TIMING IMPROVEMENT OF FORWARD COLLISION WARNING SYSTEMS

MISS PEACHANIKA THAMMAKAROON

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE DEGREE OF DOCTOR OF PHILOSOPHY
(ELECTRICAL AND COMPUTER ENGINEERING)
FACULTY OF ENGINEERING
KING MONGKUT'S UNIVERSITY OF TECHNOLOGY THONBURI
2014

Timing Improvement of Forward Collision Warning Systems

Peachanika Thammakaroon M.Eng. (Control System and Instrumentation Engineering)

A Thesis Submitted in Partial Fulfillment of the Requirements for
the Degree of Doctor of Philosophy (Electrical and Computer Engineering)
Faculty of Engineering
King Mongkut's University of Technology Thonburi
2014

Thesis Committee

……………………………………………… (Assoc. Prof. Pakorn Kaewtrakulpong, Ph.D.)	Chairman of Thesis Committee
………………………………………………. (Assoc. Prof. Poj Tangamchit, Ph.D.)	Member and Thesis Advisor
………………………………………………. (Lect. Jumpol Polvichai, Ph.D.)	Member
………………………………………………. (Lect. Arbtip Dheeravongkit, Ph.D.)	Member
………………………………………………. (Asst. Prof. Charnchai Pluempitiwiriyawej, Ph.D.)	Member

Copyright reserved

Thesis Title	Timing Improvement of Forward Collision Warning Systems
Thesis Credits	36
Candidate	Miss Peachanika Thammakaroon
Thesis Advisor	Assoc. Prof. Poj Tangamchit, Ph.D.
Program	Doctor of Philosophy
Field of Study	Electrical and Computer Engineering
Department	Computer Engineering
Faculty	Engineering
Academic Year	2014

Abstract

We propose a systematic method for improving the response time of forward collision warning (FCW) on vehicles. First, a performance indicator of FCW, called the warning lag time, is introduced to use instead of the pre-warning time. The warning lag time is a time period between an actual brake of the driver and a warning signal and this period is calculated based on the cross-correlation method. We use the warning lag time because its measurement is practical in real driving situations. Next, we discuss two ideas, which are a systematic method to improve this warning lag time of FCW system, vertical approach and horizontal approach. The vertical approach is developed in an individual vehicle by providing an additional warning, derived from the cause of a car crash, to a typical FCW system. For the experiment, we selected the location-based warning (LW) system to combine with the FCW system. The result shows that it can improve the warning lag time by an average of 0.31 sec. compared with a traditional FCW system. The horizontal approach uses distributed sensing among vehicles to expand the range of sensing. We used the Supported Vector Machine (SVM) to create unbiased warning rules with the aim to compare two FCW setups: FCW of a single host vehicle (FCW_{HV}) and FCW of the host vehicle with data from the preceding (FCW_{HV+PV}). The results show that the horizontal approach can also improve the warning lag time by an average of 1.08 sec. compared with a single host vehicle FCW.

Keywords : Active Safety in Vehicles / Cooperative Vehicles / Forward Collision Warning / Intelligent Vehicle

หัวข้อวิทยานิพนธ์	การปรับปรุงประสิทธิภาพเชิงเวลาของระบบเตือนการชนในรถยนต์
หน่วยกิต	36
ผู้เขียน	นางสาวพีชานิกา ธรรมการุณ
อาจารย์ที่ปรึกษา	รศ. ดร.พจน์ ตั้งงามจิตต์
หลักสูตร	ปรัชญาดุษฎีบัณฑิต
สาขาวิชา	วิศวกรรมไฟฟ้าและคอมพิวเตอร์
ภาควิชา	วิศวกรรมคอมพิวเตอร์
คณะ	วิศวกรรมศาสตร์
ปีการศึกษา	2557

บทคัดย่อ

วิทยานิพนธ์นี้นำเสนอวิธีการปรับปรุงประสิทธิภาพเชิงเวลาอย่างเป็นระบบสำหรับของระบบเตือนภัยการชนรถคันหน้า และนำเสนอวิธีการวัดประสิทธิภาพเชิงเวลาแบบใหม่เพื่อใช้แทนวิธีการแบบเดิมที่วัดระยะเวลาเมื่อเกิดการชนเท่านั้น ซึ่งประสิทธิภาพเชิงเวลาแบบใหม่คือช่วงระยะเวลาระหว่างการใช้เบรคของผู้ขับกับการเตือนซึ่งเป็นเอาท์พุทจากระบบเตือนการชนโดยใช้วิธีการหา Cross-correlation ระหว่างการใช้เบรคของผู้ขับกับการเตือนของระบบ ในแง่การปรับปรุงประสิทธิภาพเชิงเวลาในระบบเตือนภัยการชนรถคันหน้า ได้นำเสนอ 2 วิธีการ วิธีการแรกคือวิธี Vertical เป็นวิธีที่ใช้ในรถยนต์คันเดียว โดยวิธีการนี้ปรับปรุงระบบด้วยการใส่ระบบการเตือนอุบัติเหตุเพิ่มเข้าไปทำงานร่วมกับระบบเตือนภัยการชนรถคันหน้าแบบเดิม โดยได้ทดลองเพิ่มระบบเตือนสถานที่อันตราย จากผลการทดลองพบว่าเมื่อปรับปรุงระบบด้วยวิธีดังกล่าวมีผลให้ประสิทธิภาพเชิงเวลาดีขึ้น โดยระบบเตือนภัยแก่ผู้ขับเร็วขึ้น 0.31 วินาที ส่วนวิธีที่สองคือวิธี Horizontal เป็นวิธีปรับปรุงระบบระบบเตือนภัยการชนรถคันข้างหน้าด้วยการเพิ่มขอบเขตของเซ็นเซอร์โดยอาศัยข้อมูลจากรถยนต์คันอื่นร่วมกับข้อมูลจากเซ็นเซอร์ในรถโฮสท์ผ่านเครือข่ายสื่อสารไร้สาย ในการทดลองได้สร้างระบบเตือนภัยการชนรถคันข้างหน้าขึ้นมา 2 ระบบคือระบบเตือนภัยการชนรถคันข้างหน้าที่ใช้ข้อมูลจากรถโฮสท์คันเดียวและระบบที่ใช้ข้อมูลจากรถโฮสท์ร่วมกับข้อมูลจากรถคันข้างหน้า ซึ่งทั้งสองระบบใช้เทคนิค Supported Vector Machine (SVM) ในการจำแนกผลการเตือนภัยการชน ผลการทดลองพบว่าวิธี Horizontal สามารถเพิ่มประสิทธิภาพเชิงเวลาจากระบบเตือนภัยการชนรถคันหน้าใช้ข้อมูลจากรถโฮสท์คันเดียวได้ โดยทำให้ระบบสามารถเตือนการชนได้เร็วขึ้น 1.08 วินาที

คำสำคัญ : รถยนต์อัจฉริยะ / ระบบความปลอดภัยในรถยนต์เชิงป้องกันก่อนเกิดเหตุ / ระบบเครือข่ายระหว่างรถยนต์ / ระบบเตือนภัยการชนรถคันหน้า

ACKNOWLEDGEMENTS

I would like to express my sincere gratitude to my advisor, Assoc. Prof. Dr. Poj Tangamchit from Department of Control System and Instrumentation Engineering for the continuous support of my Ph.D study and research. Special thanks goes to Assoc. Prof. Dr. Pakorn Kaewtrakulpong from Department of Control System and Instrumentation Engineering for his valuable guidance, kind suggestions on this dissertation and kindly serving as the chairman of thesis committee.

Besides my advisor, I would like to thank you to the rest of the committees: Dr. Jumpol Polvichai from Department of Computer Engineering (KMUTT), Dr Arbtip Dheeravongkit from Institute of Field Robotics (KMUTT), and Asst. Prof Dr. Charnchai Pluempitiwiriyawej from Department of Electrical Engineering, Chulalongkorn University for kindly serving as committee members of this dissertation, their valuable comments, and suggestions. I also would like to acknowledge the King Mongkut's Brilliant Student Scholarship, Higher Education Research Promotion and National Research University Project of Thailand, and National Electronics and Computer Technology Center (NECTEC) for their financial supporting my doctoral study and research.

I would never have been able to finish my dissertation without the help from friends, and support from my family and my partner. Sincerely thanks to all members of the INC graduated student group, INC staffs, and Ph.D classmates for their friendship and support. I would also like to thank my parents and my sisters. They were always supporting me and encouraging me with their best wishes. Finally, I would like to thank my partner, Kawin Tantaweewong for his understanding and love. He was always there cheering me up and stood by me through the good times and bad.

CONTENTS

CHAPTER **PAGE**

LIST OF TABLES

LIST OF FIGURES

FIGURE **PAGE**

FIGURE **PAGE**

FIGURE **PAGE**

LIST OF SYMBOLS

SYMBOL		UNIT
B_a	Actual brake of the hot vehicle	-
W_f	Warning signal from the FCW system	-
k	Number of W_f data points	-
v	Current velocity of the host vehicle	m/s
v_{th}	Speed limit	m/s
d	Distance between the host vehicle and the nearest hotspot	m.
d_{th}	The range of warning distance from hotspots	m.
h	Heading of the vehicle	deg.
h_D	The angle from the vehicle position to the nearest hotspot in the database	deg.
T_s	Time to collision	sec.
d_f	Current following distance	m.
σ	Standard deviation of comparison between the warning time of LW and the actual brake	sec.
v_h	Speed of the host vehicle	m/s
d_h	Following distance obtained from the host vehicle	m.
b_h	Actual brake of the host vehicle	-
v_p	Speed of the preceding vehicle	m/s
d_p	Following distance obtained from the preceding vehicle	m.
b_p	Actual brake of the preceding vehicle	-
$\boldsymbol{X}$	The normalized data set	-
$\boldsymbol{S}$	Covariance matrix	-
λ	Eigenvalues	-
$\boldsymbol{Z}$	Eigenvectors of covariance matrix $\boldsymbol{S}$	-
I	Identity matrix	-
$\boldsymbol{P}$	Score on each principal component	-
$\boldsymbol{w}$	Weights of SVM	-
$\boldsymbol{b}$	Bias	-
$\boldsymbol{Z}_{HV}$	Eigenvectors from the data of the host vehicle only	-
$\boldsymbol{Z}_{HV+PV}$	Eigenvectors from the data of the host vehicle and the preceding vehicle	-
Th	Distance threshold	m.
$Th_{(new)}$	New Distance threshold value after adapted	m.
A	Adaptive value	m.
ΔTh	Difference between levels of distance thresholds $=Th_1 - Th_2$ or $Th_2 - Th_3$	m.
FDS	Free driving space value	%
FDS_{max}	The maximum value of free driving space	%
$Redlight$	Binary image of extracted red color	-

SYMBOL		UNIT
H	Hue channel image of the original image	-
S	Saturate channel image of the original image	-
Red	Binary image result of the red color traffic signs detection	-
Yelllow	Binary image result of the yellow color traffic signs	-
R	Red channel image of the original image	-
G	Green channel image of the original image	-
I	Intensity channel image of the original image	-
red	Red channel image of New Color Map of the original image	-
green	Green channel image of New Color Map of the original image	-
yel	Yel channel image of New Color Map of the original image	-

LIST OF TECHNICAL VOCABULARY AND ABBREVIATIONS

FCW	=	Forward collision warning
LW	=	Location-based warning
HV	=	Host vehicle
PV	=	Preceding vehicle
PCA	=	Principal Component Analysis
PC	=	Principal component
SVM	=	Supported Vector Machine
GPS	=	Global Positioning System
FSR	=	Force sensing resistor
FL	=	Front left of the host vehicle
FF	=	Front of the host vehicle
FR	=	Front right of the host vehicle
LL	=	Left side of the host vehicle
RR	=	Right side of the host vehicle
BL	=	Bottom left of the host vehicle
BB	=	Bottom of the host vehicle
BR	=	Bottom right of the host vehicle
FDS	=	Free Driving Space
ROI	=	Region of interest
RGB	=	Red-Green-Blue color model
HSV	=	Hue-Saturate-Value color model
SURF	=	Speeded-Up Robust Feature

CHAPTER 1 INTRODUCTION

For the past century, vehicles have made an important impact on people's life. Since modern life needs high mobility, vehicles can make our life easier and more comfortable. This led to a significant growth of vehicle usage. The high growth of vehicle usage has made automobile accidents be the number one cause of death in the world. In many accidents, the damage to lives and properties is so severe that it cannot be estimated. This problem brings about the development of safety systems in order to reduce both accidents[0] and injuries. The research will first aim at an intelligent vehicle, with a future aim for being used in normal cars as standard equipment. In vehicle safety research, many researchers focus on integrating computer technology with automobiles to construct efficient intelligent safety system for these vehicles.

A common form of active safety of intelligent vehicle is system that detects common causes of vehicle accidents and warns the driver. One common cause of vehicle accidents is driver’s inattentiveness to the driving task because of interrupting calls or readiness of his driving conditions such as fatigue or sleepiness. Since the major cause of accidents comes from human errors, active safety and intelligent driving assistance system is a necessary solution for future transportation. We emphasize our research on forward collision warning (FCW) systems, a device that warns drivers when there is a high potential for vehicle collision. Typical FCW systems consist of a range sensor, which measure the relative distance and the relative velocity to the front cars. The system warns the drivers when they drive too close to the front according to the current speed. However, current FCW systems have an average pre-warning of 2-3 seconds before the real collision. This is quite short and sometimes inadequate for the drivers to react on time.

1.1 Background of the Problem

Forward collision warning (FCW) is a vehicle technology that helps drivers be aware of what will happen ahead of the vehicle and avoid collisions by giving them warning signals when imminent dangers are detected. Most forward collision warning systems implement a variety of sensors to measure the distance from the car in front, the velocity, and the acceleration of the equipped car. These quantities are used to construct a kinematic model of collisions to alert the driver to a potential crash when the distance from the car in front is shorter than the distance required for safe braking according to the current velocity.

There are several models proposed by different researchers. All these models use threshold methods on a custom-defined indicator of danger in order to divide severity of danger into several levels. The drivers are then notified with the appropriate warning level. Figure 1.1 shows a typical scheme of FCW systems.

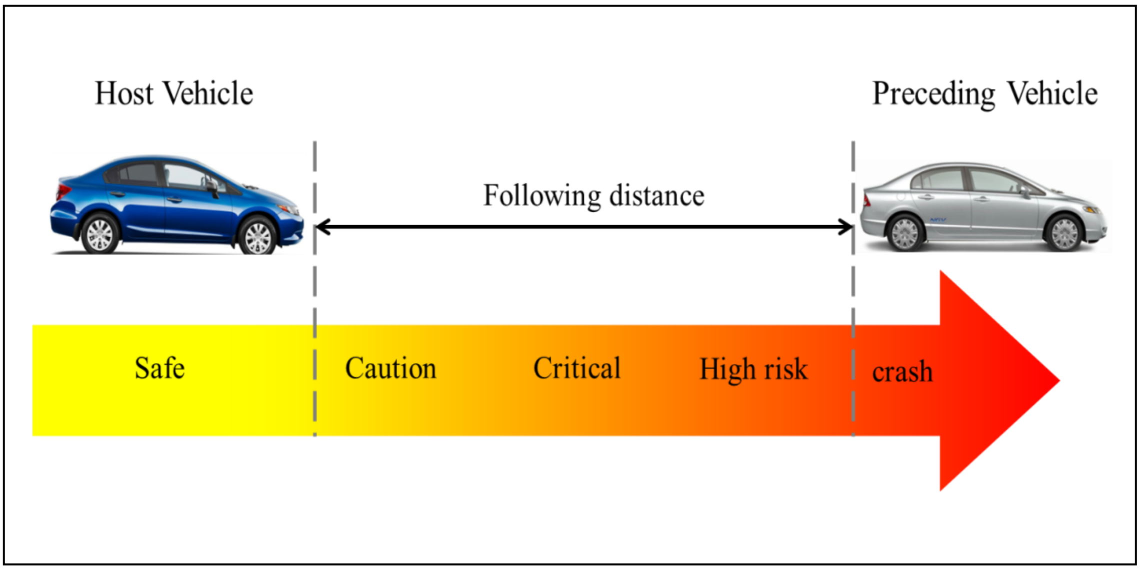


Figure 1.1 A Typical Scheme of FCW

Different researchers proposed different methods to estimate warning or risk level. All of these methods are based on the kinematic model of car crash. The model involves using position, velocity, acceleration, and time in equations of motion to estimate the probability of car accident. The results were that these FCW systems can warn drivers about few seconds before the real crash. Nonetheless, this short period of time is considered as useful. In many car accidents, just a portion of a second can make a difference between life and death. It can allow a driver to perform quick maneuver such as brake and sharp turn to avoid accident.

1.2 Motivation: Timing Improvement of FCW system

The FCW system has been developed extensively and many of research focus on the accuracy of warning. Nevertheless, there is another FCW performance that has to be concerned, the timing performance. We believe that the sooner the dangers are detected, the more likely safety can be achieved. Therefore, we want to increase the time period between the moment when the warning signal is issued and the crash moment. This time period is called the pre-warning time.

Pre-warning time depends on several factors such as the relative distance, the velocity, and the deceleration of both vehicles. It also involves some uncontrolled factors such as the readiness and the response time of the driver. The main problem in studying the timing performance of FCWs is the measurement of pre-warning time. Although some previous works use the pre-warning time as an indicator of timing characteristic, the measurement of pre-warning time requires an occurrence of a real crash. We found that the measurement of pre-warning time is quite difficult. Some previous work measured the pre-warning time by performing crashes in driving simulator, which is of questionable realism to the driving model. Taking a different approach, we want our work to measure the pre-warning time of FCWs in real driving situations.

Since the average pre-warning time of typical FCW systems is quite short, there are efforts to increase this pre-warning time. This is included in our work. All of the previous works tried to improve the pre-warning time by tweaking the kinematic model of crash or adding more parameters. This method is quite limited in term of a new idea and the achieved result. In our work, we lay a systematic method for timing improvement of FCW system. We propose that the improvement of FCW can be achieved in two ways with the aim to increase the performance in term of warning lag time. The first way is implemented in the individual vehicle called the vertical approach. The second way is done by using a communication channel to promote cooperative driving among several vehicles called the horizontal approach.

1.3 Objectives

We propose a systematic method for improving the response time of forward collision warning system on vehicles. This thesis provides three main contributions as follows.

- A timing performance metric, which can be measured in real driving situation, is introduced, called "the warning lag time".

- Propose two methods to improve the warning lag time of FCW system; vertical approach and horizontal approach.

- Construct the enhanced FCW system following two proposed methods and test the systems on city roads to demonstrate that the proposed methods can help improve the warning lag time.

1.4 Overview of Proposed Timing Improvement of FCW

In our work, we develop a systematic method for the improvement of timing in FCW. As shown in Figure 1.2, we propose that the improvement of FCW can be achieved using two approaches, with the aim of increasing the performance in term of warning lag time.

1. The vertical approach: This method is developed an individual vehicle. We combine a warning system with FCW system. We analyze the pre-crash of driving situation and divide it as the characteristics of crash prevention which consists of five levels from a normal driving situation to a crash: normal, open condition, critical moment, crash unavoidable and after crash. The FCW system typically operates in the critical moment level. To prevent the driver getting into the critical moment of driving situation, our idea is combining a warning system with FCW system by adding a warning system which operates in the level before the critical moment, open condition level.

2. The horizontal approach: This approach is based on distributed sensing. We use a communication channel to promote cooperative driving among several vehicles. Traditionally, FCW systems use data acquired from sensors inside their own vehicles. This limits the view of a single FCW by the range of sensors. The use of distributed sensors among other nearby vehicles helps expand sensor range of the host vehicle. This means that the distributed FCW can estimate the collision risk in the further future and with higher accuracy. Therefore, by utilizing data from other vehicles, we can implement an FCW system that has better performance and can detect more dangers.

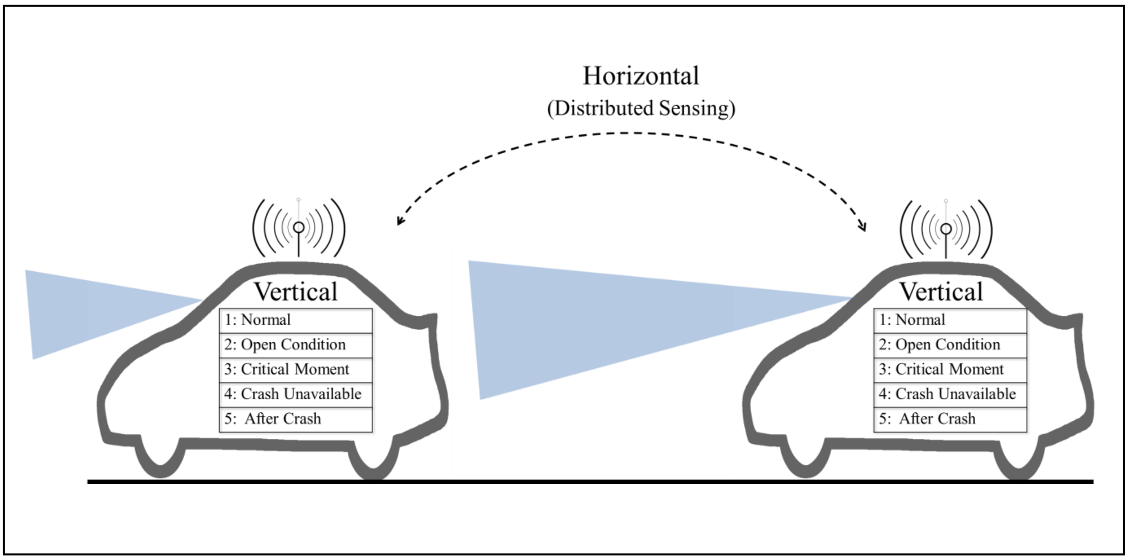


Figure 1.2 Overview of our Timing Improvement of FCW Systems.

1.5 Thesis Organization

The details of the research work are organized as the list below:

- In Chapter 2, the literature reviews and related work of the FCW system are provided including performance indicator of FCW system and FCW in an individual vehicle and cooperative vehicles.

- In Chapter 3, FCW system is introduced and we also briefly provide our previous work details about enhancement of FCW systems.

- In Chapter 4, this chapter describes the overall of our proposed work. The measurement of timing performance, called the warning lag time, is introduced. The warning lag time is used as the performance indicator for this work because it can be used in real driving without performing a crash situation.

- In Chapter 5, the vertical approach uses the multifunctional warning to improve the warning lag time. The characteristics of a vehicle collision were analyzed and divided into five levels according to the collision risk. We implemented a warning system that operates on these multiple safety levels. In the real driving test, the location-based warning system was selected to combine with the traditional FCW system. The result shows that this approach achieves increasing the warning lag time.

- In Chapter 6, the horizontal approach is described. This approach improves the FCW system based on the distributed sensing. The Principal Component Analysis (PCA) was used to reduce the data dimensions and Supported Vector Machine (SVM) was applied to construct the warning rules without any bias. Two FCW setups, FCW of a single host vehicle (FCW_{HV}) and FCW of the host vehicle with data from the preceding (FCW_{HV+PV}), were performed in real driving test. The horizontal approach's result shows it can also improve the warning lag time.

- In Chapter 7, this chapter presents conclusions and criticism of the research work.

CHAPTER 2 LITERATURE REVIEW AND RELATED WORK

This chapter provides a review of the literature work. Our work presents ideas to improve the performance of FCW system which focuses on improving the timing characteristic. The literatures of performance indicator of FCW system are firstly presented. Then, the literature work of forward collision warning system in an individual vehicle and cooperative vehicles are described.

2.1 Performance of Forward Collision Warning System

The important performance metrics of FCW system can be divided into two main types: accuracy and timing. The FCW accuracy is the warning correctness of comparison between actual brakes or hazardous situations and system warnings. The timing is the time period between the moment when the warning signal is issued and the crash moment. This time period is called the pre-warning time. For the importance of FCW system, the warnings have to be activated before crashes and the period have to be long enough for avoiding accidents. This is the point that motivates researchers make efforts to enhance FCW system to predict accurate warnings and increase the pre-warning time. However, literature work did not present neither the pre-warning time nor proving that their warnings were raise before or after crashes. Most previous work on FCW focused only on the accuracy of warning. Since hazardous situations are hard to perform on real city road, Hui and Jinfeng [1] performed their experiments on the road test. The driving scenarios consisted of both hazardous and normal cases. The warning accuracy was calculated by counting the correctness of estimated warnings for each driving case. Lai and Huang [2] evaluated a warning accuracy of their system with crash situations. However, the crash situations are difficult and harmful to perform in real driving. The different collision scenarios were performed in the computer simulation. Their warning accuracy was a ratio computed by dividing the system warnings by the number of collision cases.

Moreover, some previous work [3-7] performed the tests to demonstrate operating performance of their systems without warning accuracy or timing performance. For example, Dagan et al. [5] tested their FCW system with real driving in a test area. They performed crash situation without bump by driving to the stopped car on a different lane. The predicted distance-based warnings were compared with actual distance to collisions. The result showed that this system was accurate below two seconds to crash. With this performance evaluation, it indicates only a capability of obtaining driving information from sensors. The FCW accuracy is not pointed out. Nedevschi et al. [6] proposed FCW using 3D information from a Stereo Vision System. This system was tested in real driving to show that the system was able to operate machine vision to extract information and trig the warnings in real time but they did not show the warning accuracy. Takatori and Yashima [7] evaluated the system performance in a term of traffic safety. They assessed performance of their vehicle cooperative driving assistance by using traffic simulator, and the result showed that the system can help decrease traffic accidents.

For the timing performance of FCW system, we believe that the sooner the dangers are detected, the more likely safety can be achieved. Therefore, we want to increase this time period. This thesis focuses on improving the timing characteristic. The main problem in studying the timing performance of FCWs is the measurement of pre-warning time, which requires an occurrence of a real crash. However, real crashes are costly and happen only by accident. Therefore, existing works [7-9] use driving simulators, which is of questionable realism to the driving model. There is a work [10] that compared the system warning signals and the signals of driver's brake in order to show that they can increase the pre-warning time. They developed a FCW system based on THASV-II platform. The result demonstrated the examples that the system warnings correspond to driver's brake behavior without measurement of the pre-waning time.

With the aim to mitigate traffic accidents, FCW systems have been developed extensively to increase their performances. The performances of FCW system can be illustrated in the term of warning accuracy and the pre-warning time but most researchers made their effort to increase accuracy of FCW. For our work, we are making an effort to enhance FCW system by increasing the pre-warning time. We use the warning lag time as a performance indicator, which is proposed in chapter 4, because FCW requires a responsive vehicle maneuver in a short period of time to avoid accidents. The increase of pre-warning time in just a fraction of a second can mean life or death. Therefore, pre-warning time is a crucial property, in which we chose to be our performance indicator. Furthermore, we perform our experiments in real driving on the city road in order to evaluate our system performance in real traffic environments.

