Project Title

An Innovative Non-contact Sensing Platform to Prevent Traffic Accident due to Driver Drowsiness

Final Report

The Ohio Transportation Consortium

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PROJECT OVERVIEW

This project conducted pilot investigations on the development of an in-vehicle measurement system that monitors the physiological signals (i.e., heart rate, heart rate variation, breathing and eye brinking) of drivers. These physiological signals will be utilized to detect the onset of driver fatigue, crucial for timely applying drowsiness countermeasures. Fatigue driving is one of the most significant factors causing traffic accidents. Clinic research has found physiological signals are good indicators of drowsiness. A conventional bioelectrical signal measurement system requires the electrodes to be in contact with human body. This not only interferes with the normal driver operation, but also is not feasible for long term monitoring purpose. This study developed a non-contact sensing platform that can remotely detect bioelectrical signals in real time. With delicate sensor electronics design, the bioelectrical signals associated with electrocardiography (ECG), breathing and eye blinking can be measured. The current sensor can detect the Electrocardiography (ECG) signals with an effective distance of up to 30 cm away from the body. It also provides sensitive measurement of physiological signals such as heart rate, breathing, eye blinking etc. The sensor performance was validated on a high fidelity driving simulator. Digital signal processing algorithms has been developed to decimate the signal noise and automate signal analyses. The characteristics of physiological signals indicative of driver fatigue, i.e., the heart rate (HR), heart rate variability (HRV), breath frequency and eye blinking frequency, can be determined. A robust drowsiness indicator will be developed by coupling the multiple physiological parameters to achieve high reliability in drowsiness detection.

INTRODUCTION

Traffic accident is predicted to be the third leading cause of death and disability in 2020 (Murray and Lopez, 1997). Driver fatigue, one of the most prevalent root causes of accidents, leads to nearly 17% of all fatal crashes in recent years, according to the new data analysis from AAA Foundation for Traffic Safety of National Highway Traffic Safety Administration (NHTSA) (Copeland, 2010).

Two out of every five drivers (41.0%) reported having ever fallen asleep or nodded off while driving, including 3.9% within the past month, 7.1% within the past 6 months, and 11.0% within the past 12 months". (Tefft 2010)

Truck driver fatigue is a factor in 3 to 6 percent of fatal crashes involving large trucks. Fatigue is also a factor in 18 percent of single-vehicle, large-truck fatal crashes1. Overall drowsy driver crashes cost $12 billion and contribute to up to 35% of the 4,400 annual truck driver deaths (FHWA 2005). Commercial drivers themselves recognize fatigue and

[1] http://www.its.dot.gov/ivi/8MPA.html#DC

inattention as significant risk factors, having identified these conditions as priority safety issues at a 1995 Truck and Bus Safety Summit (FHWA 1998). Fatigued drivers are often unaware of their condition, frequently driving for 3-30 seconds with their eyes closed. Twenty-four hour operations, high annual mileage, exposure to demanding environmental conditions and demanding work schedules make drowsiness a major cause of combination-unit truck (CUT) crashes (Table 1).

Table 1 Drowsy Driver Problem (Tefft 2010, USDOT 2005, Knipling and Wang 1995)

	Passenger Vehicles	Heavy Trucks
Total Est. Drowsy Crashes	96,000	3,300
Total Est. Involvement	95.9%	3.3%
Drowsy Related Fatalities	1,429	84
Fatalities Outside Vehicle	12%	37%
Drowsiness Cited by Police	.52%	.82%
Miles/Year Exposure	11 k	60 k
Years Operational Life	13	15
Primary Driving Period	Day	Night

It has already drawn growing attention to public safety in general, and several measures, i.e., work-shifting, Hours of Service (Federal Motor Carrier Safety Administration, 2008), etc., have been adopted to avoid this situation. Although these measures can reduce the road risk, they cannot prevent the occurrence of driver fatigue. Timely detection and countermeasure of driver fatigue are important to reduce fatigue related accidents.

TECHNICAL BACKGROUND

Methods to Evaluate Driver Drowsiness

Generally speaking, methods to assess driver fatigue falls into two major categories (i.e., subjective methods and objective methods). The subjective assessment is based on the state of drivers described by participants using questionnaires (Chalder et al, 1993; Johns, 1993). Due to the variations of individuals and driving conditions, the accuracy of subjective assessment cannot be guaranteed. The objective methods are based on testing the performance of drivers or parameters of motor vehicles without impacting the attention of subjects. Therefore the results are believed to be more reliable than subjective methods. Currently, an increasing number of Fatigue Management Technologies (FMT) are available to detect the operator fatigue.

Great strides have been made in the last fifty years with regard to knowledge about sleep, sleep need, the effects of sleep loss on performance, and related issues. Even more recently, major advances have occurred in human circadian rhythms research, leading to an improved understanding of these daily rhythms and their control by the human circadian pacemaker in the brain.

