Wireless and Wearable EEG Sensor for Preventing the Vehicle Accident

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Abstract
A real time wireless Electroencephalogram (EEG) sensor system for drowsiness detection. Drowsy driving has been implicated as a casual factor in many accidents. Therefore real time drowsiness monitoring can prevent traffic accidents effectively. In this study, EEG sensor system was developed to monitor the human cognitive state and provide biofeedback to the driver when the drowsy state occurs. The proposed system consist a driver status in order to link the fluctuation of driver performance with changes in brain activity and process the EEG recordings. This detection system allows for earlier detection of driver drowsiness than driving pattern detection, But it is limited accuracy and insufficient reaction time in current driver drowsiness detection system have lead to the exploration of new techniques based on changes in body physiology as a function of fatigue. One promising method is the use of signals recorded from scalp electrodes that measure pattern of changing electrical activity in the brain as someone goes from a state of complete alertness to fatigue and drowsiness. This work performed a sustained-attention driving task and warning feedback system might lead to a practical closed-loop system to predict, monitor and rectify.

1. Introduction

Real-time detection of sleep by focusing on three critical parameters in EEG recordings: waveform amplitude, waveform frequency, in duration of synchronization of the waveform. This last parameter is critical in that the waveform amplitude may meet a predefined voltage threshold for a frequency band for short periods of time, but this does not necessarily indicate sleep unless it meets the threshold for a given duration. The frequencies of focus were 8-12 Hz (Alpha) and 11.5-15 Hz (low Beta). Two counters were used to detect EEG threshold crossing with one counter for the number of sequential pattern matches indicative of sleep, and the other counter for the number of sequential non-matches.

When a frequency and amplitude matched the focus frequencies and thresholds the matching counter was incremented. When it did not match, a non-matching counter was incremented. When the match counter reached 3, sleep was indicated.

The signal was separated in to delta, theta, alpha, and beta waves. An EEG baseline was recorded before the subject was drowsy. Driver drowsiness detection is a car safety technology which prevents accidents when the driver is getting drowsy. Various studies have suggested that around 20% of all road accidents are fatigue-related, up to 50% on certain roads. Some of the current systems learn driver patterns and can detect when a driver is becoming drowsy squared distance from the closet center already chosen.

The system is a Bluetooth audio module with a single dry-sensor electrode. These devices do not have the accuracy of a clinical EEG, however they can detect general patterns in brain activity. These devices are small and inexpensive. Their size and general use of dry sensors makes them more practical than clinical EEG equipment for driver drowsiness detection.

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Sleep is typically separate into four sleep stages proceeded by Rapid Eye Movement (REM) sleep. Stage 1 sleep is the transition from wakefulness to sleep. At this stage, a person can be work easily, and may not be aware that they were sleeping. During stage 1 sleep, EEG signals are low amplitude and low frequency. During stage2 sleep, body temperature decreases and the heart rate slows. In stage 2 sleep, alpha waves are periodically interrupted by alpha spindles or sleep spindles. Alpha spindles are 12-14 Hz bursts of brain activity that last at least half a second.

In the power spectra were successfully linked with behavioral performance by regression models. Additionally, the advantage of using the EEG signals of the posterior brain region has been shown in a recent study that the classification performance of the drowsiness detection system using the EEG signals of parietal and occipital regions is significantly better than that using the EEG signals of the frontal region. However, these studies still used conventional wet EEG electrodes in measuring EEG signals. Hence, acquiring the EEG signal of the hair region is a critical factor in developing a successful vigilance monitoring system. Recent studies have measured EEG signals using dry sensors, including silicone conductive rubber, comb-like electrode, gold-plated electrode, bristle-type electrode, and foam-based sensor. Table I lists some commercially available EEG systems. Most of these dry sensors are useful for hairy sites. EEG acquisition from the posterior region is available; This study develops an EEG-based in-vehicle system for assessing human vigilance level. EEG dynamics and behavioral changes of participants are simultaneously recorded via a new dry-contact EEG device with spring-loaded sensors when they perform a sustained-attention driving task.