2.2 The Literature Work of Forward Collision Warning System

Forward collision warning (FCW) system is a system that warns a driver of a potential crash when the distance to the front car is closer than the distance required for safe brake according to the current velocity in order to avoid accidents. In general, FCW is estimated based on a kinematic model of collision. Thus, most of the FCW systems usually implement variety of sensors in order to measure the distance to the front cars, the velocity, and the acceleration of the equipped car. The systems utilize various equipment together, such as GPS, lasers or radars, cameras and on-board vehicle sensor for obtaining vehicles' status and surrounding environment. Vehicles' statuses are the information about vehicle such as position, speed, steering angle, acceleration etc. Surrounding environments, especially a front view, are other vehicles, traffic signs, traffic lights, brake lights of the front car, etc. These are generally observed by using image processing.

After reviewed the previous work about an intelligent vehicle safety system which involves FCW, we found that most previous studies on the intelligent vehicle safety have developed systems that function in an individual vehicle. There have been some works on a group of several intelligent vehicles, cooperative vehicle safety. Individual vehicle safety is a safety system that uses self-information from on-board sensors or/and other sensors to evaluate critical situations and warning. For cooperative vehicle safety, it has same objective as individual vehicle safety but cooperative vehicle safety uses both individual and shared data among vehicles via communication module.

2.2.1 Literature Work of FCW System in an Individual Vehicle

In general, FCW signals can be issued within the last few seconds before crash, called the critical moment. This may not be enough for sluggish drivers to avoid a crash in tight situations. Therefore, there are many researchers who made efforts to predict car crashes and increase time period between a warning and a crash called pre-warning time.

Broad surveys of FCW system in an individual vehicle have been developed based on kinematic model [3,5,8,9] by using causes of frontal collision, such as following distance, speed, acceleration, road environment, etc. The following distance or time to collision (TTC) is considered the collision risk that is used to issue warnings. There are some researchers who have enhanced the FCW by adding more driving parameters. Dagan et al. [5] proposed the FCW based on vehicle kinematic model in the term of time-to-contact. This work tried to fix the pre-warning time by keeping the relative distance within two seconds from the front car. Nakaoka et al. [3] proposed the FCW based on road friction coefficient and driver characteristics. They tried to increase the pre-warning time by adding the braking reaction time of the driver and a relative safety distance margin to the vehicle's motion model as shown in Figure 2.1. This work was tested by using driving simulator experiments and real driving in urban area. They calculated the critical warning distance based on TTC as following equation:

$$R_w = \tau_r + \frac{V^2}{2a} - \frac{V_p^2}{2a_p} + R_{stop} \tag{2.1}$$

where τ_r is the braking reaction time of driver depending on driver characteristics and behavior, V is the following vehicle speed, V_p is the preceding vehicle speed, a is the host vehicle longitudinal deceleration, a_p is the preceding vehicle longitudinal deceleration, and R_{stop} is the relative distance margin in case both vehicles stop. This work set R_{stop} = 2 m.

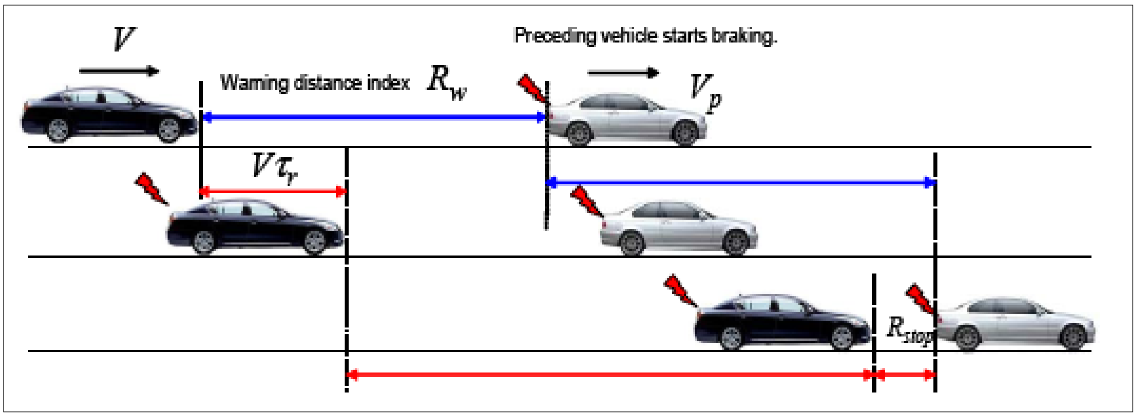


Figure 2.1 Description of Warning Distance Index [3].

There is a research of FCW system that measured a minimum deceleration of the host vehicle, which is required to avoid a collision with the front vehicle, to estimate warnings. Hiraoka et al. [9, 10] used deceleration for collision avoidance (DCA) as a significant parameter of a collision model to indicate forward collision risk. The warnings were estimated based on vehicle kinematic models and rule-based which were performed for certain driving situations. This work was tested with a driving simulator which performed four types of dangerous deceleration patterns of the front vehicle. They tried to construct the accurate vehicle motions but limitations of the accurate vehicle motions are that they can be used in only their certain driving situations performed with virtual driving.

Some interesting works combined road environment detection together with FCW to improve accuracy [11-15]. Previous work has combined multiple detected features into a single indicator to quantify collision risk and initiate a warning. Road environment detection, such as lane departure, and frontal obstacles, is utilized to improve the performance of FCW systems. One example is a combination of frontal collision and lane departure detection. Tokoro et al. [11] integrated following distance, lane detection, and obstacles detection together for implementing an adaptive cruise control (ACC). Chih-Li Hou et al. [13] combined a rear-end collision warning system and a lane departure warning system together. This work added more warning functions that combined longitudinal warning and lateral warning.

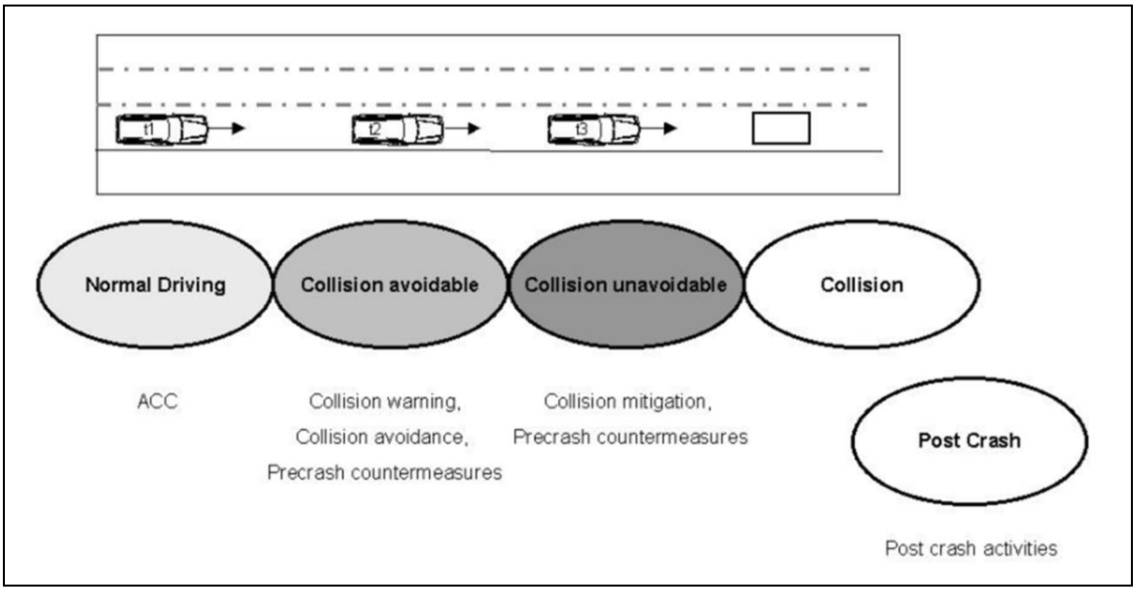


Figure 2.2 Driving states of a vehicle approaching a stationary obstacle. [4]

There are some work [4, 14] presented that the driving situation of a vehicle consists of several states and suggested the safety systems that should execute in each driving state. Jansson and Gustafsson [4] divided driving situation into five states: Normal driving, Collision avoidable, Collision unavoidable, Collision, and Post collision state as shown in Figure 2.2. However, they implemented their work to estimate collision risk only when the vehicle is at the border between the collision avoidable state and collision unavoidable state. The collision risk was calculated by using the probabilistic methods based on vehicle kinematic information and distance from an obstacle in front, obtained by a laser and a radar sensor. Their work was used to support collision mitigation by braking (CMBB) system. The CMBB will let a vehicle autonomously apply brakes when the collision risk is high. The full brake actions should be applied when the collision unavoidable state is coming. The system was tested with several different scenarios that could become the collision unavoidable state.

Figure 2.3 CAPS: Mutiphase Safety Concept. [14]

Another related work [14] introduced a new concept of assistance system, the Combined Active and Passive Safety (CAPS) system as shown in Figure 2.3. This safety concept aims to safe a driver for all driving situations that consists of five risk phases. A CAP identifies the functions that should be autonomously applied in each risk phase in order to avoid/ mitigate collision.

For the development of FCW in the individual vehicle, the collision is predicted in near future. The warnings are issued in only one stage of accidents, the high collision risk stage. According to the categorization of driving situation as mentioned above, we believe that combination of several subsystems for each driving stage can improve the pre-warning time and prevent the driving situation getting into the high collision risk stage.

2.2.2 Literature Work of FCW System in Cooperative Vehicles

Another way to develop the FCW system is the cooperative vehicles (CV). The cooperative vehicles are a group of several intelligent vehicles that are equipped wireless communication systems for sharing vehicle information to other surrounding vehicles. The motivation of the cooperative vehicles is that the communication benefits extending the field of view of the driving environment through the vehicle in front.

We divide the literature work of FCW in the cooperative vehicles into two groups according to the method for estimating the collision risk. The first group is positioning-based method. It uses vehicle position from GPS and status data from on board vehicle sensors such as speed, acceleration etc. The second one is perception-based method. It uses vehicle information and surrounding environment obtained by using external sensors.

2.2.2.1 The Positioning-based Method

The position-based method uses vehicle position as a main quantity together with vehicle status data such as speed, acceleration, steering angle etc. These data are used to create world model of the road and estimate collision based on vehicle kinematic model. Most positioning-based cooperative collision warning systems rely on GPS to obtain vehicle speed and position. Although GPS has uncertain radius about 5 to 20 meters which results error of estimating collision increases, it is acceptable to use to develop the cooperative vehicle system because of its low cost.

There have been some works that studied on the cooperative vehicles for two vehicles. Miller and Huang [16] proposed a cooperative intersection collision warning system by using factors in vehicle kinematics: location, speed and heading from GPS. The system alerts are based on an assumption that if two vehicles are expected to get into each other's path at the same time, their Time-to-Collision (TTC) will be equal (Figure 2.4). The time-to-avoidance (TTA) was calculated by using the response time of a driver and the braking time from speed and constant deceleration. This work appropriates with only at an intersection. It is not flexible for various road situations.

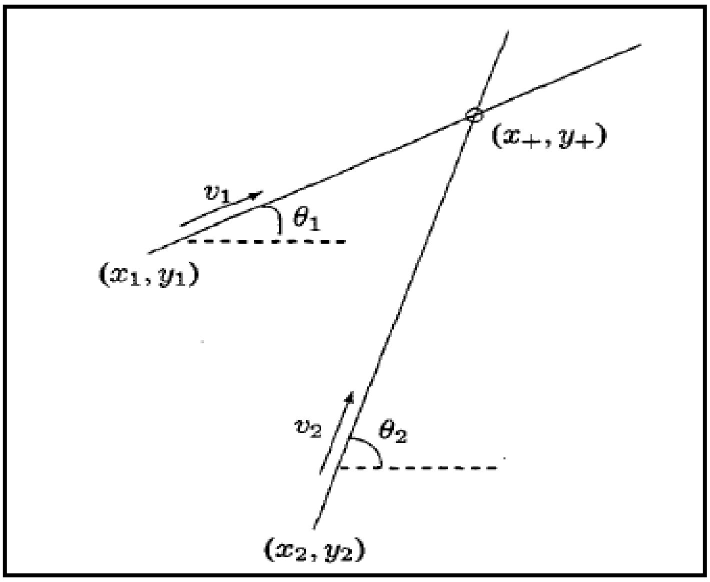


Figure 2.4 Two-vehicle Route Contention. [16]

Lytrivis et al. [17] presented path prediction algorithm for cooperative collision warning. They used the sharing data of two vehicles consisting of position, velocity and yaw rate. The cooperative path was predicted based on Kalman filter and Mamdani fuzzy model. Then, the future path was used to estimate collision warning by comparing distance between vehicle's trajectory points with thresholds. This work modeled the road based on clothoid model and used constant acceleration that is not suitable with real road situation.

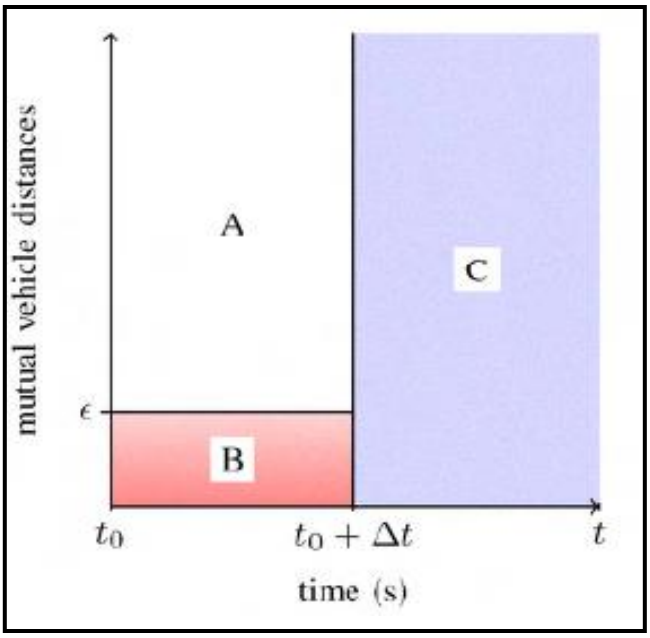


Figure 2.5 A: Predicted mutual distances within a forecast horizon of ~t are above a critical level ε (threshold). B: Distances too small and time too short = danger. C: Enough time ahead for the drivers to manage the situation safely. [18]

Batz et al. [18] proposed the detection of upcoming dangerous situations within a cooperative group of vehicles by using vehicles' status; GPS position, speed, heading, acceleration and yaw rate. The system predicted distance between pairs of cars and the dangerous situation was assessed by threshold method as shown in Figure 2.5. This model was used to predict the near future situation $t \varepsilon [t_0, t_0+\Delta t]$, where t_0 is the current time and Δt the short time prediction horizon.

Furthermore, some previous works [19-21] used the positions of both the host vehicle and the surrounding vehicles to construct a world model. However, this method is not flexible, and the accuracy depends on the resolution of the GPS. The world model for the positioning-based cooperative collision warning systems uses positions of both a host vehicle and surrounding vehicles and collects vehicles' status to construct the model. Papp et al. [19] proposed a real-time world model by using Local Dynamic Map (LDM). The LDM was created based on high resolution digital maps and the relevant relationships between vehicles. The weakness of this work is that it is not flexible because it needs high resolution and updated digital maps. Moreover, it relies on accurate vehicle positions to construct accurate model. There is another work about world model without digital maps. Actions between vehicles and their information were presented as graphs. Sebastian et al. [20] introduced the algorithm to model the interactions between multiple vehicles at a specific region and time as a graph model by using vehicles' status; GPS position, heading, speed and acceleration. This work did not use digital maps. The aim of the work is to improve the cooperative collision warning system. This algorithm considered 3 cases of traffic scenarios as shown in Figure 2.6; following, opposite and intersections, to construct the graph. As shown in Figure 2.7, the interaction between possible pairs of cars was determined based on a vehicle kinematic model and the graph was generated by using a rule-based method.

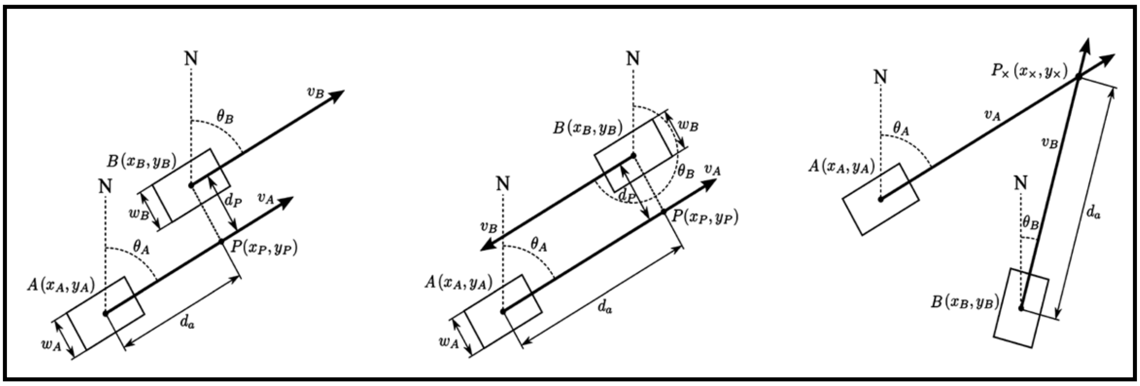


Figure 2.6 Left to right: two vehicles are following each other; two vehicles are heading toward each other and two vehicles with intersecting paths. [20]

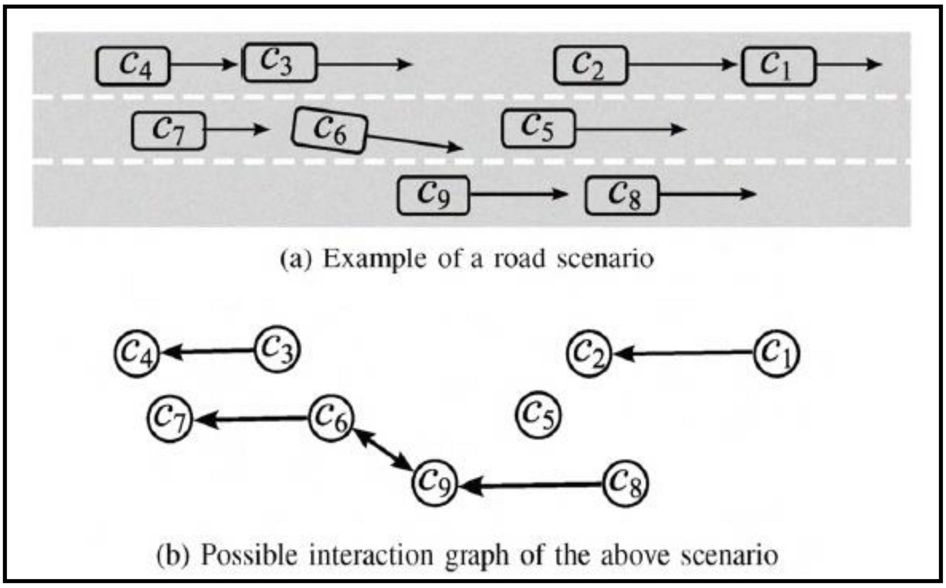
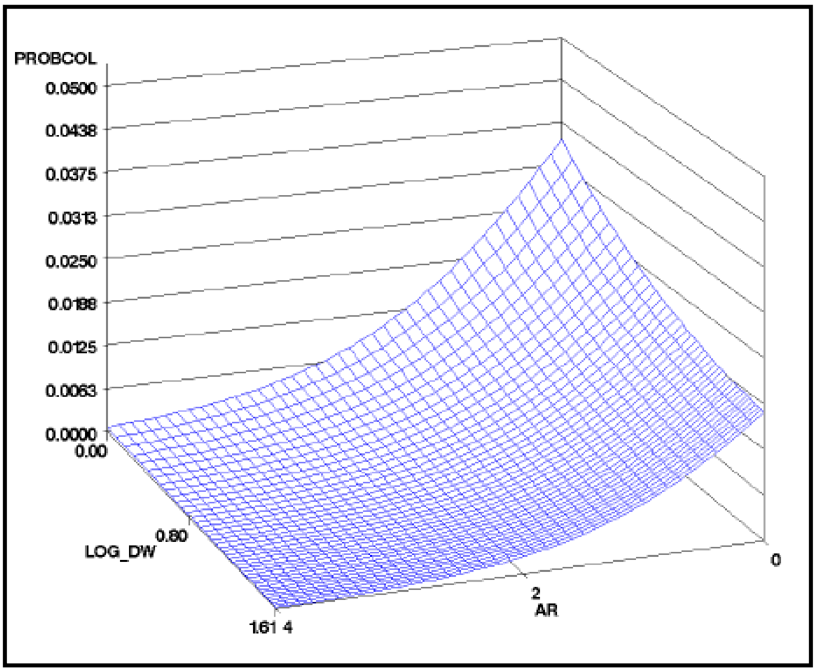
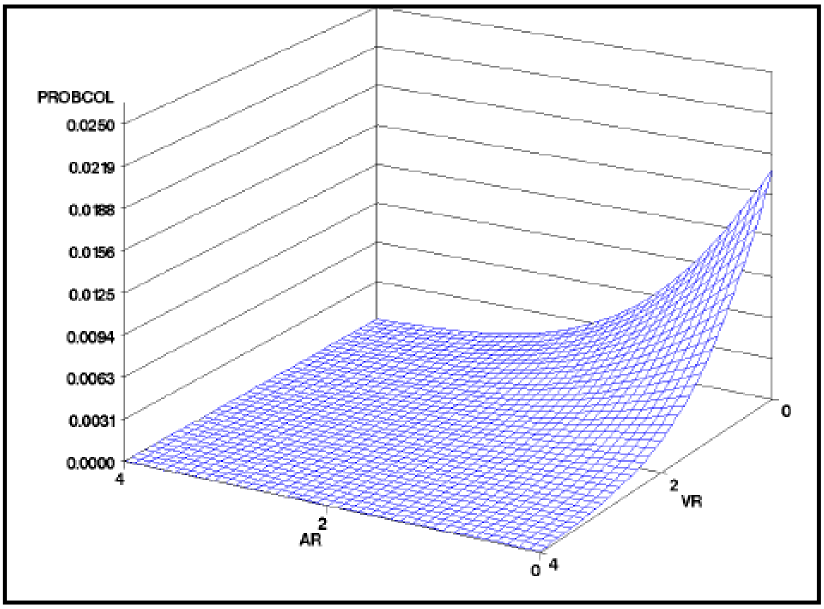


Figure 2.7 Modeling of Multiple Vehicle Interaction [20]

Yan et al. [21] proposed a collision prediction in the same direction based on mobility parameters and conditional collision probability. The vehicle information they used consisted of headway distance, relative acceleration, relative velocity and warning time (Dynamic mobility).The numerical results from MATLAB (Figure 2.8) shows the probability of a collision when provided a certain value of distance, speed and acceleration.



(a)



(b)

Figure 2.8 (a) The Probability of Collision vs. v_r and a_r
(b) The Probability of Collision vs. log D_w and a_r [21].

There is a literature work that utilized cooperative collision warning safety applications together and demonstrated it in various real driving scenarios [22]. The system utilized existing assistant systems: forward collision warning assistant, intersection assistant, and blind-spot and lane change assistant (Figure 2.9). The data they used consisted of GPS position, speed and heading, steering angle, wheel speed, and yaw rate. They performed the test in real driving situations with nine scenarios in order to show how the systems work.

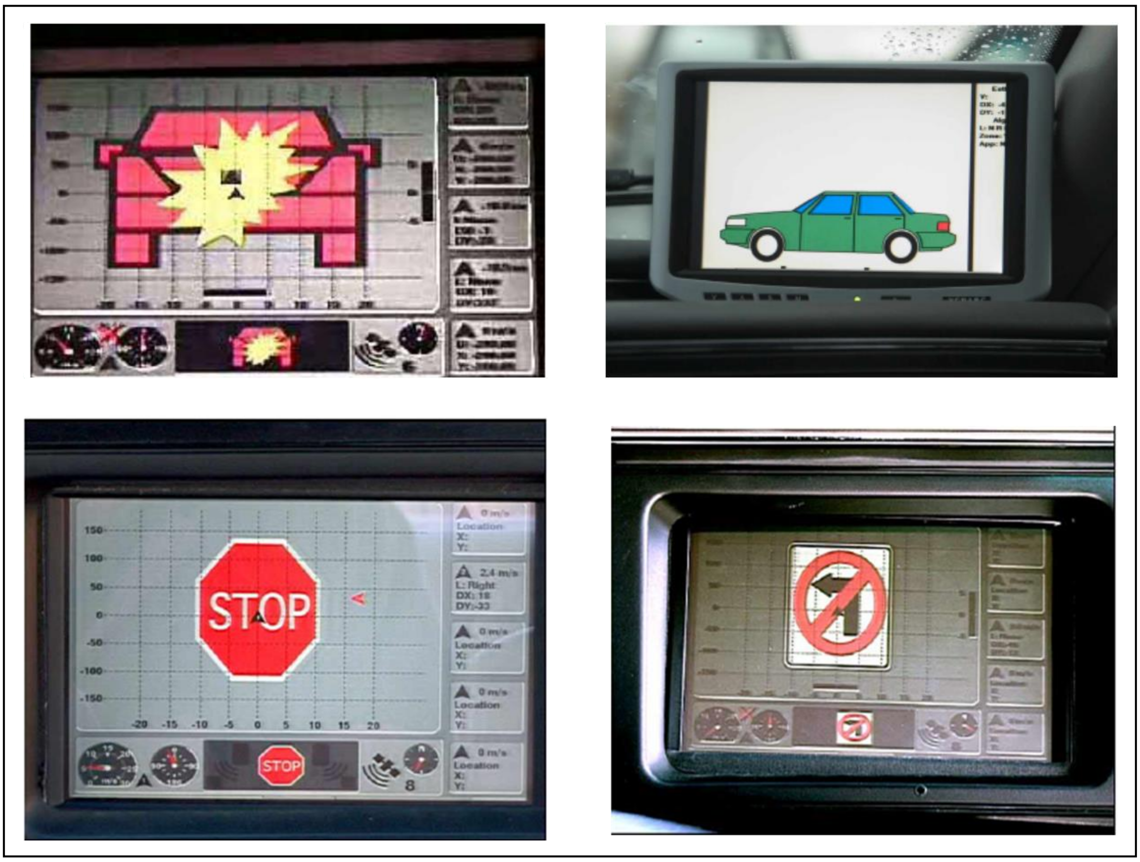


Figure 2.9 The example of warning safety applications [22].

This system provided the overview of the vehicle-to-vehicle cooperative collision warning system that integrated existing driving assistance systems together. The system has a display for interfacing with driver. From the test, it showed that the systems can work together in various scenarios as mentioned above.

The accuracy of most literature work depends on the resolution of the GPS. The accuracy of a mainstream-market GPS is approximately five meters, which is not suitable for same-lane detection. There exists a differential GPS (DGPS) with a resolution of approximately one meter that can achieve high-accuracy positioning to predict a collision. Tan and Huang [23] used DGPS in order to obtain high resolution position to estimate collision. As shown in Figure 2.10, they predicted future trajectory for cooperative collision warning system (CCWS) by using current position from differential GPS (DGPS) and vehicle information from in-vehicle sensors together with information from surrounding vehicle. The future trajectory was predicted based on the vehicle model by using vehicle future states predicted through model based propagation. Moreover, they also detected future trajectories of surrounding vehicles in order to predict the potential collisions. The potential collisions were detected based on time-to-position conflict (TTPC).

