Driver Drowsiness Detection Using EEG Features

Se-Hyeon Hwang[1], Myoungouk Park[1], Jonghwa Kim[2], Yongwon Yun[2], and Joonwoo Son[1](✉)

[1] DGIST (Daegu Gyeongbuk Institute Science and Technology), Daegu 42988, Republic of Korea
json@dgist.ac.kr
[2] KATRI (Korea Automobile Testing & Research Institute), Hwaseong-si 18247, Republic of Korea

Abstract. The objective of this paper is to discover the EEG (Electroencephalogram) features that expressed meaningful changes during drowsy driving state compared to the normal driving. For this purpose, 8 healthy male and female participants were recruited to conduct drowsy driving experiment in a fixed-base driving simulator, which reproduced the inside of the actual vehicle. The experimental scenario was driving a 37 km straight highway without any obstacles. The data obtained through this experiment were analyzed using brain wave analysis software. As a result, we found that the alpha RMS (Root mean square) and differentiated alpha RMS waves showed meaningful changes during drowsiness state compared to normal state. In addition, we suggested new brain activity index, which was composed of four brain waves that are alpha, beta, theta and delta, to amplify meaningful change in transition from normal state to drowsiness.

The statistical significances of the selected EEG features were tested using One-way ANOVA (Analysis of variance). The result indicated that all three EEG features showed statistical significance ($p < 0.005$). In conclusion, this paper suggested EEG features which have high accuracy for drowsiness detection. Currently, EEG measurement equipment such as dry type and non-contact type is actively developed. Therefore, it is expected that the drowsiness prevention system using the EEG features will be available in the near future.

Keywords: Drowsy driving · EEG (Electroencephalogram) Brain activity index · Drowsiness detection

1 Introduction

1.1 A Subsection Sample

The SHRP 2 NDS (Second Strategic Highway Research Program Naturalistic Driving Study) survey to determine the prevalence of driver drowsiness before the crash showed that drowsiness driving is far more dangerous than our perception [7]. Currently, drowsiness driving detection is performed using various factors such as EEG,

C. Stephanidis (Ed.): HCII Posters 2018, CCIS 852, pp. 367–374, 2018.
https://doi.org/10.1007/978-3-319-92285-0_49

EOG (Electrooculography), PERCLOS (Percentage closure of eyes) and so on. The EEG-based studies uses the ratios of EEG slow and high frequency bands, VSWs (Vertex Sharp Waves), and the changes of alpha wave to detect drowsiness [8, 15]. However, EEG has a disadvantage that is difficult to accurately detect drowsiness because there is a large difference between individuals.

This study suggests EEG features that can be used to detect drowsiness for any drivers using Z-score values of EEG features. Furthermore, these factors have the possibility that can be made into a real-time model because the state of driver can be calculated in 100 ms interval. In addition, the ANOVA result shows significant difference for the three EEG features.

2 Method

2.1 Apparatus

Figure 1 showed the fixed-base driving simulator used in the research. The device consisted of a DLP (Data loss prevention) projector, a screen, a control PC, and a simulator vehicle that reproduced the interior of Hyundai Genesis's interior. The driving simulation software was STISIM Drive of Systems Technology, Inc. of USA.

Fig. 1. Fixed-based driving simulator

2.2 Data Collection

B-ALERT X10 [1] was used as a device to measure the EEG data of participants. The EEG data was collected by attaching electrodes to 9 positions, i.e. POz, Fz, Cz, C3, C4, F3, F4, P3, P4 according to 10–20 system. We used decontaminated signals window that eliminates five disturbance factors caused by EMG, eye blinks, excursions, saturations, and spikes. To analyze the measured EEG data, BIOPAC AcqKnowledge 5.0 Software was used [5]. The EEG frequency bands were set to 0.5–4 Hz for delta wave, 4–8 Hz for theta wave, 8–13 Hz for alpha wave, 13–30 Hz for beta wave, and 36–44 Hz for gamma wave.

2.3 Experiment Procedure

The experiment procedure was designed so that the participants visited twice. On the first day, the participants were checked about the eligibility and wrote consent of the experiment. On the second day, we checked the compliance and conducted the drowsy driving experiment twice. During the experiment, the face of participant was logged as shown in Fig. 2. Then, the time when the participant's drowsiness was marked based on the predefined drowsiness state (Table 1) through manual video inspection. Table 1 shows the criteria for judging the status of participants. The criteria were developed based on the Karolinska sleepiness scale (KSS) [2].

