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A Portable Device for Real Time Drowsiness Detection Using Novel Active Dry Electrode System

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Abstract—**Electroencephalogram (EEG) signals give important information about the vigilance states of a subject. Therefore, this study constructs a real-time EEG-based system for detecting a drowsy driver. The proposed system uses a novel six channels active dry electrode system to acquire EEG non-invasively. In addition, it uses a TMS320VC5510 DSP chip as the algorithm processor, and a MSP430F149 chip as a controller to achieve a real-time portable system. This study implements stationary wavelet transform to extract two features of EEG signal: integral of EEG and zero crossings as the input to a back propagation neural network for vigilance states classification. This system can discriminate alertness and drowsiness in real-time. The accuracy of the system is 79.1% for alertness and 90.91% for drowsiness states. When the system detects drowsiness, it will warn drivers by using a vibrator and a beeper.**

I. Introduction

ALTHOUGH driving drowsy is not considered as dangerous as drunk driving, it still is a major factor in crashes. According to Lyznicki et al, it represents 1 to 3 percent of all police reported crashes and 4 percent of fatalities [1]. On the other hand, Horne concluded that 16 to 20 percent of crashes are sleep related [2]. Additionally, the result of a New York State driver survey indicates that more than 55 percent admitted that they had driven while drowsy in the past year [3]. These results indicate that the frequency of driving drowsy is much higher than reported crashes. Most of the drowsy driving accidents are single vehicle running off on higher-speed roadway, thus resulting in serious injuries. People who are more likely to involve in driving drowsy are those who are sleep deprived, those who drive at night, who drive on long trips, who drive on long stretches of monotonous roadway, and who drive by themselves [1]. Commercial vehicle operators, especially tractor trailer operators, are the population that best matches these criteria. However, most of the everyday drivers are exposed to some of these conditions regularly. To reduce the danger and damages of driving drowsy, it is desirable to have a reliable monitoring system that can not only determine the drowsiness of the driver but also issue a warning in real time [4].

There are three major categories of drowsy monitoring system proposed by researches in the past, systems based on the duration of eye closure [4, 5], systems based on the EEG [6] and systems based on vehicle behaviors [7]. Systems based on eye closure duration are reliable and have a very high discernment rate [8, 9]. However, it is not very practical in a real-life scenario due to the fact that it requires drivers to maintain their head position in order for the CCD system to track the eye movement. Systems based on vehicle behaviors measure parameters such as time-to-line crossing, lateral position of the car et al., and have very good practicality but poor extendibility [7]. To achieve these measurements, it requires attaching additionally hardware to the vehicle that raises integrity and liability issues. The systems based on EEG use the knowledge that raising alpha (8-11Hz) and theta (4-7Hz) activities in the EEG indicate increasing sleepiness and drowsiness [10]. The electronic circuit and hardware for the EEG based systems are relatively cheap and thus these systems are promising [9]. However, it is a challenge to place EEG electrodes correctly and effortlessly. Thus, this study proposes to build an EEG based driver drowsiness detection system using a novel electrode system to obtain the EEG signals reliably.

The process of gradually declined alertness from a normal state to the onset of sleep does not have distinct stages. Thus, a successful EEG based drowsiness detection system requires not only a reliable electrode system but also an effective decision making mechanism to discriminate states of drowsiness. The ability of artificial neural networks (ANN) in detecting driver drowsiness was demonstrated by Lin [11] and Eskandarian [12]. However, the accuracy of ANN classification depends on how well the characteristic vector represents state of drowsiness [13]. For example, for ECG classification, researchers used digital filtering, Fourier transform, wavelet transform (WT), principal component analysis (PCA), and independent component analysis (ICA) to extract features in order to improve the accuracy of classification [13]. Different feature extraction methods may affect the outcomes of classification significantly. Subasi extracted wavelet coefficients from the wavelet scales that have a similar frequency bandwidth as α, β, θ and δ, and achieved a 92% discrimination rate between alert, drowsy and

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sleep [14]. Thus, this study proposes to use two new features extracted from the EEG signals transformed by Daubechies 2 stationary wavelet transform. With these new software and hardware features, the purpose of this study is to develop a reliable EEG based drowsiness detection system for real-time determine the drivers' drowsiness and issue warning accordingly.