2. System Architecture

The proposed EEG-based in-vehicle system, designed to monitor human vigilance level continuously during automobile driving.

2.1 Dry EEG Sensor

A Noval dry-contact EEG device with spring-loaded sensors was proposed for potential operations in the presence or absence of hair and without any skin maintaining the Integrity of the Specifications preparation or conductive gel usage. Each probe was designed to include a probe head, plunger, spring, and barrel. The 17 probes were inserted into a flexible substrate using a one-time forming process via an established injection molding procedure. With 17 spring contact probes, the flexible substrate allows for a high geometrical conformity between the sensor and the irregular scalp surface to maintain low skin-sensor interface impedance. Additionally, the flexible substrate also initiates a sensor buffer effect,

There by eliminating pain when force is applied. This sensor is more convenient than conventional wet electrodes in measuring EEG signals without any skin preparation or conductive gel usage. The flexible substrate also initiates a sensor buffer effect, and not as an independent document.

The EEG collected from the dry-sensor EEG device. The frequency content of the signals were divided into clinically relevant frequency bands Delta (0.2-3) Alpha (8-13 Hz), Beta (14-30 Hz), and Theta (4-7 Hz) waves. It was expected that, as in clinical studies, alpha and beta waves would decrease when drowsy and theta waves would increase in sleep stage. In the study using EEG signals obtained from the dry EEG sensor device, alpha and beta waves did decrease when drowsy, but theta waves remained constant. Frequency increases during deep sleep stage at delta wave ranges are less than 4 Hz. These results suggest that EEG signals obtained from low-cost EEG sensor and prove a useful target for drowsiness detection.

A few dry-sensor EEG devices are ability to detect drowsiness. They found that these devices made suitable candidates for further research in the detection of drowsiness states and produce a warning when drowsiness was detected.

2.2 EEG Signal Acquisition

The EEG acquisition module consists of four major components [28]: a amplifier , a front-end analog-to-digital converter, Analog Devices, , a microcontroller (PIC 16F977A)), and a wireless transmission (BM0403, Unigrand Ltd., Taiwan). The voltage between the electrode and the reference was amplified using a biosignal amplifier with high input impedance. Meanwhile, the common-mode noise was rejected to precisely detect microvolt-level brain wave signals from the scalp. In particular, transfer function of the preamplifier, i.e., equivalent to the form of a high-pass filter with input signals of frequency, is as follows:

The amplified signal was digitized via an ADC with a 24 bit Resolution and 256 Hz sampling rate. The minimum input voltage of ADC ranges from to 1.94 mV. The maximum input voltage of ADC ranges from to 23.30 mV. In the microcontroller unit, the power-line interface was removed using a moving average filter with a frequency of 60 Hz. The digitalized signals after amplification and filtering were transmitted to a PC or a mobile device via Bluetooth with a baud-rate of 921600 bits/s. Power was supplied by a high capacity (750 mAh, 3.0 V) Li-ion battery, which provided 23 hr of continuous operation at maximum power consumption.

2.3 EEG Signal Processing and Analysis

During a 90 min driving experiment , the study participants encountered hundreds of unexpected lane-departure events. In the signal processing, all 2 s baseline data (512sampling points) before the stimuli were extracted from continuous EEG signals. The data in this baseline period, without any confounding factors (i.e., events, motion stimuli, and motor actions) were an appropriate segmentation of EEG signals to link the physiological message with the driving performance. The data pair of the t-th trial is denoted as number of trial and refers to the driving performance, as measured by the reaction time (RT) in response to the lane-departure event. First, a type I Chebyshev band-pass filter with cut-off frequencies of 0.5 Hz and 50 Hz was applied on the raw data to remove artifacts. Second, physiological features were extracted by transforming the EEG signals of all trials,

In to a frequency domain using FFT to characterize the spectral dynamics of brain activities. As shown in Fig. 4, the EEG signal was successively fed into a weighted time-frequency analysis before applying support vector regression. Power spectral density (PSD) of the EEG signal at time

2.4 Wireless and Wearable EEG Devices

Wireless and wearable EEG device is mainly worked under by the Sensor, In sensor 17 flexible probe is inbuilt the are sense the signal and give the corresponding output signal to the microcontroller. The microcontroller will convert the analogue to digital convertor and the output of microcontroller signal is send to the Bluetooth module.

