



Examination of Prefrontal Cortex Activity After EEG-Neurofeedback Stimulation in Overweight Cases

Mohammed I. Al-Hiyali¹, Asnor J. Ishak^{1,2,4,*}, Hafiz R. Harun^{1,4}, Siti A. Ahmad^{1,2,4}, Wan A. Wan Sulaiman^{2,3}

¹Department of Electrical and Electronic Engineering, University Putra Malaysia, 43400 UPM Serdang, Selangor, Malaysia

²Malaysian Research Institute on Ageing, University Putra Malaysia, 43400 UPM Serdang, Selangor, Malaysia

³Faculty of Medicine and Health Sciences, University Putra Malaysia, 43400 UPM Serdang, Selangor, Malaysia

⁴Control System and Signal Processing Research Center, University Putra Malaysia, 43400 UPM Serdang, Malaysia

*Corresponding author

DOI: <https://doi.org/10.30880/ijie.2019.11.03.003>

Received 25 February 2019; Accepted 9 July 2019; Available online 3 September 2019

Abstract: Food intake regulation is considered the key to weight control and overweight prevention. The brain activity in PreFrontal Cortex (PFC) plays a role in food intake behaviors. Most of the previous studies were aimed to PFC stimulation in overweight cases to modify the food intake behaviors. The EEG-neurofeedback is one of the brain stimulation techniques; therefore, this study aims to find the effect of EEG-NF stimulation on PFC function by EEG features analysis. For the purpose of analysis, the theta/beta ratio was extracted from ten healthy overweight participants in this study. All participants were divided into two groups, experimental group and control group with two phase-terms, pre and post-stimulation phase. The experiments were run using EEG-NF device. The results in this study indicate that success of EEG-Neurofeedback in PFC stimulation of overweight cases may have an influence on changing the food intake behavior.

Keywords: Electroencephalography (EEG), Body Mass Index (BMI), Food-Intake, Overweight, Obesity, Neuromodulation, Neurofeedback Training, Prefrontal Cortex.

1 Introduction

The prevalence of excess weight individuals has increased noticeably in Malaysian societies. Recently, the Institute for Public Health in Malaysia (IPH) has reported that around 45% of the Malaysian population are excess weight cases[1]. The ever-increasing number of excess weight cases in societies is commonly due to excessive eating and lack of physical activity.

Another effect factor is the increase in eating of high caloric food rich in sugars and fat. Beside excessive eating of fat and sugar, daily meal types have changed over the last decades, noting a trend for increased meal frequency (i.e. snacking behavior)[2]. Snacking has been proposed to weight increase as well as to its metabolic rate. Thus, a decrease in physical activity, an increase in calorie food rate, and snacking behavior all result in excess weight [3].

The prevalence of excess weight individuals can be said to have reached high sizes thus evidencing that at least an overweight case occurs because of an inability to regulate their own eating behavior which is a key to weight gain prevention. Eating regulation is a complex process involving internal factors such as genetics, neural, and endocrine signals, as well as external factors including the environmental factors that excite eating desire such as sight, smell, and taste[4].

However, studies have shown that specific areas of the brain are involved in the interactive processing of food vs. nonfood-related visual stimuli in the different states of hunger and satiety. These include the PreFrontal Cortex (PFC) and the amygdala. Another study shows that food, even when presented only as an image, will cause a larger CNS

“hunger response” in evolutionarily conserved brain areas, sustaining survival because the visual presentation of the food was possibly the first way of food contact[5].

The recent progress in brain activity research found a therapeutic program that targeted stimulation in the decision-making process may lead to an encouraging approach in the prevention of weight gain. The literature in neurosciences studies have been mentioned to stimulation of the PreFrontal Cortex has been suggested as such an approach for change eating behavior in overweight cases [6].