II. Method

A. System

The proposed system consists of an EEG electrode system and signal condition circuits, a microcontroller, and a digital signal process module (Fig. 1). To acquire EEGs through dense hair without the usage of electrode conducting gel, a novel dry active electrode that consists of multiple arch Ag-AgCl conductors is proposed. Six of these dry electrodes are placed, on the inside ring of a baseball cap, approximately at the FP1, FP2, T5, T6, O1 and O2 locations. The user wears the hat while he/she is driving without requiring any additional action from the user. The system extracts EEG characteristics using stationary wavelet transform and uses artificial neural network to determine the drivers' state of alertness. Whenever the system determines the driver is driving while drowsy, it outputs a warming signal through a vibrator that is secured on the seat belt. The proposed system can not only determine the drivers' drowsiness and issue warnings in real time but also is convenient to use in a day-to-day environment.

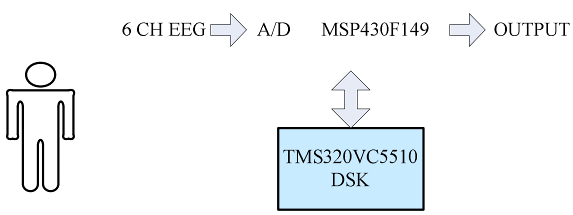

Fig. 1. System block diagram.

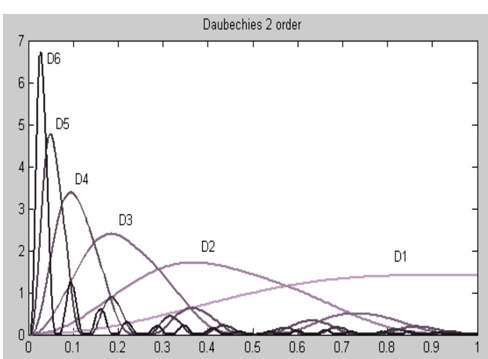

Fig. 2. The equivalent filters response of the stationary wavelet transform.

TABLE I
THE FREQUENCY RANGE OF EQUIVALENT FILTERS

Scale	Frequency Range (Hz)
D1	130 − 260
D2	65 − 130
D3	32.5 − 65
D4	16.25 − 32.5 (β)
D5	8.125 − 16.25(α)
D6	4.0625 − 8.125(θ)
A6	0 − 4.0625

B. Signal Processing

This study uses the Daubechies 2 stationary wavelet transformation to separate the acquired EEG signals into six scales each. The equivalent filter responses of these scales are illustrated in Fig. 2. At a sampling rate of 520Hz, three scales, scale 4, 5, and 6, have similar frequency bandwidth as β, α, and θ waves, respectively (Table I).

This study extracts two characteristic features from the wavelet transformed signals: zero crossing (ZC) and integrated EEG (IEEG). The IEEG is closely related to the energy in that particular channel. On the other hand, the ZC is the representation of the EEG clotting phenomenon. Where IEEG and ZC are defined as follow:

$$IEEG = \sum_{k=1}^{N} |x_k| \tag{1}$$

$$ZC = \sum_{k=1}^{N} \left[\text{sgn}\left(-x_k \times x_{k+1}\right) and \; |x_k - x_{k+1}| \geq threshold \right] \tag{2}$$

where $\text{sgn}(X) = \begin{cases} 1, & if \quad x > 0 \\ 0, & otherwise \end{cases}$

After wavelet transform, IEEG and ZC are computed from scale 4, 5 and 6 for each EEG channel. This study uses these 36 features as the input vector to an ANN that has 18 hidden nodes and two output nodes.

C. Reaction Time Test

The reaction time test was used by Kamdar [15] and Modarres-Zadeh [16] to quantize the level of drowsiness. The subject responds to the sound stimulation by pressing a button and the reaction time is defined as the time difference between stimulation and response. This study uses 4 to 10 s random interval between sound stimulations for the reaction time test. The frequency of the sound is 2.8 KHz and lasts for 60 ms. When the reaction time is longer than 1.2 s, it is denoted and recorded as "failure to respond."