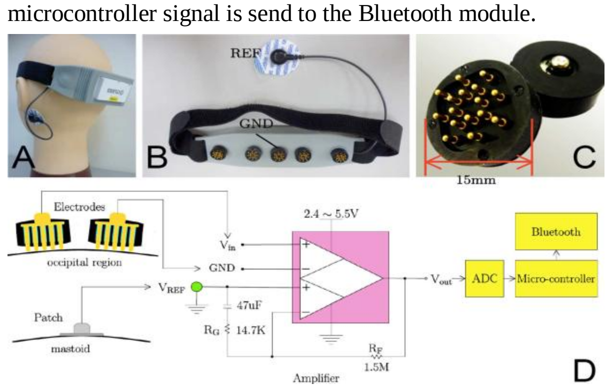

Fig: 1. Wireless and wearable EEG devices. (a) Wireless and wearable EEG headsets. (b) Five dry EEG electrodes and one patch sensor. (c) Spring-loaded probes. (d) Block diagram of the circuit

2.5 PIC Microcontroller 16F877A

The sensor is an input signal, while it is connected to Microcontroller Port 2 is a general purpose input/output, standby mode deactivation input, comparator c1 and comparator c2 are negative input and analog to digital converter and Port 3 is a general purpose input/output, comparator c1 and comparator c2 are negative input and analog to digital converter. Here we need transmitting and receiving part there are, Port 25 is general purpose input/output, Tx USART asynchronous output and synchronous clock and port 26 is Rx USART asynchronous input and synchronous data. The output is shown by using Buzzer Alarm with Bluetooth Module.

2.6 Raw EEG Data

This data showed that the majority of the changes occurred in the low alpha, high alpha, low beta, high beta, and overall raw signal. This is consistent with sleep stage. Sleep stages indicated when the amplitude of the raw signal is low, and the higher frequencies have dropped off. The transition from awake to asleep is estimated to be at about 60 seconds due to the drop in power in the raw and high and low beta signals. This graph shows that the signal power in each band drops off during the transition to sleep. This fits with a trend of decreased power compared to the baseline for the high alpha, low beta, high beta, and the raw signal.

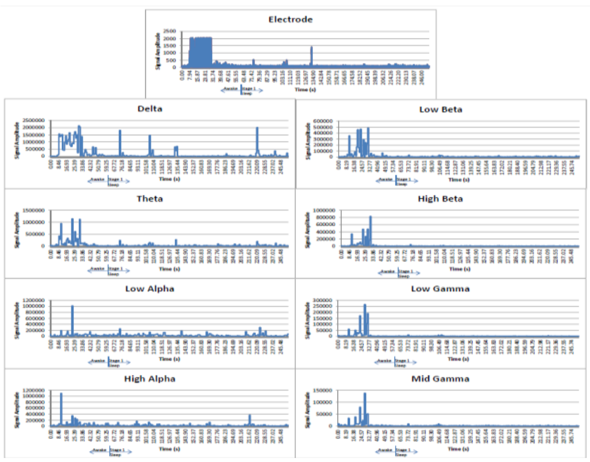

Fig: 2. Example for Raw EEG Sleep Data

This drop is most noticeable in the raw and beta signals. The low alpha signal can spike high while a wake, but it also periodically spikes after sleep has been reached. This is likely caused by alpha spindle epochs. Since the purpose is to detect the onset of sleep, and not deeper sleep, these alpha spindle epochs do not help detect stage 1 sleep. The data in figure 10 was used to establish initial proportionality constants.