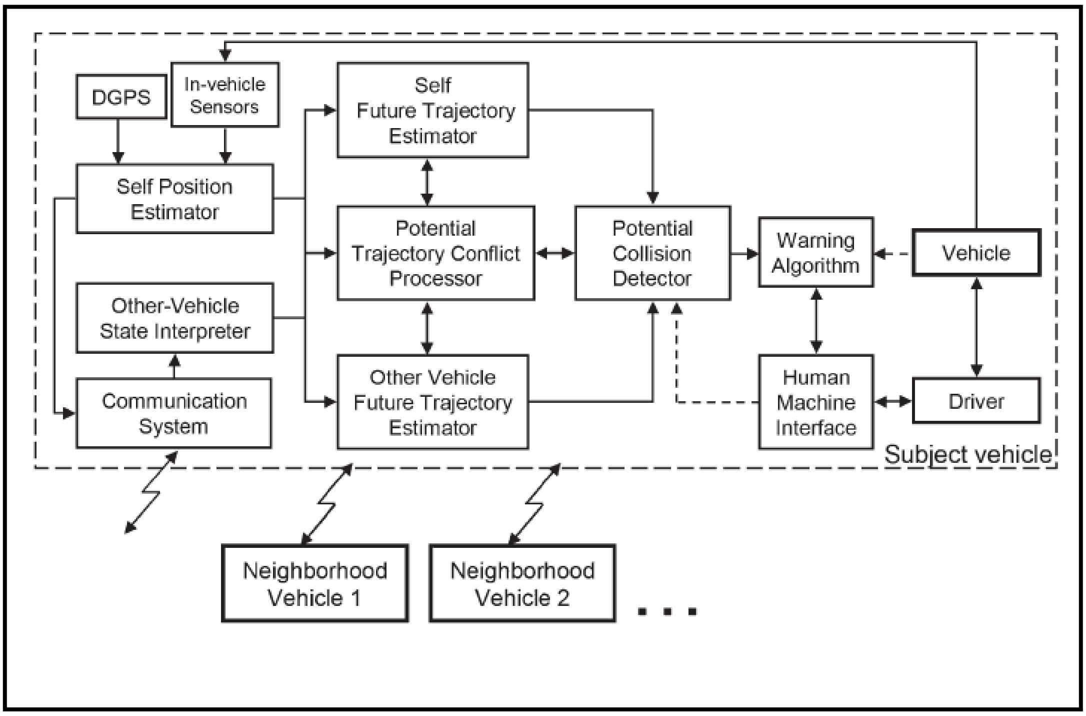


Figure 2.10 Block Diagram of the Proposed Future-trajectory-based Example. [23]

This work shows that the high resolution of DGPS can help to predict future trajectory which results to very few miss detections. However, this work is not reliable because the tests were not performed under real-time constrains and in real scenarios. Furthermore, DGPS is an expensive instrument and needs ground-based reference stations. The literature work mentioned above is the systems that can estimate collision/ vehicle position/ future trajectory/ world model for each driving situation case. These system is not flexible, when road environment changes.

2.2.2.2 Perception-based Method

The perception-based method is the multi- intelligent vehicles which are equipped perceptive sensors such as laser scanner, camera, etc. Thus, both of vehicle status and their perceptions can be shared between vehicles that resemble seeing through other vehicles. There is a work that operates for supporting the cooperative vehicle safety system. Ahlers et al. [24] fused environment perception data obtained from a laser scanner with motion data of host vehicle, information of other vehicles and a digital map (LDM). This information exists in previous work that is part of research project SAFESPOT. The fusion data was used as object description.

Another interesting work [25] is about augmented reality for driver assistance. They used a laser scanner and a camera as a perceptive sensor to obtain the visual perception of the front vehicle. Computer vision was applied to this work to transform the images from the front vehicle to the visual perception of the host vehicle based on 3D perspective. Then, the driver of the host vehicle can see through the front vehicle as shown in Figure 2.11. The procedure of this work consisted of two main steps. First step is to estimating relative position of two vehicle references. Rough positions were estimated by a GPS receiver, and then refined by a laser scanner. Second step is performing the 3D perspective transform between the visual perceptions of the two vehicles. This work helps drivers by displaying the occluded environment as the augmented reality on the visual perception to the driver of the host vehicle.

The positioning-based method mostly relies on GPS as well that provides uncertain data with less radius accuracy about five meters. Although there is a DGPS that has high accuracy, it has high cost need ground-based reference stations.

Figure 2.11 Augmented Reality: 'See' through the Front Vehicle. [25]

Most of the previous studies focused on measuring the accuracy of forward collision warning (FCW), while few studies tried to use reaction time as a performance indicator. This may be because their concepts could be verified only by driving simulations. We believe that timing is an important component in forward collision warning. If we can achieve 100% accuracy of warning but with only a short period of time for the driver to react, the warnings will not be useful at all. This is the main reason why we focus our study on the improvement of timing in general FCW systems. As mentioned above, the literature work attempted to predict frontal collisions and demonstrated their system's performance in the form of accuracy. Our proposed idea to enhance FCW system is that the improvement of FCW system can be done in both the individual vehicle and cooperative vehicles. With the advantages of categorization of driving situations, the classification of driving situation and corresponding safety systems can help prevent the driving situation getting into the high collision risk stage. For the cooperative vehicles, we focus on the perception-based method. This method extends the range of sensors by using external sensors (e.g. camera, laser range finder) and sharing data from surrounding vehicles. This means that the system can predict collision warnings in further future.

CHAPTER 3 FORWARD COLLISION WARNING

Currently, vehicle accidents are the major cause of injuries and death. Forward collision in vehicles are mostly caused by simple mistakes such as driver's inattentiveness to driving task, fatigue or sleepiness, improper distance kept between him/her car and the front car. With the aim of reducing these problems, forward collision warning systems have been developed intensively for a decade.

Forward collision warning (FCW) is an emerging technology that has been developed to help drivers avoid this incident. Typically, FCW detects impending crash situation and provide a crash warning to the driver in order to help a driver to be aware of keeping safe distance and safe speed. Forward collisions can be avoided if the following vehicle keeps a safe distance by ensuring that it is at least two seconds behind the vehicle in front. This scenario is shown in Figure 3.1, which is known as the two-second rule [27].

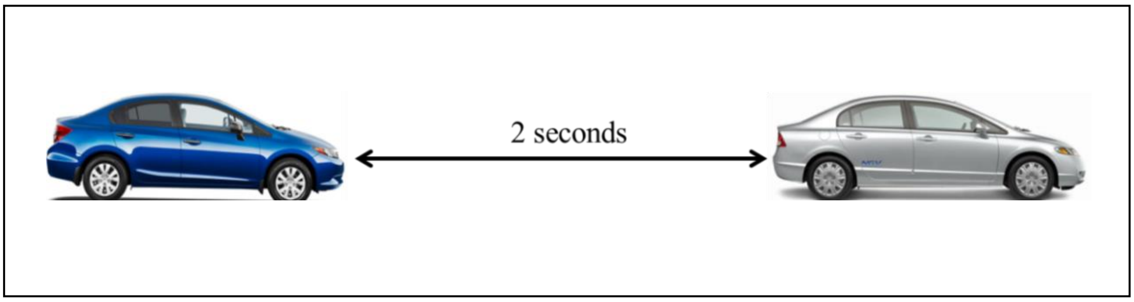


Figure 3.1 Keeping a safe distance by using the two-second rule.

Most of FCW systems generally use variety of sensors to obtain the following distance to the vehicle in front, the vehicle's speed, and the acceleration of the equipped car. Typical FCW systems use these quantities to construct a model of collision based on a condition that the systems provides potential crash warning to the drivers when the distance to the front car is closer than the distance required for safe brake according to the current speed. There are several models proposed by different researchers. All these models use threshold methods on a custom defined indicator of danger in order to divide severity of danger into several levels. The drivers are then notified with the appropriate warning level. Forward collision warnings simply warn the driver when a collision probably happens, but do not automatically apply the brakes.

For our research work, we have continuously developed FCW systems. In following sections, we briefly present the examples of FCW systems which are our previous work on enhancement of FCW. At first, we used a vehicle kinematic model to construct a FCW system based on 2-second rule. Then, we extracted driving environment data using machine vision algorithm and included these data to the collision risk estimation. Our previous FCW have been developed by using the driving environment data which involve the forward collision to achieve more precise warnings. For this work, we concern the pre-warning time of FCW which is important for FCW improvement. We propose a systematic method to improve the FCW systems and a measurement method for timing performance evaluation.

3.1 Forward Collision Warning Using Kinematic Model

The kinematic modeling of the FCW system in most work considers velocity and following distance as inputs. Since frontal collision can be avoided if a driver keeps his car at least 2 seconds behind the car in the front. This safety rule is known as the 2-second rule, which is a common practice in defensive driving. A driver is alerted when the current following distance is shorter than the distance thresholds, based on the 2-second rule. The level of brake warning is calculated based on the 2-second rule. With this rule, the driver has to keep his car at least 2 seconds behind the front car. Therefore, when a driver increases the velocity, the distance between the host car and the car in front must also be proportionally increased. If a driver cannot keep enough distance, following the car in front too close, it may lead to an accident. As demonstrated in Figure 3.2, it is the brake warning conditions which is used to classify the brake warning level. In our system, the brake warning level 1 to 4 correspond to the time that the driver keeps his car behind of 2, 1.5, 1, 0.5 seconds respectively.

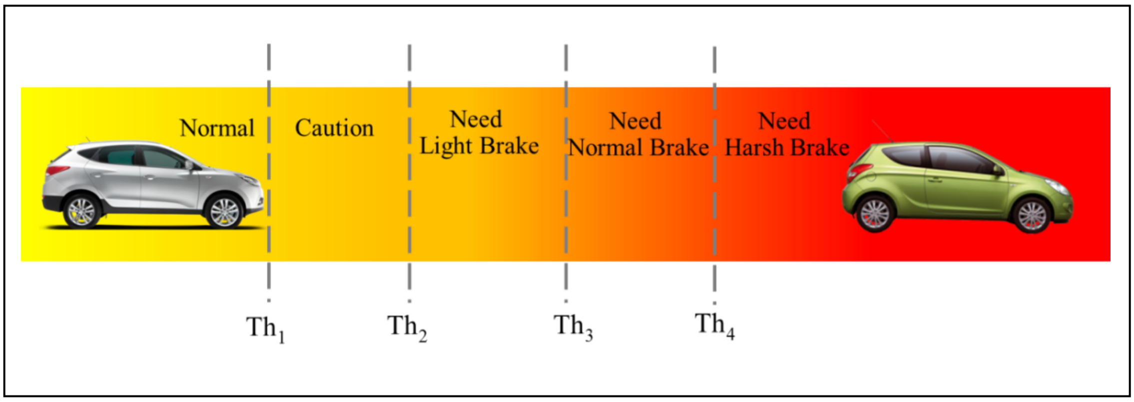
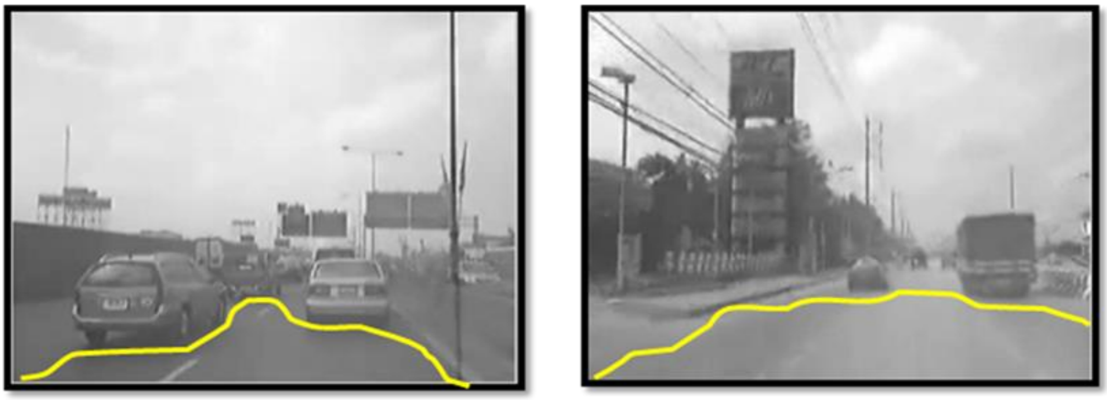


Figure 3.2 Brake warning conditions of FCW system.

3.2 Adaptive Brake Warning for FCW System

From previous work presented above, we found that the number of cars on the road ahead of the host car or the traffic density affects a forward collision risk. The idea is that when there are many cars on a road, the probability of future brakes will be higher than that when the car density is low. Therefore, if the car’s density on the road is high, our car should keep more distance. With machine vision, the free driving space will be taken into consideration. For the traffic density, “Free driving space” method [35] was used as an indicator to the density of other cars on the road. As shown in Figure 3.3, small free driving space reflects high concentration of cars. On the other hand, large free driving space means that there are few cars on the road.



(a) (b)

Figure 3.3 Free driving space in the case of (a) High traffic density and (b) Low traffic density.

We implemented this idea by increasing the warning level up one level when the free driving space is low (high car's density) [34]. This makes our threshold (Th_i) adaptable with the free driving space value (*FDS*). The thresholds (Th_i) are adjusted as ($Th_{(new)i}$) by the adaptive value (*A*) for more safe distance as following equations.

$$Th_{(new)i} = Th_i + A \qquad ; i = 1,2,3,4 \tag{3.1}$$

$$A = \Delta Th \times \left(\frac{FDS_{max} - FDS}{FDS_{max}} \right) \tag{3.2}$$

where $\Delta Th = Th_1 - Th_2$ or $Th_2 - Th_3$. FDS_{max} = 60% which is the maximum value of free driving space (no other cars/obstacles around) which can be determined from the ratio of ground/sky pixels according to the camera's azimuth.

The procedure and the result of free driving space estimation are illustrated in Figure 3.4. We calculated free driving space based on an assumption that cars and surrounding objects are texture–rich. Roads, on the other hand, have low texture. The procedures to calculate free driving space are as follows. First, we perform canny edge detection on the captured image. Then, the image is scanned from bottom-up column-by-column in order to count the total number of pixels until the number of edge pixels reaches a specified threshold. Each pixel counted is treated as a part of a road, a free driving space pixel. We also limit the count on only the ground portion of the image, because the sky also has low texture. We assumed a fixed height of the ground portion due to a fixed angle of the camera. The total number of free driving space pixels is normalized with the size of the whole image to be the free driving space value (*FDS*).

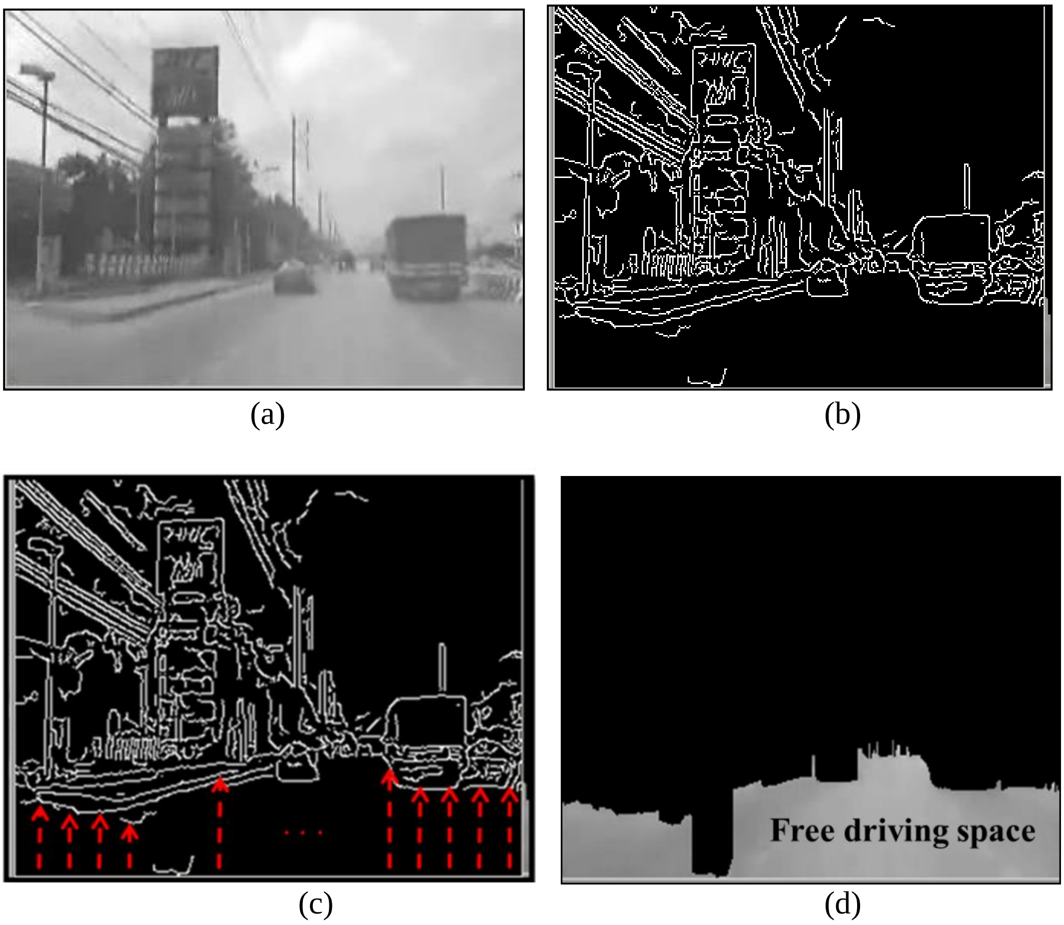


Figure 3.4 Free driving space estimation: (a) Original image, (b) Result of canny edge detection, (c) Count free driving space pixels and (d) Free driving space.

3.3 Improvement of FCW with Real Driving Environment Data Using Machine Vision

The Adaptive threshold using FDS as described above, it suggested the way to improve FCW by using features of the surrounding environment. For this work, we introduced the FCW system using a kinematic model coupled with driving environment data extracted from machine vision algorithms to achieve higher accuracy of predicting brake actions [36]. We employed a rule-based method, which is adaptable to the environment data, to identify the level of the appropriate collision warning.

3.3.1 Driving Environment Data

We used easy and robust features of the surrounding environment that can be extracted from a camera. These features are free driving space, red light (brake light of preceding vehicle), and turn rate of vehicle turn's movement. They can help improve the performance of the warning to be suited to different driving situation, instead of relying on just speed/distance modeling. These features were used with active sensors that measure the following distance and the host vehicle's speed to construct a warning model.

1. Vehicle Turn's Movement

The vehicle's turn movement was detected in order to alleviate the limitation of the laser rangefinder which points its beam straight toward to the preceding vehicle. In the case of a curve road, it point to roadside instead. Therefore turn movements has to be detected and differentiate from the straight path movements in order to apply different rules.

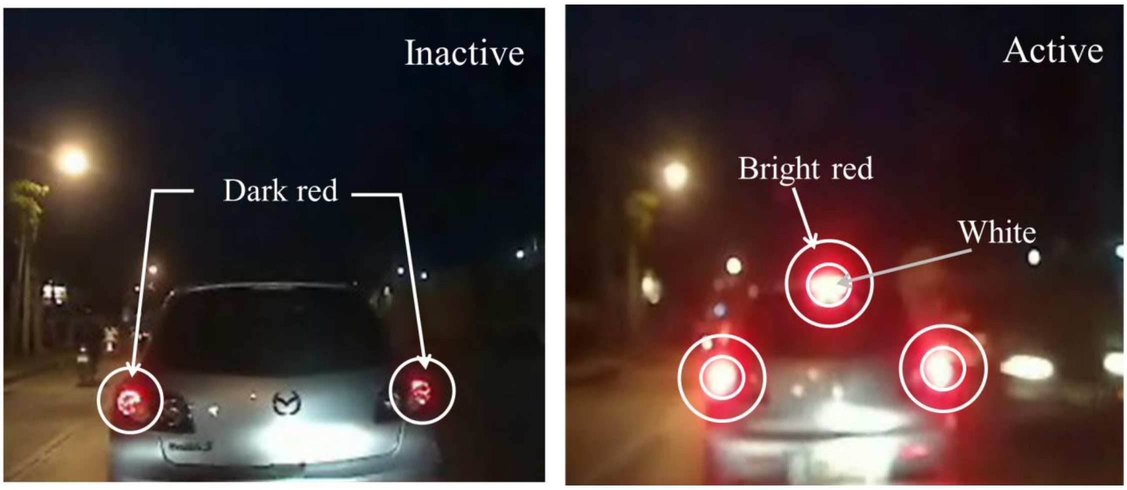
The vehicle’s movement was observed by estimating the camera motion which was determined from the optical flow of images. The KLT algorithm [37] was employed to recognize turn movement. Figure 3.5 demonstrates the result of detected vehicle’s movement by using the KLT algorithm. The red vectors in the images represent the displacement of good features in the current frame and the previous frame. In the case of the car moving forward (Figure 3.5(a), the vectors in the left part of the image will move away from the center toward the left and the vectors in the right part of the image will move toward the right. In the case of turn movements (Figure 3.5 (b)), all vectors in the image will point toward the same direction. These behaviors can be used to differentiate turn movements from the straight–path movements.

(a) (b)

Figure 3.5 Detection of vehicle turn’s movement using KLT algorithm: (a) Moving forward, and (b) Turning.

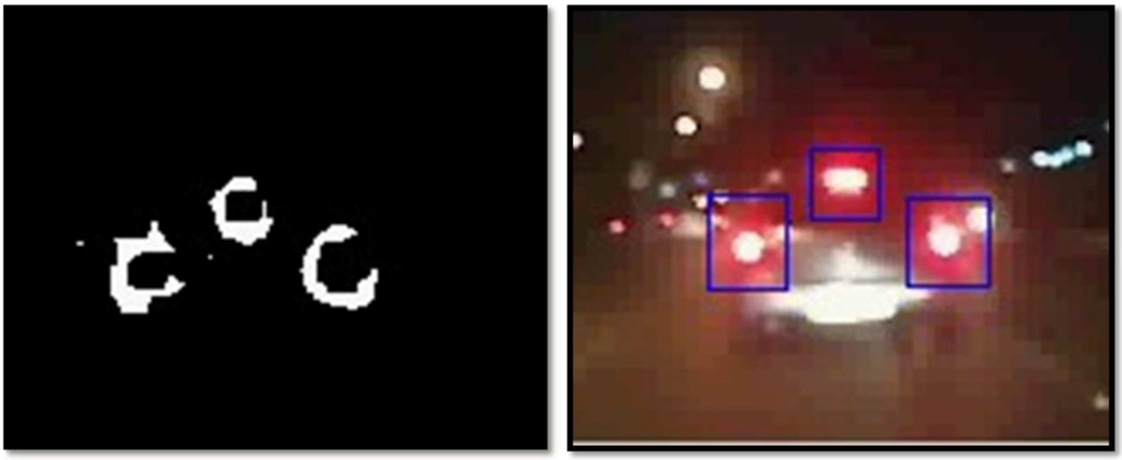
2. Brake Lights of the Preceding Vehicles

Red lights in traffic from vehicles and infrastructure implies stop or danger. It can effectively predict the slow-down in short future. The brake light detection was activated only in nighttime, because the intensity of brake lights was too low for using in daytime. In daytime, red lights cannot be easily distinguished from other red objects. We identified brake lights by detecting red color, which is based on the RGB color model. We classified the stage of brake lights based on an assumption that the taillights have two degrees of red color, which indicate that the brake is active or inactive [38]. When the driver brakes the car, the taillights have red color brighter than that when the brake is inactive. Furthermore, in an image frame, when the brake lights glow, they can be seen as red rings with white color in the centers as illustrated in Figure 3.6. We classified the brake lights by color thresholding for the bright red color of the rings. The example of brake light’s color thresholding is shown in Figure 3.7. The area of red lights, the size of the largest brake lights, and the vehicle’s speed can be used as an indicator to danger that potentially leads to frontal collision.



(a) (b)

Figure 3.6 The brightness of the taillights: (a) Inactive taillights. (b) Active taillights.



(a) (b)

Figure 3.7 Example of the detected brake lights. (a) The white pixels from color thresholding for the bright red color of the rings. (b) The detected brake lights are indicated by the bounding boxes.

3.3.2 Inference Mechanism of the FCW System

In order to identify the brake warning level that is appropriate with different situations, the inference system was divided into two modes: daytime mode and nighttime mode. For daytime mode, when the car moves forward, the velocity, following distance, and density of cars on the road are considered. The car should keep a proper distance away from the front car according to its velocity based on the 2- second rule. In addition, when the density of cars on the road is high, the safe following distance should increase along with it. Brake warning levels were designed to have a range from 0 to 4, where level 0 means safe. Level 1 is the situation that needs caution. Level 2, 3, and 4 means light brake, normal brake, and harsh brake respectively. From warning level 1 to 4, the driver will be alerted by a beeping sound at different frequencies according to the warning level detected. Each case is detailed as follows. In the case when the car turns left or right in daytime, the inference system used the velocity and turn rate as inputs. The idea is that the car should slow down at curves. The maximum velocity while turning should be proportional to the curvature of the road. In the case of the car's forward movement of the nighttime, the velocity, following distance and the points of brake lights are used in the inference system. At night, we used the same idea as that in daytime except the use of free driving space. The free driving space cannot be measured at night because the camera only sees a small portion of the road. Instead, the brake lights from other cars are used as an indicator of closed dangers. Our vehicle had to keep a safe distance from the front cars, and this distance should increase if large areas of brake lights are seen. Therefore, in the case of the car's forward movement at nighttime, the velocity, the following distance, and the area of brake lights are used in the inference system. For turn movement at night time, we excluded the use of measuring the distance from the laser range finder and used only the turn rate, the host vehicle's speed, and the brake lights. When turn, the vehicle could have a maximum velocity proportional to the turn rate. However, if brake lights are presented, the maximum velocity should be lower to provide more caution to the surrounding environment.

CHAPTER 4 TIMING IMPROVEMENT OF FORWARD COLLISION WARNING SYSTEMS

This chapter presents the overall of our proposed work. Firstly, the importance of timing performance of FCW systems is described in order to understand the point that we focus on, and then the measurement for FCW performance evaluation is proposed. In final section, we introduce the overview of our systematic methods for timing improvement of FCW systems. The detail of each method is described in the next chapter.

