Real Time Pedestrian Protection System: Pedestrian Environmental Awareness Detection and Augmented Reality Warning System

by

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Author

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List of Abbreviations

AR Augmented Reality
ECG Electrocardiography
EEG Electroencephalography
FOV Field of View
GPS Global Positioning System
HF High Frequency
HOG Histogram of Oriented Gradients
HRV Heart Rate Variability
HUD head-up display
IMU Inertial Measurement Unit
ISO International Organization for Standardization
LF Low Frequency
PNS Parasympathetic Nervous System
RBF Radial Basis Function
RR Interval Time Intervals Between Peaks of The R Waves
SDNN Standard Deviation of Normal to Normal
SNS Sympathetic Nervous System
SVM Support Vector Machine
V2X Vehicle to Everything
VLF Very Low Frequency
WHO World Health Organization

Abstract

To improve the safety of the pedestrians via V2X communications, it is important to detect pedestrians' environmental awareness and give warnings to those with low environmental awareness. Based on the characteristics of pedestrians, a real-time algorithm was developed to detect pedestrians' environmental awareness, then an Augmented Reality (AR) warning system was developed to carry out the warning to the pedestrians who have low environmental awareness. In this study, the heart rate variability (HRV) analysis and phone position analysis were used to understand the mental state and distractions of pedestrians, the projection method was used to develop the AR warning system. The HRV analysis was used to detect the fatigue and alert states of the pedestrians, and the phone position was used to define the phone distractions of the pedestrians. Support Vector Machines (SVM) algorithms were used to classify the pedestrians' mental state. After the user analysis, the AR warning system was developed based on the perspective projection method. After the data collection and experiment, the results show that the accuracy of the pedestrian state detection was about 85% for the mental state detection and 100% for the phone position detection. Also, the AR warning system works well for to carry out the warning to the pedestrian.

Chapter 1 Introduction

Background

It is very important to protect the vulnerable road users in the public area. Pedestrians are some of the vulnerable road users, and their safety is a big concern across the world. A report from the World Health Organization (WHO) mentioned that each year, there were 1.2 million people who die, and 50 million people were injured due to traffic accidents, and the number of traffic deaths and injuries is expected to rise if no preventative effort is done (Peden, et al., 2004). Until 2016, the rate of pedestrian death over total motor vehicle death still remained high and continued to rise (Retting & Schwartz, 2018). A report also shows that autonomous vehicles can collide with pedestrians and lead to their death (National Transportation Safety Board, 2018).

By equipping vehicles with advanced sensing, computing, and decision-making capabilities, automated vehicle technologies have the potential to create a safe vehicle-to-pedestrian environment. Such an environment requires a clear understanding of pedestrians' status in real time. Increasing pedestrian safety should work both on the vehicle side and pedestrian side. Alerting the driver or designing a good driving assistant system is not the only thing can be done with in regard to pedestrian safety. It is also necessary to warn the pedestrians when they are under low environmental awareness and have the potential to conflict with vehicles. Current studies were mostly focued on the driving assistant system, and limited researched were studied the system for the pedestrians.

Reduced environmental awareness may increase the unsafe behavior among pedestrians when they are walking in public areas (Nasar & Troyer, 2013) or trying to cross the road (Nasar, Hecht, & Wener, 2008). Information about pedestrian environmental awareness could further assist drivers and automated vehicles in making a correct decision. Different road users understand the same road environment differently (Walker, Stanton, & Salmon, 2011; Salmon, Lenné, Walker, & Filtness, 2013; Salmon, Young, & Cornelissen, 2013). These differences could cause serious conflict between the vehicle and pedestrian. Understanding the environmental awareness can help both a driver and an automated vehicle understand the possible actions the pedestrian may take, and in turn, can protect the pedestrian from serious injury. Another study shows that one-third of pedestrians with severe head injuries were due to vision obstructions by other vehicles, road infrastructures, buildings, trees or bushes (Fredriksson & Rosén, 2011). Besides helping the driver and automated vehicle understand the state of the pedestrian, if the pedestrians could get the warning before they step in traffic when they are under lower environment awareness or their view is blocked, accidents could be prevented, and pedestrians could be protected.

Environmental awareness could be considered as "know what is going on" (Endsley, 1995a). In this thesis, two factors which influence the pedestrians' ability to know what is going on were used to detect the environmental awareness of the pedestrians. First, the pedestrians' mental state, which was defined as fatigue state or alert state, was used as one of the factors.

There are different states of the human's mental state, for example, fatigue, alert, stressed, sad, fear, and so on. Fatigue and alert was the most common state the pedestrians could have while they were walking in public area. Also, fatigue and alert can represent the ability of "know what is going on" best among other mental state. When the pedestrians were under fatigue state, their reaction would become slower and less accurate (Kosinski, 2013). Knowing what is going on would be inefficient when the pedestrians were fatigued. So, fatigue and alert state was used to detect the pedestrian's mental state. Another factor that was used to detect the pedestrian's environmental awareness was the presence of phone distractions. When the pedestrians were distracted by their phone, their ability to perceive an element in the environment would be reduced (Hatfield & Murphy, 2007). Also, when the pedestrians were distracted by their phone, their efficiency of processing information and reaction would also decrease due to the secondary tasks (Patten, Kircher, Östlund, & Nilsson, 2004). Therefore, pedestrians' mental state and phone distractions would be used to detect the pedestrian environmental awareness in this thesis. The detailed information regarding these two factors would be discussed in the following chapters.

AR is a state of the art technic that can "augment" digital information in the real world so that users can get the overlaid information by perceiving the real world. Current devices which can display AR include eyeglasses, heads-up-displays (HUD), contact lenses, virtual retinal displays, eye taps, handheld devices, and so on (Wikipedia, 2018). Because of the limitation of the pedestrians' carrying ability, AR technology can be used to develop a graphic warning system for pedestrians. In this thesis, we assume that people would wear some AR devices when they are walking in public areas so that the graphic warnings can be carried out by the AR devices.

Related Work

There are many different studies that talked about environmental awareness detection among drivers. Most of them focused on the fatigue/drowsiness detection of drivers. The eye/face detection-based methods were used to analyze the driver's facial expression, yawning, and eye blinking to detect if they were fatigued (Ji & Yang, 2002; Ji, Zhu, & Lan, 2004; Saradadevi, & Bajaj, 2008). Electroencephalograph (EEG) based methods were analyzing the changes in major EEG bands to detect the fatigue status of the driver (Lal, Craig, Boord, Kirkup, & Nguyen, 2003; Lin et al., 2005; King, Nguyen, & Lal, 2006). Electrocardiograph (ECG)/HRV based methods analyzed the heart rate and heart rate variability to detect if the driver was fatigued or drowsy (Yang, Lin, & Bhattacharya, 2010; Jung, Shin, & Chung, 2014).

Although many methods were developed to detect the environmental awareness of the drivers, the number of studies regarding pedestrian environmental awareness detection is still limited. Existing studies about the driver's environmental awareness detection all require a fixed seated position of drivers with measuring instruments mounted inside the vehicle. However, such a set-up is not feasible for the pedestrians. The pedestrians have limited capacities to carry measuring instruments while walking. In this case, the methods used to detect the driver's environmental awareness are not fit.

Many studies have been done to design warning systems or pedestrian protection systems for drivers or autonomous vehicles. These studies detected the pedestrians first and then developed the warning system or pedestrian protection system for drivers and autonomous vehicles. There are different methods that have been developed to detect the pedestrians for the vehicles and drivers (Dolla, Wojek, Schiele, & Perona, 2012). For example, the Histogram of Oriented Gradient (HOG) is an algorithm using the histogram of oriented gradient and linear SVM to do the pedestrian detection (Dalal & Triggs, 2005). Based on these pedestrian detection methods, some studies added the driver warning system (Hakkert, Gitelman, & Ben-Shabat, 2002) or automatic brake system (Coelingh, Eidehall, & Bengtsson, 2010; Keller, et al., 2011) to develop the pedestrian protection system. However, these studies are all about warning the drivers about crossing pedestrians. There are limited studies that have researched the pedestrian warning system.

There is one study that has talked about a warning system for a vehicle, pedestrian, and bicyclists (Greene, et al., 2011). However, it was only focused on the algorithm development, not the interface design. This means that even if the algorithm can detect the potential collection correctly, there is no good way to carry out the warning to pedestrians.

Some studies also talked about the AR interface design for the driver warning system. Kim, Wu, Gabbard, and Polys (2013) developed an in-vehicle HUD user interface for crash warning systems. Another study has evaluated different AR warning systems for the driver in an urban environment (Plavsic, Bubb, Duschl, Tonnis, & Klinker, 2018). Again, all these studies are only mention the user interface for the in-vehicle warning system, so an AR interface designed for pedestrians is still needed.

Objective

The goal of this thesis is to develop a pedestrian protection system. An algorithm was developed to assess the real-time environmental awareness of the pedestrian while they were walking in a public area. Then an AR warning system was designed to carry out the warnings to the pedestrians when their environmental awareness was low. The real-time phone position analysis and real-time pedestrians' HRV analysis were combined to come up with the pedestrian environmental awareness detection. User analysis was performed to design the user interface and a perspective projection method was used to develop the AR layout algorithm.

Chapter 2 Pedestrian Environmental Awareness Detection

As mentioned in chapter 1, pedestrians' mental state and phone distractions would be used to detect the pedestrian's environmental awareness in this thesis. The HRV was used to detect the pedestrian's mental state and phone position was used to detect the distractions. Environmental awareness was classified by synchronizing the mental state and phone distractions.

Heart Rate Variability and Mental State

Various methods could be potentially used to measure the pedestrian's mental state including Physiological Techniques, Performance Measures, Subjective Techniques (Endsley, 1995b), Freeze Probe Techniques, Real-time Probe Techniques, Self-rating Techniques, Observer-rating Techniques, Performance Measures, and Process Indices (e.g. Eye Tracker) (Salmon, Stanton, Walker, & Green, 2006). Because the aim of this thesis is to develop a pedestrian protection system that needs to give a real time warning to the pedestrians, all the detections and algorithms should be in real time. As real-time pedestrian environmental awareness detection is needed, techniques that were not real time, such as Freeze Probe, or Self-rating could not be used. Those techniques that require physiological measures could be used to detect the pedestrian's mental state. HRV is widely used to detect the pedestrian mental state (Lal & Craig, 2001). The equipment used to collect the data to perform HRV analysis is lightweight and easy for the pedestrian to carry. So, HRV is used to detect the pedestrian's mental state in this study.

Nervous Systems and Mental state

Before talking about how HRV can reflect the mental state, it should to be clear how the nervous system can reflect the pedestrian's mental state. There are two components of the human nervous system: the Peripheral Nervous System and the Central Nervous System. The Central Nervous System is the system that includes the brain and spinal cord, while the Peripheral Nervous System is the nervous system that is connected to the Central Nervous System. The Peripheral Nervous System further has two components: the Somatic Nervous System and the Autonomic Nervous System (Mai & Paxinos, 2012). The activity of the Autonomic Nervous System was considered in this thesis and detected by the HRV analysis. Figure 1 shows the structure of the human nervous system.

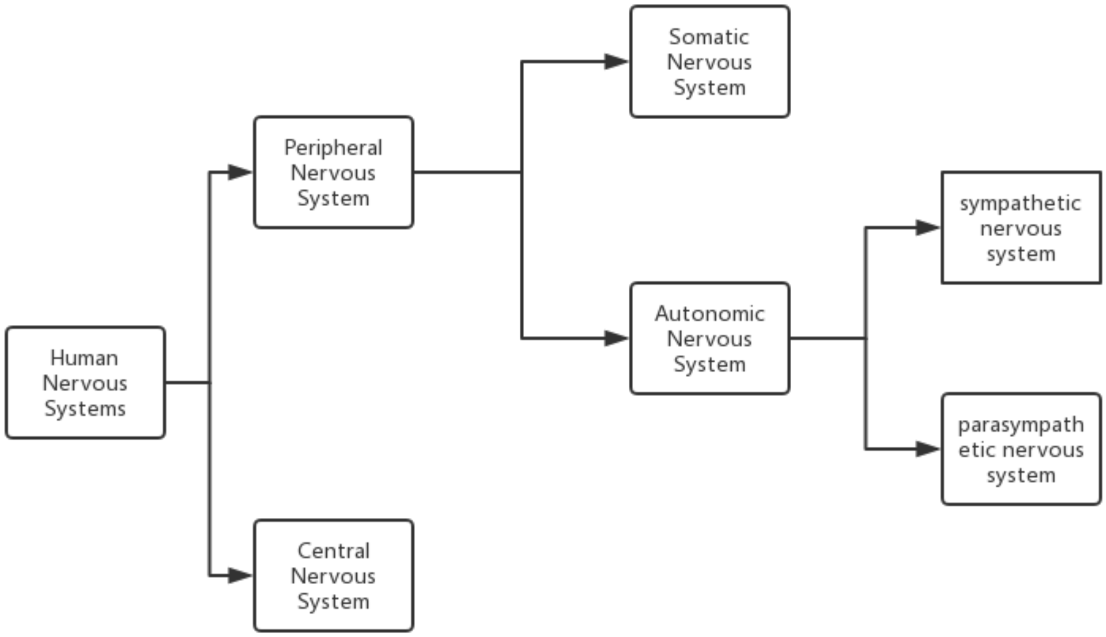


Figure 1. Human nervous systems

The Autonomic Nervous System can regulate bodily function and is in control of the fight or flight reaction in humans (Schmidt & Thews, 1989). Fight or flight is the reaction where when a human encounter some stressor, the body may prepare to fight with the perceived hazard event or flight from the event (Cannon , 1963). The two branches of the Autonomic Nervous System are the Sympathetic Nervous System (SNS) and Parasympathetic Nervous System (PNS). The SNS is in charge with the fight-flight system and the role of the PNS is to help people rest (Schmidt & Thews, 1989). There are five steps that occur when people react to a stressor. When people received the stressor, they firstly recognize the environmental requirement, then appraisal of the demand. At this time, the SNS will be in charge of the reaction. It automatically signals our body to prepare for a reaction (fight-flight reaction). While people are in this reactive state, they will react faster and better to the perceived signal. However, systems like the immune system and digestive system, which are not necessary for the stress reaction, will be suppressed.

After the person deals with the stress, the body needs to go back to its base line, triggering the PNS to where it is in charge of the body now. It will undo the stress response and give the body signals to let it calm down (Mills, Reiss, & Dombeck, 2008). This means that while the PNS is in domain, people normally are in a fatigued state and will react slower.

In real life, the stressor could be anything and is not limited to a physical hazard. For example, it could be a deadline of a homework assignment or an exam for students. In this situation, after they deal with the stressor, the PNS is in charge and they will go into a fatigued state and will react slower to their environment. So, in real life, the fatigue state could be any state that the pedestrian feel tired.

HRV, Nervous System, and Mental State

There are communications between the heart and brain, and the activity of the brain and the nervous systems can be reflected by the heart signals. Figure 2 shows the heart-brain communication pathways.