The raw signal was most highly correlated to sleep, so it was given the highest weighting with respect to the sleep counter increment or decrement value. Low beta and high beta had the second highest correlation. Low alpha and high alpha were weakly correlated to Sleep stage.

3. Conclusion

This study developed a driver drowsiness prediction system with wireless and wearable EEG device, an efficient prediction model, and a real time Bluetooth App to remedy for drowsy driving. Based on the proposed EEG system, a link was established between the fluctuation in the behavioral index of driving performance and the changes in the brain activity. Experimental results indicated that the SVR with a RBF kernel was applied as the prediction model. Additionally the prediction model was implemented in real time for the subjects are the warning feedback system might lead to practical closed loop system to predict, monitor and rectify.

References

[1] Bao Hong Tan CMU-CS-12-134, Using a Low-cost EEG Sensor to Detect Mental States, School of Computer Science Computer Science Department Carnegie Mellon University Pittsburgh, PA, 2012
[2] Bryan Van Hal, Real-time Stage 1 Sleep Detection and Warning System Using a Low-Cost EEG headset, Grand valley state university, graduate research and creative practice, 2013
[3] Chin-Teng Lin, Fellow, che-Juichang, Bor –shyh Lin, Member, Shao-Hang Hung, Chih-Feng Chao, I-Jan Wang, A Real Time Wireless Brain-Computer Interface System For Drowsiness detection, IEEE Transaction on Biomedical Circuit and Systems, 4(4), 2010
[4] Chin-Teng Lin, Fellow, Chun-Hsiang Chuang, Student Chih-Sheng Huang, Shu-Fang Tsai, Shao-Wei Lu, Yen-Hsuan Chen, Li-Wei Ko, Member, Wireless and Wearable EEG System for Evaluating Driver Vigilance, IEEE, Transaction on biomedical circuit and systems, 8(2), 2014
[5] H. J. Eoh, M. K. chung, S-H Kim, Electroencephalographic study of drowsiness in simulated driving with sleep deprivation, International journal of India, Ergonom., 35(4)
[6] J. R. Estepp, J. W. Monnin, J.C. Christensen, G. F. Wilson, Evaluation of a dry electrode system for electroencephalography: Applications for Psychophysiological cognitive workload assessment
[7] M. A. Haberman, E. M. spinelli, A Multichannel EEG acquisition scheme based on signal ended amplifier and digital DRL, IEEE Transaction on biomedical circuits and system, 6(6), 2012
[8] Ji Hyun Yang, Zhi-Hong Mao, Louis Tijerina, Tom Pilutti, Joseph F. Coughlin, Eric Feron, Detection of driver fatigue caused by sleep Deprivation, IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans, 39(4), 2009
[9] Kofi A. A. Makinwa, Fellow, RefetFiratYazicioglu, JiaweiXu, SrinjoyMitra, Akinri Matsumoto, ShrishailPatki, Chris Van Hoof, A Wearable 8-Channel Active-Electrode EEG/ETI Acquisition System for Body Area Networks, IEEE Journal of Solid-State Circuits, 49(9), 2014
[10] Nidhi Sharma M.Tech Scholar ACET Amritsar, Punjab, Development of a Drowsiness Warning System Based On The fuzzy Logic, India International journal of computer applications, 8(9), 2005
[11] Patricgriss, peter Enoksson, heliK.Tolvanen-Laakso, pekkaMerilainen, Stigollmar, Goranstemme, Micromachined electrodes for biopotential Measurement, IEEE Journal of microelecectromechanical system, 10,(1), 2001
[12] Seoul, Korea correspondence, eng.2013.55B019, Development of 16-channels Compact EEG System Using Real-time High-speed Wireless Transmission, 2013
[13] S. L. Veena, R. Subhashini, Driver Alertness Based on Eye Blinking and Bio-signals, India International Journal of Advanced Research, 2(3), 666-670
[14] Yu-Te Wang, Chung-Kuan Cheng, Cell-phone Based Drowsiness Monitoring and Management System