Progress has also been made for drowsiness detection. Wierwille et al (1994) generated a measure of drowsiness based on measuring the eye, PERCLOS, associated with degradation in driving performance in a simulated roadway environment. Experimental studies performed by Dinges, et al (1998) showed that PERCLOS was able to accurately predict fatigue-induced lapses in vigilance. Studies by Grace, et al (1999) of overnight commercial trucking operations have produced a real-time monitor capable of detecting driver drowsiness in an operational setting. Furthermore, this monitor used in conjunction with a driver feedback system has been shown to decrease drowsiness and improve driver performance in simulated driving conditions (Mallis et al, 2000). Electronics manufactures and motor vehicle industry are delving into this important issue that can significantly improve the transportation safety. A few pilot drowsiness detection systems are being studied; examples include those based on 3D optical sensing of eye lips (e.g. Siemens DOV2).

The European Commission (EC) has recently announced two extensive activities for promoting the monitoring of driver fatigue: AWAKE and Sensation. The preliminary recommendation is to adopt a behavioural analysis (e.g. limb, gaze or head movements, etc.) of the driver and also to utilise driving performance measures (e.g. lane-keeping or steering wheel reversal rate) (Boverie 2004). These progresses, for the first time, make accurate detection and management of drowsiness feasible.

These technologies can prevent accidents to a certain extent (Williamson and Chamberlain, 2005, Barr et al., 2005). Edwards et al. (2007) evaluated the performance of 22 available technologies and ranked them according to objective and subjective scores. Based on the survey, they found that fatigue detection based on the eye feature detection reached higher reliability; products with the highest ranking typically involve multiple sensors or integrate the ability to process multiple features. The survey also found that although there are a number of commercial detection methods for fatigue, they do not achieve sufficient reliability. Moreover, the cost of the fatigue-detection products is another key factor affecting their wide adoption. Therefore, development of reliable, low cost driver fatigue assistance system are necessary to further advance in this area.

Relationship between Physiological Signals and Drowsiness

Bioelectricity is generated on the cell level and acts as the charge flow on human surface. The electrical charges on the skin off the chest are mainly caused by the depolarization of heart muscles during each heartbeat cycle. In each cycle, nerve excitability is triggered by sinoatrial

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[2] http://findarticles.com/p/articles/mi_m0KJI/is_6_115/ai_103990202 (Siemens DOV)

node, and then spreads through atrium, intrinsic conduction pathways and ventricles. As a result, it causes the change of action potential in cells manifested as the form of tiny rises and falls of potential on body surface. The electrical activity of heartbeat cycle is adjusted rhythmicly by central and peripheral nervous system. Fatigue causes changes in spontaneous rhythmic activity, breathing, cardiovascular reflex activity, blinking, nodding, etc. The comprehensive regulation of these changes by the central nerve system will finally cause changes in the physiological signals.

A few physiological signals of drivers have been found to be good drowsiness indicators. It is generally believed that fatigue is the behavior of the central nervous system. When stress response of organs occurs during fatigue, cardiovascular nervous system will adjust accordingly. Therefore onset of fatigue causes changes in the bioelectrical signals, such as the electrocardiogram (ECG), a recording of electrical signals produced by the electro-dynamic functioning of the heart. Previous work has found that the ECG signal and its derived information, which includes the information of the heart rate (HR), heart rate variability (HRV) and frequency of breathe, has affinity with fatigue. HR is the number of heartbeats per unit of time, typically expressed as beats per minute (bpm); while HRV is a physiological phenomenon where the time interval between heart beats varied, which is measured by the variation in the beat-to-beat interval. Riemersma et al (1977) found that HR of drivers would decrease during long-time night driving. Wilson and Donnel (1988) pointed out that HR reflected the physical and mental level under different task requirement and therefore could be applied to fatigue detection. Hartley and Amoid (1994) concluded that fatigue had significant effect on the change of HR. Busek et al (2005) presented that the spectrum of HRV varied significantly during the experiments of fatigue driving. It is also commonly accepted that onset of fatigue is accompanied with decreasing breathing frequency. The onset of fatigue causes increases in the blinking frequency as the driver tries to keep the eyes open.

Electrocardiography (ECG or EKG) is a transthoracic interpretation of the electrical activity of the heart over time captured and externally recorded by a non-invasive electrocardiographic device. It has been known for many years that a measurable amount of electric current is associated with activity of the heart.

