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Method for Visualization and Analysis of EEG Pattern in Terms of Stereopsis Cognition

Daejune Ko[1], Min Woo Park[1] and *Eui Chul Lee[1]

[1]*Department of Computer Science, Sangmyung University, Seoul, Republic of Korea*
E-mail: {kodaejune, nogood79dle}@gmail.com, eclee@smu.ac.kr
**Corresponding author*

Abstract

In this paper, a method for measuring 3D cognitive load is proposed. For that, 8-channel EEG data when watching 2D and 3D displays are 2-dimensionally reduced using principal component analysis then the reduced features are visualized and compared. Consequently, we confirmed that the difference between two feature distributions of watching 2D and 3D at early stage was significant then the difference was reduced through watching time flow. The result can be analyzed that the cognitive load caused by 3D binocular visual combination at early stage and the adaptation of 3D watching time.

Keywords: *3D visual cognitive load, dimension reduction, visualization.*

1. Introduction

Recently, 3D display fields are rapidly grown. For example, numerous movies and animations are released and supplied through theater and IPTV. When people are watching the 3D display, they could feel cyber-sickness which cannot be felt in watching 2D display. For example, people could be often sense visual fatigue, disgust or dizziness during watching the 3D movies or animation. To quantitatively measure such cyber-sickness, researchers have been studied comparative physical reactions of the people when watching 2D and 3D display [1, 2].

In previous works, several researches have been performed by using image or signal based methods. Firstly, image based methods focused on measuring data which are an eye blink or a pupil size variation by using Near Infra-Red (NIR) image when watching 2D and 3D display [1, 3, 4]. By using NIR, images were captured with clear edge between a pupil and iris. However, because of the occlusion problems caused by head mounted device to capture eye images, interference against 3D perception can degrade the measured result of eye fatigue.

Secondly, signal based methods were used in which Central Nervous System (CNS) using ElectroEncephaloGram [5-7] (EEG) and Autonomic Nervous System [8] (ANS) signals could be considered [5-8]. Generally, EEG can be obtained from the pre-defined positions of the scalp based on the International 10-20 System. For Examples of ANS, SKin Temperature (SKT), Galvanic Skin Response (GSR), and ElectroCardioGraphy (ECG) are commonly used. Even though these signal based methods can measure biological responses of display viewers, they have several problems as follows: Firstly, people could be uncomfortable by attaching sensors on body. Especially, many electrodes attachment is a serious problem for measuring EEG signals based on the international 10-20 system. Secondly, the quality of obtained signal is not good because the signal is obtained from the skin although its source is in the body. Besides, the quality can be even more degraded in case of unnecessary motions of subject.

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All of the mentioned previous works focused on comparing difference of the amount of fatigues caused by watching 2D and 3D display. However, these researches were performed under the assumption that 3D caused more fatigue than 2D. Especially, EEG signal based research should be focused on the visual cognitive process rather than the fatigue.

Therefore, EEG temporal tendencies of watching 2D and 3D displays are visualized and analyzed in this paper. 8-channel EEG signals are 2-dimensionally visualized by dimension reduction using Principal Component Analysis (PCA). By comparatively analyzing the tendencies, the visual cognitive processes for watching 2D and 3D can be estimated.

2. Proposed Methods

In this experiment 30 subjects were participated. They had enough sleep and did not consume caffeine, alcohol and cigarettes in the 12 hours prior to the experiment. In this experiment, a 30-minute clip of a 3D enabled movie was used. For this experiment, the 30 subjects were randomly assigned into two groups that watched the 2D or 3D display respectively. As shown in Figure 2, when watching the display, subjects wore a device which could measure EEG signals and sat a comfortable chair at a 50 cm distance from the display.

