Mobile-based Wearable-Type of Driver Fatigue Detection by GSR and EMG

Lee Boon-Leng
Department of Electronic Engineering
Pukyong National University
Busan, South Korea
boringdragonlee@hotmail.com

Lee Dae-Seok
IoT Research Center,
N.EX.T
Busan, South Korea
leezzang@gmail.com

Lee Boon-Giin
Department of Electronic Engineering
Keimyung University
Daegu, South Korea
bglee@kmu.ac.kr

***Abstract*—Driver fatigue had been a major reason that leads to road accidents. This paper focuses on investigating the usage of electromyography and galvanic skin response to detect the driver fatigue symptoms. The study reveals that the variation of EMG signal patterns can be mapped to simulate the driving behavior. In the study, five attachment positions of EMG sensors are observed to indicate the best position of the mapping for wheel steering control behavior. Hereby, the study also reveals that the changing variations of EMGs in frequency-domain are excellent and significant fatigue indicator than the usual time-domain features. On the other hand, existing systems only focused on analyzing the signal pattern of GSR, but not the variation of GSR in accordance to frequency analysis, which is one of our main objectives study. The sensed EMGs and GSRs are transmitted to the mobile device via Bluetooth Low Energy. The analysis takes part in mobile device with implemented fatigue monitoring application. If the developed classifier indicates the driver vigilance level dropped to dangerous pre-defined threshold, a vibration warning will be triggered to alert the driver. In fact, the experiment results revealed that the significant differences in EMG and GSR features are managed to determine the driver fatigue in five seconds interval. The developed SVM classifier of mobile application shows average of 92% fatigue detection accuracy rate.**

Keywords—electromyography; galvanic skin response; fatigue; frequency-domain; mobile

I. Introduction

Road accidents had become a critical issue in the society that caused human life in recent decade. Fatigue or drowsiness, is one of the major factors that affects the drivers, resulting in reduced awareness as well as reaction time [1]. This situation directly reduced the driving aptitude of drivers. Therefore, methods or ways of detecting the driver low awareness are necessary to reduce the tragedies.

There are numerous methods to detect the driver drowsiness either from the driver physiological status, facial features or driving behavior [2-5]. Szypulska et al. [6] used LF/HF ratio in HRV analysis extracted from ECG to determine the sleep syndromes whereas Li et al. [7] performs the similar analysis that categorize the frequency bands into VLF, LF and HF based on PPG signals. On the other hand, Du et al. [8] utilized the time sequence energy from eye opening and size of the pupil region to predict the driver drowsiness. Meanwhile, Friedrichs et al. [9] extracted features from the steering and lane data under real driving conditions to indicate the driver drowsiness level.

Nevertheless, other measurements such as GSR and EMG can be observed to determine a driver condition in real-time as illustrated in [10-11]. However, those studies are only concentrated on the driver stress pattern rather than the specific fatigue behavioral changes. Therefore, in thus paper, we are focusing on developing a mobile wearable-type vigilance monitoring system based on GSRs and EMGs features to derive the driver fatigue status.

II. Methods

A. Experiment Setup

Fig. 1 illustrates the design of the wearable device which includes a EMG circuit board and a GSR circuit board that are connected to a Lilypad Arduino [12], powered by a 3.3V lithium battery. The received EMG and GSR signals are further transmitted to a LG G smartwatch [13] via a Bluetooth 4.0 Low Energy (BLE) [14]. The sensors readings are recorded at 64-Hz sampling rate.

Experiment test subjects are recruited from the department students with total of 6 healthy subjects with no sleeping disorders, sleep apnea or other sleep related illness. The test subjects consisted of 4 male students and 2 female students aging from 21 to 32 years old. Each test subject evaluated his/her own level of fatigue based on a commonly used Karolinska Sleepiness Scale (KSS) in every 3 minutes. Also, a voluntary physician aided in this experiment as a third party observer to evaluate the driver fatigue level, as references to

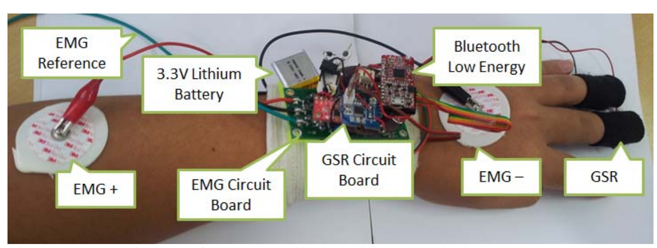


Fig. 1. Wearable-type fatigue prediction device includes a GSR, and a EMG circuit board connected to a Lilypad Arduino, that is able to transmit the sensing data to a smartwatch device via Bluetooth low energy (BLE).