The methods for drowsiness identification based on ECG signal include Heart Rate (HR) analysis, Heart Rate Variability (HRV) analysis and amplitude analysis of T wave. Based on the

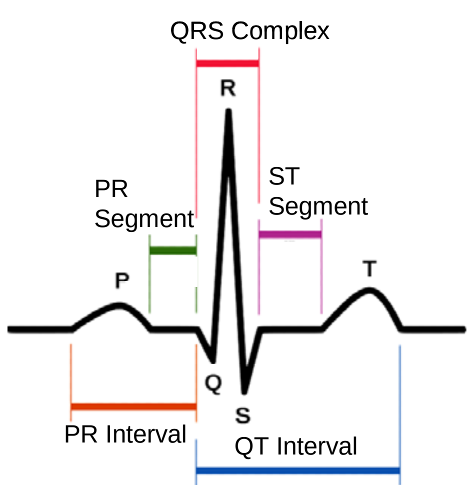


Fig.3 Schematic of normal ECG

results of a great number of experiments, Wilson et al. (1988) concluded that HR signal is an overall indictor, which reflects the physical and mental level under different task requirement. Hart et al. (1990) agreed, and summarized that HR signal reflect the combined effect of tasks, feelings, etc, on operators. Riemersma et al. (1977) found that HR of drivers would decrease during long-time night driving. Hartley et al. (1994) considered that the change of HR has potential significance on driving fatigue. Y. Liu et al. (2003) also studied the change of blood pressure and heart beating under drowsiness. Heart rate variability (HRV) is a measure of the variations in heart beating rate. Itoh (1989) found that HRV can differentiate the levels of workload and fatigue. Hanlon found HRV varies significantly during the experiments of fatigue drivers. The research of Kramer indicated that HRV signal can reflect the workload of human cognitive to certain degree and warrant further investigation.

The combined effects of HR and HRV have also been studied. Kalsbeek and Wartna illustrated that with the mental workload increasing, HRV signal would decrease while the HR signal almost remained the same. However, Mulder et al. (1973) found that with the load increasing, HRV decreased and HR increased significantly. The different of the results may be caused by that the physical and mental load were not distinguished in study, and they may influenced on each other. Dhong et al. (1990) improved the previous researches and differentiated the load into two categories, heavy physical- light mental and light physical-heavy mental load, in order to reduce the interaction. The results illustrated that with the increasing of physical loads, there are appreciable amount of decrease in HRV while HR increases.

Development of Non-contact ECG Sensor

Significant technical advances have been made in electrocardiogram over the past decades. A typical clinic ECG system is based on 12-lead electrodes placed at different positions in contact with human skin. The input impedances of these probes are 10^6-$10^7\Omega$. The relatively low impedance requires the probe to be in good electrical contact with skin, which is typically accomplished with a conductive gel. Besides, the electrical currents flowing in the body changes the surface electrical potentials (Harland et al, 2002). Nevertheless, the contact mode has advantages in achieving high signal quality, the signals are immune to electromagnetic interference, etc. Such ECG systems, while has achieved good performance under clinic settings, are not suitable for long term monitoring purpose.

Alternative sensors have been studied to further improve over the traditional ECG system. For example, Wikswo (1995) studied the use of high sensitivity magnetometer, Superconducting Quantum Interference Device (SQUID) magnetometer, for bioelectricity measurement. This sensor, while found capable of non-contact bioelectricity sensing, requires cryogenic operations and extremely magnetically shielded environments. These make it impractical for mobile applications. Electric field sensor is another way for remote bioelectrical sensing. Lopez and Richardson (1969) reported the success in the development of a non-contact electrical field sensor for ECG detection. Major efforts have been made to improve its performance and fabrication technology. Prance et al (2000) and Harland et al (2002) developed high-input-impedance probes with low input-bias current amplifiers. Further advances in non-contact ECG sensors were introduced by Matthews et al (2005) and Park et al (2006), who designed a wearable wireless ECG monitoring system. Sullivan et al (2007) described a compact low-noise EEG/ECG sensor. Although the reported sensors do not need to be contact with skin directly, they still need close proximity of the electrode to human body.

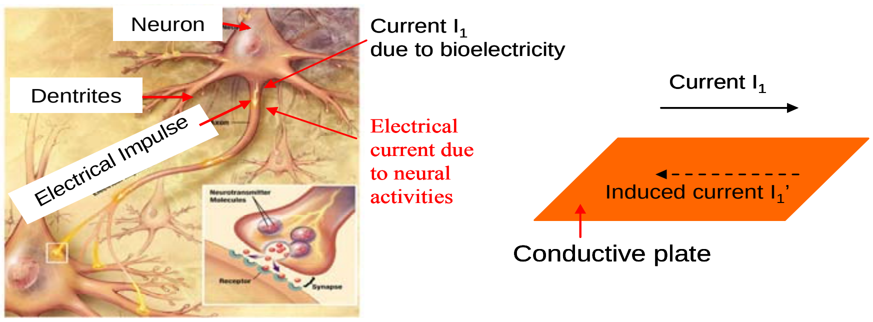
In summary, although ECG signals have been widely used as a vital signal and used in health care industry, its measurement typically requires expensive equipment and contact electrodes. This causes inconveniences and interferes with normal driver behaviors. In this study, we developed an innovative non-contact sensing system that detects the ECG signal away from the body, from which the information of HR, HRV and breathing frequency can be determined in real-time. Moreover, the system was also able to detect the eye blinking due to electromyography (EMG) by using glasses as the sensing element. A robust drowsiness indicator can be developed by coupling the four physiological indicators to achieve reliable detection of driver fatigue. Therefore, countermeasures can be applied timely to enhance the road safety.