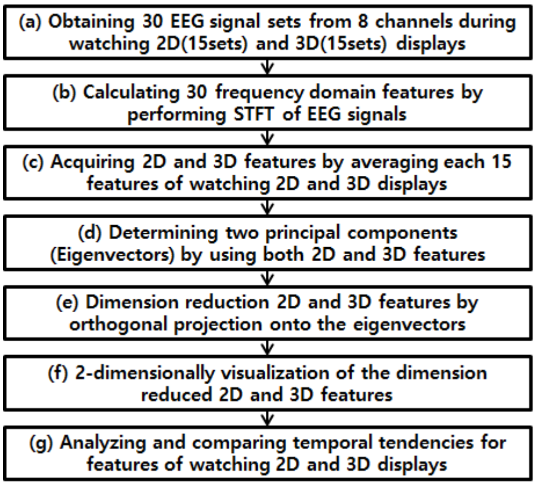

Figure 1. Procedure of Proposed Method

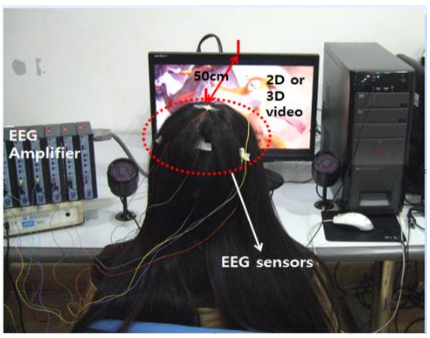

Figure 2. Experimental Setup

As shown in Figure 3, EEG signals were obtained from 8-channel (F_3, F_4, C_3, C_4, P_3, P_4, O_1, O_2) which are located as four positions per the left and right hemispheres, respectively. The positions were consisted of frontal lobe, central position, parietal lobe, and occipital lobe. The functionality of each position was shown in Table 1 [9].

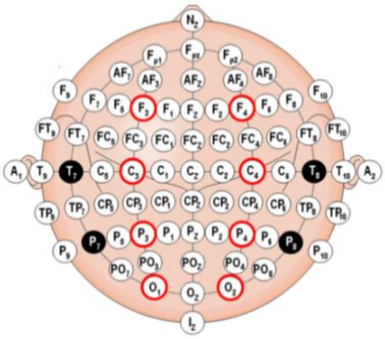

Figure 3. EEG Electrodes Attaching Positions by International 10-20 System [5] and Actually Attached Positions (Red Circles) in this Research

Table 1. EEG Acquisition Positions and Their Functions [9]

Name	Function
frontal lobe	mathematical, logical
central position	center region of the cerebral
parietal lobe	body movement, spatial Information
occipital lobe	visual processing

Obtained EEG temporal signals were transformed into frequency domain by performing Short Time Fourier Transform (STFT) at every 1 second region. After that, the total amount of magnitude at beta bandwidth (14~30Hz) was calculated as feature which generally means human state of tension or concentration. Consequently, 1,800 (sec) × 8 (channels) features of each subject can be obtained as shown in Table 2.

Table 2. Obtained Signals Set

	F_3	F_4	C_3	C_4	P_3	P_4	O_1	O_2
~ 1 sec	2.857	3.581	0.353	1.019	3.243	3.898	1.401	0.925
~ 2 sec	2.066	2.061	0.379	0.620	3.779	3.794	0.690	0.605
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
~ 1799 sec	0.957	1.169	0.220	0.249	3.388	4.287	0.617	0.986
~ 1800 sec	1.226	1.683	0.246	0.237	3.010	3.857	0.716	0.897

As shown in Figure 1, our method has seven procedures. Procedure (d) says “using both 2D and 3D features”. If 2D signals and 3D signals are visualized on different space, to compare between two visualized signals is not meaningful. Therefore to compare between two visualized signals, EEG signals were visualized on same space when watching 2D and 3D display. So signal sets of two groups were combined as 3600sec × 8-channel. To obtain EV_n and ev_n, channels of combined signals were represented like vector, as Eq. (1), for principal component analysis (PCA) [10, 11].

$$A_i = [a_i(1), a_i(2), \cdots, a_i(n)] \quad (1 \leq i \leq 8, n = 3600) \quad (1)$$

As shown in Eq. (3), average is obtained as Eq. (2) by using channel vectors to calculate covariance value.

$$\overline{A_i} = \frac{1}{n}\sum_{k=1}^{n} a_i(k) \; (1 \leq i \leq 8, \; n = 3600) \quad (2)$$

The covariance value was calculated by two channels vectors as Eq. (3).

