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Risk Assessment for Improved Vehicle Safety using Front Vehicle Dynamic States through Vehicular Communication

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Abstract

Risk Assessment for Improved Vehicle Safety using Front Vehicle Dynamic States through Vehicular Communication

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In recent years, advanced driver assistance systems or highly automated driving systems are expected to enhance road traffic safety, transport efficiency, and driver comfort. Practical applications have become possible due to recent advances in vehicle local sensors and inter vehicle communications. These advances have opened up many possibilities for active safety systems to be more intelligent and robust. The further enhancement of these technologies can be utilized as a risk assessment system of automated drive.

This dissertation presents a risk assessment for improved vehicle safety using Front Vehicle Dynamic States through vehicle-to-vehicle wireless communication. A vehicle-to-vehicle wireless communication (V2V communication) has been implemented and fused with a radar sensor to obtain the prediction of remote vehicle's motion. Based on the predicted behavior of remote vehicles, a collision risk and a human reaction time are determined for a better driver acceptance and active safety control intervention. A human-centered risk assessment using the V2V communication has been incorporated into a collision avoidance algorithm to monitor threat vehicles ahead and to find the best intervention point. The performance of the proposed algorithm has

been investigated via computer simulations and vehicle tests for application to urban and highway driving situation. It has been shown from both simulations and vehicle tests that the proposed integrated risk assessment algorithm with the V2V communication can be beneficial to active safety systems in decision of controller intervention moment and in control of automated drive for the guaranteed safety.

Keywords: Threat assessment, autonomous vehicle, automated drive, human-machine interactions, active safety, vehicular communication, cooperative driver assistance systems, vehicle-to-vehicle communication, intelligent vehicle

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List of Tables

List of Figures

Contents

Chapter 1

Introduction

1.1. Background and Motivation

Vehicular communication technology has been progressing rapidly, which enables the connection between vehicles through wireless networks. After several years of massive research and standardization, so called IEEE 802.11p or Wireless Access in Vehicular Environments (WAVE) standard, communication technologies for information transmission between vehicles are finally in the stage of development for market introduction [Enache10]. The practicality of such technologies have already been shown in some extensive field tests [O'Malley10]. These technologies aim for mitigation, avoidance of crash and improvement of driving comfort and facilitate more efficient transportation. These are main applications for intelligent transportation systems (ITSs) either by improvements of the infrastructure or by acting on the vehicles themselves [Yoon07].

However, the V2V communication requires high market penetration to deliver value reliable and DSRC based vehicle to infrastructure (V2I) may require significant infrastructure investment. Moreover, the V2V

communication experiences random power fluctuations over time due to changing reflections and attenuations. These power fluctuations cause time-varying data rates and intermittent connectivity [Seong-Woo15].

In contrast to V2V communication, radar systems have been used in the automotive area for decades. The radar is one of the most popular applications for adaptive cruise control (ACC) since it allows precise relative positioning of objects in the line-of-sight vicinity of a vehicle [Kato02]. And the automotive radar has been known as the best fitted vehicular surround sensing technology with respect to functionality, robustness, reliability, dependence on weather conditions and etc. [Nilsson15].

Although the radar has been widely used for application to active safety vehicle, it has its own limitations. The information which can be obtained is limited to the relative position, and approximate shape. Many heuristics are applied to the object detection, which leads to a compromise between sensitivity and false positive rates. As long as the preceding vehicle is located within the detection zone and no obstacles obstruct the line-of-sight, conventional signal propagation errors exist when it detects the target [Schubert12]. It results in an uncertain measurement model problem which is wandering on the target's physical boundary.

Despite the fact that both technologies have their own shortcomings, they can be complimentary to each other once they fuse together. Radar can provide a constant passive scanning of the surrounding, detects every candidate with reliable relative positioning measurements. If those candidates are properly fused with V2V communication message, almost all uncertainties can be

eliminated and the information of candidates will be enriched. In other words, the environment perception capability can be significantly enhanced in terms of sensing reliability and perception range. This allows great advancement of existing driver assistant system or active safety vehicle. In a nutshell, if information from V2V communication can be attached to radar detected objects, shortcomings of both systems can be eliminated. Hence, we propose to fuse radar and V2V communication data.

With the accurate estimate of remote vehicle from multi-sensor fusion, active safety systems can be enhanced by reducing the risk of accidents, improving the driver's comfort and driving performance. Current automotive safety systems can be grouped by which driving state it occurs. The driving states can be described by following sequential five states: normal driving state, warning state, crash avoidable state, crash unavoidable state, and post event state. The first three states focus on accident avoidance, while the last three states focus on damage mitigation (with an overlap of the third state). Using the above sequential driving state flow, it is apparent that automotive safety concerns should be addressed with an integrated system approach. Accordingly, as the next-generation of the active safety systems, current safety systems on vehicles are becoming integrated and merging so that each system interacts with the other. Therefore, the core of the integrated automotive safety system can be summarized as a threat assessment and decision making method which defines the current driving state of safety and makes the control decision.

The driver support function (the so-called 'co-driver') [Flemisch10] allows a human factor considered active safety system to find best intervention point

from human (manual) driving mode by monitoring traffic and risk. Wei et. al [Wei09] investigates that autonomous vehicle performance, robustness and safety can be improved by cooperation between human-driver and vehicle's intelligence. A human driver has to take part in the driving and strategy planning of an autonomous vehicle. Thus, in order to fully guarantee the safety, future automated drive system has to find a best trade-off between the human sense and automated function such as an active safety by implementing human driver's ability.

1.2. Previous Researches

The rapid progress in vehicle to vehicle wireless communication (V2V communication) technologies allow advanced driver assistance systems (ADAS) to be dramatically improved with shared sensor information such as remote vehicle's GPS location, yaw rate, absolute velocity and acceleration. Drivers would extend their sight range or field of view via information passed over vehicular networks [Kim13]. Xu et al. [Qing02] proposed a Cooperative Adaptive Cruise Control (CACC) system to investigate the effectiveness of the V2V communication in highway merging scenario compared to Adaptive Cruise Control (ACC). Because of the V2V communication, the CACC vehicle responds 2.5 seconds before the vehicle in the adjacent lane cuts in, which is half of the lane change time. Because the CACC vehicle has longer response time, it brakes much less than the ACC vehicle. The braking effort is smaller than 0.5 m/s2, and the sharp notch in the simulation results.

In contrast to V2V communication, radar systems have been used in the automotive area for decades. The radar is one of the most popular applications for adaptive cruise control (ACC) since it allows precise relative positioning of objects in the line-of-sight vicinity of a vehicle [Breu14]. And the automotive radar has been known as the best fitted vehicular surround sensing technology with respect to functionality, robustness, reliability, dependence on weather conditions and etc. [Kim15].

The two technologies can be complimentary to each other by fusing their information together. Information fusion in object tracking has been used for a long time in the aerospace industry for tracking aircraft with radar. The texts [Blackman99] provide a comprehensive overview of different sensor data fusion configurations and methods of fusion. In airborne radar applications, the detected objects are assumed to be point-targets, since the distance between the radar station and the detected aircraft is relatively large. However, this assumption does not hold in automotive applications, since a detected object, such as an overtaking vehicle, can fill the entire field-of-view of a sensor. Therefore, sensor data fusion algorithms and architectures must be newly investigated for ADAS.

According to [Aeberhard11], the author provided quick overview of the basic fusion architectures and their application in ADAS. In the high-level fusion, all sensor relevant details are kept at the sensor-level, allowing the fusion module to process the data abstractly. This makes the high-level fusion architecture favorable in applications where modularity and simplicity of design is required. Thus we propose the high-level fusion and this has been successfully and widely demonstrated in automotive applications, e.g. for ACC [Takizawa04] and for safety systems [Floudas07].

In order to well represent the risk with the accurate estimate of remote vehicle, s, a threat assessment and decision making are the core of the integrated automotive safety system. Various situation assessment methods have been studied previously by many researchers [Wardziński08]. Generally, the driving situation assessment consists of the following three steps: an estimation of

current driving states, a prediction of future driving states and an evaluation of collision risk or their collision type. The current stages of risk metrics are mainly based on the predicted time at which some predefined risky event occurs. The typical predicted time based indices include the time to collision (TTC) or time to impact [Labayrade07]. Polychronopoulos el al. proposed the predicted time to minimum distance with sensor-fusion method [Polychronopoulos07]. Recently, several researchers have focused their research on development of new concept of risk index and elaboration of estimation and prediction steps with consideration of uncertainties. According to a number of literature reviews, main concerns in risk assessment can be summarized as three requirements: 1) a description of a traffic situation containing the geometric description of the road, dynamic and static obstacle tracking, 2) a prediction of multiple traffics' reachable set under the reasonable behavior restriction, and 3) an assessment of collision risk which corresponds with driver sensitivity and can be applied to many complex situations without loss of generality.

The author in [Wardziński08] gives the meaning of the risk level with predicted minimal distance, and uses the Dempster-Shafer logic [Górski04] to represent uncertainty in risk assessment. This approach can be aligned with the probabilistic threat assessment method because it also uses target prediction uncertainties. Since the exact meaning of a risk level is a subject to interpretation, experiments were conducted to verify the proposed risk level and its meaning are well matched to the uncertainty in the risk assessment [Wardziński08].

According to [Junqing 09], finding the optimal intervention point of active

safety system is important for safety, robustness and performance on the real time cooperative driving interface between human drivers and vehicles. The author addresses safety control intervention point has to be the trade-off moment. In order to express pure manual driving status and intuitive human feedback, the human reaction time [Layton97] with respect to predicted minimal distance can be considered. In order to express the status of active safety system, collision risk with respect to predicted minimal distance [Wardziński08] is considered. In [Ben-Yaacov02], the author also defines the automatic system's performance by its probability of detection. The human's behavior is based both on his or her own processing.

1.3. Thesis Objectives

This dissertation describes a front side risk assessment algorithm for collision avoidance. A vehicle-to-vehicle wireless communication (V2V communication) has been implemented and fused with a radar sensor to obtain the prediction of remote vehicle's motion. Based on the predicted behavior of remote vehicles, a collision risk and a human reaction time are determined for better driver acceptance and active safety control. A human-centered risk assessment using the V2V communication has been incorporated into a collision avoidance algorithm to monitor threat vehicles ahead and to find the best intervention point. The performance of the proposed algorithm has been investigated via computer simulations and vehicle tests for application to urban and highway driving situation. It has been shown from both simulations and vehicle tests that the proposed integrated risk assessment algorithm with the V2V communication can be beneficial to active safety systems in decision of controller intervention moment and in control of automated drive for the guaranteed safety.

Mainly three research issues are evaluated in terms of forward collision case:

1. Effects of V2V communication on the automated vehicle risk assessment performance are investigated.
2. Human factors are considered in the human-centered risk assessment for more human-like behavior of self-driving car which can be more acceptable system from the driver and other road users.

3. Information fusion of V2V communication and conventional ADAS sensors are discussed with the applications for front side risk assessment and collision avoidance.

1.4. Thesis Outline

This dissertation is structured as follows: the concept and application use cases for the V2V communication is discussed in Section 2. In Section 3, the human factors are introduced for the enhancement of safety and driver acceptance of automated drive active safety system. A human reaction time and probabilistic threat assessment approach are described to determine the best intervention point of active safety system in Section 4. In addition V2V/Radar information fusion method and its performance verification are discussed. For the decision of active safety control intervention moment, predicted collision distance is derived in Section 4. In Section 5, simulation and vehicle tests are performed to validate the effectiveness of V2V communication on the risk prediction and vehicle control. For the threat assessment, a novel human-centered risk assessment approach is validated in the urban and highway situation. Finally, vehicle tests results are investigated.

Chapter 2

Vehicular Communication

In this section, descriptions for the V2V communication and its application for autonomous vehicle are presented. The increasing trend of vehicle to vehicle communication makes the autonomous vehicle more safely driving beyond the limitations of current in the market local sensors. According to the National Highway Safety Administration, all car manufacturers would be required to install dedicated short-range communication (DSRC) radios in to new vehicles, probably starting in about 2020. DSRC, the technology that underpins V2V communications is actually a variant of common WiFi that falls under the 802.11p standard. DSRC radios send and receive short messages 10 times per second over a range of about 1,000 to 1,500 ft depending on the conditions. The messages broadcast by vehicles include information like position, heading, speed and braking status. In vehicles receiving the messages, drivers would get alerts for things such as a vehicle further up the road suddenly activating ABS due to a slippery condition, an approaching vehicle while attempting to make a left turn or a vehicle approaching an intersection that might not be visible. Unlike the sensors we have in today's driver assist systems, V2V isn't limited to line of sight. A camera, radar or Lidar sensor can't see through other vehicles like a large truck or bus or around a corner. V2V can help expand situational

awareness for both human drivers and automated driving systems.

For the autonomous vehicle application, following six are necessarily considered : Fast network acquisition, Priority for safety applications, Low latency, Interoperability, High reliability, Security and privacy. These features are especially important for active safety applications, because safety-critical communication must be reliable, immediate, network and device “agnostic,” and secure.

The following part will introduce two key factors of V2V communication in terms of empirical modelling, sampling and interpolation. In order to develop the realistic model of IEEE 802.11p, a hybrid simulation model that analytically represents the probability of packet reception in an IEEE 802.11p network is announced. Two critical communication issues are related to communication delay and packet loss. Two literatures are studied to handle these issues and to reliably resolve in the next part.