The brain activity in overweight or obesity cases is a cognitive deficit in the eating behavior; this functional modification is often related with electroencephalography signals (EEG). The studies of brain stimulation in excess weight individuals showed that it was effective in changing eating behavior. Most of previous studies have been used in the self-report questionnaires as a tool to assess the food-intake behavior in pre and post-stimulation without brain activity assessment[7]. Hence, this problem can be addressed by the research question: what is the quantitative difference in EEG signals between pre and post stimulation sessions? For this problem, it is hypothesized that EEG-NF alters the PFC function.

However, The EEG-Neurofeedback (EEG-NF) is one of brain stimulation devices that operates a real-time of EEG signal to modify brain activity[8]. Despite that it is a non-surgical interventional, the EEG-NF hasn't been applied yet in PFC stimulation for excess weight cases[9]. The aim of this study is a preliminary examination of prefrontal cortex activity after NF stimulation sessions by quantitative assessment of EEG signals.

2 Study Structure

2.1 Preparation of Study

The present study was conducted by the research team, under the supervision of a therapist, experienced in neuroscience. Regarding the study location, the study was performed at the Clinical Neurophysiology Clinic at Medical Lab-Faculty of Medicine and Health Sciences, University Putra Malaysia. EEG-NF device is 2 channels Atlantis Clinical System manufactured by BrainMaster Company for EEG recording and neurofeedback stimulation. The EEG-MF setup illustrated in Figure 1:

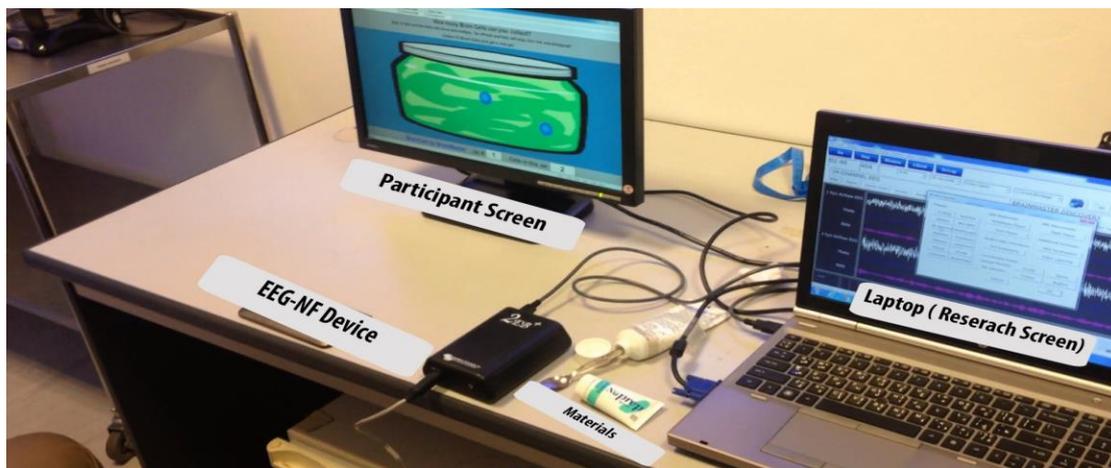


Fig. 1 - EEG-NF setup

The study design was based on Randomized Control Trial (RCT) for recruited the participants. Ten healthy participators were divided randomly into two groups, Experimental Group (EX) and Control Group (C) with two conditions (pre and post-intervention). The details of the participant flow are illustrated in diagram (Fig.2).