$$cov(A_i, A_j) = \frac{1}{n-1}\sum_{k=1}^{n}\left(a_i(k) - \overline{A_i}\right)\left(a_j(k) - \overline{A_j}\right) \; (1 \leq i,j \leq 8, \; n = 3600) \quad (3)$$

Covariance matrix is represented by covariance values which were calculated by 8-channel vectors as Eq. (4).

$$covM = \begin{pmatrix} cov(F_3, F_3) & \cdots & cov(F_3, O_2) \\ \vdots & \ddots & \vdots \\ cov(O_2, F_3) & \cdots & cov(O_2, O_2) \end{pmatrix} \; (\text{Order}, \; F_3, F_4, C_3, C_4, P_3, P_4, O_1, O_2) \quad (4)$$

EV_n and ev_n are calculated by satisfying Eq. (5).

$$covM \cdot EV_n = ev_n \cdot EV_n \ \ (EV_n = [x_1, x_2, \cdots, x_n]) \ (1 \le n \le 8) \quad (5)$$

New data set (x, y) are calculated by Eq. (6) in every 1sec. In this case, θ_A is an angle between EV_7 and signal set of n sec, θ_B is an angle between EV_8 and signal set of n sec. ($1 \le n \le 1800$)

$$(x_i, y_i) = \begin{pmatrix} ||(a_1(i), \cdots, a_8(i))|| \cos\theta_A, \\ ||(a_1(i), \cdots, a_8(i))|| \cos\theta_B \end{pmatrix} \ \ (1 \le i \le 1800) \quad (6)$$

As above mentioned PCA and visualization, visualized signals were represented as Figure 4.

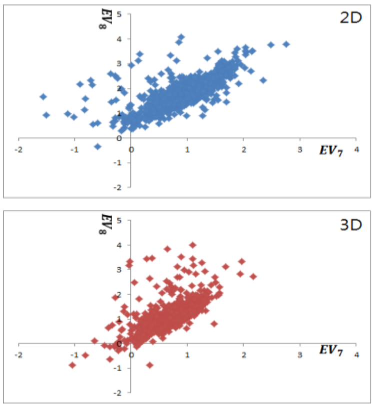

Figure 4. Examples of Visualized Feature Distributions about Watching 2D and 3D Displays

3. Result and Discussion

Table 3 shows the obtained eigenvalues (ev_n) and their corresponding eigenvectors (EV_n) which was calculated by performing PCA of 8-channel features at frequency bands. In here, all features of watching both 2D and 3D were used in order to obtain non-biased eigenvectors against 2D or 3D features. Among the obtained 8 eigenvectors, only two eigenvectors should be selected as axes for dimension reduction. Because the 8 eigenvalues and their corresponding eigenvectors were obtained from the 8×8 covariance matrix as Eq. (4), the calculated eigenvalue mean variance of the dimension reduced features onto the corresponding eigenvector. After orthogonal projection of features onto an eigenvector, the greater variance means features' well representation because the distance between two dimension reduced features is greater. Therefore, two eigenvectors having the greatest eigenvalues such as EV_7 and EV_8 were selected for visualization of EEG features.

Table 3. 8 Eigenvalues and Corresponding Eigenvectors by Using Combined Signals

n	ev_n	EV_n							
		F_3	F_4	C_3	C_4	P_3	P_4	O_1	O_2
1	0.121	0.016	-0.080	0.082	0.070	0.750	-0.273	-0.334	-0.483
2	0.077	-0.009	-0.041	-0.203	-0.098	-0.617	-0.348	-0.294	-0.600
3	0.101	-0.995	0.058	0.068	0.027	0.003	0.007	-0.022	-0.012
4	0.120	0.060	0.986	-0.015	0.030	0.025	-0.039	-0.147	0.001
5	0.1432	-0.046	-0.057	-0.417	-0.643	0.126	-0.172	-0.422	0.428
6	0.265	0.033	-0.097	0.349	0.480	-0.166	-0.408	-0.487	0.455
7	1.228	0.046	-0.016	0.663	-0.408	-0.116	0.466	-0.384	-0.120
8	1.345	-0.009	-0.064	-0.461	0.418	-0.002	0.625	-0.466	-0.040