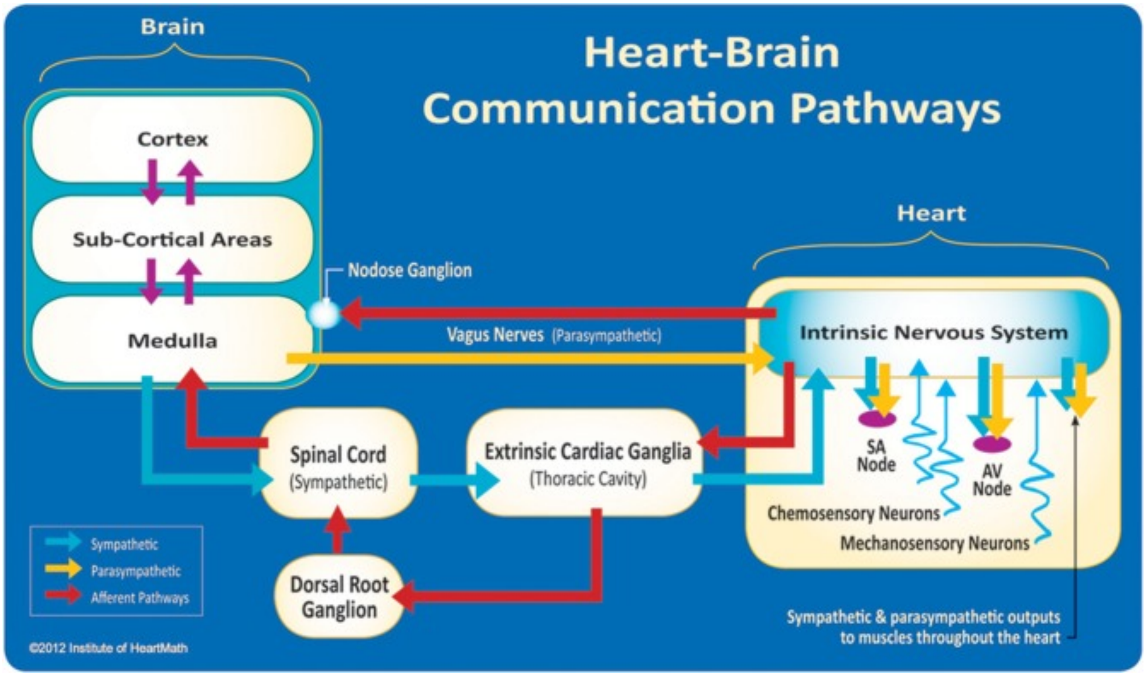


Figure 2. Heart- Brian communication pathways (McCraty & Royall, 2015).

Figure 2 shows that the neural systems were interacting with the heart and brain, so the activity of the SNS and PNS can be reflected by the data about the heartbeat (McCraty & Royall, 2015). HRV shows the beat-to-beat changes of human heartbeats. It can reflect the interplay between the sympathetic nervous system and the parasympathetic nervous system (Cygankiewicz & Zareba, 2013). While the SNS is in domain, the beat-to-beat interval would be shorter and while the PNS is in domain, the beat-to-beat interval would be longer (Shaffer, McCraty, & Zerr, 2014). This means that the RR intervals (time intervals between peaks of the R waves) can reflect the alert or fatigue state of a person, and HRV analysis could be used to detect the mental states of pedestrians.

Studies have shown that HRV can be used as an indicator of environmental awareness. Saus et al. (2006) found that there is a relationship between the HRV and environmental awareness. The same result was confirmed by another study regarding navigation training (Saus, Johnsen, Eid, & Thayer, 2012). Research about vagal influence on working memory and attention indicated that the HRV has a positive relationship with reaction time, correct response, and executive function (Hansen, Johnsen, & Thayer, 2003). Moreover, studies support that HRV also can be used as an indicator of fatigue and drowsiness. One study showed that HRV measures are a sensitive indicator of fatigue (Egelund, 1982). Byeon et al. (2006) also stated that HRV analysis can be used to detect drowsiness status.

There are different ways to analyze HRV, including Time Domain Analysis, Frequency Domain Analysis, Rhythm Pattern Analysis, and Nonlinear Methods (Camm, et al., 1996). In this thesis, Time Domain Analysis and Frequency Domain Analysis were used to detect the pedestrian's mental state. Standard Deviation of Normal to Normal (SDNN) is the time domain measure that was used in this thesis. "Healthy individual has more irregular and complex HRV signal" (Medicore, 2018). When people were fatigued, their heart beat will trend to be more similar in time. So, when human is under a bad mental state, their heart rate may have less variance, and the SDNN will be decreased when the pedestrian is fatigued. Research shows that SDNN is related to the human mental state. Reduced SDNN indicates a poor mental state (Burton, Rahman, Kadota, Lloyd, & Vollmer-Conna, 2010). Lower SDNN would be considered as a factor of poor environmental awareness in this study.

The Frequency Domain Analysis counts the number of RR intervals that match different frequency bands. Three bands were assigned to the Frequency Domain Analysis: high frequency (HF), which is from 0.15 to 0.4 Hz; low frequency (LF), which is from 0.04 to 0.15 Hz; and the very low frequency (VLF), which is from 0 to 0.04 Hz. The ratio of low-frequency power and high-frequency power indicate the autonomic activity of the body, which can describe the mental state of a human (Camm, et al., 1996). As mentioned above, the LF/HF ratio can reflect the interplay between the sympathetic nervous system and the parasympathetic nervous system. The LF will increase while the SNS is in domain and the HF will increase while the PNS is in domain. Since the SNS reflects the alert state and PNS reflects the fatigue state, when people are in a fatigue state, the HF will increase and the LH will decrease. So, decreased LF/HF can be considered a factor of fatigue state of the pedestrian in the study (Egelund, 1982). In this thesis, RR intervals were collected from heart rate sensors to perform the Time Domain Analysis and Frequency Domain Analysis.

Phone Position and Distraction

Studies showed that being distracted by a phone could cause reduced environmental awareness. Talking on the phone could cause decreased driving environmental awareness and increased workload among drivers (Ma & Kaber, 2005; Kass, Cole, & Stanny, 2007). It is also shown that phone use has a significant influence on pedestrian safety (Schwebel, et al., 2012). Talking on a phone is related to the distractions of the pedestrian which may threaten their safety (Hatfield & Murphy, 2007). When the pedestrian is distracted by their phone, they may have more unsafe behavior while crossing (Thompson, Rivara, Ayyagari, & Ebel, 2012). All the studies mentioned above support that phone use can be considered an important factor in detecting pedestrian environmental awareness.

The position of the phone can be used to approximately identify if the pedestrian is using the phone and distracted by it. If the pedestrian was using a phone, that could be considered as a distraction. If the pedestrian was not using a phone, that could be considered as the pedestrian not being distracted by their phone. People normally were not using their phone while the phone was in their pocket, bag, or swinging in their hand. The phone was normally in use if they were holding it near their ear (talking on the phone) or holding it in front of them in a texting position. In this thesis, five phone positions were predetermined as five classes. These five classes were further defined as two different phone using states. Holding the phone/texting and talking on the phone were defined as being distracted by the phone. Swinging the phone in one's hand and having the phone in one's bag or pocket was defined as not being distracted by the phone. Gyroscope analysis would be performed to classify which phone using state the gyroscope data fell in.

The data of phone inertial measurement unit (IMU) can be collected directly from the phone to determine the phone's position. The gyroscope data from an IMU sensor's output can be used to do the classification. Variance of the gyroscope from three axes can be calculated and combined into one. Let the gyroscope on the x axis was A_{x1}, A_{x2}, A_{x3}......A_{xn}, the gyroscope on the y axis was A_{y1}, A_{y2}, A_{y3}......A_{yn}, and the gyroscope on the z axis was A_{z1}, A_{z2}, A_{z3}...... A_{zn}. The calculation and combination can be performed by using the equation shown below:

$$\overline{A_n} = \frac{\sum_{i=1}^{n} A_n}{n} \tag{1}$$

$$A_{rms} = \frac{\sum_{i=1}^{n} (A_i - \bar{A}_n)^2}{n} \tag{2}$$

$$\mathrm{RMS} = \sqrt{\mathrm{A}_{\mathrm{xrms}}^2 + \mathrm{A}_{\mathrm{yrms}}^2 + \mathrm{A}_{\mathrm{zrms}}^2} \tag{3}$$

Equation 1 can be used to calculate the mean value of gyroscope on each axis, $\overline{\mathrm{A}_{\mathrm{n}}}$ is the calculated mean value of the gyroscope. Then, equation 2 can be used to calculate the variance on each axis, $\mathrm{A}_{\mathrm{rms}}$ is the variance on each axis. Equation 3 can be used to combine the variance that have been calculated on each axis, RMS is the combined variance. Because the phones will have more movement while they were not used, for example, swing has lot more movement than hold the phone near ear. So, the RMS would be larger when the phone was not used and would be smaller when the phone was in use. Detail thresholds were determined in the experiment described in the later chapter. After the experiment, RMS = 0.5 rad/s was used as the threshold of distracted or not distracted by the phone.

Environmental Awareness Detection Algorithms

Pedestrian Mental State Detection.

Different people could have different absolute value on HRV based on different personal characteristics, such as age, gender, etc. (Camm et al., 1996). It is not feasible to set a universal value of HRV for everyone. It is also not feasible to train the model for each person for their own data. Because the data needs to be labeled during the training, and the user cannot easily input the label for the training purpose. In order to have a higher accuracy of classification, a two-step classification algorithm was built. The first step of the algorithm can be used to classify the people that have different characteristics. People that have the same characteristics would be classified in same group. In this thesis, age and gender were the two characteristics predetermined to do the classification. Based on the result of the first step, different groups of people would use a different model in the second step about the HRV classification. So, the HRV classification models could be more personalized, and in turn, be more accurate. In this thesis, the first step was to build regression models about heart rate under different speeds to classify the user's age and gender group. In the second step, different SVM models were used for different group of people to classify the pedestrian's environmental awareness.

The heart rate when people are standing (speed = 0 km/h), walking slowly (speed = 3 km/h), and walking quickly (speed = 5 km/h) could be different for different age and gender (Melo, et al., 2005; Chiu & Wang, 2007) So, the people's age and gender group can be classified based on their heart rate under different walking speeds. In this thesis, regression models about heart rate were built for different age and gender groups. As the assumption of this thesis was the pedestrians would wear the heart rate sensor (eg. a smart watch) daily, their heart rate under different walking speeds would be collected. The collected heart rate under different walking speeds would be compared with the model built in this thesis. Then the age and gender group of the pedestrian would be classified based on which model their heart rate fell in. This thesis was focused on the environmental awareness of two age groups: the young adult groups were aged between 20 to 30, and the senior groups were aged between 45 to 55 years old. The two age groups were further separated into male and female groups. So, there were four groups were considered in this thesis: young adult males, young adult females, senior males, and senior females. Three linear regression models about the heart rate in these groups at different speeds were built.

$$\text{Young male heartrate} = 69.429 + 5.7143 * \text{Speed (km/h)} \tag{4}$$

$$\text{Young female heartrate} = 76.429 + 5.7143 * \text{Speed (km/h)} \tag{5}$$

$$\text{Senior female heartrate} = 74.079 + 2.908 * \text{Speed(km/h)} \tag{6}$$

To build these models, the heart rate data was collected from participants while they were walking under different speeds. The young adult groups' model was built based on 7 peoples' data and the senior group's model was built based on 2 peoples' data. Due to the difficulty of recruiting senior participants, the model of the senior male group was not able to be acquired and the senior female group's model is not accurate enough. Only the young adult groups and female senior group were analyzed in this thesis. The model for the young adult groups were significant as mentioned in the later chapter.

After the walking speed and gender group was identified, SVM was used to classify the mental state of the pedestrian. Support vector machines were widely used for the classification. A study shows that SVM can give the best classification accuracy on mental state detection when using the HRV as the analysis method (Zhang & Yu, 2010).

Support Vector Machines theory was proposed by Vladimir Vapnik in 1979 (Vapnik,1979) and gained more and more attention after the 1990s. SVMs use a linear separating hyperplane, which is optimal in the sense of being a maximal margin classifier with respect to the training data, to create a classifier (Hearst, Dumais, Osuna, Platt, & Scholkopf, 1998). With the development of technology, some software, such as MATLAB/SIMULINK, packages multiple SVM algorithms and the packaged tools are flexible and powerful to configure. One of the advantage of SVMs was that they can find out the optimal classification principle and further defined the optimal classification boundary by calculating the max margin. A margin is defined as the distance between the hyperplane and the nearest of the positive and negative examples (Hearst, Dumais, Osuna, Platt, & Scholkopf, 1998). Figure 3 displays a two-dimensional data classification example where every data is defined within two classes.

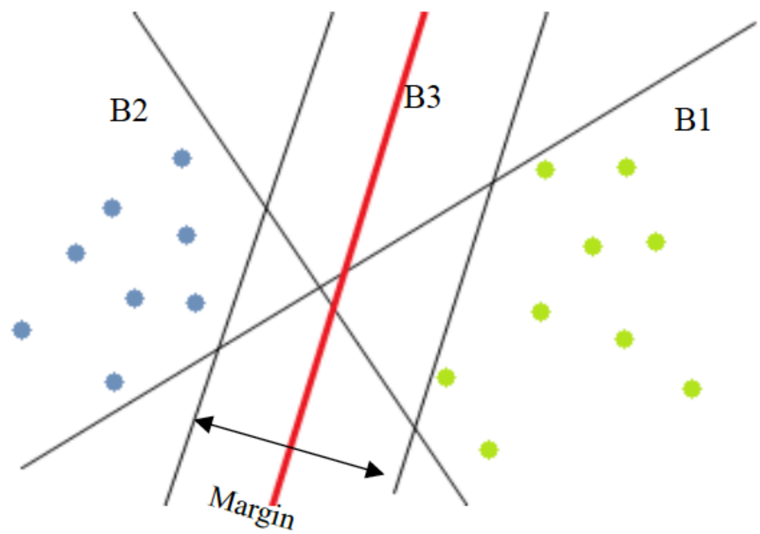


Figure 3. Two-dimensional data classification example.

In figure 3, the blue and green dots represent samples of class +1 and -1. B1, B2, B3 are classification boundary. B1 and B2 does not classify the boundary optimal, and B3 is the optimal. The margin was the distance between the nearest dots to the B3. For issues that cannot be linearly separated in the original input space, there are non-linear transformations can be performed. They can transform the original input space into a higher dimensional feature space where a linear optimal classification boundary could be found (Alex & Schölkopf, 2004). The kernel functions, such as Polynomial of degree, Gaussian radial basis function (RBF) and Hyperbolic tangent kernel, are used in the space transforming processing. The basic RBF kernel on two-dimensional data x and y is shown in equation 7 (Souza, 2010).

$$k(x,y) = e^{-\frac{\|x-y\|^2}{2\sigma^2}} \tag{7}$$

In equation 7, the square of $\|x\text{-}y\|$ represents the squared Euclidean distance between two feature vectors. The parameter σ represents the Gaussian function width.

In this thesis, different methods of SVM, including the Linear SVM, Quadratic SVM, Cubic SVM, Fine Gaussian SVM, Medium Gaussian SVM, and Coarse Gaussian SVM were trained and compared to find which one had the best performance. It is proven that the Gaussian SVM (RBF kernel) has the highest accuracy (Tong, Jia, Wang, & Yang, in-press). Different σ was used for different age and gender groups' model. It shown that for the young adult male group, the $\sigma = 1.7$ had the highest accuracy, for the young adult female group, the $\sigma = 5$ had the highest accuracy, and for the senior female group, the $\sigma = 5.7$ had the highest accuracy. SVM classifiers with Gaussian Radial Basis Function Kernel was created to define the optimal classification boundary for fatigue.

