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Driver drowsiness is one of the major causes of serious traffic accidents, which makes this an area of great socioeconomic concern. Continuous monitoring of drivers' drowsiness thus is of great importance to reduce drowsiness-caused accidents. This proposed research developed a real-time, nonintrusive driver drowsiness detection system by building biosensors on the automobile steering wheel and driver's seat to measure driver's heart beat signals. Heart rate variability (HRV), a physiological signal that has established links to waking/sleepiness stages, is analyzed from the heat beat pulse signals for the detection of driver drowsiness. The novel design of measuring heat beat signal from biosensors on the steering wheel means this drowsiness detection system has almost no annoyance to the drivers, and the use of a physiological signal can ensure the drowsiness detection accuracy.

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Real-time Nonintrusive Detection of Driver Drowsiness

Final Report

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We thank the funding support from the Northland Advanced Transportation System Research Laboratory (NATSRL) at the University of Minnesota Duluth. NATSRL is a cooperative research program of the Minnesota Department of Transportation, the ITS Institute, and the University of Minnesota Duluth College of Science and Engineering. We also thank Dr. Eil Kwon for many productive discussions.

We also thank the hard work of the students involved in this project: Master degree graduate student Ms. Shan Hu and undergraduate student Mr. Ryan Bowlds.

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Executive Summary

In this FY08 Northland Advanced Transportation Systems Research Laboratories (NATSRL) project, a nonintrusive driver drowsiness detection system is developed by measuring and analyzing the driver's heart beat signals (ECG signal).

Two non-intrusive ECG measurement methods are developed for vehicle drivers, which will be used for drive drowsiness and fatigue detection. In the first method, each half of steering wheel is wrapped with conductive fabric as electrode. In the second one, two pieces of conductive fabric with the same dimension are placed on the driver seat's backrest as electrodes. Signal conditioning circuit and impedance matching circuit are specifically designed for each method. In addition, adaptive filter is utilized to suppress baseline noise that cannot be eliminated by the previous circuitries. Heart rate variability (HRV), a physiological signal that has established links to waking/sleepiness stages, is then analyzed from the heat beat pulse signals for the detection of driver drowsiness.

Experimental results show that ECG signals obtained by both methods are of satisfiable energy level, although the measurement from the seatback will be slightly affected by cloth materials. Results also demonstrate that both the signal conditioning circuitries and adaptive filter can effectively suppress noise and improve signal quality. Results also show a change in the driver's heart rate variability (HRV) with fatigue/drowsiness.

The design of measuring heat beat signal from biosensors on the steering wheel means this drowsiness detection system has almost no annoyance to the drivers, and the use of a physiological signal can ensure drowsiness detection accuracy.

Chapter 1
Introduction

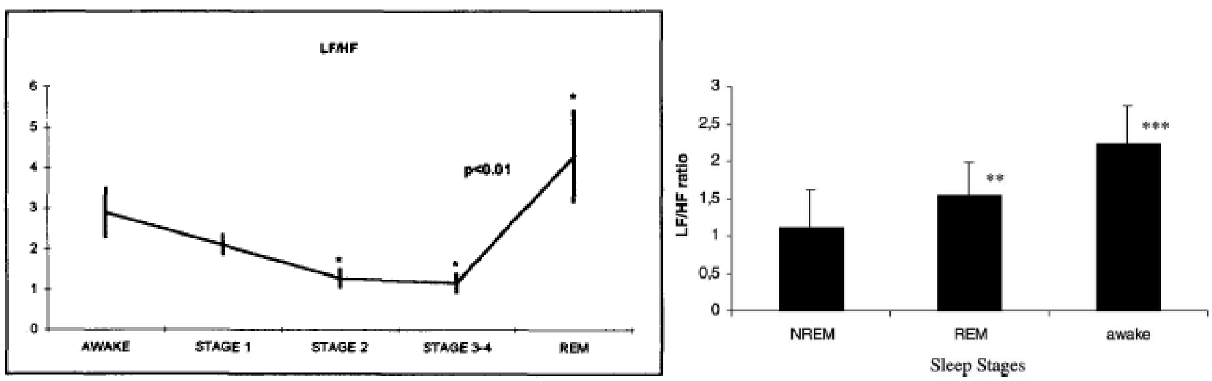
Driver drowsiness is one of the major causes of serious traffic accidents. According to the National Highway Traffic Safety Administration (NHTSA) [1], there are about 56,000 crashes caused by drowsy drivers every year in US, which results in about 1,550 fatalities and 40,000 nonfatal injuries annually. The actual tolls may be considerably higher than these statistics, since larger numbers of driver inattention accidents caused by drowsiness are not included in above numbers [1]. The National Sleep Foundation also reported that 60% of adult drivers have driven while felling drowsy in the past year, and 37% have ever actually fallen asleep at the wheel [2]. For this reason, a technique that can real-time detect the drivers' drowsiness is of utmost importance to prevent drowsiness-caused accidents. If drowsiness status can be accurately detected, incidents can be prevented by countermeasures, such as the arousing of driver and deactivation of cruse control.