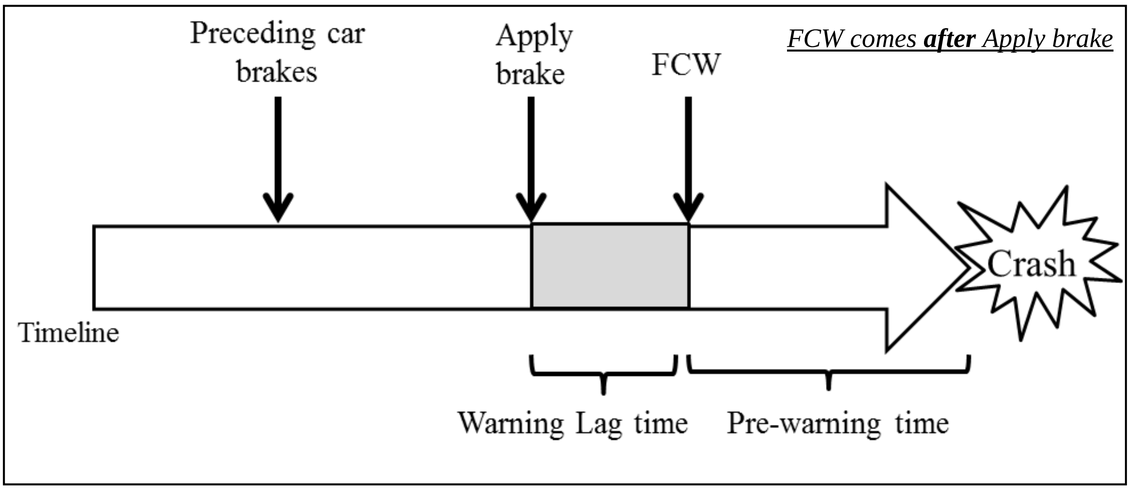
4.1 Importance of Timing Performance of FCW System

Timing is a critical property in FCW systems. Although drivers can take action quickly, a slight delay in an emergency situation can mean the difference between life and death. Our work will focus on the improvement of timing in FCW, i.e., issue a warning signal as fast as possible while preserving the accuracy. For the previous work, they focused on enhancing the FCW system to increase accuracy of detection and warnings. We believe that the timing characteristics of FCW systems should also be taken into account. Pre-warning time is defined as the time period from the initial warning to the crash impact, and it depends on several factors such as the relative distance, the velocity, and the deceleration of both vehicles. It also involves some uncontrolled factors such as the readiness and the response time of the driver. Some researchers [3, 9, 10, 26, 28] determined the pre-warning time by adding a constant value, such as the driver's reaction time or the braking distance to the vehicle kinematic model and did not show the results that the warnings of the systems happened before/after actual brakes, after tuning the sensitiveness of FCW. If an average pre-warning time is measured, we could tell how much the performance of the enhanced FCW system is increased in the term of timing.

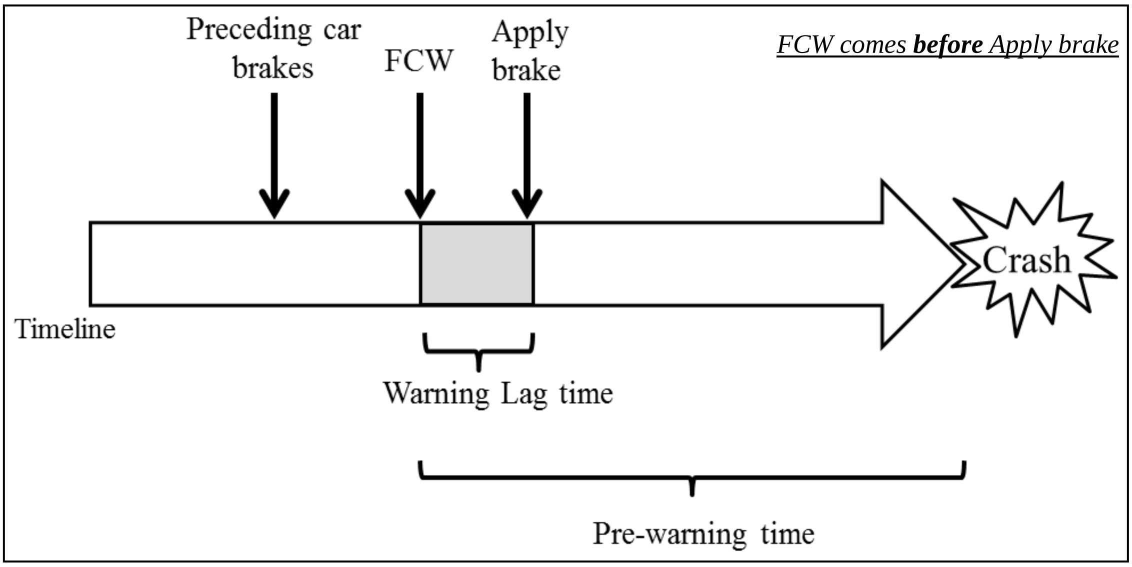
Although some previous works used the pre-warning time as an indicator of the timing characteristic, we feel that the measurement of the pre-warning time is not practical. As the pre-warning time is defined as the time period from the warning to the crash, a real crash has to occur. Therefore, the measurement can only be performed in driving simulator or in a mock-up crash, but not in real driving situation. Taking different approach, our work wants to assess the timing performance of FCW systems in real driving situations. Therefore, we propose using another time metric called "warning lag time", which can be measured in real driving situations without a crash.

4.2 Warning Lag Time for Performance Evaluation

The warning lag time is defined as the time between the moment when a sensible driver performs the braking, and the time when the warning signal is issued. This parameter can be measured when a driver drives his car normally in real driving situations, and identifies whether the warnings precede the actual brakes. As demonstrated in Figure 4.1, there are three events happening from left to right in the timeline of the driving during a pre-crash situation; the preceding car brakes, the driver of the host car applies a brake, and the FCW system provides a warning. The name "warning lag time" does not imply that the actual brake of drivers always occurs before FCW. In fact, FCW can occur either before or after the actual brakes.



(a) FCW comes after apply brake



(b) FCW coms before apply brake

Figure 4.1 The pre-warning time and the warning lag time in a timeline of driving situation.

4.3 Warning Lag Time Calculation

To use the warning lag time, we have to make an assumption that the driver is well alert and has fair driving skills. These reasonable drivers perceive the leading car brake and should apply their brake accordingly. However, the weakness of using the warning lag time is the human factor, which generates inconsistency in the response time when the driver applies his brake. However, if the measurement of the warning lag time can be averaged on several brake situations over a long period of time, this problem can be alleviated, and the average warning lag time can be a good indicator of the timing performance of FCW systems. The warning lag time is used as an indirect indicator of the pre-warning time. The warning lag time will increase or decrease by the same amount as the change of the pre-warning time. The strong benefit of using the warning lag time is that it can be evaluated during normal driving for a long period of time. Thus, it will reflect the average value of timing performance. More importantly, the measurement can be performed in a regular driving environment without a car crash.

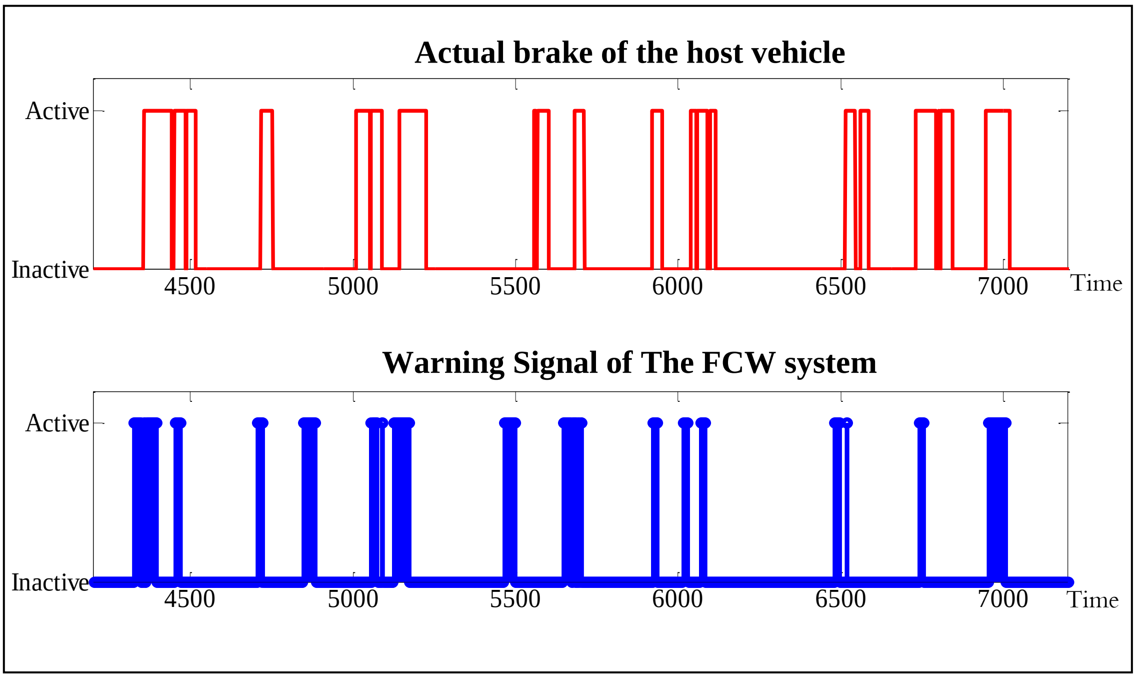


Figure 4.2 Example of the actual brake of the host vehicle and the warning signal of the FCW system.

To calculate the warning lag time, we recorded the warning signal from the FCW system and the brake signal during a test drive with equal sampling times. The actual brakes, as earlier, are harsh brakes that use more force on the brake pedal than normal brakes. In our work, we filtered out soft brakes using a thresholding method, so that only the harsh brakes are selected and used to calculate the warning lag time. The actual brakes in the tests represent the brakes for potentially dangerous situations, which should correspond to the warnings from the FCW system. We evaluated the warning lag time of our system based on the assumption that the pattern of the system warning signal is similar to the pattern of the actual brake signal. However, the system warning has a short time-shift from the actual brake. Thus, this short time-shift is the warning lag time of the system warning. As shown in Figure 4.2, it is an example of the actual brake from a driver and the warning signal of the FCW system which will be used to calculate the warning lag time. The actual brake and the warning signal consist of two states: active and inactive. The active state of the actual brake means the driver pushes a brake and the inactive state is no brake. For the warning signal of FCW system, the active state is the system give a warning and the inactive state is no warning from the system.

After obtaining both data, we can evaluate the warning lag time by following these steps. First, we calculate the cross-correlation between the actual brake and the warning signal of the FCW system as demonstrated in (4.1).

$$B_a * W_f(k) = \sum_{i=-k}^{k} B_a(i)\ W_f(k+i) \tag{4.1}$$

where B_a is the actual brake of the hot vehicle, W_f is the warning signal from the FCW system, and k is number of W_f data points.

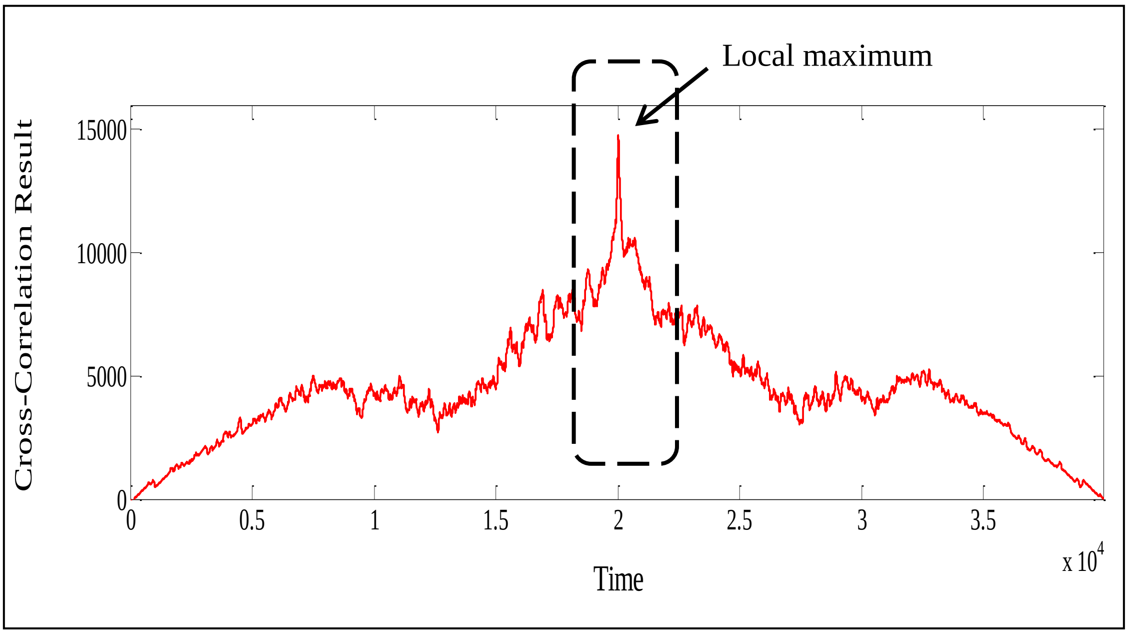


Figure 4.3 Example of the cross-correlation result between the actual brake and the warning signal of the FCW system.

The second step is searching for the local maximum around the center of the correlation output. This is because the shift between the two signals is small compared to the total driving time (lag time ≈ 1 sec). Therefore, the local maximum will not deviate much from the center. Finally, we obtain the warning lag time by measuring the distance between the center of the cross-correlation output and the local maximum. Figure 4.3 shows the example of the cross-correlation result and the dashed rectangle presents the region of the local maximum which is the same region as illustrated in the Figure 4.4. The measurement of the warning lag time by the cross-correlation of the actual brake and the system warning from our FCW system is demonstrated in Figure 4.4. The vertical line indicates the center of the cross-correlation output (no shift). The rectangular box is the enlarged local maximum to show the distance from the center which is the warning lag time. If the local maximum is on the right of the center, it means that the system warning happened before the actual brake, while if the local maximum is on the left, it indicates that the system warning was delayed from the actual brake.

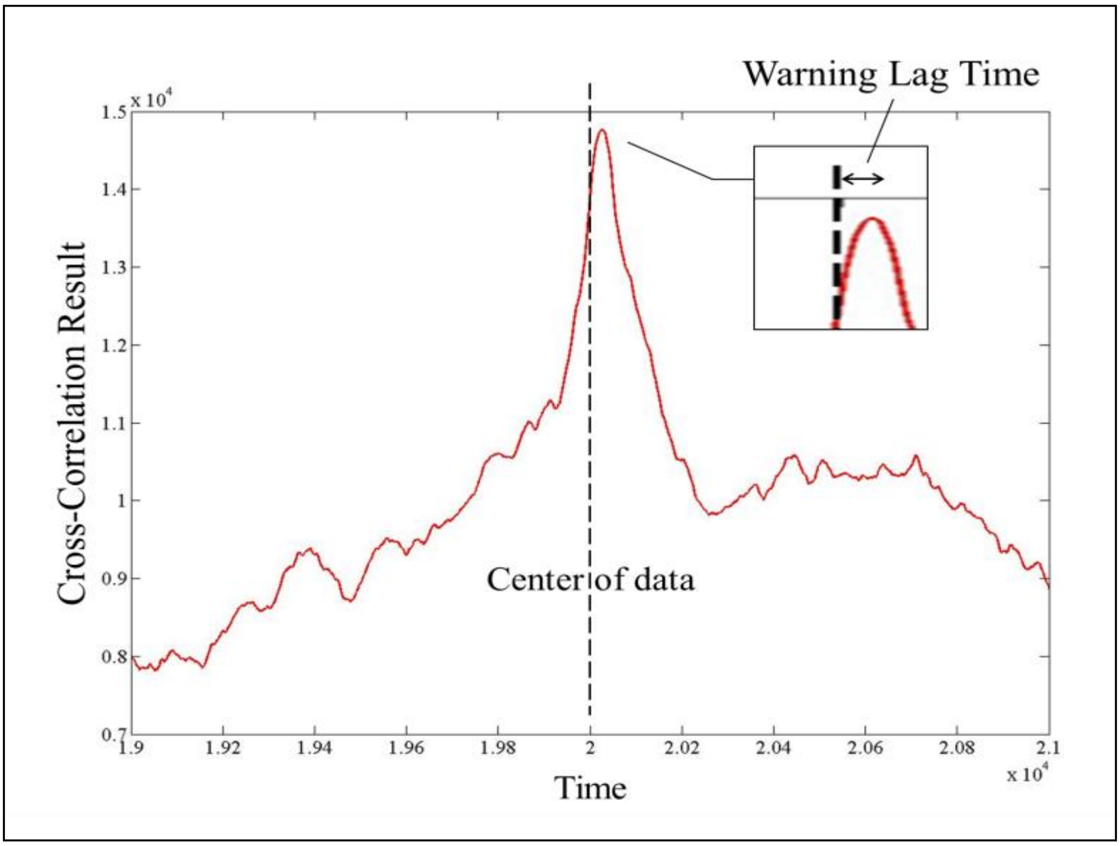


Figure 4.4 Measurement of warning lag time from cross-correlation between the actual brake and the warning signal of the FCW system.

CHAPTER 5 VERTICAL APPROACH: MULTIFUNCTIONAL WARNING

This chapter describes the first approach to improving the warning lag time. The idea is to add warning signals from several clues other than an approaching car, especially those that precede a crash by a significant period of time. To do this, we looked back into the causes of car accidents. In section 5.1, we analyzed the characteristics of a vehicle collision and divided them into five levels according to [14] and [16]. We then implemented a system that operates on multiple layers of these safety levels as described in section 5.3. Then, we demonstrate adding a static warning system to improve the warning lag time in section 5.4. Finally, the experiments are presented.

5.1 Multilevel of Crash Prevention

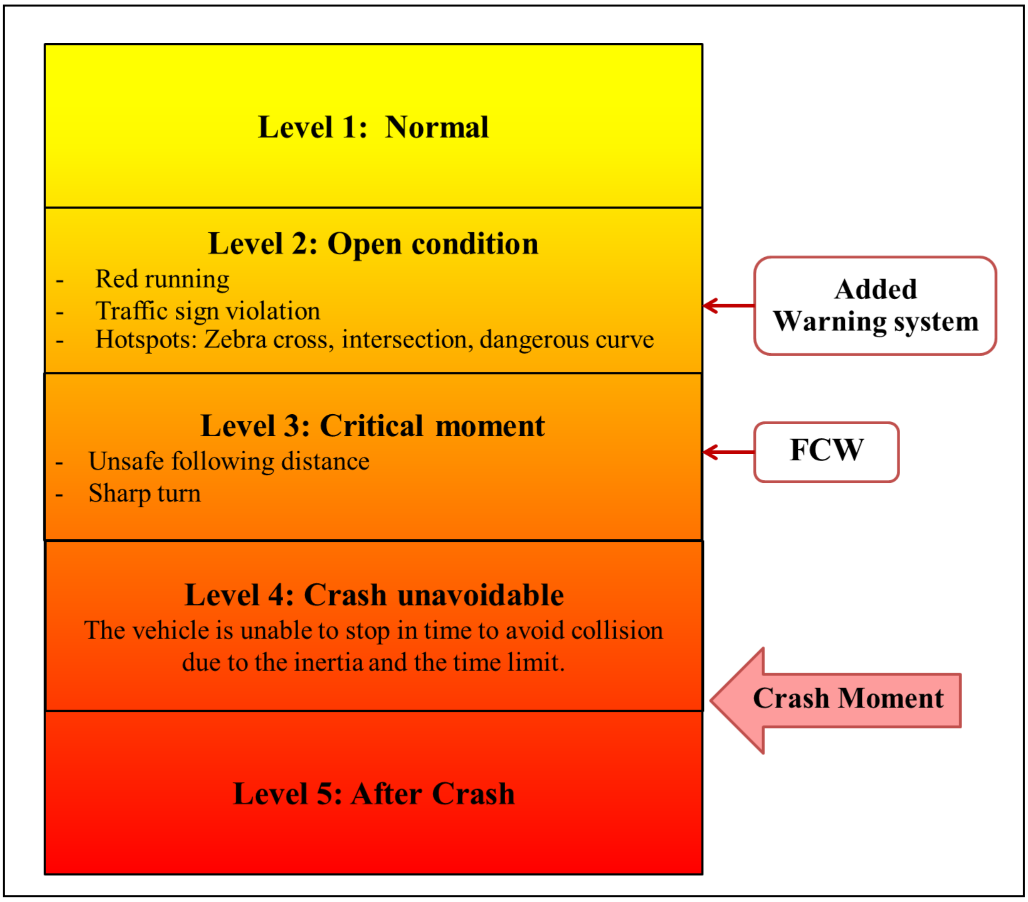


Figure 5.1 Five levels for crash prevention.

In the vertical approach, we seek to generate warning signals from multiple clues, which are the causes of accidents. We studied a typical car crash and divided it into five levels according to the collision risk, as illustrated in Figure 5.1. The minimal collision risk is classified as the first level. In this level, the driver is very alert and strictly follows traffic laws. The probability of accidents is therefore very low. From the first level, if the driver places himself in an open condition to collide, he will be in the second level. The open condition to collide is usually caused by violations of traffic regulations. In the second level, if the driver does not take a suitable maneuver to recover the driving situation back to the first level, the driving situation will turn into the third level, which is a critical moment of crash avoidance. In the third level, the driver can avoid collision if he has good skills of maneuvering the vehicle, such as harsh braking or crisp turning. When the crash becomes unavoidable, the moment before the crash is classified as the fourth level, in which damage mitigation devices, such as airbags, should be activated. The fifth level is the time period after the crash.

5.2 Adding Warning Systems to Second Level of Crash Prevention

From the five levels of crash prevention, typical FCW systems operate on level 3, the critical moment. For level 3, the main purpose is to notify the driver as fast as the system detects the future danger, in order for the driver to perform special car maneuver to avoid crash. This is the moment approximately 2-3 seconds before the impact when the approaching vehicle is detected. To increase the pre-warning time, we added the warning systems for the open condition combining with an FCW system. The added warning will help prevent the driver from entering level 3, the critical moment and promptly recover himself back to the normal driving condition (level 1) before it is too late. It also helps improve the warning lag time because it detects the cause of accidents that occurs before the critical moment (level 3).

We initialed our work on vertical approach by designing multifunctional warnings as described in section 5.3. A traffic light warning and a traffic sign warning were added to work together with FCW. The warnings from the traffic light warning and a traffic sign warning are generated from dynamic environment. Therefore, the warning systems have a limitation operating under complex road environments. We, then, implemented another warning system which generates warnings from static environments to achieve the improvement of the warning lag time using the vertical approach as presented in section 5.4.

5.3 Multifunctional Warnings

The warning signals we added are from several clues which are the causes of accidents. Thus, we implemented a traffic light warning and a traffic sign warning operating together with the FCW system. Detecting the status of traffic lights was chosen because running on a red traffic light is the main cause of accidents at intersections. Another cause of an accident is avoidance of traffic sign violations. Traffic signs are indicators to traffic laws imposed in that area, which aim to prevent accidents by warning drivers to follow the meaning of the sign. Detecting the traffic sign and giving the warning to the driver will help the driver to be aware of the accidents. The systems will display the detected result on a screen and give a warning sound to the driver.

The components of this combination system consist of three sensors as shown in Figure 5.2. The first sensor is a laser rangefinder mounted at the front of the car and pointed forward in order to help the driver keeps safe/proper following distance. The second sensor is a GPS receiver used to obtain the speed of the host vehicle. A camera is used capture a driving scene which is the same viewing angle as the driver to observe the traffic signs and the traffic lights. All data are sent to the main computer via USB connection for the warning systems which are operated on the computer. The data from the laser rangefinder and the GPS receiver will be used to estimate the FCW and the data from the camera will be the input of the traffic light warning and the traffic sign warning. Each warning system is detailed as follows.

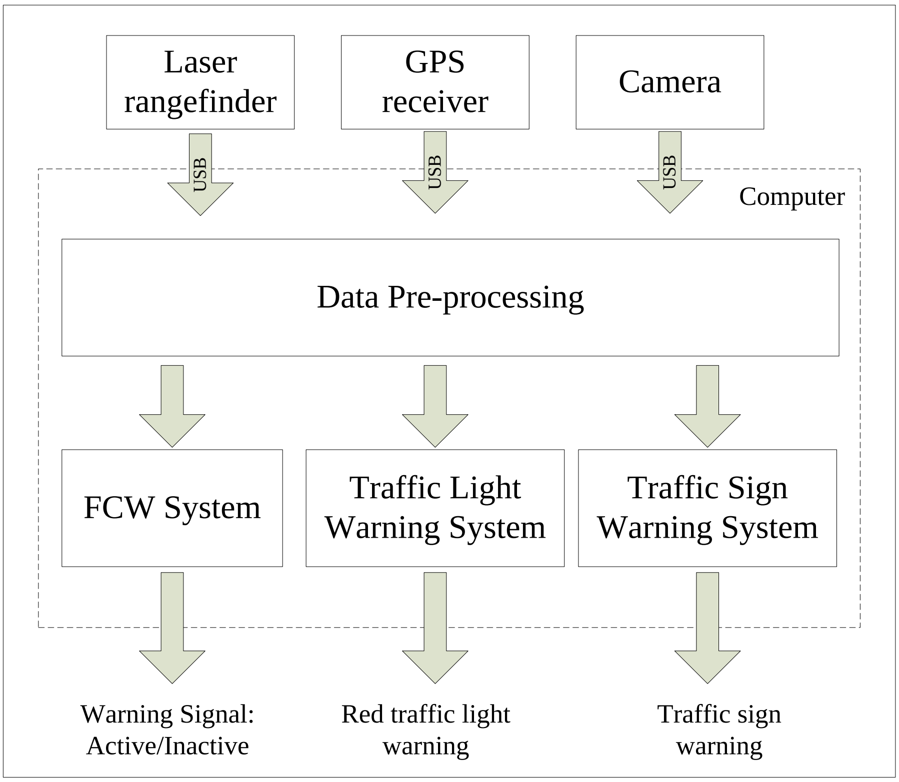


Figure 5.2 Block diagram of the combination systems.

5.3.1 Traffic Light Warning

In our work, we focus on detecting red lights based on their location on both vertical and horizontal stacks and the aspect ratio of the traffic light stack as shown in Figure 5.3. The machine vision algorithms were applied to extract the traffic lights in the image frame with a resolution of 320x240 pixels. The procedure of the traffic light detection consists of two main steps. First, the hypothesis generation is to accomplish the traffic light stack candidates. Then, the candidates will be verified in the hypothesis verification step.

Figure 5.3 Example of the traffic light characteristic: horizontal and vertical stacks.

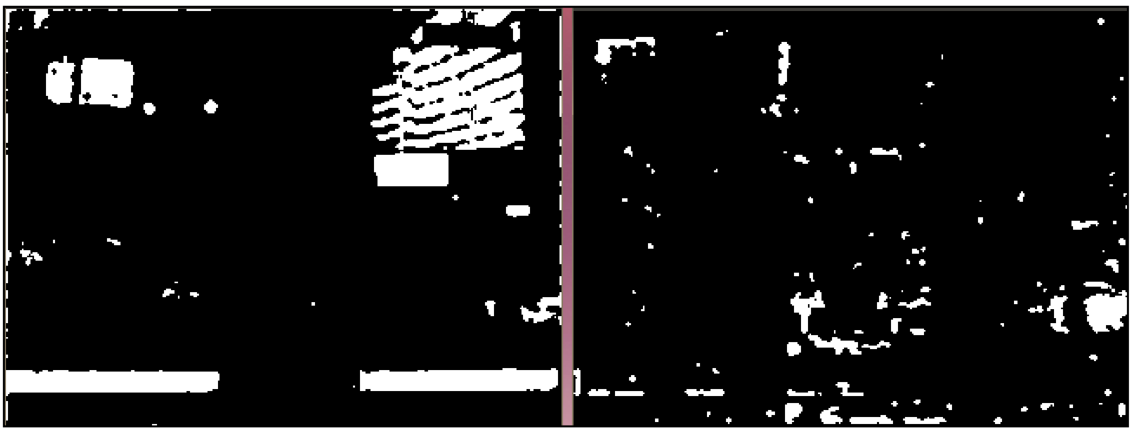
1. Hypothesis Generation

For detecting red traffic light, we performed color thresholding based on the HSV color model to extract red lights in the original image. The color thresholding is only applied with the Hue and Saturate channel image of the original image from the camera according to (5.1). The result is a binary image which white pixels (‘*1*’) indicate the red light candidates and ‘*0*’ means other colors. Figure 5.4 demonstrates the example of extracting the red lights. Figure 5.5 shows a binary image which contains the red light candidates.

$$Redlight_{(i,j)} = \begin{cases} 1 \,;\left(H_{(i,j)}>150\right)\cap\left(S_{(i,j)}>100\right) \\ 0 \,;\, otherwise \end{cases} \tag{5.1}$$

where *Redlight* is a binary image which white pixels (‘*1*’) indicate the red light candidates and ‘*0*’ means other colors.
H is Hue channel image of the original image.
S is Saturate channel image of the original image.
(i,j) indicates the pixel position.