D. Experiment

Ten volunteers, ages from 20 to 25, were recruited for this study. The temperature and lighting of the test environment were controlled such that it was conducive to dozing. During the experiment, subjects were asked to hold the reaction time button while sitting in a comfortable chair. There are two stages in this experiment, a five-minute baseline period and 20-minute test period. During the baseline period, the subject was asked to stay fully aware and the reaction times obtained during this period would be used as the baseline reference. On the other hand, during the 20-minute test period, the subject was requested to look at the projected scenery simulating the front window view of a car driving on a monotonous road and try to stay alert as long as they could. The EEGs, reaction times, as well as physical conditions of the subjects were also recorded for future analysis.

This study used the EEG signals, 4 s before the sound stimulations, as the input signal and the corresponding reaction time as the index of subject's drowsiness to test the system's ability to detect drowsiness. The EEG signals obtained during the first period were used as the reference for alertness. On the other hand, the EEG signals from the latter period were used to test the detection of drowsiness.

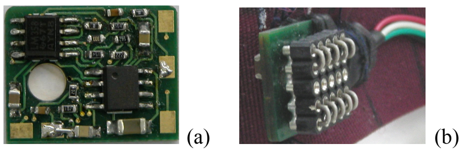

Fig. 3. Active dry electrode. (a) component side, (b) skin side. Skin side consists of 10 Ag-AgCl arc conduction points.

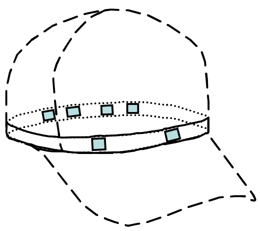
Fig. 4. Six active electrodes were arranged around a strip of Velcro, simulating the cap-ring, in the approximate location of Fp1, Fp2, T5, T6, O1 and O2.

III. Result

This study realized the proposed dry active electrode on a 1.9cm by 1.5cm circuit board. There are 10 Ag-AgCl arc conduction points on the skin side (Fig. 3). When one of the conduction points comes in contact with the skull a high fidelity EEG can be obtained. Six active electrodes were arranged around a piece of Velcro, simulating the cap-ring, in the approximate location of Fp1, Fp2, T5, T6, O1 and O2 (Fig. 4). All the electronic components, including DSP module, micro-controller, amplifier and filter circuit, reaction time test subsystem and warming module, are enclosed in a 24.5cm x 17.5cm x 5cm box. The complete system can operate on a single 5V power supply converted from the 12V DC of the cigarette lighter inside the vehicle.

The ability of the proposed electrode system to acquire reliable EEG signal can be illustrated by the two typical EEG signals that were acquired when subject was awake and drowsy (Fig. 5). It is clear that when the subject was alert, EEG signals contain much less low frequency components than the EEG signals acquired when the subject was drowsy.

All the real-time algorithms, such as wavelet transform, characteristic features extraction and artificial neural network, were realized and tested using Matlab before being implemented in a TMS320C5510 assembler. Fig. 6 illustrates the EEG signals and the six scales after stationary wavelet transform. When comparing the results between Matlab and assembler, it was found that the differences are negligible.

Typical results of real-time drowsiness detection while subject was alert and drowsy are illustrated in Figs. 7(a) and 7(b), respectively. In the upper panels of Figs. 7(a) and 7(b) are the results of reaction time test. The red-dotted lines are the 700 ms threshold. When the subject took 700 ms or longer to react, he/she was considered to be drowsy. The lower panels of Figs. 7(a) and 7(b) are the results of ANN. An output of one indicates the system considers the subject was drowsy and a warning signal was issued. Table II illustrates the detection accuracies of the proposed system in both alert and drowsy states. The detection accuracy when the subjects were alert (79.1%) was much less than the accuracy when the subjects were drowsy (90.9%).