Combined Mental State and Distraction.

As mentioned above, the pedestrian mental state used the SDNN and HRV as the criteria. Distractions used the variance of phone gyroscopes as the threshold. Table 1 summarizes the classification criteria for both mental state and distraction.

Table 1. Classification criteria for both mental state and distraction.

Status	HRV	Phone use	Variance(gyro)
Distracted by phone	N/A	Talking on the phone Holding the phone/ texting	<0.5 rad/s
Not distracted by phone	N/A	In bag Swing	>0.5 rad/s

		In pocket	
Fatigue	LF/HF decrease; SDNN decrease	N/A	N/A
Alert	LF/HF increase; SDNN increase	N/A	N/A

When taking both mental state and distractions into consideration, there are a total of 4 different situations that could be defined. Figure 4 shows the structure chart of the 4 situations.

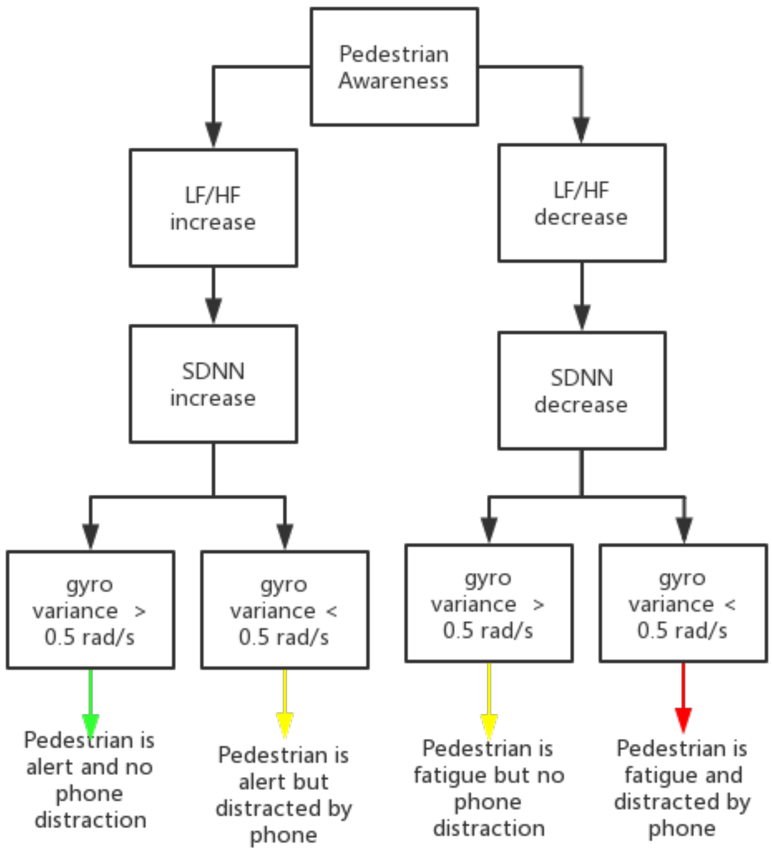


Figure 4. Structure chart of different situations.

In figure 4, there are four different situations of the pedestrian's environmental awareness, and they were classified as three different awareness levels. The red arrow is the danger environmental awareness level of pedestrian, the yellow arrows are the relative danger level, and the green arrows are good environmental awareness level. When the pedestrians would get the warning for potential conflict would be based on which environmental awareness level they had.

While pedestrians are under the danger environmental awareness level, the warning would be triggered early, so they could have more time to react to the potential conflict. While pedestrians were under the good environmental awareness level, the warning would be triggered later because they could react faster in this situation.

Summary of the Environmental Awareness Detection Methods

Overall, the structure of environmental awareness detection algorithms can be described as is Figure 5.

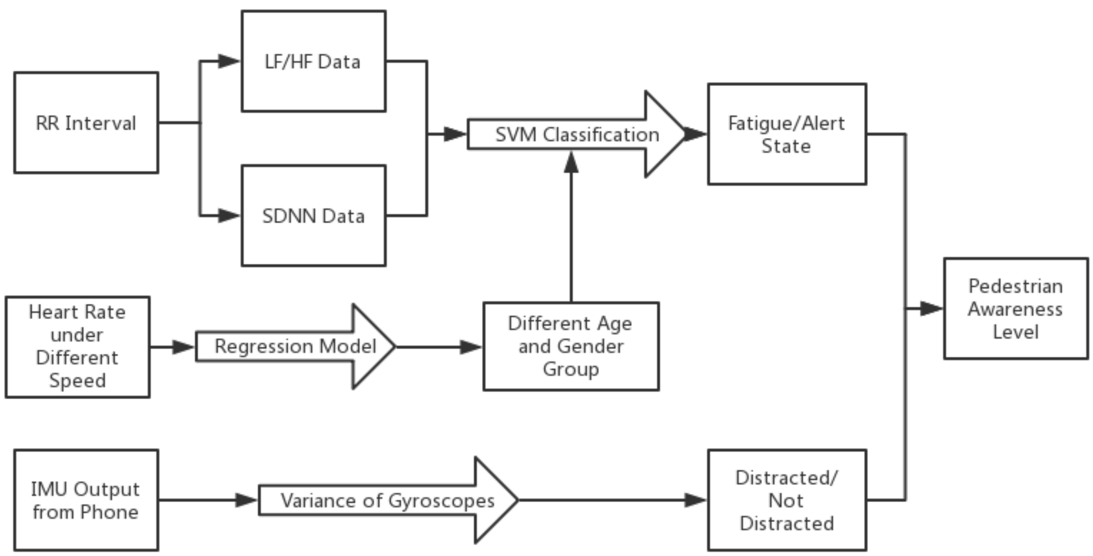


Figure 5. Pedestrian's environmental awareness detection algorithm

The necessary data to detect the environmental awareness of the pedestrian include the RR interval, heart rate, speed, and IMU from the phone of the pedestrian. The RR interval data would be used to calculate the LF/HF data and SDNN data, and the heart rate and speed data would be used in the regression model to get the age and gender group of the pedestrian. Based on the different age and gender groups, the HRV (ie, LF/HF and SDNN) data would be put in different SVM models to do the classification. Then the fatigue/alert state can be detected. The IMU data from the pedestrian's phone would be used to calculate the variance of gyroscope, then compared with the threshold that have been mentioned above. So, the distraction state can be detected. Then combined with the mental state and the distraction state, the pedestrian's environmental awareness state can be detected.

Chapter 3 AR Warning System

After the environmental awareness levels have been detected, graphical warnings would be used to warn the pedestrians. As mentioned in chapter 1, AR technology can overlay the digital, which include the graphic information in the real world. Also, the wearable AR devices are easy to carry for pedestrians and have the ability to give the graphical warning to them. So, the AR warning system would be used to carry out the graphical warning to the pedestrian. Because the AR glasses were the most developed wearable AR devices now, they could be used to carrying out the warnings. Based on the environment awareness level mentioned from pervious chapter, the warning would be carried out in different time.

User Research

Scenarios

In this thesis, we assume that the pedestrian would wear the AR glasses while they are walking in the public area so that the warning signals can be carried out through the AR glasses. Because the pedestrian would wear the AR glasses while they are walking, the warning interface should not be on all the time, otherwise, the interface would interrupt the pedestrian's normal walking. For example, it is not acceptable if the warning window is always on and show the warning signal when the potential collision is detected. In this case, the warning system should be off if no potential conflict has been detected. If there are some potential conflicts that are detected, based on the pedestrian's environmental awareness level, the warning system would turn on at different times and give the warning signal to the pedestrian. Moreover, based on the nature of the AR device, the interface should not be too complicated so that the warning system would shade real-world information. Redundant information in the AR interface could cause distractions rather than increase the safety of pedestrians. Also, based on the warning system design rules, the distractions and mental workload should be minimized in order to have a faster time to minimize the time to detect the warning signal (Boff & Lincoln, 1988). So that only necessary information should be shown in the warning interface.

The AR warning system would be active when the pedestrian is under low environmental awareness. The two representativeness scenarios are that the pedestrian's sight was obstructed or they were distracted. When the pedestrian's sight was obstructed, it would be necessary to show the pedestrians the direction of oncoming vehicles, the expected path of the oncoming vehicles, the conflict point, and how long it would take for the oncoming vehicle to drive to the conflict point. When the pedestrian was distracted, the warning system should give the warning to the pedestrian and direct the pedestrian's attention to the oncoming vehicle. In summary, the necessary information should be shown in the interface including the vehicle location, the expected vehicle path, the expected conflict point, the expected time counting in seconds from conflict happen, and a warning sign. All other information would not show in the warning interface in case that could disrupt the user and influence the user's perception of real-world and reaction times.

User Characteristic

Because of humans' use of top-down perception, people perceive information based on their expectations and knowledge. It is necessary to use some standardized design that is currently used in the user's normal life. Another assumption of this thesis is that the user of the AR warning system should be someone who use smartphones or PC devices frequently. This is so they would familiar with the smartphone and PC interfaces. In this case, the design of the AR interface would use the standard rules that were used in the smartphone and PC interface design because they can fit humans' top-down perception.

Summary of User Study

In summary, the AR interface design should follow the following rules based on the user scenario and user characteristic analysis:

- The warning interface should only turn on when the warning is needed. If no warning is needed, the whole warning interface should be off.
- The interface should be simple and easy, and only show the necessary information in the interface.
- The necessary information includes the vehicle location, the expected vehicle path, the expected conflict point, the expected time counting in seconds from conflict happen, and a warning sign.

- Use of the standard rules utilized in smartphone interface design and PC interface design.

User Interface Design

Size and Position of the Warning Window

To ensure the user can receive all the information from the warning system, the sizes and position of the warning interface were defined first. In horizontal view, the central field of the vision of most healthy people is about 30 degrees on each side. In this area, most humans can see the shape and color of objects. In vertical view, a person's normal line of sight is between 10 and 15 degrees (Panero & Zelnik, 1979). Another study about the alert design also mentioned that the visual alert should be located as close as the line of sight as possible, and should not exceed 30° from the line of sight (Boff & Lincoln, 1988). Based on the data mentioned above, the warning window was defined as a 60° by 30° rectangle area where the middle point of this rectangle was located in the pedestrian's sight line. Current commercial AR glasses (i.e. HoloLens) recommend that 2 meters is an optimal distance to project the contents (Turner, Zeller, Cowley, & Bray, 2018), which means the warning window can be defined as a rectangle of 2.309 meters * 1.155 meters in 2 meters in front of the eyes.

Vehicle Straight Crossing Scenario

The AR user interface while the vehicle drove straight was shown in Figure 6. This shows the warning interface when a vehicle is coming from the left side of the road.

Figure 6. User interface when vehicle go straight

Figure 6 shows the designed user interface when the vehicles drive straight. The overall color used was red because research shows that the higher priority warning signals should be colored in red (Boff & Lincoln, 1988). A warning symbol that is similar to the ISO general warning sign (ISO, 2018) was used to show the pedestrians that this is a warning signal. A symbol that is similar to the ISO symbol was used because of the top-down perception theory. Based on a report about in-vehicle HUD design guideline, the screen should not be centered in the user's field of view (FOV) (Gish & Staplin, 1995). The warning signal was located at the top of the warning window based on this rule so that the warning symbol would not affect the pedestrian's sight to perceive real-world information. A bar with an arrow was located on the left side of the warning window to point out that the vehicle location was on the left side. Also, based on the normal standard rule of smartphone and PC interface design, a sidebar with an arrow could mean that there is more information hidden or could mean that you need to turn your view to that direction. So that a sidebar with the arrow could also help the distracted pedestrian look toward the oncoming vehicle. When the pedestrians turned their head and see the vehicle, the sidebar would disappear. The red dot in the middle of the screen shows the expected conflicted point, and the red arrow connected with it shows the expected vehicle path. The seconds counts on top of the arrow shows the time left for the oncoming vehicle's arrival at the conflict point. Other than the warning symbol, which would be fixed at the upper middle of the window, all other elements would overlay on the real-world road based on the algorithms discussed below. When the pedestrian was turning their head, all the positions of these elements would be recalculated.

Vehicle Turning Scenario

The design for the vehicle turning scenario was similar to the vehicle driving straight scenario. The difference is that this scenario more likely happens at crossroads. When the pedestrian was trying to cross and the vehicle was making a turn, there is the potential to conflict with a pedestrian. Figure 7 shows an example of the vehicle right turn scenario.

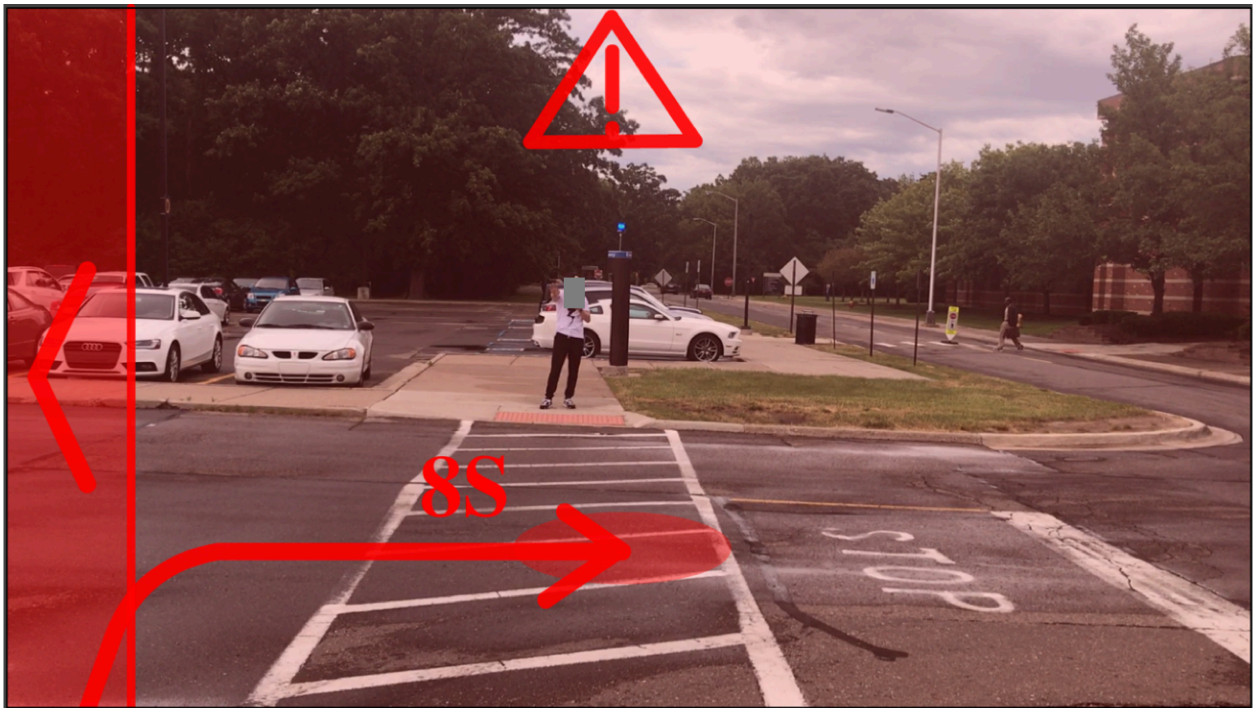


Figure 7. User interface of vehicle right turn

In Figure 7, most of the design elements were the same as the vehicle driving straight scenario, but the shape of the arrow was different. The end of the arrow was no longer a straight line. It became a curve where the end was on the direction of the vehicle. As shown in Figure 7, the user could easily understand that there is a vehicle coming from the left behind, and they need to turn their head to see the location of that vehicle.