Sleep cycle is divided into nonrapid-eye-movement (NREM) sleep and rapid-eye-movement (REM) sleep, and the NREM sleep is further divided into stages 1-4. Drowsiness is stage 1 of NREM sleep – the first stage of sleep [3]. A number of efforts have been reported in the literature on the developing of drowsiness detection systems for drivers. NHTSA also supported several research projects on the driver drowsiness detection. These drowsiness detection methods can be categorized into two major approaches:

- **Imaging processing techniques** [4-11]: this approach analyzes the images captured by cameras to detect physical changes of drivers, such as eyelid movement, eye gaze, yawn, and head nodding. For example, the PERCLOS system developed by W. W. Wierwile *et. al.* used camera and imaging processing techniques to measure the percentage of eyelid closure over the pupil over time [8-10]. The three-in-one vehicle operator sensor developed by Northrop Grumman Co. also used the similar techniques [11]. Although this vision based method is not intrusive and will not cause annoyance to drivers, the drowsiness detection is not so accurate, which is severely affected by the environmental backgrounds, driving conditions, and driver activities (such as turning around, talking, and picking up beverage). In addition, this approach requires the camera to focus on a relative small area (around the driver's eyes). It thus requires relative precise camera focus adjustment for every driver.
- **Physiological signal detection techniques** [12-14]: this approach is to measure the physiological changes of drivers from biosignals, such as the electroencephalogram (EEG), electrooculograph (EOG), and electrocardiogram (ECG or EKG). Since the sleep rhythm is strongly correlated with brain and heart activities, these physiological biosignals can give accurate drowsiness/sleepiness detection. However, all the researches up to date in this approach need electrode contacts on drivers' head, face, or chest. Wiring is another problem for this approach. The electrode contacts and wires will annoy the drivers, and are difficult to be implemented in real applications.

To overcome the limitations of current drowsiness detection methods, this proposed research aims to develop a real-time, easy implementable, nonintrusive, and accurate drowsiness detection system. More specifically, we propose to embed biosensors into steering wheel to nonintrusively measure heart beat pulse signals for the detection of driver drowsiness.

Time series of heart beat pulse signal can be used to calculate the heart rate variability (HRV) – the variations of beat-to-beat intervals in the heart rate [15], and HRV has established differences between waking and sleep stages from previous psychophysiological studies [16-22]. The frequency domain spectral analysis of HRV shows that typical HRV in human has three main frequency bands: high frequency band (HF) that lies in 0.15 – 0.4 Hz, low frequency band (LF) in 0.04 – 0.15 Hz, and very low frequency (VLF) in 0.0033 – 0.04 Hz [15]. A number of psychophysiological researches have found that the LF to HF power spectral density ratio (LF/HF ratio) decreases when a person changes from waking into drowsiness/sleep stage [16-21], while the HF power increases associated with this status change [16, 22]. The HRV analysis therefore can be an effective method for the detection of driver drowsiness. Although a few studies have tried to use heart rate or HRV analysis to study driver fatigues [23-25] or driver stress level [26], no previous researches have tried to use HRV analysis for the driver drowsiness detection (driver fatigue is related but also different to driver drowsiness [1], e.g., a tired person not necessary feel sleepy and a sleepy person may not be tired). In this proposed research, heart beat pulse signals will be measured by biosensors embedded in steering wheel, HRV will then be analyzed to detect driver drowsiness. The key to the proposed drowsiness detection approach is to have an accurate and non-invasive heart rate signal measurement system.



(A) (B)

Fig.1. Representative literature results showing the changes of LF/HF ratio in various sleep stages: (A) was cited from reference [19], (B) was cited from reference [20].

Chapter 2
Non-intrusive ECG Measurement on Steering Wheel and Driver Seat

HRV is typically measured and analyzed from RR interval time series (peak-to-peak) of the electrocardiogram (ECG) signal. Although ECG measurement techniques are well developed, most of them involve electrode contacts on chest or head, for example the conventional fixed-on-chest Ag-AgCl electrodes. Wiring and discomfort problems inherent in those techniques prevent their implementations on vehicles. Those heart rate monitor for fitness equipments also need a chest belt or needs both hands to touch a device to measure heart rate. In this project, several approaches were investigated to non-intrusively measure the driver's heart beat signal.

2.1 Non-intrusive Conductive Fabric ECG Sensor on Steering Wheel

For the non-intrusive ECG sensor, each half of steering wheel is wrapped with electrically conductive fabric (ECF) as two ECG electrodes. ECF is textile plated with conductive metal. Because of its flexibility, it can be easily deformed to fit the contour of steering wheel without causing discomfort to the drivers. ECG signals from electrodes are severely affected by the common mode noise (CMN) from human body. The noise prevents the calculation of correct heart rate from ECG signals. To improve signal quality, signals from ECG electrodes are filtered by signal conditioning circuitry consist of differential low pass, band pass and 60 Hz notch filter. The filters are designed to cancel CMN with a high Common Mode Rejection Ratio. A Driven Right Hand circuit, which is similar to the Driven Right Leg circuit in traditional ECG measurement system, is used to further suppressed CMN. The circuit reads the noise from the human body by the ECG electrodes, inverts the noise by analog amplifier, and feeds the inverted noise back to human body to actively negate the CMN. After the signal conditioning circuitry, clear ECG signals will be digitized and transmitted to the computer for further HRV analysis by wireless transmitter. The real-size developed ECG sensor and the block diagram of the circuitry are shown in Fig.2.