Fig. 2. Face image of participant

Table 1. Table captions should be placed above the tables.

State	Drowsiness pattern
Awakening state (0)	Eye blinking was relatively constant and stable driving
Initial drowsiness state (1)	Eye blinking was slower than arousal and the eyelids were closed and did not open for more than 2 s
Drowsiness state (2)	If the driver lost the center of gravity of the head, If the accident was occurred, If the eyelids were closed and did not open for more than 3 s

2.4 Data Collection

Based on the previous study [6], the values of alpha, delta, alpha RMS(or A RMS, it is windowed root mean square value of the signal using a window width of 0.25 s) wave were obtained by averaging waves measured from POz, Fz, and Cz. Theta wave was obtained by averaging waves measured from POz and Fz. Beta wave was measured from POz.

2.5 Data Reduction

We extracted 240 s length of each EEG data. Each data was extracted between 10 s before the beginning of drowsiness period and 10 s after the end of drowsiness period and included all drowsiness periods. All data were normalized by converting the data into Z-score values and reduced by averaging the data values at every interval of 100 ms for ANOVA test.

3 Results

3.1 Simulated Driving Experiment

Fourteen experimental data were obtained from 8 participants. One participant's data was seriously contaminated by movement artifact, e.g., he had heavy arm movements during the experiment and moved his head very severely at the drowsiness state. Therefore, the data was removed from the analysis. Finally, we used 13 data from 7 participants in the study.

3.2 EEG Feature Selection

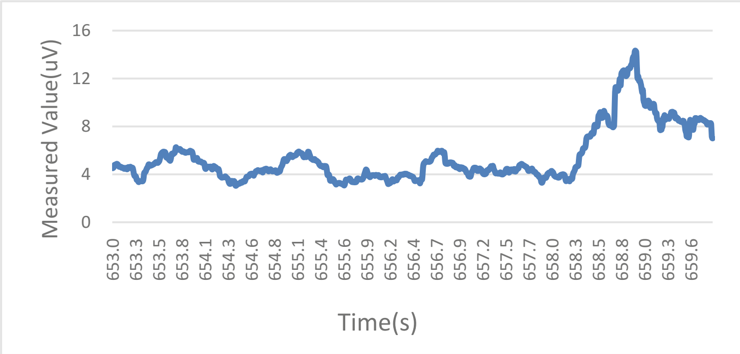
In this study, we suggested three EEG features for drowsiness driving detection. The first EEG feature was A RMS. Based on the previous studies [4, 12] that showed the relationship between RMS and human state, we used A RMS as a drowsiness detection factor. Figure 3(a) shows that the value of A RMS increased dramatically at the drowsy state.

The second EEG feature was the value of differentiated A RMS that is called dA RMS. It was devised in view of the sudden increase in the value of A RMS at the drowsy state. Figure 3(b) showed that the average value of dA RMS at the drowsiness state was generally lower than the average value at the normal state even if there were several sudden sharp rises at the drowsy state.

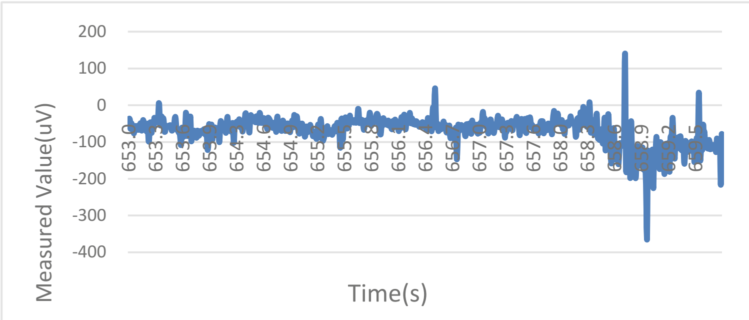
The third EEG feature was the most emphasized function expression in the paper. It is called the BAI (Brain activity index). Equation (1) represented the expression of BAI.

$$\mathrm{BAI} = \left| \left(\frac{dAlpha\,value}{dt} + \frac{dTheta\,value}{dt} \right) * \frac{dDelta\,value}{dt} - \frac{dBeta\,value}{dt} \right| \quad (1)$$