Algorithms Development

Build Local Coordinate

Available data. We assumed that the pedestrian would wear the AR glasses so that the Global Positioning System (GPS) and IMU data could be extracted from them. The vehicle would have the GPS and IMU data as well since it was a basic configuration of current vehicles.

Also, we assumed that this system was designed after the potential conflict had been detected so that the expected conflicted point could be calculated based on the conflict detection. Overall, the data that could be used in the system included the vehicle GPS data, pedestrian GPS data, conflict point GPS data, pedestrian orientation data, vehicle orientation data, and pedestrian head rotation.

Local coordinate. It is necessary to build a local coordinate to perform the Perspective Projection Method. Differences in the devices' global coordinates need to be converted and synchronized into a local coordinate in order to project the calculated vehicle path to the AR screen. So a two steps algorithms was developed for the projection. First step, the vehicle's position and other positions that needed to project were convert to a local pedestrian's coordinate. In second step, the perspective projection methods were performed to project the positions on the projection plane. The local coordinate uses the pedestrian's position as (0,0) and the pedestrian's initial facing direction as the +y so that the pedestrian's right-hand direction would be the +x. Figure 8 shows the method to build the local coordinate.

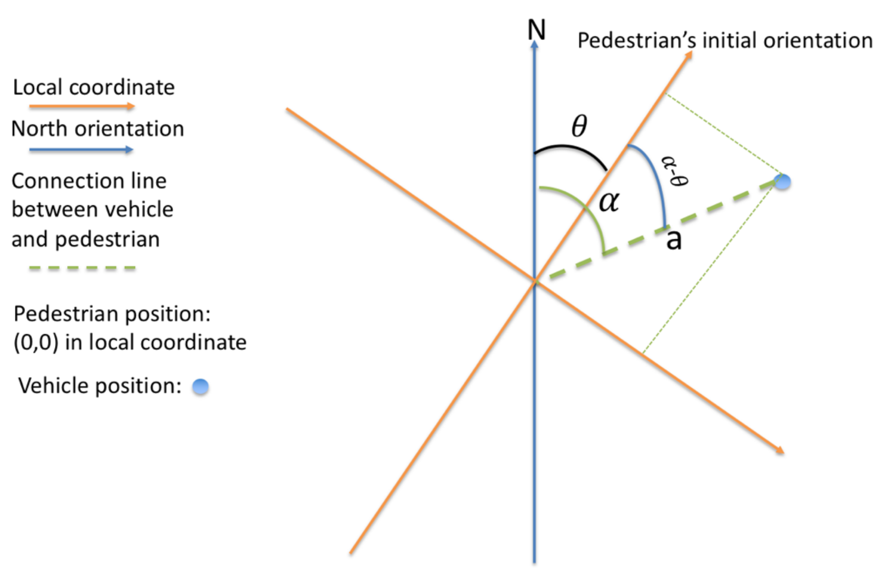


Figure 8. Build the local coordinate

As shown in Figure 8, to convert vehicle's GPS data into the local coordinate, the angle θ, which is the angle between the pedestrian's facing direction and the north direction, can be calculated based on the pedestrian's GPS data and IMU data. Then the angle α, which is the angle between the line connected to the vehicle and pedestrian and north direction can be calculated based on the vehicle and pedestrian's GPS data. As the pedestrian's position is the (0,0) in the local coordinate, the angle between the +y direction of local coordinate and vehicle point can be calculated as α-θ. The length a, which is the length between the vehicle position and pedestrian position can be calculated based on the vehicle's GPS and pedestrian's GPS. So that the vehicle's position in local coordinated can be calculated as $(a\sin(\alpha-\theta), a\cos(\alpha-\theta))$.

In the study, the conflicted position was assumed to be already known by the conflict detection. So that the same method could be used to convert the conflict position into the local coordinate. The vehicle turning position needs to be calculated in the turning situation. The vehicle and pedestrian's GPS data and facing direction data was used to do the calculation. We assumed that the pedestrian would face the road when the conflict was detected so that the road would in front of the pedestrian paralleled. Based on this assumption, a line was drawn in front of the pedestrian paralleled. The length between the line and pedestrian was based on the conflict detection. Another line of vehicle's facing direction was also drawn based on the vehicle’s data. The intersection point between these two lines was defined as the vehicle turning position in the local coordinate.

In summary, the positions have been converted into the local coordinate including the pedestrian position (0,0), the vehicle position (asin(α-θ), acos(α-θ)), the conflict position, and the vehicle turning position (if in the turning situation).

Projection Method

After the GPS data have converted into the local coordinate, the perspective projection method would be used to project the vehicle's potential path on the AR screen. There are different ways to project the 3D world onto a 2D plane. Orthographic projection's projection lines are all orthogonal to the projection plane (Maynard, 2005), which means the projected image would lose the depth cue. As we need the projected items to overlay onto the real world, the depth cue is necessary for the projection. Weak perspective projection method used some similar methods as the orthographic projection methods (Banerjee, 2002a) so that it cannot be used in this thesis either. Perspective projection is another method that can project the 3D object onto a 2D plan and would not lose the depth cue (Banerjee, 2002b). Thus, the perspective projection method would be used in this study to do the projection.

Perspective projection matrix. The basic perspective projection matrix is shown in equation 8 (Dynamic Graphics Project lab of the University of Toronto , 2018).

$$\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 1/d & 0 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \\ 1 \end{bmatrix} = \begin{bmatrix} x \\ y \\ z \\ z/d \end{bmatrix} \tag{8}$$

The (x,y,z) was the location of the point needed to be projected and d was the distance from the point to the projecting plane. The x,y, z, and d can be acquired from the local coordinate built previously. Based on this equation, a 2D coordinate can be built for the projecting plane. The location of the projected point on the projection plane would be (x*d/z, y*d/z). However, this projection matrix cannot be used directly to do the projection in this thesis. The pedestrian would rotate their head while looking at the vehicle so that the coordinates would need to be updated in real-time. A coordinate transformation needs to be done before this matrix can be used to project the expected vehicle path on the AR screen.

Coordinate transformation and projection. To do the coordinate transformation, first, we defined that the user's eye was the original point of the coordinate built for the projection, and the pedestrian's sight line was the +z direction. The AR screen, which was the projection plane, would be perpendicular to the z-axis all the time. Based on the pedestrian's head rotation, the coordinate could be updated in real-time as follow (Goldstein, 1980; Riley, Hobson, & Bence, 2006):

$$\begin{bmatrix} 1 & 0 & 0 \\ 0 & cos(\gamma_x) & sin(\gamma_x) \\ 0 & -sin(\gamma_x) & cos(\gamma_x) \end{bmatrix} \begin{bmatrix} cos(\gamma_y) & 0 & -sin(\gamma_y) \\ 0 & 1 & 0 \\ sin(\gamma_y) & 0 & cos(\gamma_y) \end{bmatrix} \begin{bmatrix} cos(\gamma_z) & sin(\gamma_z) & 0 \\ sin(\gamma_z) & cos(\gamma_z) & 0 \\ 0 & 0 & 1 \end{bmatrix} \left(\begin{bmatrix} V_x \\ V_y \\ V_z \end{bmatrix} - \begin{bmatrix} S_x \\ S_y \\ S_z \end{bmatrix} \right) = \begin{bmatrix} C_x \\ C_y \\ C_z \end{bmatrix} \tag{9}$$

In equation 9, the γ_x, γ_y, γ_z, were the pedestrian's head rotations retrieved from the AR glasses' IMU sensor. The $\begin{bmatrix} V_x \\ V_y \\ V_z \end{bmatrix}$ were the coordinates of the vehicle position, which was the position that needed to be projected, from the coordinate before transformed. The $\begin{bmatrix} S_x \\ S_y \\ S_z \end{bmatrix}$ were the coordinates of the camera, which were the pedestrian's eyes, from the coordinate before transformed. The $\begin{bmatrix} C_x \\ C_y \\ C_z \end{bmatrix}$ were the vehicle position coordinates after the coordinate transformation. As we assumed that the AR screen was located in the middle of the user's sight line, the C_x and C_y were assumed to be 0. After the transformation, the projection matrix could be used as follows:

$$\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 1/d & 0 \end{bmatrix} \begin{bmatrix} C_x \\ C_y \\ C_z \\ 1 \end{bmatrix} = \begin{bmatrix} P_x \\ P_y \\ P_z \\ P_w \end{bmatrix} \tag{10}$$

$\begin{bmatrix} P_x \\ P_y \\ P_z \\ P_w \end{bmatrix}$ was the vector calculated after the perspective projection matrix performed. As mentioned in Equation 8, the projected vehicle point's coordinate located on the AR screen should be (P_x/P_w , P_y/P_w).

Points projected and specific scenarios. The vehicle's position was not the only thing that needed to be projected to the AR screen. The algorithms mentioned above cannot directly project the whole vehicle path. To show the whole vehicle's path on the AR screen, not only does the vehicle position need to be projected, but the conflict position and vehicle turning position (under the vehicle turning situation) need to be projected as well. The same perspective projection method would be used to project the conflict position and vehicle turning position separately. After projecting these three positions on the AR screen as three ptojected points, the vehicle's path could be formed by connecting these three projected points. Figure 9 shows an example of the how the vehicle path arrow was formed based on the three projected points.

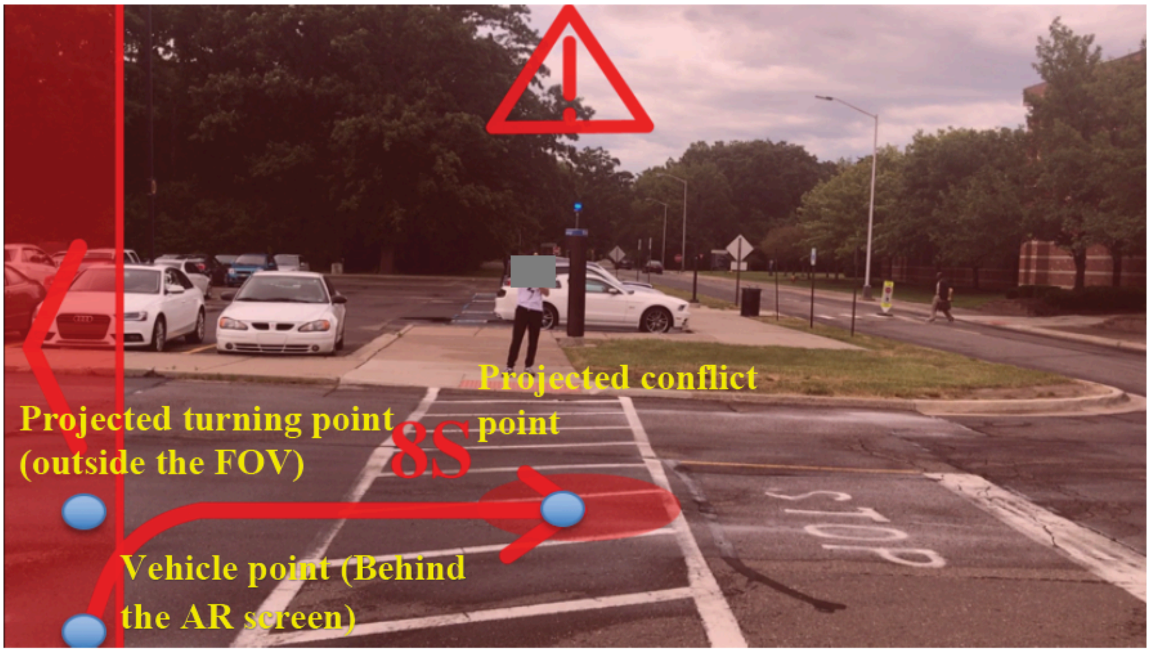


Figure 9. Projected points and arrow in interface

There are some situations that the perspective projection method needs to be customized. For example, while the vehicle was turning right, and the vehicle's location was behind the AR screen. While under this situation, the vehicle's position cannot be projected on the AR screen. Figure 10 shows an example of such situations.

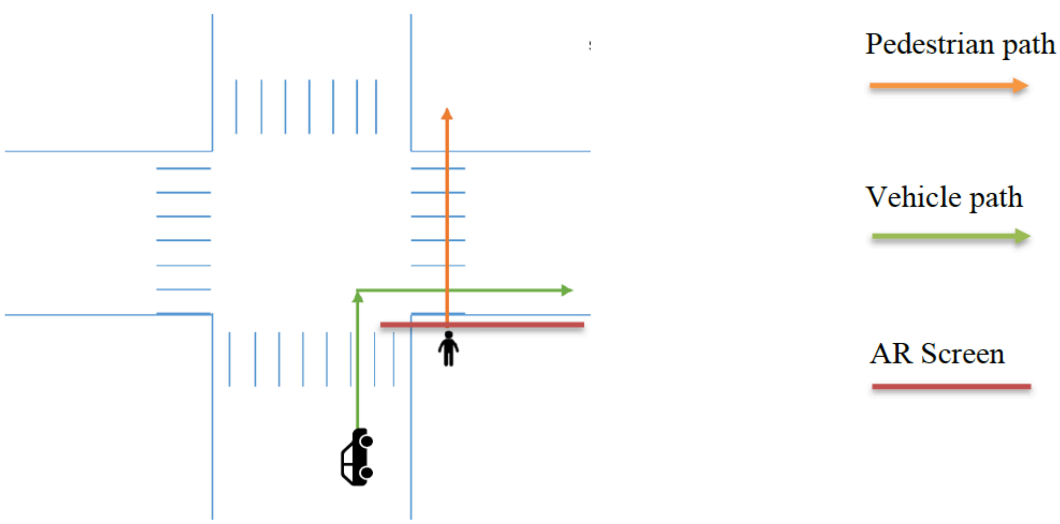


Figure 10. The situation that perspective projection methods does not work

To deal with such situations, four different scenarios have been considered. Different solutions have been carried out for different scenarios. The coordinate of the vehicle position, vehicle turning position, the conflict position, and the coordinated of the projected points of these three positions were used to determine if all three points can be projected or if the they fall in to the four scenarios shown below. For example, if the y-coordinate of the vehicle position is less than 2.0, and the y-coordinate of the projected vehicle turning point is less than -1.15, that means it was the scenario one. Figure 11 shows the four scenarios, and all four scenarios can be determined by the coordinates mentioned above.