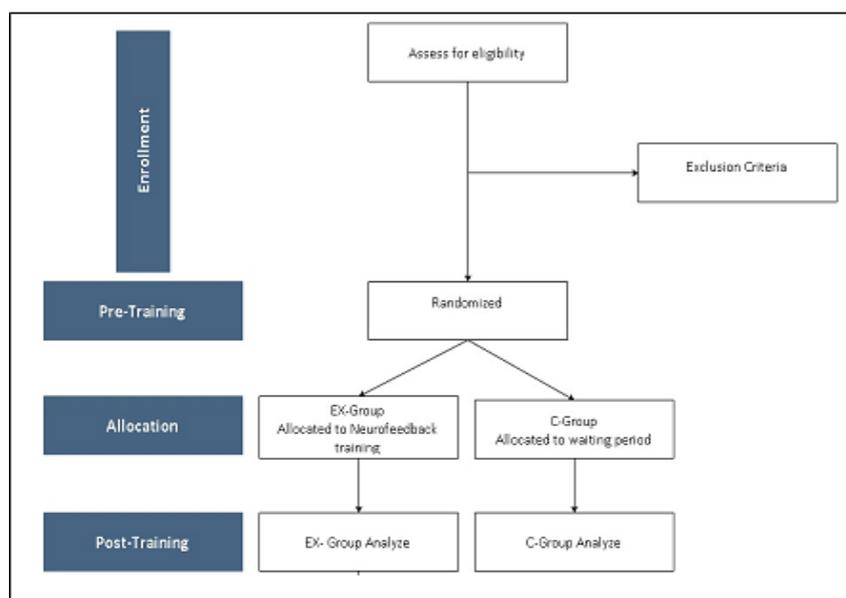


Fig. 2 - Study Design

All participants were undergoing a screening to following criteria; the inclusion criteria are as follows: participants must be overweight or obesity and within the defined age limit (18 – 45) years; participants must not be having/must not have had any brain disorders. The exclusion criteria are as follows; failed to meet the inclusion criteria; currently pregnant; smoking; failed to provide written consent.

In general, all participants in the present study were randomly assigned to Experimental group (EXG=5) or Control Group (CG= 5). The EX-Group undergoes Neurofeedback sessions and control group undergoes a period of waiting (no-Neurofeedback session). The study design consists of 3 phases for data collection: Pre and Post Stimulation phases, and Across Stimulation phase. The duration of study was 4 weeks.

2.2 Data Collection Phases

Pre-Stimulation Phase

The participants were equipped with the screening form for personal details. After that, they were moved to EEG recording session. During this session, they were asked to relax but without sleeping and had to keep their eyes open to focus on one of colors that are shown on the participant screen. The duration of recording was approximately 5 minutes.

Across Stimulation Sessions

The stimulation phase was designed based on the requirements for good neurofeedback study that had been suggested in the literature studies [10]. The number of neurofeedback sessions index in this study were eight sessions (each session lasted 17 minutes) as mentioned in previous neurofeedback studies [12], [11]. Each participant was given two sessions per week for four weeks; the flow chart for each session is shown in figure (fig.3).

The pre-EEG screening presented pictures of food items that were chosen by the participant before session starting. After 90 seconds, the neurofeedback trails started by flash video games. The feedback was provided in the form of a spheres moving within a jar; the spheres were produced when the participant had matched the criteria continuously for a certain period (above 0.5 seconds). The spheres moved with a fast motion in the jar when the criteria were matched, and they moved with a slow motion in otherwise. The spheres' activity gives a fast feedback on the participant's state. The number of spheres reflects the success in keeping in case over a period. If the participant drops out of case for a period—just under 1 second—, one sphere will turn red and fades away. Thus, the spheres can be both formed and crashed by the stimulation process. When the participant fills up one jar (25 spheres), a new jar is loaded, and the sequence begins again. After that, the flash game is removed and post-EEG screening starts for 90 sec before the end of session.

Post-stimulation phase

After 4 weeks of stimulation session, all participants were called for post stimulation session. In this phase the participants (EX-Group and C-Group) were moved to perform another EEG recording sessions for 5 minutes as the same condition of pre-phase session.

