35th Annual International Conference of the IEEE EMBS
Osaka, Japan, 3 - 7 July, 2013

Analysis of EEG Signals Regularity in Adults during Video Game Play in 2D and 3D

Hamizah R. Khairuddin, Aamir S. Malik, *Senior Member, IEEE* , Wajid Mumtaz, Nidal Kamel, *Senior Member, IEEE,* Likun Xia *Member, IEEE*

***Abstract*— Video games have long been part of the entertainment industry. Nonetheless, it is not well known how video games can affect us with the advancement of 3D technology. The purpose of this study is to investigate the EEG signals regularity when playing video games in 2D and 3D modes. A total of 29 healthy subjects (24 male, 5 female) with mean age of 21.79 (1.63) years participated. Subjects were asked to play a car racing video game in three different modes (2D, 3D passive and 3D active). In 3D passive mode, subjects needed to wear a passive polarized glasses (cinema type) while for 3D active, an active shutter glasses was used. Scalp EEG data was recorded during game play using 19-channel EEG machine and linked ear was used as reference. After data were pre-processed, the signal irregularity for all conditions was computed. Two parameters were used to measure signal complexity for time series data: i) Hjorth-Complexity and ii) Composite Permutation Entropy Index (CPEI). Based on these two parameters, our results showed that the complexity level increased from eyes closed to eyes open condition; and further increased in the case of 3D as compared to 2D game play.**

I. INTRODUCTION

The new wave of 3D technology coming in since the debut of *Avatar* in 2009 [1], has certainly raised great interest to invest on 3DTVs, just to be able to experience 3D vision at home. Among the two popular types of 3D viewing technology are 3D passive glasses and 3D active glasses.

Basically, in order to perceive depth, each eye needs to see slightly different information. Based on this theory, the two technologies mainly differ in how each 3D glasses works. The 3D passive uses polarized glasses (cinema type), which is inexpensive and lightweight. In this technology, as the polarized images (i.e. horizontally and vertically) are projected simultaneously on the screen, the polarized 3D glasses block different kinds of light hence create the depth illusion in each eye. As a result, the image resolution is somehow compromised since technically, each lens blocks the incoming light thus viewer might not be able to get a full resolution of the image.

On the other hand, the active shutter glasses used in 3D active technology alternately dim the right and left lenses at a very high speed. This means that only one eye can see at a time as the other eye is blocked when the shutter is closed (opaque). True to its name, this type of 3D actively synchronizes with the TV screen in order for the 'seeing eye' to see the intended image. In comparison to the passive polarized 3D glasses, 3D active shutter glasses are generally more expensive since they depend on batteries to run. Despite the cost, this technology gives full high definition to each eye and wide range of viewing angles.

The development of 3D definitely has given huge impact in game industry as most gamers tend to demand more immersion and get real experience with the game they play. Starting 2006, game developers had finally come up with the stereoscopic 3D gaming solutions that had a relatively low cost and high quality, such as Konami's Tobidacid Solid Eye, Vuzix iWear, and Nvidia 3D vision. Later in 2010, Sony began to aggressively market 3D technology through their TVs, cameras, and their popular video game console, the PlayStation 3 which has gained popularity worldwide [2].

To date, the effects of playing video games in 3D are not well established. Nonetheless, previous studies had shown that many non-gamers lose focus while playing 3D video games, and that they are more distracted or that they do not observe important details [3]. The increase in distraction among non-gamers may be explained by the results of a recent study which found that in 3D video, an increase in dimensions produced a wider array of visual objects and an increase in eye movements directed to those objects [4]. In another game research, it was found that during a game play, the increase of heart rate was also accompany with brain activation, and it was relatively high compared to rest condition [5-6].

As human brain is complex and is able to perform multiple cognitive tasks at a time, non-linear time series analyses may help to reveal the underlying mechanism while performing these tasks. Currently, many EEG studies have worked in this area involving healthy subjects at rest [7] or performing cognitive tasks such as game play [8], patients with epilepsy [9-10] and Alzheimer disease [11] as well as in sleep [12] and anaesthetical studies [13-14].

However, EEG studies on 3D games using time series analysis has not been reported. Many have found that the time series analysis is capable to indicate the dynamical changes in EEG signal. In this study, we employed two regularity measures, namely Hjorth Complexity parameter and Composite Permutation Entropy Index (CPEI) to investigate the EEG activity when playing video games in 2D and 3D modes. For this work, these two methods were selected mainly because both take advantages of low computational cost compared to conventional frequency analysis while providing results that can be easily to interpret (in correlation with physiological conditions).