2.1 Literature Review

In this section, two literatures are reviewed to model the IEEE 802.11p based vehicular wireless communication. The proposed design of vehicular communication network is a hybrid simulation model that analytically represents the probability of packet reception in an IEEE 802.11p network based on four inputs: the distance between sender and receiver, transmission power, transmission rate, and vehicular traffic density. It also describes the process of building our model which utilizes a large set of simulation traces and is based on general linear least squares approximation techniques.

The second part of the survey-2.1.2 is about the research from the viewpoint of vehicle chassis control. It presents a design method of preview controller for vehicle stability with V2V communication. By considering the variable vehicle speed, the previewed disturbance based on the time information is resampled. This can be useful for the application of highway situation for the good ride quality while ensuring vehicle controllability and safety.

2.1.1. An Empirical Model for V2V communication

This section addresses the construction of an empirical model that represents the probability of successfully receiving one-hop packet transmissions under various circumstances. The model is conceived as a flexible tool for developers to use in the application design process and thus takes varying traffic conditions into account. Therefore, we span the problem space as follows: assuming a traffic density of δ vehicles per kilometer that all periodically broadcast

messages with a certain transmission power ψ at a rate f and denoting the distance to the sender by x, the model M provides the corresponding probability of one-hop packet reception $P_R(x, \delta, \psi, f)$. While the distance as input factor can naturally be explained by an attenuated radio signal over distance, we consider the remaining three input dimensions for the following reason. First of all, because all vehicles communicate over a shared medium, communicating nodes in close proximity need to cooperatively agree on adequately time-separated transmissions if packet collisions are to be avoided. As the number of neighboring nodes and quantity of packets to be served increase, the coordination of transmissions becomes more stressed. Hence, the frequency of transmissions (and thus the amount of packets) and the product of traffic density and communication distance (and thus the number of nodes) become major indicators for the challenge of collision-free distributed channel allocation.

Clearly, the presented four input dimensions do not completely cover the entire parameter space of the problem at hand. Hence, we begin the following section by presenting our key assumptions and delineate the model generation process, which involves analytical and simulative derivations and general linear least squares curve fitting techniques.

The model assumes all nodes in the network to communicate according to the IEEE 802.11p draft standard, which offers a range of data transmission rates from 3 Mbit/s to 27 Mbit/s. Lower data rates facilitate a robust message exchange by offering better opportunities for countering noise and interferences. In consideration of safety applications, which are especially dependent on robust communication, we chose the lowest data rate of 3 Mbit/s. The minimum

contention window of the IEEE 802.11 mechanisms was set to the standard size of 15. Regarding packet sizes, we assume all vehicles in the scenario to transmit datagrams of equal size. Bearing in mind that data packets require security protection, we allocate 128bytesforacertificate, 54bytes for a signature, and 200 bytes of available payload, which adds up to a default packet size of 382 bytes.

A key decision in VANET research concerns the assumed radio wave propagation model. Early, simplistic proposals assumed a deterministic attenuation of the radio signal power over the transmission distance. However, as a successful packet reception is determined by the comparison of the received signal power to the noise level on the medium, a deterministic reception behavior is thereby induced. Figure 2.1 illustrates the deterministic characteristic in a scenario containing a single sender only; we do not consider interferences from simultaneous transmissions. Obviously, a packet is received with certainty within the conFigure d communication range (here: 250 m). At any distance beyond the communication range, however, message receptions are ruled out. Clearly, this model hardly corresponds to behavior we would expect in reality. Indeed, measurements of inter-vehicle communications have shown a probabilistic character. Due to the highly mobile environment and to the multitude of reflecting objects, radio strengths vary at certain distances over time. Taliwal et al. have shown that the Nakagami-m distribution seems to suitably describe the radio wave propagation in vehicular networks on highways in the absence of interferences. From the Nakagami-m distribution we can consequently infer a probabilistic reception behavior, depicted also in Figure 2.1. Apparently, in contrast to deterministic propagation models, we can

no longer identify a “communication range”. Nevertheless, a deterministic model will henceforth be assumed whenever we declare the transmission power for the Nakagami model, that is, the power necessary to reach a communication range of ψ meters. Additionally, in the following our study assumes moderate radio conditions, expressed in a relaxed fast fading parameter (m=3) of the Nakagami-m distribution. Varying channel conditions, that is, changing values of the m-parameters, were not considered in the model-building process.

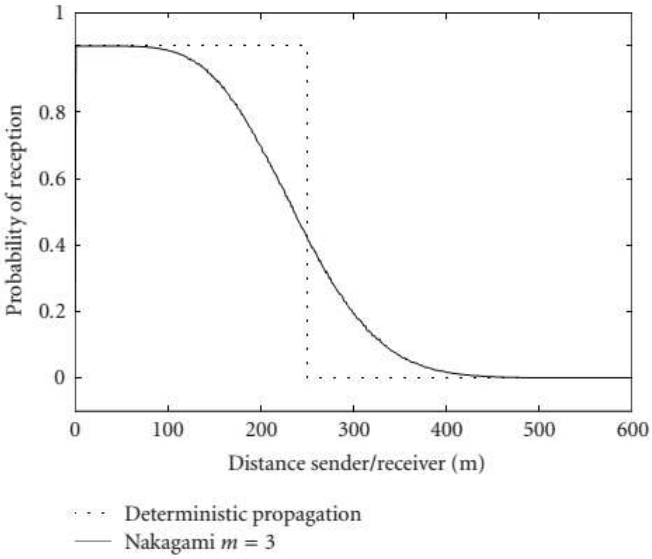


Figure 2.1 Probability of reception based on the distance between sender and receiver. Comparison of deterministic and probabilistic radio wave propagation models [Killat09]

2.1.2. Position based Sampling and Distance based Interpolation

Generally, the preview control is applied under the assumption that vehicle speed is constant. The disturbance is previewed over the preview period Tp which is equally spaced by the sampling period Ts. This is the time-based

sampling. Under ITS environment, vehicle can communicate with each other through WAVE device. In the situation, the inter vehicle distance and the relative velocity between two vehicles vary over time. So, the preview disturbance based on the time information should be resampled with the consideration of the changed vehicle speed. For resampling, a position-based sampling is easier to use than the time-based one.

Figure 2.2 shows the position based sampling on the steering angle of the preceding vehicle. In Figure 2.2, the dotted and solid lines represent the center line of the lane and the trajectory of the preceding vehicle, respectively. In Figure 2.2, the dots on the trajectory of the preceding vehicle represent the sampling points with the steering angle information.

The position information, i.e., the longitude and latitude, of the preceding vehicle can be obtained by high-precision GPS. The pair of the position and the steering angle of the preceding vehicle is transmitted into the following vehicle. Generally, the sampling period of GPS signal is 100ms. Transmitting interval of DSRC device is 20ms, which means the message update rate of 50Hz. So, the transmission interval is set to 100ms or 10Hz, which is the maximum of the sampling rate of GPS and the transmission interval of a WAVE device. On the contrary, the controller sampling period Ts is 10ms. This is a multi-rate condition. So, the previewed steering input should be resampled to obtain the time-based one using interpolation with the controller sampling period of Ts.

It is assumed that the following vehicle will go to the path that the preceding one went. From the point-based sampling data, the inter-point di in Figure 2.2

can be easily calculated. By cumulatively summing the inter-point distances on the trajectory of the preceding vehicle as follows,

$$r_i = \sum_{m=1}^{i} d_m \tag{2.1}$$

The distances from the current position of the following vehicle to each sampled point on trajectory are calculated in the following vehicle. In (2.1), r_1, r_2, … are the relative distances calculated from the position information with respect to the following vehicle.

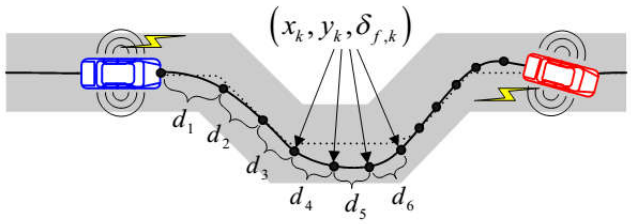


Figure 2.2 Position-based sampling on the steering angle of the preceding vehicle from double lane change maneuver [Yim16]

Figure 2.3 shows the steering angle of the preceding vehicle with respect to the relative distance from the following one. In Figure 2.3, (rk, df,k) is the pair of the relative distance and the steering angle. This is called the distance-based preview data. As shown in Figure 2.3, the transmission intervals of the distance-based preview data are not equal to one another due to the speed change and the transmission delay or packet loss. If there are no severe fluctuations in the steering input, it has little effect on the preview control. Moreover, the yaw and roll dynamics caused by the driver's steering input are slow in general. Given the previewed data, the equally spaced query points for

interpolation are given in (24). In (24), v_x(k) is the current speed of the following vehicle. As shown in (24), the query points are equally spaced by v_x(k)×Ts from the assumption that the current speed v_x(k) is maintained constant for the preview period of Tp. Linear interpolation is used to resample the time based steering input from the distance-based one.

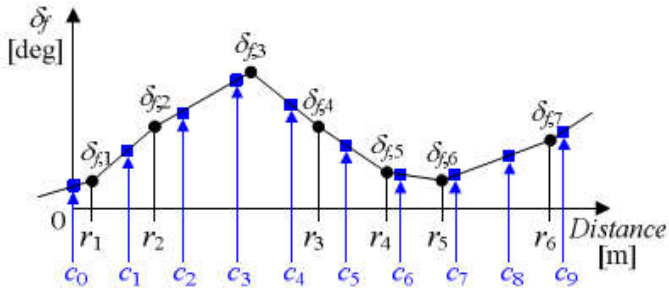


Figure 2.3 Interpolation with distance-based steering angle data [Yim16]

2.2 Communication Delay and Packet Loss Ratio

When using V2V communication for vehicle control, packet loss and transmission delay may occur if the network traffic becomes heavy. The previous research thoroughly analyzed the effect of variation of the packet size and frequency on the packet loss and communication delay [Shen05]. According to the research, the acceptable data exchange rate is 9600bytes/ second, which means the packet size of 1200bytes and the frequency of 80Hz. Under that condition, the maximum communication delay and packet loss ratio are smaller than 100ms and 1%, respectively. In this paper, the packet size is much smaller than 100bytes and transmission frequency is set to 10Hz. Under that condition, the mean and maximum of communication delay are smaller than 5ms and 20ms, respectively. Moreover, the packet loss ratio is nearly 0%. So, the packet loss ratio can be neglected.

2.2.1Compensation of V2V Communication Delay

In order to compensate the constant time delay of the V2V communication, the augmented Kalman filter (AFK) is used. A state augmented estimation algorithm AKF is implemented to compensate the communication delay based on EKF. A kinematic vehicle model to describe the behavior of target vehicle is derived. And a standard measurement model is defined to describe target vehicle's CAN bus which transmits the vehicle information. In order to estimate target vehicle's state the system can be represented with process model like below (2.2).

$$x(k+1) = F \cdot x(k) + v(k) \tag{2.2a}$$

where

$$F = \begin{bmatrix} 1 & \Delta t & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & \Delta t \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{2.2b}$$

where x is state variable and v is system disturbance. The states of kinematic vehicle model is described as follows :

$$x = \begin{bmatrix} v & a_x & \gamma & \dot{\gamma} \end{bmatrix}^T \tag{2.3}$$

Measurement model can be defined as below.

$$z(k) = h(x(k)) + w(k) \tag{2.4a}$$

where

$$z = \begin{bmatrix} a_x & \gamma & v_{w,1} & v_{w,2} & v_{w,3} & v_{w,4} \end{bmatrix}^T \tag{2.4b}$$

$$h(x(k)) = \begin{bmatrix} \dfrac{\sqrt{4 \cdot V_x^{\,2} - 4 \cdot V_x \cdot l_w \cdot \gamma + l_w^{\,2} \cdot \gamma^2 + 4 \cdot l_t^2 \cdot \gamma^2}}{2\pi r_e} \\ \dfrac{\sqrt{4 \cdot V_x^{\,2} + 4 \cdot V_x \cdot l_w \cdot \gamma + l_w^{\,2} \cdot \gamma^2 + 4 \cdot l_t^2 \cdot \gamma^2}}{2\pi r_e} \\ \dfrac{2 \cdot V_x - l_w \cdot \gamma}{2\pi r_e} \\ \dfrac{2 \cdot V_x + l_w \cdot \gamma}{2\pi r_e} \end{bmatrix} \tag{2.4c}$$

where z denotes measurements, w denotes measurement noise, V_x denotes longitudinal velocity, l_w denotes wheel base, l_t denotes vehicle width, γ denotes yaw rate and r_e denotes wheel effective radius. As shown in Figure 2.4, the problem of constant delay involves every measurement being delayed by the same, constant lag.

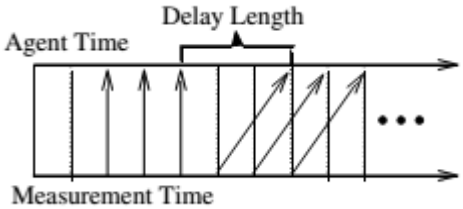


Figure 2.4. Delayed measurements sequence

The relationship between current measurement and the state variable is given in (3) when time delay exists in the measurements.

$$z(k) = h(x(k-\tau)) + w(k-\tau) \tag{2.5}$$

where τ is delayed time.