This research was supported by the Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education (2014R1A1A2059406).
978-1-4799-8641-5/15/$31.00©2015 IEEE

correlate with the KSS. Surveys are filled up by the test subjects before and after the experiments which include their personal views, suggestions and comments of the conducted experiments.

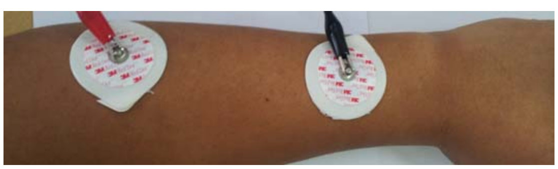
As mentioned above, the placements of EMG sensors are one of the major objectives in this study to investigate the most relevant position to stimulate the driver driving aptitude. Thus, five distinct EMG sensors placement are considered as depicted in Fig. 2. The sensors are primarily placed close to the lower part of the hand, as they are more prone to the responses while operating on the steering wheel.

B. Signal Processing

The received sensing data, EMG and GSR are first filtered with a median filter with cutoff frequency of 50-Hz to remove the power noise. Features are extracted from the GSR and EMG sensors in both time- and frequency-domain. Table I illustrates the extracted features serve as training dataset to Support Vector Machine (SVM) classifier. The SVM is trained with Matlab processing toolbox in desktop PC. The support vectors of the trained SVM model are further implemented in the mobile-based application for vigilance prediction. The complexity of the trained SVM model increases as the increment on the number of support vectors. Therefore, to reduce the complexity of trained SVM model in low-processing mobile device, only significant support vectors are utilized.

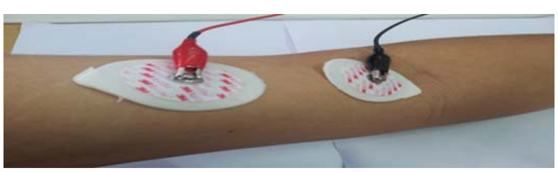
(a)

(b)



(c)

(d)



(e)

Fig. 2. Different placements of EMG sensors on the lower part of the hand close to the fingers which are denoted as (a) P1, (b) P2, (c) P3, (d), P4, and (e) P5 respectively.

TABLE I
FEATURES EXTRACTED FROM GSR AND EMG

Features	Description
EMG_MN / GSR_MN	Mean of EMG and GSR
EMG_VR / GSR_VR	Variance of EMG and GSR
EMG_KR / GSR_KR	Kurtosis of EMG and GSR
EMG_SK / GSR_SK	Skewness of EMG and GSR
EMG_PF / GSR_PF	Peak Frequency of EMG and GSR
EMG_MF / GSR_MF	Mean Frequency of EMG and GSR
EMG_MD / GSR_MD	Median Frequency of EMG and GSR
EMG_LF / GSR_LF	Low Frequency of EMG and GSR
EMG_HF / GSR_HF	High Frequency of EMG and GSR
EMG_LH / GSR_LH	Low/High Frequency of EMG and GSR

III. RESULTS AND DISCUSSION

First of all, the EMG signals that stimulate the gripping force of the steering wheel is analyzed based on their power spectrum distribution extracted with wavelet packet transform (WPT) method [15]. Fig. 3 illustrates the normalized power spectral density (PSD) of GSR signals for awake and fatigue patterns where the red line denotes the "drowsy" normalized PSD and green line denotes the "awake" normalized PSD. It is observed that GSR have the peak power spectrum in low frequency band (0 ~ 0.08 Hz) during awake. In contrast, it exhibits peak frequency at high frequency band (0.08 ~ 0.5 Hz) when driver fatigue is increased.

On the other hand, Fig. 4 described the normalized power spectral density for EMGs with five different electrodes positioning. It is found that the position P1 (Fig. 4(a)) and P4 (Fig. 4(d)) show large significant discrimination for power spectral distribution. Accordingly, P1 during "drowsy" state exhibits higher average spectrum at high frequency range than during the "awake" state. Meanwhile, P4 demonstrates distinct frequency peaks which "awake" state exhibits peak frequency at low frequency band whereas "drowsy" state exhibits peak frequency at high frequency band. Position P3 (Fig. 4(c)) also displays high peak frequency near to 1-Hz for drowsy state.

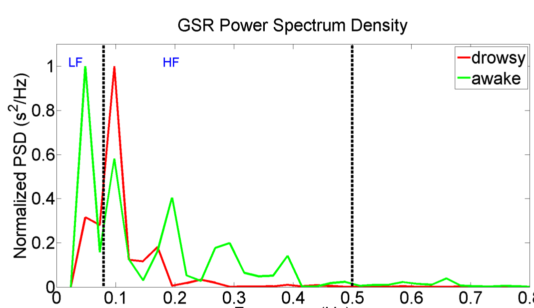


Fig. 3. GSR power spectrum indicated two different power spectral density distributions for drowsy and awake state.