SYSTEM DESIGN

Principles for Bioelectricity Sensing

In this research we developed a sensor that can detect the ECG signal 20 cm to 30 cm away through cloth. Such high sensitivity makes it possible for practical implementation for driver physiological signal monitoring purpose. Our non-contact ECG sensor detects the potential of on the human body caused by neural activities through capacitive coupling. Figure 1 (a) shows the mechanism in the generation of bioelectrical current, and (b) expresses the mechanism of sensing via the induced current.

The conductive plate of the sensor, which is made of metal or conductive polymer, and the human surface act as a coupling capacitor. In practice, the dielectric spacer is air layer, thus the sensor is a remote detecting device. Due to capacitive coupling, the charges on the conductive plate remain the same amount as the effective area parallel to the human body. Moreover, our device can also be used to detect the EMG associated with eye blinking, which is another good indicator of fatigue. The induced signals can be detected by designing high impedance and high quality signal amplification systems elaborated in the following sessions.



(a) (b)

Figure 1 Principle of non-contact ECG sensor. (a) The generation of bioelectrical current caused by neural activities; (b) principle of induced current.

Preamplifier

The preamplifier is a circuit that processes the bioelectrical signal detected on the human surface. Table 1 shows the magnitude and frequency of typical bioelectrical signals. In this paper, ECG and EMG signals are detected to evaluate fatigue. Therefore the preamplifier is configured with a gain of 10V/V.

The circuit contains an amplifier and a filter. To obtain high input impedance and low noise, an instrument amplifier (INA116, Texas Instrument Inc.) was used for amplification. The input impedance of amplifier is around 10^{18} Ω. Due to the impedance matching, the common mode rejection ratio (CMRR) of the instrument amplifier can be ideally infinite, which means the circuit can achieve high SNR, since the noise is considered to couple into the circuit as the common mode signal. The block diagram is outlined in Figure 2. The bioelectrical signal is first coupled to the conductive electrode through capacitance. For ECG detection, a conductive plate is used as the electrode; while for the eye blinking detection, an electrode is fabricated and connected using extension cable (Figure 5 (b)). The signal then acts as a potential at the input of the amplifier via current bias component. In practice, the first signal amplification is completed with CMRR of 90dB at 0-1kHz at gain of 10V/V. The next stage is a lowpass filter with a cutoff frequency of 45Hz. The shielding package is accomplished by a metal box covering the printed circuit board (PCB).

Table 1 Magnitude and frequency range of main bioelectrical signals

Bioelectrical Signal	Magnitude	Frequency
Electrocardiogram (ECG)	50μV-50mV	0.05Hz-100Hz
Electroencephalography (EEG)	2μV-10μV	10Hz-2kHz
Electromyography (EMG)	20μV-10mV	10Hz-10kHz
Electrooculography (EOG)	10μV-4mV	0.1Hz-100Hz
Electrogastrogram (EGG)	10μV-80mV	0Hz-1Hz

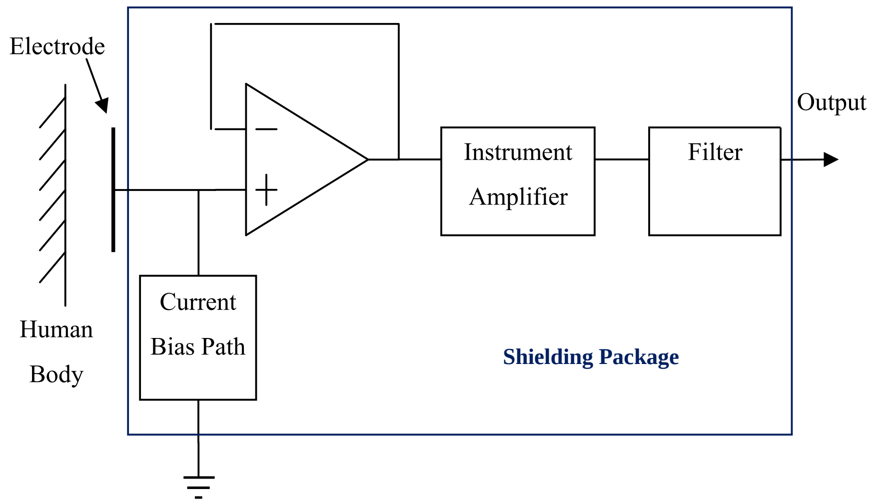


Figure 2 Block Diagram of the non-contact ECG sensor preamplifier.

