Thesis for the Degree of Master of Engineering

Wearable Driver Drowsiness Detection System in Smartwatch

by

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List of Abbreviations

EEG	Electroencephalography
ACC	Adaptive Cruise-Control
LDW	Lane-Departure Warning
SVM	Support Vector Machine
BCI	Brain-Computer Interface
ECG	Electrocardiogram
PPG	Photoplethysmogram
EOG	Electrooculography
HMM	Hidden Markov Model
KSS	Karolinska Sleepiness Scale
GSR	Galvanic Skin Response

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Wearable Driver Drowsiness Detection System in Smartwatch

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Abstract

Driver drowsiness detection system had been developed as comprehensive application but this has the potential risk of distracting the driver's attention, causing accidents. Thus, a wearable-type drowsiness detection system is proposed to overcome such issue. The proposed system used self-designed wristband consisted of photoplethysmogram sensor and galvanic skin response sensor. The sensors data are sent to the smartwatch which served as a main analyzing processing unit. Those data are analyzed along with the motion data collected from built-in accelerometer and gyroscope sensors. Features extracted from the data based on data time-domain, frequency domain, and phase domain. The correlation of each feature was calculated using PEARSON correlation method. Those top features are further served as computation parameters to a support vector machine (SVM) to derive the driver drowsiness state. The accuracy of system had calculated based on number of input features into SVM. The testing results indicated that the accuracy of the system with SVM model reached up to 98.15% with 8 features. If drowsy detected, driver will be

alerted using graphical and vibration alarm generated by the smartwatch. In fact, the integration of driver physical behavior and physiological signals is proven to be an outstanding solution to detect driver drowsiness in a safer, more flexible and portable used.

1.0 Introduction

Drowsy drivers caused a lot of life lost in past few years. A foundation study in 2014 showed that drowsy drivers are involved in an estimated 21% of fatal crashes, up from 16.5% from the previous 2010 study, as most drivers drift out of their lanes or off the road [1]. According to foundation, an estimated 328,000 crashes each year, including 109,000 injury crashes and 6,400 fatal crashes, involve a drowsy driver. There are several laws and regulations implemented to reduce the number of drowsy driving across the world but it's cannot stop a driver to fall asleep suddenly. Thus, a real-time driver drowsiness system should be implemented to decrease the risk of driver getting into accident.

There are different types of driver drowsiness detection system based on different analysis of drowsiness. These analysis generally categorized into 3 different approaches which are biological, image processing, and driver behavior. This research is focusing on detecting driver drowsiness using wearable devices which emphasized on driver comfort based on biological and driver behavior analysis.

This chapter discusses the motivation, research aims, challenges faced, contribution, and organization of this thesis.

1.1 Motivations

The number of drowsy accidents was increasing nowadays. This might due to stress and tiredness accumulated from work onto drivers especially those drivers need to work overtime and can only go home in late night. Drivers will still fall asleep even they takes energy drinks, sugar or listening to music. Considering long-term driving alone that needed to maintain alertness, an automatic driver drowsiness detection system must be setup to warn the driver if the driver fall asleep.

Although there are some ready-made driver drowsiness system installed in the vehicle, but these driver drowsiness system normally will only installed in high-end brand vehicle such as Benz. These systems normally use lane tracking method to estimate driver behavior which further estimate the drowsiness of driver. There is also some driver drowsiness systems that required driver to wear some sensors which might cause distraction to driver when driving such as electroencephalography (EEG) system which driver need to wear several electrodes on their head with wire connecting to processing unit. Such systems might cause distraction to drivers which was the major cause of accidents happened. Some researchers used imaging method to detect driver drowsiness such as detecting the eye openness, the gesture of head or the facial expression but such system had very huge disadvantage when the ambient intensity is not sufficient.

This thesis focused on developing a wearable driver drowsiness detection system which neither limited to ambient intensity factor nor distracted drive attention toward driving. The system is developed using a self-designed wrist band to collect biological data and send to smartwatch through Bluetooth. Smartwatch combines the biological data received with the motion data collected from its built-in motion sensor to analyze the driver drowsiness and show the results of analysis. Some warning according to different stage of drowsiness will be given if drowsiness detected.

1.2 Challenges

Smartwatch is a new wearable device that can synchronize with smartphone. The device getting more and more popular as it can enables users to check smartphone messages without actual reaching out for the smartphone. Driver drowsiness detection application implemented in smartwatch can help driver in monitoring their drowsiness level by wearing self-designed wrist band. Few challenges met when developing this system, such as:

a) Features extraction of bio-logical signals

- Bio-logical data measurement in real-time

b) Computational time of applications

- Fast response time to warn driver when drowsiness detected

c) Memory used in Smartwatch

- Amount of memory limited in Smartwatch
- Performance needs to have a good tradeoff with accuracy of system

d) Bluetooth Low Energy usage

- Manually activate and connect Bluetooth low energy device using smartwatch

e) Type of Alarm

- Limited as smartwatch doesn't have speaker

1.3 Research Objectives

In this research, driver drowsiness detection system was developed using 2 non-distractive wearable devices which are self-designed wrist band and smartwatch. The proposed system aims to:

a) Develop wristband to monitor driver's bio-logical signals

b) Develop biological and motion analyze algorithm to identify driver's drowsiness level

c) Develop a driver drowsiness detection application in smartwatch

d) Develop alarm system to alert driver if drowsy detected

1.4 Contribution

Throughout the research progress, lots of efforts had been contributed to overcome the challenges faced during the system implementation. In contrast to the driver drowsiness detection system available on the markets nowadays, we are dedicating on presenting the driver drowsiness detection in smartwatch with low-cost solution, differentiating our system from the others. Collaboration works are required in both hardware and software sides to perfect the system. The fundamental ideas are as follows:

a) Predicted the driver drowsiness based on two distinct methods which are motion features and biological signals analysis.

b) Design a wristband to measure the biological status which is heartbeat and stress level.

c) Implemented the sensor modules with built-in filtering circuits to remove noise affected by the power noise or motion artifacts.

d) Validate the Bluetooth Low Energy connection establishment between sensor modules and smartwatch.

e) Conduct real-time simulations under various conditions including the experimenters' health status, environment.

f) Validated simulation results by recorded images using standardized analyzes method.

1.5 Chapter Organization

Chapter 2 briefly introduces the background and related work of this research. Chapter 3 introduces the system design and implementation. Chapter 4 illustrate about real time analysis and extraction of motion signal from motion sensors. Chapter 5 describes about real time analysis and extraction of biological signal from self-designed wristband. Chapter 6 depicts the driver drowsiness system implemented in Android-based platform smartwatch device. The experiments result and evaluation are discussed in chapter 7. Finally, Chapter 8 summarizes the thesis work and discusses the potential future work for system enhancement in the future.

2.0 Background and Related Works

Driver drowsiness detection system is a system that monitors drivers' drowsiness status to prevent driver from falling sleep in the middle of driving. There are several existing driver drowsiness detection system developed using image processing, bio-logical, and drivers behavior as functions to decide whether the driver is awake or sleep. The main objective of this research is to develop a wearable driver drowsiness system that can have the same function like others but reduce the distraction of drivers driving to nearly zero, thus using only motion and biological signal for driver drowsiness detection. This research is aiming for comfort and non-distraction of drivers while keep them safe and sound on the road.

In this chapter, a brief driver drowsiness detection system is introduced. Following, some studies is conducted to analyze and comparing different type of features. Next, analysis techniques of related driver drowsiness detection system are explained.

2.1 Driver Drowsiness Detection

There are many safety applications to be applied on the driver to drive safe as it is their responsibility not only for their life but also other road user such as walker or biker. Applications such as overspeed detection using camera or drunken detection using alcohol detection blower are the universal solution to keep the driver from speeding or drive after alcohol drinking. Driver drowsiness has no universal solution so far as it happened uncontrollable. It might due to insufficient sleep, weather, music, or food intake before the driving. Thus, a preferable solution needed to be proposed to warn the driver about their drowsiness when driving to avoid any accidents especially fatal accidents happened on highway.

There are researches or commercial product on driver drowsiness detection system based on steering pattern monitoring, vehicle position in lane monitoring, driver eye or face monitoring, and physiological measurement.

2.2 Vehicle Controls

There are embedded systems in passenger car for road safety such as automatic collision notification, vehicle security, and speed control available nowadays [2]. Some researchers studied the drivers performances extracted from the driver-vehicle interaction. The research artworks of researchers are listed as follow:

a) Lai et al. [3] developed a fuzzy-control massage seat to keep drivers awake by measuring the driver impairments including actual driving performance, subsidiary task performance, and subjective ratings of drowsiness, which integrates criterion of steering behavior and tendency index that could evaluate the driving drowsiness effectively over prolonged driving.

b) Pauwelussen et al. [4] developed a traffic-simulation model in which a vehicle is equipped with an adaptive cruise-control (ACC) and lane-departure warning (LDW) system to monitor driver behavior in a real traffic environment.

c) Zhao et al. [5] studied the reliability of steering behavior to detect driver fatigue by multiwavelet packet energy spectrum using a support vector machine (SVM).

d) Yang et al. [6] demonstrated that drowsiness has a greater effect on rule-based driving tasks than on skill-based tasks using a Bayesian network (BN) paradigm through simulator-based human-in-the-loop experiments.

e) Wang et al. [7] introduced a dangerous-driving warning system that uses statistical modeling to mine the safe/dangerous driving pattern from time-series data with very limited labeling information. Although the labeling information is only provided for accidents, the learned model is able to predict non-crash dangers such as near miss or other dangerous driving maneuvers.

f) Liang et al. [8] developed a system to detect driver distraction and adapt in-vehicle system accordingly by using SVMs, in which collected data in the simulator experiment were trained and three characteristics were investigated: how distraction was defined, which data were input to the model, and how the input data were summarized.

g) Desai et al. [9] presented a hypothesis to characterize driver alertness by computing the spikiness index of the jerk profile on gas pedal. It showed that alert driver maintains high-frequency interactions at the vehicle-driver interfaces while drowsy driver causes sluggish or flatter responses from the driver, which could be clearly distinguish from the alert-state driving data pattern.