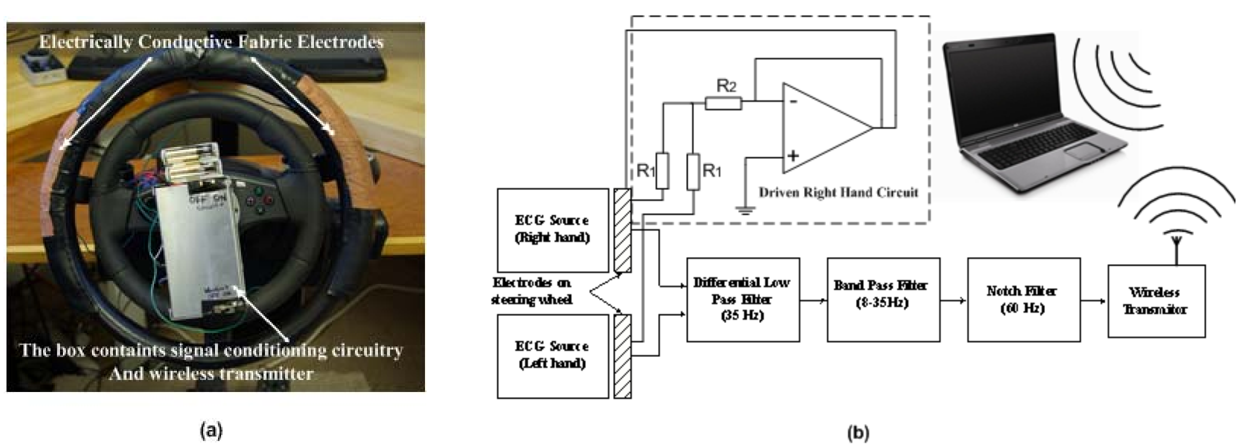


Fig.2. (a) The real-size developed ECG sensor. (b) the block diagram of the signal conditioning circuitry

2.2 Non-intrusive ECG Measurement on Driver's Seat

In this method, two pieces of conductive fabric with the same dimension (8cm×8cm) are placed on driver seat's backrest (Fig. 3). Unlike electrodes in the previous method, electrodes on backrest do not contacted with drivers' skin directly. Therefore, there exists high impedance between the electrode and skin due to the poor permittivity of commonly available clothes. Since low impedance is required by the subsequent circuitry, an impedance matching circuit is needed to mediate the high impedance between electrodes and skin. Figure 4 shows the ECG measurement circuitry for electrodes on backrest. An operational amplifier OPA 124 with high input impedance is used in the impedance matching circuit. Resistor *R* provides a path for bias current of OPA 124. *V*s is the ECG source. *R*s, *C*s are resistance and capacitance between body and electrodes respectively. For the convenience of future discussion, they are also included into impedance matching circuitry. If driver's back and electrodes are coupled firmly, *R*s and *C*s can be calculated by

$$C_s = \frac{\varepsilon S}{d} \qquad (1)$$

$$R_s = \frac{\rho d}{S} \qquad (2)$$

where ε and ρ are the permittivity and static resistivity of the clothes, *S* is the area of the electrodes, and *d* is the thickness of the clothes. Since the area of electrodes is fixed, *R*s and *C*s are determined by the properties of clothes. The output (*V*o) to input (*V*s) ratio of the impedance matching circuitry couple can be calculated by

$$\frac{V_o}{V_s} = \frac{R}{R+R_s} \times \frac{1+j\omega R_s C_s}{1+j\omega \frac{RR_sC_s}{R+R_s}} \qquad (3)$$

which shows that the impedance matching circuit is a high pass filter, with cut-off frequency $f = (2\pi\, RR_sC_s / R+R_s)^{-1}$ and gain $G= R/R+R_s$, and the clothes properties (e.g. thickness, electrical properties) will affect the cut-off frequency and gain by affecting *R*s, *C*s. According to the expression of gain, *R* should be big enough so as to be comparable with *R*s, otherwise the circuitry will not be able to provide ECG signals of satisfiable energy level for successive signal processing. Another difference from the circuitry for electrodes on steering wheel is that ECG signals from electrodes on backrest are first filtered and amplified separately by identical band pass filters to remove electrode DC offset potential, before going into a differential amplifier. Since ECG signals obtained without direct contact with skin are very small compared to those obtained by direct contact, their differential signal is even smaller. If they are not amplified separately first, a bigger gain is needed to convert the feeble differential signals into representative signals, causing the circuit to saturate easily.