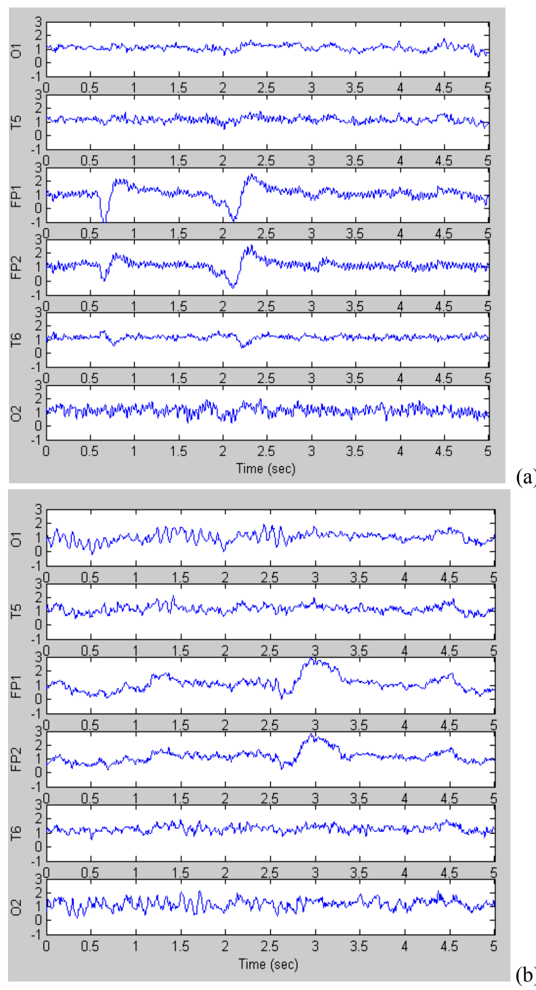

Fig. 5. EEG signals acquired using the proposed electrode system. (a) alertness EEG, (b) drowsiness EEG.

IV. Discussions and Conclusions

This study demonstrates the effectiveness of the proposed novel dry electrode system in EEG signals acquisition. For most of the subjects, the proposed dry electrode system can be employed without any difficulty. However, some of the subjects required multiple adjustments to obtain good quality EEG signals. The potential solution is to replace the Velcro with an elastic band to obtain a better electrode-skin contact.

The results in Table II indicate that the proposed system has much higher accuracy when subjects are in the state of drowsiness. The consequence is the system may issue too many unnecessary warning signals while the subject is totally alert. In turn, users may choose to turn off the device due to the excessive harassment. Thus, it is the future goal of this study to improve the detection accuracy in both alert and drowsy states.

REFERENCES

[1] J. M. Lyznicki, T. C. Doege, R.M. Davis, and W. A. Williams, “Sleepiness, driving, and motor vehicle crashes,” *JAMA*, 279(23), pp1908-1913, 1998.

[2] J. A. Horne and L. A Reyner, “Sleep-related vehicle accidents,” *British Medical Journal*, 310, pp.565-567, 1995.

[3] A. T. McCartt, S. A. Ribner, A. I. Pack, M. C. Hammer, “The scope and nature of the drowsy driving problem in New Youk State, “ *Accident Analysis and Prevention*, 28 (4), pp. 511-517, 1996.

[4] T. Hayami, K. Matsunaga, K. Shidoji, and Y. Matsuki, “Detecting Drowsiness While Driving by Measuring Eye Movement-A Pilot Study,” *in Proc. 5th International Conference on Intelligent Transportation Systems*, Singapore, 2002, pp. 156-161.

[5] T. Hamada, T. Ito, K. Adachi, T. Nakano, and S. Yamamoto, “Detecting Method for Drivers’ Drowsiness Applicabel to Individual Features,” *In Proc. 2003 Intelligent Transportation Systems*, Vol. 2, 2003, pp 1405-1410.

[6] A. Vuckovic, V. Radivojevic, A. C. N. Chen, D. Popovic, “Automatic recognition of alertness and drowsiness from EEG by an artificial neural network,” *Medical Engineering & Physics*, 24, pp. 349-360, 2002.

[7] H. Ueno, M. Kaneda, M. Tsukino, “Development of Drowsiness Detection System,” *in Proc. 1994 Vehicle Navigation & Information Systems*, 1994, pp 15-20.

[8] R. Grace, V. E. Byrne, D. M. Vierman, J. M. Legrand, D. Gricourt, R. K. Davis, J. J. Staszewski, B. Carnahan, “A Drowsy Driver Detection System for Heavy Vehicles,” *in Proc. 17th Digital Avionics Systems Conference*, Bellevue, WA, USA, 1998, ppI36/1-I36/8.

[9] G. Renner, S. Mehring, “Lane Departure and Drowsiness – Two Major Accident Causes – One Safety System,” *Transport Reasearch Laboratory, TRL Report* 220, 1997.

[10] D. F. Dinges, “An Overview of Sleepiness and Accidents,” *J. Sleep Research*, 4(2), PP 4-14, 1995.