(a)



(b) (c)

Figure 5.4 The example of red light thresholding: (a) Original image, (b) Saturate channel and (c) Hue channel after applying the red color thresholding.

Figure 5.5 Binary image of extracted red color.

After obtaining the binary image of *Redlight*, we removed noise by using median filter. Then, we applied the morphological operators (dilation and erosion) to fill the holes of the group of white pixels (candidates) in the binary image. Next step is the hypothesis verification. The candidates of traffic light will be verified in this step.

2. Hypothesis Verification

The hypothesis verification, the second step, performed template matching to further reject false positives and identify the types of traffic lights in the case of true positives. First, we applied the size extraction and elimination with the candidates of red and green lights from the hypothesis generation to reject the candidates that have undesired size. Then, we scoped the region of interest (ROI) around the each of candidates based on the aspect ratio of the traffic light stack. The aspect ratio was approximated to be 1:3 as shown in Figure 5.6. Finally, we applied the template matching to identify the types of traffic lights. The result of detecting the traffic light is shown in the bottom left with a red circle as in Figure 5.7.

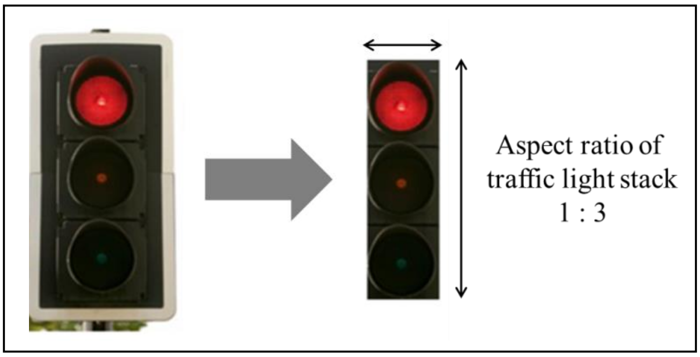


Figure 5.6 The aspect ratio of the traffic light stack.

Figure 5.7 Display of detecting the traffic light. The rectangles show the candidates of traffic lights and the red circle is the result of detection.

5.3.2 Traffic Sign Warning

The purpose of the traffic sign detection system is to make sure that the driver is aware of the presented traffic signs. It operates for level 2, in which the driver is warned to confirm that the driver obeys the signs. Generally, traffic signs are divided into two types: enforcement sign and warning sign. Moreover, each type of traffic signs can be differentiated from one another by noticing their color and shape. In Thailand, enforcement signs have red color and circle shape, and warning signs have yellow color and rectangular shape. Therefore, we observed traffic signs based on their visual characteristics. We initially constructed our traffic sign warning system with existing methods based on the image processing algorithm. The method of our traffic sign warning consists of two main stages: detection and recognition. Since the recognition stage need the prototype images for recognition, we designed our traffic sign warning to observe the 10 traffic signs as shown in Figure 5.8.

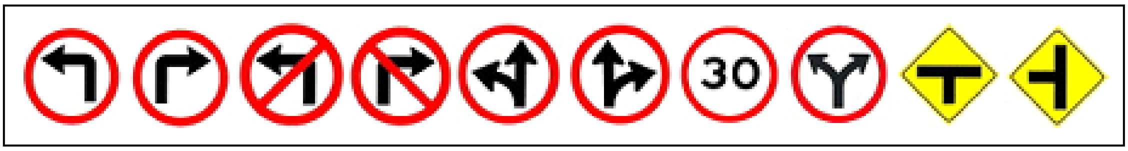


Figure 5.8 The traffic sign prototypes.

1. The Traffic Sign Detection

The traffic sign detection observes traffic sign candidates based on their color (red and yellow) and shape (circle and rectangle), locates them, and sends to the recognition stage. For the traffic sign detection, we firstly applied the color detection, and then the shape detection. We observed red and yellow colors of traffic signs by the color thresholding method with RGB color model, HSV color model, and red, green, yel from New Color Map [33]. The following equations are the conditions of color thresholding for red and yellow traffic sign, respectively.

$$Red_{(i,j)} = \begin{cases} 1 \;; (30 > H_{(i,j)} > 330) \cap (S_{(i,j)} > 0.5) \cap (red_{(i,j)} > (0.1 \times 255)) \\ 0 \;; otherwise \end{cases} \qquad (5.2)$$

$$Yellow_{(i,j)} = \begin{cases} 1 \ ;(25<H_{(i,j)}<65) \cap (R_{(i,j)}+G_{(i,j)}>0.1I_{(i,j)}) \\ \quad \cap \left(green_{(i,j)}<(0.1\times 255)\right) \cap (yel_{(i,j)}>(0.15\times 255) \\ 0 \ ; otherwise \end{cases} \tag{5.3}$$

where *Red* is a binary image result of the red color traffic signs detection and *Yelllow* is from yellow color traffic signs detection.
H and *S* are Hue and Saturate channel image of the original image.
R and *G* are Red and Green channel image of the original image.
I is the intensity channel image of the original image.
red, green and *yel* are the New Color Map channel images of the original image.
(i,j) indicates the pixel position.

After applied the color thresholding, the result is two binary images (*Red* and *Yellow*) which white pixels ('*1*') indicate the detected color and '*0*' means other colors. The examples of color thresholding of red and yellow traffic lights are illustrated in Figure 5.9 and 5.10. Then, the size extraction is applied to reject the undesired size of the white pixel groups in the *Red* and *Yellow* images before sending to shape detection step.

(a) (b)

Figure 5.9 Red traffic sign detection by color thresholding method.
(a) The original image, (b) The binary image of color thresholding result (*Red*).

(a) (b)

Figure 5.10 Yellow traffic sign detection by color thresholding method. (a) The original image, (b) The binary image of color thresholding result (*Yellow*).

For the shape detection, we will observe the circular shape in the *Red* image and the rectangular shape in the *Yellow* image because the enforcement signs have red color and circular shape, and the warning signs have yellow color and rectangular shape. For the circular shape, we found that the circular shape of traffic sign in the image frame is not perfectly round and it is another mathematical curve which is ellipse. Therefore, we extracted the circular shape from the groups of white pixels in the *Red* image by considering their size with the ratio of the major to minor axes between 0.8 and 1.2. After that, the extracted groups of white pixels are filled the holes and applied by template matching method to verify their shapes, and we also apply the template matching method to the groups of white pixels to find the rectangular shape in the *Yellow* image. The detected the groups of white pixels in the binary images are located to the original image and used as the candidates in traffic sign recognition. Figure 5.11 is the templates we used to match the circular and rectangular shape in the template matching method.

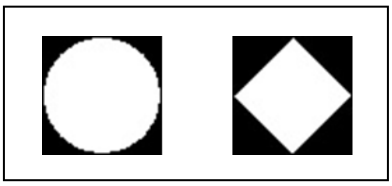


Figure 5.11 The circular and rectangular shape of the traffic signs for template matching.

2. The Traffic Sign Recognition

In the recognition stage, the candidates with their features, color, shape, location and size, are applied with Speeded-Up Robust Feature (SURF) [31, 32] and template matching method to recognize the type of traffic sign. We used OpenCV library for our image processing algorithms. First, we extracted the key points in traffic sign's prototype image, as shown in Figure 5.12, and used them as the database for SURF. The steps of traffic sign recognition are as follows. First, we extract the SURF key points of candidate image. Then, the SURF key points of candidate image are matched with the key points in the database. The large number of matching pairs indicates the best matching traffic sign. Although an advantage of SURF is invariant to rotation, there are some the traffic signs that have the same sign when they rotate such as yellow signs in Figure 5.12. We applied the template matching to the candidates to fix this. For template matching, we used gray scale images of traffic signs as the templates as shown in Figure 5.13. Finally, the result of SURF matching is compared to the result of template matching. If their results are the same traffic sign, the system will give a warning.

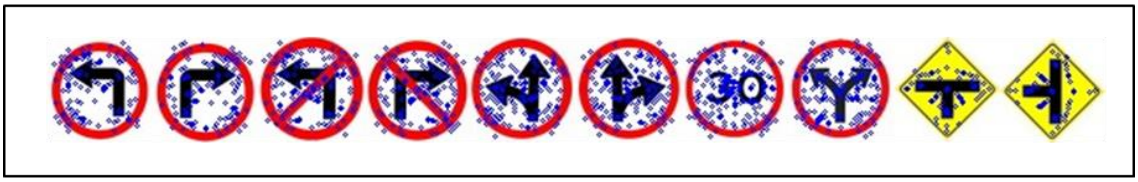


Figure 5.12 The key points of the of traffic sign's prototype image.

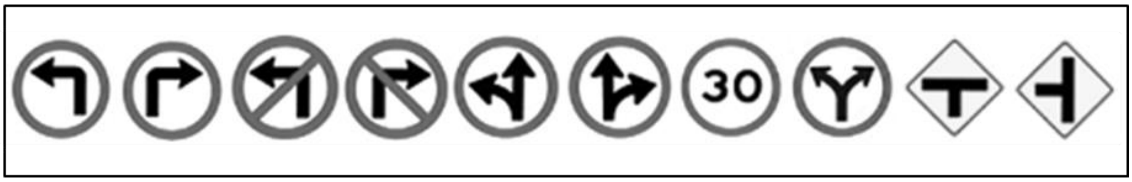


Figure 5.13 Traffic sign templates for template matching method.

5.3.3 Forward Collision Warning

For this combination system, we used our previous forward collision warning [34]. The purpose is to handle the critical moment in level 3 and help a driver keep a safe/proper distance from the cars in the front. The system will alert the driver when the system detects that the vehicle has high risk of collision based on the two-second rule. The system obtains data from three sensors to evaluate the risk of accident and identify the level of brake warning that is appropriate with different situations. The first sensor is a laser range finder used to measure distance between the host vehicle and the preceding vehicle in order to help a driver keep a safe following distance. A GPS receiver, the second sensor, was used to measure the vehicle's speed. The last one is a camera used to observe and extract driving environments by using the machine vision algorithm. The image sequence was used to extract four driving environments, day-night time, the car's turn movement, the density of cars on the road, and the brake lights of the car in the front. These measured quantities were combined using fuzzy logic in order to compute the level of warning. The output of the system is a brake warning level which has four levels ranging from 0 to 4, where level 0 means safe. Level 1 is the situation that is mild risky. Level 2, 3 and 4 means risky, quite dangerous and dangerous respectively.

5.3.4 The Warning System Assessment

This combination of the traffic light warning, the traffic sign warning and the FCW were implemented on a single vehicle and designed to operate concurrently. For testing purpose, each warning system was independently tested in real driving to avoid warning conflict with each other.

The collision warning system was tested in real driving situation in a city road, for two hours: one hour in daytime and one hour in nighttime. The purpose of the experiments is to evaluate the system performance by comparing the warning output with the subsequent brakes by the driver. From the experimental results, we achieved the accuracy of 75.39% in daytime and 71.92% in nighttime.

For the traffic light warning, we tested this subsystem with 50 image frames recorded from real driving situation to evaluate the detection accuracy of hypothesis generation and hypothesis verification. The 50 input images consist of 23 positive events and 27 negative events. The images of positive event have red traffic lights from different distances and negative events are images without red traffic lights. The result extract red lights in the hypothesis generation were then used as the candidates in hypothesis verification.

Table 5.1 Result of traffic light warning: Hypothesis generation

Event	Number of input	Correct	Fault	
			Positive	Negative
Positive	23	15	1	7
Negative	27	25	2	-
Total	50	40	3	7
Percent %	100.00	80.00	6.00	14.00

Table 5.2 Result of traffic light warning: Hypothesis verification

Event	Number of input	Correct	Fault	
			Positive	Negative
Positive	15	12	-	3
Negative	3	1	2	-
Total	18	13	2	3
Percent %	100.00	72.22	11.11	16.67

For the traffic sign warning, it was tested 50 image frames recorded from real driving situation which consist of 20 images with traffic signs (positive events) and 29 images without traffic signs (negative events). The accuracy of traffic sign detection and recognition are shown in Table 5.3 and 5.4.

Table 5.3 Result of traffic sign warning: Traffic sign detection

Event	Number of input	Correct	Fault	
			Positive	Negative
Positive	20	7	-	13
Negative	29	26	3	-
Total	49	33	3	13
Percent %	100	67.35	6.12	26.53

Table 5.4 Result of traffic sign warning: Traffic sign recognition

Event	Number of input	Correct	Fault	
			Positive	Negative
Positive	7	5	-	2
Negative	3	3	0	-
Total	10	8	0	2
Percent %	100.00	80.00	0	20.00

From the results, we found that the traffic light warning achieves the accuracy of detecting red traffic lights by 76% which is 80 % for hypothesis generation and 72 % for hypothesis verification as shown in Table 5.1 and 5.2. Most errors were negative faults because traffic lights are quite small in image and distance between camera and traffic light also results to the size of the traffic lights in image. For the traffic sign warning, the subsystem gives accurate warnings by approximately 59% which is the accuracy of traffic sign detection 67.35% and the accuracy of traffic sign recognition 80%. We found that most errors were negative faults because traffic signs were occluded by trees or other object and some traffic signs were pale. For the FCW, we used our previous FCW system which was completed and tested in real driving situation [34]. The system achieved the accuracy of 75.39% calculated by comparing the warning output with the subsequent brakes by the driver.

The combination system of FCW, the traffic light warning and the traffic sign warning was initially implemented to provide warnings covering level 2 and 3 of the multilevel of crash prevention. The performances of subsystems show that they archived operating in real driving situation. However, the traffic environment is always complex which results the performance of traffic light and traffic sign detection decrease. Therefore, we then tried adding a location-based warning (LW) which generates warnings from static environment. The warnings from LW system cover traffic light and traffic sign warnings because the traffic lights and traffic signs are located near intersections and accident-prone locations.

5.4 Improvement of Warning Lag Time by Combination of FCW and Location-based Warning

To demonstrate the improvement of the warning lag time using the vertical approach, we added more functionality to the traditional FCW system according to the five levels of crash prevention described previously. Level 2 is the target because it is the precursor to a crash. The warning can be obtained from clues such as speeding and the presence of traffic signs or traffic lights. To verify our hypothesis on the vertical approach, we chose a simple location-based warning system (LW) for this purpose. The LW is a warning system that operates at level 2 and its warnings are generated from static environments. It warns the driver when the driver drives toward a dangerous spot (see Figure 4.14) such as an intersection or a sharp curve at high speed. The vehicle may go past the intersection without a problem if there is no car around. However, this move has a high risk. If there is another car approaching from the side, the situation will turn from level 2 into level 3, and the driver may have to suddenly apply the brakes. Therefore, warning when approaching an intersection is considered warning on level 2 because the driver has placed himself into an open condition by driving too fast.

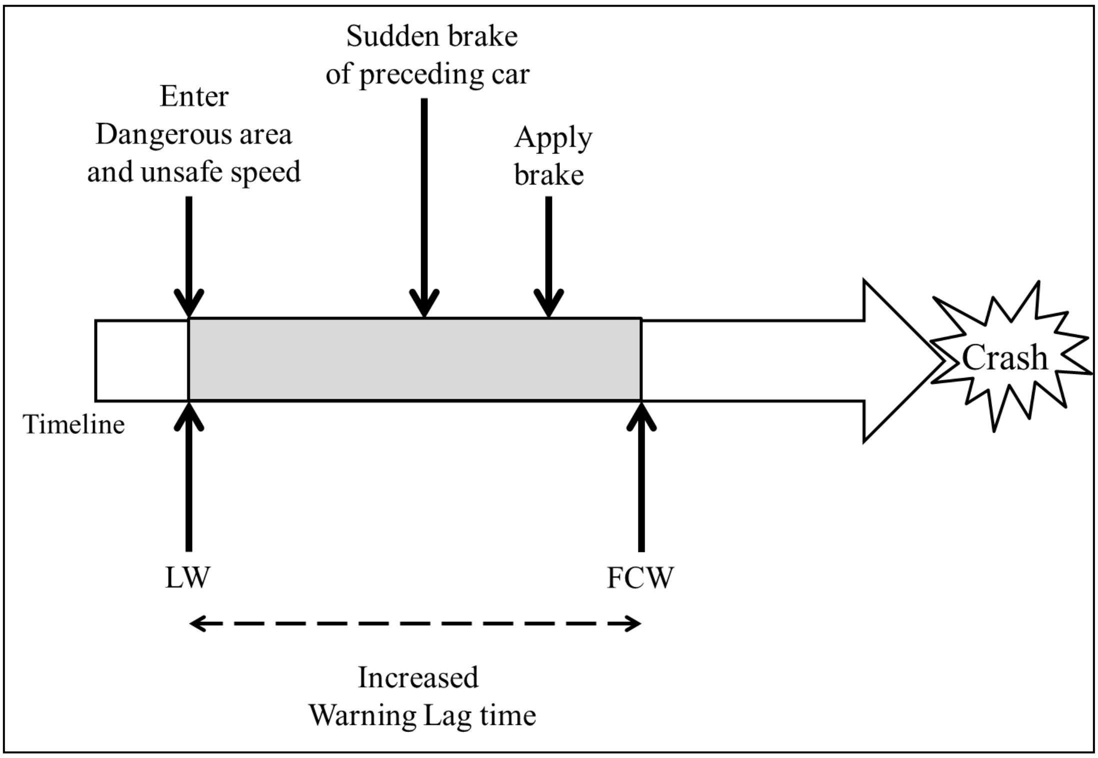


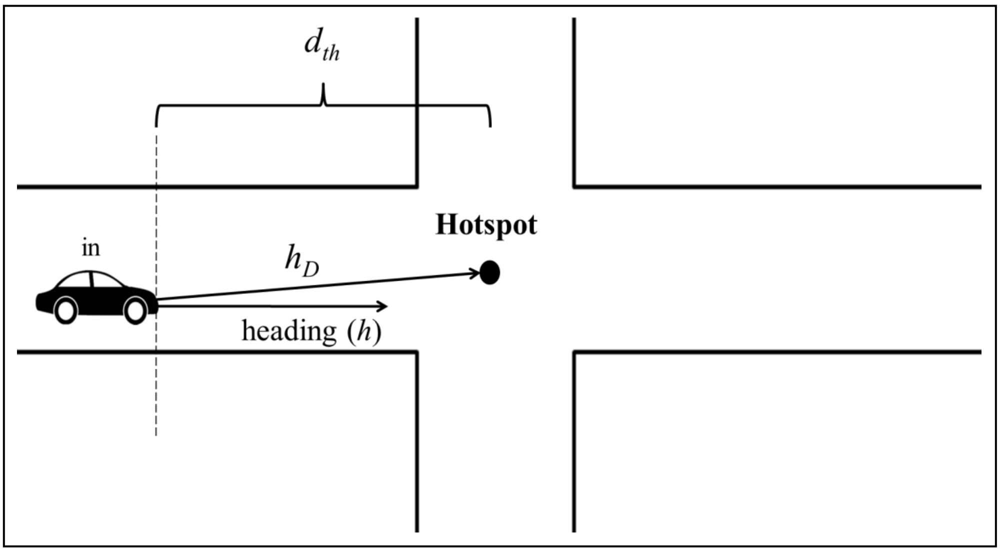
Figure 5.14 Increased warning lag time by adding Location-based Warning.

5.4.1 Added Functionality: Location-based Warning

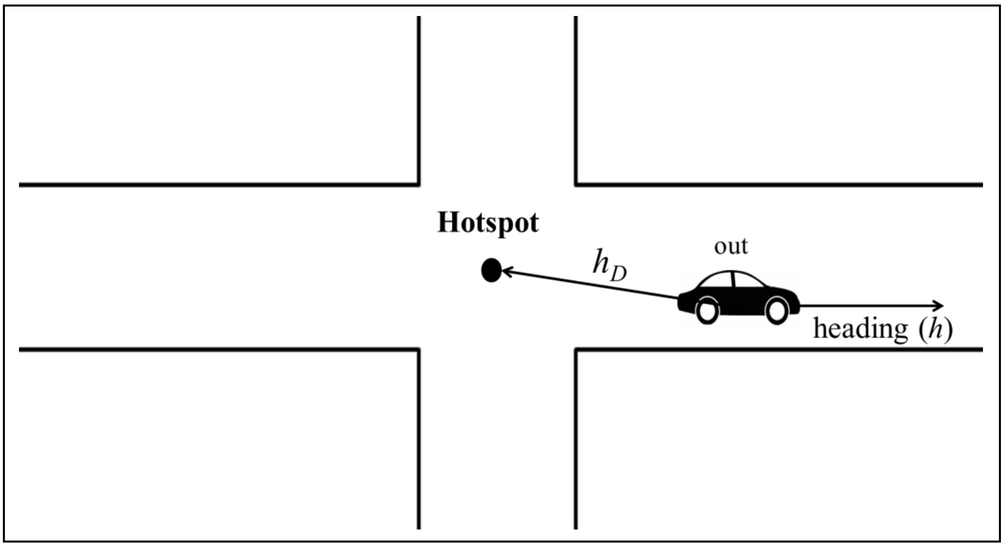
In the LW system, all accident hotspots were gathered together as points in a database. Each data point consists of latitude, longitude, speed limit and heading. The car's geolocation from a GPS will be compared to every data point nearby. If the location is close enough, the current velocity (v) exceeds the speed limit (v_{th}), and the heading (h) of the vehicle points toward a dangerous place, then a system warning will be issued (LW is active). The warning conditions for the LW system we used is as follows.

$$LW = \begin{cases} Active(1) & , \ (d < d_{th}) \wedge (v > v_{th}) \wedge (|h - h_D| < h_{th}) \\ Inactive(0) & , \ otherwise \end{cases} \tag{5.4}$$

The speed limit (v_{th}), and the range of warning distance from hotspots (d_{th}) is 8.33 m/s (30km/h) and 30 m., respectively. h_D is the angle from the vehicle position, used as an origin point, to the nearest hotspot in the database. If the absolute difference of h and h_D is not over h_{th}, it means that the car is moving toward the hotspot. As illustrated in Figure 5.15, we differentiate a vehicle direction that is going into or going out of a hotspot by considering a vehicle heading (h) and an angle from the vehicle position to the nearest hotspot in the database (h_D). When a vehicle is going into a hotspot, h and h_D are in the same direction (see Figure 5.15 (a)). In contrast, h and h_D are in the opposite direction when a vehicle is going out of a hotspot as shown in Figure 5.15 (b).



(a) The vehicle is moving toward the hotspot.



(b) The vehicle is going out of the hotspot.

Figure 5.15 Warning Condition of Location-based Warning System

5.4.2 Combination System of FCW and LW Systems

To demonstrate that the multifunctional warning can help increase the warning lag time, we performed an experiment by combining FCW with LW. The standard FCW system that we intended to improve is based on a simple formula of a vehicle kinematic model, as shown in (5.5). More complex models were not our preference, because they involve more quantities that are hard to measure in a real driving environment. We calculate the estimated time to collision (T_s) from the current position of the host car to a front car by using the current velocity of the host vehicle (v) and the current following distance (d_f). The vehicle's acceleration and the velocity of obstacle/car in front are assumed to be zero in order to make the model as simple as possible.

$$T_S = \frac{d_f}{v} \tag{5.5}$$

The warnings are determined based on the two-second rule [27], which is a concept from defensive driving techniques. The rule suggests that a driver has to keep at least 2 seconds of following distance from the car in the front. The warning is active when T_s is less than this 2-second threshold. However, we found that 2 seconds was not suitable for roads in Bangkok, Thailand, whose drivers have quite aggressive driving habits. Therefore, we reduced the threshold down to 1.6 seconds. This number came from trial and error in real driving experiments, in which we found that this value is the most suitable. The system repeatedly computes the T_s value according to the formula below, and gives a warning if the value is less than the threshold.

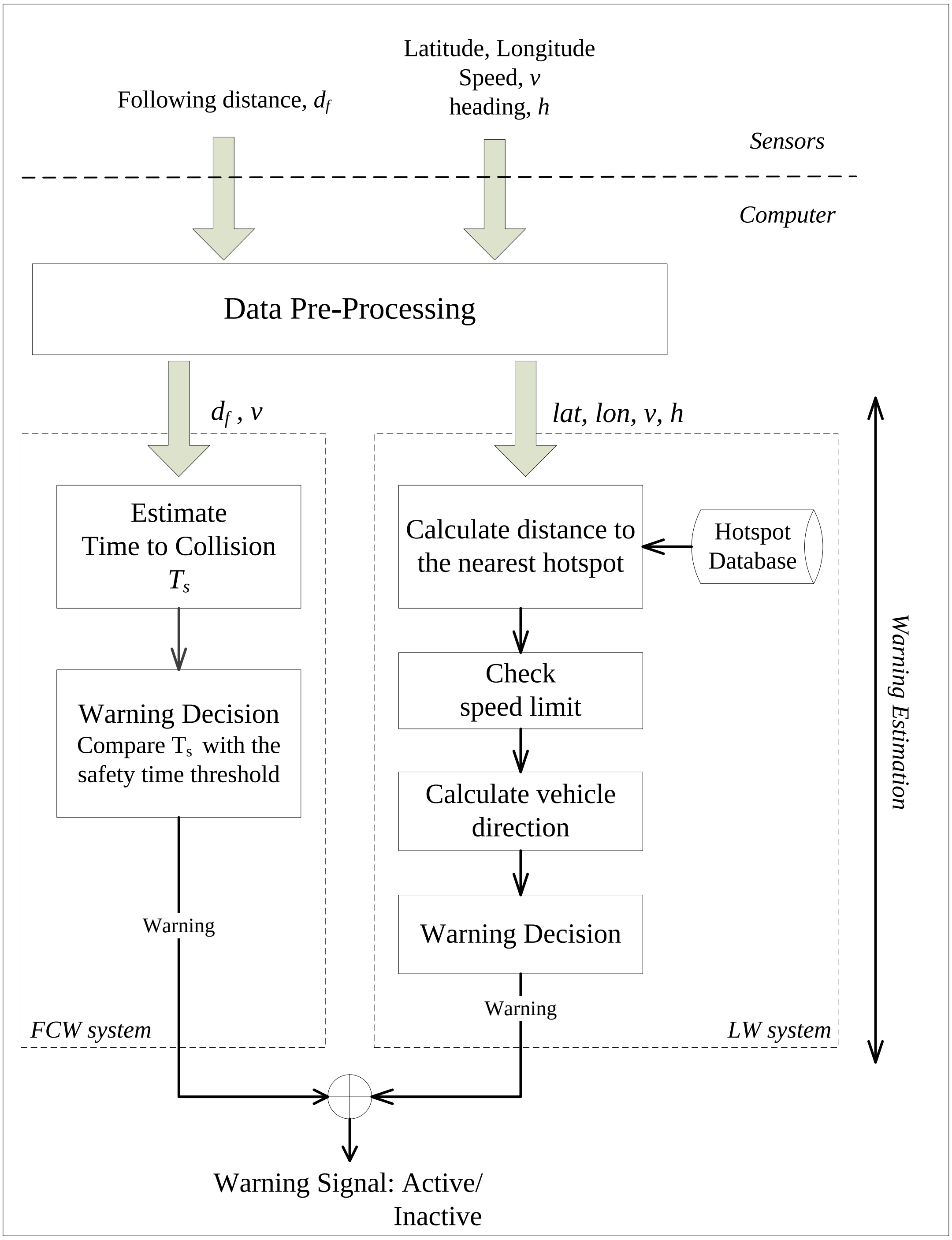


Figure 5.16 The combination of FCW and LW Systems.