2.3 Steering Pattern or Motion Monitoring

Some researchers studied the drivers drowsiness extracted from the motion. The research artworks of researchers are listed as follow:

a) Takei et al. [10] estimate a driver's fatigue through steering motion. In this research, the Chaos theory was applied to explain the change of steering wheel motion. If there is Chaos in the motion, a strange trajectory called attractor can be found by applying the Takens' theory of embedding.

b) ShuanFenget al. [11] investigate the relationship of driver fatigue with steering wheel motion. They showed the results of computer simulation demonstrate that the information of driver fatigue hide in steering wheel motion.

c) Mingdeet al. [12] developed vibration fatigue test system for vehicle driver seat to aim at fatigue failure driver seat. The six degree of freedom hydraulic-servo motion base as an experimental research device is applied to test vibration fatigue of vehicle driver seat.

d) Jianjunet al. [13] present to use a driving motion capture system to capture and interpret driving motion for a better understanding of driver behaviors which is crucial to highway traffic safety.

2.4 Bio-logical Methods

Most healthcare system developed by monitoring biological signal such as heart rate, respiration rate, blood pressure, etc. Sabetet al. [14] aimed to locate, track and analyze both the driver's face and eyes to compute a drowsiness index to prevent accidents. Hachisukaet al. [15]classify the driver's drowsiness level by pattern classification based on facial features by image processing on driver's facial image. Lin et al. [16] proposed a real-time brain-computer interface (BCI) system to monitor human physiological, cognitive states by analyzing the EEG signals. They demonstrated that the amplitude of EEG peak value represents the driving error estimated by the drowsiness detection system. Bell et al. [17] combined power spectrum estimation and artificial neural network technique to create a non-invasive and real-time system that is able to categories EEG into three level of attention: “High”, “Relax” and “Drowsiness”. On the other hand, Wang et al. [18] proposed a latent variable to represent the attributes of individual drivers for recognizing the emotional state of drivers using four sensors, specifically for respiration, skin conductance, temperature and blood pressure. Shin et al. [19] described the design of an Electrocardiogram (ECG) and Photoplethysmogram(PPG) sensor to measure the driver’s metabolic condition. Khushaba et al. [20] maximized the drowsiness-related information extracted from Electrooculography (EOG), EEG and ECG signals to classify driver attentiveness. A neural network approach to classify mental fatigue and drowsiness in driver was proposed by Bundele et al. [21], where the fatigue measurements are based on skin conductance and pulse oximetry. Yang et al. [22] used a first order Hidden Markov Model (HMM) to compute the dynamics of BN for compiling information regarding to multiple physiological characteristics such as ECG and EEG signals to infer the level of driver fatigue. Li et al. [28] estimated the extent of eye closure by using an electroencephalograph, but the drivers were required to attach the electroencephalogram (EEG) sensor to their heads, which could cause distraction. Lee et al. [29] combined facial features and bio-signals to monitor driver alertness.

2.5 Chapter Summary

A summary of others research is shown in table 2.1. This chapter discusses the prior work in predicting driver drowsiness level and correspondingly warns the driver to prevent from crushing into accident. Basically, the analysis of drowsiness features can be classified into three categories, namely, (a) driving pattern or behavior as well as the controlling of vehicles, (b) steering pattern of motion features, and lastly (c) bio-logical methods. These features are then given as inputs to the classifier to derive the conclusion or summary on the driver current drowsiness state in real-time. In fact, the existing developed system required installation of extra hardware or modification of vehicle structure to perform driver drowsiness evaluation.

Table 2.1: Different type of Driver Drowsiness Detection System.

Type	Explanation
Steering pattern monitoring [3-9]	Primarily analyze steering input data from electric power steering system. Any abnormal or drowsiness act that already been recognized will trigger warning or alarm
Vehicle position in lane monitoring [10-13]	Uses lane monitoring camera that installed in-front of the vehicle to make sure the vehicle following the lane.
Driver eye or face monitoring	Using a camera watching the driver's face. Percentage of Eye Closure (PERCLOS) or expression of driver been analyzed and monitored from the image captured by camera.
Physiological measurement [14-29]	Uses body sensors to measure parameters like brain activity, heart rate, skin conductance, and muscle activity to extract physiological data.

3.0 System Design and Implementation

This chapter showed that this proposed system consists of several modules which are bio-logical analysis module, motion analysis module, smartwatch device module, and system alert module. This system collected bio-logical data from driver's wristband combining with motion data collected from smartwatch built-in motion sensor to analyze and interpret driver drowsiness level. The proposed wearable system is designed mainly focused on comfort of driver while driving without any distraction when detecting driver drowsiness in wearable devices.

3.1 System Overview

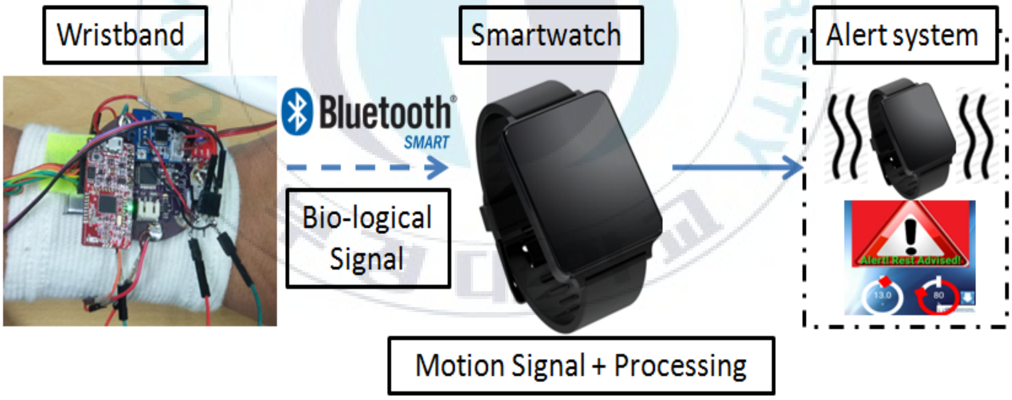


Figure 3.1: System design overview.

In fact, the smartwatch received bio-logical signal from self-designed wristband via Bluetooth Low Energy and also motion signal from smartwatch built-in accelerometer and gyroscope. Features are extracted from received data and further analyzed and classified into driver drowsiness level by using support vector machine (SVM) classifier. By using pre-set SVM model, the driver drowsiness level can be classified and results are displayed in smartwatch device screen. The alert system is triggered if driver drowsiness is detected.

3.2 Smartwatch Device Module

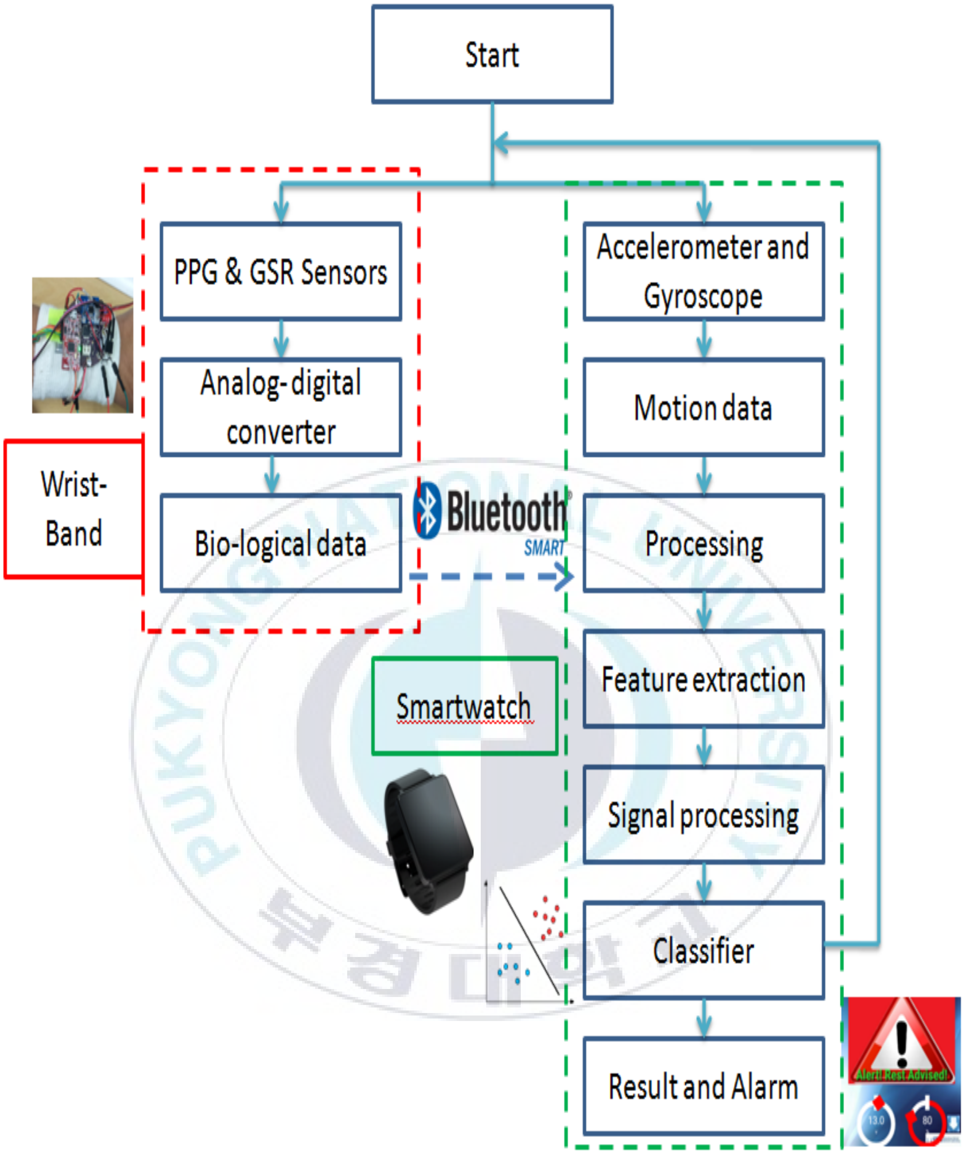


Figure 3.2: Block diagram of system overview.