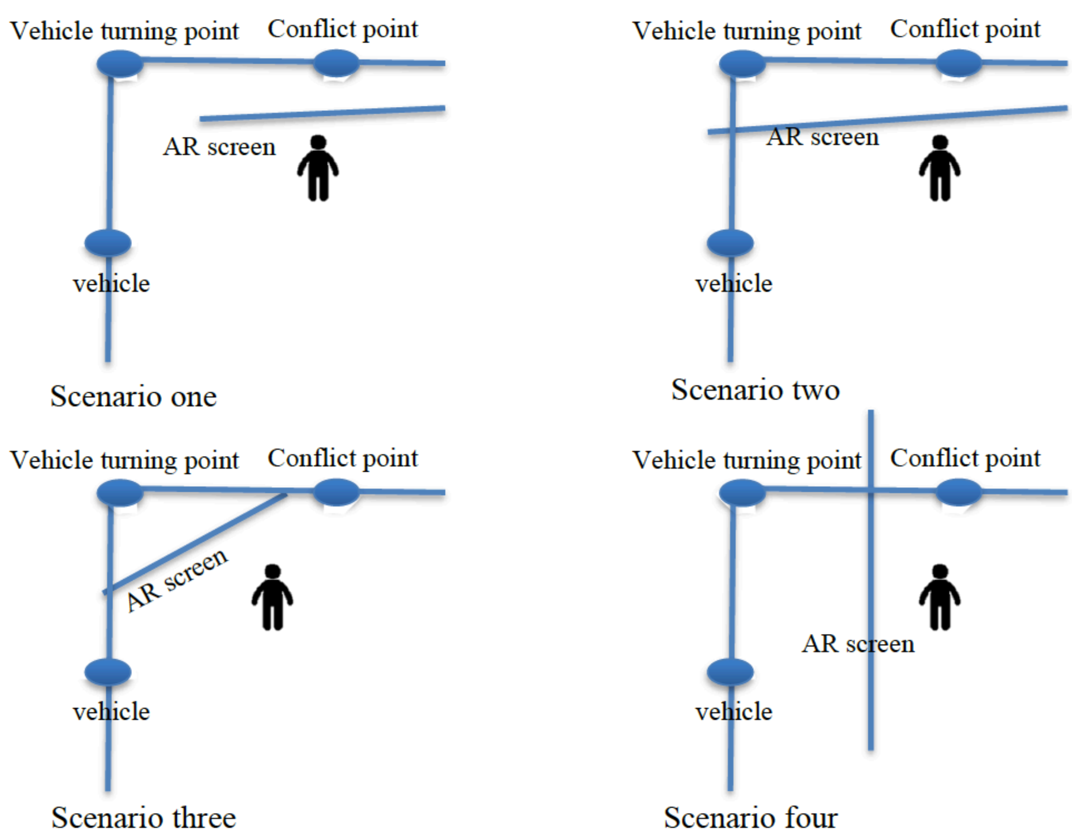


Figure 11. Four scenarios that perspective projection does not works well

In scenario one, the vehicle turning position and the conflict position were in front of the AR screen, the vehicle location was behind the AR screen, and the projected vehicle turning point was outside the FOV. To solve this problem, vehicle turning position and conflict position were used to do the projection by using the perspective projection method. After connecting these two projected points, there was an intersection point formed between the connection line and the FOV boundary. The intersection point, the projected conflict point, and the lower or upper boundary (depending on where the car was coming from) of the FOV would be used to form the arrow. Figure 7 is an example of the scenario.

Scenario two was the situation that the vehicle turning position and the conflict position were in front of the AR screen, the vehicle position was behind the AR screen, and the projected vehicle turning point was inside the FOV. To deal with this scenario, a similar method was used as in scenario one, but the intersection point between vehicle path and the boundary of FOV was not necessary since the vehicle point was inside the FOV. Figure 12 shows an example of scenario two.

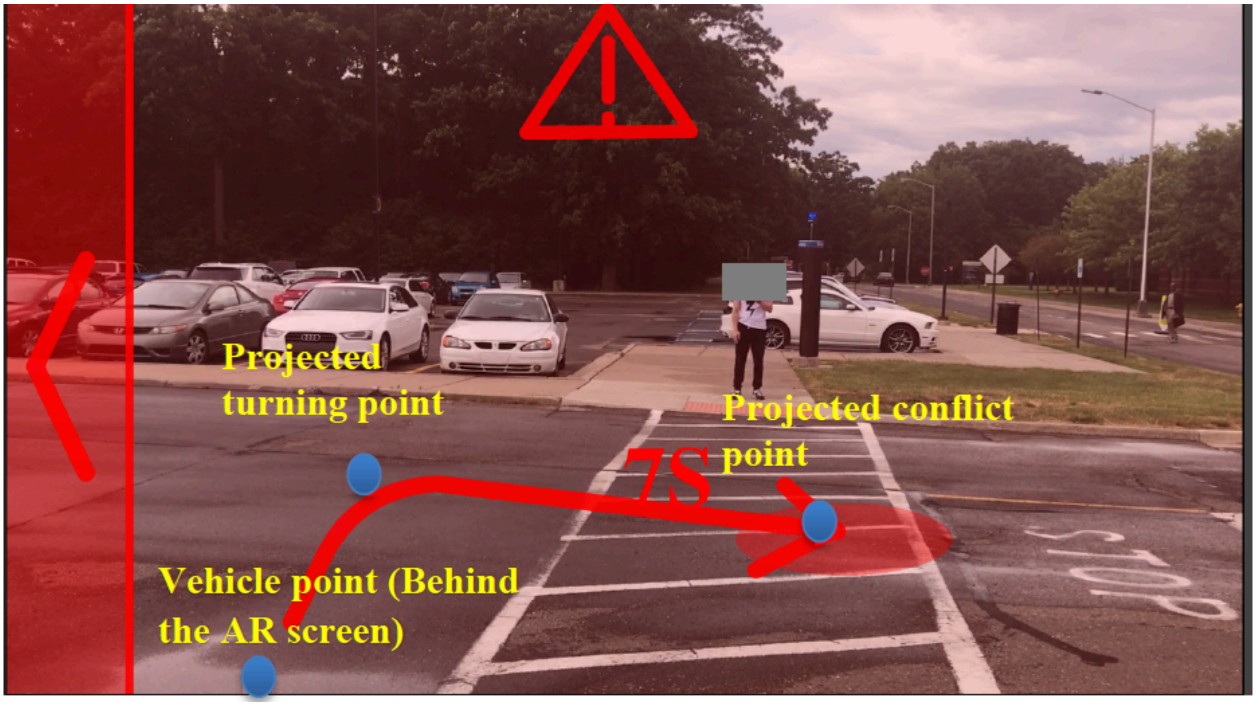


Figure 12. An example of scenario two

Scenario three was the situation where only the vehicle turning position was in front of the AR screen. To deal with this situation, only the vehicle turning position would be projected as a point on the AR turning screen. After the perspective projection method has been performed, a curved arrow would be formed while the middle point of the curve is the projected vehicle turning point. Figure 13 shows an example of the scenario three.

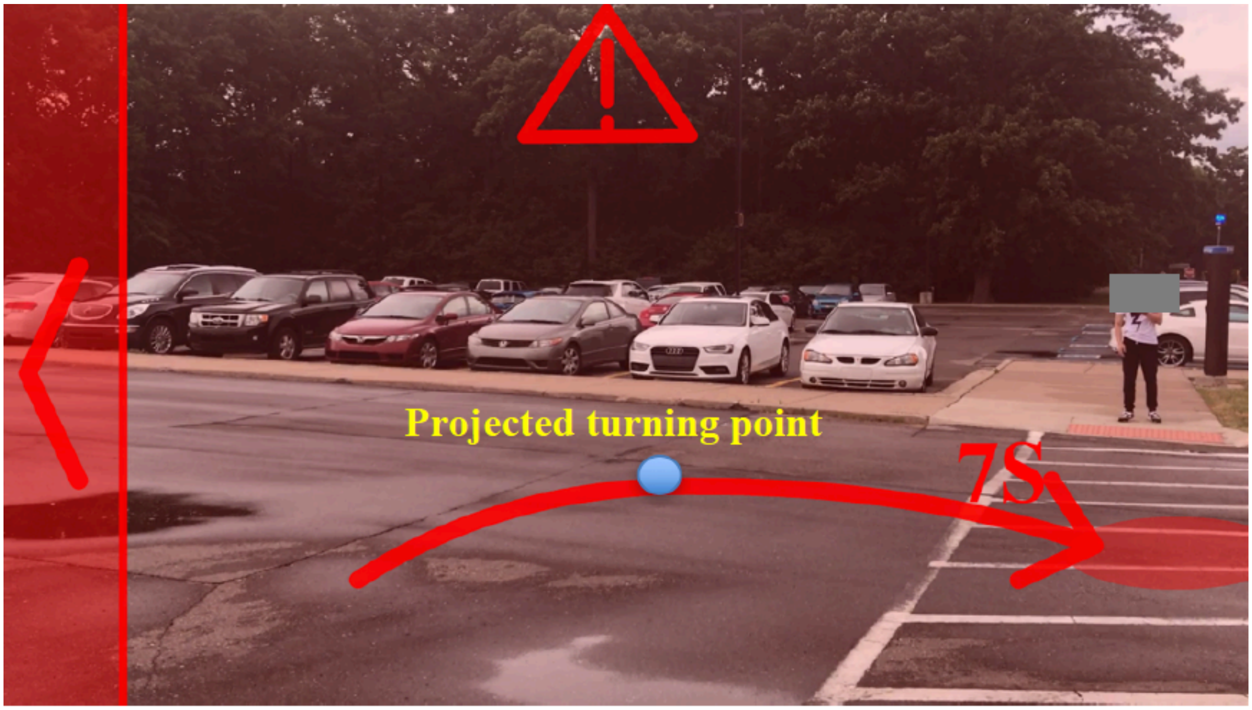


Figure 13. An example of scenario three

Scenario four was the situation where the conflict position was behind the AR screen. For such a situation, no matter whether the vehicle turning position was in front of the AR screen or not, the vehicle turning position would not be used. To deal with this, the vehicle's position of the current second and previous second would be used for two projection points. A line would connect these two projection points and this line would be extended into the user's FOV. The arrow would be formed based on this line. The end of the arrow would have a turn when it reached the boundary of FOV and it would point to the direction of the conflict location (based on which direction the pedestrian turned their head). Figure 14 shows an example of such a situation.

Figure 14. An example of the scenario four

Other than these four specific scenarios, all three positions would be needed to be projected in the AR screen as three points and the arrow would be formed by connecting these three projected points.

Summary of AR Warning Algorithms

In summary, to show the expected vehicle path in the AR warning window, the perspective projection method would be used. To use the perspective projection method, first, the GPS data needs to be converted into the local coordinate. Then, the local coordinate needs to be transformed into a coordinate that can perform the perspective projection. Vehicle location, vehicle turning location (in-vehicle turning situation), and the conflict location would be projected on the AR screen as three projected points, and the warning arrow would be formed by connecting these three projected points. Four specific scenarios, which are the scenarios that could not project all three locations, would be considered, and the arrow would be formed based on different scenarios. Figure 15 shows the flowchart of the whole algorithm.

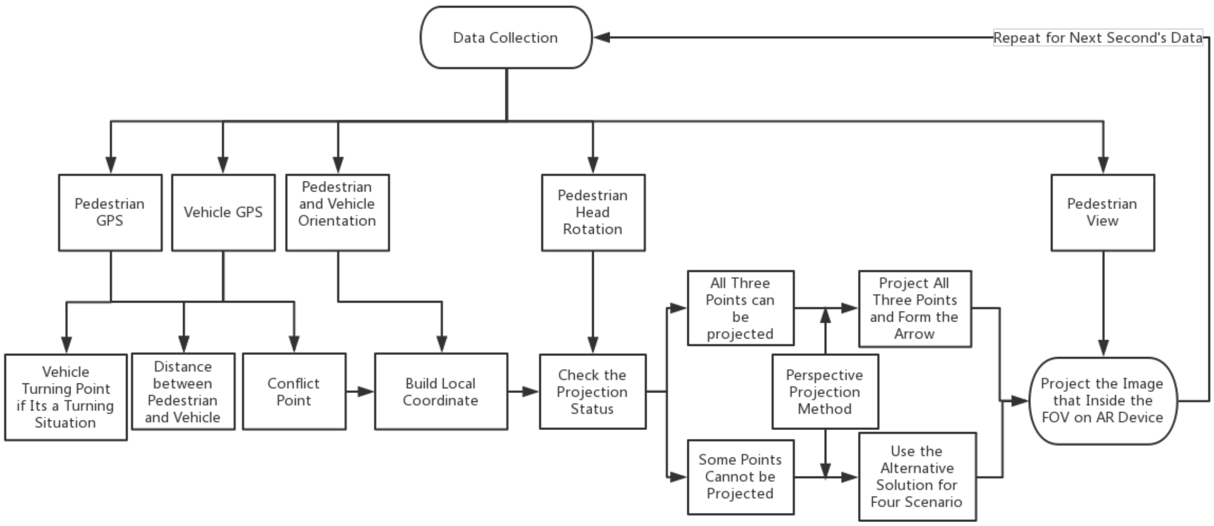


Figure 15. Warning system algorithm

Chapter 4 Experiments and Test of the Systems

Environmental Awareness Detection

Experiment

Participants. There were nine participants in total. Seven health students enrolled in the University of Michigan-Dearborn and two health faculty of the University of Michigan-Dearborn participated in the study. There were 7 female and 2 male participants. As mentioned above, two groups were used to classify the participants: young adult group (ages between 20 to 30) and senior group (ages between 45 to 55). The nine participants were distributed as follows:

Table 2. Descriptive statistic of participants

	Number of the Participants	Actual age range	Actual mean of the age
Young adult female	5	23-27	25.2
Young adult male	2	25-25	25
Senior female	2	45-52	48.5
Senior male	0	N/A	N/A
Total	9	23-52	30.33

Verification of mental state. An experiment was conducted to evaluate and validate the environmental awareness detection algorithm developed. In the experiment, fatigue state was defined as the state where participants had a whole day's work (over 10 hours in total) or had a continuous work over 4 hours and had the feeling of mental fatigue or drowsiness. Alert state was defined as the state where participants collected the data between 60-180 mins after getting up in the morning (eg. Get up at 7:00 am, data should be collected between 8:00am-10:00 am), and felt alert. Because caffeine intake may influence the HRV results (Richardson, et al., 2004; Notarius & Floras, 2012), the participants were asked to not drink or eat any food containing caffeine. The participants were asked to make two appointments while they were fatigued and alert. A guideline of what can be defined as fatigue and what can be defined as alert state was given to the participants to make sure they were actually fatigued or alert. Appendix A shows the guidelines the participants received.

Data collection devices. RR intervals and the heart rate data were collected by the Polar 10 heart rate sensor. Figure 16 shows how the participants were asked to wear the Polar 10.