*Research supported by eScience Fund, Ministry of Science, Technology and Innovation (MOSTI), Malaysia.

H. R. Khairuddin, *A.S. Malik, W. Mumtaz, N. Kamel, L. Xia are with the Centre for Intelligent Signal and Image Research (CISIR), Department of Electrical and Electronics Engineering, Universiti Teknologi PETRONAS, Bandar Seri Iskandar, 31750 Tronoh, Perak, (phone: +605-368-7853; fax: +605-365-7443; e-mail: aamir_saeed@petronas.com.my).

II. METHODOLOGY

A. Subjects

29 subjects (24 male, 5 female), aged between 19 – 25 participated in the study but three subjects (2 male, 1 female; age mean 22.33 ± 2.31 years) were excluded due to data corruption. Therefore, sample size was reduced to 26 subjects (22 males, 4 females; mean age 21.73 ± 1.59). All subjects have no unknown cognitive impairments and have normal or corrected-to-normal vision. Also, before participating in the study, they were briefed about the experimental procedure and upon agreement, all gave their written consent. In the past, none of the subjects had ever played the video game used in this experiment either in 2D, 3D active or 3D passive mode.

B. EEG Recording

The EEG data were recorded from 19 scalp locations (Fp1, Fp2, F3, F4, C3, C4, P3, P4, O1, O2, F7, F8, T3, T4, T5, T6, Fz, Cz and Oz channels) based on the international 10-20 system where ear-linked was used as reference. The sampling rate was 256 Hz. The experiment began with a five minutes of eye-closed, five minutes of eyes open and followed by 20 minutes of video game play in 2D, 3D passive and 3D active modes, sequentially.

For 3D experiments, two 3DTVs were in use: i) LG 42-inch TV with passive polarized glasses (3D Passive) and ii) Sony 40-inch TV with active shutter glasses (3D active). Subjects were seated about 2.0 meters away from the screen. Each subject needed to complete five game levels within the time frame. At the end of each session, they were given a simulator sickness questionnaire (SSQ) regarding their general experience when playing game in the respective mode.

As we aimed to investigate the effect of 3D game play on brain responses, the following measures were taken into consideration to minimize the exposure effect when playing game for the first time and playing them in 3D modes (active and passive):

- Participants played the game prior to the experiment.
- Only the middle three levels out of five were considered for analysis. The first and the last level were excluded due to excitation and fatigue effects, respectively.
- Half of the subjects played game in 3D active first, followed by 3D passive while half played the game firstly in 3D passive then in 3D active. This was to randomize the order as well as to reduce the order effect of having to play the game in both 3D modes sequentially.

After data collection, Neuroguide software was used for data cleaning. Artifacts like eye blinking, eye movement, and muscle movement were removed from the data prior to time series analysis.

C. Hjorth Parameters

Hjorth parameters are based on statistical calculations which used to describe the characteristics of EEG signal in time domain. The three Hjorth parameters which alternatively known as normalized slope descriptors (NSDs) include activity, mobility and complexity [15].

The activity parameter, which is the variance $\sigma_x{}^2$ of the signal amplitude where σ_x is the standard deviation of the EEG for a given epoch is the mean power of the EEG signal which represents the signal activity (1). While mobility is the estimate of the mean frequency, defined as the square root of the ratio of the activity of the first derivative of the signal $\sigma_x{}^{2\prime}$ to the activity of the original signal $\sigma_x{}^2$ (2). The complexity parameter corresponds to the change in frequency is defined by the ratio of mobility of the first derivative of the signal to the mobility of the signal itself (3).

The parameters can be computed based on the following derivations [15-16]:

$$Activity = \sigma_x{}^2, \tag{1}$$

$$Mobility = \sqrt{\frac{\sigma'_x{}^2}{\sigma_x{}^2}} = \frac{\sigma'_x}{\sigma_x}, \tag{2}$$

$$Complexity = \frac{\sigma''_x / \sigma'_x}{\sigma'_x / \sigma_x} \tag{3}$$

D. Composite Permutation Entropy Index (CPEI)

Composite Permutation Entropy Index (CPEI) describes the complexity of any non-linear time series, in this case the EEG signals. In this work, the computational steps were as proposed by [14].