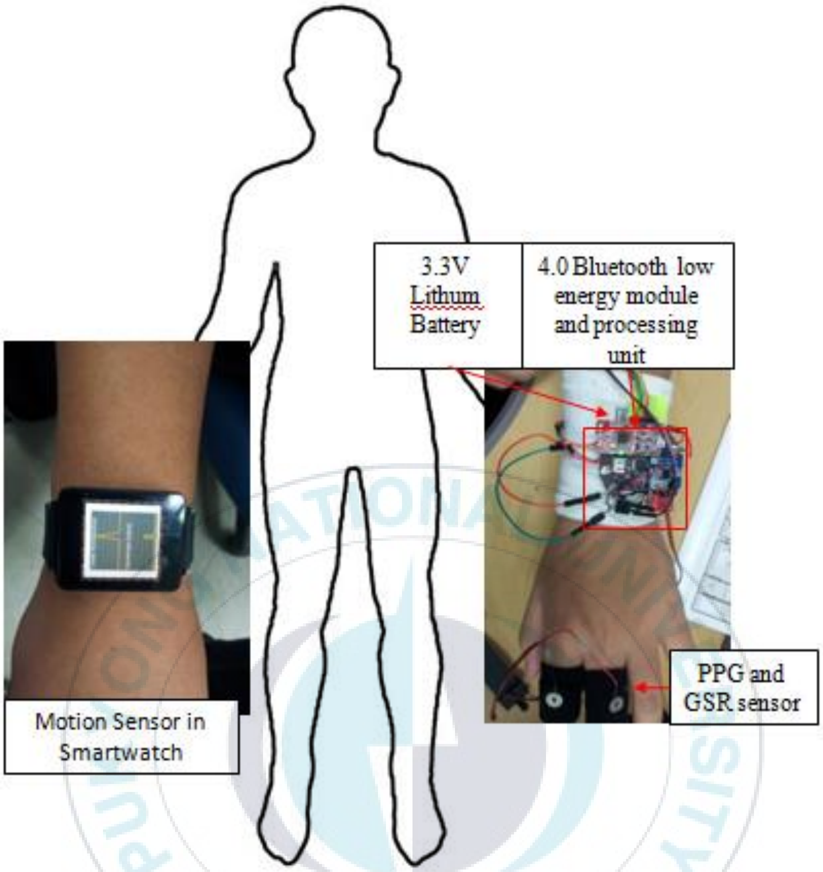


Figure 3.3: Driver wearing smartwatch at right hand while self-designed wrist band on left hand.

Firstly, the application in smartwatch is initialized by activate the Bluetooth Low Energy function in smartwatch. After searching for available device and connected with wrist-band, it activates the built-in motion sensors in smartwatch which are gyroscope and accelerometer. With bio-logical data received from wristband and motion data received from built-in motion sensors, the features extraction is done to extract useful features such as respiration rate, heartbeat, and number of adjustment.

Generally, the smartwatch is operated as:

a. Information flows and details processing view.

b. Driver drowsiness monitoring.

c. Features extraction (Hand motion and bio-signal features)

d. Chart plotting of features extracted.

e. Wireless connection configuration (Bluetooth Low Energy)

f. Driver drowsiness classifier with SVM model

g. Alert system

3.3 Hand motion Module

In the proposed system, the hand motion behaviors or patterns are contributed as one of the important features for driver drowsiness analysis. Instead of acquiring the driver images using external motion sensor, the proposed system take advantages of the smartwatch device built-in motion sensor to detect motion. Using built-in motion sensor, packet lost due to communication error will not occur.

After the SVM model initialized, the system will start receive data from the motion sensor. There are several default settings for data acquisition frequency, but not all the frequencies suited to smartwatch due to its slower processing and power issue. Thus, the acquisition frequency of motion data must be sufficient slow enough for motion tracking sensitivity yet not too high to affect overall performance of the system. Some important features can be extracted from these received motion data which will then applied to classifier as input variables.

3.4 Bio-signals Analysis Module

The bio-signal features extraction is preceded in classifier if a valid bio-signal detected. Different vital signs exhibit distinct behavior and so as its analysis techniques. In the proposed system, two biomedical signals are being considered which are PPG, and GSR signals. The extraction methods and attributes will be explained in details in the following chapter. Likewise to motion features module, the extracted features are further generated as input to the classifier model. Another concern is the noises appeared that are possibly caused by the power noises, motion artifact or environment conditions. It was crucial because noises can "feed" the inference network with affected signals; stimulate the wrong decision at the final stage. Indeed, the noises are filtered with low-pass filter and band-pass filter circuit designed in the sensor module. Noises cancellation in software part might increase the processing weight of the smartwatch device that too many computations might crash the system or slow down the system primary speed in long term.

3.5 SVM classifier

In machine learning, SVM are supervised learning models with associated learning algorithms that analyze data and recognize patterns, used for classification and regression analysis. Given a set of training examples, each marked for belonging to one of two categories, an SVM training algorithm builds a model that assigns new examples into one category or the other, making it a non-probabilistic binary linear classifier. An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall on.

This module took in the extracted features from the motion features module and spectral analysis of bio-signal module to derive the driver drowsiness. This analysis section consumes most of the resources applicable in the system where the algorithm consists of composite calculations and derivations. In our proposed system, SVM classification is being implemented on the smartwatch device which will be discussed further in chapter 6. Overall, the classifier manage to analyze the features acquired from discrete methodologies and formulated the trustful drowsiness result.

The derived output is further send to the system alert module and Smartwatch device module (information display). At any rate, this module can deliver the status update in 1 second and warned the driver if low arousal state is detected.

3.6 System Alert Module

Various types of alerts had been considered to wake the driver once drowsiness is detected in real-time. In fact, some alert system can cause reserve effects to the driver such as surprisingly loud music, and vibration on the chair or steering wheel. Due to limitation of smartwatch, the alarm only can be presented in vibration and graphical view.

3.7 Chapter Summary

Conclusively, this chapter discussed the system overview and structure in wearable driver drowsiness system. The system is decomposed into several modules to reduce the system complexity and increase its flexibility in module debugging. The modules are: hand motion module, bio-signals spectral analysis module, SVM classifier and system alert module. The principal focus aspect of such implementation is the utilization of a smartwatch device that is capable of multi-tasks execution without reliance on peripheral devices.

4.0 Features Extraction

The prior chapter illustrated the details designation of the driver drowsiness detection system. Several methods are exercised to extract the motion features from built-in motion sensor which are accelerometer and gyroscope. Due to the constraint of the smartwatch device capabilities, extraction algorithm performs on desktop-based is rarely eligible to be enforced on the smartwatch device. The mobile-based applications are regularly endeavor on the quick response or results feedback to the user instead of focusing on delivering high competence outputs that mostly performed in extremely long execution time. These motion feature extraction analysis was done in MATLAB.

Analysis of driver vital-sign is done to indicate the vigilance state. As it is generally conceived, emotion is bound up with feeling, so as to do the drowsy state. The drivers may exhibit some easily observable physiological features from which their fatigue can be inferred. Using the fact that driver's biomedical signals can represent abundant information on the human cognitive states, algorithms based on the changes in the signals during fatigue can be developed to detect different level of drowsiness. Moreover, critical aspect of driving impairments associated with drowsiness are slow reaction times, reduced vigilance, and deficits in information processing that all lead to an abnormal driving behavior.

The foremost step in much of the aforementioned reported studies included the extraction of a set of features that correlated with drowsiness. This work studied on the indication of different levels of fatigue based on

GSR and PPG signals collected from in-door driving simulation and real-time driving scenarios.

4.1 Motion Measurement

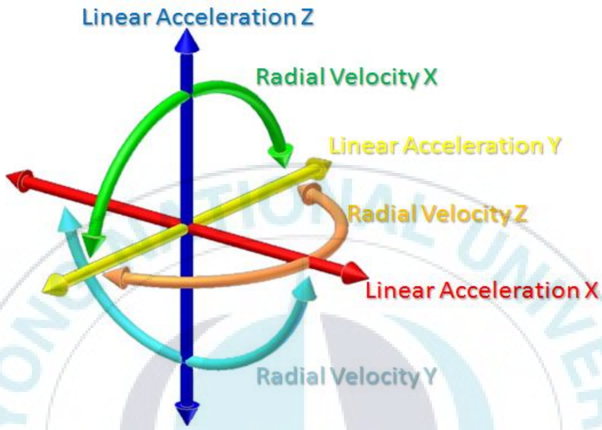


Fig. 4.1 Linear acceleration and radial velocity components

The linear acceleration and radial velocity were collected from the built-in accelerometer and gyroscope of the smartwatch. A gyroscope is a device that uses Earth's gravity to help determine orientation. Its design consists of a freely-rotating disk called a rotor, mounted onto a spinning axis in the center of a larger and more stable wheel. As the axis turns, the rotor remains stationary to indicate the central gravitational pull, and thus which way is "down." [25]

An accelerometer is a compact device designed to measure non-gravitational acceleration. When the object it's integrated into goes from a standstill to any velocity, the accelerometer is designed to respond to the vibrations associated with such movement. It uses microscopic crystals that go under stress when vibrations occur, and from that stress a voltage is generated to create a reading on any acceleration. Accelerometers are important components to devices that track fitness and other measurements in the quantified self movement. [25]

The linear acceleration and radial velocity components are shown in Fig.4.1. The resultant magnitude was calculated by

$$Resultant\ magnitude = \sqrt{x^2 + y^2 + z^2} \tag{4.1}$$

where x, y, and z were the linear acceleration and radial velocity in each direction. The sampling rates for the motion sensors were 5 Hz. The data was analyzed at 1 minutes using the moving average method of 1s interval. Drowsiness is crucial and should be able to be detected as quick as possible, so 1s interval overlap is an ideal periodical analysis time period.

4.2 Motion Features Extraction Methods

The motion data was analyzed in the time, frequency, and phase domains. Twenty eight features (14 for each of linear acceleration and radial velocity) were extracted using these analyses and are listed in Table 4.1, 4.2 and 4.3.

Table 4.1: Features extracted from the motion data using time-domain analysis.

Time-Domain	
Feature	Descriptions
Mean Amplitude	Average amplitude of linear acceleration and radian velocity over 1 minute
Standard Deviation Amplitude	Standard Deviation of amplitude of linear acceleration and radian velocity over 1 minute
Average Power	Average of squared linear acceleration and radian velocity amplitude over 1 minute
Mean Velocity Between Zero-Crossing	Average velocity of all data when crossing the x-axis
Wavelet Packet Entropy	Order of the number of wavelet packet that decomposed among 1 minute of linear acceleration and radian velocity
Amplitude Duration Squared Theta	Duration of amplitude of linear acceleration and radian velocity exceed squared data

Table 4.2: Features extracted from the motion data using frequency-domain analysis.

Frequency-Domain	
Feature	Descriptions
Peak Power Frequency (PPF)	Peak of the signals among 1 minute after the data converted into frequency-domain graph
Median Power Frequency (MPF)	Middle amplitude of the signals among 1 minute after the data converted into frequency-domain graph
Mean Power Frequency (MNF)	Average of the signals among 1 minute after the data converted into frequency-domain graph
Low Power Frequency (LPF)	Sum of frequency amplitude from 0~3Hz
High Power Frequency (HPF)	Sum of frequency amplitude from 4~5Hz
Low / High Power Frequency (LHF)	Ratio of LPF over HPF

Table 4.3: Features extracted from the motion data using phase-domain analysis.