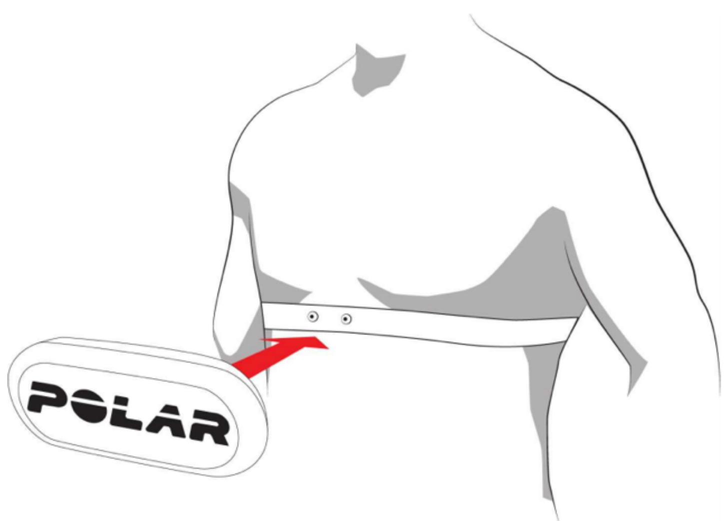


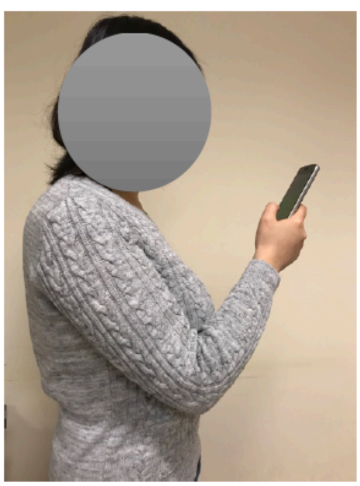
Figure 16. Wear the Polar 10 (Polar, 2018)

The phone position data was collected by the Moto Play Z smartphone. As mentioned above, five predetermined phone positions would be used as five classes to classify the distractions. The phone IMU data would be used to do the classification. The participants were asked to bring the smartphone with them while they were walking during the first 2 minutes of walking. Each participant was randomly assigned one of the phone positions mentioned in Chapter 2. The data sampling rate of the IMU sensor was 1 HZ. Figure 17 shows what each position looks like.

a. Swing phone

b. Phone in pocket

c. Phone in bag



d. Hold/texting

e. Talking on phone

Figure 17. Five phone positions

Environmental control. The temperature, noise level, and other environmental elements could have an influence on the heart rate and HRV. To ensure the heart rate and HRV would not affected by these non-related elements, all the participants took their lab visit in the same hallway outside of the lab.

Lab visit and data collection procedure. As mentioned above, the participants were asked to schedule two lab visits for the fatigue and alert states. At the first lab visit, they were asked to go through screening questions to make sure that they were eligible to participate in this study. Appendix B shows the screening script. For each lab visit the participants scheduled, they needed to answer another eligibility recheck questionnaire to see if they were actually fatigued or alert. Appendix C and D shows the eligibility recheck questionnaires for fatigue and alert state. If they are not actually fatigued or alert, they would be asked to reschedule the lab visit.

After the participants passed the eligibility recheck, they were asked to wear the Polar 10 as shown as Figure 16. 2 to 5 minutes was taken to make sure the sensor was adjusted and the signal was received well. For the first lab visit, the participants were asked to stand, slow walk (speed = 3km/h), and fast walk (speed = 5km/h) before the RR interval data began collecting. The heart rate data was collected while their heart rate reached a steady level when they were standing, slow walking, and fast walking. For both lab visits, 25 mins of RR interval data were collected from each participant. The participants were asked to walk in a hallway outside of the lab with their normal walking speed during the 25 minutes. The phone position data was also collected during the first 2 minutes of the 25 minutes. The collected RR interval data were saved on a phone that installed the Elite HRV app. After the data was collected, the saved data was exported to the PC for later processing.

Data Analysis

RR interval raw data process. The alert data of participant 4 from the young female group was lost due to device failure. All other participants' collected data was eligible to use and went into the raw data process. Overall, there were 8 participants' alert RR intervals and 9 participant's fatigue RR intervals that were used in this thesis. The small number of participants is a potential limitation of this study.

Because the participants were walking without any speed change or stimulation during the RR interval data collection, the RR intervals should not have a huge change during walking. To remove the inaccurate data from the raw data, the mean value of the RR interval data was calculated. Any value that was greater or less than 50% of the mean value was removed from the raw data. Then a comparison between one RR interval data and the one before that RR interval data was performed. The RR interval was considered inaccurate data and was deleted if it was 20% greater or lesser than the previous data. The HRV spectral analysis needs the raw data to be at least 2 minutes long to ensure the accuracy of the analysis (Camm et al., 1996). The 25 mins of raw data collected were cut into smaller sections of 2 minutes each. MarcusVollmer/HRV version 1.0 was used to perform the HRV spectral analysis (Vollmer, 2015).

After the data cleaning and initial processing, a total 208 sets of LF/HF and SDNN data were collected. There were 110 sets data for the young female group, 52 sets of data for the young male group, and 46 sets of data for the senior female group. For the young adult female group, 52 sets of the collected data were under alert state, and 60 sets of the collected data were under fatigue state. For the young adult male group, there were 27 sets of data for both alert and fatigue state. For the senior female group, 25 data sets were in alert state and 23 data sets were in fatigue state. Those 208 sets of data were further input into the SVM to perform the classification. Appendix E, F, and G show all 208 data sets. Table 3 shows the descriptive statistical data for those 208 data sets after the HRV analysis.

Table 3. Descriptive statistic of HRV data

			Mean	Media	Maximum	Minimum	Standard deviation
Young adult female	Alert	LF/HF	1.86	1.71	3.44	0.88	0.69
		SDNN	24.06	21.4	43.2	14.4	7.83
	Fatigue	LF/HF	1.58	1.55	2.52	0.95	0.39
		SDNN	33.23	32.1	57.3	2.7	9.19
Young adult male	Alert	LF/HF	1.82	1.715	2.79	1.38	0.34
		SDNN	25.42	24.35	45.2	13.3	6.81
	Fatigue	LF/HF	0.84	0.84	1.49	0.46	0.28
		SDNN	30.42	32.1	48.2	20.1	8.09
Senior female	Alert	LF/HF	1.34	1.345	1.81	0.78	0.27
		SDNN	29.25	31.5	61.7	12.8	13.74
	Fatigue	LF/HF	1.08	1	1.94	0.66	0.37
		SDNN	26.4	26.95	44.1	10.2	12.01

For the young adult female group, the mean of the LF/HF was 1.86 under the alert state and 1.58 under fatigue state, and the mean of the SDNN was 24.06 under the alert state and 33.23 under the fatigue state. For the young adult male group, the mean of the LF/HF was 1.82 under the alert state and 0.84 under fatigue state, and the mean of the SDNN was 25.42 under the alert state and 30.42 under the fatigue state. For the senior female group, the mean of the LF/HF was 1.34 under the alert state and 1.08 under fatigue state, and the mean of the SDNN was 29.25 under the alert state and 26.4 under the fatigue state.

Heart rate raw data process. As the heart rate data was taken after the heart rate already steady on a certain level, no further cleaning was performed. The heart rate data under different speeds was used to do the regression analysis.

Gyroscope raw data process. In total, there were 17 sets of 2 minutes of phone position data were collected. The gyroscope data was collected by the phone IMU sensor. One of the phone position data, which supposed to be talking position data, was lost due to the device failure. Overall, there were 11 sets of none distracted data including 4 swing data, 3 in bag data, and 3 in pocket data. Six distracted data was 4 holding/texting data and 2 talking data. The first 45 seconds of data were not used because the phone may not be in the position needed for the study. One minute of the gyroscope data was used to detect the phone position, which means that the gyroscope data between 46 seconds and 106 seconds were used to do the variance calculation. One minutes data may be too long for the further real-time use, but the thresholds would not change. To develop a real-time system, 10 seconds would be a reasonable time period to calculate the variance of gyroscope.

Data Process and Results

Regression model. Multiple regression model and simple regression model were used to do the regression analysis. For the young adult group, the multiple regression model in Minitab was used. The calculated regression model was shown in Chapter 2. The coefficients analysis shows that both speed and gender were significant in the regression model under $\alpha = 0.05$ level. Table 4 shows the result of the coefficients analysis.

Table 4. Coefficients analysis table for young adult group regression model

Term	Coef	SE Coef	95% CI	T-Value	P-Value
Constant	76.429	2.354	(71.482, 81.375)	32.46	<0.0001
Speed	5.7143	0.6525	(4.3435, 7.0851)	8.76	<0.0001
Gender					
M	-7.000	2.968	(-13.235, -0.765)	-2.36	0.0298

The R square of this model was 82%, which means that most of the variability of the response data around its mean can be explained by this model. The fitness of this model is not bad.

The senior group does not have enough participants, so, the senior male group's regression analysis cannot be performed. For the senior female group, the simple regression model was used to do the regression analysis. However, the regression model was not significant. The R square of the model was also low (31%). The model of senior female still shows in Chapter 2, but this model needs more data to make it accurate.

Mental state. The input features to the SVM were LF/HF ratio and SDNN for young adult groups and senior group separately. A Gaussian SVM classifier from the MATLAB toolbox was used to do the classification of pedestrian mental state. The output were the mental states classes: +1=fatigue and -1=alert.

The Coarse Gaussian SVM with five-fold cross-validation method was chosen to design the classifier. Figure 18 displays the SVM classification result of the young female group.

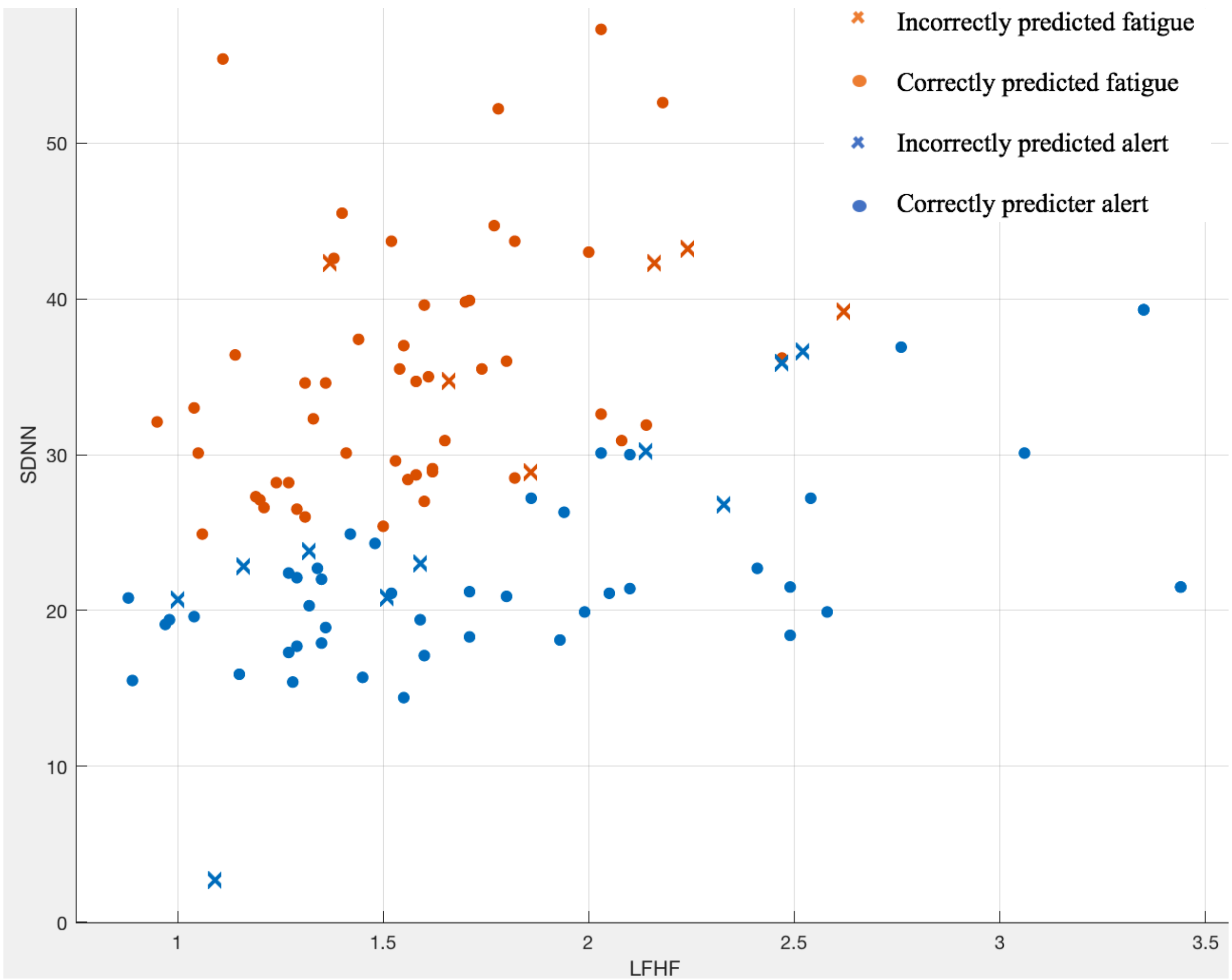


Figure 18. Prediction result of young adult female

In Figure 18, the red dots represent the correctly predicted fatigue samples. The red multiple signs represent the alter samples that were wrongly predicted as fatigue. The blue dots represent the correctly predicted fatigue samples. The blue multiple signs represent the fatigue samples that were wrongly predicted as alert. Figure 19 shows a two-diagonal cell for the young adult female group result.

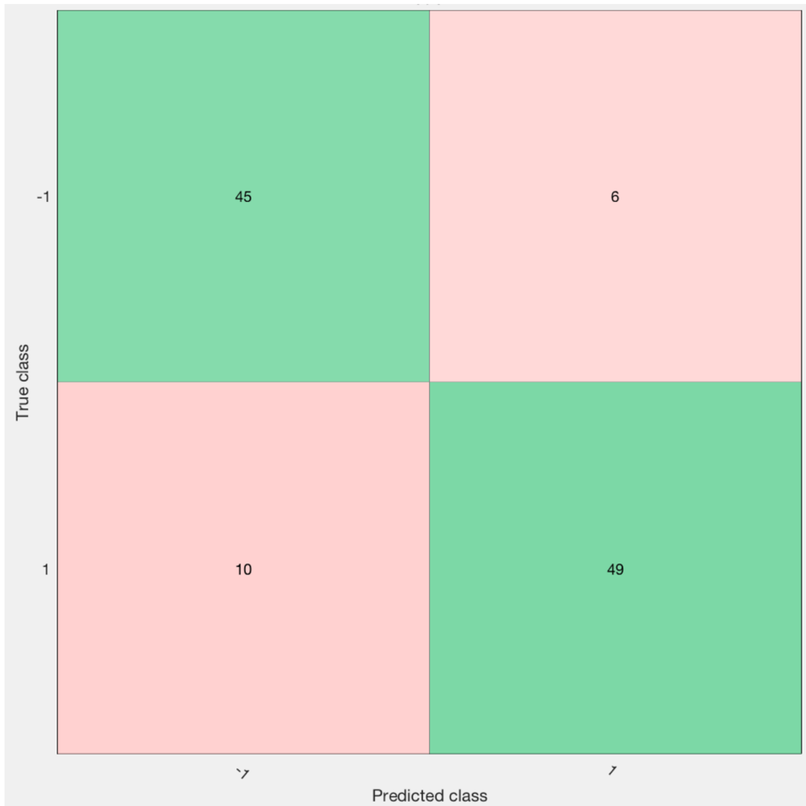


Figure 19. Two-diagonal cell of young adult female group

For the young adult female group, 94 of the predictions were correct and 16 were wrong. The overall accuracy of the young female group model is 85.5%. Forty-five alert data were correctly classified as -1 (alert), corresponding to 88% of all alert data. Forty-nine fatigue data were correctly classified as +1 (fatigue), corresponding to 83% of all fatigue data. Six alert data were wrongly classified as +1 (fatigue), corresponding to 12% of all alert data. Ten fatigue data were wrongly classified as -1(alert), corresponding to 17% of the fatigue data.

Figure 20 shows the prediction result of the young adult male data.