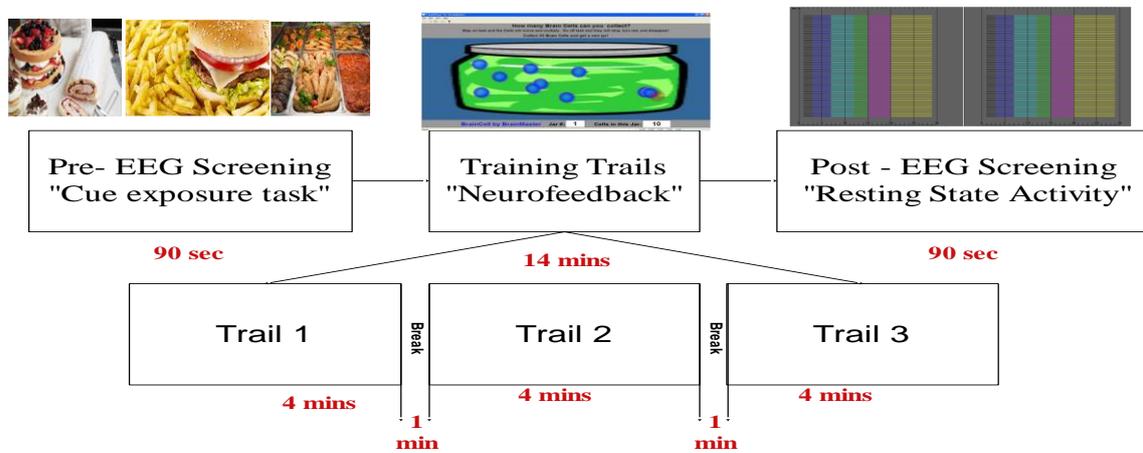


Fig. 3 - Neurofeedback Session

2.3 EEG Electrodes placement

In each session during all phases except the follow-up phase, the EEG signals were recorded. The target brain area of stimulation is PFC. The electrodes were placed according to 10/20 international system, and the head-size was measured for participants to identify the prefrontal positions. In order to identify the left and right PFC, the center of PFC (Fpz) should be marked. The Fpz was marked after measuring the length between bridge of the nose (nasion) to the occipital bone (Inion); the 10% of the total length from the nasion will be the Fpz. The head circumference had been measured for Fp1 and Fp2 determination, the electrodes positioning illustrated in fig.4.

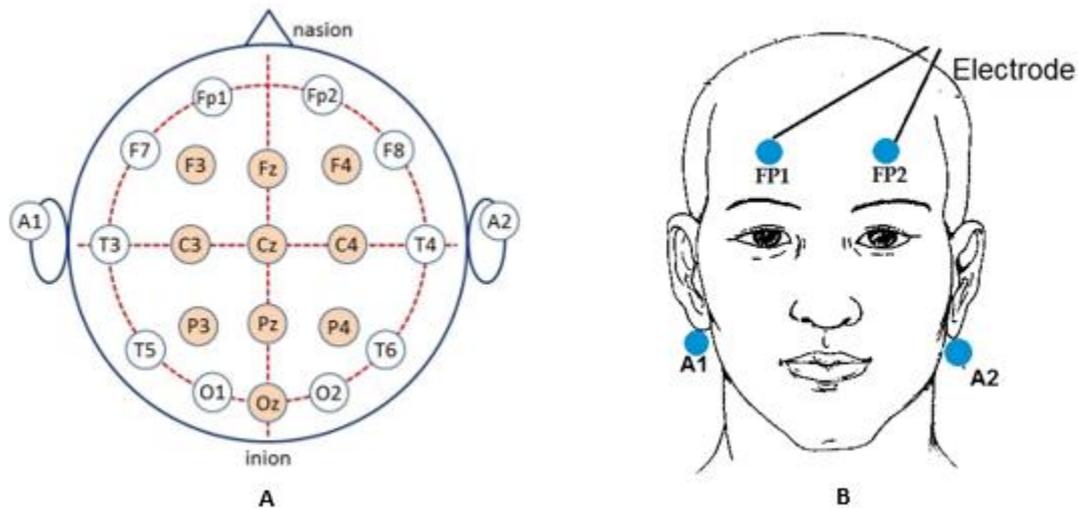


Fig. 4 - Electrodes Placement

3 Data Analysis

After the data was collected, the features were extracted from EEG signals then the data in SPSS was inserted for statistical analysis. Next, features were analyzed by the statistical methods to assess the EEG signals in pre-post stimulation session and across stimulation sessions. The EEG signal processing and statistical analysis methods are explained in next section.