Phase-domain Features	
Feature	Descriptions
Percentage Points outside Control Ellipse	Percentage of number of points outside control Ellipse over the total number of points in the Phase-domain graph
Weight Flat Zero	Percentage of number of points exceed zero points over the total number of points in the Phase-domain graph

4.2.1 Time domain

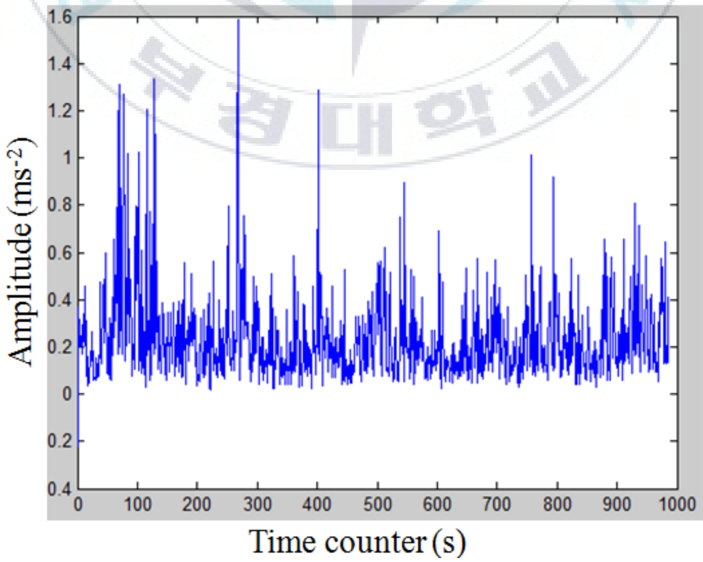


Figure 4.2: Time-domain signal for 1 minute.

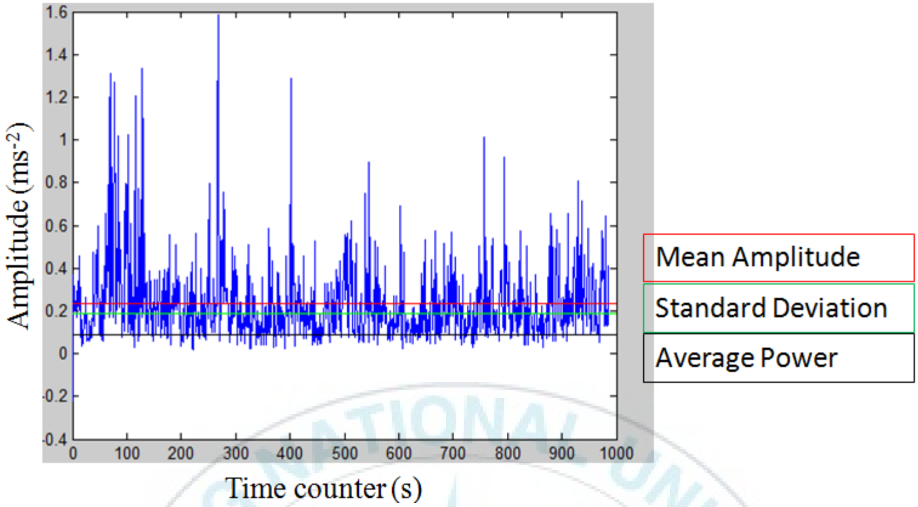


Figure 4.3: Mean Amplitude, Standard Deviation and Average Power of Time-domain signal for 1 minute.

The time domain analysis was the analysis of motion data with respect to time. The mean and the standard deviation of the amplitude were based on 1 min of motion data. The average power was the average of the squared motion data. The equation is as below:

$$Mean\ Amplitude = \frac{1}{n} \times \sum_{i=1}^{n} x_i \qquad (4.2)$$

$$Standard\ Deviation = \sqrt{\frac{1}{n} \times \sum_{i=1}^{n} (x_i - \bar{x})^2} \qquad (4.3)$$

$$Average\ power = \frac{1}{n} \times \sum_{i=1}^{n} {x_i}^2 \qquad (4.4)$$

Where x = amplitude of linear acceleration or radian velocity, n =

total number of set, $\bar{x}$ = average amplitude of linear acceleration or radian velocity over 1 minute, i = number of set.

For the mean velocity between zero-crossing, first, any zero-crossing point is identified with its time counter. After that, the difference between each time counter is calculated to get the velocity between them. Finally, the mean of that velocity is calculated.

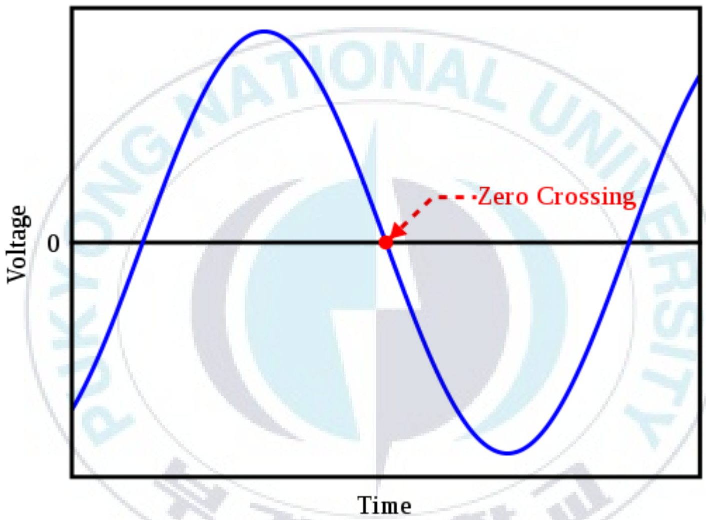


Figure 4.4: Definition of Zero-crossing.

Wavelet packet entropy was calculated based on the WENTROPY function in MATLAB [17] using the "Shannon" mode. The amplitude duration squared theta was calculated over 1 min of motion.

4.2.2 Frequency domain

In electronics, control systems engineering, and statistics, the signal analysis often refers to the analysis of mathematical functions or signals with respect to frequency, rather than time [23].

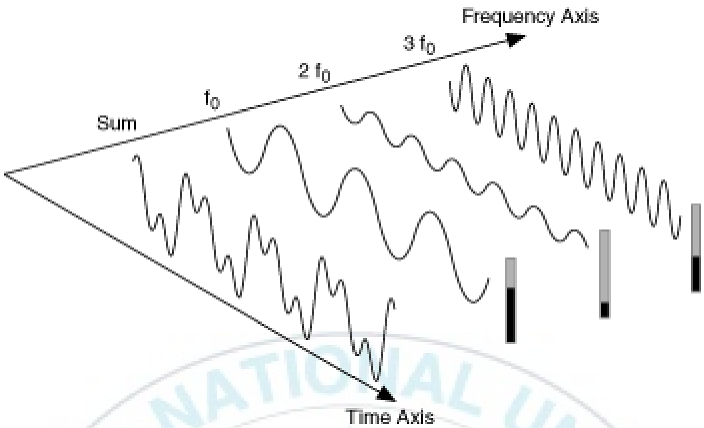


Figure 4.5: Changing from time-domain to frequency domain [24].

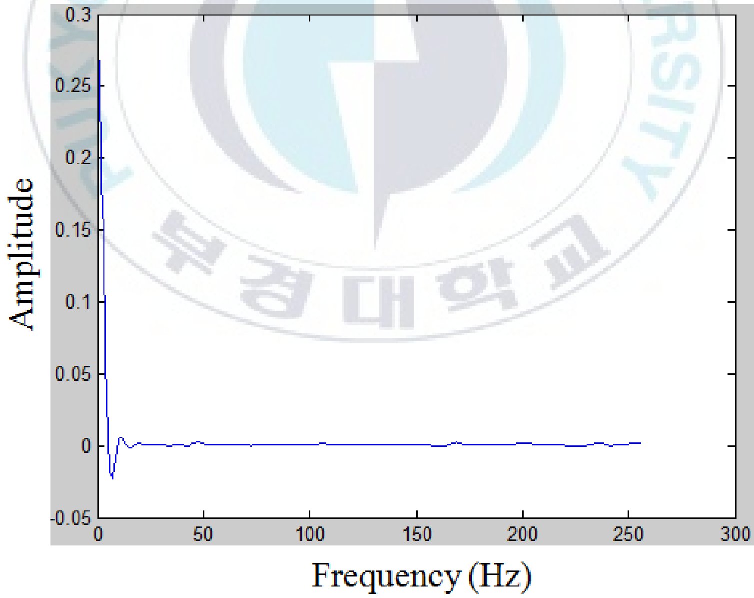


Figure 4.6: Sample from analysis.

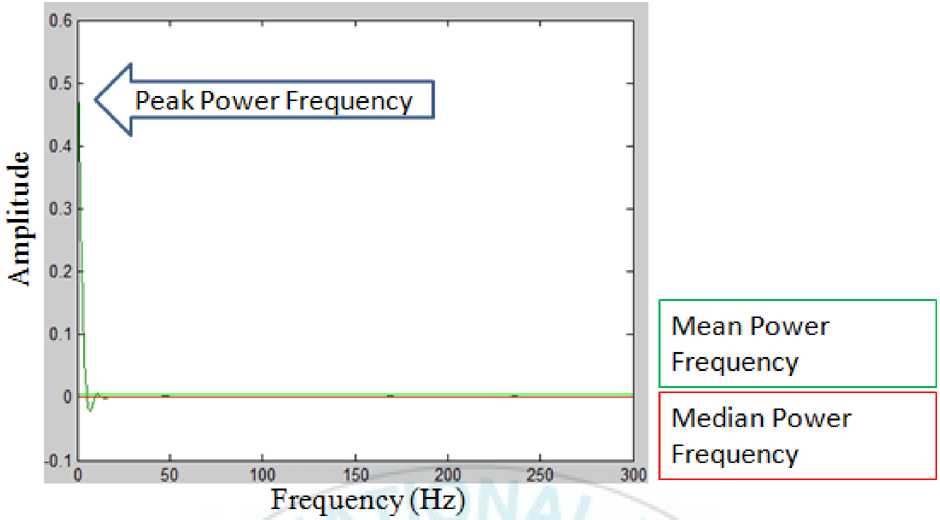


Figure 4.7: Peak Power Frequency, Mean Power Frequency, and Median Power Frequency.