[11] C. T. Lin, S. F. Liang, Y. C. Chen, Y. C. Hsu and L. W. Ko, “Driver’s Drowsiness Estimation by Combining EEG Signal Analysis and ICA-based Fuzzy Neural Networks,” *in Proc. 2006 IEEE International Symposium on Circuits and Systems*, 2006, pp.2125-2128.

[12] A. Eskandarian, and A. Mortazavi, “Evaluation of a Smart Algorithm for Commercial Vehicle Driver Drowsiness Detection,” *in Proc. 2007 IEEE intelligent Vehicles Symposium*, Istanbul, Turkey, 2007, pp. 553-559.

[13] L. Y.Shyu, W. C. Hu, “Intelligent Hybrid Methods for ECG Classification - A Review,” *Journal of Medical and Biological Engineering*, 28(1), pp. 1-10, 2008.

[14] A. Subasi, “Automatic recognition of alertness level from EEG by using neural network and wavelet coefficients,” *Expert Systems with Applications*, 28, pp. 701–711, 2005.

[15] B. B. Kamdar, K.A. Kaplan, E. J. Kezirian, W.C. Dement, “The impact of extended sleep on daytime alertness, vigilance, and mood,” *Sleep Medicine*, 5, pp. 441–448, 2004.

[16] M. Modarres-Zadeh, “A neuro-behavioral test and algorithms for quantification of sleepiness and characterization of wake-sleep transitions,” in Proc. Engineering in Medicine and Biology 27th annual conference, Shanghai, China, 2005, pp. 5746-5749.

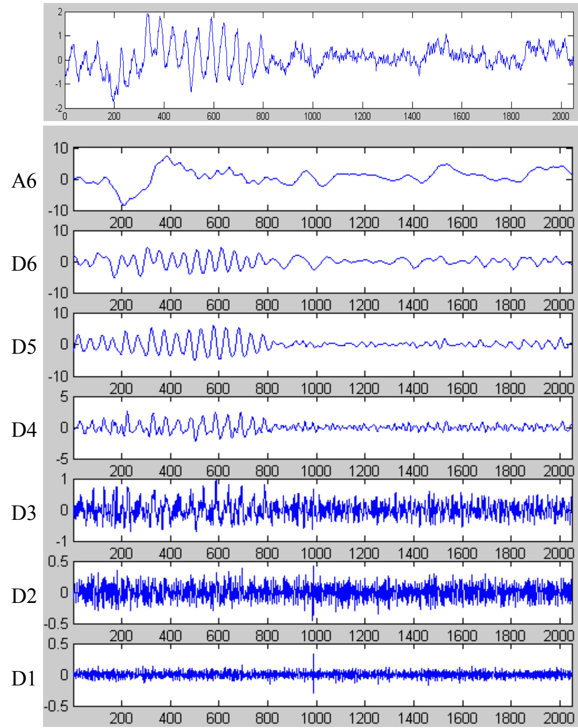

Fig. 6. (a) EEG signal and (b) the results of stationary waveform transform where D4, D5, and D6 contain the same frequency bandwidth as β, α, θ, respectively.

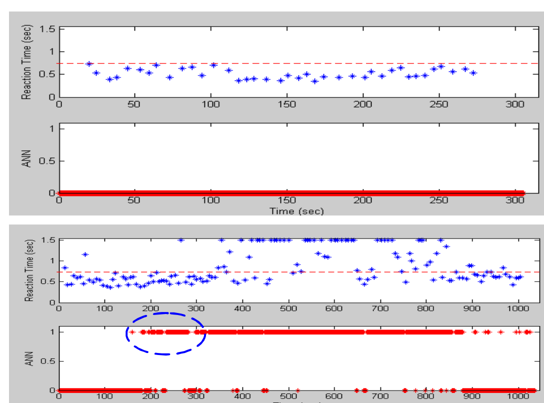

Fig. 7. Typical results of reaction time test (upper panel) and ANN detection results (lower panel) during (a) alert and (b) drowsy. Whenever the reaction time was longer than 700 ms, the subject was declared drowsy. The dotted circle indicates fault detection of drowsiness.

TABLE II
RESULTS OF REAL-TIME DROWSINESS DETECTION

	Number of Cases		Accuracy	
	Training	Test	Training	Test
Alert	120	311	100%	79.1%
Drowsy	120	209	97.5%	90.9%