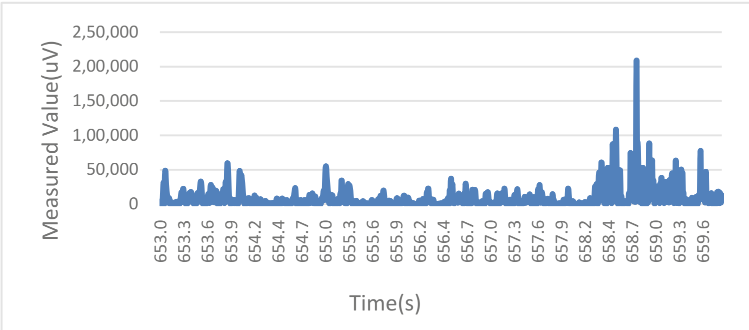
Based on the previous study [3], BAI used the differential values of the four bands of alpha, theta, delta and beta of the EEG. In addition, based on the other studies [6, 9, 14], we summed the differential values of alpha and theta waves and then multiplied by differential value of delta wave, and subtracted the differential value of beta wave. The BAI had large values at the drowsiness state as shown in Fig. 3(c).



(a) A RMS at drowsy state



(b) dA RMS at drowsy state

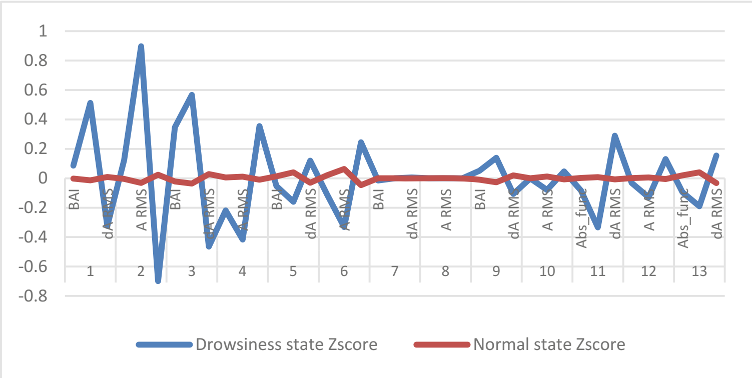


(c) BAI at drowsy state

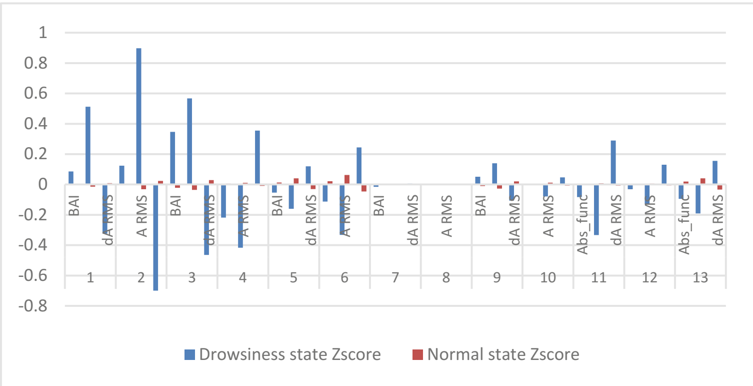
Fig. 3. EEG features at the drowsy state of the same participant (In these graphs, it entered the drowsiness state at around 658 s)

3.3 The Difference Between Normal and Drowsy States

Figure 4 showed that the absolute values of all the mean Z-score values of EEG features at the drowsy state were larger than at the normal state. After taking all the values as absolute values, we performed One-way ANOVA using each EEG feature and state as input values. As shown in Table 2, the normalized values of EEG features between normal and drowsy states were significantly different.



(a) Linear graph of EEG Features



(b) Vertical Bar graph of EEG Features

Fig. 4. Graphs of mean values at the two states of each EEG feature

Table 2. ANOVA test result.

EEG feature	d.f.	F-value	P-value
BAI	1	11.0126	0.0031
A RMS	1	15.4335	0.0007
dA RMS	1	15.8506	0.0006

4 Discussion and Conclusion

The signs of the mean Z-score values of BAI and A RMS at the drowsy state were the same in all data. In four data BAI and A RMS had positive signs, but in the others BAI and A RMS had negative signs. By comparing the results with the previous studies [10, 11, 13], we confirmed that there is no problem even if BAI and A RMS have any sign. Therefore, the EEG features of this paper can be used to detect drowsiness for any drivers.