Fig. 3. ECG measurements on driver's seatback

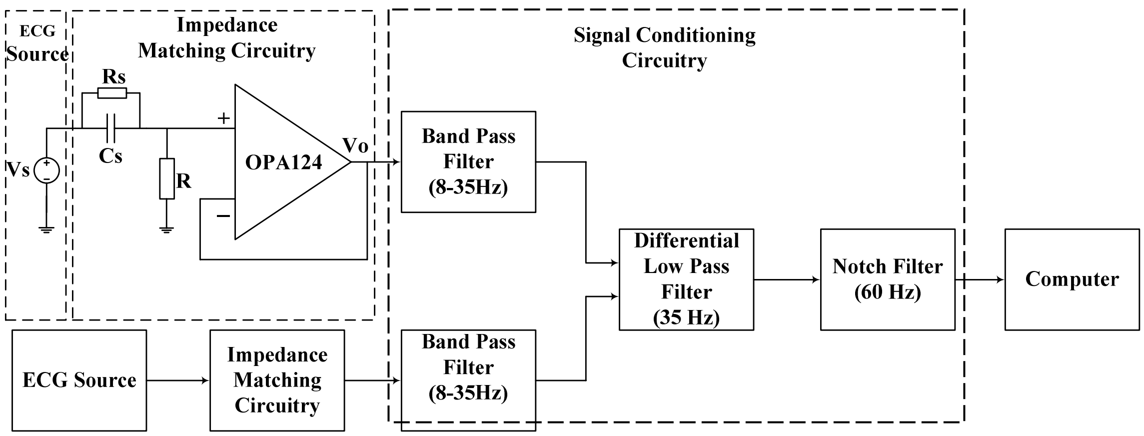


Fig. 4. ECG measurement circuitry for electrodes on backrest

2.3 Adaptive Baseline Noise Cancellation

By using the signal conditioning circuitry, most noise in ECG signals can be canceled. However, some noise (e.g. baseline noise) whose frequency overlaps with the frequency range of ECG signal can not be effectively eliminated by those filters mentioned above. Undesirable signal distortion will be introduced into ECG signal. To address this challenge, an adaptive filter based on the least-mean squares (LMS) algorithm is employed for baseline noise cancellation [27, 28]. Figure 5 illustrates the block diagram of the adaptive baseline noise canceller. The primary input *d (n)* is the mix of ECG signals and baseline noise that are uncorrelated to each other, while the reference input u (n) is constant "1". *w (n)* is the adaptive weight for inference input at time n. The adaptive filter uses the reference input to provide (at its output y (n)) an estimation of the baseline noise contained in the primary input. Thus, by subtracting the adaptive filter output from the primary input, the baseline noise is diminished. The error e (n) between the output of the adaptive filter and primary input is the desired ECG signal without baseline noise, which is used by the adaptive filter to adapt filter weight *w(n)*. Equations (4) to (6) describe how the filter weight *w (n)* coefficient is adapted by means of the LMS algorithm.

$$y(n) = \mathbf{w}^T(n)\mathbf{u}(n) \qquad (4)$$

$$e(n) = d(n) - y(n) \qquad (5)$$

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu\mathbf{u}(n)e(n) \qquad (6)$$

where μ is the adaptation step-size. In our adaptive filter, only one weight is used, making the input vector u (n) and weight vector w (n) scalars. It could be dynamically adjusted to obtain the desired response.

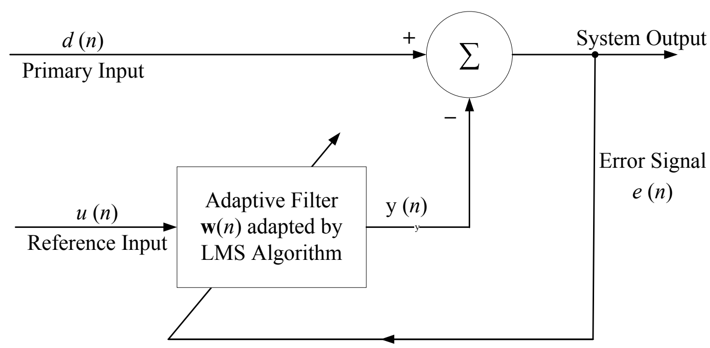


Fig. 5. Diagram of the adaptive baseline noise canceller

Chapter 3
ECG Measurement Results

3.1 Results for Electrodes on Steering Wheel

Figure 6 and Figure 7 show test results on male and female subjects respectively. Top trace is the output signals after conditioning circuitry; second trace is the output signals after the adaptive baseline noise canceller; and third trace is the estimated baseline noise. Outputs of the signal conditioning circuitry demonstrate that the circuitry is able to amplify ECG signals to a satisfiable energy level and effectively suppress noise, especially 60 Hz power line noise. Outputs of the adaptive filter show that the adaptive filter can effectively eliminate baseline noise. For instance, Figure 6 (a) shows that there is a baseline noise at the end of recording. Since heart beat interval is usually detected by using peak detector, the baseline noise adds the difficulty of correctly detecting the subject's heartbeat interval by shifting the peak value of heart beats suddenly. Figure 6 (b) shows that the adaptive filter can successfully remove the baseline noise without introducing much distortion.

In Figure 7 (a), it can be noticed that the peak values of S-segments are sometimes larger than those of R-segments, which increases the likelihood of false heartbeat interval detection (as is shown in Figure 7 (a), some intervals can be determined as interval between R-S peaks, instead of R-R peaks). According to Figure 7 (b), the proposed adaptive filter can effectively reduce the peak values of S-segments while keep those of R-segments almost unchanged. By doing this, it actually helps the peak detector to identify the R-peaks more precisely.

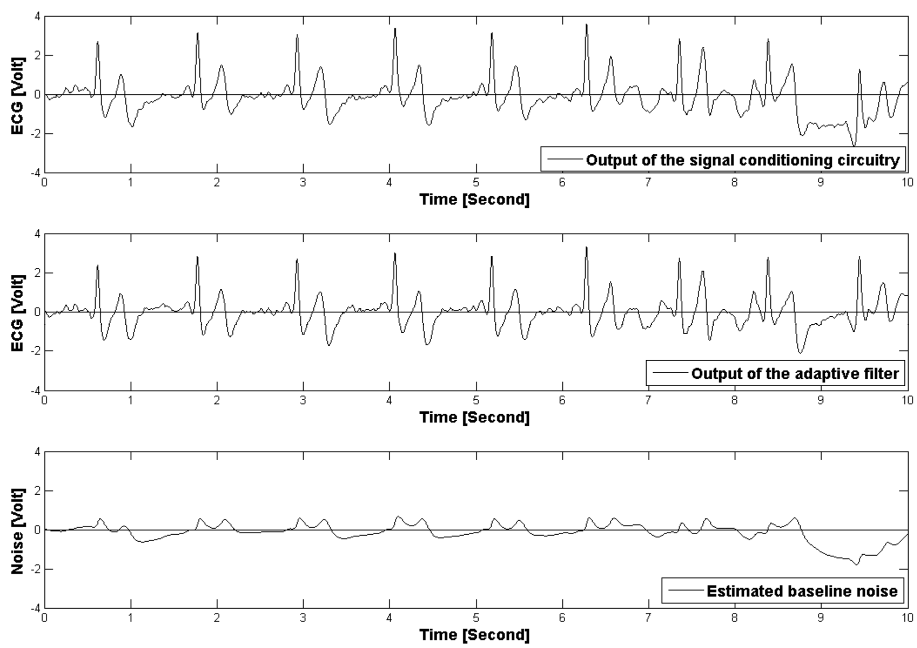


Fig. 6. ECG test results of a male subject (from the steering wheel electrodes)