EXPERIMENT

Evaluation of sensor performance has been carried out in stages. The first stage was in a electromagnetic shielded room, the second stage under ordinary lab conditions, in the third stage, experiments were conducted on driving simulators located in Haptic Interface Laboratory, Case Western Reserve University, which is an unshielded room. Sensor design has been further improved with experience from each evaluation stage. Only example data in the third stage are reported in this paper.

Experiment 1- Sensitivity in ECG Detection

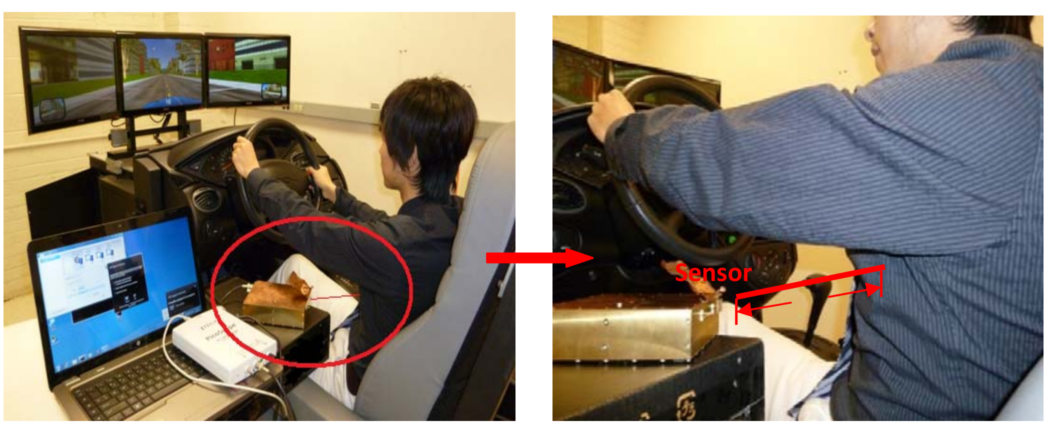
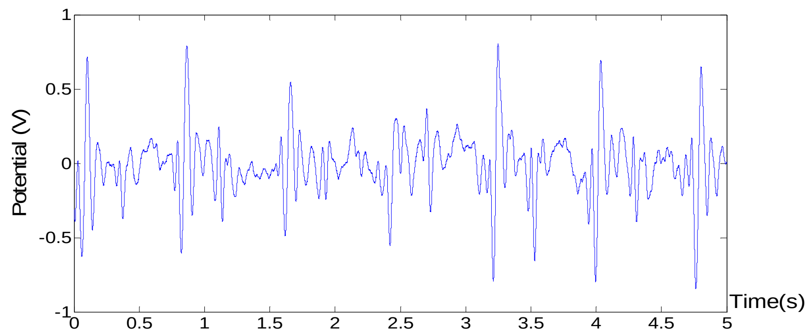


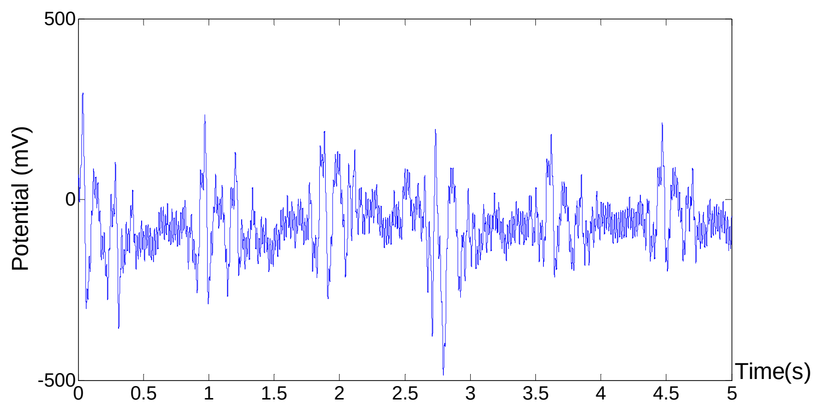
Figure 3 Detection system setup for ECG signal

During the experiment, the subject was seated in the driving simulator which was located in an unshielded room, and the sensor was placed off body in front of left chest at distances of up to 30 cm. Photos of experimental set up are shown in Figure 3. A sensitivity study was conducted where the human body was in different distances away from the body. The signals from 10cm, 20cm and 30cm away were detected and the raw data are displayed in Figure 4.