3.1 EEG Signal Processing

The EEG signals characteristic is basically non-linear and non-stationary; hence, the important data can be extracted by using signal processing techniques. Studies over the past two decades have provided different signal processing techniques used to extract the EEG features in different mental events to comprehend the behavior and neuron activity in several linear and non-linear signals processing techniques and it's a correlation in the psychological events.

The EEG signal processing can be divided into two steps in assessment studies, pre-processing and features extraction. The pre-processing includes the detection and removal of artefacts from the EEG signal. The main artefacts causes are eye-blinking, respiratory activity, and head or body motion and electric power-line source of EEG device[13].

The next step in signal processing is feature extraction. The EEG raw signals transferred into a set of features called 'feature vector'. It includes several mathematical methods to extract the data or variable values. Previous studies have been utilizing time domain, frequency domain and time-frequency domain depending on the study domain and objectives. Traditionally, the features extraction is considered the most significant step in EEG signal assessment [14].

However, the power spectral density (PSD) is one of the popularly used methods for quantification of EEG signal. It provides distribution of power over frequency. The PSD analysis is a mathematical method for analysing the frequency of complex waveforms, which provides a sensitive means to detect periodicity within the waveforms and to determine the relative energy content of the periods [15]. This method has been applied to estimate the power of EEG signals after the data collection phase.

The non-parametric method is one of PSD analyses that deals with the estimation of the autocorrelation from a given EEG data-set. The useful non-parametric method in the computerized analysis of EEG uses the Welch method.

This method is used for estimating the power of signal at different frequencies; it is suitable for EEG raw signal. Welch method is considered one of Fast-Fourier Transform (FFT) methods. The original signal is split up into overlapping segments, then windowing and after that periodogram calculation; also, Welch methods offers to reduce noise if compared to the standard periodogram with fewer computations.

In EEG-NF applications, the usual feature extraction method is Frequency Domain (FD). Most of previous studies that aimed to EEG assessment in EEG-NF stimulation have used the absolute EEG power or relative power ratio between slow and fast EEG frequency bands to examine the EEG-NF stimulation impact [10]. In the current study, the Theta Beta Ratio (TBR) was selected as the EEG feature to monitor in pre-post phase and across stimulation phase.

3.2 Statistical Analysis

Analysis of Variance (ANOVA) technique aims to deal with the same features or terms in different trial phases to find out the significance difference between two or more means values of them as that of linear regression analysis. The probability value (P-value), used to hypothesis testing, examines the significance difference between means values. In the significant difference, the P-value should be less than 0.05 ($P\text{-value} < 0.05$).

In summary, the signal processing approach is applied on EEG signals to extract the features, and the statistical analysis methods such as ANOVA is used for comparison between the means of TBR features between participants' groups in study phases.

4 Result

The data of this research collected, from ten participants recruited, the mean of their ages (27.7 ± 2.67) years and the mean of BMI (33.02 ± 7.33) Kg/m^2 . The TBR was observed at each phase in each group.

The mean of TBR at pre and post stimulation phase in control group is shown in table 1 and fig.4, and the details of Ex-group are shown in table 2, fig. 5.