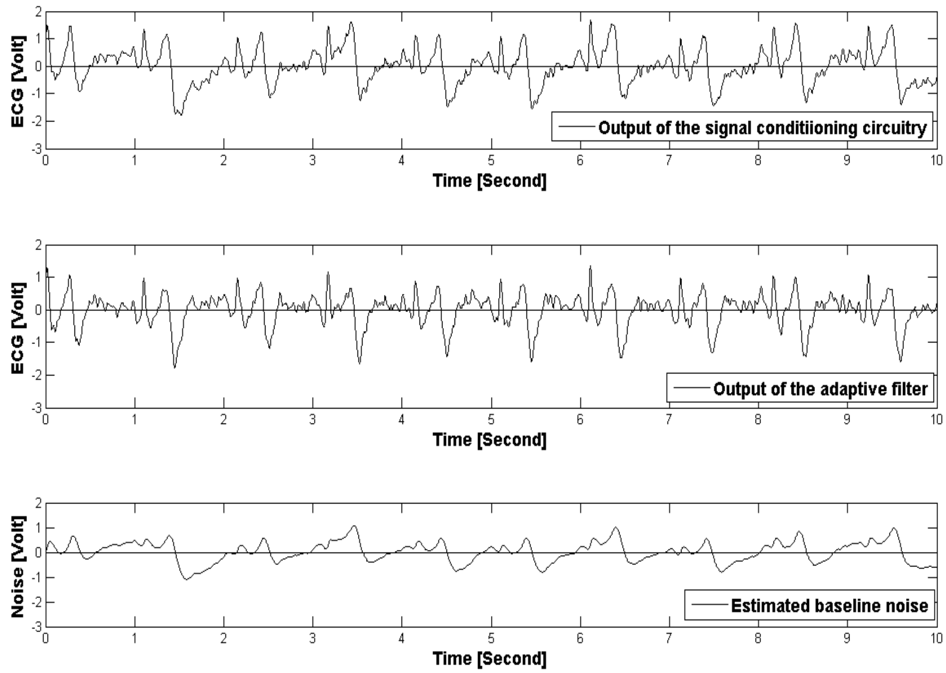


Fig. 7. ECG test results of a female subject (from the steering wheel electrodes)

3.2 Results for Electrodes on Backrest

In the test of electrodes on backrest, to verify that driver's clothes can affect the frequency response of impedance matching circuitry, the female subject is asked to do three tests wearing three different kinds of clothes: cotton hoody (thickness 0.30 inches), wool jacket (thickness 0.67 inches) and acrylic sweater (thickness 0.30 inches). Figure 8 shows the three test results. Top, second and third traces are ECG signals with wearing cotton hoody, wool jacket, and acrylic sweater respectively. As can be seen in Figure 8, maximum gain is obtained when subject is wearing acrylic sweater, gain is medium when wearing wool jacket and smallest when wearing cotton hoody.

To better understand the reason why different clothes result in different gains, the frequency responses of different clothes with impedance matching circuitry were analyzed. To perform analysis, the clothes were inserted between the electrode surface and a copper clad PCB board, whose area is made much bigger than that of the electrode in order to make sure the whole electrode surface is involved into the capacitive couple. The frequency responses were then measured by a dynamic signal analyzer (Photon II, LDS Ltd.). Fig.9 shows the frequency response of different clothes. As can be seen in Fig. 7 and Fig.8, higher gain in frequency response will yield higher ECG signal gain.

Results shown in Figure 8 also support the impedance analysis in Equation (3), i.e., the impedance matching circuitry is a high pass filter and the clothes properties will affect the gain and cut-off frequency of the circuitry.

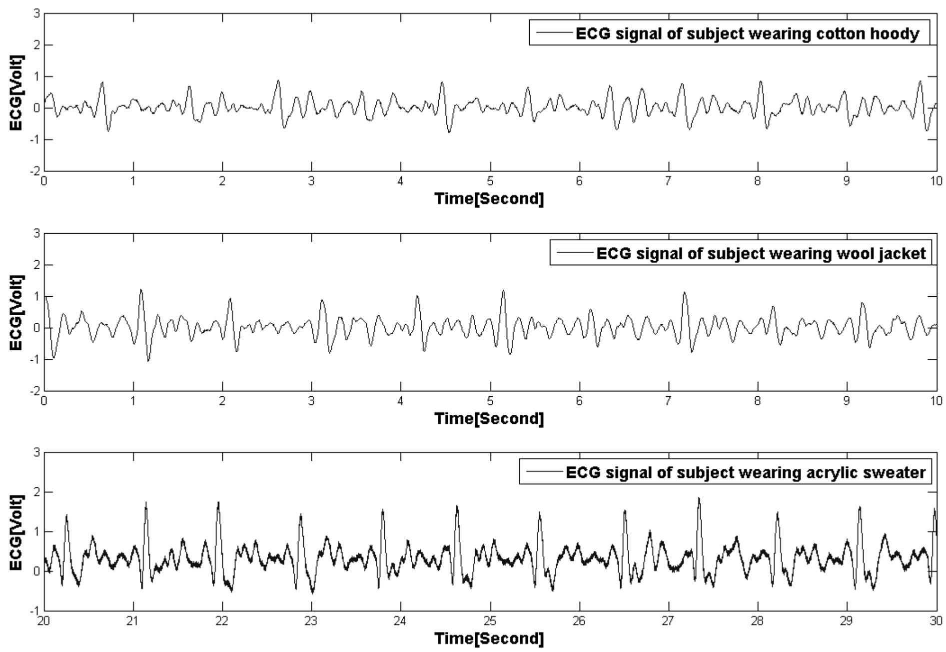


Fig. 8. ECG signals of a female subject when wearing three different types of clothes (from the backrest electrodes)