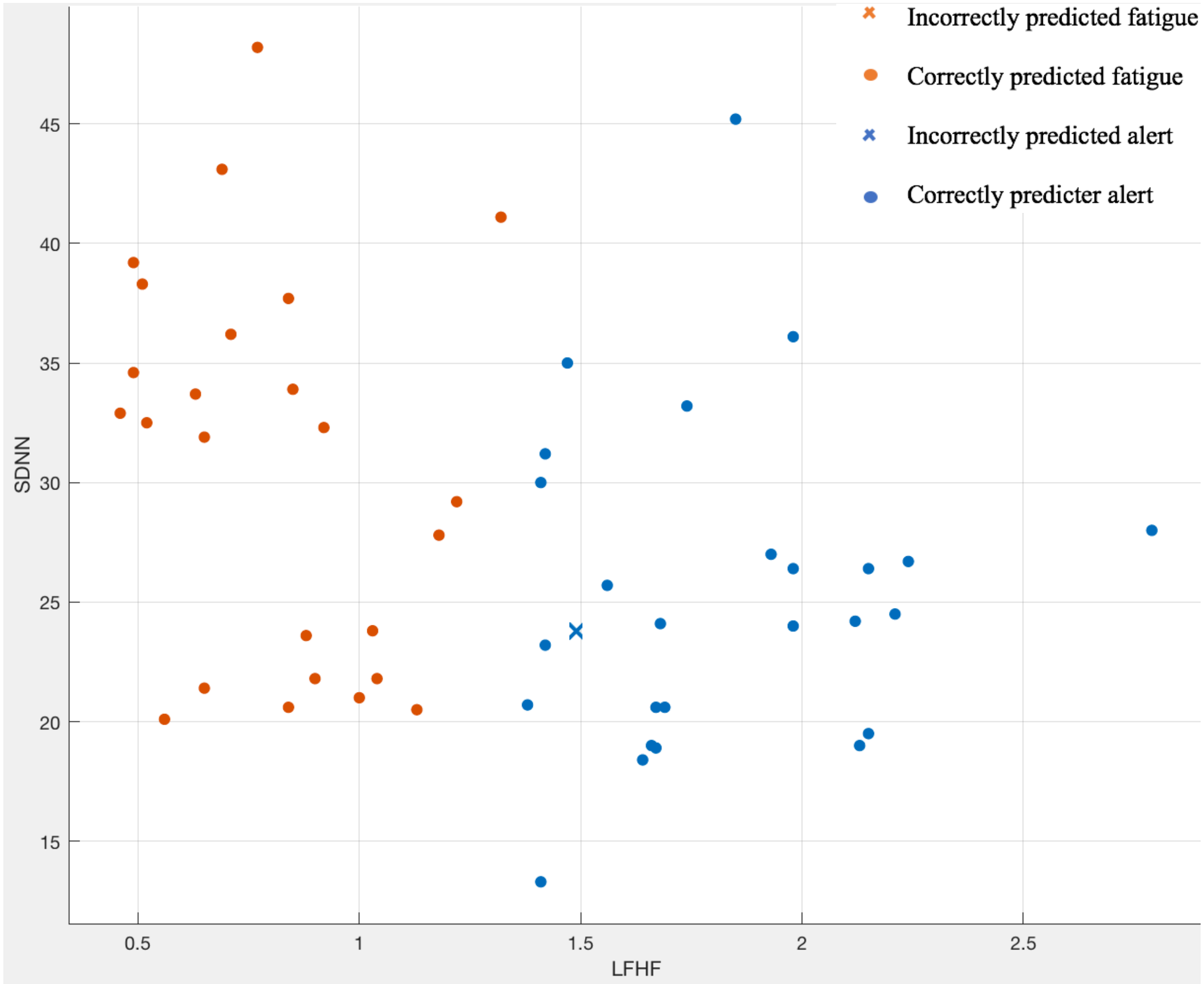


Figure 20. Prediction result of young adult male

Same as figure 18, the dots and multiply signs show the correct and incorrect predicted result. The young adult male group had a better result than the young adult female. The overall accuracy of the young adult male group was 98%. Fifty-one of the predictions were correct while 1 was wrong. All 26 alert data were correctly classified as -1 (alert). Twenty-five fatigue data were correctly classified as +1 (fatigue), corresponding to 96% of all fatigue data. One fatigue data were wrongly classified as -1(alert), corresponding to 4% of the fatigue data. Figure 21 shows the two-diagonal cell of the young adult male group.

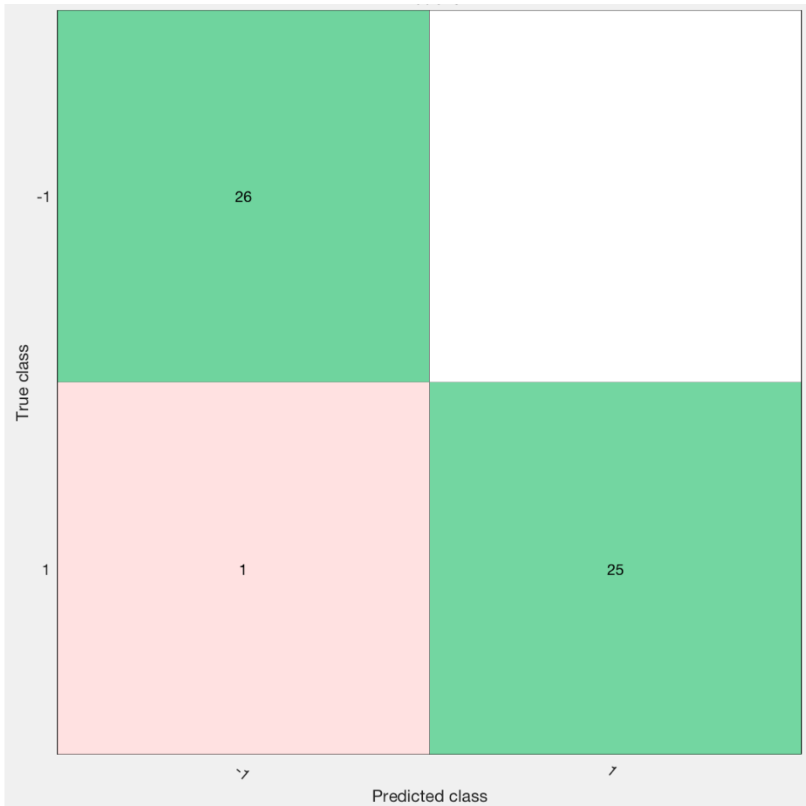


Figure 21. Two-diagonal cell of young adult male group

The prediction result of the senior female group has the worst result; the overall accuracy of the senior female group was 67.4%. Figure 22 shows the result of the prediction of the senior female group.

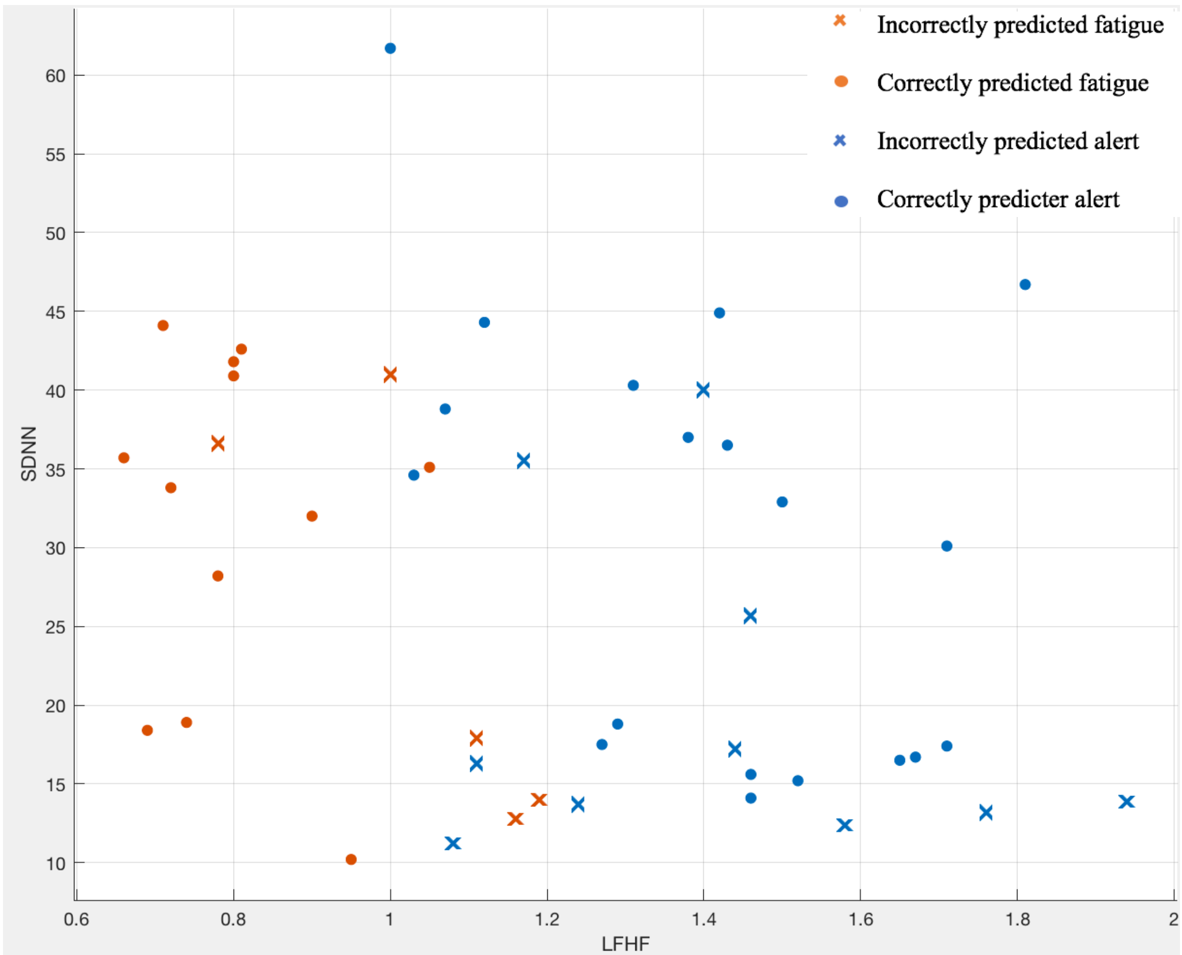


Figure 22. Prediction result of senior female group

For the senior group, 31 of the predictions were correct and 15 were wrong. Nineteen alert data were correctly classified as -1(alert), corresponding to 79% of all 24 alert data. Twelve fatigue data were correctly classified as +1 (fatigue) corresponding to 55% of all fatigue data. Five alert data wrongly classified as +1 (fatigue), corresponding to 21% of all alert data. Ten fatigue data were wrongly classified as -1 (alert), corresponding to 45% of the fatigue data. Figure 23 shows the two-diagonal cell of the senior group.

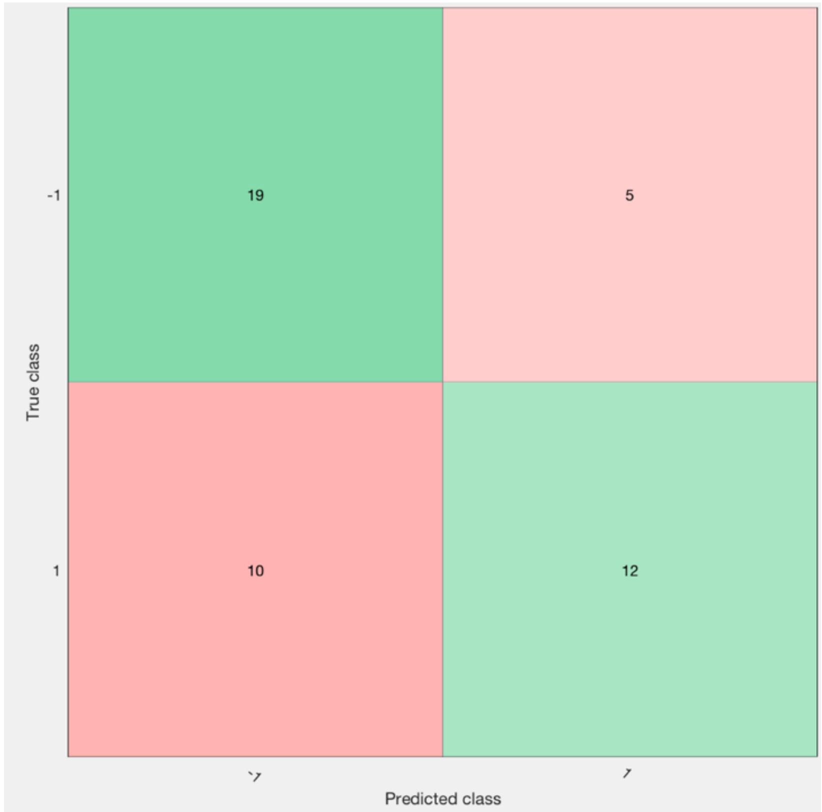


Figure 23. Two diagonal cells of the senior female group

When combined all three groups, 176 out of 208 predictions were correct and 32 were wrong. The accurate rate for all three groups was 84.6%. Ninety data were correctly classified as -1 (alert), corresponding to 89% of all alert data. Eighty-six cases were correctly classified as +1 (fatigue). This corresponds to 80.4% of all fatigue samples. Eleven data were wrongly classified as +1 (fatigue), corresponding to 11% of all alert data, and 21 data were wrongly classified as -1 (alert). This corresponds to 19.6% of all fatigue samples.

Phone distraction. The equations in chapter 2 were used to calculate the variance of the gyroscope. The data from participants 4, 5, 6, 7, and 11 were used to develop the threshold and the data from participants 1, 2, 3, and 12 were used to do the validation. Based on the observation, the variance of 0.5 rad/s can be used as the thresholds as mentioned above. Table 5 shows the combined variance of the data collected.

Table 5. Combined variance of the phone position analysis

Subject	Position	Variance(rad/s)	Distract t+1 / None distract -1
1	swing	7.588	-1
2	swing	1.207	-1
3	bag	6.45	-1
4	bag	2.676	-1
4	swing	2.766	-1
5	bag	5.024	-1
6	pocket	0.6373	-1
7	pocket	0.767	-1
11	swing	9.732	-1
12	pocket	0.884	-1
12	swing	4.016	-1
1	hold	0.2	1
2	hold	0.3867	1
3	hold	0.387	1
5	talking	0.227	1
6	talking	0.361	1
11	hold	0.2213	1

The data from participants 1, 2, 3, and 12 were used to do the validation. It is clear that all the phone position data were classified correctly with the threshold of 0.5 rad/s. The accuracy of the classification was 100%.

Overall, the results showed a good classification accuracy to detect the pedestrian mental state and distraction. When synthesizing the mental state detection with distraction detection, we can detect 4 situations shown in Figure 4 with a good accuracy rate.

AR Warning System

Data Collection

To verify the algorithm of AR warning system was working, real data was collected, and the algorithm was performed offline in the MATLAB. The data was collected in a parking lot of the UM-Dearborn campus. Vehicle crossing straight from the left side of the pedestrian situation was used in this test. A phone's camera was used to stimulate the human eye on the height of the 1.65-meter; the video was recorded by this phone to imitate what the pedestrian can see. The vehicle's GPS and IMU data were collected from a study phone that was carried by the vehicle. The pedestrian's GPS and IMU data were collected by the phone which was used to record the video. After the algorithm was performed and three projected points' location had been calculated, the projected points were drawn on top of the recorded video based on their coordinate location. The sampling frequency of the data was 1Hz, so the projected points were updated every 1 second. Adobe Animate was used to fill the time between each updating.