Firstly, for a given continuous EEG data, the signal was fragmented into a sequence of motifs. Next, each motif was classified as one of the six possible types, according to the shapes of the waves either 'slopes', 'peaks' or 'troughs'. Then, the probability of motifs to appear in each type was calculated. Sequentially, the permutation entropy (PE) for the resultant normalized probability distribution of the motifs was computed based on Shannon uncertainty formula, as in

$$\mathrm{PE} = -\frac{\sum p_i \times \ln(p_{i)}}{\ln(number\ of\ motifs)}. \tag{4}$$

Finally, the CPEI was computed using two additional parameters of permutation entropy, noise threshold *tie*, and lag τ, which may be equal to 1 or 2. The formula for CPEI used in this work is as shown in (5). This formula combined the PE of different lags (τ =1 and τ =2), to distinguish periods of delta waves and to differentiate mid-frequency waves from very slow delta oscillation respectively. This composite index is based on the summation of entropies and the components of two PEs. The six motifs for each PE_τ and one for PE_{ties}, hence a total of 49 (7×7) was used to normalize the denominator.

$$\mathrm{CPEI} = -\frac{\sum p_i \times \ln(p_{i)}, _{tie<0.5,\tau=1} + \sum p_i \times \ln(p_{i)}, _{tie<0.5,\tau=2}}{\ln(49)} \tag{5}$$

To reduce the computation for all 19 electrodes, the electrodes were grouped accordingly into five brain regions such as frontal (Fp1, Fp2, F3, F4, F7, F8 and Fz); central (C3, C4 and Cz); temporal (T3, T4, T5 and T6), parietal (P3, P4 and Pz) and occipital (O1 and O2).

III. RESULTS

The Hjorth and CPEI parameters were computed for all five conditions: i) Eyes Closed (EC) ii) Eyes Open (EO) iii) 2D Game play iv) 3D Passive Game play and v) 3D Active Game play. However, in this work we considered the third Hjorth parameter, (i.e. complexity) as the results using the first two parameters were very not significant. The mean values for Hjorth complexity parameter and CPEI are plotted with respect to conditions, are shown in Figure 1 and Figure 2, respectively.

The complexity measure is higher for sudden and frequent changes in the signal over time. In Figure 1, the initial rest condition (EC) had the lowest complexity for all brain regions and rapidly increased during eyes open condition. Similarly, the complexity level was further increased with the presence of visual stimuli from eyes open to 2D game play and 3D game play. Overall, the complexity in 3D Active was the highest with the exception for frontal region.

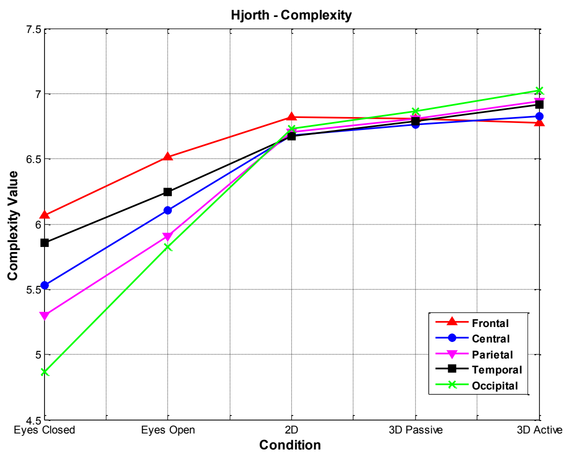

Figure 1. Hjorth complexity with respect to subjects' condition

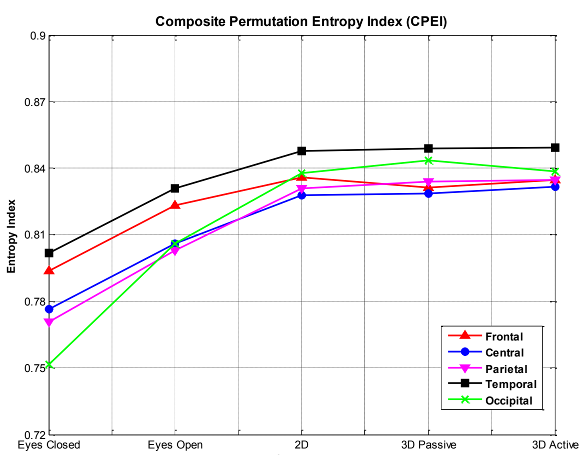

Figure 2. CPEI with respect to subjects' condition

We also applied the CPEI method as a measure of signal complexity on the same 2D-3D game play data. In Figure 2, the resulting index lies between 0.75 to 0.80, while the maximal entropy is when the CPEI value equals to 1. Interestingly, the CPEI result also showed similar trend where at rest conditions (both EC and EO), the index was lower compared to the game play conditions (i.e., 2D or 3D). Although the difference between 3D Active and 3D Passive was comparable; overall, the index was slightly higher for 3D game play in comparison with 2D.