In the paper, only three of the EEG channels, i.e. Cz, Fz and POz were used, since the contaminations were severe in other channels. We performed a limited EEG analysis using a small number of EEG channels. Above all, the Z-score values of the EEG features were used in this paper, so it cannot be used for actual driving immediately. Therefore, it is a future work to develop a tool to measure EEG data without the driver feeling uncomfortable and collects EEG data which is not contaminated by movement artifacts.

Despite the limitation, the proposed EEG-based drowsiness detection model that has simple calculation process just using three EEG features and can be a real-time model because calculates the data in 0.1 s increments will be a promising approach in the near future.

Acknowledgements. This work was supported in part by a grant (code 18TLRP-B131486-02) from Transportation and Logistics R&D Program funded by Ministry of Land, Infrastructure and Transport of Korean government, and by DGIST R&D Program (18-BT-01) of the Ministry of Science and ICT of Korean government.

References

1. Advanced Brain Monitoring. http://www.advancedbrainmonitoring.com/xseries/x10/. Accessed 16 Mar 2018
2. Åkerstedt, T., Gillberg, M.: Subjective and objective sleepiness in the active individual. Int. J. Neurosci. **52**(1–2), 29–37 (1990)
3. Antoniol, G., Tonella, P.: EEG data compression techniques. IEEE Trans. Biomed. Eng. **44** (2), 105–114 (1997)
4. Bernstein, A.S., Riedel, J.A.: Psychophysiological response patterns in college students with high physical anhedonia: Scores appear to reflect schizotypy rather than depression. Biol. Psychiatry **22**(7), 829–847 (1987)
5. BIOPAC Systems, Inc. https://www.biopac.com/manual/acqknowledge-5-software-guide/. Accessed 16 Mar 2018
6. Borghini, G., Astolfi, L., Vecchiato, G., Mattia, D., Babiloni, F.: Measuring neurophysiological signals in aircraft pilots and car drivers for the assessment of mental workload, fatigue and drowsiness. Neurosci. Biobehav. Rev. **44**, 58–75 (2014)
7. Dingus, T.A., Hankey, J.M., Antin, J.F., Lee, S.E., Eichelberger, L., Stulce, K.E., McGraw, D., Perez, M., Stowe, L.: Naturalistic driving study: technical coordination and quality control (No. SHRP 2 Report S2-S06-RW-1) (2015)
8. Eoh, H.J., Chung, M.K., Kim, S.H.: Electroencephalographic study of drowsiness in simulated driving with sleep deprivation. Int. J. Ind. Ergonomics **35**(4), 307–320 (2005)

9. Jarrett, D.B., Greenhouse, J.B., Miewald, J.M., Fedorka, I.B., Kupfer, D.J.: A reexamination of the relationship between growth hormone secretion and slow wave sleep using delta wave analysis. Biol. Psychiatry **27**(5), 497–509 (1990)
10. Lal, S.K., Craig, A.: Driver fatigue: psychophysiological effects. In: 4th International Conference on Fatigue and Transportation, Fremantle, Western Australia (2000)
11. Lal, S.K., Craig, A.: A critical review of the psychophysiology of driver fatigue. Biol. Psychol. **55**(3), 173–194 (2001)
12. Mak, J.N., McFarland, D.J., Vaughan, T.M., McCane, L.M., Tsui, P.Z., Zeitlin, D.J., Sellers, E.W., Wolpaw, J.R.: EEG correlates of P300-based brain–computer interface (BCI) performance in people with amyotrophic lateral sclerosis. J. Neural Eng. **9**(2) (2012)
13. Santamaria, J., Chiappa, K.H.: The EEG of drowsiness in normal adults. J. Clinical Neurophysiol. **4**(4), 327–382 (1987)
14. Visu, P., Varunkumar, K.A., Srinivasan, R., Kumar, R.V.: Brainwave based accident avoidance system for drowsy drivers. Indian J. Sci. Technol. **9**(3) (2016)
15. Yeo, M.V., Li, X., Wilder-Smith, E.P.: Characteristic EEG differences between voluntary recumbent sleep onset in bed and involuntary sleep onset in a driving simulator. Clin. Neurophysiol. **118**(6), 1315–1323 (2007)