For the frequency-domain analysis, the fast Fourier transform (FFT) [18] was applied to a 1 min window of motion data using MATLAB. A series of frequency data was generated from the FFT as shown in figure 4.2.4.

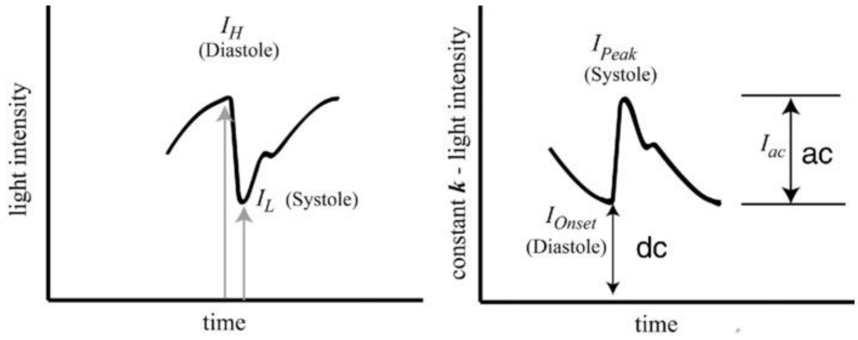
The low power frequency (LPF) was defined as the sum of the low frequency in the 1–3 Hz range in the series, while the high power frequency (HPF) was defined as the sum of the high frequency in the 4–5 Hz range in the series. The ratio (low / high power frequency) is given by LPF divided by HPF.

4.2.3 Phase domain

For the phase-domain analysis, a control ellipse was estimated using the difference between the data and its relative magnitude. The percentage of points outside the control ellipse was computed over 1 min of motion data. The weight flat zero was computed using the weight function based on the points outside the control ellipse.

4.3 Photoplethysmography Signal (PPG)

PPG signal is a non-invasive optical technique that measures changes in skin blood volume and perfusion. PPG signal contained components that are synchronous with respiratory and cardiac rhythms. This technique measured the changes in skin blood using a light probe that is placed on the surface of the skin. The PPG waveform comprised of a pulsatile (“AC”) physiological waveform (cardiac synchronous that changes in the blood volume with each heartbeat) and is superimposed on a slowly varying (“DC”) baseline with various lower frequency components (respiration, sympathetic nervous system activity and thermoregulation). The PPG technology had been used in a wide range of commercially available medical devices for measuring oxygen saturation, blood pressure, and cardiac output, assessing autonomic function and also detecting peripheral vascular disease.



(a) (b)

Figure 4.8: Typical photoplethysmographic signal. (a) A raw signal measured from a photodetector, and (b) final signal, constant k-reflected light intensity.

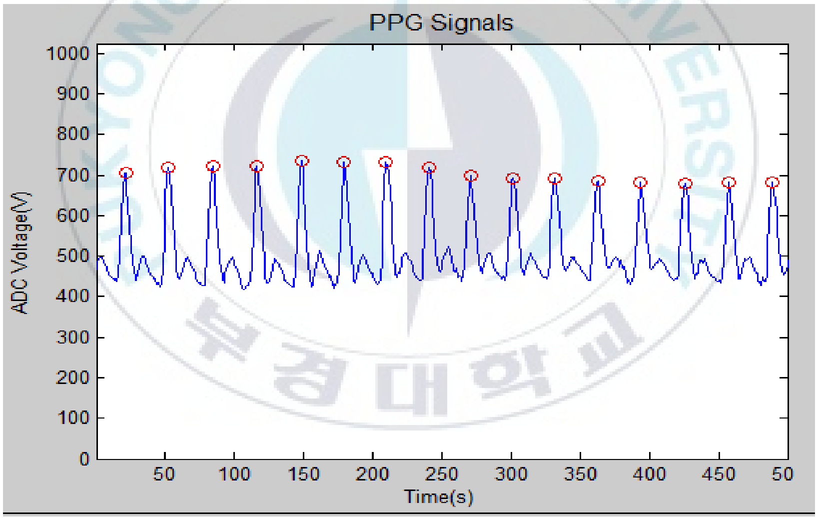


Figure 4.9: PPG shown in analysis process.

The peak of PPG signal was detected using adaptive threshold method. Adaptive threshold method is any point contact with "peak threshold" will treat as peak of the signal. The "peak threshold" decrease over time if no peak is detected. The "peak threshold" will be updated to the new amplitude same as new detected peak amplitude if a new peak detected. The heartbeat of driver is measured by the distance between each peak. PRV is inverse of heartbeat. Respiration rate is measured by the amplitude changes of PPG signal. The peak of each PPG signal was transformed into another waveform which we called respiration waveform. The distance between the peaks of this respiration waveform become respiration peak distances and thus respiration rate is calculated using following equation.

$$Heartbeat = \frac{Sampling\ Rate\ per\ Minute}{Peak\ distances} \times 60 \tag{5.1}$$

$$PRV = \frac{1}{Heartbeat} \tag{5.2}$$

$$Respiration\ Rate = \frac{Sampling\ Rate\ per\ Minute}{Respiration\ Peak\ distances} \times 60 \tag{5.3}$$

4.4 Galvanic Skin Response (GSR)

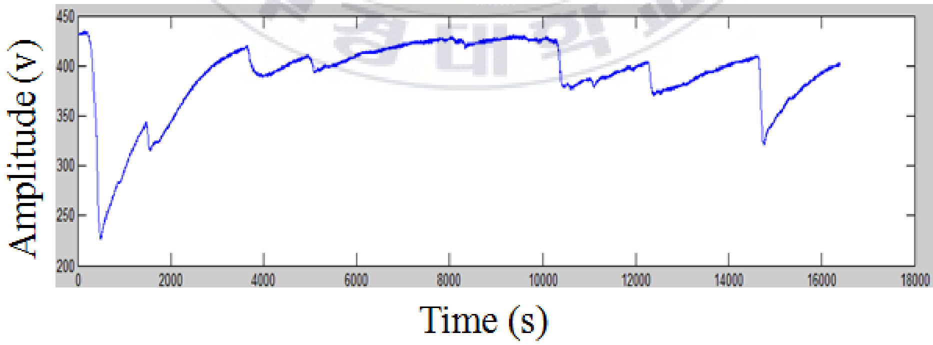


Figure 4.10: Typical galvanic skin response signal.

GSR signal is an electrical technique that measures changes in skin resistance. GSR signal contained components that are synchronous with stress of users. This technique measured the changes in skin resistance using 2 electrodes that is placed on the surface of the skin. The GSR waveform comprised of increasing waveform (synchronous with aroused state), decreasing waveform (synchronous with relaxing state) and constant waveform (synchronous with stressed state). The GSR technology had been used in a wide range of commercially available medical devices for measuring stress and mental status of patient.

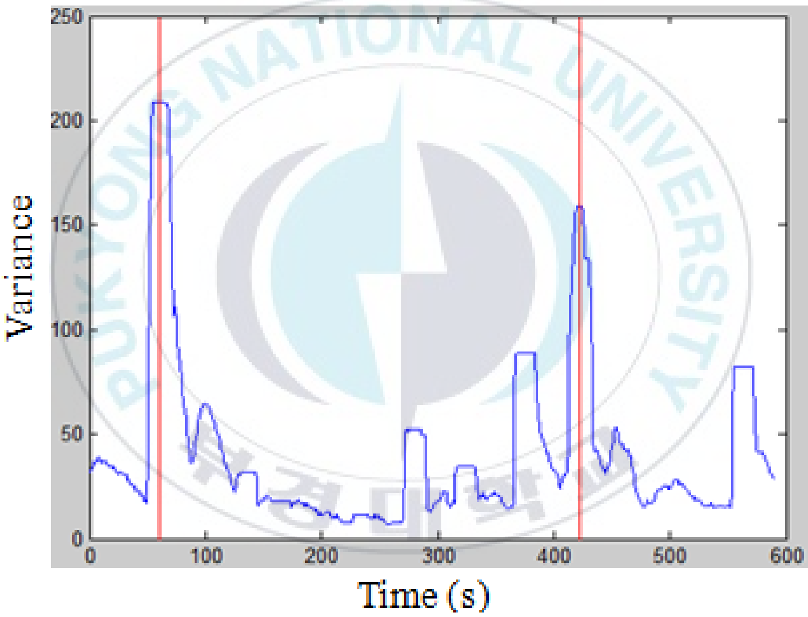


Figure 4.11: High variance when the state change occurs.

Due to high variance is observed when there are state changes, thus variance of this GSR signals is used to state the changes of stress state. Any changes in GSR amplitude after the state change indicated the stress level of the driver. For example, if current state is stress, increase in amplitude equals to the stress level increase. This is due to a human will produce more sweat when he is in stress state, which further reduce his skin resistance and increase GSR amplitude. If a high variance detected, the state will be changed into relax state, and any decrease in amplitude indicate the awareness of driver become weaker. Driving in stress state will results in concentration of driving draining too fast while driving in over relax state will results in slow response to any accidents.

4.5 Chapter Summary

The motion features extraction is discussed in this chapter that highlighted on the methods for extraction and features to be used as the elements for driver drowsiness analysis. Our proposed system utilized 3 motion analysis domains which are time-domain, frequency-domain, and phase domain. Moreover, fourteen features are being studied which are Mean Amplitude, Peak Power Frequency (PPF), Standard Deviation Amplitude, Median Power Frequency (MPF) and etc. Those features served as input variables to SVM classifier. The bio-logical features extraction is discussed in this chapter that highlighted on the methods for extraction and features to be used as the elements for driver drowsiness analysis. Our proposed system utilized adaptive threshold method to detect the peak of PPG signal and several equations to extract the features from the peaks whereas using variance and change of amplitude in GSR signal to indicate the change of stress level. Those features served as input variables to SVM classifier.

5.0 Android™-based Fatigue Analysis System

Google's Android™ framework [27] is the most significant smartphone operating systems that have arisen recently. Google Android, a Linux-kernel-based operating system, comes along with a quite new credo within this market: it is supposed to be open! This, in prominent, means all elements used shall be provided in source code form so that developers will have the chances to take a closer look into the system to suit their needs. Figure 5.1 introduced the relationship of Android among "**Users**", "**Industry**", and "**Developer**".