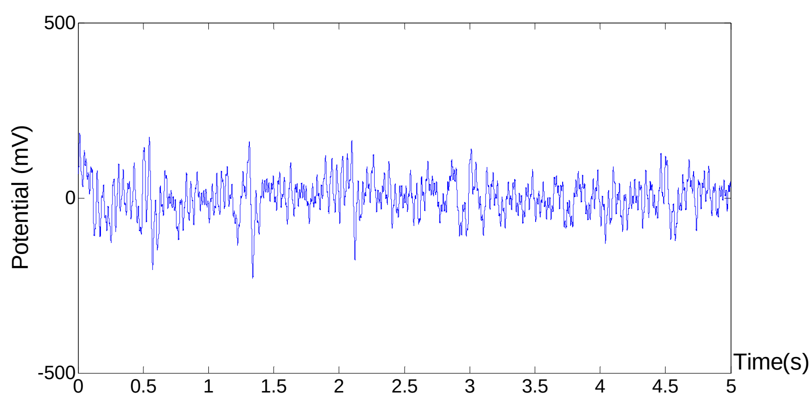
From this figure, the SNR decreases apparently with the distance from body. At the distance less than 20cm, the sensor can clearly detect the ECG signal (Figure 4 (a) (b)). When the distance is between 25cm and 30cm, the signal is detectable but vague (Figure 4 (c)). This might imply that 30cm is the upper bound where the sensor can detect the ECG signal.



(a) ECG signal at the distance of 10cm.



(b) ECG signal at the distance of 20cm.



(c) ECG signal at the distance of 30cm

Figure 4 ECG signal detected off body through clothing at different distance**.**

Experiment 2-Eye Blinking Detection

Drowsy drivers typically have problems to control their eyes. Physiologically this demonstrates as rapid blinking at the on-set of drowsiness and slow blinking as the drivers are deeply affected. This experiment aims to evaluate the capability of our sensor to detect the eye blinking, which might reflect the degree of drowsiness. In the experiment, a soft conductive plate was attached to the frame of glasses and acted as a detection element, as shown in Figure 5. The electrode was connected to the system via an extension cable. The subject was allowed to breathe and move close to normal while driving a high fidelity driving simulator.

(a) (b)

Figure 5 Driving fatigue detection: (a) High fidelity driving simulator; (b) photo of subject driving the driving simulator while being monitored by the eye blinking detection sensor.

Experiment 3-Driving Fatigue Detection

To evaluate the performance of our system for driver fatigue signal extraction, controlled fatigue experiments was conducted on a high fidelity driving simulator (Figure 5 (a)). The driving simulator has six-screen displays for the scenery around the driver, which emulate the driving experience on the road. During this experiment, a high-way scenario was programmed with moderate traffic. The subject was seated in the simulator and equipped with the bioelectrical measurement based system developed in this study (Figure 5 (b)). Prior to the testing, the subject was subjected to slight sleep deprivation until he indicated he felt sleepy. The ECG signal and the eye blinking information were detected and recorded for 15 minutes. Chalder subjective scale (Chalder et al., 1993) was used before and after driving to estimate the fatigue degree of subjects. In the scale, fourteen questions are listed and answered by the driver. Four options were “better than usual”, “no more than usual”, “worse than usual”, “much worse than usual”, and scoring of the questionnaire was carried as 1-4. The average of score reflects the fatigue level. 1 refers to non-fatigue; 2-4 are mild, moderate and severe fatigue. The subject reported score of 1 (non-fatigue) at the beginning and reported score of 3 (mild drowsy) around the end of the experiment.

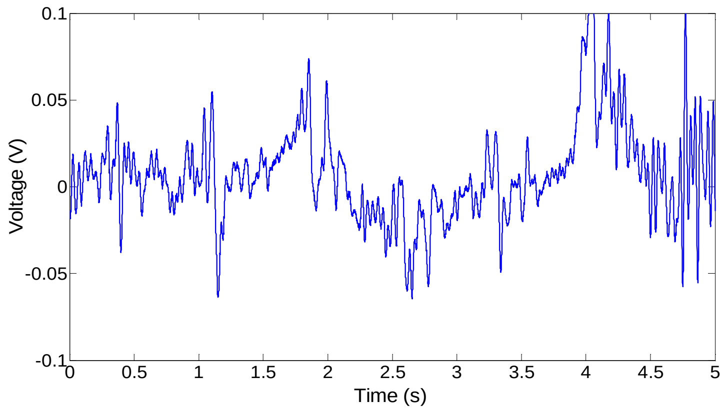
EXPERIMENTAL DATA AND ANALYSIS

HR and HRV

According to Table 1, the frequency components of normal ECG signal ranges from 0.01 to 100Hz with energy concentrates in 5-45Hz. During the experiments, several sources of noise can interfere with the original bioelectrical signal, such as EMG, power line interference, electronic noise and baseline drifts. EMG signal is caused by human motion and muscle contraction, which typically ranges between 2-5kHz; power line generates 60Hz noise; and baseline drift caused by low frequency interference, such as the movement of electrode and breathing, is usually 0.05~2Hz. Therefore, besides the hardware filer, a digital bandpass filer with bandwith bwtween 0.5-30Hz was introduced to recover the ECG signal from noise. Figure 6 (a) shows a typical raw signal collected during the experiments. Figure 6 (b) shows the signal after processed with digital filtering. It is clear enough to detect the heart beating cycle, and therefore compute the Heart Rate (HR) and Heart Rate Variability (HRV). As described in the literature review, there were a strong link between the physiological parameters HR and HRV and fatigue.