To further test the significance of the difference between two conditions (i.e., 3D (active or passive) versus 2D, 3D active versus 3D passive), we performed the statistical paired t-test on the computed values. The corresponding *P*-values for Hjorth complexity measures are presented in the Appendix section (Table I) and the CPEI t-test results are shown in Table II.

Since our goal was to see the difference between playing game in 2D and 3D, the gameplay for 2D was used as the baseline. For 3D active versus 2D, the difference was very significant (P-value < 0.05) particularly in the occipital region for both parameters. However, for Hjorth, the difference was also significant in the temporal area too. Apparently, the difference between 3D passive and 2D was not apparent.

In another comparison, the two viewing technologies were compared; 3D active versus 3D passive. Although the result was not obvious, the *P*-value for the visual processing area (occipital) was relatively low compared to all other brain regions.

IV. DISCUSSION

During eyes closed condition, generally subjects are more likely to be relaxed. Thus it is expected that the frequency changes was very minimal at this state. On the contrary, as subjects opened their eyes, the complexity level began to increase and this was reflected by the sudden changes of frequency found in all brain regions (refer Figure 1 and Figure 2).

In addition to that, as more complex visual stimuli are present (in this case from 2D to 3D visualization), the complexity level of vision was further increased especially in the occipital region where most of the visual processes take place. Looking at this trend, we could say in general, that the CPEI results conformed to the Hjorth method. A low CPEI value indicates that the time series is regular (signal consists only few motifs or pattern) while a value of 1 (maximum PE) is when all permutation have equal probability. As the CPEI values get higher with respect to the complexity of the visual stimulation (i.e., from eyes open to 2D and 3D), this indicates that there is an almost even distribution for all six motifs (i.e., a signal is claimed to be complex as it is composed of various patterns). So these results provide evidence that it is possible that our brain used more resources to decode the 3D content that is more complex and has more information to process compared to 2D.

Our findings especially in the occipital lobe as well as in the temporal and frontal lobes suggest the possibility that there exist interaction between 3D perception and working memory. When subjects were exposed to the 3D environments, the complexity level was increased mainly in these two regions as the activation in the temporal and frontal lobe was associated with working memory tasks (i.e., memory retrieval, encoding and storage).

In comparing 3D active and 3D passive modes, the result however was more apparent using Hjorth complexity parameter (see Figure 1), where 3D active had the highest complexity nearly in all brain regions compared to 3D passive. Although it seems that 3D active has higher complexity than 3D passive, the *P*-value did not reach significance level (*P*-value >0.05) for both parameters. Also, based on user preference, it was found that the preference was equally divided between the two 3D modes (i.e., 3D active and 3D passive).

V. Conclusion

Our research work provides an application of time series analysis on EEG data in adults while playing video game in 2D and 3D modes. We compared the signal regularity with respect to viewing conditions (i.e., 2D, 3D active and 3D passive) by evaluating Hjorth complexity and CPEI parameters.

From the results, we would conclude that the use of Hjorth complexity parameter as well as the CPEI showed a good indication that these two methods may be useful in quantifying the EEG activity during 2D and 3D visualization. However, further investigation is required in analyzing other EEG complexity features in order to understand better about the relationship between EEG complexity and different brain regions, with respect to other 3D visual tasks.

Appendix

TABLE I. Hjorth Complexity *P*-Values

Brain Region	Comparison Groups		
	3D A vs. 2D	***3D P vs. 2D***	***3D A vs. 3D P***
Frontal	0.505	0.880	0.757
Central	0.106	0.348	0.560
Parietal	0.340	0.229	0.208
Temporal	0.003[a]	0.081	0.100
Occipital	0.006[a]	0.088	0.085

a. *P*-value < 0.05

TABLE II. CPEI *P*-Values

Brain Region	Comparison Groups		
	3D A vs. 2D	***3D P vs. 2D***	***3D A vs. 3D P***
Frontal	0.120	0.699	0.421
Central	0.552	0.281	0.548
Parietal	0.148	0.144	0.977
Temporal	0.423	0.486	0.936
Occipital	0.052[a]	0.378	0.076

a. *P*-value < 0.05

Acknowledgment

This work is supported by eScience Fund, Ministry of Science, Technology, and Innovation (MOSTI), Malaysia.