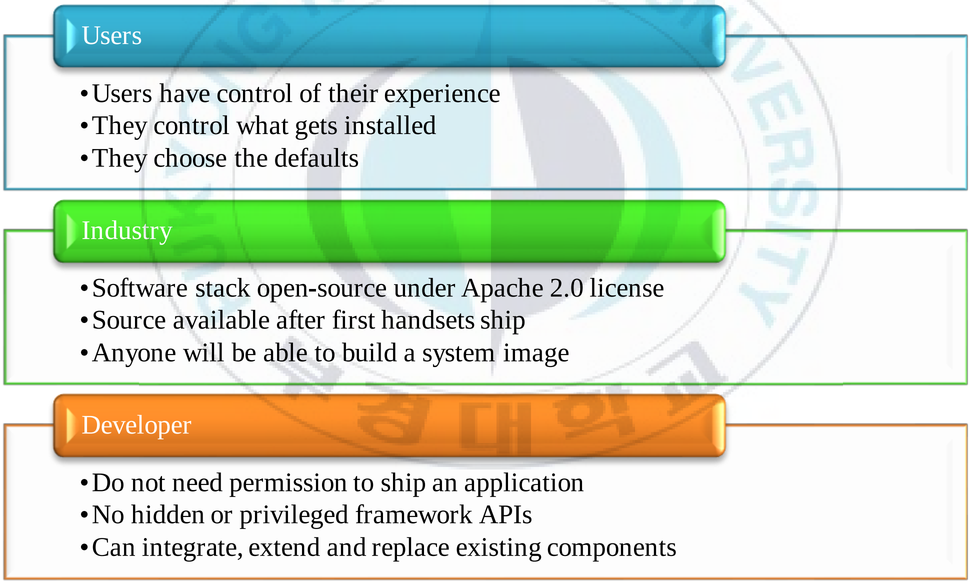


Figure 5.1: Different Android roles in users, industry and developer sides.

5.1 What is Android Wear™?

Current trend of wearable technology focus on smartwatch operate in

Android Wear^{TM} [30]. Many popular brand of smartwatch had been commercialized such as LG G watch, Samsung Gear Live and etc. Some of the smartwatch is programmable while some are not such as Pebble which only functions as factory setting and user cannot customize the function according their flavor.

The basic idea of Android Wear^{TM} is to communicate with smartphone without physically take it out from your pocket or bag. This can saved a lot of time while benefit the user. Moreover, smartwatch can monitor user's health status by monitoring the movement and heartbeat using integrated sensor in the smartwatch. User can customize the looks of his smartwatch by using Android Studio such as develop a new watch face for his own Smartwatch using his desired graphic or interface.

5.2 Android Studio

Android Studio is the official IDE for Android application development, based on IntelliJ IDEA. On top of the capabilities you expect from IntelliJ, Android Studio offers:

- Flexible Gradle-based build system
- Build variants and multiple apk file generation
- Code templates to help you build common app features
- Rich layout editor with support for drag and drop theme editing
- lint tools to catch performance, usability, version compatibility, and other problems

- ProGuard and app-signing capabilities
- Built-in support for Google Cloud Platform, making it easy to integrate Google Cloud Messaging and App Engine

5.3 Chapter Summary

This chapter concludes the application development of Android Wear by using Android Studio. Several examples of Smartwatch commercialized had been discussed and overview of Android Studio had been introduced. Finally, the real screenshot of the driver drowsiness detection system is shown.

6.0 Experiment and results

Driving simulation and experiment was carried out to collect data for analysis. The features extracted from the data collected in the experiment according to method aforementioned are moved to feature selection and correlation between each feature with ground truth is calculated. Using SVM classifier to indicate the accuracy of the features, certain number of features had been selected for driver drowsiness detection system.

6.1 Driving Simulation and Experiment

Twenty driving simulations were performed by engaging 20 different subjects, to acquire raw motion data (linear acceleration and radial velocity) from the smartwatch built-in motion sensors (accelerometer and gyroscope) and bio-logical data from self-made wrist band. The raw motion data was monitored for both hands simultaneously with two different smartwatches. The biological data includes PPG and GSR collected from PPG and GSR sensor that installed on wristband.

With the hand movements detected by using the smartwatch built-in motion sensor, there was no need to attach potentiometers to the steering wheel. The smartwatches in Figure 6.2 were the LG G Watch and Samsung Gear Live. Both watches have an approximately 1.64-in display with 4-GB external memory and a 512-MB RAM with an android operating system. The motion data was acquired by using the built-in motion accelerometers and gyroscopes of the smartwatches.

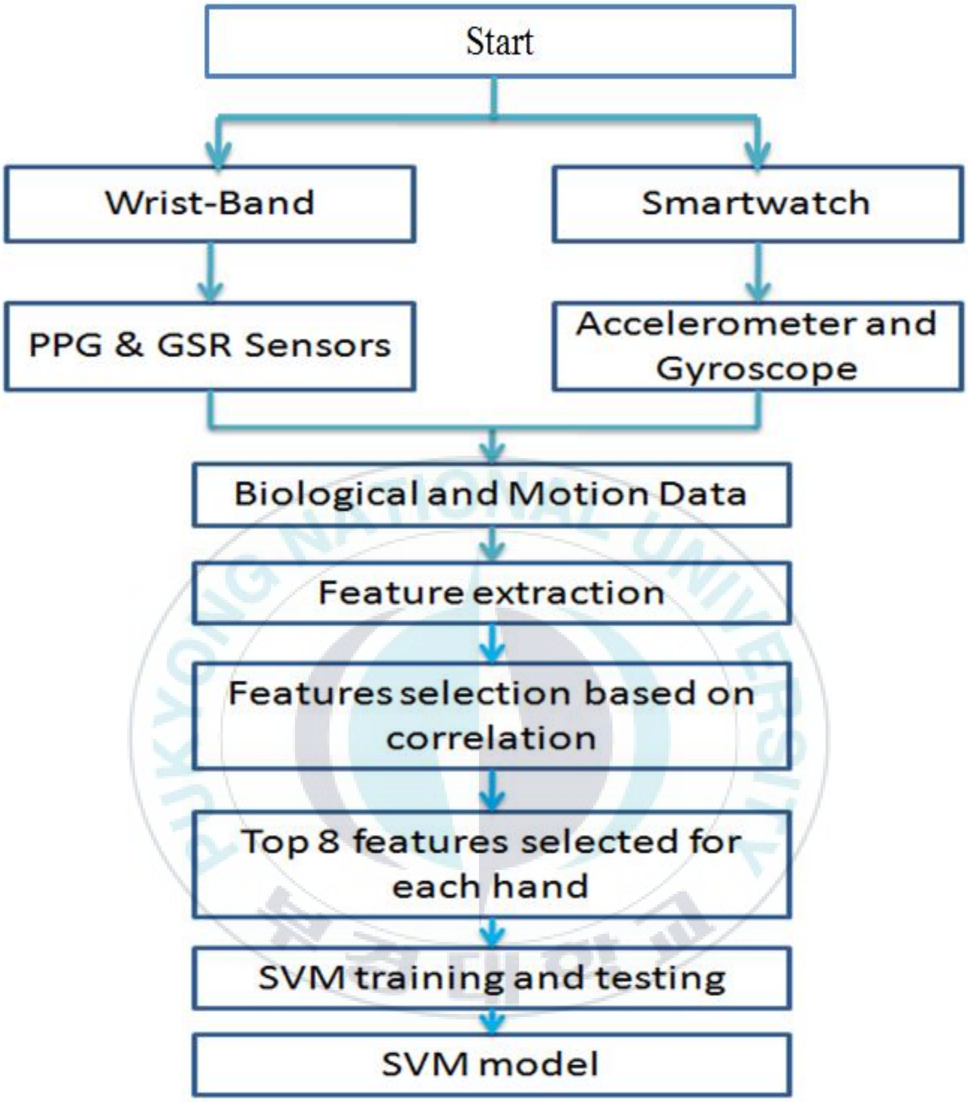


Figure 6.1: System model training.

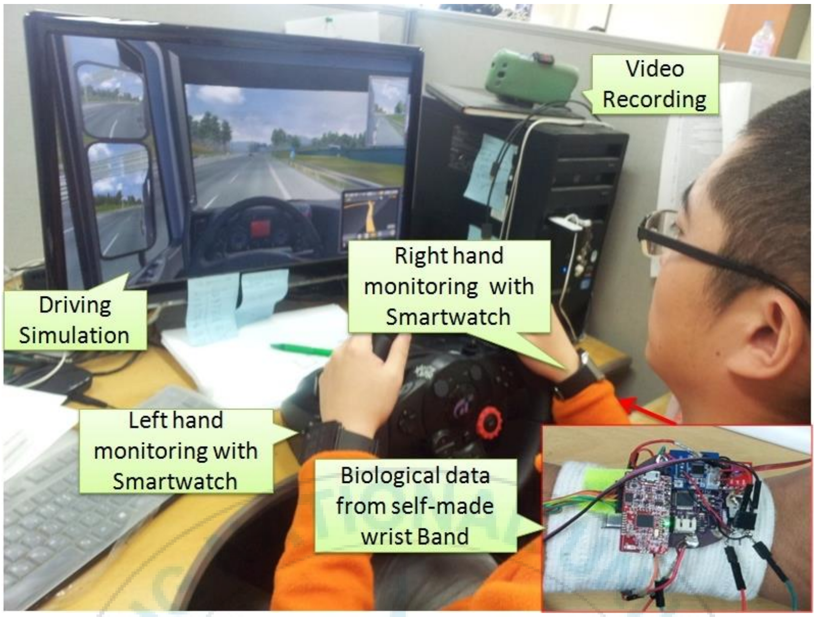


Figure 6.2: Experiment Setup

The simulation was performed by using Euro track Simulator 2, which realistically imitates the driving process, including the need to slow down and stop at red light, speed traps in highways, and limited speed of commercial trucks. Still, our simulation and field testing differed in some ambient elements. It is too dangerous to conduct driver drowsiness simulations in real driving, because owing to the experiment nature serious accidents may occur, resulting in loss of money or even life. Drivers still need to adjust their vehicle even on the straight highways because all vehicles cannot travel absolutely straight at all time theoretically.

