analysis (ICA)

Independent component analysis (ICA) is one of the common methods for artifact removal in EEG signal. The concept of ICA filtering is based on the assumption that various signal channels are a linear mixing of sources. ICA attempts to reverse the superposition of the linear mixing of sources by separating the EEG into mutual independent components. This is fundamental concept in separation and denoising the signals.

The concept of artifacts removal using ICA was illustrated in the work by [3]. EEG signals recorded at different electrodes is the input matrix X, rows of output matrix U representing activation of the ICA components arising from distinct or overlapping brain or extra-brain network, and columns of W^{-1}, gives the projection strengths of respective components onto the scalp sensors. Analysis is done (once ICA converges) to find W which recovers independent components of the EEG signals. Hence, EEG signals of interest can be derived as

$$X' = W^{-1}U' \tag{1}$$

where U' is the matrix of activation waveforms. Setting rows of U that representing artifact sources to zero, artifacts can be filtered out and the remaining independent components can be further analyzed for EEG signal classification. One of the major problems of ICA is the necessity to manually identify each component as artifactual or not.

From the work by [5] and [6], several enhanced ICA algorithms were introduced, i.e. Infomax, SOBI, and fastICA. These enhanced ICA algorithms allow more sensitive automated detection of small artifacts and applying the same detection and filtering method to produce better artifact-free EEG signal for further analysis.

(iii) EEG Signal Processing using Wavelet Transform

Wavelet transform as a signal processing method was introduced to overcome the limitation of Fourier transform when dealing with a non-stationary signal, where Fourier transform cannot have the signal described fully and correctly. Wavelet transform overcome the limitation by replacing modulation with scaling to achieve frequency modulation.

The concept of wavelet transform is by using a set of functions to approach a signal or function. The main character in wavelet transform is the mother wavelet. The function sets are derived or composed from the shifted and dilated mother wavelet. Original signal can be described with various coefficients. Wavelet transform provides an optimal resolution in both the time and the frequency domain. Wavelet transform is defined as:

$$WT_x(a,\tau) = \left(1/\sqrt{a}\right)\int_{-\infty}^{+\infty} x(t)\phi^*\left((t-\tau)/a\right)dt \tag{2}$$

where $x(t)$ is an inner product, $\phi^*\left((t-\tau)/a\right)$ is the shifted function by τ on various scale a, where a is the dilation coefficient. $\phi(t)$ has time widths adapted to the frequency and this yields narrow signal with high frequency and broader signal with low frequency. $\phi(t)$ is to represent a filter, and wavelet transform means to observe signals using bandpass filters with different centre frequencies and have constant quality factors [8].

[9] presented a novel approach of EEG Waves Classification using Wavelet Transform and Fourier Transform. The work is aimed to calculate the EEG waves (delta, theta, alpha, and beta) using Discrete Fourier Transforms (DWT) and followed by Fast Fourier Transform (FFT). In his work, wavelet transform is used as a classifier of the EEG frequencies and FFT is implemented to visualize the EEG waves in multi-resolution of wavelet transform. Wavelet transform was proven to be an effective method to represent various aspects of non-stationary signals like the EEG signals.

(iv) EEG Signal Processing with Control Data Referral

In this study, artifact filtering is performed by simply referring to a set of control EEG data which are obtained beforehand where the subjects are placed in a quiet place. The EEG signals obtained with respect to different frequency sound waves are subtracted with the referral data. The referral data is per individual. With the subtraction, line noise, and maybe eye-blinking artifacts might be filtered.

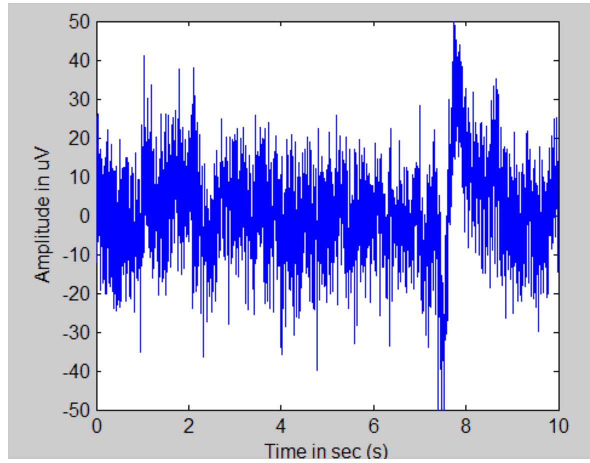
The filtered and normalized EEG signals are going through Fast Fourier Transform (FFT) to obtain the frequency response of the EEG signals. The data is processed using MATLAB built in functions. Signal smoothing is performed with simple moving average filter. Characteristics of the EEG data can be extracted from the frequency response of the signals.