Meanwhile, P2 (Fig. 4(b)) and P5 (Fig. 4(e)) do not show high significant differences in power spectrum distribution for "awake" and "drowsy" state. It is clear that as the electrodes placed close to palm and fingers, it is more clearly to signify the steering wheel operation rather than placing the electrodes at the bicep as shown in Fig. 2(e). Therefore, the further analyses are only focused on the positions from P1 to P4 for EMGs signals.

Next, features are extracted from both "awake" and "drowsy" state for GSR and EMG at P1 and P4. Those features are further trained with SVM classifier. The dataset is divided into training set (70%) and testing set (30%). The trained SVM model is then developed in the smartwatch application. The reliability of the trained SVM classifier is further tested with the testing set. Fig. 5 shows the precision rate for each subject where subjects 1 and 6 are female test subjects. From the testing results, the female test subjects EMGs signals showed least significant differences compare to the male test subjects. On the other hand, test subject 3 who has been involved in the muscle training for at least five times per week has higher precision rate than the rest of the test subjects. This is due to the more active muscular activities of subject 3 that indirectly exhibit higher variation in the obtained EMG signals. On the other hand, test subjects 2, 4 and 5 also show satisfactory test results over 90% precision rate. Lastly, Fig. 6 shows the screenshots of smartwatch application plotting the EMG and GSR signals received from the wearable smartwatch device via BLE. The application will trigger the vibration and information display warnings to the driver if the trained SVM classifier signifies the probability of driver fatigue is dropped under a dangerous threshold.

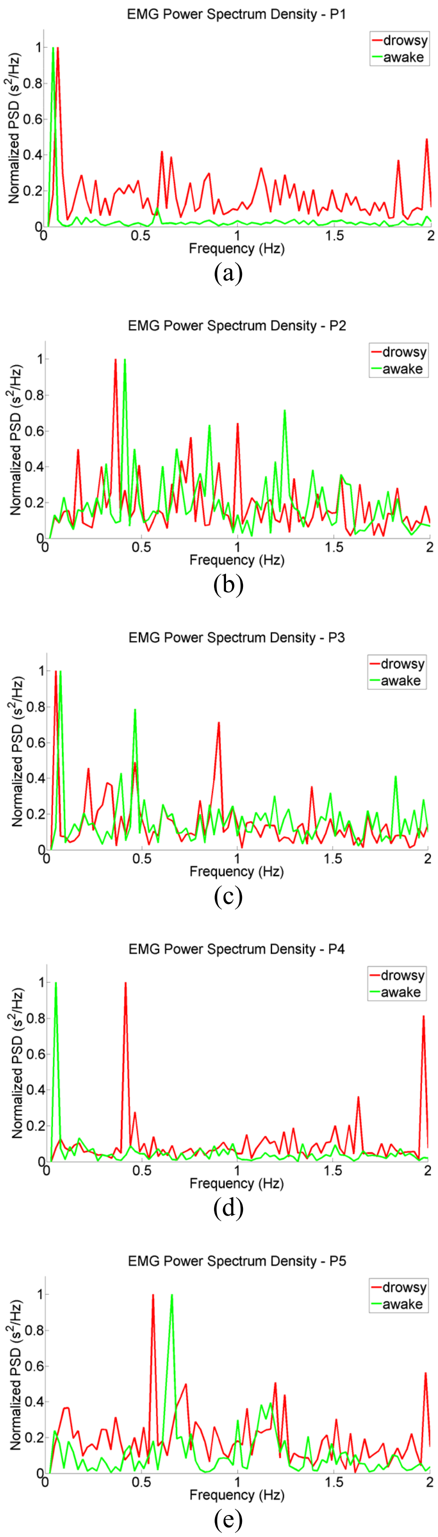


Fig. 4. EMG power spectrum indicated two different power spectral density distributions for drowsy and awake state at different positions (a) P1, (b) P2, (c) P3, (d) P4, and (e) P5.