The twenty subjects included 15 males and 5 females with the average age of 35±14 yr. The subjects were mentally healthy people who did not suffer any illness during the experiments to ensure the system reliability. The study participants were asked to fill a survey to record their actual driving experience and mental condition, including the number of hours slept, their emotional state, and other factors shown in figure 6.3. After filling the survey form, the participants underwent ~30–60-min training to familiarize themselves with the driving simulation system shown in figure 6.2. In each case, a video recording started at the beginning of simulation. Any event that occurred during the simulation that could affect the result was documented in the survey form. These events included driving with one hand on the steering wheel (SH), an accident (AC), and restarting the simulation after an accident (RE). The full list is in Figure 6.3 in the top right corner of the survey form. The events were recorded on the left side of the survey form. The participants' drowsiness levels were also recorded on the right side of the survey form, based on the number of minutes and respective Karolinska sleepiness scale which will be explained in section 6.3 during the driving simulation. After the simulation, the participants were asked to provide some comments and verify the Karolinska sleeping scale based on the recorded video. The event records and drowsiness level records in the survey were used during the motion processing step and for the SVM training and testing.

Name: Ong ZhenYang	SIGN:	SH : Single Handed	SW : Swallowing
ID / IC No: 201455772		YA : Yawning	AC : Accident
Phone Number: 010-4882-3614		SC : Scratching	RS : Recording stop
Age: 24		AD : Adjustment	RE : Reset/Restart
Gender: M / F		DR : Drinking	SL : Sleepy
Driving License: Y / N		SI : Sigh	FU: Refill fuel
Longest Driving Experience(hours): 8			
Coffee before simulation: Yes / No	Subject ID:	Time Start: 13:23:23	Time End: 14:46:00
Training before simulation: Yes / No	Drowsiness Feeling after simulation: Yes / No		
Last sleeping time (hours): 9	Obvious drowsy time: 48th minute		
Emotion: Excited / Happy / Tender / Scared / Angry / Sad / Others: Peace			

Time	Event	Time	Event
13:23:23	start		
13:52:16	SH		
13:52:35			
14:11:00	YA		
14:12:18	SL		
14:12:30	AC & RE		
14:12:50			
14:14:20	left SC		
14:26:20	DR		
14:28:20	SC		
14:36:48	SC		
14:46:00	finish		

Koralinska Sleepiness Scale (KSS)
1 Extremely alert
2 Very alert
3 Alert
4 Fairly alert
5 Neither alert nor sleepy
6 Some signs of sleepiness
7 Sleepy, but no effort to keep alert
8 Sleepy, some effort to keep alert
9 Very sleepy, great effort to keep alert, fighting

no. of minute & KSS

1st : 3	21st : 5	41st : 6	61st : 5	81st : 3
2nd : 3	22nd : 6	42nd : 6	62nd : 5	82nd :
3rd : 3	23rd : 7	43rd : 6	63rd : 4	83rd :
4th : 3	24th : 6	44th : 7	64th : 4	84th :
5th : 4	25th : 5	45th : 6	65th : 4	85th :
6th : 4	26th : 5	46th : 6	66th : 4	86th :
7th : 3	27th : 4	47th : 7	67th : 4	87th :
8th : 4	28th : 4	48th : 9	68th : 4	88th :
9th : 5	29th : 4	49th : 7	69th : 4	89th :
10th : 6	30th : 4	50th : 6	70th : 4	90th :
11th : 7	31st : 5	51st : 5	71st : 4	91st :
12th : 7	32nd : 5	52nd : 5	72nd : 4	92nd :
13th : 6	33rd : 5	53rd : 5	73rd : 3	93rd :
14th : 5	34th : 5	54th : 5	74th : 3	94th :
15th : 4	35th : 5	55th : 5	75th : 3	95th :
16th : 4	36th : 5	56th : 5	76th : 3	96th :
17th : 4	37th : 5	57th : 5	77th : 3	97th :
18th : 4	38th : 5	58th : 4	78th : 3	98th :
19th : 4	39th : 5	59th : 4	79th : 3	99th :
20th : 5	40th : 6	60th : 4	80th : 3	100th :

Comments by Participants: Good driving simulation and I slept at 48th minute

Figure 6.3: Actual survey form completed by the subject OngZhenYang.

6.2 Karolinska Sleeping Scale (KSS)

The Karolinska Sleepiness Scale (KSS) is a 9-point Likert scale based on a self-reported, subjective assessment of the subject's level of drowsiness at the time [26]. In its original format the KSS had word descriptors only for scores of 1, 3, 5, 7 and 9. Those descriptors varied from 1= "very alert" to 9="very sleepy, fighting sleep, an effort to keep awake". However, additional descriptors were later added for all scores, as shown in Table 6.2.The KSS is assumed to be an ordinal scale with a unitary structure, although that has not been confirmed. The KSS has been used widely, particularly for describing changes over time within subjects. KSS scores may require standardization to control for differences between subjects. The changes observed in the biological and motion with drowsiness does not usually appear until KSS scores reach 7 and higher. Lower KSS scores (<5) may reflect differences in the subjective awareness of fatigue as much, or more than, levels of drowsiness. Higher KSS scores (7+) may refer more specifically to the state of drowsiness because the subject may then have experienced involuntary dozing behavior, with "lapsing" episodes and brief loss of awareness of the here-and-now, followed by arousal and the return of awareness, including some awareness of recently having dozed off.

Due to insufficient processing power of smartwatch, this driver drowsiness detect on system reduces the KSS into 5 classes. Scale 1 and 2 in KSS represented level 1 of drowsiness in the system while scale 3 and 4 in KSS represented level 2 of drowsiness and so on until scale 9 represented level 5 of drowsiness in our system. Level 1, 2 and 3 in this system considered awake state while level 4 in this system represent slightly drowsy state, and furthermore level 5 represent heavily drowsy state. Alarm is triggered to warn the driver about their drowsy when level 4 and level 5 detected which will be discussed later.

Table 6.1.KSS with the classification of drowsiness level for our system [26].

No.	Karolinska Sleeping Scale	Level of drowsiness for system
1	Extremely alert	Level 1
2	Very alert	
3	Alert	Level 2
4	Rather Alert	
5	Neither alert nor sleepy	Level 3
6	Some signs of sleepiness	
7	Sleepy, but no difficulty remaining awake	Level 4
8	Sleepy, some effort to keep alert	
9	Extremely sleepy, fighting sleep	Level 5

6.3 Feature Selection

Ideally, all of the features in Table 6.2 should be used for obtaining the most accurate estimate of driver drowsiness; however, given the limited processing power of smartwatch, it is not practical to extract and analyze all features in real-time applications. Therefore, the correlations between the features and the driver drowsiness level were computed by using the Pearson correlation method in MATLAB [18], based on the Karolinska Sleepiness

Scale (KSS) as drowsiness level. The ground truth of the KSS drowsiness level for the participants during the simulations was first estimated and then further verified by the participants by reviewing the recorded video soon after the simulation, as mentioned in Section 6.1. The top 8 features are shown in Table 6.2. The feature with the highest correlation was weight flat zero extracted from the radial velocity data with value was 0.9719.

Because different participants have different hand gestures and different driving habits, it is possible for the different features to exhibit higher correlations with ground truth for the different hands. Our data were combined together as a generalized data set, incorporating all of the different gestures and habits of the study participants. The correlation was calculated programmatically.

Table 6.2: Top 8 features with highest correlation with the KSS drowsiness level by using Pearson's correlation for both hands.

No.	Feature	Correlation
Left Hand		
1	Weight Flat Zero [RV]	0.9719
2	Heartbeat [Bio]	0.9523
3	Respiration Rate [Bio]	0.9178
4	Amplitude Duration Squared Theta [RV]	0.9216
5	Median Power Frequency [RV]	0.9147
6	Median Power Frequency [LA]	0.8684
7	Stress Level State [Bio]	0.8537
8	Mean Amplitude [RV]	0.8224
Right Hand		
1	Median Power Frequency [RV]	0.9689
2	Median Power Frequency [LA]	0.9536
3	Heartbeat [Bio]	0.9523
4	Respiration Rate [Bio]	0.9178
5	Stress Level State [Bio]	0.8537
6	Relax Level State [Bio]	0.8127
7	Mean Velocity Between Zero-Crossing [RV]	0.8078
8	Mean Velocity Between Zero-Crossing [LA]	0.8078

[LA] – Linear acceleration

[RV] – Radial velocity

[Bio] – Biological signal

Weight Flat Zero extracted from radial velocity in left hand has highest correlation which is 0.9719 while Median Power Frequency both extracted from linear acceleration and radial velocity has first and second highest correlations which are 0.9689 and 0.9536. Next features after these are heartbeat and respiration rate extracted from bio-logical data which is 0.9523 and 0.9178. Note that bio-logical signal is same for both hand because only one bio-logical data collected throughout the experiment to avoid any ground collision. Although Median Power Frequency that extracted from linear acceleration and radial velocity in left hand has respectively high correlation of 0.9147 and 0.8684 but driver's stress level no matter in stress level state or in relax level state occupied number five and six in right hand with correlation of 0.8537 and 0.8127.

6.4 SVM classifier Model

The generalized data sets were partitioned into random 70% for training and the rest 30% for testing. After that, SVM training was performed by using from one to eight features. The test results yielded the highest accuracy of 98.15% for the eight features combined for the left hand, while the accuracy of 97.75% was obtained for the right hand (Figure 6.4).When more features were added, the accuracy increased along with the relative reliability. The accuracy rate for both hands increased linearly as the number of features increased from one to six. The accuracy rate remained relatively constant when the number of features was six and higher. Higher processing requirements translate into higher battery consumption. In light of our goal to design a long-lasting driver drowsiness detection system, we considered six features as the best tradeoff between the accuracy rate and the system battery life.