The block diagram of the combination of FCW and LW systems is illustrated in Figure 5.16. The two systems run separately and concurrently. All data needed in the FCW and LW systems are acquired from the sensors and processed by computer to estimate the warnings. In the main computer, all data from sensors are firstly pre-processed to extract the data from the data packet before used to estimate warnings. Then, the data are sent to each FCW and LW system to estimate warnings. The final output is the result of the OR logic operation of both FCW and LW systems.

5.4.3 System Components

Our system utilized a laser rangefinder and a GPS receiver together, as shown in Figure 5.17 and 5.18. These two sensors were used to obtain driving information for the FCW and LW. The system was designed to operate on both FCW and LW systems. Moreover, we used a force sensing resistor or FSR (Figure 5.19) to measure the force applied to the brake pedal which represents the actual brake of the driver. This sensor was used only for performance evaluation purpose. The laser rangefinder was used to measure the distance between the test car and the preceding car. The GPS receiver was used to obtain the vehicle status, i.e., speed, vehicle position (latitude and longitude) and heading.

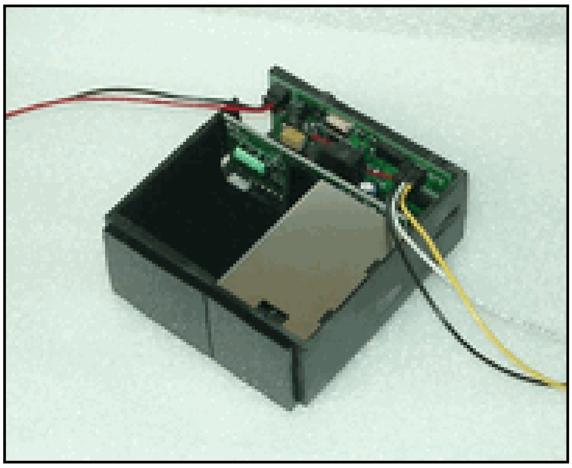


Figure 5.17 Laser rangefinder module.

Figure 5.18 GPS receiver.

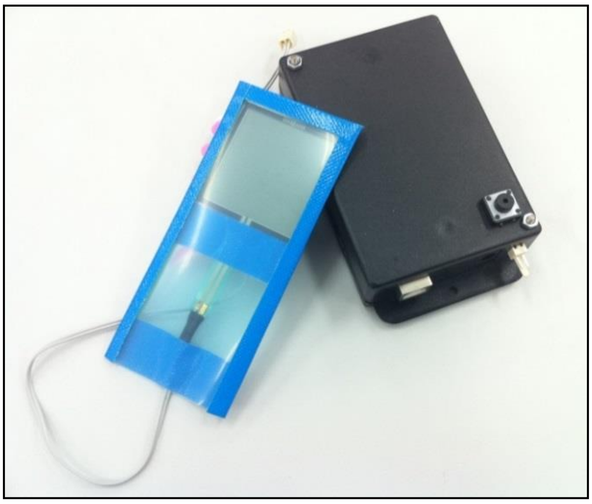


Figure 5.19 Force Sensing Resister (FSR).

The block diagram of system components is shown in Figure 5.20. Data from all sensors are sent to the main computer via USB connections to process and record the data. Since the tests we performed were blind tests. The warning signals were not sent out to the driver but the warning signals were recorded to evaluate the system performance, while running the tests.

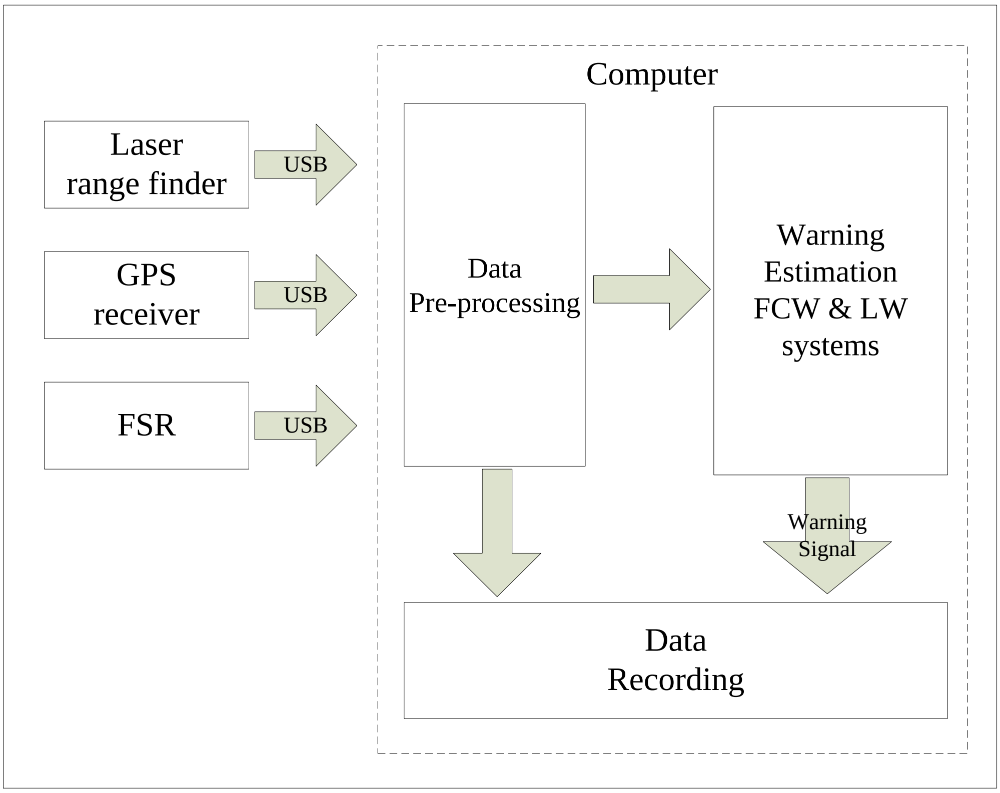
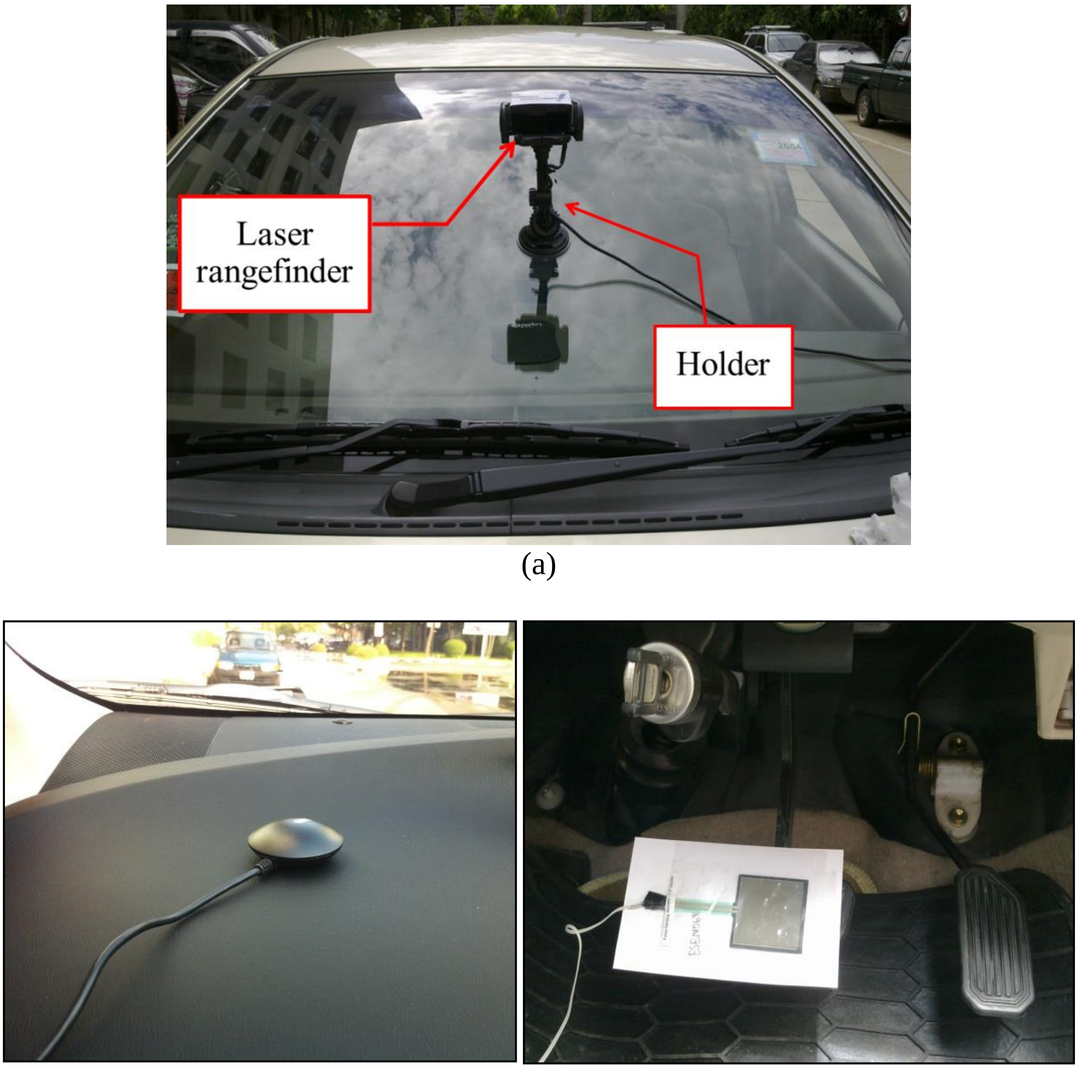


Figure 5.20 Block diagram of the system components.

5.4.4 Experiments and Results

5.4.4.1 Real Driving Test Setup

We setup a test car in order to perform our systems in real driving. We equipped three sensors on the test car. The first sensor is a laser rangefinder mounted at the car's windshield with a holder and pointed forward. The second sensor is a GPS receiver. We placed the GPS receiver on the vehicle's console. The last one is a force sensing resistor (FSR). We equipped the FSR on the brake pedal to obtain the actual brake actions of the driver. The force sensor is used only for performance evaluation and is not needed for normal operation of the warning system. The installation of three sensors on the test car is demonstrated in Figure 5.21.



(a)

(b) (c)

Figure 5.21 The installation of the sensors on the test car.
(a) Laser Rangefinder on the vehicle's windshield,
(b) GPS receiver on the vehicle's console,
(c) Force Sensing Resistor on the brake pedal.

Figure 5.22 The main computer for processing and recording the data.

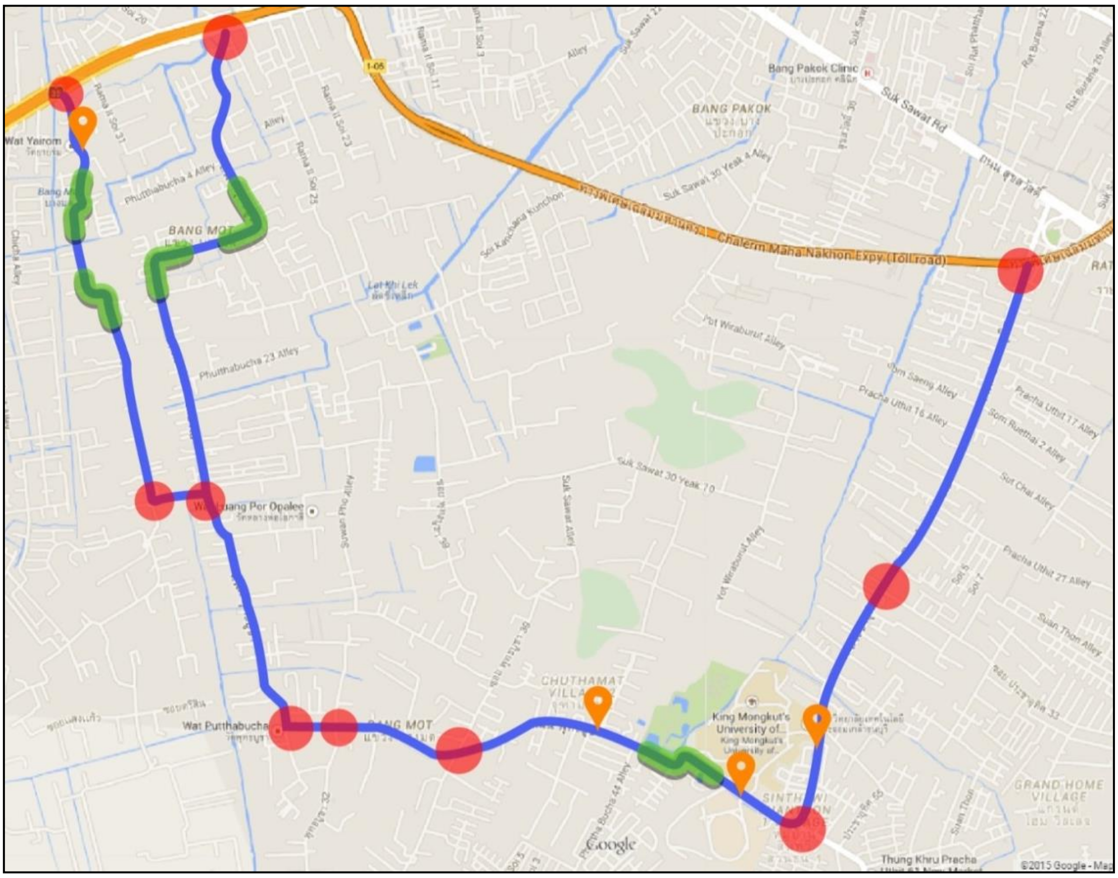


Figure 5.23 Map of the test route.

The purpose of this experiment is to demonstrate that the warning lag time can be increased by enhancing the functionality of an FCW system by incorporating an LW system. To assess the performance of the combination of the FCW and LW systems, we performed two tests on the same route with real driving situations: the LW system test and the combination system test. The route was city roads with mild traffic and hotspots based on yellow traffic warning signs. The accident hotspots consisted of 28 dangerous locations including intersections and dangerous curve roads. Before performing the tests, the locations of hotspots on the test route were collected to create the database for LW system. As shown in Figure 5.23, it is the route that we performed our experiments. The equipped vehicle was driven along the blue route in the map passing through intersections, dangerous curve roads and important places which are marked by circles, curve lines and map pins, respectively. For the important places, we selected from the number of vehicles entering/ leaving such as markets, residence areas, university and school. All tests we performed were blind tests. The driver drove an FCW equipped vehicle, but the warning sound was disabled. Therefore, the driver applied brakes without any bias from the warning systems.

5.4.4.2 Location-based Warning System Test and Result

The first test is for evaluating the performance of LW system alone. An LW equipped vehicle was driven on the route for 2 rounds. During these tests, no false alarm was observed. There were 23 hotspots at which the LW system generated warnings because the equipped car approached the hotspots under the warning conditions of LW system.

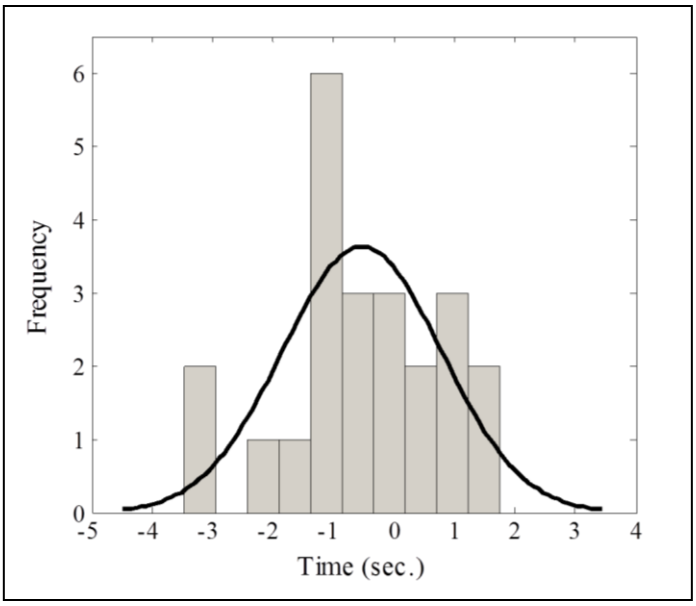


Figure 5.24 Histogram with normal distribution of the time difference between the warning signals of LW system and the actual brakes.

The results shows that the 23 warnings from LW took place before the actual brakes with an average time of 0.53 sec. and $\sigma = 1.29$ sec. The histogram in Figure 5.24 demonstrates the distribution of the time difference between the issues of LW signals and the actual brakes from the driver. We constructed a 10-bin histogram with a bin width of 0.5 sec. Most of the results indicated that the LW signals were issued earlier than the actual brakes. However, there were some cases where the equipped car ran toward intersections and curves at high speed and the driver was aware of the traffic lights and other cars near the hotspots, so the actual brakes occurred quite early when compared to the LW signals.

5.4.4.3 Combination System Test and Result

The second test is to evaluate the performance of FCW system enhanced by adding a warning system. We tested the FCW system with LW and the FCW system without LW in real driving situations on the same route. The results from the test show a comparison of the warning output from the FCW system without LW system (FCW), the warning output from the combination system of FCW and LW (FCW+LW), and the actual brakes from the driver. For performance evaluation, we determined two performance parameters, which are the warning lag time and the accuracy of the system warning. The accuracy of the system warning is the comparison result between the system warnings and the actual brakes, as shown in Figure 5.25. After determining the warning lag time, the time-scale of the system warnings was shifted by the warning lag time before calculating the accuracy to measure the system warnings corresponding to the actual brakes.

Table 5.5 The Results of Performance Evaluation of The FCW system without and with Location-based Warning System

Warning System	**Warning lag time (s)**	**Accuracy of system (%)**		
		Correct	**False positive**	**False negative**
FCW	+1.69	75.43	11.95	12.62
FCW + LW	+1.38	75.39	12.48	12.13

(-) and (+) means the warning lag time happens before and after the actual brake respectively.

From Table 5.5, the output from FCW system has an average warning lag time of 1.69 sec. from the actual brake, whereas the warning lag time of the combination system of FCW and LW is 1.38 sec. These results indicate that enhancing the FCW system with an LW system can help improve the warning lag time by 0.31 sec. We also calculated the timing performance of LW system alone comparing with FCW near the hotspots. The result shows that LW system provided warning signals before the actual brake at the hotspots with an average warning lag time of 0.15 sec. This result demonstrates that the FCW system with an LW system is improved because of adding the LW system. The example of signals recorded while testing is shown in Figure 5.25 to explain that adding the LW to the FCW results improving the warning signals. Considering the signals between time 2000 to time 2500 recorded near a hotspot, the actual brake (Figure 5.25 (a)) and the signals from FCW without LW (Figure 5.25 (b)) happened around the same time whereas the waning signals from LW of the combination system of FCW and LW (Figure 5.25 (c)) came before the actual brake and the warning signals from FCW without LW.

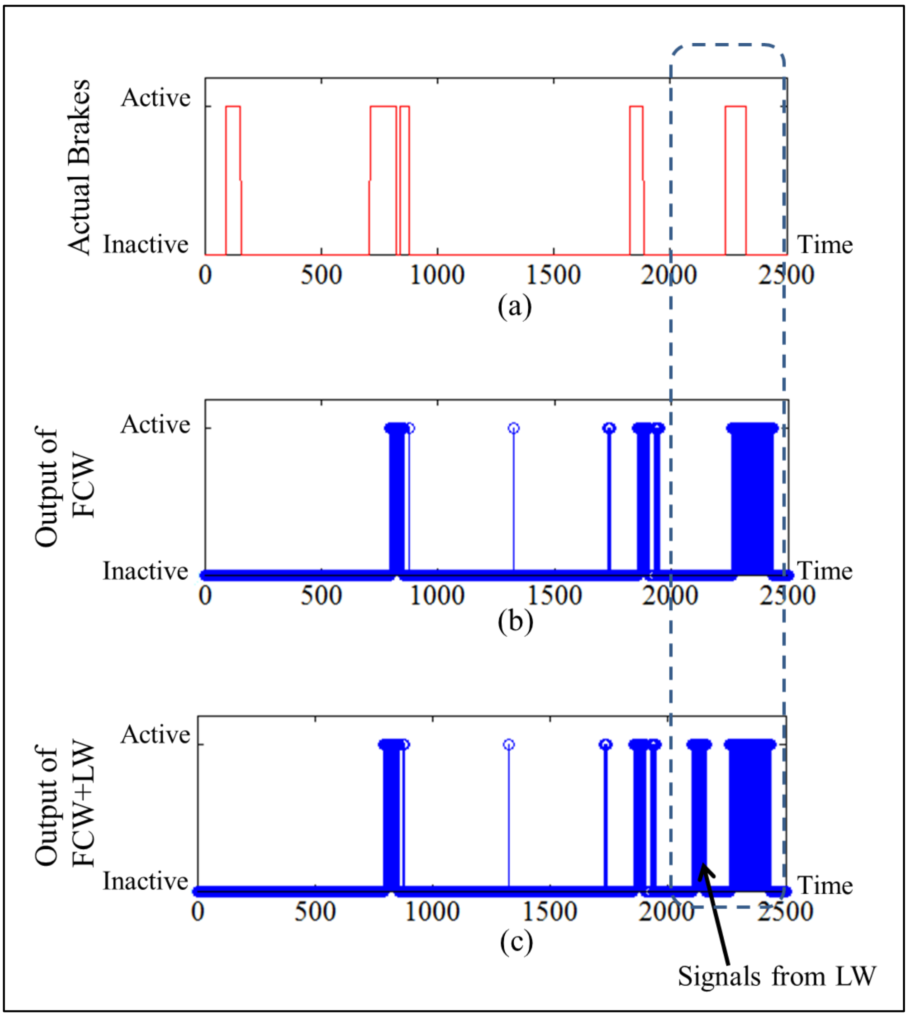


Figure 5.25 Example of The comparison of (a) the actual brakes with (b) the output from the FCW system and (c) the output from the combination FCW and LW systems.

CHAPTER 6 HORIZONTAL APPROACH: DISTRIBUTED SENSING

This chapter describes the second approach to improving the warning lag time, by using distributed sensing. We call it the horizontal approach because it expands the warning functionality by using data from the surrounding vehicles. In this chapter, we first examine the type of data that should be shared from other vehicles to enhance the performance. Next, we present the system design and the machine learning technique we used. Lastly, the experiments are described. We performed our systems on two vehicles which were driven following each other in a real driving environment.

6.1 Sharing Data among Vehicles

Distributed sensing requires a communication channel among vehicles. Therefore, the work in cooperative vehicle safety system can be divided into two fields: communication and intelligent safety. Our work focuses on the intelligent safety part. We make an assumption that the communication channel is nearly perfect with minimum delay because we transmit only a small amount of data compared to the bandwidth of current communication technology. However, we leave an exploration of the communication issue to a future work for researches in inter-vehicle communication field in the case of transmitting large data.

6.1.1 Relative Positions around The Host Vehicle

Distributed sensing relies on data transmitted from surrounding cars to the host car. We used standard Wi-Fi in ad-hoc mode. Each vehicle is supposed to broadcast its state and sensor information periodically. Data from vehicles at various positions have different impacts on our car. For example, a brake signal from the car in the front is more significant than a brake signal from the car in the rear because the first action causes a danger to approach the host car. Therefore, we divided the data from the surroundings according to their relative position into eight zones, as shown in Figure 6.1. The three columns represent the left lane, middle lane, and right lane, and the three rows are the front, middle, and back positions. This will cover the surrounding area of the host vehicle. The data that are shared among vehicles will be tagged along with the GPS data of each vehicle. The host vehicle can determine the location that the data comes from by comparing with its position and heading. When data can come from all around, the amount of data can be tremendous. We have to limit and focus our study for the situation that two vehicles follow each other on the same lane, i.e., the FF case only. This is because the direct front vehicles have the most impact on an accident. The significance of data from other zones is left for further investigation.

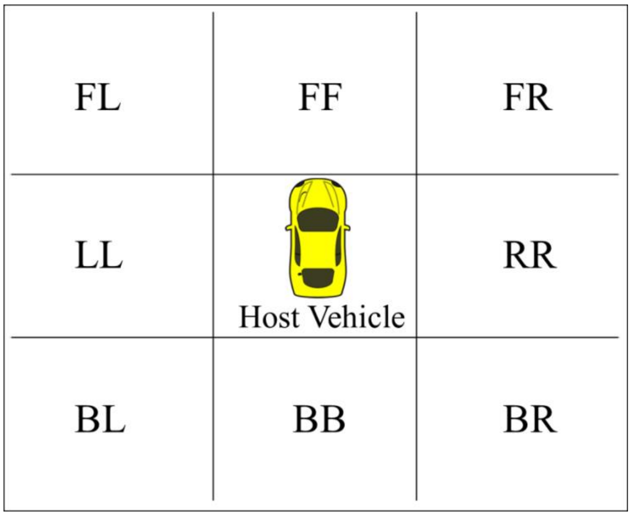


Figure 6.1 Eight zones of the relative positions around the host vehicle.

6.1.2 Significant Sharing Data between Vehicles

In driving situation, there are a lot of data that can be obtained and used to evaluate safety warnings. We analyze and categorize the data to discard unnecessary data types. We divided the data into two main groups according to types of warnings which are static object warning and dynamic object warning.

1. The static object warning

The static object warning is about traffic environments which certainly exist on roads such as traffic signs and dangerous places. These data is unnecessary to be shared to other vehicles.

2. The dynamic object warning

The dynamic object warning is about road, traffic and vehicle data that always change. These data can be divided into three groups; vehicle data, environment data and processed data.

- *Vehicle data* is the information of vehicle status such as actual brakes, speed, position and heading.

- *Environment data* is the data obtained from traffic and road around the host vehicle such as pedestrians, other vehicles, following distances, traffic lights and brake lights.

- *Processed data* is the output of safety warnings such as forward collision warning, location-based warning, lane departure warning, etc. This data can be processed in each vehicle.

From data categorization above, we found that the vehicle and environment data of the dynamic object warning are important for estimating a collision risk. However, these data are various and we do not know which types of data significantly impact on the functionality of FCW. Therefore, Principal component analysis (PCA) is used to identify the most significant dimension in order to reduce data dimensions.