In order to compensate delayed state variable using delayed measurements, state variable is augmented to incorporate previous state variable. Thus the process model is transformed to as below.

$$\begin{bmatrix} x(k+1) \\ x(k) \end{bmatrix} = \begin{bmatrix} F \cdot x(k) + v(k) \\ x(k) \end{bmatrix} \tag{2.6}$$

With the multiple steps of time delay, the process model contains state variables of previous multiple steps.

$$\begin{bmatrix} x(k+1) \\ x(k) \\ \vdots \\ x(k-n) \end{bmatrix} = \begin{bmatrix} F & 0 & \cdots & 0 \\ I & 0 & 0 & \vdots \\ 0 & \ddots & 0 & 0 \\ 0 & 0 & I & 0 \end{bmatrix} + \begin{bmatrix} I \\ 0 \\ \vdots \\ 0 \end{bmatrix} v(k) \tag{2.7}$$

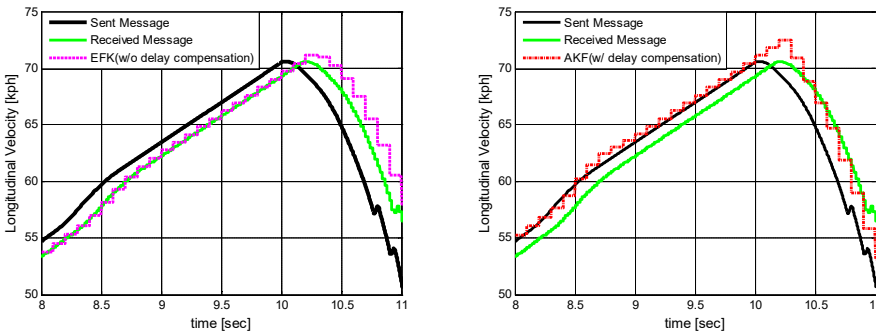
where n denotes the maximum time delay which is contained by measurement. Therefore the measurement model can be expressed below (2.8) using the transformed state variables $X(k)$.

$$z(k) = h(X(k)) + w(k-\tau) \tag{2.8}$$

Figure 2.5 demonstrates estimation results on the straight road with certain amount of abrupt acceleration and deceleration. Compared to EKF, AKF estimates the preceding vehicle's sent message as well as compensating time delay of received message as shown in the Figure 2.5. Estimated result is quite identical to preceding vehicle's sent message in terms of its magnitude and phase delay. It is expected to be believed that response performance of future autonomous emergency braking system (AEBS) will be improved because of precise preceding vehicle's filtered wireless communication information.

A double lane change is simulated on a dry road (0.85) as shown in Figure 2.6. The steering wheel angle is determined by a Carsim driver model. The initial speed is set to be 80kph. A spike brake and the certain amount of throttle input are applied during the simulation and its acceleration is described in Figure 2.7.

Figure 2.7 shows estimation results of in double lane change. From Figure 2.7, AKF estimates the preceding vehicle's sending message by compensating time delay of received message. Figure 2.7 (c) have a small amount of magnitude differences between AKF estimation results and sent messages since the



(a) Estimation without delay compensation (b) Estimation with delay

Figure 2.5. Estimation results on the straight road

dimension of AKF's covariance matrix increases so that the algorithm becomes computationally more involved and numerical inaccuracies has occurred [14]. As shown in Figure 2.7 (a) , longitudinal velocity difference between sent message and AKF descends by 2kph at 3sec otherwise it was 10kph in the case of conventional EKF. Figure 2.7 (c) demonstrates that yaw rate error can be reduced by 1.5deg/s in the case of AKF. However EKF shows 16.5deg/s of error since it does not compensate delay.

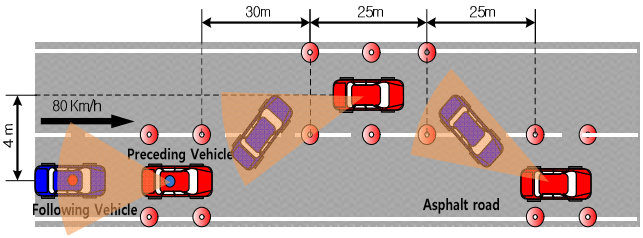
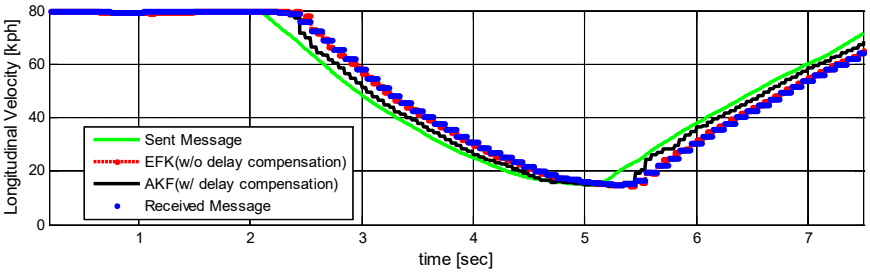
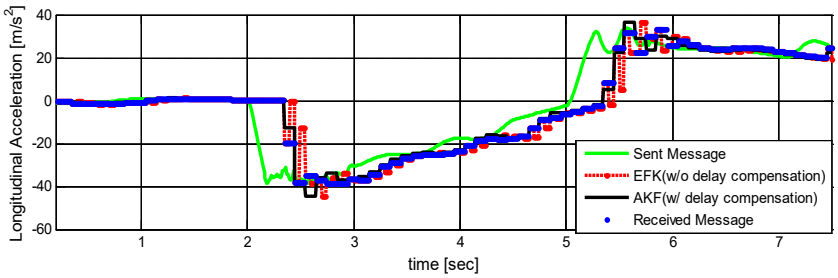


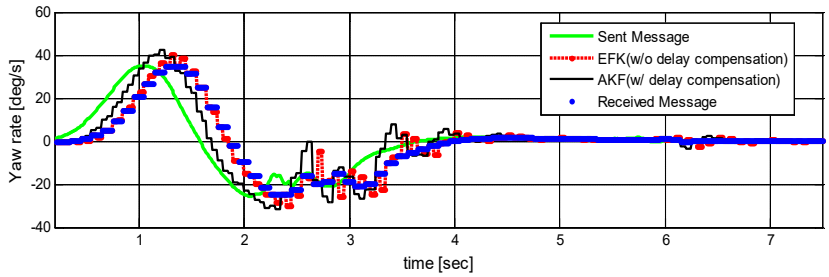
Figure 1.6 Double lane change with V2V Communication



(a) Longitudinal velocity compensation



(b) Longitudinal acceleration compensation



(c) Yaw rate compensation

Figure 2.7 Estimation results in double lane change

Chapter 3

Human Factor Considerations

The purpose of this chapter is to present some of the human factors and its application for autonomous vehicle. One of the key autonomous driving design concept is naturalistic driving aimed at creating the system that are 'less robotic' and perhaps more acceptable to vehicle occupants and other road users.

A common terminology with taxonomy and definitions of on-road vehicle automation have been raised by industry and governmental communities. Generally, the levels of driving automation can be divided into Conditional, High and Full Automation, see Figure 3.1.

At Level 0, there is of course a lot of driver's experience, and it is easy to underestimate the safety performance. According to US traffic statistics in 2012 [Gordon15], out of roughly three trillion vehicle miles travelled, there were a total of 5.6 million police-reported traffic accidents, 30,800 of them involving a fatality. This compares to the currently quoted million-plus miles of accident-free (supervised) travel for Google's self-driving cars, when the development team selects roads and timing, intervenes when necessary, and presumably does so with high attention levels. For humans, tactical driving requires experience and attention. It is also the level that is most demanding for highly automated cars. It seems infeasible to replicate all aspects of human driving at the tactical

level, at least no without artificially intelligent computers that are beyond anything currently proven. Gordon [Gordon15] formulates a Turing driving test on this topic : if a self-driving car behaves in all traffic condition such that other road users cannot tell any difference from a human driver, then we might assume that we have a safe and acceptable system. This allows predictable human-machine interactions by reducing risk of unpredictable motion. It can be achieved by expressing human perception-reaction time as human (pure manual) driving status. This is called human-centered active safety function which means human-like driving intelligence has been implemented by maximizing driver acceptance. By relating the system or machine's status with the human sense (reaction time), the human-like behavior of autonomous driving is possible.

In order to fully develop autonomous drive, mainly two factors should be considered. One is the driver acceptance and the other is the sight distance. The driver acceptance is especially crucial for the rear end collision avoidance applications. The system warning should result in minimum load on driver attention. For the normal driving operation, active safety feature should not interfere the driver and the system should perform well in a variety of driving conditions. Thus, driver inattention, mode confusion and motion sickness are investigated for the future autonomous drive.

The sight distance is investigated and applied to the safety algorithm for human-like behavior of autonomous driving. The sight distance consists of stopping sight distance and decision sight distance. The stopping sight distance can be used for the active safety system since it reflects test data based human

behavior when the confronted emergency situation. And this can be useful for the driver to monitor its driving status as well as machine's safety level.

LEVELS OF *DRIVING* AUTOMATION FOR ON-ROAD VEHICLES - **SAE J3016**

SAE Level	SAE Name	SAE Narrative Definition	Execution of Steering/ Acceleration/ Deceleration	Monitoring of Driving Environment	Fallback Performance of Dynamic Driving Task	System capability (driving modes)	BASt Level	NTHSA Level
Human Driver monitors the driving environment								
0	No Automation	the full-time performance by *the human driver* of all aspects of the *dynamic driving task*	Human Driver	Human Driver	Human Driver	N/A	Driver only	0
1	Driver Assistance	the *driving mode-specific* execution by a driver assistance system of either steering or acceleration/deceleration	Human Driver and Systems	Human Driver	Human Driver	Some Driving Modes	Assisted	1
2	Partial Automation	Part-time or driving mode-dependent execution by **one or more driver assistance systems** of both steering and acceleration/deceleration. Human driver performs all other aspects of the *dynamic driving task*	**System**	Human Driver	Human Driver	Some Driving Modes	Partially Automated	2
Automated driving system ("system") monitors the driving environment								
3	Conditional Automation	*driving mode*-specific performance by an *automated driving system* of all aspects of the *dynamic driving task* - *human driver* **does** respond appropriately to a *request to intervene*	System	**System**	Human Driver	Some Driving Modes	Highly Automated	3
4	High Automation	*driving mode*-specific performance by an *automated driving system* of all aspects of the *dynamic driving task* - *human driver* **does not** respond appropriately to a *request to intervene*	System	System	**System**	Some Driving Modes	Fully Automated	3/4
5	Full Automation	**full-time** performance by an *automated driving system* of all aspects of the *dynamic driving task* under all roadway and environmental conditions that can be managed by a *human driver*	System	System	**System**	All Driving Modes		

Figure 3.1 Summary of levels of driving automation for on-road vehicles (after SAE International [SAE14]).

3.1 Driver Acceptance

Vehicle active safety systems must be accepted by drivers. In general, this means that the system has to be useful to the driver and must not interfere with normal driving habits. This has several interpretations: Driver inattention and distraction, mode confusion and motion sickness. One of the factor that influences driver responses is warning frequency. [2]. Frequent warnings may desensitize the driver and cause future warnings to be ignored. Rare warnings can distract the driver during critical situations. Therefore, the method of warning the driver and the frequency at which warnings are given must be chosen carefully. One potential solution is to give constant visual feedback to the driver. Unlike random warnings, constant visual feedback in the form of graduated light displays or relative distance displays may not be obtrusive to the driver. Therefore, the driver may not be desensitized by this type of warning. This type of warning should actually cause the driver to become accustomed to the CW/CA system so that they should not be startled when a critical warning is given.

Furthermore, automatic control of the brakes should not interfere with normal driving operation. A driver who is attempting an avoidance maneuver, such as steering, may be startled and possibly lose vehicle control if the system automatically applies the brakes [3]. Therefore, a very conservative CA system may be able to prevent all possible collisions. However, it will also be more likely to disrupt the driver by applying the brakes at inappropriate times. A

more reasonable goal is to design an unobtrusive algorithm which prevents some collisions and reduces the severity of all other impacts.

3.1.1. Driver inattention and distraction

First, warnings given by the system should result in a minimum load on driver attention. An increase in warning frequency produces a tradeoff between two harmful driver responses. Although this is usually intended to lighten driver workload, this is not necessarily beneficial for driving and does not always lead to increased road safety. If the workload on the driver is too little during periods of automation, the driver may experience passive fatigue, which is argued to stem from situations in which cognitive load is low and there a lack of direct control over the task at hand. And this had happened in Tesla model S's accident on 7th of May, 2016. Two recent studies conducted in driving simulators support this premise, showing that drivers are more likely engage in secondary activities and spend more time looking away from the forward.

3.1.2. Mode Confusion

Mode confusion is a phenomenon that refers to a discrepancy between how the vehicle driver believes the vehicle to be operating and how the vehicle is actually operating [Cummings2014]. In lay terms, it is a sense of confusion concerning which aspects of vehicle performance is controlled by the driver and which is controlled by the automation at a particular instance [Martens2013]. If a driver is unaware of the state of the automated vehicle, he or she could make decisions based on the (incorrect) belief that the vehicle is

in a certain state or in control of a certain aspect of driving when it currently is not [Bredereke2002].

3.1.3. Motion Sickness

A relatively unexplored, yet important, human factors issue in the realm of automated driving is that of an increased propensity for motion sickness of vehicle occupants. Motion sickness is a condition marked by symptoms of nausea, dizziness, and other physical discomfort [Golding1992] and can be associated with various modes of transportation [Byrne1996]. The condition is most frequently caused by a conflict between visual and vestibular inputs[Benson1999], loss of control over one's movements [Rolnick1991] and reduced ability to anticipate the direction of movement [Golding05]. Interestingly, [Sivak15] purport that up to 10% of American adults are expected to experience motion sickness often in autonomous vehicles. The authors also contend that remedies for motion sickness in the form of the design of the automated vehicle are limited as the crux of the issue is that automation controls the drivers' direction of motion, not the driver themselves, which may present issues of driver acceptance.