References

[1] ABC News, "'Avatar' Wins Box Office, Nears Domestic Record". Archived from the original on February 03 2010. http://abcnews.go.com/Entertainment/wireStory?id=9711561. [Accessed: December, 2012].

[2] Edwards, B. (2011). The History of Stereoscopic 3D Gaming. Retrieved December 30, 2012, available at: http://www.pcworld.com/article/220922/the_history_of_steroscopic_3d_gaming.html

[3] M.S. El-Nasr and Y. Su, " Visual attention in 3D video games". Paper presented at the 2006 ACM SIGCHI International Conference on Advances in Computer Entertainment Technology, New York, USA, 2006.

[4] J. Häkkinen, T. Kawai, J. Takatalo, R. Mitsuya, and G. Nyman, "What do people look at when they watch stereoscopic movies?" Paper presented at the Society of Photo-optical Instrumentation Engineers (SPIE), Electronic Imaging: Stereoscopic Displays and Applications XXI.

[5] A.R. Subhani, L. Xia, and A.S. Malik, "Association of Autonomic Nervous System and EEG Scalp Potential During Playing 2D Grand Turismo 5", 34th Annual International IEEE EMBS Conference, August 28 - September 1, 2012, San Diego, California, USA.

[6] A.S. Malik, D.A. Osman, A.A. Pauzi, and R.N.H.R. Khairuddin. "Investigating Brain Activation with respect to Playing Video Games on Large Screens", International Conference on Intelligent & Advanced Systems (ICIAS) 2012. pp.1067-1071, 12-14 June 2012.

[7] C.J. Stam, J.P.M. Pijn, P. Suffczynski, F.H. Lopes da Silva, "Dynamics of the human alpha rhythm: evidence for non-linearity?" *Clinical Neurophysiology*, 1999, 110:1801–13.

[8] W. Mumtaz, L. Xia, A.S. Malik, and M.A. Mohd Yasin, "Complexity Analysis of EEG Data during Rest State and Visual Stimulus" ICONIP 2012, Part I, LNCS 7663, pp. 84-91, Springer-Verlag Berlin Heidelberg, 2012

[9] S.-F. Liang, H.-C. Wang, and W.L. Chang, "Combination of EEG complexity and spectral analysis for epilepsy diagnosis and seizure detection". EURASIP *Journal of Advanced Signal Processing* 2010, Article 62 (February 2010), 15 pages.

[10] U.R. Acharya, S.V. Sree, P.C. Alvin Ang, R. Yanti, and J.S. Suri, "Application of Non-Linear and Wavelet Based Features for The Automated Identification Of Epileptic EEG Signals", *International Journal Of Neural Systems*, 22:02, 2012.

[11] D. Abásolo, R. Hornero, P. Espino, J. Poza, C.I. Sánchez, R. de la Rosa, "Analysis of regularity in the EEG background activity of Alzheimer's disease patients with Approximate Entropy", *Clinical Neurophysiology*, Volume 116, Issue 8, August 2005, Pages 1826-1834.

[12] Van Hese, P., Philips, W., De Koninck, J., Van de Walle, R., Lemahieu, I., "Automatic detection of sleep stages using the EEG", Engineering in Medicine and Biology Society, 2001. Proceedings of the 23rd Annual International Conference of the IEEE , vol.2, no., pp. 1944- 1947 vol.2, 2001.

[13] D. Li, Z. Liang, Y. Wang, S. Hagihira, J.W. Sleigh, and X. Li, "Parameter selection in permutation entropy for an electroencephalographic measure of isoflurane anesthetic drug effect", *Journal of Clinical Monitoring and Computing*, pp. 1-11, Springer Netherlands, 2012.

[14] E. Olofsen, J.W. Sleigh, and A. Dahan, "Permutation entropy of the electroencephalogram: a measure of anaesthetic drug effect" *British Journal of Anaesthesia* 101 (6): 810–21 (2008).

[15] B. Hjorth, EEG analysis based on time domain properties, Electroencephalography and Clinical Neurophysiology, Volume 29, Issue 3, September 1970, Pages 306-310

[16] B. Hjorth, "The physical significance of time domain descriptors in EEG analysis", *Electroencephalography and Clinical Neurophysiology*, Volume 34, Issue 3, March 1973, Pages 321-325.