6.2 Machine Learning Technique for FCW Prediction

We propose the horizontal approach aiming to demonstrate that the proposed method helps increase the timing performance. In order to verify this claim, we use a supervise learning approach on the data to compare two FCW setups; FCW of a single host vehicle (FCW_{HV}) using only its own data and FCW of the host vehicle with data from the preceding vehicle (FCW_{HV+PV}) as shown in Figure 6.2.

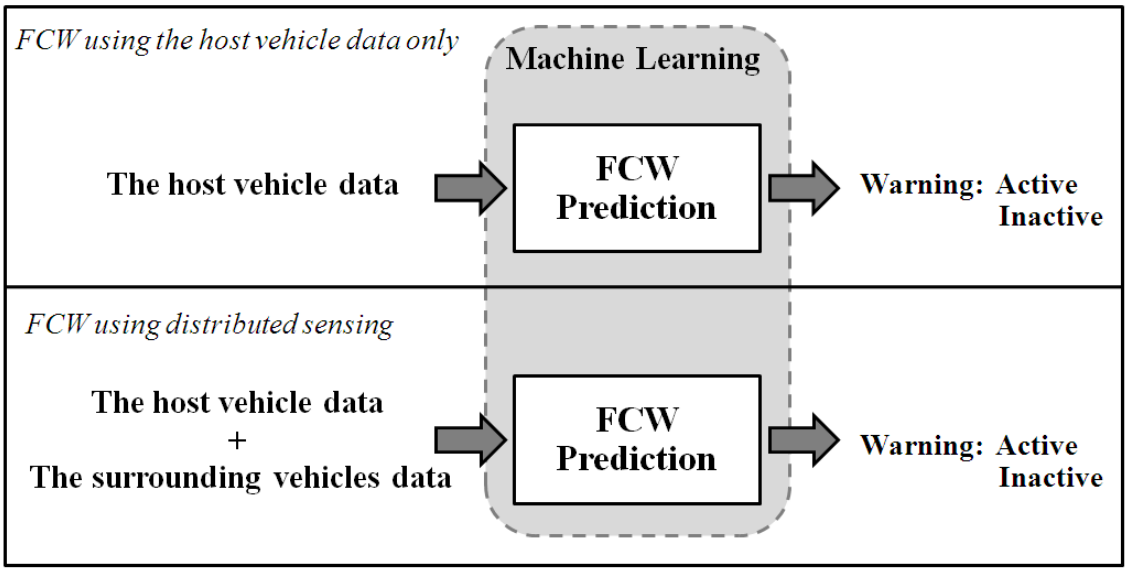


Figure 6.2 Construct FCW systems with the Machine Learning.

The data from the surrounding vehicles broadcasted to the host vehicle come from several types, and it may be a large amount of vehicle data. In addition, the use of other vehicles' data for FCW is still new and has no standard practice. This creates a problem of how to appropriately set a warning rule from these data such as the vertical expansion. To create unbiased rules, we employed standard machine learning techniques to automatically create a model for the warning signal. Moreover, we perform a dimension reduction to help process the increased amount of data from the surrounding vehicles.

6.2.1 FCW Prediction Using PCA and SVM

We constructed the FCW systems that predict warnings based on the same algorithm, machine learning as shown in Figure 6.3. The learning approach is divided into two main stages; reduce dimensions stage and classification stage. In the reduce dimensions stage, the principal component analysis (PCA) [29, 41] was first used in order to reduce the data dimensions before applying machine learning. . PCA quantifies the importance of each dimension before used in data classification. Then, the data were passed into the classification stage. Initially, we assume that the input data of our system is linearly separable. Therefore, the support vector machine (SVM) [30, 39, 40] is employed to perform linear classification. The SVM is a supervise learning that predicts which of two possible classes forms the output for each given input data set. In this stage, we implement SVM to train and classify the driving data set. For our system, the input data set will be classified as active or inactive warning.

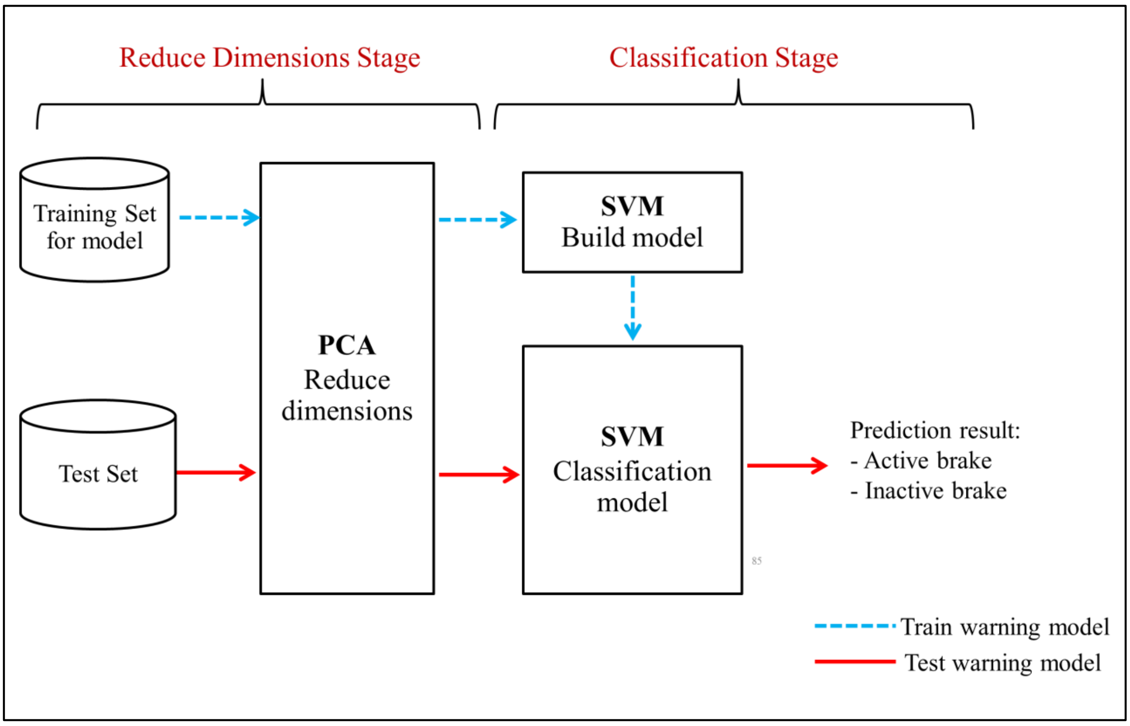


Figure 6.3 Block diagram of the overall process of horizontal approach.

6.2.2 Principal Component Analysis

The principal component analysis (PCA) [29, 41] is a reliable and simple statistical technique for handling high dimensional, noisy, and correlated measurement data by projecting the data onto a lower dimensional data. The PCA converts correlated variables into uncorrelated components by identifying directions in the data where the variation is at a maximum or the most spread out, called components. Below are several steps to compute the scores of principal components.

1.) Calculate covariance matrix of the normalized data set. This data set is the input data set which is formed in matrix $\boldsymbol{X}$ and scaled to [0,1].

$$\boldsymbol{S} = cov(\boldsymbol{X}) = \left(\frac{1}{m-1}\right) \boldsymbol{X}^T \boldsymbol{X} \tag{6.1}$$

Then, we calculate eigenvalues (λ) and eigenvectors ($\boldsymbol{Z}$) of covariance matrix $\boldsymbol{S}$. The eigenvalues is computed by (6.2), where I is identity matrix. Then, each eigenvalue is used to calculate the corresponding eigenvector of covariance matrix $\boldsymbol{S}$ (6.3).

$$det(\boldsymbol{S} - \lambda I) = 0 \tag{6.2}$$

$$(\boldsymbol{S} - \lambda I)\boldsymbol{Z} = 0 \tag{6.3}$$

2.) Equation (6.4) is used to calculate the scores ($\boldsymbol{p}$) on each principal component (PC).

$$\boldsymbol{p} = \boldsymbol{X} \cdot \boldsymbol{Z} \tag{6.4}$$

where $[\boldsymbol{p}]_{mxn}$ is a matrix of principal components scores, $[\boldsymbol{X}]_{mxn}$ is matrix of input data set (scaled original data matrix) and $[\boldsymbol{Z}]_{mxm}$ is a square matrix of eigenvectors.

Each eigenvalue indicates the variance of each principal component. The first principal component contains the most percentage of total variance of the data. Then, the scores on chosen principal components are used as input of SVM system.

6.2.3 Support Vector Machine

Support Vector Machine (SVM) [30, 39, 40] is a supervise learning and one of the most popular classification methods. The goal of SVM is to build a model based on the training data and use the model to predict the class of the test data. The SVM procedure has two main steps which are training model and test model. The training model step is to obtain a set of support vectors and the minimization of the weight vector for the model. The training data set contains one target value (the class labels) and features or observed variables. Then, the model is used to predict the class of the test data set which is given only features or observed variables.

In our work, we used SVM to produce a forward collision warning rules for a binary classification (two-class), inactive (-1) warning and active warning (1), because SVM can autonomously build the model without any bias. We construct the FCW model based on the assumption that the input data of our system is linearly separable. Thus, linear kernel was chosen as a classifier. The general form of a hyperplane for separating the data into two classes is usually represented by (6.5) and the decision function of the hyperplane is a shown in (6.6) which is used as a classification rule. A data point is identified to the positive class (1) if $f(p) \geq 0$, and to the negative class (-1) for otherwise.

$$\langle \boldsymbol{w}, \boldsymbol{p} \rangle + b = 0 \tag{6.5}$$

$$f(\boldsymbol{p}) = \langle \boldsymbol{w}, \boldsymbol{p} \rangle + b \tag{6.6}$$

where $\boldsymbol{w}$ is weights b is a bias of SVM which are used to classify each data point of vector $\boldsymbol{p}$. $\langle\, , \rangle$ indicates the inner product of two vectors.

6.3 System Design Based on Horizontal Approach

We implemented the FCW system on the host vehicle (HV) that uses data from its own sensors together with data from sensors of the preceding vehicle (PV) via wireless communication. Our system is designed according to its functionality as shown in Figure 6.4.

- **Sensors:**
  We used the same sensors as using in the vertical approach to obtain raw data of the vehicles. A GPS receiver used to obtain the vehicle's status. A laser rangefinder is used to measure distance from the preceding vehicle. We obtained the actual brake actions of the driver by using the FSR equipped on a brake pedal for performance evaluation purpose. All data from the sensors are sent to the computer through USB connections to process and record.

- **Data Pre- processing:**
  Data pre- processing operates in the main computer. The data pre- processing will extract the usage data from the sensors and the external data from another vehicle before sending to the FCW estimation. For the PV, all needed data from sensors are extracted and transmitted to the HV via wireless connection.

- **Wireless communication:**
  The HV and the PV directly communicate with each other over peer-to-peer wireless network. The PV needs to send the distance from the vehicle in front, PV's position (latitude and longitude), heading, speed and actual brake of driver in a format understood by both vehicles.

- **FCW estimation:**
  The FCW estimation is implemented on the HV only. All required data from the data pre-processing are sent to the FCW estimation to assess the collision risks and provide warnings. In the test, all data were recorded for performance evaluation.

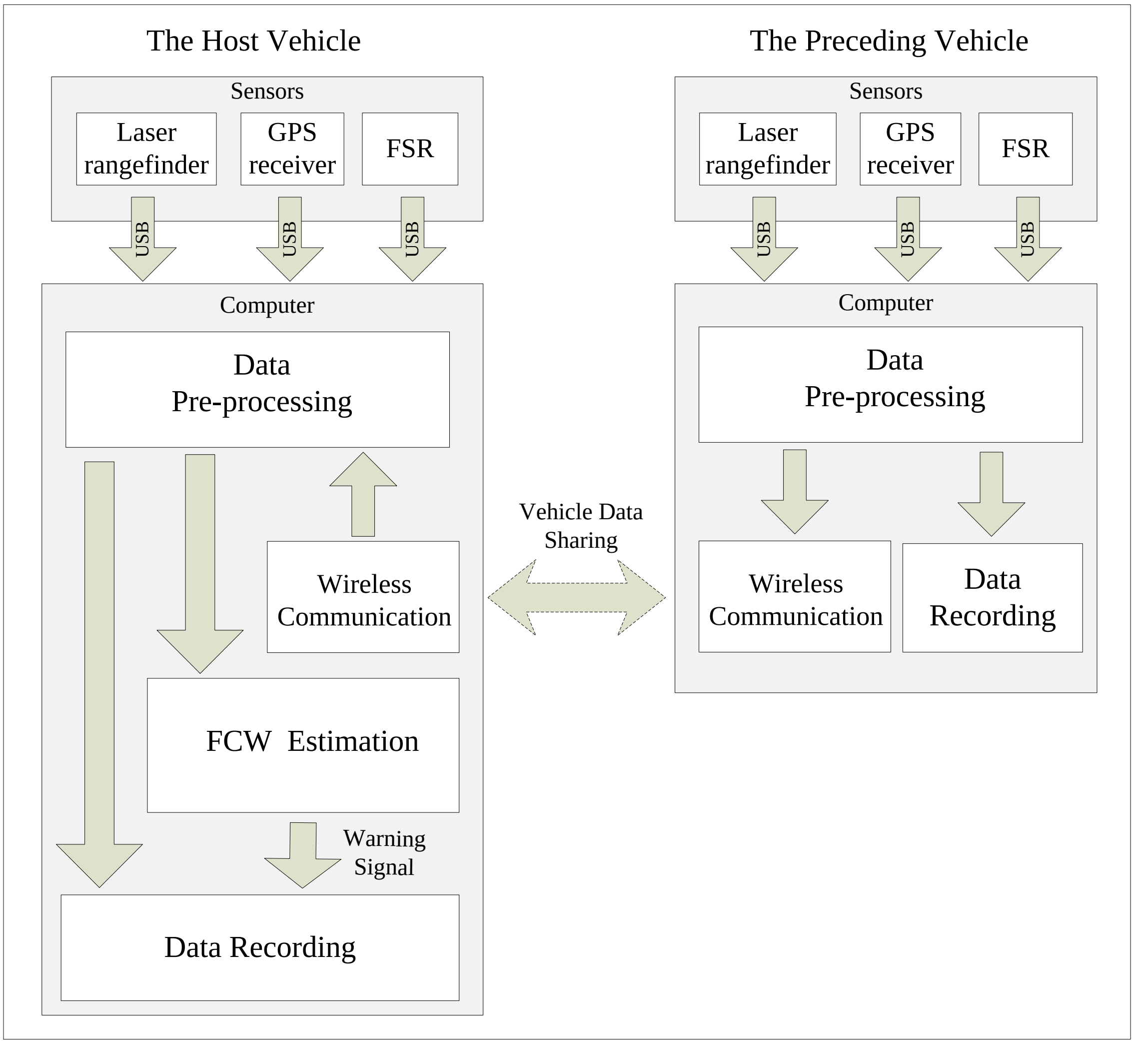


Figure 6.4 The design of FCW System based on horizontal approach.

6.4 Experiments and Results

To demonstrate the horizontal expansion of FCW, we design two sets of FCW systems using off-the-shelf equipment, FCW_{HV} system and FCW_{HV+PV} system. Our experiment used two vehicles that loosely formed a platoon, the HV and the PV. Three sensors were equipped on each vehicle as explained above to obtain the speed (v), the following distance (d), and the actual brake (b). We implemented the FCW system on the HV that uses data from its own sensors together with data from sensors of another vehicle in the front via wireless communication.

The FCW$_{HV}$ case used two quantities, HV's speed (v_h) and HV's following distance (d_h). This is the same data type as that used in the two-second rule described in the vertical approach, but the warning rule is automatically learned instead of fixed. The FCW$_{HV+PV}$ case adds three more variables: PV's speed (v_p), PV's following distance (d_p) and PV's actual brake (b_p). The input data is formed in matrix $\boldsymbol{X}$ with size of n rows and m columns indicating numbers of input samples and types of input variables, respectively. Therefore, the data tuples of the two cases are as follows and the data sets are normalized to be on the same scale of [0, 1].

For the FCW system without using shared data: $\boldsymbol{X} = [v_h\ d_h]_{nxm}$
For the FCW system using shared data: $\boldsymbol{X} = [v_h\ d_h\ v_p\ d_p\ b_p]_{nxm}$

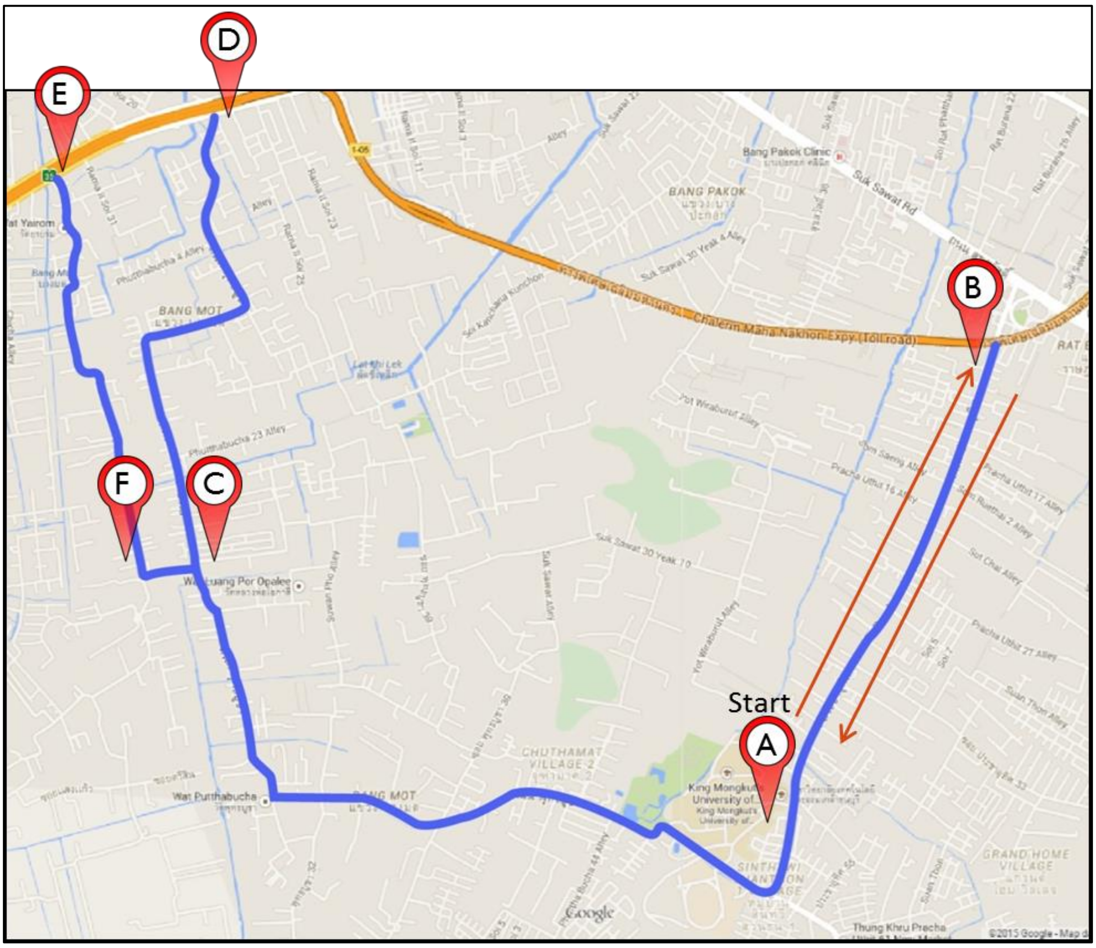


Figure 6.5 Map of driving route in the test.

In the driving experiment, we used two well-trained drivers. The first driver drove the PV, leading the way onto a regular local city road. Another driver was asked to drive the HV following the PV most of the time. The driving data from the PV are transmitted over wireless communication to be processed and recorded with the data at the HV. We performed two driving sessions continuously on the same route as shown in Figure 6.5. The first session was used to train the warning model, while the second session was used to test the model. In order to demonstrate that using PCA help improve the SVM model performance, we performed two classifier methods based on SVM without PCA and SVM with PCA.

6.4.1 Training FCW Systems with Real Driving Data

For training FCW system purpose, we collected driving data from both car, HV and PV, removed missing value, and use these data to train FCW system model. After collected driving data, we obtained 4802 data points which were then used as a training data set. The training data set consists of speed, following distance and actual brake from both HV and PV. The actual brake of HV (b_h) has two classes; active brake (1) and inactive brake (-1) for SVM training stage. Each element of b_h specifies the group of the corresponding row of training data set.

For training FCW systems without shared data (FCW_{HV}), training data set ($\boldsymbol{X}$) is the data obtained from HV only [v_h, d_h]. In PCA stage, we got two PCs, 1^{st} PC contains 93.97 percent of total variance and the 2^{nd} PC contains 6.03 percent of total variance. In order to contain the variance of data more than 90 percent, both 1^{st} PC and 2^{nd} PC are chosen and the eigenvectors of PCA stage of FCW_{HV} are as follows.

$$\boldsymbol{Z}_{HV} = \begin{bmatrix} 0.9871 & -0.1599 \\ 0.1599 & 0.9871 \end{bmatrix}$$

The scores on both PCs and the actual brake data set ($\boldsymbol{b}_h$) are used in SVM training stage. After training, the SVM classification system of FCW_{HV} is constructed with trained value of weight and bias. The result of training SVM is shown in Figure 6.6.

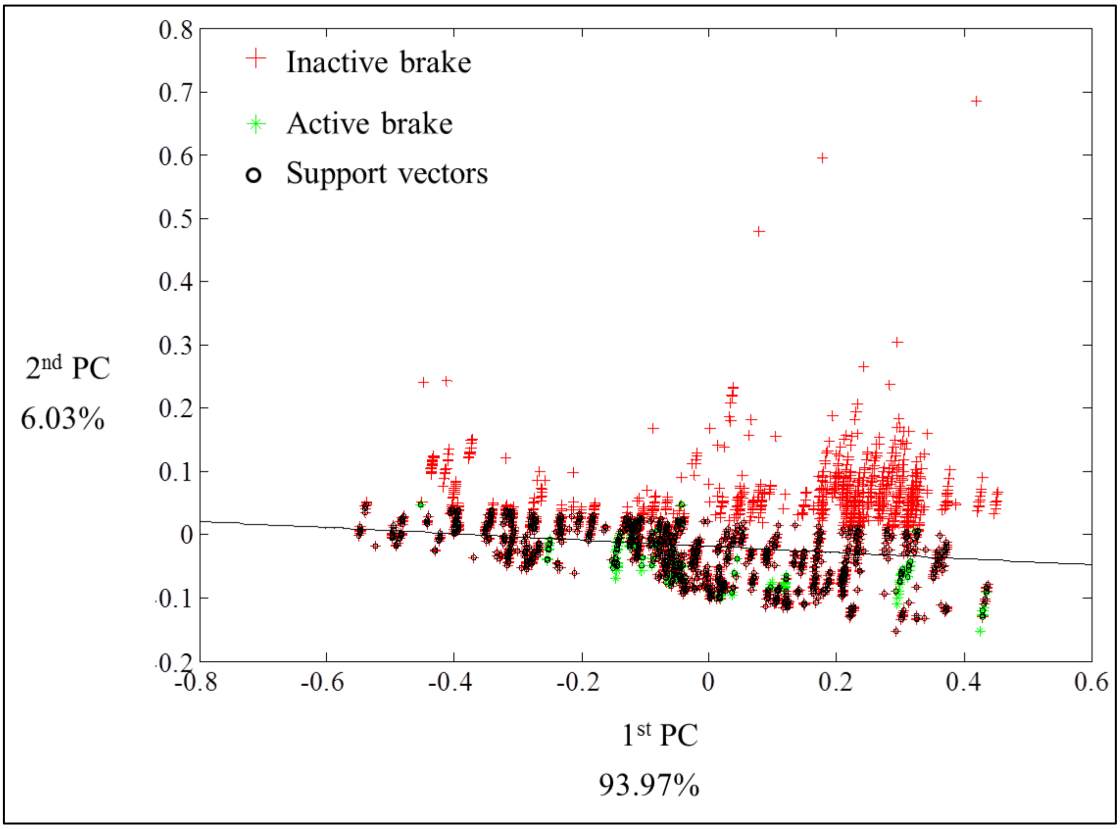


Figure 6.6 Result of SVM training on principal components for FCW_{HV} system.

For training FCW system using distributed sensing (FCW_{HV+PV}), the procedure is same as training FCW_{HV} system but the training data set (***X***) is *[v_h d_h v_p d_p b_p]*. After applied the PCA, we found that the FCW_{HV+PV} case needs three components (Figure 6.7) containing 92.67 percent of total variance. The training result of SVM model of FCW_{HV+PV} is shown in Figure 6.8.

This is first three eigenvectors chosen to use in PCA stage of FCW_{HV+PV} for transforming the data to the principal component coordinate. The training results of PCA and SVM are used to construct both FCW systems and tested in real driving.

$$Z_{HV+PV} = \begin{bmatrix} 0.7318 & -0.2085 & -0.0262 \\ 0.1453 & 0.0306 & -0.0062 \\ 0.6324 & -0.0846 & -0.0026 \\ 0.2082 & 0.9689 & 0.0953 \\ 0.0019 & -0.0983 & 0.9951 \end{bmatrix}$$

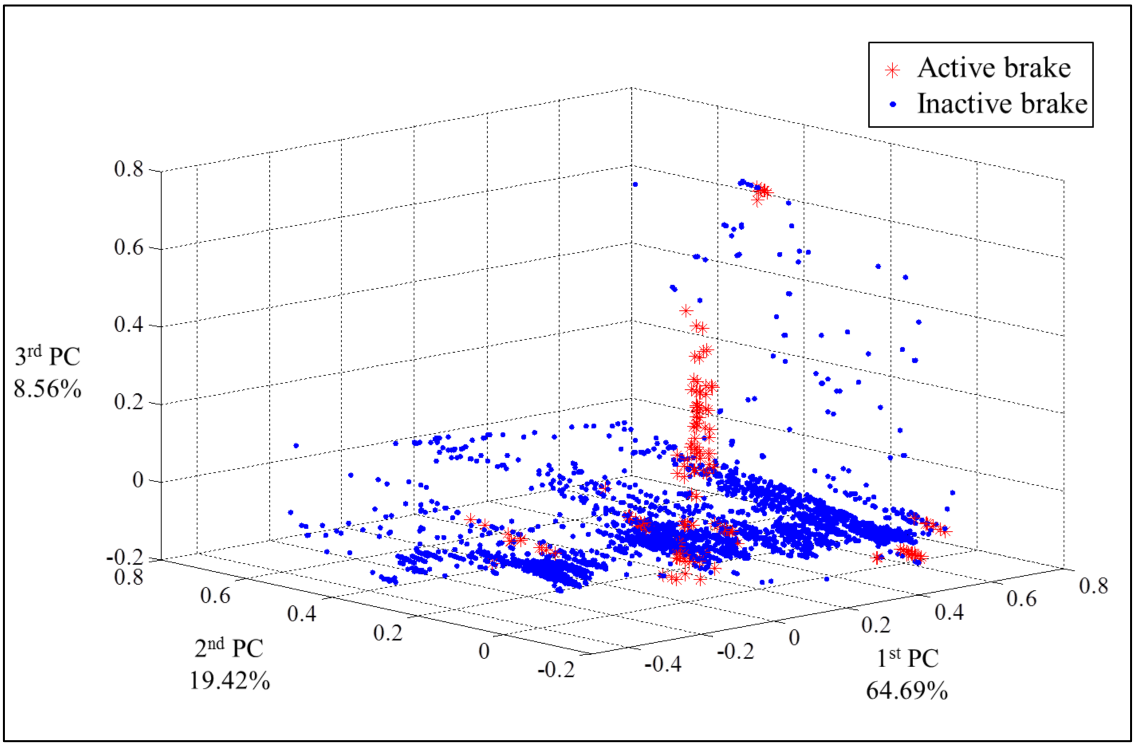


Figure 6.7 Transformation of The training data set FCW_{HV+PV} on 1st PC, 2nd PC and 3rd PC.