Table 1. Mean of TBR – Control Group

#	BMI	Age	Pre-Phase (T0)	Post-Phase (T1)
1	44.47	34	1.51	1.52
2	39.36	28	1.31	1.26
3	27.06	28	1.40	1.39
4	25.16	27	1.32	1.28
5	36.93	25	1.54	1.56

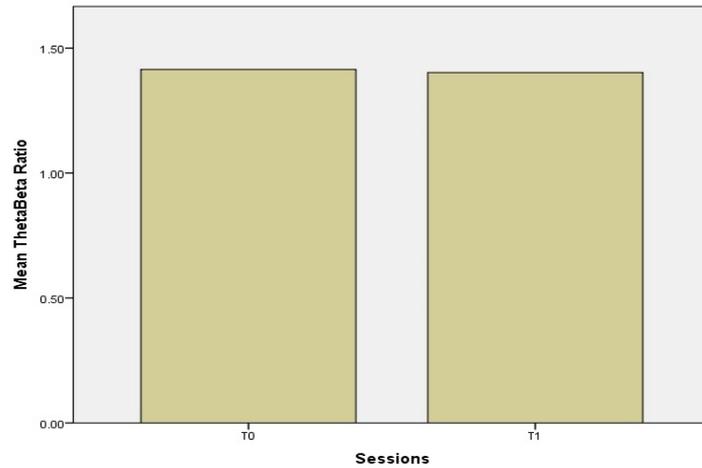


Fig. 5 - Mean of TBR Between Phases – Control Group

Table 2. Mean of TBR - Experimental Group

#	BMI	Age	Pre-Phase (T0)	Post-Phase (T1)
1	25.44	28	1.85	1.35
2	38.87	29	1.84	1.32
3	25.14	25	1.23	0.9
4	38.51	25	1.52	1.21
5	29.34	28	1.41	1.17

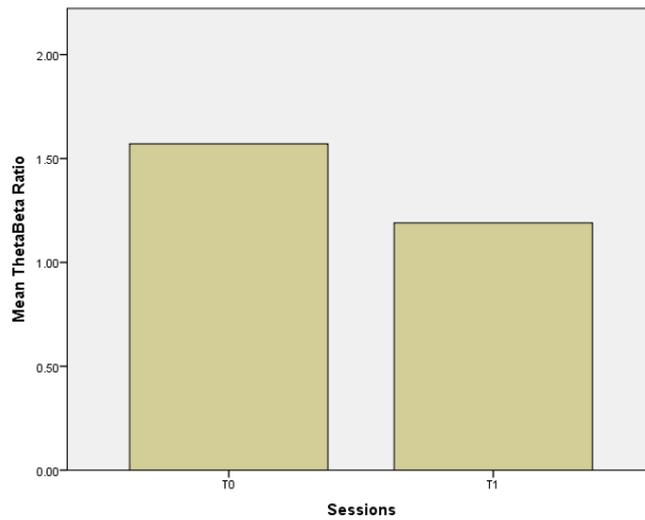


Fig. 6 - Mean of TBR between Phases – Experimental Group

The results obtained from above tables and figures, the mean value of TBR at pre-stimulation phase (T₀) and post-stimulation phase (T₁) could be non-significant difference in C-group, while the TBR in EX-group could be significant difference between pre and post stimulation phases.

The ANOVA technique is applied to compare the difference between mean values for each group at the study phases. The results obtained from the analysis are presented in table 3. The P-value refers to significant difference between the two phases in EX group while no significant difference between the two phases in C-group is referred to.

Table 3. Comparison Between Mean Value At Two Phases

Group	Phase	Mean	Std. Error	95% Confidence Interval		Total P-value
				Lower Bound	Upper Bound	
EX-Group	Pre	1.570	.092	1.357	1.783	0.000
	Post	1.190	.071	1.026	1.354	
C-Group	Pre	1.416	.092	1.203	1.629	0.223
	Post	1.402	.071	1.238	1.566	

As shown before, the stimulation phase involved 8 sessions. The TBR monitored between stimulation sessions and the relationship between TBR and session index number was negative as explained in figure 6. There was a reduction in TBR values with increasing session index number and the ANOVA statistics details are illustrated in table 4. The correlation analysis was used to predict the relationship between variance in mean value of TBR and sessions numbers. The negative relationship between mean value of TBR and session number in more significant correlation ($P < 0.01$), $F=73.20$, correlation coefficient $R=0.81$ and $R^2=0.65$, the equation for 40 values with observed power line is explained in figure 7.