IV. Conclusion

In this paper, a wearable device has been implemented to study the driver fatigue level based on GSR and EMGs signals. The study shows that the power spectrum density of GSR and EMGs can be favorable features to measure the driver fatigue level. Moreover, our proposed system doesn't include complex signals like PPG, EEG, EEG and etc. for driver fatigue measurement. However, different person exhibited different pattern of muscular behaviors that are well simulated by the EMGs signals in this study. Distinct parts of the muscular activities show different events, and the experiment results show that the features extracted from the EMG measurement close to palm or fingers have higher significant patterns relevant to the driver steering wheel operation which closely related to the fatigue level. Future work will consider on

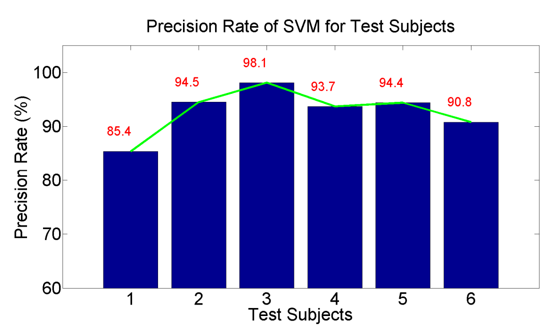


Fig. 5. Precision rate of SVM classifier after being trained with the dataset for each subject.

(a)

(b)

Fig. 6. Screenshots of the smartwatch application showing the received (a) EMG and GSR signals, (b) the warning is triggered to the driver if the classifier model signifies the probability of driver exhibits high fatigue level.

implementing a reliable classifier which would take different muscular events into consideration to measure driver fatigue level.

ACKNOWLEDGMENT

The author likes to thank L. B. L. and Dr. L. D. S. for highly support collaboration in succeeding this research. Moreover, the author is very appreciated for all the aids given by L. B. L. in building the wearable device.

REFERENCES

[1] P. S. Rau, "Drowsy Driver Detection and Warning System for Commercial Vehicle Drivers: Field Operational Test Design, Data Analysis, and Progress," Nat. Highway Traffic Safety Admin., US, 05-0192, Apr. 2005.

[2] L. M. Bergasa, J. Nuevo, M. A. Sotelo, R. Barea and M. E. Lopez. (2006, Mar.). Real-time system for monitoring driver vigilance. IEEE Trans. Transp. Syst. [Online]. 7(1), pp. 63-77. Available: http://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=1603553

[3] C. C. Liu, S. G. Hoskinga and M. G. Lennea. (2009, Aug.). Predicting driver drowsiness using vehicle measures: Recent insights and future challenges. J. Safety Res. [Online]. 40(4), pp. 239-245. Available: http://www.sciencedirect.com/science/article/pii/S0022437509000668

[4] Y. Sun and X. Yu. (2014, Feb.). IEEE J. of Biomed. and Health Informat. [Online]. PP(99), pp. 1. Available: http://ieeexplore.ieee.org/xpl/articleDetails.jsp?arnumber=6736087

[5] H. Park, S. Oh and M. Hahn, "Drowsy driving detection based on human pulse wave by photoplethysmography signal processing," in Proc. IUCS09, New York, USA, 2009, pp. 89-92.

[6] M. Szypulska and Z. Piotrowski, "Prediction of fatigue and sleep onset using HRV analysis," in Proc. Of 19th Int. Conf. MIXDES, Warsaw, Poland, May 2012, pp. 543-546.

[7] G. Li and W. Y. Chung. (2013, Dec.). Detection of driver drowsiness using wavelet analysis of heart rate variability and support vector machine classifier. Sensors. [Online]. 13(12), pp. 16494-16511. Available: http://www.mdpi.com/1424-8220/13/12/16494

[8] Y. Du, P. J. Ma and X. H. Su, "Combine feature selection with time sequence energy analysis for driving drowsiness detection," in 1st Int. Conf. on Pervasive Comput. Signal Proc. And App., PCSPA, Harbin, China, Sept. 2010, pp. 666-669.

[9] F. Friedrichs, and B. Yang, "Drowsiness monitoring by steering and lane data based features under real driving conditions," in 18th European Signal Process. Conf., EUSIPCO-2010, Aalborg, Denmark, 23-27 August 2010, pp. 209-213.

[10] M. M. Bundele, and R. Banerjee, "Detection of fatigue of vehicular driver using skin conductance and oximetry pulse: a neural network approach," in Proc. of the 11th Int. Conf. on Inf. Integrat. And Web-based Appl. & Services, Kuala Lumpur, Malaysia, 14-19 December 2009, pp. 739-744.

[11] A. Sahayadhas, K. Sundaraj, and M. Muragappan. (2013, June). Drowsiness detection during different times of day using multiple features. Astralas Phys. Eng. Sci. Med. [Online]. 36(2), pp. 243-250. Available: http://link.springer.com/article/10.1007%2Fs13246-013-0200-6

[12] Lilypad Arduino. [Online]. Available: http://arduino.cc/en/Main/arduinoBoardLilyPad

[13] LG G Watch. [Online]. Available: http://www.androidcentral.com/ lg-g-watch-specs

[14] Bluetooth BLE 4.0 (HM-10). [Online]. Available: http://www.espruino.com/Bluetooth+BLE