3.2 Sight Distance

Sight distance criteria have impact on virtually all elements of highway design, many elements of the operation/control, and recently, access management implementation. The roadway geometric design features, presence of obstacles to sight at the roadsides and the pavement surface condition are fixed by sight distance requirements. The nature of traffic controls and their placement must take account of sight distance requirements. At times, the effects of traffic stream conditions, such as traffic queues, must be viewed from adequate distance to stop. The provision of roadside access and accommodation of pedestrian crossings must assure a safe stopping distance [.

Adequate stopping sight distance must be provided on 100% of the street and highway system so a driver with the standard eye height can see an object of standard height with sufficient time to stop safely. This assumes a certain level of alertness on the part of the driver and no influence on a driver's perception and reaction due to added complexity of traffic, control and local environmental conditions. Some research has indicated that driver behavior, expectations and alertness change with the type of area and with the operating conditions on the roadway.

The determination of stopping sight distance requires the definition of six of the seven primary design variables defined previously. It is not necessary to specify both deceleration rate and a design coefficient of friction because they both measure the required rate of slowing for the vehicle.

Under some conditions the added complexity of traffic, local activities and driver expectancy may require longer times to accommodate long perception-reaction times due to situation complexity, expectations and alertness, as well as longer distance for normal vehicle maneuvers of lane changing, speed changes and path changes, or for stopping. The current standards for stopping sight distance take these factors into account.

These increased perception-reaction times and longer maneuvering distances are accommodated by decision sight distance. Decision sight distance is applied where numerous conflicts, pedestrians, various vehicle types, design features, complex control, intense land use, and topographic conditions must be addressed by the driver. Stopping sight distance is applied where only one obstacle must be seen in the roadway and dealt with. Decision sight distance is different for urban versus rural conditions, and also for maneuvers ranging from stopping to speed, path or direction change within the traffic stream.

Stopping in the context of decision sight distance, as distinct from stopping sight distance, may be necessary to avoid a vehicle that is forced to stop for some traffic condition, such as a queue of vehicles, or roadside conflicts, such as, congestion in a driveway.

In view of the complexity and variations in drivers' expectancy for situations associated with access management, in general, decision sight distance is a more logical requirement for many access management situations than stopping sight distance, as currently defined. Decision sight distance is covered in a companion paper, "Decision Sight Distance: A Discussion Paper," Kiewit – 2012/03, OSU, March 2012.

3.2.1. Stopping Sight Distance

Sight distance is the length of the roadway ahead that is visible to the driver. The available sight distance on a roadway should be sufficiently long to enable a vehicle travelling at or near the design speed to stop before reaching a stationary object in its path. Although greater lengths of visible roadway are desirable, the sight distance at every point along a roadway should be at least that needed for a below-average driver or vehicle to stop.

Stopping sight distance is calculated as the sum of (1) the distance a vehicle travels from the instant a driver sees an object necessitating a stop until the instant the brakes are applied, and (2) the distance required to actually stop the vehicle once the brakes are applied. In roadway design, the SSD is used to determine if drivers will have sufficient time to stop.

The 2001 and 2011 AASHTO Greenbooks recommend a minimum stopping sight distance based on design speed with a deceleration rate of 3.4 m/sec2) and a perception-reaction time of 2.5 seconds for design. The "minimum" stopping sight distance based on running speed has been abandoned [AASHTO01 & AASHTO11].

3.2.2. Decision Sight Distance

The decision sight distance as defined by the AASHTO Green Book is "the distance required for a driver to detect an unexpected or otherwise difficult-to-perceive information source or hazard in a roadway environment that may be visually cluttered, recognize the hazard or its threat potential, select an appropriate speed and path, and initiate and complete the required maneuver

safely and efficiently." According to 1990 and 1994 AASHTO, the decision sight distance requires about 6 to 10s to detect and understand the situation and 4 to 4.5s to perform the appropriate maneuver [AASHTO90 & AASHTO94]. For 1990 and 1994 AASTHO Greenbook, the sight distance was typically measured from a 1070 mm height of eye to 150 mm object; however, this should depend on the condition that requires the decision sight distance. For example, if the condition of concern is a vehicle, such as the rear of a queue of vehicles, an object height of vehicle tail lights of 600 mm would be appropriate. A table showing the recommended decision sight distances for various maneuvers is given below.

Table 3.1 Decision Sight Distance

Design Speed (km/h)	Decision Sight Distance for Avoidance Maneuver, (meters)				
	A	B	C	D	E
50	70	155	145	170	195
60	95	195	170	205	235
70	115	235	200	235	275
80	140	280	230	270	315
90	170	325	270	315	360
100	200	370	315	355	400
110	235	420	330	380	430
120	265	470	360	415	470
130	305	525	390	450	510

*Note: Avoidance Maneuvers
1. Avoidance maneuver A: Stop on rural road - t = 3.0^s
1a. Stop on suburban road - Assume t = 6.0^s
2. Avoidance maneuver B: Stop on urban road – t = 9.1^s
3. Avoidance maneuver C: Speed/path/direction change on rural road – t=10.2 – 11.2^s
4. Avoidance maneuver D: Speed/path/direction change on suburban road – t=12.1 – 12.9^s
5. Avoidance maneuver E: Speed/path/direction change on urban road – t=14.0 – 14.5^s
Source: AASHTO Greenbook, 2001.

Various operating conditions require different maneuvers in response to a situation, as well as different perception-reaction times. The perception-reaction times are shorter for the less complex rural conditions than for urban.

Chapter 4

Human-Centered Risk Assessment using Vehicular Wireless Communication

Intelligent vehicles and collision avoidance systems have been considered to enhance the safety of drivers and passengers. It helps drivers to avoid or mitigate crashes using warnings and/or interventions. Collision avoidance systems already have been introduced to the market by several automotive companies. The Volvo City Safety [Distner09] monitors the threat vehicles ahead via a radar, and brakes without driver intervention when an imminent crash situation is detected. For more capable and enhanced collision protection systems, a vehicular wireless communication (V2V communication) is implemented to allow the exchange of information between vehicles [Xu02]. This system allows to reduce inherent uncertainty of traffic environments and incomplete knowledge due to radar sensor limitations.

With the aid of V2V communication, lots of research efforts are underway with the goal of enhancing the safety, efficiency and comfort of highway/urban traffic. The next step in the development of ADAS points toward vehicle-to-vehicle (V2V) communications to obtain more extensive and reliable information about vehicles in the surrounding area, representing cooperative intelligent transportation systems (ITS). Using wireless communication,

potential risk situations can be detected earlier to help avoid crashes, and more extensive information about other vehicles' motions can help improve vehicle control performance.

Common measure of collision risk is time-to-collision (TTC) and it focuses on warning state, crash avoidable state, crash unavoidable state, and post event state. The TTC is calculated by assuming all objects being detected, their positions being computed and their velocities remaining constant relative to the host vehicle. For a time horizon, the TTC is implemented effectively in accident mitigation systems. However, for a few seconds of the time horizon, TTC may not be expected to always prevent collision. Therefore, predicting the future behaviors of other traffic participants is necessary for more improved estimation of collision risk.

In order to fully guarantee the safety and acceptable system during any driving situation, predicting the future behaviors of other traffic participants is necessary. The best way to predict the unknown future behavior of remote vehicle is probabilistic approach [Laugier11]. Kim et al. [Kim15] proposed a probabilistic threat assessment method to predict and avoid almost all possible collision in multi-vehicle traffics. The proposed method had been compared with the time to collision (TTC) method when the preceding vehicle starts its evasive lane-changing as soon as it detects the invisible stopped leading vehicle ahead. And the host vehicle applied hard brake, however, the TTC level of the leading static vehicle had still maintained to 2s~3s which overestimates the risk. However, in the case of the proposed collision risk, the collision probability had grown up to 80~90% during which leading static vehicle appeared and it

remarkably dropped by 10~20% during the host vehicle applied the hard brake. Since the TTC assumes vehicles' constant speed using range and range-rate, there will be uncertainty over any deceleration of the lead vehicle, thus, the active safety system may not be expected to always prevent collision and to guarantee driving comfort.

The driver support function (the so-called 'co-driver') [Flemisch10] allows a human factor considered active safety system to find best intervention point from human (manual) driving mode by monitoring traffic and risk. Wei et. al [Wei09] investigates that autonomous vehicle performance, robustness and safety can be improved by cooperation between human-driver and vehicle's intelligence. A human driver has to take part in the driving and strategy planning of an autonomous vehicle. Thus, in order to fully guarantee the safety, future automated drive system has to find a best trade-off between the human sense and automated function such as an active safety by implementing human driver's ability.

The human-like behavior of self-driving car is assumed to be safe and acceptable system from the drivers as well as other road users [Gordon15]. This allows predictable human-machine interactions by reducing risk of unpredictable motion [Gordon15]. For the human centered active safety function, human-like driving intelligence has to be implemented and it maximizes driver acceptance. In order to express human (pure manual) driving status, the human reaction time [Layton97] with respect to predicted minimal distance is considered in this paper. In order to express the status of active safety system, collision risk with respect to predicted minimal distance [Wardzinski08]

is considered. Based on this idea, we propose a novel human-centered risk assessment approach.

Effects of V2V communication on the automated vehicle risk assessment performance are investigated in this paper. Many authors proposed the information fusion of V2V communication and ADAS sensors for a better target vehicle tracking performance. To date, however, its applications for risk assessment and collision avoidance have not been discussed. If the V2V communication is fused with a radar sensor, it can be possible that more accurate collision risk and human reaction time are computed with decision of active safety control intervention timing.

This chapter is organized as follows. In section 4.1, the fundamental descriptions for the human centered design is discussed. In the following section, the limitations of sensor-based vehicle safety system is investigated by providing the advantages of convergence with V2V communication. Section 4.4 describes related works for the implementation of radar sensor based risk prediction algorithm. And previous human-centered approach is announced to clarify the effectiveness of human factor in the automated vehicle control. The V2V communication is fused with the radar sensor and estimation performance are demonstrated in the following section. The probabilistic collision risk analysis is introduced and predicted collision distance are derived accordingly. With the human factor considerations, the active safety intervention moment decision is described.

4.1 Human−Centered Design

Many driver assistance systems were proposed over the last decade to enhance the comfort, safety and efficiency of ground vehicles. Examples include adaptive cruise control (ACC), vehicle stability control (VSC) systems, electric power-assist steering (EPAS), anti-rollover control (ARC), four wheel steering (4WS), etc. Some of these driver assistance systems were designed to relief human drivers from certain (lower-level) driving tasks, and others were designed to work collaboratively with human drivers. As oppose to fully automated designs, for driver assistance systems, the human driver retains ultimate authority and thus the responsibility of safe driving. Since driver assistance systems (DAS) always work with a human driver co-existing, the overall vehicle performance will depend on, not how well the DAS works by itself, but rather its interaction with the human driver. For the fully automated drive, the active safety intervention function has to interactively work with the normal automated drive function for the naturalistic decision of driving status. This can be achieved by developing a human like prediction and active safety control decision model. This requirement is non-trivial because of the time varying and uncertain nature of human drivers. Furthermore, human decisions are complex and involve pre-cognitive, planning-strategic as well as servo-regulation actions, and the switching among different goals, as well as sensory cues. In addition, for certain driving tasks, human drivers' employee preview-predictive strategies which are usually difficult to implement. Finally, human

perception and decision process were sometimes based on fusion of complex visual and motion feedbacks that are difficult to understand and reproduce in mathematical models. When we focus on the specific goal of evaluating DAS with a driver (model) in the loop, for maneuvers with short durations, the driver modeling problem becomes considerably simpler. This is due to the fact that most of the existing DAS perform clearly defined functions such as time headway keeping, vehicle side slip angle regulation, etc. Within short time horizons, it is assumed that human drivers neither demonstrate significant learning or adaptation, nor switching among complex rules. In other words, the planning/strategic part of the driver action is assumed to be well defined, and the key issue is on the development of the servo-level human driving model.

4.2 Convergence

A V2V communication or Dedicated Short Range Communication (DSRC) systems will become ubiquitous among vehicles in the near future. Because this technology enables communication between any set of DSRC-equipped vehicles, precise knowledge of these other vehicles is available to the host car. In addition to the DSRC system, onboard radars are able to provide high fidelity dynamics measurements of other objects within the sensing range. Given these two methods of measurement, environmental perception for driver assistance systems can be greatly improved, especially if the measurements are fused together. In this chapter, shortcomings of sensor-based systems and advantages of convergence between on-board sensors and V2V communication are discussed.

4.2.1 Sensor-Based Solutions

The automotive industry is currently developing sensor-based solutions to increase vehicle safety in speed zones where driver error is most common: at lower speeds, when the driver is stuck in traffic, and at higher speeds, when the driver is cruising on a long stretch of highway. These systems, known as Advanced Driver Assist Systems (ADAS), use a combination of advanced sensors, such as stereo cameras and long- and short-range RADAR, combined with actuators, control units, and integrating software, to enable cars to monitor and respond to their surroundings. Some ADAS solutions, such as lane-keeping and warning systems, adaptive cruise control, back-up alerts, and parking

assistance, are available now. Companies are also developing sensor-based, driver-assisted solutions, which use stereo cameras and software and complex algorithms "to compute the three-dimensional geometry of any situation in front of a vehicle in real time from the images it sees." Such sensor-based systems offer varying degrees of assistance to the driver, but, in their current form, are not yet capable of providing self-driving experiences that are complete and cost competitive.