Table 4. ANOVA Statistics Details

TBR	Correlation	Coefficient		F-Value	P-Value	Equation
		R	R ²			
sessions	- 0.81**	0.81	0.65	73.20	0.000	$y=2.13 - 0.13*x$

**more significant at the 0.01 level (P-Value). *significant at the 0.05 level (P-Value).

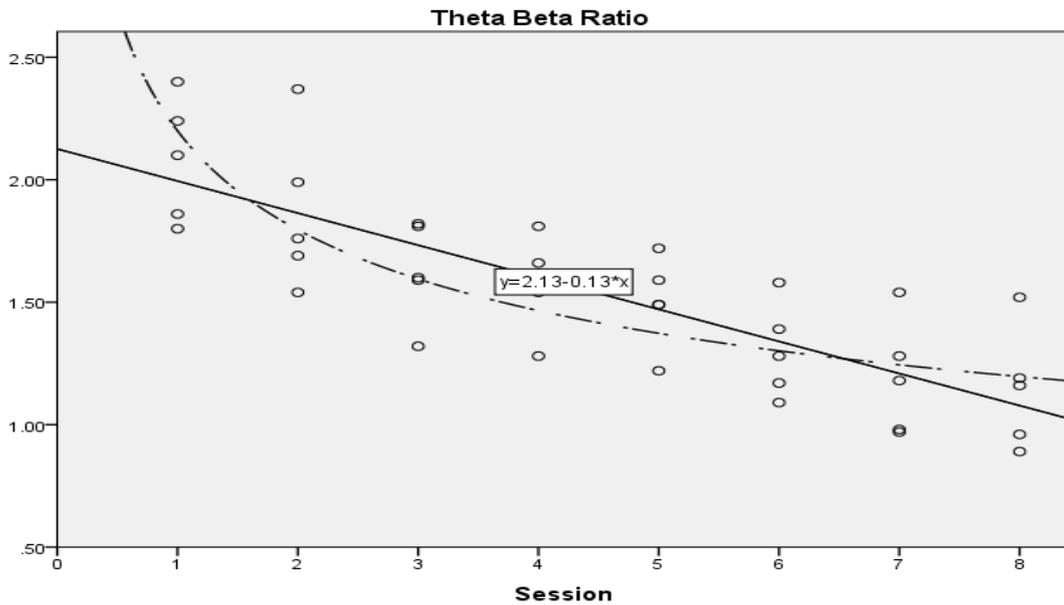


Fig. 7 - Mean Of TBR During Stimulation Phase

5 Discussion

The EEG-NF that have been applied by flash game shows a significant effect on PFC activity. The comparison between control and experimental groups is done and has found the neurofeedback impact on TBR of PFC stimulated in the experimental group while no change in TBR of PFC in the control group which hadn't stimulated.

The result has indicated a decreasing in TBR strong correlation with an increase in stimulation sessions index numbers. Furthermore, The TBR value has a negative linear correlation with decreasing whole EEG power at statistically significant $p < 0.01$. The decreasing in TBR means the decreasing in theta power band and an increasing in beta power band, and that confirmed that the beta band in PFC had strong impact on cognitive behavior which is related to decision making for eating.

6 Conclusion

The EEG-NF is one of the brain stimulation techniques, safe, non-surgical, affordable system and easy to handle compared to other techniques. Furthermore, numerous studies have used EEG-NF as a stimulation technique for neurological disorders treatment such as ADHD, stress, depression and addiction. However, there has not been any study, yet, that has examined the possibility of using EEG-NF for PFC stimulation for food eating disorder treatment or modifying the food intake behavior in overweight cases.

Finally, this study's result revealed the effectiveness of EEG-NF in PFC stimulation; the EEG-NF stimulation had the positive result in decreasing TBR that could be a valuable contribution to change their food intake behavior.

Acknowledgement

The present research was financially supported by a Putra Grant from University Putra Malaysia.