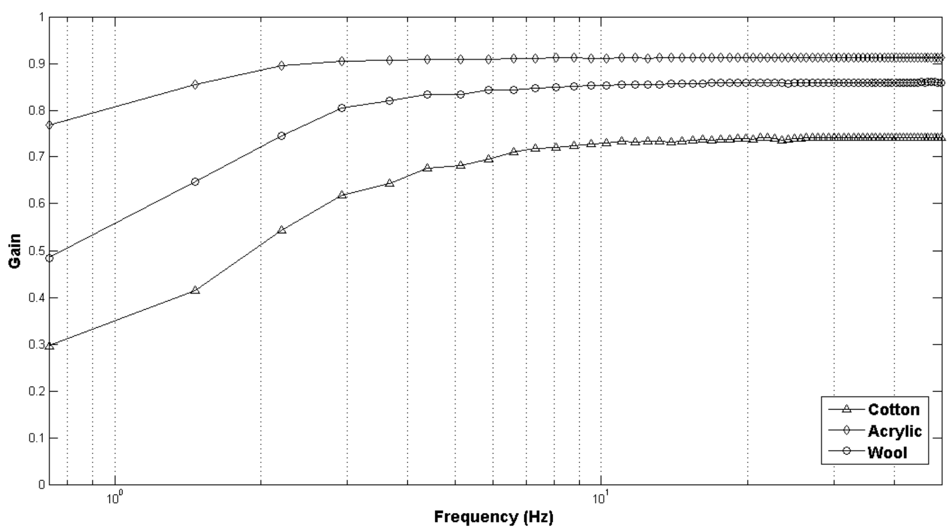


Fig. 9. Frequency responses of impedance matching circuitry when coupled with different clothes

Chapter 4
HRV Analysis and System Tests

4.1 HRV Analysis for Drowsiness Detection

As clear ECG signals are obtained after noise cancellation procedure, HRV analysis will be performed to extract information for drowsiness detection. Fig. 10 shows the flow diagram of the signal processing sequences.

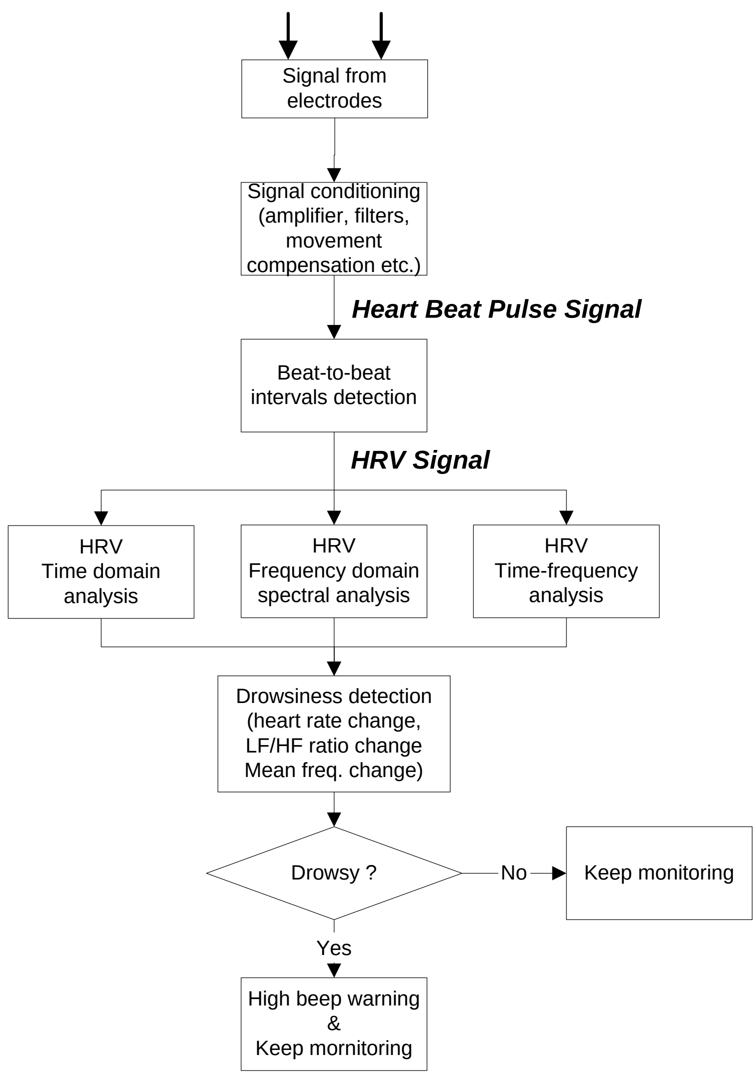


Fig. 10. Flow diagram of the signal processing and HRV analysis system

First, a peak detector computes the peak-to-peak interval (or heart rate) time series from ECG signals and pulse wave signals. Since the time intervals between peaks are not uniform, to enable the frequency analysis on heart rate time series, resampling is needed to turn the original heart rate time series into evenly sampled. Then the resampled time series is analyzed in two domains:

frequency domain and time-frequency domain. In frequency domain, the power spectral density (PSD) of every two-minute heat rate time series will be estimated by the autoregressive method [29]. Then the PSD is divided into three main frequency bands: high frequency band (HF) that lies in 0.15-0.4 Hz, low frequency band (LF) in 0.04-0.15 Hz, and very low frequency (VLF) in 0.0033-0.04 Hz. A number of psychophysiological researches found that the LF to HF ratio (LF/HF ratio) decreases when a person becomes sleepy [19, 20]. As a result, we choose to calculate LF/HF ratio as an indication of drowsiness instead of other kinds of HRV. For time-frequency analysis short-time Fourier transform (STFT) is performed on heart rate time series to see how the heart rate frequency contents change as the driver becomes drowsy. The STFT uses a window to slide through heart rate time series and perform Fourier transform inside each window. The result of STFT is a spectrogram showing the magnitude of the STFT versus time.