Demonstration

Figure 25 shows the situation that the pedestrian just got the warning signal and has not turning his head yet.

Figure 24. Real data test, vehicle go straight scenario

In Figure 25, the red shaded area is the warning interface area. It shows how the pedestrian feels when looking through the AR glasses while the warning system was active. Figure 26 shows the situation that the pedestrian was turning their head and the vehicle can be seen by the pedestrian.

Figure 25. Real data test, after pedestrian see the vehicle

In figure 26, the pedestrian has seen the vehicle, so the side warning bar has disappeared.

The arrow was still there showing the vehicle's potential path and the "12s" shows that the vehicle would reach the conflict point in 12 seconds.

Chapter 5 Discussion

Applicability

The system was developed to detect the environmental awareness of the pedestrians during walking and give the pedestrians warnings when their environmental awareness is low. The data collection equipment could be replaced by smartwatch or other wearable devices, which are light in weight and convenient to wear for the pedestrians. The detected pedestrians' environmental awareness could not only be used for the pedestrian's warning, but also can warn the driver and other road users. Moreover, not only the warnings can be carried out while the pedestrians' environmental awareness is low, but also can be carried out in some other situations. For example, this pedestrians' warning system can cooperate with some driver state detection systems, so that the pedestrians can get the warning while the driver is under some abnormal states. Also, this design could further extend in the automotive driving environment. It can give the warnings while there are some malfunctions happening in the automotive vehicles. For example, this system could warn the pedestrian while the potential conflict has been detected but the automotive driving vehicles have not taken any reaction. Last, the algorithm of the AR warning system does not need the camera support, which means it can work well while the sight line was blocked by obstructions. Overall, the pedestrian protection system could work well to protect the pedestrian from the potential collision and injury.

Limitations

First, only the health situation was considered in this thesis, so no other health conditions were considered in this thesis. Only healthy participants were used in this study. Second, exercise habits may have an influence on the HRV analysis results (Melo, et al., 2005). This thesis does not consider exercise habits as factors to detect the mental state. Moreover, this real-time pedestrian protect algorithm theoretically worked, but some analyses were still worked offline. This thesis did not develop a real-time app to do the detection and warning. Third, the number of the participants was not enough due to the limitation of resources. The male senior group does not have the regression model and other regression models may not be accurate enough. The SVM models also need collect more data to do the training. Fourth, the projection algorithm was heavily depending on the GPS data of the vehicle and pedestrian, which means if the GPS has errors or is inaccurate, the projection method would not work well. Also, current commercial AR glasses have the limitation on hardware. The FOV of the glasses were small, for example, the Microsoft HoloLens only have about 35° by 17° FOV (SeanL@WCC, 2015), and the Sony glasses are even smaller, which is 19° by 6° (SONY, 2018). So, the designed size of the AR warning screen, which is 60° by 30°, cannot fully show in current commercial AR glasses. Due to the limitation of hardware of the AR glasses, current commercial glasses are still too large and heavy to wear daily in a normal life. The concept has not been supported by the hardware yet. Last, the AR warning system has not considered the multiple vehicle situation. Both the interface and algorithms only worked for the single conflict warning.

Further works

Future work should be completed to address these limitations and improve the performance of the algorithm. First, health conditions and exercise habits could have a large influence on the HRV result. It is necessary to have further works done to build a more accurate model based on different health conditions and exercise habits. Also, the real-time app should be developed for the AR glasses and phone app to test if this system can work in real time. Third, more participants should be recruited, and more data should be collected to fill and make the regression models and SVM models accurate. Moreover, some work needs to be done to improve the GPS signal so that the vehicle path can be projected more accurate. Last, the situation that more than one vehicle has the potential conflict with a pedestrian should be considered in the further design of the AR warning system.

Appendix A Guidelines

Guidelines

You will be asked to schedule two lab visits to collect the heat rate data under mental alert state and mental fatigue state. When scheduling and visiting the lab, please make sure you have fulfilled the following requirement:

If you are coming for a lab visit for ALERT STATE, please:

1. Make sure to have enough sleep before the day of the lab visit
2. Do not take any caffeine drink or food on the day of lab visit, some examples of caffeine drink and food are: any kind of coffee, decaf coffee, tea, energy drink, Pepsi, Coke, chocolate, coffee or chocolate flavored dessert or snack, pain relief pill, etc.
3. The scheduled lab visit time should within 3 hours after you get up (e.g, you need have your lab visit before 10:00 am if you get up at 7:00 am)
4. Do not have any strenuous exercise before the lab visit which may cause the physical fatigue
5. If you feel you are not fulfilling the requirement above before the visit, you can contact us to rescheduling the lab visit.

If you are coming for a lab visit for FATIGUE STATE, please:

1. Make sure you mentally focused on any kind of intellectual work over 4 hours continuously right before your scheduled lab visit or mentally focused on any kind of intellectual work over 10 hours cumulatively in the day of your scheduled lab visit (e.g, you studied from 2:00 pm to 6:00 pm without any break and your lab visit scheduled at 6:30 pm, or you worked from 8:00am to 6:00pm, you may take some breaks during your working, and the scheduled lab visit at 6:30 pm.)
2. Do not take any caffeine drink or food on the day of lab visit, some examples of caffeine drink and food are: any kind of coffee, decaf coffee, tea, energy drink, Pepsi, Coke, chocolate, coffee or chocolate flavored dessert or snack, pain relief pill, etc.
3. Do not have any strenuous exercise before the lab visit that may cause the physical fatigue
4. If you feel you are not fulfilling the requirement above before the visit, you can contact us to rescheduling the lab visit.

Contact information:
Yourui Tong
tongy@umich.edu
313-482-7021

Appendix B Edibility Screen Script

Study ID: HUM00142752   IRB: Dearborn   Date Approved: 4/23/2018
Title: Detecting Pedestrian Situation Awareness in Real-Time: Algorithm Development Using Heart Rate Variability and Phone Position
Application No.: HUM00142752
Principal Investigator: Yourui Tong
Date: 04/04/2018

In-lab Screening Script

Introduce yourself

Hello, my name is ______________ from the department of Industrial and Manufacturing Systems Engineering here at University of Michigan-Dearborn.

Tell the person the purpose of the research study: With your participation, we want to understand how heart rate variability and phone position can present the pedestrian's mental fatigue and situation awareness.

We are working on a research study about Algorithm Development Using Heart Rate Variability and Phone Position.

- ***Request person's permission to ask questions to see if he/she qualifies for the research study.***
- ***If person says "No," thank the person for his/her time and politely end the screening interview.***
- ***If person says "yes," inform them about use of their information that will be collected during the interview. Use the following language:***

We will collect information about you during this screening session. Your participation in this interview is completely voluntary.

Your information will only be seen by researchers at University of Michigan - Dearborn. We try to make sure that the information we collect from you is kept private and used only for the research study we are discussing.

Tell the person their information will not be kept if they choose not to enroll in the study or if they do not qualify to be in the study.

If you are not eligibile or you choose not to partcipate this study, your personal information will not be kept.

If interview will continue, list below the questions you will be asking.

I would like to ask you a few questions to see if you would be eligible to participate. Questions that would be posed follow:

"How old are you?"

The person will be disqualified if the answer for above question is younger than 20, between 30 to 45, or older than 55.

Are you able to walk continuously for 25 mins without stop?

The person will be disqualified if their answer for above question is "no".

"Have you been diagnosed with any illnesses or injuries, within the past year that restrict your daily activities?"

" Have you been diagnosed with any cardiovascular disease or related condition?"

"Have you been diagnosed with any psychological disorders?"

"Do you have any type of implanted electrical devices in your body?"

"Do you have any known allergy? Specifically, do you know whether you are allergic to cleansing liquid? Such as isopropyl alcohol"

The person will be disqualified if any of their answers for the above questions is yes.

If person meets screening eligibility, then briefly describe study procedures, including the number of study session and how long the person would be in the study based on the consent form.

Briefly describe potential risks:
1) You may experience some fatigue or discomfort after the experiment because of 25 mins of walking.
2) There is a small chance that you may have an allergic reaction to the cleansing liquid that we use during the study. If you have a known allergy to those liquid, you will be excluded from the study.
3) As with any research study, there may be additional risks that are unknown or unexpected.

Describe there will be no potential direct benefits to the participant. But their participation will help us understand sitting comfort related car seat design.

Title: Detecting Pedestrian Situation Awareness in Real-Time: Algorithm Development Using Heart Rate Variability and Phone Position
Application No.: HUM00142752
Principal Investigator: Yourui Tong
Date: 04/04/2018

Describe there will be no costs to participants if they join the study.

Describe that participants will be paid hourly at the rate of $10/hr for taking part in the study.

After finishing your explanation of the study, ask the following:

- **Do you have any questions?**
- **Do you think you would like to take part in this research?**

Provide the person with contact numbers of research team for any further questions about the study.

Appendix C Eligibility Recheck Questionnaire (Fatigue)

Study ID: HUM00142752 IRB: Dearborn Date Approved: 4/23/2018

Eligibility recheck questionnaire (For the lab visit for FATIGUE state)

1. How many hours of intellectual work or study have you take today in total? (eg. You worked from 8:00am to 6:00pm today and you may took some breaks during you working, it was 10 hours work in total.)

2. Have you continuously studied or worked over 4 hours (intellectual work) right before you came to the lab? (eg. You studied from 2:00 pm to 6:00 pm without any break and your lab visit scheduled at 6:30 pm.)

3. Have you drink or eat any food may contain the caffeine today? Some examples of caffeine drink and food are: any kind of coffee, decaf coffee, tea, energy drink, Pepsi, Coke, chocolate, coffee or chocolate flavored dessert or snack, pain relief pill, etc.

5. Have you did any exercise before you come to the lab? If yes, was it strenuous?

6. Do you feel fatigue/sleepy/drowsiness now?

Appendix D Eligibility Recheck Questionnaire (Alert)

Study ID: HUM00142752   IRB: Dearborn   Date Approved: 4/23/2018

Eligibility recheck questionnaire (For the lab visit for AWAKE state)

1. Normally, how many hours have you sleep each night?

2. How many hours of sleep have you take last night?

3. When did you get up this morning?

4. Have you drink or eat any food may contain the caffeine this morning? Some examples of caffeine drink and food are: any kind of coffee, decaf coffee, tea, energy drink, Pepsi, Coke, chocolate, coffee or chocolate flavored dessert or snack, pain relief pill, etc.

5. Have you did any exercise this morning before you come to the lab? If yes, was it strenuous?

6. Do you feel awake now?

Appendix E HRV data of young adult female

SDNN	Subject	Fatigue LF/HF	SDNN	Subject
24.9	1	1.38	42.6	1
21.2	1	1.78	52.2	1
22.7	1	1.31	34.6	1
30.1	1	2.14	30.2	1
27.2	1	1.59	23	1
28.9	1	1.6	27	1
18.4	1	1.82	28.5	1
19.9	1	2.33	26.8	1
14.4	1	2.52	36.6	1
19.9	1	1.53	29.6	1
18.3	1	1.62	29.1	1
18.1	1	2.14	31.9	1
20.3	1	2.18	52.6	2
39.2	2	1.52	43.7	2
27.2	2	2.03	57.3	2
34.7	2	1.77	44.7	2
42.3	2	2.47	35.9	2
42.3	2	1.41	30.1	2
21.5	2	1.54	35.5	2
39.3	2	1.74	35.5	2
21.5	2	2.47	36.2	2
36.9	2	1.8	36	2
21.5	2	2.03	32.6	2
30.1	2	1.58	34.7	2
43.2	2	1.61	35	2
39.3	2	1.05	30.1	3
22.7	3	1.32	23.8	3
24.3	3	1.16	22.8	3
22	3	1.62	28.9	3
21.1	3	1.2	27.1	3
15.7	3	1.29	26.5	3
20.9	3	1.65	30.9	3

19.4	3	1.51	20.8	3
22.1	3	1.31	26	3
30	3	1.19	27.3	3
15.9	3	1	20.7	3
17.1	3	1.5	25.4	3
21.4	3	1.06	24.9	3
20.8	7	1.4	45.5	4
19.1	7	1.55	37	4
15.5	7	1.7	39.8	4
17.7	7	1.71	39.9	4
17.9	7	1.82	43.7	4
15.4	7	1.33	32.3	4
21.1	7	2.08	30.9	4
19.6	7	1.6	39.6	4
22.4	7	2	43	4
19.4	7	1.36	34.6	4
17.3	7	1.44	37.4	4
18.9	7	1.58	28.7	4
26.3	7	0.95	32.1	4
		1.11	55.4	7
		1.14	36.4	7
		1.24	28.2	7
		1.21	26.6	7
		1.04	33	7
		1.56	28.4	7
		1.09	2.7	7
		1.27	28.2	7

Appendix F HRV data for young adult male

Alert	SDNN	Subject	Fatigue	SDNN	Subject
1.42	31.2	5	0.52	32.5	5
2.24	26.7	5	0.84	37.7	5
1.67	18.9	5	0.92	32.3	5
1.98	36.1	5	1.32	41.1	5
2.21	24.5	5	0.63	33.7	5
2.15	19.5	5	0.71	36.2	5
1.41	13.3	5	0.65	31.9	5
2.13	19	5	0.85	33.9	5
1.38	20.7	5	0.46	32.9	5
1.67	20.6	5	0.51	38.3	5
1.42	23.2	5	0.49	34.6	5
1.98	24	5	0.77	48.2	5
2.79	28	5	0.49	39.2	5
1.66	19	6	0.69	43.1	6
1.41	30	6	1.13	20.5	6
2.15	26.4	6	1	21	6
1.47	35	6	1.49	23.8	6
1.56	25.7	6	0.9	21.8	6
1.68	24.1	6	1.04	21.8	6
1.85	45.2	6	1.22	29.2	6
1.64	18.4	6	0.65	21.4	6
1.98	26.4	6	1.03	23.8	6
1.93	27	6	0.88	23.6	6
1.74	33.2	6	0.56	20.1	6
1.69	20.6	6	0.84	20.6	6
2.12	24.2	6	1.18	27.8	6

Appendix G HRV data of senior female

Alert	SDNN	Subject	Fatigue	SDNN	Subject
1	41	11	0.72	33.8	11
1.03	34.6	11	0.8	41.8	11
1.81	46.7	11	0.71	44.1	11
1	61.7	11	0.78	28.2	11
1.38	37	11	0.81	42.6	11
1.42	44.9	11	0.66	35.7	11
1.12	44.3	11	0.8	40.9	11
1.07	38.8	11	1.17	35.5	11
1.43	36.5	11	1.4	40	11
0.78	36.6	11	0.9	32	11
1.5	32.9	11	1.05	35.1	11
1.31	40.3	11	0.69	18.4	12
1.27	17.5	12	1.46	25.7	12
1.46	14.1	12	0.74	18.9	12
1.16	12.8	12	1.76	13.2	12
1.29	18.8	12	1.08	11.2	12
1.67	16.7	12	1.24	13.7	12
1.19	14	12	1.44	17.2	12
1.65	16.5	12	0.95	10.2	12
1.52	15.2	12	1.94	13.9	12
1.71	30.1	12	1.11	16.3	12
1.71	17.4	12	1.58	12.4	12
1.11	17.9	12			
1.46	15.6	12			

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