References

- [1] "World health Organization," 2017. [Online]. Available: <http://www.who.int/entity/mediacentre/factsheets/fs311/en/>. [Accessed:01-Sep-2018].
- [2] B. H. Vos MB, Kimmons JE, Gillespie C, Welsh J, "Dietary Fructose Consumption Among US Children and Adults: The Third National Health and Nutrition Examination Survey.," *Medscape J Med*, vol. 10, no. 7, p. 160, 2008.
- [3] H. Bertéus Forslund, J. S. Torgerson, L. Sjöström, and A. K. Lindroos, "Snacking frequency in relation to energy intake and food choices in obese men and women compared to a reference population," *Int. J. Obes.*, vol. 29, no. 6, p. 711, Apr. 2005.
- [4] T. Huang, T. Marsh, and M. Moodie, "Changing the future of obesity: science, policy, and ... [Lancet. 2011] - PubMed - NCBI," vol. 378, no. 9793, pp. 838–847, 2012.
- [5] M. Führer, D. Zysset, S., & Stumvoll, "Brain Activity in Hunger and Satiety: An Exploratory Visually Stimulated fMRI Study," *Obesity*, no. 16(5), pp. 945–950, 2008.
- [6] J. McClelland, N. Bozhilova, I. Campbell, and U. Schmidt, "A systematic review of the effects of neuromodulation on eating and body weight: Evidence from human and animal studies," *Eur. Eat. Disord. Rev.*, vol. 21, no. 6, pp. 436–455, 2013.
- [7] K. Jauch-chara *et al.*, "Repetitive electric brain stimulation reduces food intake in humans 1 – 3," no. 7, pp. 1003–1009, 2014.
- [8] J. H. Gruzelier, "EEG-neurofeedback for optimising performance. II: Creativity, the performing arts and ecological validity," *Neurosci. Biobehav. Rev.*, vol. 44, pp. 142–158, 2014.
- [9] M. I. Al-hiyali, A. J. Ishak, H. Harun, S. A. Ahmad, and W. S. Wa, "A Review in Modification Food-Intake Behavior by Brain Stimulation : Excess Weight Cases," *Neuroquantology*, vol. 16, no. 12, pp. 86–97, 2018.
- [10] S. Enriquez-Geppert, R. J. Huster, and C. S. Herrmann, "EEG-Neurofeedback as a Tool to Modulate Cognition and Behavior: A Review Tutorial," *Front. Hum. Neurosci.*, vol. 11, no. February, pp. 1–19, 2017.
- [11] W. Nan, F. Wan, M. I. Vai, and A. C. Da Rosa, "Resting and Initial Beta Amplitudes Predict Learning Ability in Beta/Theta Ratio Neurofeedback Training in Healthy Young Adults," *Front. Hum. Neurosci.*, vol. 9, 2015.
- [12] C. W. E. M. Quaedflieg, F. T. Y. Smulders, T. Meyer, F. Peeters, H. Merckelbach, and T. Smeets, "The validity of individual frontal alpha asymmetry EEG neurofeedback," *Soc. Cogn. Affect. Neurosci.*, vol. 11, no. 1, pp. 33–43, 2015.
- [13] A. Mayeli, V. Zotev, H. Refai, and J. Bodurka, "An automatic ICA-based method for removing artifacts from EEG data acquired during fMRI in real time," in *Biomedical Engineering Conference (NEBEC), 2015 41st Annual Northeast*, 2015, pp. 1–2.
- [14] A. F. Hussein *et al.*, "Focal and non-Focal Epilepsy Localisation: A Review," *IEEE Access*, vol. PP, no. c, pp. 1–1, 2018.
- [15] S. Motamedi-Fakhr, M. Moshrefi-Torbati, M. Hill, C. M. Hill, and P. R. White, "Signal processing techniques applied to human sleep EEG signals - A review," *Biomed. Signal Process. Control*, vol. 10, no. 1, pp. 21–33, 2014.