For example, radar (camera and LIDAR systems as well) has its own limitations. The information obtained is limited to the relative position, speed and acceleration measurements, as well as an approximate shape. Object detection is further restricted by object occlusion and the sensor coverage area. Many heuristics are applied to the object detection, which leads to a compromise between sensitivity and false positive rates. Static objects or objects in far distances are very hard to detect reliably.

4.2.2 The Benefits to Convergence

Several extensive field tests have shown the practicality of V2V Communication [simTD13]. This kind of communication among vehicles and infrastructure components is an enabling technology for a various set of applications which increase driving safety, improve driving comfort and facilitate more efficient transportation [Sichitiu08]. Dedicated Short Range Communication (DSRC) is one term for this technology, and acts as a basis for Vehicular Ad Hoc Networks (VANETs) or Vehicle-to-Vehicle Communication (V2V). However, rolling out DSRC or V2V communication on all vehicles will

take a long period of time; therefore DSRC cannot help to locate the non-equipped vehicles. The information flow from equipped vehicles is not always reliable, especially in a busy VANET network, where information updates often suffer delays and drops. The information quality is also restricted by the sensor quality, especially the positioning information based on low cost GPS receivers is prone to a high degree of noise [Alam13]. Therefore information from DSRC is often considered not to be reliable enough to initiate automated maneuvers. Many vehicle-safety related applications developed on DSRC systems provide only warnings to drivers. So far applications of DSRC in driver assistance systems are limited.

Despite the shortcomings in both technologies, two are complimentary to each other. Once data is fused, the environment perception capability can be greatly enhanced, in terms of sensing reliability and range. Therefore, improvements to existing driver assistance systems or safety guaranteed decisions of autonomous drive are possible.

4.2.3 V2V/Radar Information Fusion

According to [Aberhard11], the author provided quick overview of the basic fusion architectures and their application in ADAS. In the high-level fusion, all sensor relevant details are kept at the sensor-level, allowing the fusion module to process the data abstractly. This makes the high-level fusion architecture favorable in applications where modularity and simplicity of design is required. Thus we propose the high-level fusion and this has been successfully and widely demonstrated in automotive applications, e.g. for ACC [Takizawa04]

and for safety systems [Floudas07]. The high-level track to track information fusion will be specifically discussed in Section 4.3.4.

4.3 Related Work

The radar based probabilistic threat assessment has been surveyed in this chapter. In order to realistically model the radar sensors, its sensing characteristics are investigated and verified via vehicle tests. With the radar model, probabilistic threat assessment algorithm is implemented and it is compared with the conventional threat assessment method such as Time to Collision (TTC).

The human factor considered vehicle control research has been surveyed as well. One is the human driving data based design of a vehicle ACC and the other is human-centered design of an ACC with braking and forward crash warning system. Two works consider human factors and its effectiveness is investigated. And it gives us motivations for the reason why the human centered design actually matters in terms of automotive safety control.

4.3.1 Radar Sensing Characteristics

Radar sends out wave beams to scan its surroundings and collect the reflected signals. Based on the wave traveling time, distance can be computed in high accuracy. Reflected signals are registered as points in the vehicle coordinate system. Those with high confidence are output by the radar system as a list of detected remotes. Usually each remote vehicle contains an internal tracking ID, distance, speed measurements and acceleration estimates based on the Doppler Effect. Advanced radar systems can even give rough dimension estimations based on the L-shape reflecting points. However, the radar only sees a side or a corner of the remote vehicle, thus remote dimension estimation is not always consistent. The classification of remotes types can also be difficult. The vehicle's behavioral status, such as the intention to make a turn or brake, is even harder to determine by a radar system. Those intentions cannot be effectively detected until the remote vehicle motion has a noticeable changes during a few seconds. In order to reflect the characteristics above, realistically and elaborately modelled radar has been used in [Kim 15]. Changes in the remote aspect with respect to the radar can cause the apparent point of radar reflections (relative position seen by the antenna) to wander significantly. To represent

Table 4.1. Initial Setting Condition for Sensor data collection

	Host Vehicle	Remote Vehicle
Speed	30/35/40/45/50/55/60/65/70/75/80kph	20kph
Range	5 to 70 m	

these, the measurement model can be elaborated by introducing new parameters to specify the sensor position and the measured point. These are depicted in Figure 4.1. As the result, the measurement vector of remote vehicle is defined as follows.

$$\begin{aligned}\mathbf{z}_{rv}^{radar}[k] &= \mathbf{h}\left(\mathbf{x}_{rv}^{radar}[k], \mathbf{u}[k]\right) + \mathbf{v}_{rv}^{radar}[k] \\ &= \begin{bmatrix}\mathbf{h}_{n1} & \mathbf{h}_{n2} & \mathbf{h}_{n3}\end{bmatrix}^T + \mathbf{v}_{rv}^{radar}[k] \\ \mathbf{v}_{rv}^{radar}[k] &\sim \left(0, \mathbf{V}_{rv}^{radar}[k]\right)\end{aligned} \tag{4.1}$$

where

$$\mathbf{x}_{rv}^{radar} = \begin{bmatrix} p_{rv,x}^{radar} & p_{rv,y}^{radar} & \theta_{rv}^{radar} & v_{rv,x}^{radar} & \gamma_{rv}^{radar} & a_{rv,x}^{radar} & \dot{\gamma}_{rv}^{radar}\end{bmatrix}^T$$

$$\mathbf{u} = \begin{bmatrix} v_x & \gamma \end{bmatrix}^T$$

$$\begin{aligned}\mathbf{h}_{rv1} &= p_{rv,x}^{radar} - s_x + b_{rv,x}^{radar}\cos\theta_{rv}^{radar} - b_{rv,y}\sin\theta_{rv}^{radar} \\ \mathbf{h}_{rv2} &= p_{rv,y}^{radar} - s_y + b_{rv,x}^{radar}\sin\theta_{rv}^{radar} + b_{rv,y}\cos\theta_{rv}^{radar} \\ \mathbf{h}_{rv3} &= v_{rv,x}^{radar}\cos\theta_{rv}^{radar} - v_x + p_{n,y}\cdot\gamma + \left(b_{n,x}\sin\theta_{rv}^{radar} + b_{rv,y}\cos\theta_{rv}^{radar}\right)\ldots \\ &\quad \ldots\left(\gamma - \gamma_{rv}^{radar}\right)\end{aligned}$$

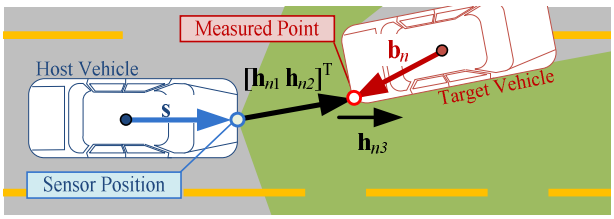


Figure 4.1. Parameters to derive the standard form of the refined measurement model

Table 4.2. Variance and Standard deviation of range error: RADAR sensor

C_x[m]	5	10	20	30	40	50	60	70
Var	0.12	0.59	1.81	2.98	2.87	2.86	2.82	2.32
Std	0.35	0.77	1.35	1.73	1.70	1.70	1.65	1.52

where subscript rv denotes remote vehicle, p denotes the relative position, θ denotes the relative yaw angle, v denotes the velocity, γ denotes the yaw rate, a denotes the acceleration, and $\dot{\gamma}$ denotes the yaw acceleration. And variable without subscript n and rv means "variable of the host vehicle". $\mathbf{h}$ is nonlinear measurement equation which describe the state of measured point on the sensor based moving frame {2}. $\mathbf{s}$ is sensor position vector defined on the host vehicle's body-fixed moving frame {1} and $\mathbf{b}_{rv}$ is measured point vector of remote vehicle defined on the remote vehicle 's body-fixed moving frame {3}. The first order approximation of the measurement error covariance has been presented in previousworks as follows

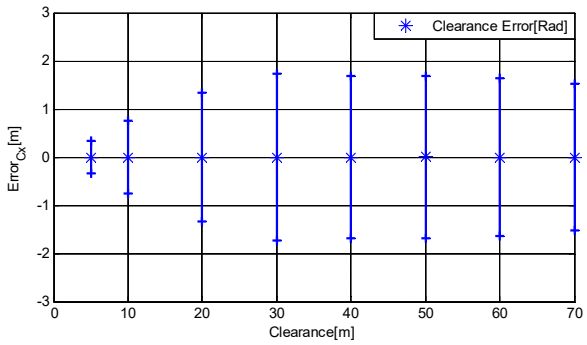


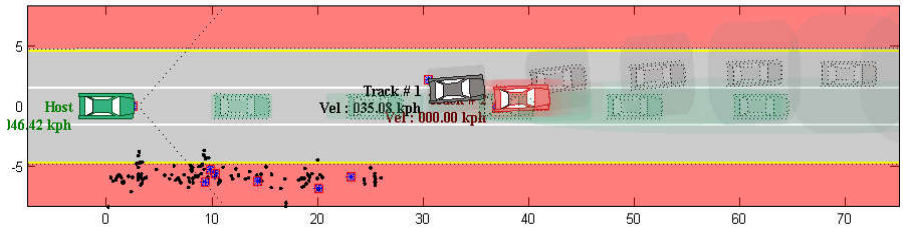
Figure 4.3. Parameters to derive the standard form of the refined measurement model

[Kim15].

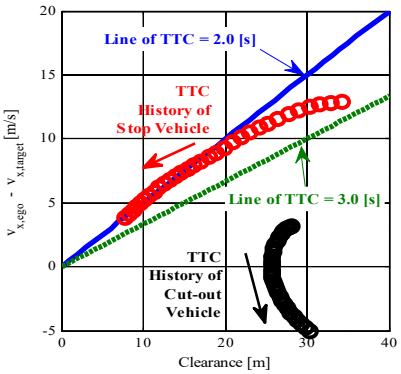
In order to incorporate radar sensing characteristics into the algorithm, an experiment was performed by using the host vehicle equipped with radar sensor system to measure the range and range-rate with respect to the remote vehicle. Data is acquired during which the host vehicle cruises behind the remote vehicle. The range and relative velocity vary as seen in Table 4.1. The data was collected on the test road without other vehicle or obstacle interruption. The variance and standard deviation of range error is presented in Figure 3. As shown in Table 4.2, the variation and the standard deviation are saturated to specific values as clearance values increases.

4.3.2 Probabilistic Threat Assessment

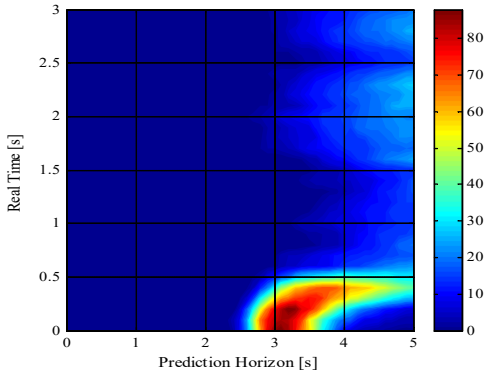
With the accurate estimate of remote vehicle from multi-sensor fusion, active safety systems can be enhanced by reducing the risk of accidents, improving the driver's comfort and driving performance. Current automotive safety system can be grouped into five driving states as follows: normal driving state, warning state, crash avoidable state, crash unavoidable state, and post event state. Common measure of collision risk is time-to-collision (TTC) and it focuses on the last three states which are accident mitigation. The TTC is calculated by assuming all objects being detected, their positions being computed and their velocities remaining constant relative to the ego-vehicle. For a time horizon, the TTC is implemented effectively in accident mitigation systems. However, for a few seconds of the time horizon, it is less efficient to



(a) Environment description and multi-traffic prediction



(b) TTC analysis in a domain of clearance with respect to relative velocity



(c) Probabilistic collision risk assessment results in a domain of prediction horizon with respect to real time

Figure 4.4. Test results from which the preceding vehicle starts to change the lane and the invisible stopped lead vehicle appears. [Kim15]

guarantee the collision avoidance. Therefore predicting the future behaviors of other traffic participants is necessary for more improved estimation of collision risk. Other traffic participants like preceding vehicle's probabilistic prediction is required since its future behaviors can never be known exactly [Christian11]. Figure 4.4 illustrates the limitation of TTC as the sole estimate of risk when the preceding vehicle starts its lane-changing and the invisible stopped lead vehicle

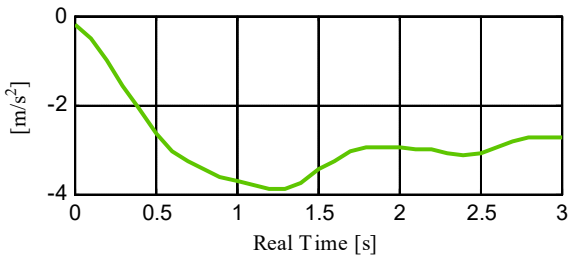


Figure 4.5. Test results from which the preceding vehicle starts to change the lane and the invisible stopped lead vehicle appears.

appears suddenly. The TTC history in Figure 4.4-(b) with static vehicle has maintained 2s~3s of TTC levels although the host vehicle's deceleration as seen in Figure 4.5. However, in the case of the proposed collision probabilities in Figure 4.4-(c), its peak value had grown to 80~90% during 0 to 0.6 seconds and has remarkably dropped by 10~20% after reaching the sufficient declaration level as shown in Figure 4.5. Therefore TTC is hard to evaluate the collision risk in non-stationary state and it is difficult to reflect driver's sensitivity, on the other hand, the probabilistic collision risk assessment well represents the driver's own perception of risk.