EEG signals were visualized on every 10mins for analyzing detail. As shown in Figure 5 (b) and (c), visualized signals were not represented difference. Also generally, fatigue is defined by the reaction which is felt by long-term experiments in body. As shown in Figure 5 (a) to (c), visualized 2D signals and 3D signals are getting more similar as time goes on. As a result, the factors that caused fatigue were almost similar when watching both 2D and 3D display. However, the difference was represented by two groups as shown in Figure 5 (a). Visualized signals were concentrated in watching 3D display more than watching 2D display. In the other words, EEG signals by stimulation of 3D display than 2D display are focused on a specific position at the beginning of watching. As a result, a special stimulus was found by watching the 3D display.

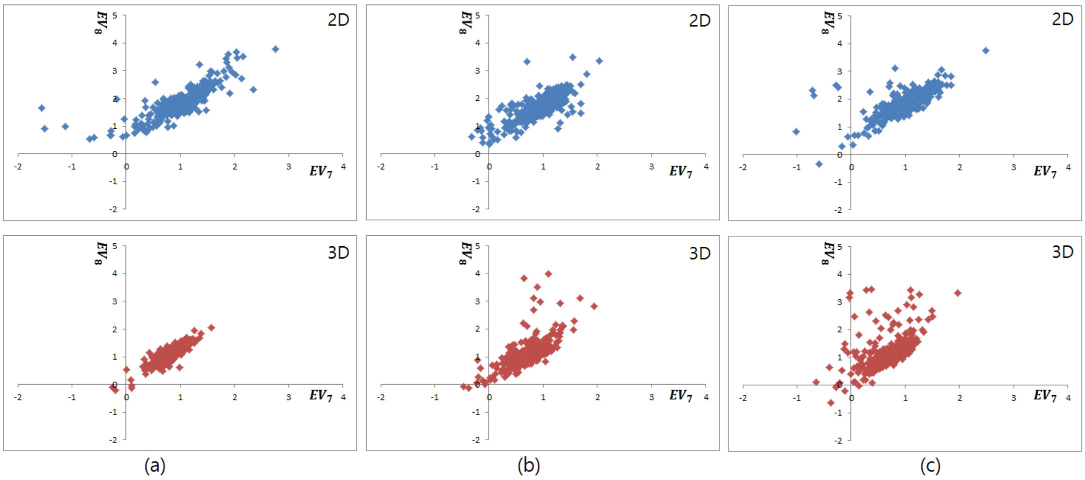

Figure 5. Visualized Feature Distributions about Watching 2D and 3D Displays in Every 10mins. (a) 0~10mins. (b) 10~20mins, (c) 20~30min

Angles between unit axes and *EV* were obtained for finding visual position of *EV*. The unit axes are consisted of as Eq. (7) (Order, F_3, F_4, C_3, C_4, P_3, P_4, O_1, O_2). The angles were obtained by using Eq. (8). In Eq. (8), *EV*·(unit axis) means inner product between *EV* and unit axis. ‖EV‖ and ‖(unit axis)‖ mean the size of vector respectively. $cos^{-1}\theta$ means arccosine.

$$F_3 = (1,0,0,0,0,0,0,0) \ \cdots \ O_2 = (0,0,0,0,0,0,0,1) \quad (7)$$

$$angle = cos^{-1}\frac{EV\cdot(\text{unit axis})}{\|EV\|\|(\text{unit axis})\|} \quad (8)$$

By using Eq. (7) and (8), results were obtained as shown in Table 5. To find more meaningful position, the smallest and next angles were represented with Bold and Underline text type in EV_7 and EV_8, respectively.

Table 5. Angle between Two EV and Unit axes Bold: smallest, Underline: Next

	F_3	F_4	C_3	C_4	P_3	P_4	O_3	O_4
EV_7	87.37	90.92	**48.50**	114.06	96.64	<u>62.22</u>	112.58	96.89
EV_8	90.51	93.68	117.43	<u>65.30</u>	90.09	**51.35**	117.79	92.28

Based on Bold and Underline in Table 5, expected point is the bright yellow in triangle of Figure 6. If EEG signals were obtained by 1-channel, it can be said that this position is most similar with information obtained from 8-channel signals.