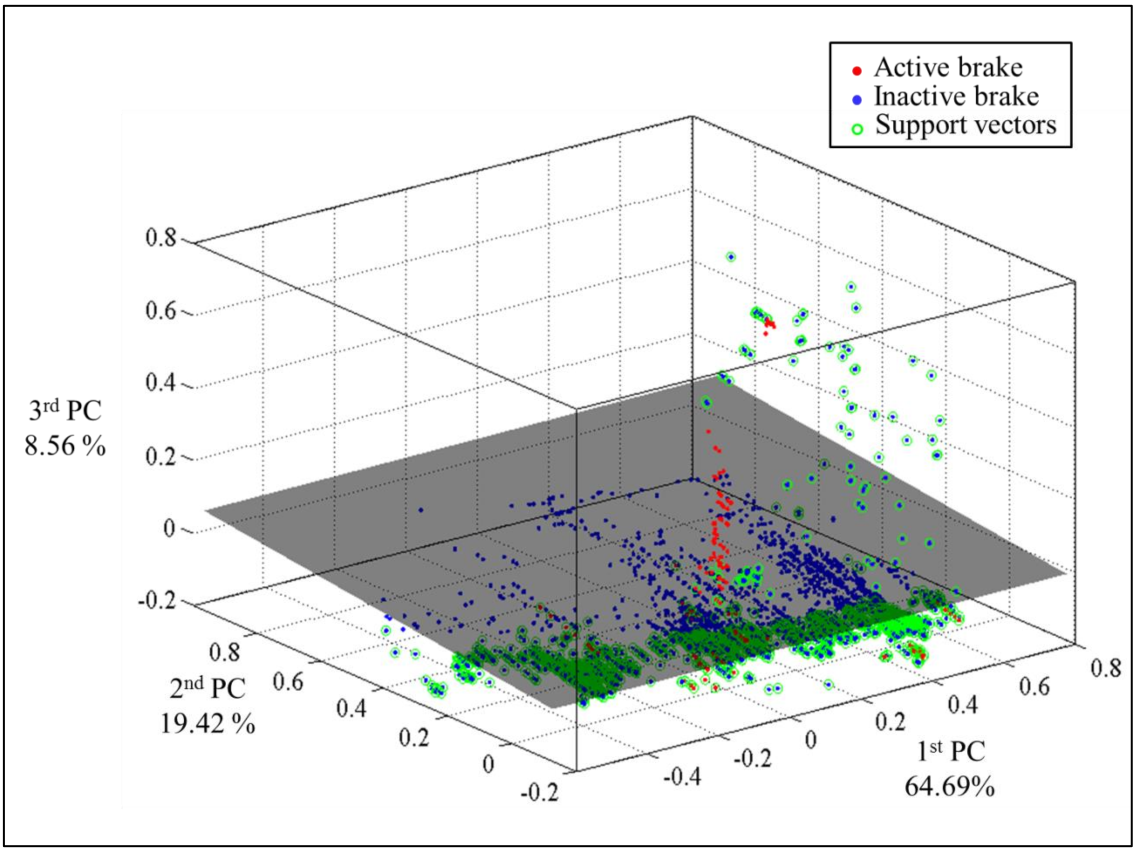


Figure 6.8 A decision surface of SVM training model on principal components for FCW_{HV+PV} system.

After training stage, we constructed FCW_{HV} system and FCW_{HV+PV} system by using trained parameters. Then, we evaluated the accuracy of the trained FCW systems by using the training data set as input data set of the systems. The accuracy of FCW prediction is 62.79 percent for FCW_{HV} system and 94.58 percent for FCW_{HV+PV} system.

6.4.2 Testing FCW Systems in Real Driving

For the second session of the test, we used trained parameters to construct the FCW_{HV} system and FCW_{HV+PV} system. We tested both systems, in real driving situation on city roads as shown in Figure 6.5 with sampling rate 30ms. For testing purpose, the driver of HV does not know the output of the systems, so that his driving behavior is independent to the output from the systems. While driving, the FCW system output and raw data from HV and PV were recorded for system performance evaluation.

6.4.3 Results

For the FCW_{HV} case, we fed the data [v_h d_h] into the PCA. For the FCW_{HV+PV} case, we fed the data [v_h d_h v_p d_p b_p] into the PCA. The additional data v_p, d_p, b_p were expected to improve the performance of the warning system. We chose the number of principal components to have a total variance of more than 90%. The FCW_{HV} case needed two components, while the FCW_{HV+PV} case needed three components. Then, the data were sent to perform supervised learning with SVM using the brake data of the host vehicle (b_h) as the target. We also built the FCW model using the SVM without PCA to compare the performance with the method of SVM with PCA (PCA+SVM). After the training was finished, we performed a performance evaluation on another dataset to find the accuracy and the warning lag time. The results are demonstrated in Table 6.1. The performance evaluation results shows that the PCA help improve the warning prediction of SVM model in both warning accuracy and warning lag time when comparing with the method of using SVM model alone. Although, FCW_{HV} system using SVM without PCA gives the warning lag time better than another method, it resulted from the false positive.

Table 6.1 Performance evaluation of the FCW_{HV} and FCW_{HV+PV} system

Warning System	Method	Warning lag time (s)	Accuracy of system (%)		
			Correct	False positive	False negative
FCW_{HV}	SVM	+0.15	67.81	16.70	15.50
	PCA+SVM	+0.33	80.76	2.26	16.98
FCW_{HV+PV}	SVM	-0.69	81.29	2.09	16.75
	PCA+SVM	-0.75	86.86	5.24	7.90

(-) and (+) means the warning lag time happens before and after the actual brake respectively.

From Table 6.1, we found that the warning output from the FCW_{HV} system has an average lag time of 0.33 sec. from the actual brake of HV, whereas the warning output from the FCW_{HV+PV} system has an average time lead of 0.75 sec. from the actual brake of HV. This result indicates that the sensor data from the leading car can pinpoint a potential danger faster than a human driver, who can only see with limited range. These results indicate that enhancing the FCW system by using distributed sensing can help improve the pre-warning time by 1.08 sec. Moreover, using shared data from the car in front also improves the warning accuracy of FCW system by approximately 6%.

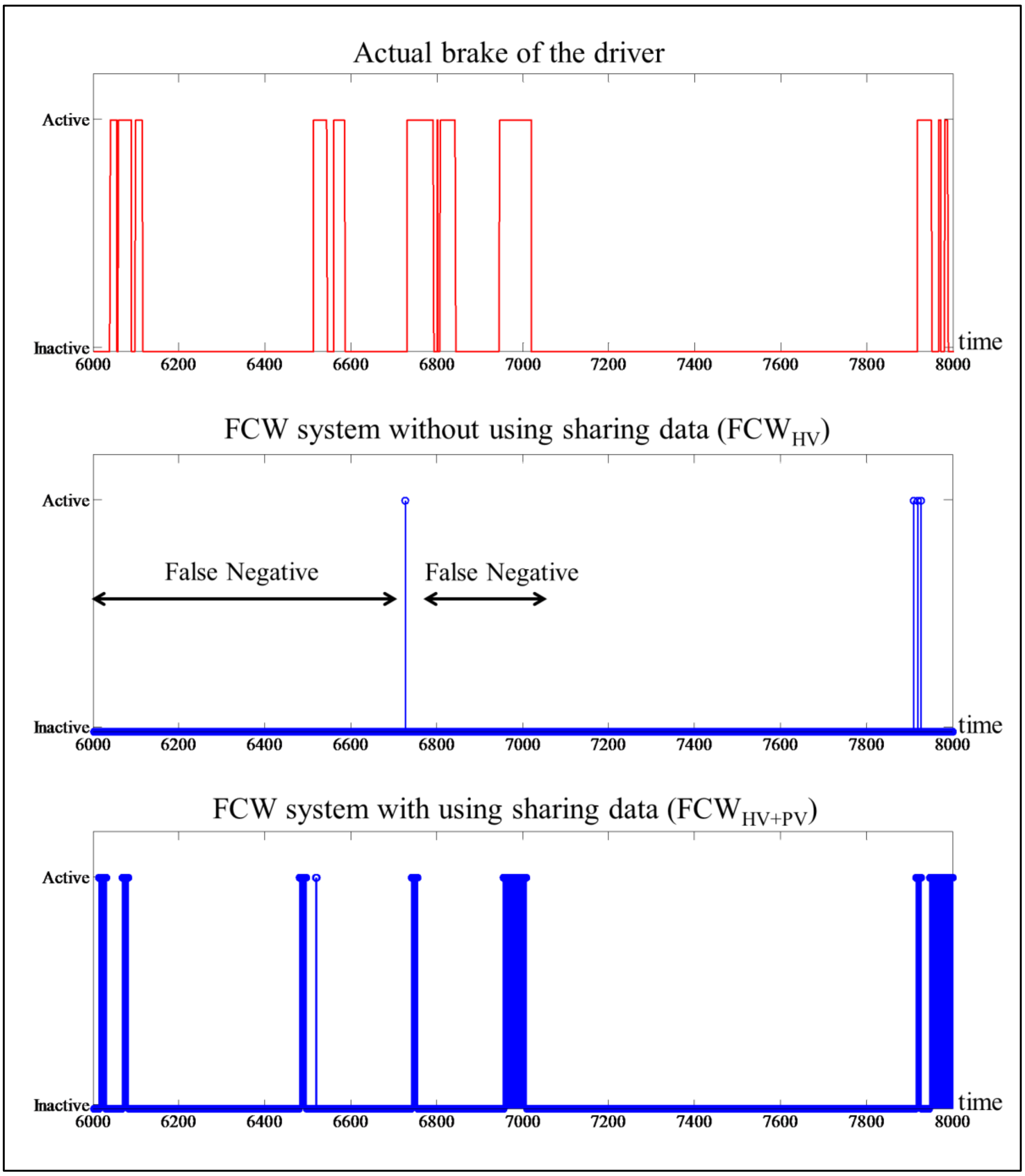


Figure 6.9 The comparison between the actual brakes, the output from the FCW$_{HV}$ systems and the output from the FCW$_{HV+PV}$ system.

CHAPTER 7 CONCLUSIONS AND FUTURE WORK

7.1 Conclusions

In this paper, the systematic methods to improve the timing performance of the FCW system are introduced and evaluated. A timing performance indicator is also proposed, called the warning lag time. The warning lag time can be measured in real driving without performing car crashes because the warning lag time is a time gap between an actual brake of the driver and a warning signal. Thus, it is used instead of the pre-warning time. We measured the warning lag time by calculating the cross-correlation between the actual brake and the warning signal of the FCW system. In the cross-correlation result, the distance between the local maximum match and the center of data is the warning lag time.

The proposed ways to improve the warning lag time of FCW system are the vertical approach and the horizontal approach. First, the improvement of FCW system based on multifunctional warning is proposed, namely the vertical approach. We presented the five levels of crash prevention, which is analyzed from a pre-crash driving situation and divided according to the collision risk from normal driving to crash. The typical FCW system operates on the third level of the five levels of crash prevention. Thus, we combined the typical FCW system with a warning system, which operates on the second level, to prevent the driver getting into the third level and also help improve the warning lag time. The LW was chosen to enhance the FCW system in our experiment because it is the most reliable system that works on level 2. The main reason is that the warnings are generated from the static environment. The LW system informs a driver about potentially dangerous places before reaching them in order to help a driver become aware of the danger and prepare to slow down before reaching the hotspot.

Second, we proposed an approach to enhance the FCW system based on the distributed sensing technique, called the horizontal approach. We used the shared data from the direct front vehicle in order to increase the sensor range. For testing purpose, the horizontal approach was performed with two vehicles following each other on the same lane. We constructed two FCW systems, FCW_{HV} and FCW_{HV+PV}. The FCW systems were implemented on the host vehicle. We firstly reduced the data dimensions. The principal component analysis (PCA) was applied to find the significant components for each FCW system before estimating the collision warnings. For FCW estimation, the SVM was then used to create a model for the warning signal. The warning models of both FCW_{HV} and FCW_{HV+PV} were trained by using vehicle's data recorded from real driving.

In the experiment, the tests on both approaches were performed in real driving situation. We determined two performance indicators, timing and accuracy. The warning lag time was used to evaluate the timing performance of the FCW systems. The accuracy of the system warning is the result of comparison between the system warnings and the actual brakes from the driver. The results show that the proposed approaches can achieve improvements of timing performance and increase the accuracy to stay within 7% of the standard case. For the vertical approach, the typical FCW system was added a dimension of warning with the LW system and it can help improve the warning lag time by 0.31 sec. For the horizontal approach, it also helps improve the warning lag time by

1.08 sec. This approach achieves more effective than the vertical approach because it can significantly expand the range of sensing.

These results suggest that the proposed vertical approach and horizontal approach for timing improvement of FCW systems warrant the further development. The both approaches' concepts were tested under real driving environments. In the experiment of the vertical approach, the database of accident hotspots on the test route was created before performing the tests. This is the limitation of the LW system that the combination system can only be used on the specific route.

7.2 Future Work

The future development of the vertical approach may further integrate more intelligent warning systems which operate in the second level (open condition level) to further cover the clues of vehicle accidents. The further work of horizontal approach may include a method to communicate with any preceding vehicle. Since the experiments as we presented were performed with two vehicles following each other on the city road. The distributed sensing requires a vehicle-to-vehicle communication infrastructure, which is still an ongoing research.

REFERENCES

1. Hui, R. and Jinfeng, G., 2010, "Study on Intelligent Control of Road Condition Perception and Forward Collision Warning System", **International Conference on Intelligent Computing and Integrated Systems (ICISS)**, October 2010, pp.285-289.

2. Lai, T. and Chung-Ming, H., 2010, "Forwards: A Map-Free Intersection Collision-Warning System for All Road Patterns", **IEEE Transactions on Vehicular Technology**, Vol. 59, No.7, September 2010, pp.3233-3248.

3. Nakaoka, M., Raksincharoensak, P. and Naga, M., 2008, "Study on Forward Collision Warning System Adapted to Driver Characteristics and Road Environment", **Proceedings of Intelligent Conference on Control, Automation and Systems (ICCAS)**, October 2008, Seoul, Korea, pp. 2890-2895.

4. Jansson, J. and Gustafsson, F., 2002, "A Probabilistic Approach to Collision Risk Estimation for Passenger Vehicles," **The 15th Triennial World Congress**, 2002, Barcelona, Spain.

5. Dagan, E., Mano, O., Stein, G. and Shashua, A., 2004, "Forward Collision Warning with a Single Camera", **IEEE Intelligent Vehicles Symposium (IV2004)**, June 2004, Italy, pp. 37-42.

6. Nedevschi, S., Vatavu, A., Oniga, F. and Meinecke, M.M., 2008, "Forward Collision Detection Using a Stereo Vision System", **4th International Conference on Intelligent Computer Communication and Processing (ICCP 2008)**, August 2008, pp.115-122.

7. Takatori, Y. and Yashima, H., 2009, "Performance Evaluation of Vehicle Cooperative Driving Assistance Systems that Uses Forward Obstruction Detecting Sensors and Inver-vehicle Communication", **9th International Conference on Intelligent Transport Systems Telecommunications (ITST)**, October 2009, pp.622-627.

8. Hiraoka, T., Tanaka, M., Kumamoto, H., Izumi, T. and Hatanaka, K., 2009, "Collision Risk Evaluation Index Based on Deceleration for Collision Avoidance (firstreport)–Proposal of a New Index to Evaluate Collision Risk Against Forward Obstacles", **Review of Automotive Engineering**, Vol. 30, No.4, 2009, pp.429-437.

9. Takada, S., Hiraoka, T. and Kawakami, H., 2011, "Forward Obstacles Collision Warning System Based on Deceleration for Collision Avoidance", **Proceedings of SICE Annual Conference (SICE)**, September 2011, pp.184-191.

10. Zhang, L., Wang, J. and Li, K., 2006, "Forward Collision Warning System Based on THASV-II Platform", **IEEE International Conference on Vehicular Electronics and Safety (ICVES 2006),** December 2006, pp.255-258.

11. Tokoro, S., Moriizumi, K., Kawasaki, T., Nagao, T., Abe, K., and Fujita, K., 2004, "Sensor Fusion System for Pre-crash Safety System," **IEEE Intelligent Vehicles Symposium,** June 2004, Parma, Italy, pp. 945-950.

12. Chang, T-H, Hsu, C-S, Wang, C. , and Yang, L-K, 2008, "Onboard Measurement and Warning Module for Irregular Vehicle Behavi," **IEEE Transactions on Intelligent Transportation Systems**, Vol. 9, No. 3, September 2008.

13. Chih-Li, H., Yu-Hsiang, Y., Jhih-Cheng, S. and Tsung-Ying, S., 2011, "Vehicle Warning System for Lane Departure and Collision Avoidance: Using Fuzzy Decision Making**", IEEE International Conference on Fuzzy Systems (FUZZ)**, June 2011, pp.1554-1559.

14. Bosch, R., 2005, **Combined Active and Passive Safety (CAPS) -right on Track to the Sensitive Car**, Bosch Media Release, April 2005.

15. Lin, C-C., Hsieh, H-W., Huang, D-C., Lin, C-W., Liao, Y-S. and Chen, Y-H., 2007, "Development of a Multimedia-Based Vehicle Lane Departure Warning, Forward Collision Warning and Event Video Recorder Systems", **Ninth IEEE International Symposium on Multimedia Workshops (ISMW'07)**, December 2007, pp.122-129.

16. Miller, R. and Qingfeng, H., 2002, "An Adaptive Peer-to-peer Collision Warning System**," In Proceedings of IEEE 55th Vehicle Technology Conference**, 2002, Birmingham, pp. 317-321.

17. Lytrivis, P., Thomaidis, G. and Amditis, A., 2008, "Cooperative Path Prediction in Vehicular Environments", **The 11th IEEE International Conference on Intelligent Transportation Systems 2008**, October 2008, Beijing, pp. 803-808.

18. Batz, T., Watson, K., and Beyerer, J., 2009, "Recognition of Dangerous Situations within a Cooperative Group of Vehicles**," In Proceedings of the IEEE Intelligent Vehicle Symposium**, June 2009, pp. 907-912.

19. Papp, Z., Brown, C. and Bartels, C., 2008, "World Modeling for Cooperative Intelligent Vehicles", **IEEE Intelligent Vehicles Symposium 2008**, June 2008, Eindhoven, Netherland, pp. 1 050-1055.

20. Sebastian, A., M. Tang, Feng, Y. and Looi, M., 2009, "Multi-vehicles Interaction Graph Model for Cooperative Collision Warning System", **In Proceedings of the IEEE Intelligent Vehicles Symposium**, June 2009, Xi'an, China, pp. 929-934.

21. Yan, G., Yang, W., Weigle, M. C., Olariu, S. and Rawat, D. B., 2010, "Cooperative Collision Warning through Mobility and Probability Prediction", **In Proceedings of the IEEE Intelligent Vehicles Symposium 2010 (IV'10)**, June 2010, San Diego, CA, pp. 1172-1177.

22. Misener, J.A. and Sengupta, R., 2005, "Cooperative Collision Warning: Enabling Crash Avoidance with Wireless Technology", **The 12th World Congress on ITS**, No. 1960, San Francisco, 2005, pp. 1-9.

23. Tan, H.-S. and Huang, J., 2006, "DGPS-based Vehicle-to-vehicle Cooperative Collision Warning: Engineering Feasibility Viewpoints", **IEEE Transactions on Intelligent Transportation System**, Vol. 7, No. 4, December 2006, pp. 415-428.

24. Ahlers, F. and Stimming, C., 2008, "Laser Scanner Based Cooperative Pre-Data-Fusion", **IEEE Intelligent Vehicles Symposium 2008**, June 2008, Eindhoven, The Netherlands, pp. 1187-1190.

25. Hao, L. and Fawzi, N., 2011, "Multi-vehicle Cooperative Perception and Augmented Reality for Driver Assistance: A Possibility to 'See' Through Front Vehicle", **14th International IEEE Conference on Intelligent Transportation** Systems, October 2011, Washington DC, USA, pp. 242-247.

26. Chen, Y.-L. and Lee, W.-J., 2011, "Safety Distance Warning System with a Novel Algorithm for Vehicle Safety Braking Distance Calculating," **International Journal of Vehicle Safety**, Vol. 5, No. 3, 2011, pp.213 – 231.

27. Road Traffic Safety Authority, 2013, **Driving Safely in Traffic – the Two-Second Rule**, in Guidebook of Rules of the road, O' Brien press, pp. 109, Ireland.

28. Cabrea, A., Gowal, S. and Martinoli, A., 2012, "A New Collision Warning System for Lead Vehicles in Rear-end Collisions," **IEEE Intelligant Vehicles Symposium (IV) 2012**, June 2012, pp. 674-379.

29. Jackson, J.E., 2003, **A User's Guide to Principal Components**, John Wiley & Sons, Inc., USA.

30. Burges, C.J.C., 1998, **A Tutorial on Support Vector Machines for Pattern Recognition**, Data Minding and Knowledge Discovery.

31. Bay, H., Ess, A., Tuytelaars, T. and Van Gool, L., 2008, "Speed-up Robust Reatures (surf)", **Computer Vision and Image Understanding**, Vol. 110, pp. 346–359.

32. Juan, S., Qingsong, X. and Jinghua, Z., 2010, "A Scene Matching Algorithm Based on SURF Feature", **International Conference on Image Analysis and Signal Processing (IASP)**, April 2010, Zhejiang, China, pp. 434 – 437.

33. Gomez-Moreno, H., Maldonado-Bascon, S., Gil-Jimenez, P. and Lafuente-Arroyo, S., 2010, "Goal Evaluation of Segmentation Algorithms for Traffic Sign Recognition", **IEEE Transactions on Intelligent Transportation Systems**, Vol. 11, Issue 4, July 2010, pp. 917 – 930.

34. Thammakaroon, P. and Tangamchit, P., 2008, "Adaptive Brake Warning System for Automobiles", **8th International Conference on ITS Telecommunications (ITST2008)**, Thailand, pp. 204-208.

35. Tzomakas, C. and Seelen, W., 1998, “Vehicle Detection in Traffic Scenes Using Shadows”, **Technical Report 98-06, Institut fur Neuroinformatik,Ruht-Universitat, Bochum, Germany**, 1998.

36. Thammakaroon, P. and Tangamchit, P., 2010, “Improvement of Forward Collision Warning in Real Driving Environment Using Machine Vision”, **International Journal of Intelligent Transportation Systems Research**, Vol. 8, No. 3, Aug. 2010, pp. 131-139.

37. Tomasi, C. and Kanade, T., 1991, **Detection and Tracking of Point Feature**. Technical Report CMU-CS-91-132, Carnegie Mellon University, April 1991.

38. Thammakaroon, P. and Tangamchit, P., 2009, “Predictive Brake Warning at Night Using Taillight Characteristic”, **IEEE International Symposium on Industrial Electronics (ISIE2009)**, Korea, pp. 217-221.

39. Hsu, C.W., Chang, C.C. and Lin, C.J., 2010, “A Practical Guide to Support Vector Classification”, **Technical Report, Department of Computer Science and Information Engineering, University of National Taiwan, Taipei**, **Taiwan**, April 2010, pp. 1-12.

40. Srivastava, D. and Bhambhu, L., 2010, “Data classification using support vector machine”, **Journal of Theoretical and Applied Information Technology**, Vol. 12, No. 1, 2010, pp. 1-7.

41. George, A., 2012, “Anomaly Detection based on Machine Learning: Dimensionality Reduction using PCA and Classification using SVM”, **International Journal of Computer Applications**, Vol. 47, No. 21, June 2012, pp. 5-8.

CURRICULUM VITAE

NAME	Miss Peachanika Thammakaroon
DATE OF BIRTH	4 October 1984
EDUCATIONAL RECORD	
BACHELOR'S DEGREE	Bachelor of Engineering (Control System and Instrumentation Engineering) King Mongkut's University of Technology Thonburi, Bangkok, Thailand, 2006
MASTER'S DEGREE	Master of Engineering (Control System and Instrumentation Engineering) King Mongkut's University of Technology Thonburi, Bangkok, Thailand, 2009
DOCTORAL DEGREE	Doctor of Philosophy (Electrical and Computer Engineering) King Mongkut's University of Technology Thonburi, Bangkok, Thailand, 2014
SCHOLARSHIP	Research Assistantship: Project Road Traffic Estimation from a Mobile Probe Vehicle with GPS and Machine Vision Supported by Higher Education Research Promotion and National Research University Project of Thailand, Office of the Higher Education Commission, 2011-2013 King Mongkut's Brilliant Student Scholarship, 2010-2012 Research Assistantship: Project Traffic Violation Warning System for Safety Supported by National Electronics and Computer Technology Center (NECTEC), 2010-2011 Research Assistantship: Project Harsh Brake Warning System for Automobiles Supported by National Electronics and Computer Technology Center (NECTEC), 2008-2009
EMPLOYMENT RECORD	Automatic Guide Vehicle Project for Planet T & S Co., Ltd., Bangkok, Thailand, Apr. - Jul. 2013

PUBLICATIONS

Thammakaroon, P. and Tangamchit, P., 2015, "Timing Performance Assessment and Improvement of Forward Collision Warning", **IEICE Transaction on Fundamentals of Electronics, Communications and Computer Sciences**, Vol. E98-A, No. 5, pp. 1105-1113.

Thammakaroon, P. and Tangamchit, P., 2012, "Improvement of Warning Lag Time in Forward Collision Warning Systems based on Multi Functional Warnings", **IEEE International Conference on Vehicular Electronics and Safety (ICVES2012)**, Turkey, pp. 146-150.

Thammakaroon, P. and Tangamchit, P., 2010, "Multilevel Safe Drive Warning System", **10th International Conference on ITS Telecommunications (ITST2010)**, Japan.

Thammakaroon, P. and Tangamchit, P., 2010, "Improvement of Forward Collision Warning in Real Driving Environment Using Machine Vision", **International Journal of Intelligent Transportation Systems Research**, Vol. 8, No. 3, August 2010, pp. 131-139.

Thammakaroon, P. and Tangamchit, P., 2009, "Predictive Brake Warning at Night using Taillight Characteristic", **IEEE International Symposium on Industrial Electronics (ISIE2009)**, Korea, pp. 217-221.

Thammakaroon, P. and Tangamchit, P., 2008, "Adaptive Brake Warning System for Automobiles", **8th International Conference on ITS Telecommunications (ITST2008)**, Thailand, pp. 204-208.