To detect HR and HRV automatically, an algorithm was developed to pick the peak of the wave and determine HR and HRV in real time. The algorithm identifies the peaks according to the threshold magnitude. Figure 6 (b) illustrates the performance of the algorithm. From this figure we can see that the algorithm has good performance in peak detection. From the peaks, HR can be determined with easiness. From the experimental ECG signals shown in Figure 4 (which was collected during Experiment 1), the heart rates measured were 78.425 bpm, 78.301 bpm, 76.033 bpm respectively. For the signal shown in Figure 6, the HR was found to be 78.907 bpm. All these results were reasonable, as the common heart rate is round 60-90 bpm under normal circumstances according to clinic record.

From the time variation of HR, HRV can be easily calculated. The average and variance of HRV in per minute is computed to estimate the spectrum and distribution of HRV. Thresholds of HR and HRV can be established and used for warning of fatigue onset.



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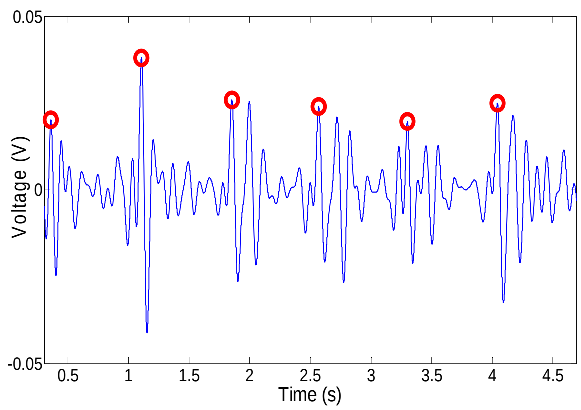

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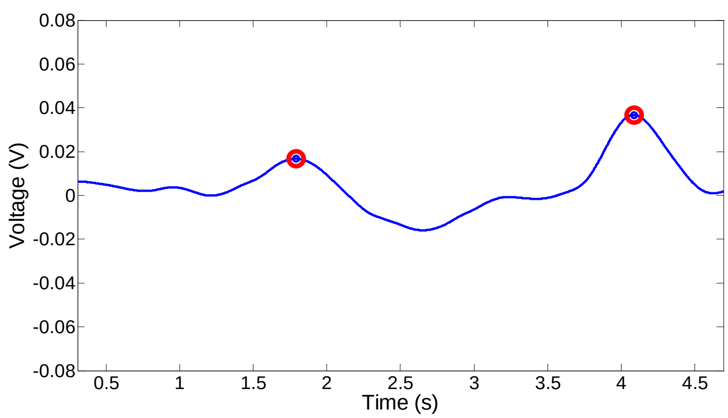

(c) Breathing detection

Figure 6 Examples on the performance of sensor and signals: (a) Raw data; (b) ECG signal after digital filtering and peak identifying algorithm; (c) Breathing signal

Breathing Detection

It was observed during experiments that the baseline variation corresponded to the breathing activities. Moreover, the frequency of baseline fluctuating and the breathing rhythm of the subject coincided very well. When the subject breathes, rising pulses in the baseline were clearly observed. Since the frequency of breathing is low, a highpass filter with cutoff frequency of 2Hz was applied. Figure 6 (c) shows the filtered signal. The breathing pulse is clearly seen from this figure. With the digital filtering and peak identification algorithms, the breathing frequency can be instantly determined. In this case, the breathing frequency was found to be 26 per min. It is generally known that during sleep, the breathing rate is typically lower than under normal awake conditions. Drowsiness is accompanied with slower than normal breathing frequency. This can potentially provide another independent indicator for driver fatigue detection.

Eye Blinking Detection

The frequency of eye blinking has been used by several researchers as drowsiness indictor (Edwards et al., 2007). Common method for eye blinking detection involves the use of a monitoring camera. The frequency of eye blinking is determined based on image analyses. Typically, people blink more frequently at the onset of drowsiness. Eye blinking results in facial muscle contracts and can be detected as bioelectrical pulse. This can be detected with our bioelectricity based system. The detected signal in Experiment 2 is displayed in Figure 7. It can be seen that eye blinking causes distinctive pulse responses in the bioelectrical signals. Using the developed peak identification algorithm, the frequency of eye blinking can be determined in the real time. This physiological parameter provides another independent indicator for drowsiness.