III. Results and Discussion

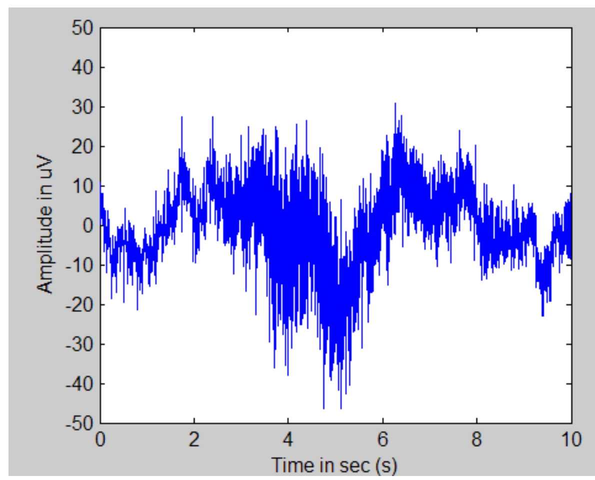
A few sets of EEG data from different subjects were collected with the subjects exposed to different frequencies of sound waves, i.e. 40 Hz, 5 kHz, 15 kHz. These 3 frequencies were chosen as benchmark of low frequency (40Hz), mid-range frequency (5 kHz) and high frequency (15 kHz). Human hearing range is 20 Hz – 20 kHz. However, for a human with normal hearing ability, listening to very low or very high frequencies of sound waves might cause uncomfortable due to our brain response. Fig. 3 shows the time response of EEG signals when the subject is exposed different frequencies of sound waves. It is hard to differentiate or extract information from these time-response EEG signals. Hence, frequency response of the EEG signals is obtained.

Frequency response of the EEG signals is obtained using FFT technique in MATLAB. Correct FFT data-point is to be set so as to extract the correct information from the EEG signals. FFT with 2048 data-point of the EEG signal is performed. Fig. 4(a) shows the pure frequency response using FFT with 2046 data-point. However, the signals are too complex to be analyzed. A moving average filter with the following equation is applied to the FFT signals shown in Fig. 4(a).

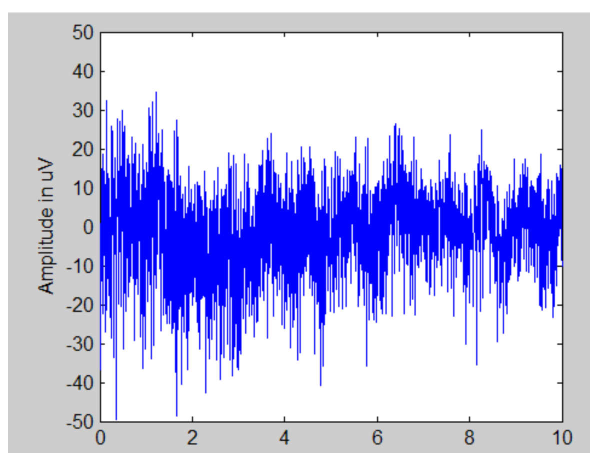
$$x(n) = \sum_{k=0}^{4} 0.2x(k)\delta(n-k) \qquad (3)$$