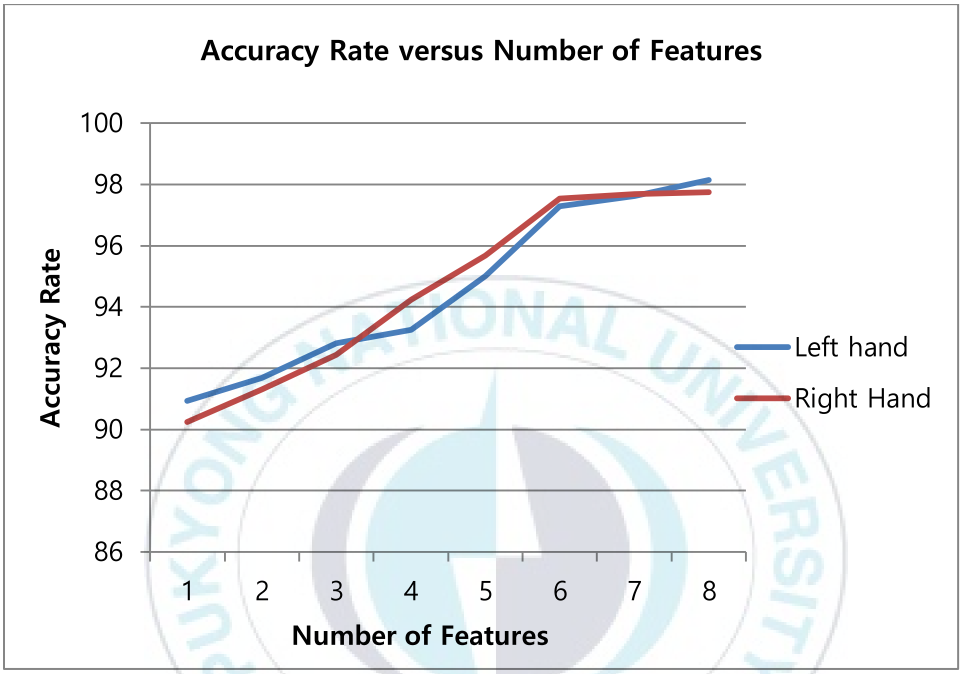


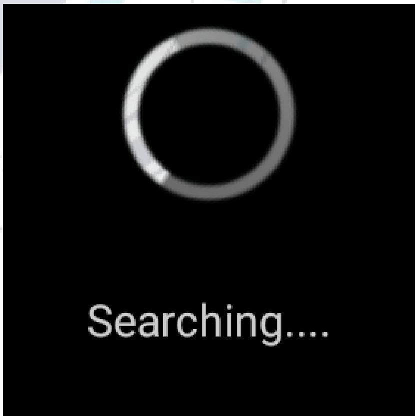
Figure 6.4: Accuracy rate versus the number of features serving as inputs to SVM training and testing.

After the SVM testing, two different SVM models were generated based on each hand and incorporated into a smartwatch application for real-time driver drowsiness detection.

6.5 Fatigue Monitoring System in Android

As shown in figure 6.5, once a user press start option in startup menu (a), available Bluetooth device is shown and appears (c). After the Bluetooth device was selected, the device would be connected and forward to startup user interface (d). (e), (f) and (g) show the GSR signal, drowsy level, heart rate, pulse rate variability, respiration rate and number of adjustment respectively. A list of recorded drowsy level with respect of time (h) was showed after the history button in (g) clicked. Slightly drowsy interface will be shown if the drowsy level of user reach drowsy level of 4 whereas alert interface will be shown if the drowsy level of user reach drowsy level of 5 and vibration of Smartwatch will be triggered together to alert the user. 0% of drowsy level equals to level 1 of drowsy level in our system while 20% equals to level 2 of drowsy level and so on until 80% representing drowsy level 5 which is the most serious drowsy state that can cause accident.

(a)



(b)


Drowsiness
Monitoring
Biscuit
20:CD:39:9E:EF:55
Quit

(c)


Awake
275.0

(d)


622.0
v
0
%
Galvanic Skin
Resistance
Stress Level

(e)


78.0
BPM
767.0
ms
Heart Beat Rate
Pulse Rate
Variability
10.0
B/m
0.0
N/m

(f)


30.0
B/m
8.0
N/m
Respiration Rate
Number of
adjustment
History

(g)


Time / level
2015-05-06 10:59:28
level 4
2015-05-06 10:59:82
level 5
1970-01-01 09:05:41
level 7
write
read
clear

(h)

Figure 6.5: Screenshot of driver drowsiness system in smartwatch, (a) startup menu, (b) searching Bluetooth device, (c) Bluetooth device found, (d) startup user interface – awake state, (e) GSR level and stress level, (f) heart rate and pulse rate variability, (g) respiration rate and number of adjustment, (h) history file which consist of time and level of drowsiness.

6.6 Alarm

When level 4 and level 5 of drowsy detected, alarm in the form of graphical and vibration is triggered. Level 4 of drowsy triggered graphical warning such as figure 6.6 (a) and 1 Hz of vibration while level 5 of drowsy which considered as serious drowsy triggered graphical warning of figure 6.6 (b) and 2 Hz of vibration.

(a) (b)

Figure 6.6: (a) slightly drowsy interface with 1Hz vibration, (b) serious drowsy detected with 2 Hz vibration activated.

6.7 Chapter Summary

This chapter summarized the results and discussion. Using PEARSON correlation method, top 8 features were selected as input for SVM classifier. After analysis of SVM classifier, considering about tradeoff of processing power and accuracy of system, 6 features were selected as final features for input features of SVM models that installed into Smartwatch as real time driver drowsiness detection system. This system can achieved 97.75% of accuracy by using 6 features.

7.0 Conclusions and Future Work

This research studied on the design and implementation of real-time wearable driver drowsiness detection system in Smartwatch. The works are concentrating on the features fusion method where those features are extracted from two distinct techniques, namely motion features and biomedical signals. The extracted features are then given as input variables to SVM classifier to predict the drowsiness. Alarm will be triggered to warn the driver if the driver drowsiness is detected in the system. The drowsiness detection of driver is performed without installation of extra and expensive hardware components. These are the reasons of dedicating the development of this proposed system. Indeed, reviewing on the existing techniques of driver drowsiness detection, greater understanding of driver drowsiness behaviors or patterns is necessary.

The rest of the chapter summarized the research work and open issues for future work that relevant to the advancement and improvement of the proposed system to become more reliable, practical and feasible in daily used.

7.1 Summary

Initially, the motivation of designed the proposed system is introduced and followed by its challenges when designing the system. The existing system implementation is focused on the precision of driver drowsiness estimation, but least are paying attention on the other aspects of the system. The proposed system is implemented into an Android-wear based smartwatch where multiple functions and processes are simultaneously executed.

Generally, the analysis methods of driver drowsiness can be classified into motion and biological signal. In fact, motions are analyzed in multiple domain analysis. Motion data collected from smartwatch built-in accelerometer and gyroscope. Based on the different domain analysis, features can be extracted and served as the element for drowsiness detection.

On the other hand, the driver biological signal can be wise elements to predict the driver drowsiness. In the proposed system, two vital signs are dedicated which are the galvanic skin response (GSR) and photoplethysmography (PPG) signals. Briefly, ECG recorded the skin resistance over time whereas PPG measured the changes in light absorption that monitored the perfusion of blood to the dermis and subcutaneous tissue of the skin. Similar to motion features, numerous features can be extracted from both signals and given as inputs to SVM classifier.

Smartwatch device can received the driver GSR and PPG signals via Bluetooth Low Energy from self-designed wrist band. After acquiring the required data, SVM classifier will analyze and calculate level of driver drowsiness. Once the drowsiness level 4 or 5 detected, the driver will be warned by the warning system in the form of graphical and vibration.

Conclusively, the proposed driver drowsiness detection system delivered tremendous perceptions to ensure and increase the safety of the driver only by utilizing a daily used smartwatch device without spending extra money to modify the vehicle structure or installed additional hardware in the transport.

7.2 Future Direction

The researches done in this thesis on the drowsiness detection in the smartwatch device yet provide a few alternatives to improve its feasibility. Limitations are existed and further studies are mandatory to achieve better performances. Improvements and issues correlated to the drowsiness detection are discussed as follow:

a) Driver drowsiness can be caused by other factors including the external factors such as ambient conditions (temperature), environment (cloudy, rainy), driver mental status (anger, hungry), road situation (damage), traffic (busy), and others more. Thus, the prediction can be more accurate if those external factors are taken into account. Nevertheless, it would cause more burdens and workload to the device processing as more inputs are gathered. The wireless communication traffic is another issue to be concern off. Too heavy traffic can easily break down the whole system.

b) The more features for acquisitions and computations in Smartwatch device required a more powerful processing capability, larger memory space, longer battery life, and other else. The short battery life will drained out the smartwatch power and the drowsiness detection can't operate in long period especially if the driver is driving in the midnight or long-distance destination. Moreover, the sensor modules battery life, traffic conditions in wireless communication, system stability, convenient and the hardware installation method must not distracted or troubled the driver. So, further improvement can concentrated on designing small-scale sensors to be flexibly wear on the wrist or hand.

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List of Publications

1. **Boon-LengLee**, Boon-Giin Lee and Wan-Young Chung, “Wearable Driver Drowsiness Detection System Based on Biomedical and Motion Sensors,” Proceedings of the IEEE Sensors Conference 2015, pp 75, 1-4 November, 2015, Busan, South Korea.

2. **Boon-Leng Lee**, Boon-Giin Lee, Gang Li and Wan-Young Chung, “Wearable Driver Drowsiness Detection System Based on Smartwatch”, in Proceeding of the Korea Institute of Signal Processing and System Fall Conference (KISPS), November, 2014.

3. **Boon-Leng Lee**, Boon-Giin Lee and Wan-Young Chung, “Driver Drowsiness Detection using Wavelet-Based EEG in Mobile”, in Proceeding of the Korea Institute of Signal Processing and System Summer Conference (KISPS), June, 2014

4. Boon-Giin Lee, **Boon-Leng Lee** and Wan-Young Chung, “Wristband-Type Driver Vigilance Monitoring System Using Smartwatch,” IEEE Sensors Journal (SCIE, IF: 1.762, ISSN: 1530-437X), Vol. 15, No. 10, pp. 5624-5633, 2015.

5. Gang Li, **Boon Leng Lee** and Wan-Young Chung, “A Wearable Brain-Machine Interface System for Real-time Driver Drowsiness Detection,” Proceedings of the 18th International Conference on Electronics, Information and Communication (ICEIC’15), pp. 590-591, 28-31 January, 2015, Grand Hyatt Hotel, Singapore.

6. Gang Li, **Boon-Leng Lee** and Wan-Young Chung, “Smartwatch-based Wearable EEG System for Driver Drowsiness Detection,” IEEE Sensors Journal (SCIE, IF: 1.762, ISSN: 1530-437X), Vol. 15, No. 2, pp. 7169-7180, 2015.

Awards

1. Excellent Paper Award – **Boon-Leng Lee**, Boon-Giin Lee, Gang Li and Wan-Young Chung, “Wearable Driver Drowsiness Detection System Based on Smartwatch”, in Proceeding of the Korea Institute of Signal Processing and System Fall Conference (KISPS), November, 2014.
2. Excellent Paper Award – **Boon-Leng Lee**, Boon-Giin Lee and Wan-Young Chung, “Driver Drowsiness Detection using Wavelet-Based EEG in Mobile”, in Proceeding of the Korea Institute of Signal Processing and System Summer Conference (KISPS), June, 2014