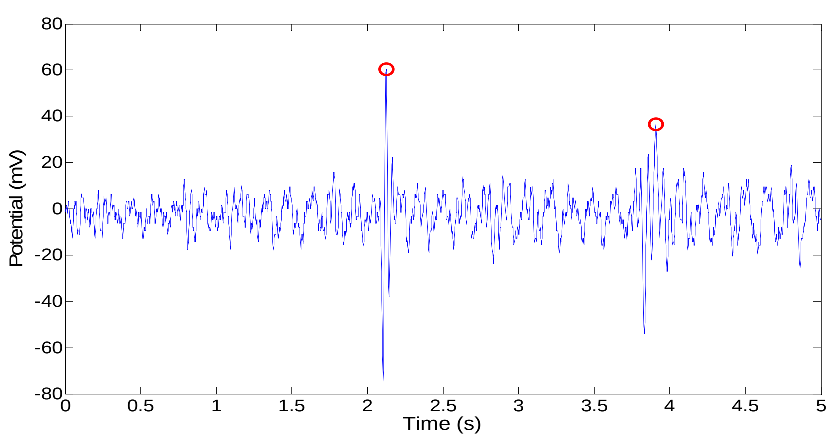

Figure 7 Example of recorded bioelectrical signal with responses to eye blinking marked

Fatigue Detection

For the experiment conducted on the driving simulator, the subject underwent a sleep deprival procedure. ECG signal and the eye blinking signal were recorded for 15 minutes while the subject was driving a high fidelity driving simulator. The status of driver was assessed based on driver's self-assessment using the Chalder subjective scale. The signals were analyzed using the developed algorithm. The physiological parameters before and after the driving test are summarized in Table 2.

In brief, the HR was 68.2 bpm at the beginning of the experiment when the subject was non-fatigue; while the HR was 65.6 bpm when the subject felt mild fatigue at the end of the experiment. Figure 8 shows the heart rate recorded during the experiment, which clearly show the trend that corresponds to the variation from non-fatigue to fatigue status. During the experiment, there was a decreasing trend of HR overall. Moreover, the spectrum of HRV reduced slightly (Table 2) when the driver became fatigue. The average of HRV proliferated while the variance decline apparently. There were apparent increase in the frequency of eye blinking when the driver felt drowsy. Using the same sensor with multiple electrodes, the system we developed can simultaneously provide four independent physiological indicators of fatigue, i.e., HR, HRV, breathing frequency and eye blinking frequency. The fusion of these four independent information can further improve the reliability of drowsiness indicator. Therefore, it will help reduce the chance of false detection. A sensor data fusion strategy is being developed as we continue our investigation.

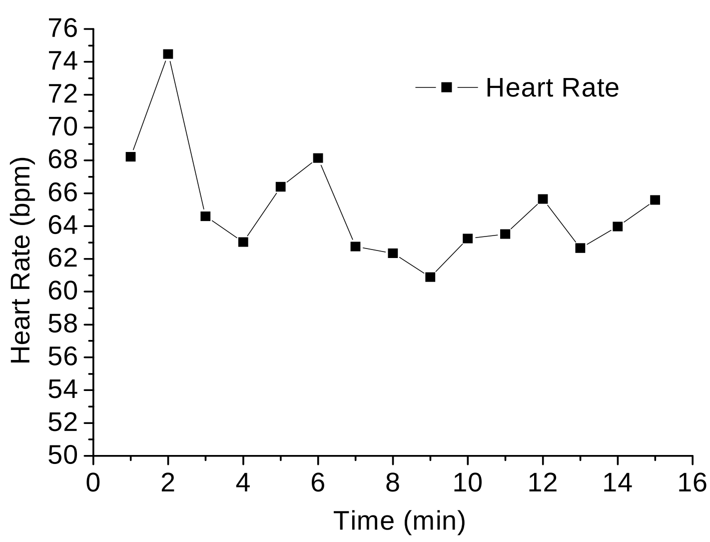

Figure 8 Heart rate during experiment

Table 2 Physiological parameters before and after driving test

	Non-fatigue	Mild fatigue
Heart Rate (HR)	68.2124 per min	65.5805 per min
HRV-average	3.1ms	6.4ms
HRV-variance	14.1ms	7.4ms
Eye blinking frequency	Relatively low	Relatively high
Breath frequency	No apparent change	

CONCLUSION

In this project, we explored the development of an innovative non-invasive bioelectrical measurement system. The system features high sensitivity in non-contact measurement of biopotentials on human body. The sensor prototype was found to be able to detect the ECG signal at a distance up to 30cm. By use of developed signal processing algorithm, the heart rate, heart rate viability and breath frequency can be obtained in real time. Moreover, the system also detects the eye blinking, another good indicator of fatigue. Experiments were conducted on a high-fidelity driving simulator to evaluate the performance of this sensor and signal processing algorithm. The results are encouraging. By monitoring the four independent physiological indicators of drowsiness under holistic driving conditions, the sensor data will provide important input for sensor fusion. Our long term goal is to develop this technology into a robust in-vehicle drowsiness monitoring system to improve driver safety.

ACKNOWLEDGEMENT

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