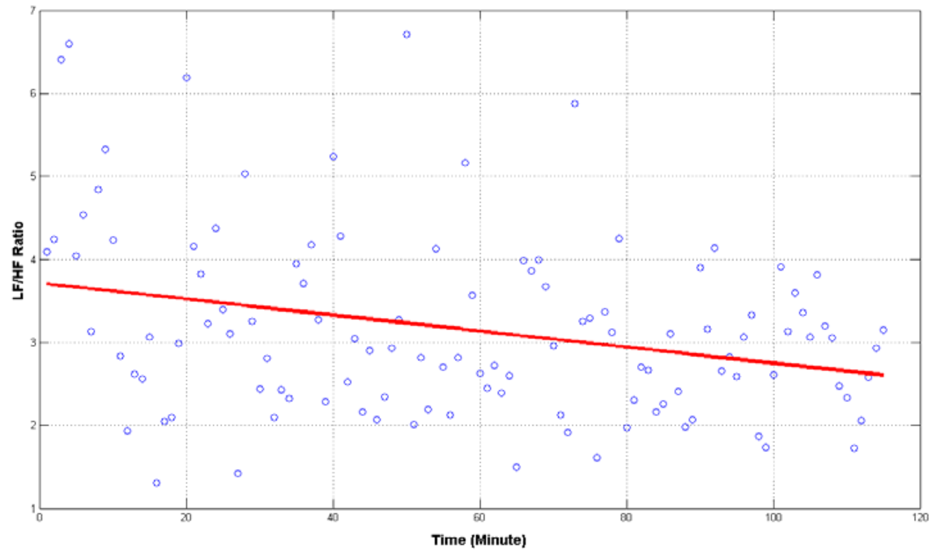
4.2 System Test Experimental Setup

A driving simulator as shown in Fig. 11 is used to test the drowsiness detection system. The simulator has a screen to display the virtual reality driving environment, a real-size driver seat and a steering wheel. A subject was asked to drive with the simulator non-stop for two hours. The subject's heart rate was continuously recorded the ECG sensors or pulse wave sensor installed on the steering wheel. A camera was used to capture the video of driver's behavior, such as yawning, long-time eye closure, etc. The video will serve as a reference for driver's drowsiness level.

Fig. 11. Layout of driving simulator

4.3 Results of HRV Analysis during Driving Simulation

Two health subjects (male, 24 and female, 24) were recruited for two-hour driving simulation. At the beginning, the subjects were not sleepy at all: the eye movements were quick and the body movement was active; whereas at the end, the drivers seemed very sleepy: eye blinking occurred slowly, the eyelids were shut sometimes and yawning happened frequently with deep respiration. The LF/HF ratios for both subjects during driving simulation are shown Fig. 12. As getting drowsy, both subjects' LF/HF ratios show a decreasing trend. However, the slope of the trend varies among two subjects. The spectrograms of two-hour heart rate time series for both subjects are shown in Fig. 13. The HF and LF ranges are marked out. The bright color on spectrogram stands for high power in frequency domain. As the subjects became drowsy, both spectrograms showed the increase of bright color (or increase of power) in HF range. This could be part of the reason why the LF/HF ratio has a decreasing trend.



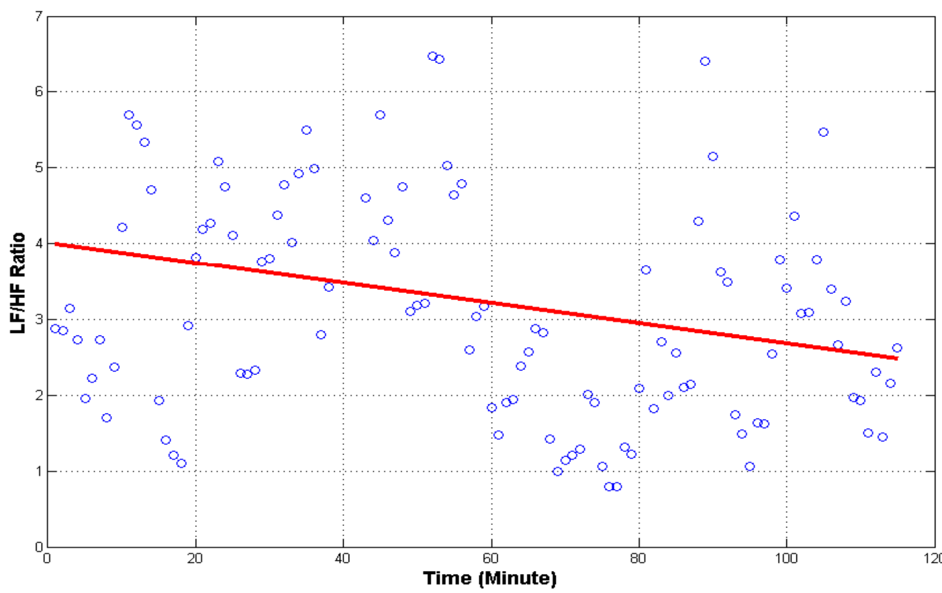


Fig.12. The LF/HF ratio during two-hour driving simulation for female and male subject respectively. In both plots, the trend line is obtained by linear curve fitting.