(a) With respect to 40Hz sound wave

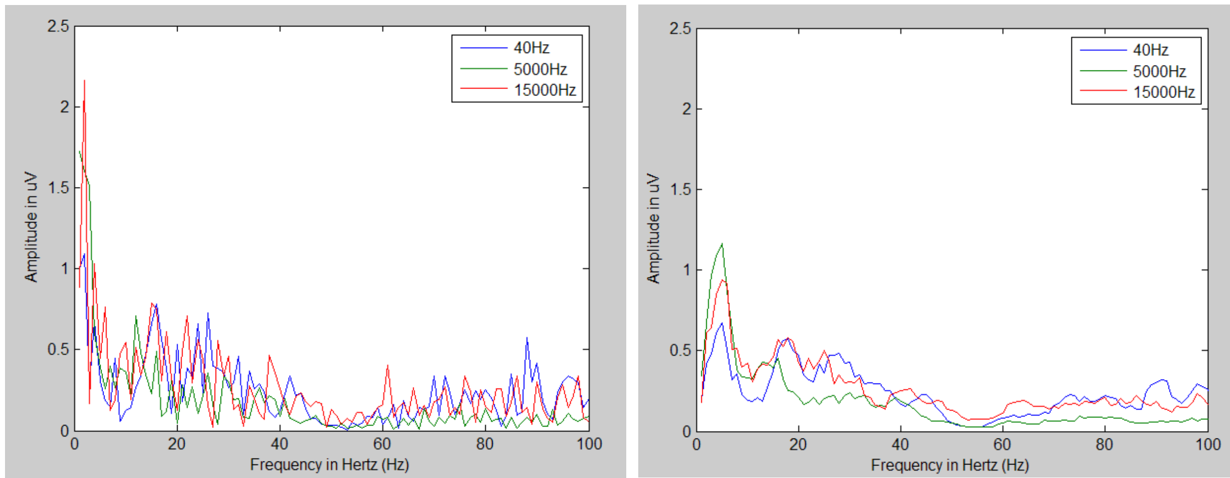


(b) With respect to 5 kHz sound wave



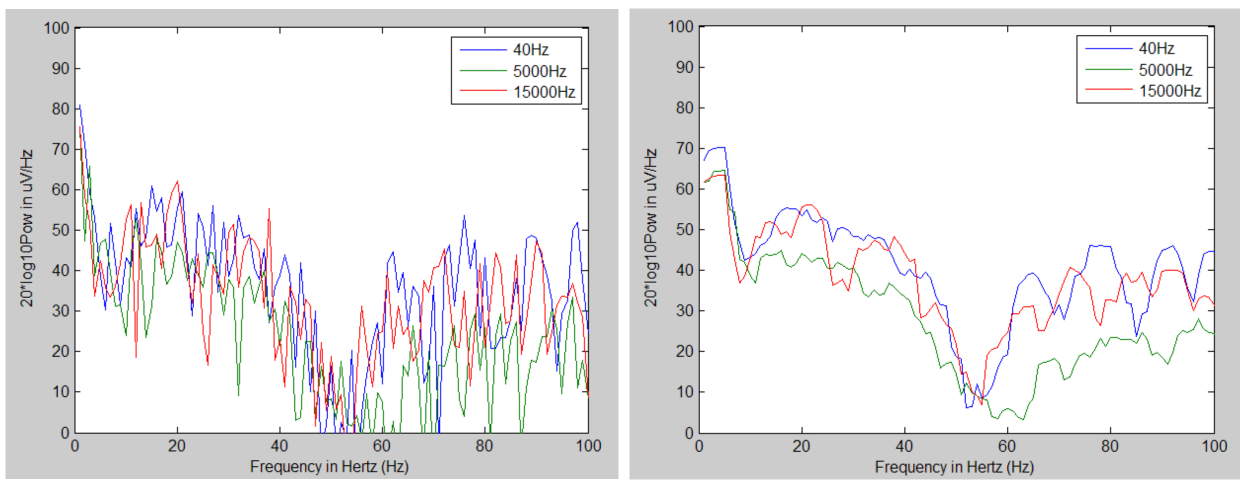
(c) with respect to 15 kHz sound wave

Fig. 3 Time response of EEG signals with respect different frequencies from channel T (temporal lobe)



(a) (b)

Fig. 4 Frequency response (FFT) of EEG signals with respect to different frequency sound waves: without moving average filter, and (b) with moving average filter



(a) (b)

Fig. 5 Power spectrum of the EEG signals with respect to different frequency sound wave: without moving average filter, and (b) with moving average filter

The FFT signals in Fig. 4(b) are significantly smoothened. Clear differences are noticed from the signals in Fig. 4(b). At low frequency, i.e. below 10 Hz, EEG signal with respect to 5000 Hz sound waves has higher amplitude than the other 2 signals. However, it is also noticed at around 20 Hz, EEG signal with respect to 40 Hz and 15000Hz has higher amplitude than EEG signal with respect to 5000 Hz.

The power spectrums of the EEG signals are obtained with the following equation:

$$S(\omega) = X(\omega)X^{*}(\omega) \tag{4}$$

where $X(\omega)$ is the FFT from EEG signals with respect to different frequencies of sound waves. Fig. 5 shows the power spectrum of the EEG signals with respect to different frequency sound waves. Again, the signals are smoothened with moving average filter for better analysis. From the power spectrum, it is noticed that power spectrum with respect to 5000Hz sound wave is the lowest among the three power spectrums. There is certain peak points from the frequency response of the EEG signals, similar applied to the power spectrums of the EEG signals. With these properties, the EEG signals can be characterized and categorized.

Low frequency as 40Hz and high frequency as 15000Hz might cause uncomfortable to human hearing. Some people even experienced pains when hearing to these extreme high or low frequencies sound waves. As such, human brain activities are high when listening to these sound waves. This is proven with the study above, where the power spectrum for the EEG signals is high for both 40Hz and 15000Hz sound waves. EEG signal with respect to 5000Hz shows the lowest power, as well as the amplitude of the frequency response. This is around the frequency of most of the musical instrument where we are enjoying when listening to the music from those musical instruments.