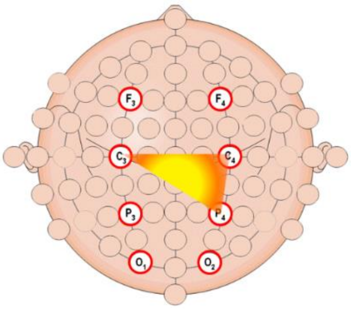

Figure 6. Visualized Position by Using Table 5 in International 10-20 System

4. Conclusions

In this paper, the difference of visualized signals was analyzed by using EEG when watching 2D and 3D display. In here, visualized signals were represented by using dimensional reduction (PCA) from 8-channel of EEG. For the result, several contribution points were represented by visualized signals as follows. Firstly, the factors that caused fatigue were almost similar as times go on. Secondly, EEG signals by stimulation of 3D display than 2D display are focused on a specific position in 0~10mins. Additionally, we referred specific position of replaceable 8-channel signals. In the future work, we will compare relationship between the position obtained by Table 5 and visualized signals.

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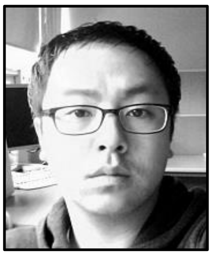
References

[1] E. C. Lee, H. Heo and K. R. Park, “Consumer Electronice”, IEEE Transactions, vol. 56, no. 3, **(2010)**.
[2] Y. J. Kim and E. C. Lee, Communications in Computer and Information Science, vol. 174, **(2011)**.
[3] E. C. Lee, K. R. Park, M. Whang and K. Min, Industrial Ergonomics, vol. 39, no. 5, **(2009)**.
[4] E. C. Lee, J. W. Lee and K. R. Park, investigative ophthalmology & visual science, vol. 52, **(2011)**.
[5] M. Jaakko and P. Robert, “Bio-electro magnetism”, Oxford University Press, United Kingdom, **(1955)**.
[6] S. Park, “Master of Thesis”, Sangmyung University, **(2013)**.
[7] S. Kim, “Master of Thesis”, Seoul National University of Science and Technology, **(2011)**.
[8] C. J. Kim, S. Park, M. J Won and M, Whang, Communication Sensors, vol. 13, **(2013)**.
[9] S. Lauralee, “In Human Physiology”, life science, Seoul, **(2011)**.
[10] C. M. Bruce, “Automatic Control”, IEEE Transactions, vol. 26, no. 1, **(1981)**.
[11] K. J. Friston, C. D. Frith, P. F. Liddle and R. S. J. Frackowiak, “Cerebral Blood Flow and Metabolism”, vol. 13, **(1993)**.

Authors

Daejune Ko, received a BS and MS degrees in the Department of Computer Science from Sangmyung University, Seoul, South Korea in 2013 and 2015, respectively. Currently, he has been Ph.D. course student in the Department of Computer Science in Sangmyung University since March 2015. His research interests include Pattern Recognition, Forgery Detection, OCR, 3D Computer Vision for Natural User Interface, and Biosignal Analysis.

Min Woo Park, received a BS and MS degrees in the Department of Computer Science from Sangmyung University, Seoul, South Korea in 2012 and 2014, respectively. Currently, he has been Ph.D. course student in the Department of Computer Science in Sangmyung University since September 2014. His research interests include Pattern Recognition, Data Mining, Image Analysis, and Biosignal Analysis.



Eui Chul Lee, received a BS degree in Software from Sangmyung University, Seoul, South Korea in 2005. He received MS and Ph.D. degrees in Computer Science from Sangmyung University in 2007 and 2010, respectively. He was Researcher in Division of Fusion and Convergence of Mathematical Sciences at the National Institute for Mathematical Sciences from March 2010 to February 2012. Since March 2012, he has been Assistant Professor in the Department of Computer Science from Sangmyung University, Seoul, South Korea. His research interests include Computer Vision, Image Processing, Pattern Recognition, Brain Computer Interface (BCI), and Human Computer Interface (HCI).