4.3.3 Human-Centered Vehicle Control

Human-centered approaches in terms of vehicle longitudinal are investigated via several researchers [Pipes53]. Pipes developed a model that represents the vehicle following behavior of the human driver. A human-driver model for heavy trucks has been proposed by Bandoet al. [Bando95]. In this model, the driver controls the acceleration in such a way that he/she maintains an optimal

safe speed according to the following distance to the preceding vehicle. Miyajakiet al. presented a human behavior model, which could be used to produce improved human-machine systems and in particular, an automated highway system to improve the safety on highways [Miyazakiet01].

Song et al. proposed a cognitive and hybrid model of human driver for comparisons between automated vehicles and human drivers [Song00]. The contribution of the cognitive approach is the formation of a driver's knowledge database and the modelling of the cognitive processes underlying the driving activity. A general architecture of the human-driver model and a model for smart AHS (Automated Highway Systems) has been investigated by Delorme and Song [Delorme01]. In this study, manual driving behavior is analyzed using real-world driving data, and a vehicle cruise control strategy based on manual driving behavior is presented. The objectives of the analysis are to find nominal characteristic parameters of manual driving of the following vehicle, which can be used in ACC algorithm development. The target of the proposed ACC controller is to work as a co-driver and to achieve naturalistic behavior of the controlled vehicle that would feel natural to the human driver in a normal driving situations and to achieve safe vehicle behavior in severe braking situations in which large decelerations are necessary. Vehicle rear-end collisions in traffic are largely due to driver's inattention of the front vehicle or inappropriate operation of throttle/brake by the driver. Since the proposed ACC control algorithm is designed to mimic average driver behavior in no-crash driving situations, including comfort driving and severe braking situations, it is guaranteed that the controller prevents the vehicle from crashing in vehicle

following situations. A vehicle longitudinal control algorithm is developed based on the driving behavior analysis in order to incorporate the driving characteristics of the human drivers into the control strategy. Vehicle following behavior of the cruise controlled vehicle are investigated via simulations using real driving radar sensor data and a validated vehicle simulator [Han06].

4.3.4 High-Level Information Fusion

The proposed high-level fusion architecture for the ADAS application consists of three main levels of sensor data processing: local filter, master filter, application-level processing as shown in Figure 4.6.

The proposed high-level fusion architecture for the ADAS application consists of two main levels of sensor data processing: local filter, master filter

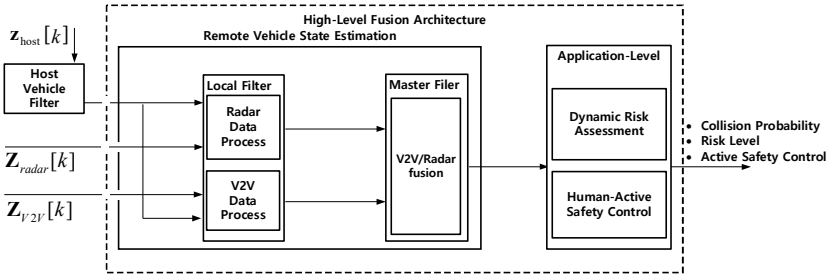


Figure 4.6. Parameters to derive the standard form of the refined measurement model

as shown in Figure 4.6

In the radar data tracking local filter, an interacting multiple model approach described in [Blackman99] using extended Kalman filters (EKF) was employed to estimate the remote vehicles' states such as heading, yaw rate, absolute velocity and acceleration as well as relative position and velocity.

Data tracking of V2V communication is processed by implementing a state augmented estimation algorithm [Emmons13] from the measurement of. To describe the behavior of remote vehicle, a kinematic vehicle model is derived. And a standard measurement model is defined to express the remote vehicle's CAN bus which transmits the vehicle information. The state vector of V2V communication is defined as follows:

$$\mathbf{x}_{rv}^{radar} = \begin{bmatrix} p_{rv,x}^{radar} & p_{rv,y}^{radar} & \theta_{rv}^{radar} & v_{rv,x}^{radar} & \gamma_{rv}^{radar} & a_{rv,x}^{radar} & \dot{\gamma}_{rv}^{radar} \end{bmatrix}^T \tag{4.2}$$

The Kalman filter is used to estimate host vehicle states such as longitudinal velocity and yaw rate. These values can be estimated from the vehicle sensor signals such as wheel speed, acceleration, and yaw rate of which each time

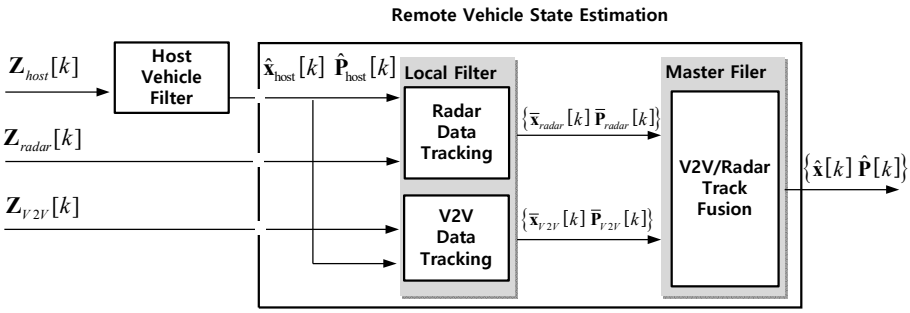


Figure 4.7. Information Fusion Architecture

derivative is considered.

Track-to-track fusion of the V2Vcommunication and radar is mainly discussed in the master filter level in Figure 4.7. In a multi sensor environment

where each sensor processes its own measurements with data process and keeps its track separately, a significant question is how to decide whether two tracks coming from different sensors present the same target. This is the track-to-track association problem. When two tracks are decided to be a form of the same target, then the next problem is to provide a single target track which has less uncertainty than that of individual tracks themselves.

1) Track-to-Track Association

To determine whether two tracks from each of the V2V communication and radar filtered data represent the same target, the method used in this paper is to test the hypothesis of whether the underlying states of the two track estimates are the same target. However, due to the same underlying process noise, the two track estimation errors are not independent. Therefore, the information from the latest tracks estimates is not sufficient to construct the optimal hypothesis test. This problem was studied in [Bar-Shalom81] where a formula was derived to compute the covariance between two track estimates of different sensors. As seen in (3), the result was then used in a suboptimal chi-square test of χKn degrees of freedom with a level threshold (generally big enough, e.g. 95%) to determine whether the two tracks correspond to the same target. And it is investigated that this approach resolves the object ambiguity issue with a high reliable degree in the case of V2V communication and Radar information fusion [22].

$$\frac{1}{K}\sum_{m=k_0}^{K-k_0+1}\tilde{\Delta}(m)T(m)^{-1}\tilde{\Delta}(m)\le\chi^2 K_{n_x}(\alpha) \tag{4.3}$$

where n_x is the dimension of association components x . The $\tilde{\Delta}(m)$ represents the difference between the radar track and V2V track at time $T(m)$. $T(m)$ is the sum of the associated covariance matrices.

2) Track-to-Track Fusion

Track to track fusion can be performed by fusing the filtered state vectors into a new estimate of the state vector [Bar-Shalom86]. In the fusion formula, local estimates which take into account the dependency between the radar and V2Vcommunicaion are combined. The two estimates from the radar and V2V communication, $\mathbf{x}^{radar}[k\,|\,k]$ and $\mathbf{x}^{v2v}[k\,|\,k]$, are combined based on a Bayesian minimum mean square error (MMSE) criterion according to the following fusion equation :

$$\hat{\mathbf{x}}_{rv}[k]=\mathbf{x}_{rv}^{radar}[k]+\mathbf{P}_{xz}\mathbf{P}_{zz}^{-1}(\mathbf{x}_{rv}^{v2v}-\mathbf{x}_{rv}^{radar}) \tag{4.4}$$

$$\mathbf{P}_{xz}=\mathbf{P}^{radar}[k]-\mathbf{P}_k^{radar,v2v}[k] \tag{4.5}$$

$$\mathbf{P}_{zz}=\mathbf{P}^{radar}[k]+\mathbf{P}^{v2v}[k]-\mathbf{P}^{radar,v2v}[k]-\mathbf{P}_k^{v2v,radar}[k] \tag{4.6}$$

where $\mathbf{P}_k^{radar,v2v}$ is the cross covariance matrix between $\mathbf{x}_{rv}^{radar}$ and $\mathbf{x}_{rv}^{v2v}$. The cross covariance is given by the recursive equation [Skolnick01].

$$
\begin{aligned}
\mathbf{P}^{radar,v2v}[k] = {} & (\mathbf{I} - \mathbf{K}^{radar}[k]\mathbf{H}^{radar}[k])\Phi[\mathrm{k}-1]\mathbf{P}^{radar,v2v}[k] \\
& \mathbf{\Phi}^{T}[\mathrm{k}-1](\mathbf{I} - \mathbf{K}^{v2v}[k]\mathbf{H}^{v2v}[k])^{T} \\
& + (\mathbf{I} - \mathbf{K}^{radar}[k]\mathbf{H}^{radar}[k])\mathbf{\Gamma}[k-1] \\
& \mathbf{Q}[k-1]\mathbf{\Gamma}^{T}[k-1](\mathbf{I} - \mathbf{K}^{v2v}[k]\mathbf{H}^{v2v}[k])^{T}
\end{aligned}
\tag{4.7}
$$

where $\mathbf{K}^{radar}$ is the Kalman filter gain matrix for the radar and the covariance matrix of the fused estimate is then given by

$$
\begin{aligned}
\mathbf{P}[k] = {} & \mathbf{P}^{radar}[k] - (\mathbf{P}^{radar}[k] - \mathbf{P}_{k}^{radar,v2v}[k]) \\
& (\mathbf{P}^{radar}[k] + \mathbf{P}^{v2v}[k] - \mathbf{P}^{radar,v2v}[k] \\
& - \mathbf{P}_{k}^{v2v,radar}[k])^{-1}(\mathbf{P}^{radar}[k] - \mathbf{P}_{k}^{radar,v2v}[k])
\end{aligned}
\tag{4.8}
$$

This method of combining tracks has been shown in [Willsky82] to be in general suboptimal solution. The advantage to using state vector fusion is a reduced computational load on the central processor.

4.3.5 Target Vehicle State Estimation Performance

To validate the performance of the enhanced integrated risk assessment algorithm, simulations are conducted with the Matlab/Simulink, connected to Carsim. The remote vehicle state estimation performance has been verified via remote vehicle cut-in scenario in Figure 4.8-(a) by comparing three cases, i.e. real (Carsim), Radar only and the proposed V2V/Radar fusion.

In remote vehicle cut-in scenario, Figure 4.8-(a), initially a host vehicle is cruising at 110kph. Then a vehicle in an adjacent lane cuts in front of the host vehicle with the 50 meters of initial longitudinal clearance. Without

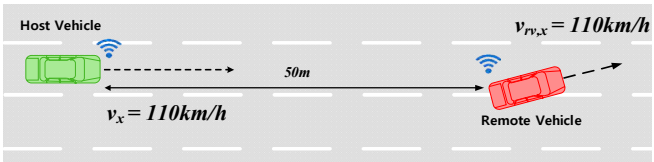
communication, the host vehicle would detect the cut-in vehicle when the latter passes the lane border. Then lower level controller commands the vehicle to brake, often abruptly, to make space in front for the cut-in vehicle. With V2V/Radar fusion based active safety, the cut-in vehicle directly transmits yaw rate information to the host vehicle at the instant it starts to cut in from the center of the adjacent lane. This means that the host vehicle has longer response time to slow down or respond with the aid of V2V communication.

Figure 4.9 shows the estimation results of the states for the remote vehicle in braking scenario. To precisely measure performance of the estimation performance, the error RMS (Root Mean Square) values are calculated and listed in Table 4.3. The simulation results demonstrate that the state estimation performance of V2V/Radar fusion algorithm is significantly improved because of more enriched information is transmitted from remote vehicle by V2V communication. From Figure 4.9, the remote vehicle's longitudinal clearance are estimated with relatively small error using V2V/Radar fusion compared to radar only case. When the host vehicle traveling at 110kph, the host vehicle covers more than 30.1 meters in just one second with the Radar only RMS error of 0.212m. This results in a significant displacement when the spacing between vehicles is predicted to be on the order of 0.1 meters for braking concerns [Utah13]. As shown in Figure 4.9, the sharp notch of Radar only case disappears remarkably in the case of V2V/Radar fusion which means that the V2V/Radar fusion host vehicle provides much better ride quality

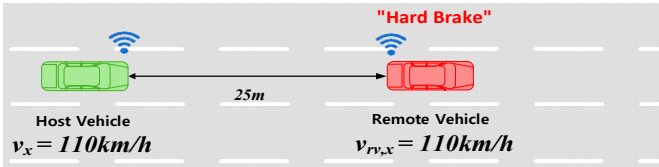
In Braking scenario, Figure 4.9-(b), two vehicles are driving in the same lane. In the simulation, the remote vehicle applies a sudden brake with deceleration

of 0.2g and the clearance is 25 meters. In conventional radar only using active safety scheme, on-board radar is used to measure the distance between the host vehicle and the remote vehicle, and the distance is numerically differentiated to get the relative velocity. With V2V communication, whenever the remote vehicle brakes, it directly transmits the deceleration information to the host vehicle. The V2V/Radar fusion case, upon receiving the message, brakes strongly enough for safety while ensuring driver's comfort [Shin15]. In other words, response time is increased by replacing the sensor and computational delay with the reliable vehicular communication Chapter II.