A few sets of EEG data with different sound waves frequencies from the same subjects are obtained at the early stage of the project. After reviewing the available methods for EEG signal processing, several testing is done to visualize the EEG signal in time domain and frequency domain using Matlab. The figures below show the EEG signal from different frequency response in time and frequency domain.

From Figure 3, which shows the time response of EEG signals with respects to sound waves of 100 Hz, 5kHz, and 15 kHz. From the time response of the EEG signals, it is hard to extract any specific characteristics from those EEG signal. Hence, FFT is performed onto the signal, to obtain the frequency response of the EEG signals.

Absolute value of the frequency response from FFT is plotted as shown in Figure 4. It is still hard to extract any specific characteristic from the graphs shown, and this might be due to noise contained in the EEG signals. However, there are slight differences noticed in term of peaks location etc. To amplify the differences, those frequency responses are smoothened using high order moving average filter. Figure 5 shows the smoothened frequency responses of the EEG signals with respect to different sound wave frequencies. Differences noticed from 3 graphs in Figure 5 in terms of peak frequency location as well as the area under the graphs.

IV. Conclusion and Recommendation

The study on EEG signal with respect to different frequency sound waves is performed. Human brain activities can be shown through the power spectrum of the EEG signals. Result from the study shows that human brain activities are the highest when the subjects were exposed to extremely high or low frequency sound waves. For mid-range frequency sound wave, i.e. 5000Hz, which is around the range of most musical instruments, power spectrum of the EEG signal is the lowest, as this is the common and comfortable frequency range perceived by human being. For further study, it is recommended that wider range of sound wave with different frequencies should be collected for better analysis of EEG signal response and characteristics.

Acknowledgement

The authors are so indebted and would like to express our thankfulness to the Universiti Teknologi Malaysia and Ministry of Science and Innovation Malaysia for supporting and funding this study under Vote 79368. Our appreciation also goes to the Biomedical Electronics and Instrumentations Research Group for their ideas and comments to this paper.

References

[1] R. Yagi, E. Nishina, M. Honda, T. Oshashi, "*Modulatory Effect of Inaudible High-Frequency Sounds on Human Acoustic Perception",* Neuroscience Letters 351, Ireland: Elsevier, 2003, pp. 191-195.

[2] Huisheng Lu, Mingshi Wang and Hongqiang Yu, "*EEG Model and Location in Brain when Enjoying Music",* in proceedings of the 2005 IEEE in Engineering in Medicine and Biology 27th Annual Conference, Shanghai, 2005, pp. 2695-2698.

[3] W. Lin, H. Chiu and C. Hsu, "*Discovering EEG Signals Response to Musical Signal Stimuli by Time-Frequency Analysis and Independent Component Analysis",* in Proceedings of the 2005 IEEE on Engineering in Medicine and Biology 27th Annual Conference, Shanghai, 2005, pp. 2765-2768.

[4] Zhang De-xiang, Wu Xiao-pei and Guo Xiao-jing, "The EEG Signal Preprocessing Based on Empirical Mode Decomposition", the 2nd Conference of Bioinformatics and Biomedical Engineering, Shanghai, 2008, pp. 2131-2134.

[5] M. Ungureanu, C. Bigan, R. Strungaru and V. Lararescu, "*Independent Component Analysis Applied in Biomedical Signal Processing*", Measurement Science Review, Vol. 4, section 2, 2004, pp.

[6] Arnaud Delorme, Terrence Sejnowski and Scott Makeig, "*Enhanced Detection of Artifacts in EEG Data using Higher-Order Statistics and Independent Component Analysis",* NeuroImage 34, 2007, pp. 1443-1449

[7] Samuel Boudet, Laurent Peyrodie, Philippe Gallois and Christian Vasseur, "*Filtering by Optimal Projection and Application to Automatic Artifact Removal from EEG*", Signal Processing vol 87(8), 2007, pp. 1978-1992.

[8] Li Yong and Zhang Shengxun, "*Apply Wavelet Transform to Analyze EEG Signal*", 18th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Amsterdam, 1996, pp. 1007-1008

[9] Maan M. Shaker, "*EEG Waves Classifier using Wavelet Transform*", International Journal of Biological, Biomedical and Medical Sciences, 2006, pp. 85-90.

[10] Abdulhamit Subasia and Ergun Ercelebi, "*Classification of EEG Signals using Neural Network and Logistic Regression*", Computer Methods and Programs in Biomedicine 78, 2005, pp. 87-99.

[11] Christopher J. James, Richard D. Jones, Philip J. Bones and Grant J. Carroll, "*Spatial Analysis of Multi-Channel EEG Recordings Through a Fuzz Rule Based System in the Detection of Epileptiform Events*", in proceeding of the 20th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Vol. 20, No 4, 1998, pp. 2715-2718