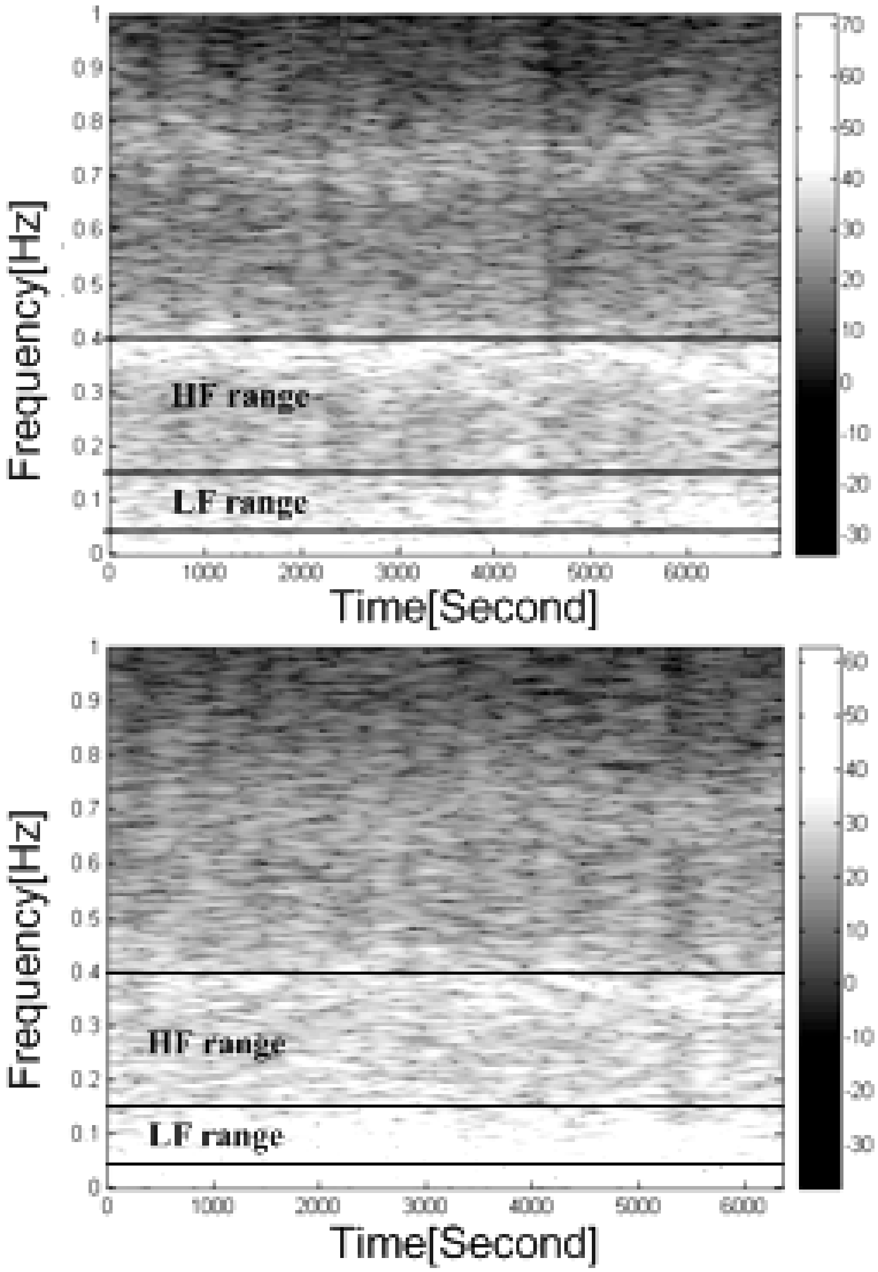


Fig. 13. Spectrogram of two-hour heart rate time series spectrogram of female and male subjects respectively

Chapter 5
Conclusion and Discussion

In this research, conductive fabric ECG sensors had been developed to measure heart pulse from driver's palms and driver's seatback for drowsiness detection. The sensor is non-intrusive and can be easily installed on vehicle steering wheel. Signal conditioning circuitry, such as bandpass, notch filters, driver right hand circuits, was designed to improve the signal quality of ECG signals from conductive fabric ECG sensors. Adaptive filter algorithm was designed to effectively eliminate the measurement baseline noise. Experimental results showed that both sensors and their signal conditioning procedure can provide reasonable heart rate time series for later heart rate variability analysis. Two hour driving simulation was conducted on two subjects. HRV analysis on the two hour heart rate time series showed that LF/HF ratio had a decreasing trend as both subjects became drowsy, although the slope of trend were different between subjects. According to the time-frequency analysis of heart rate time series, the decreasing trend can partially due to the increase of power in HF range. The driving simulation results shows that the proposed sensors were successful in continuously monitoring driver's heart rate and that the LF/HF ratio of HRV in frequency domain is promising to be used as an indicator for driver's drowsiness detection. Several limitations are also noticed during our research:

1. The ECG sensor on steering wheel needs the driver to put both hands on the steering wheel, it will not be able to detect ECG signal if the driver uses only one hand. It will also fail to measure ECG signal if the driver wears gloves.

2. The ECG sensor on the driver's seatback is very sensitive to impedance changes and disturbance resulted from environment noise.

3. Each individual has unique HRV pattern (e.g. the different decreasing trend slopes observed from two subjects), future research is needed to create personalized drowsiness detection criterion.

These challenges will be addressed in the Phase II of this research project by developing a single-touch heart pulse wave sensor and individual HRV pattern analysis.

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