Figure 4.10 shows the estimation results of the states for the remote vehicle in braking scenario. To precisely measure performance of the estimation



(a) Remote Vehicle Cut-in on the Highway



(b) Remote Vehicle Braking on the Highway

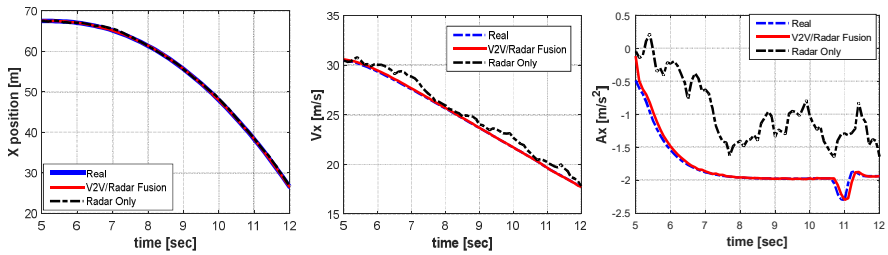
Figure 4.9. Simulation Scenarios

performance, the error RMS (Root Mean Square) values are calculated and listed in Table 4.3. The simulation results demonstrate that the state estimation performance of V2V/Radar fusion algorithm is significantly improved because of more enriched information is transmitted from remote vehicle by V2V communication. From Figure 4.10, the remote vehicle's longitudinal clearance

are estimated with relatively small error using V2V/Radar fusion compared to radar only case. When the host vehicle traveling at 110kph, the host vehicle covers more than 30.1 meters in just one second with the Radar only RMS error of 0.212m. This results in a significant displacement when the spacing between vehicles is predicted to be on the order of 0.1 meters for braking concerns [Utah 5]. As shown in Figure 4.10, the sharp notch of Radar only case disappears remarkably in the case of V2V/Radar fusion which means that the V2V/Radar fusion host vehicle provides much better ride quality.

Figure 4.11 shows the remote vehicle state estimation results for the remote vehicle cut-in scenario, Table 4.4. Estimation results of remote vehicle states for braking scenario.

Figure 4.11-(a), with sudden GPS errors of 3 to 5 meters from 7 seconds. The Root Mean Square (RMS) errors are calculated and listed in Table 4.4. The state estimation results in Figure 4.11 and Table 4.4 show that V2V/Radar



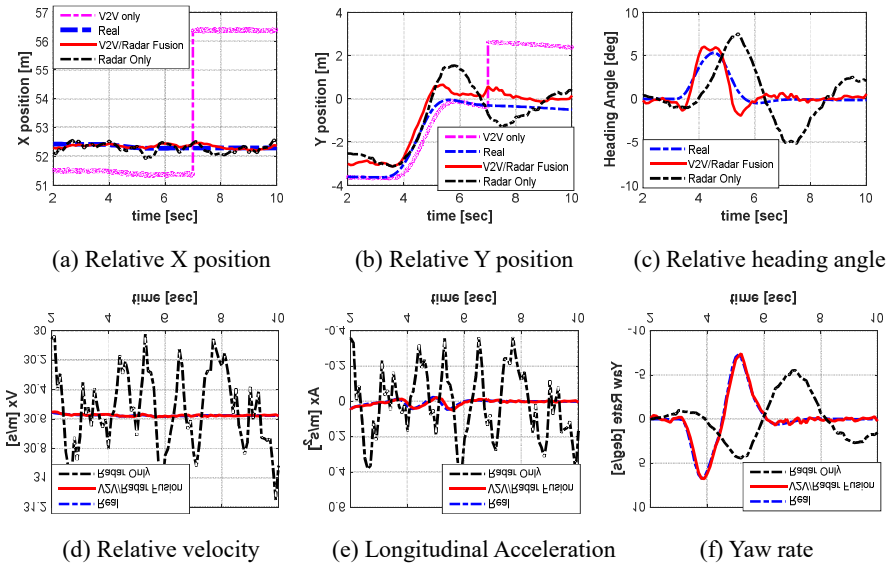
(a) Relative X position (b) Longitudinal velocity (c) Longitudinal acceleration

Figure 4.10. Estimation results of remote vehicle states for braking scenario

Table 4.3. Estimation results of remote vehicle states for braking scenario

	Relative X Position		Longitudinal Velocity (Vx)		Longitudinal Acceleration (Ax)	
	Error RMS[m]	Reduction ratio (%)	Error RMS[m/s]	Reduction ratio (%)	Error RMS[m/s^2]	Reduction ratio (%)
V2V/Radar Fusion	0.036	83.02	0.0715	89.68	0.12	86.88
Radar Only	0.212		0.693		0.89	

fusion algorithm performs really well even during at which the GPS signal is poor or V2V communication delay exists. Since remote vehicle's precise CAN signals such as yaw rate and longitudinal acceleration are directly transmitted to host vehicle, the host vehicle does not have to numerically compute the states of remote vehicle, and this results in significant improvement of the target object estimation performance.



(a) Relative X position (b) Relative Y position (c) Relative heading angle

(d) Relative velocity (e) Longitudinal Acceleration (f) Yaw rate

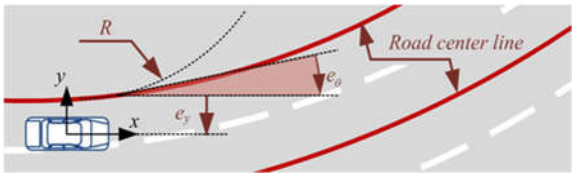
Figure 4.11. Estimation results of remote vehicle states for cutting-in scenario

Table 4.4. Estimation results of remote vehicle states for cut-in scenario

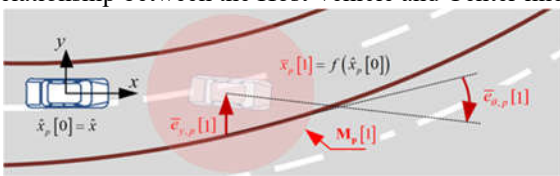
	Relative X Position		**Relative Y Position**		**Relative Heading Angle**	
	Error RMS[m]	Reduction ratio (%)	Error RMS[m]	Reduction ratio (%)	Error RMS[deg]	Reduction ratio (%)
V2V/Radar Fusion	0.0816	45.89	0.5532	31.29	0.8642	71.44
Radar Only	0.1508		0.8051		3.0254	
	Longitudinal Velocity (Vx)		Longitudinal Acceleration (Ax)		Yaw Rate	
	Error RMS[m/s]	Reduction ratio (%)	Error RMS[m/s^2]	Reduction ratio (%)	Error RMS[deg/s]	Reduction ratio (%)
V2V/Radar Fusion	0.0035	98.69	0.0076	96.31	0.2771	93.74
Radar Only	0.2675		0.2058		4.429	

4.4 Remote Vehicle States Prediction

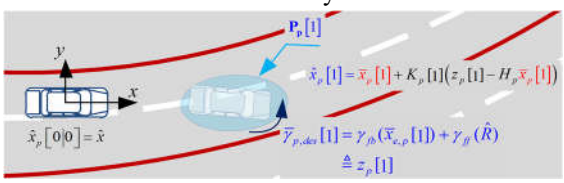
Track-to-track fusion is an important part in multi sensor fusion, the V2V communication The Kalman filter is widely used to estimate the states represented in a state space equation. In order to establish a state prediction, the vehicle state estimation method such as longitudinal velocity, yaw rate, longitudinal acceleration and yaw acceleration has been developed [Kim15]. A road geometry estimation has been established with the measurements from a vision



(a) Relationship between the Host Vehicle and Center line of road



(b) Time-update of Host Vehicle States and the Relative Error States to Road Geometry



(c) Measurement-update of Host Vehicle States with Predicted Yaw Rate for Lane Keeping as Virtual Measurement

Figure 4.12 Procedure of State Prediction

sensor. The road geometry can be described by a 2nd order polynomial. Likewise with the vehicle states estimation, the Kalman filter is used for the estimation of road geometry coefficients of the polynomial. The state prediction of the vehicle has been established under the assumptions that a host and surround vehicles maintain current behavior in the finite time horizon. The vehicle position in the finite time horizon is represented as follows :

$$\begin{aligned}\mathbf{x}_p[i+1] &= f_p\left(\mathbf{x}_p[i]\right) + \mathbf{w}_p[i], \quad i = 0,\cdots,N_p - 1 \\ &= \begin{bmatrix} f_{1,p} & f_{2,p} & f_{3,p} & f_{4,p} & f_{5,p} & f_{6,p} & f_{7,p} \end{bmatrix} + .. \\ &\quad ... + \mathbf{w}_p[i]\end{aligned} \tag{4.9}$$

where,

$$\mathbf{x}_p = \begin{bmatrix} p_{x,p} & p_{y,p} & \theta_p & v_p & \gamma_p & a_p & \dot{\gamma}_p \end{bmatrix}^T$$

$$f_{1,p} = p_{x,p} + \left(v_p \cos\theta_p\right)\Delta t + \left(a_p \cos\theta_p + \gamma_p v_p \sin\theta_p\right)\frac{\Delta t^2}{2}$$

$$\mathbf{x}_p = \begin{bmatrix} p_{x,p} & p_{y,p} & \theta_p & v_p & \gamma_p & a_p & \dot{\gamma}_p \end{bmatrix}^T$$

$$f_{1,p} = p_{x,p} + \left(v_p \cos\theta_p\right)\Delta t + \left(a_p \cos\theta_p + \gamma_p v_p \sin\theta_p\right)\frac{\Delta t^2}{2}$$

$$f_{2,p} = p_{y,p} + \left(v_p \sin\theta_p\right)\Delta t + \left(a_p \sin\theta_p + \gamma_p v_p \cos\theta_p\right)\frac{\Delta t^2}{2}$$

$$f_{3,p} = \theta_p + \left(\gamma_p\right)\Delta t + \left(\dot{\gamma}_p\right)\frac{\Delta t^2}{2}$$

$$f_{4,p} = v_p + \left(a_p\right)\Delta t + \left(-k_a a_p\right)\frac{\Delta t^2}{2}$$

$$f_{5,p} = \gamma_p + \left(\dot{\gamma}_p\right)\Delta t + \left(-k_{\dot{\gamma}}\dot{\gamma}_p\right)\frac{\Delta t^2}{2}$$

$$f_{6,p} = a_p + \left(-k_a a_p\right)\Delta t + \left(k_a{}^2 a_p\right)\frac{\Delta t^2}{2}$$

$$f_{7,p} = \dot{\gamma}_p + \left(-k_{\dot{\gamma}}\dot{\gamma}_p\right)\Delta t + \left(k_{\dot{\gamma}}{}^2\dot{\gamma}_p\right)\frac{\Delta t^2}{2}$$

$$\mathbf{w}_p[i] \sim \left(0, \mathbf{W}_p[i]\right)$$

$$\mathbf{W}_p[i] = \left(\mathbf{B}_p \Delta t + \mathbf{F}_p[i]\mathbf{B}_p \frac{\Delta t^2}{2}\right) Q_p \left(\mathbf{B}_p \Delta t + \mathbf{F}_p[i]\mathbf{B}_p \frac{\Delta t^2}{2}\right)^T$$

$$\mathbf{F}_p[i] = \left.\frac{\partial f_p}{\partial x_p}\right|_{x_p = \hat{\mathbf{x}}_p[i]} \qquad \mathbf{B}_p = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix}^T$$

The subscript 'p' in (3) denotes 'predictive'. A prediction procedure at the first future time step is depicted as Figure 4.12. The desired yaw rate for lane keeping is supposed to be a virtual measurement as shown in the following equation.

$$\begin{aligned} \mathbf{z}_p[i] &= H_p \cdot \mathbf{x}_p[i] + \mathbf{v}_p[i], \qquad i = 0, \cdots, N_p \\ &= \begin{bmatrix} 0 & 0 & 0 & 0 & 1 & 0 & 0 \end{bmatrix} \cdot \mathbf{x}_p[i] + \mathbf{v}_p[i] \\ &= \overline{\gamma}_{des,p}[i] \\ &= -C \cdot \overline{\mathbf{x}}_{e,p}[i] + \gamma_{ff,p}[i] \end{aligned} \tag{4.10}$$

where,

$$\begin{aligned} \overline{\mathbf{x}}_{e,p}[i] &= f_e\left(\overline{\mathbf{x}}_p[i], \hat{\mathbf{x}}_r[0]\right) \\ &= \begin{bmatrix} \overline{e}_y[i] & \overline{e}_\theta[i] & \overline{\gamma}_p[i] \end{bmatrix}^T \\ &= \begin{bmatrix} \overline{p}_{y,p}[i] - \left\{\hat{a}_2 \cdot \overline{p}_{x.p}[i]^2 + \hat{a}_1 \cdot \overline{p}_{x.p}[i] + \hat{a}_0 + \hat{w}_{road} \cdot N[i]\right\} \\ \overline{\theta}_p[i] - \tan^{-1}\left(2\hat{a}_2 \cdot \overline{p}_{x,p}[i] + \hat{a}_1\right) \\ \overline{\gamma}_p[i] \end{bmatrix} \end{aligned}$$

$$\mathbf{v}_p[i] \sim \left(0, \mathbf{V}_p[i]\right)$$

$$\mathbf{V}_p[i] = \mathbf{V}_{p,const} + \begin{bmatrix} \overline{e}_y[i] & \overline{e}_\theta[i] \end{bmatrix}^T \mathbf{w}_{correct} \begin{bmatrix} \overline{e}_y[i] \\ \overline{e}_\theta[i] \end{bmatrix}$$

4.5 Collision Risk Analysis

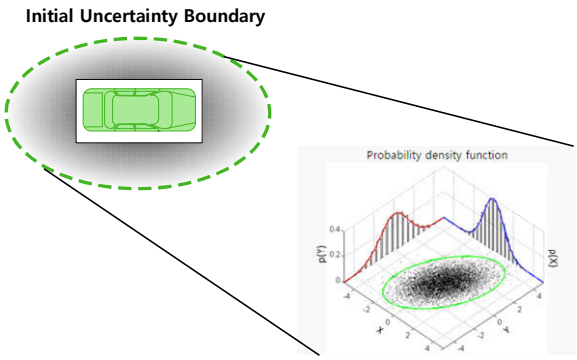
The collision probability between the host and remote vehicle can be computed by the number of collision case out of whole possible number of case that two vehicle randomly exist within uncertainty boundary. The collision case counts when two vehicles share a same part of the space as shown in Figure 4.13 –(c). In order to obtain the initial uncertainty boundary in Figure 4.13-(a), joint probability density function is used. The uncertainty boundary, grey shaded ellipsoidal area, around the vehicle in Figure 4.13–(a) describes the reachable area. The uncertainty can be modelled by the probability density function of a configuration of $\mathbf{x}_{host} = \begin{bmatrix} x_{host} & y_{host} & \theta_{host} \end{bmatrix}^T$ or $\mathbf{x}_{rv} = \begin{bmatrix} x_{rv} & y_{rv} & \theta_{rv} \end{bmatrix}^T$, having a Σ covariance matrix, and $\hat{\mathbf{x}}$ mean is

$$p(\mathbf{x}) = \frac{1}{(\sqrt{2\pi})^3 \sqrt{\det \Sigma}} e^{-1/2((\mathbf{x}-\hat{\mathbf{x}})^T \Sigma^{-1} (\mathbf{x}-\hat{\mathbf{x}}))} \tag{4.11}$$

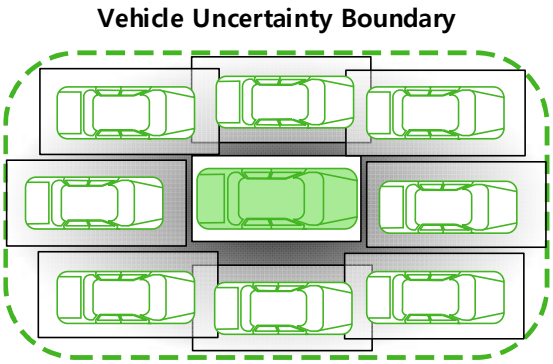
Derived covariance matrix is the result of stochastic filtering process and it can be directly defined by the prediction error for every time step (0.1seconds) in (6).

$$\Sigma = E((\mathrm{x}-\hat{\mathrm{x}})(\mathrm{x}-\hat{\mathrm{x}})^T) \tag{4.12}$$

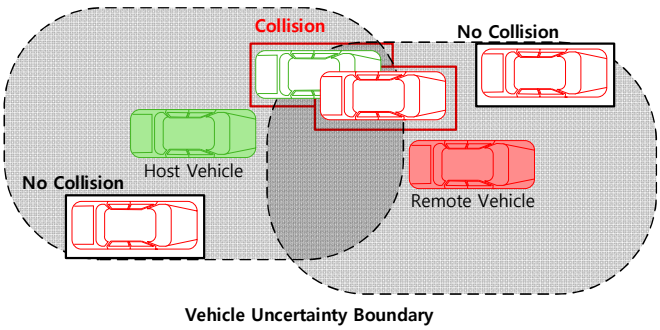
Based on the initial probability density function, particle filter is implemented to randomly generate the given number of N state vectors (particles) as depicted in Figure 4.13 –(b). For every random particle, vehicle-body-shaped-polygons of the host and remote vehicles are generated as shown Fig .4.13 –(c). If randomly generated two vehicles' polygons share the same part of the space, the collision case is counted. As there are more number of space sharing area, collision case, the collision probability increases as described in (4.13)



(a) Initial Uncertainty Boundary Generation



(b) Randomly Generated N State Vectors (Particles)



(c) Description of Collision

Figure 4.13. Procedure of Collision Probability Computation

$$\text{Collision Probability} = Cp = \frac{\text{Collision Case}}{\text{N-state}} \times 100(\%) \tag{4.13}$$

The parameter N has been selected by the user as a trade-off between computational effort and collision probability approximation accuracy.

4.6 Predicted Collision Distance

With the general concept of the peak(maximum) collision probability, ***maxCp***, most probable predicted collision time, Tp_{maxCp}, and most probable predicted collision distance, Dp_{maxCp}, are introduced.

In order to describe the concept above, a computer simulation study has been conducted. A host vehicle is initially following its preceding(red) vehicle with the speed of 110 kph and the preceding vehicle applies 0.2g of sudden brakes shown in Figure 4.14.

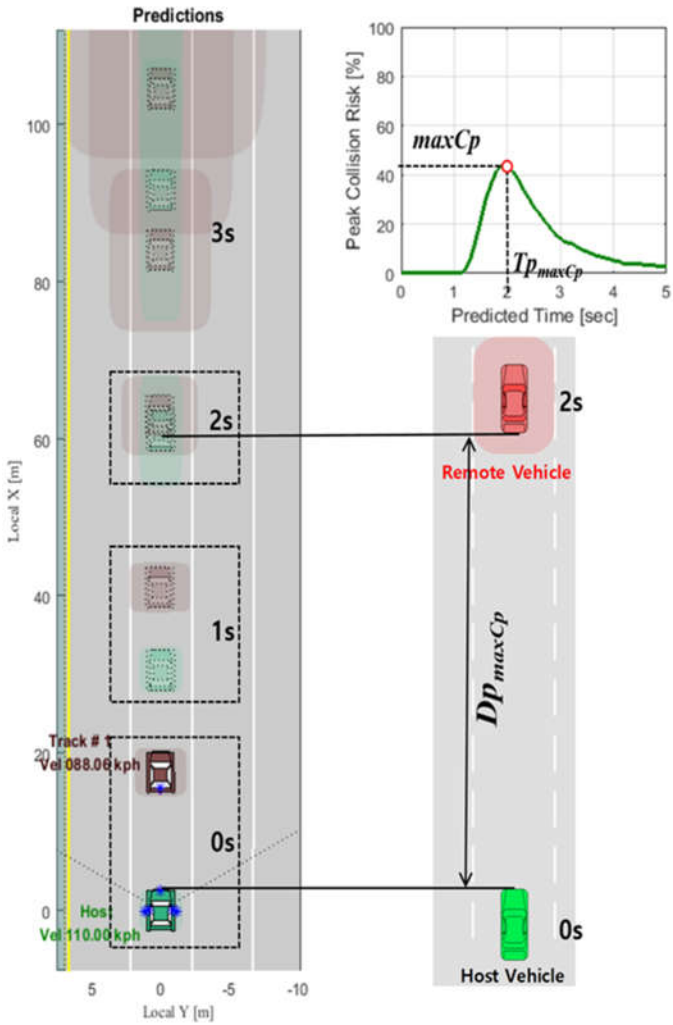


Figure 4.14. Peak collision risk based predicted distance (Distance to Collision)

As shown in Figure 4.14, the $\boldsymbol{Dp_{maxCp}}$ is a minimum vehicle-to-vehicle distance between the positions of current host vehicle and that of the remote vehicle at which the ***maxCp*** occurs which is 2 seconds of $\boldsymbol{Tp_{maxCp}}$ in this case. In other words, $\boldsymbol{Dp_{maxCp}}$ is the most probable predicted collision distance between host vehicle and remote vehicle.

4.7 Active Safety Intervention Moment Decision

In order to guarantee the safety at any speed range, a human-centered risk assessment algorithm is implemented. As shown in Figure 4.15, the proposed human-centered active safety control algorithm is based on the peak (maximum) collision probability and the human reaction time with respect to most probable predicted collision distance. To obtain the human reaction time in terms of the most probable predicted collision distance, Dp_{maxCp} , Table 4.5 describes the experimentally acquired and fitted data for the stopping sight distance with a

Table 4.5
Stopping sight distance for a range of speed [Layton97]

Speed(km/h)	Brake Reaction Distance (m)	Braking Distance on Level (m)	Stopping Sight Distance (m)
20	13.9	4.6	18.5
30	20.9	10.3	31.2
40	27.8	18.4	46.2
50	34.8	28.7	63.5
60	41.7	41.3	83
70	48.7	6.2	104.9
80	55.6	73.4	129
90	62.6	92.9	155.5
100	69.5	114.7	184.2
110	76.5	138.8	215.3
120	83.4	165.2	248.6
130	90.4	193.8	284.2

range of speed.

The study of reaction times by [Layton97] was based on data 321drivers who expected to apply their brakes. According to [Layton97], a 2.5 sec of reaction time for stopping sight situations encompasses the capabilities of most drivers, including those of older drivers.

The range of the speed is from 20 kph to 130 kph. A stopping sight distance (SSD) formula based on the design speed is derived and it incorporates driver perception-reaction time with braking distance according to Table 4.5 [Layton97].

$$\begin{aligned} SSD(t) &= \text{Driver perception - reaction distance} + \text{braking distance} \\ &= 0.278 \cdot v_x(t) \cdot T_r + 0.039 \cdot \frac{v_x(t)^2}{a} \end{aligned} \tag{4.14}$$

where,

$SSD = \text{required stopping sight distance}\,[\text{m}]$

$v_x = \text{Longitudinal Speed}\,[\text{m/s}]$

$T_r = \text{brake reaction time} = 2.5\,[\text{sec}]$

$a = \text{deceleration rate} = 3.4[\text{m/s}^2]$

Driver's deceleration magnitude is assumed to be 3.4 m/s^2. The driver deceleration results showed 3.4 m/s2 as the 10th percentile value; that is, when asked to stop as quickly as possible on wet pavements, most drivers selected decelerations of 3.4 m/s^2 or a bit greater [Layton97]. This value can be attained without a loss of steering control and is near values defined as "comfortable" by traffic engineering textbooks [NCHRP97].

The algorithm aims to completely predict, avoid collisions at any driving situation. It can be achieved by finding an active safety control intervention

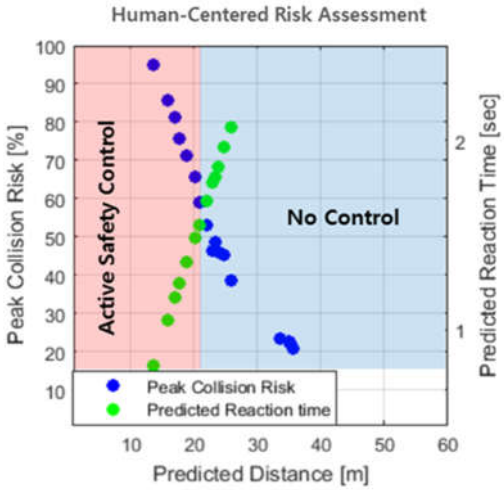


Figure 4.15. Human Centered Risk Assessment Algorithm

point(moment) which is a best trade-off between maximum collision risk and predicted human reaction time with respect to the Dp_{maxCp}. Based on previous research on human-autonomous vehicle interaction [Wei09], a human-centered risk assessment algorithm for automated vehicle is proposed. [Wei09] investigates that autonomous vehicle performance, robustness and safety can be improved by cooperation between human-driver and vehicle's intelligence. A human driver has to take part in the driving and strategy planning of an autonomous vehicle. For the autonomous vehicle to achieve better driving performance, robustness and safety, it is important to find a best trade-off between pure manual and fully autonomous driving [Wei09]. This means that using human driver's ability significantly benefits driving efficiency and safety. Thus, in order to fully guarantee the safety, future automated drive system has to find a best trade-off between the human sense and automated function such

as an active safety by implementing human driver's ability. In [Ben-Yaacov02]], the author defines the automated system's performance by its probability of detection which is collision risk in this paper. The human's behavior is based both on his or her own processing and can be expressed by human reaction time in this paper.

The simulation scenario in Figure 4.15 is the preceding remote vehicle sudden braking scenario already described above in Figure 4.14. In Figure 4.15, the maximum predicted human reaction time is set to be 2.5 seconds because previous experimental data [Layton97] checked the validity of the 2.5 seconds as the optimal design perception-reaction time (human reaction time) to avoid the collision. The collision risk, 0 to 100%, and predicted reaction time, 0 to 2.5 seconds, are simultaneously considered as shown in Figure 4.15. More than 2.5 seconds of perception-reaction time means it's enough for drivers to react to stop the vehicle safely, however, lower than that means collision risk has to be taken into account since the driver and system (machine) has to pay attention and predict the remote vehicle's behavior carefully. In order to find the active safety control intervention point, a trade off moment, predicted reaction time, RTp_{maxCp}, which is rearranged from (4.14), can be computed according to the current host vehicle speed, v_x, and predicted stopping sight distance is Dp_{maxCp}, as follows:

$$RTp_{maxCp}(t)[\text{sec}] = \frac{1}{0.278 v_x(t)}\left(Dp_{maxCp}(t) - \frac{1.075 \cdot v_x(t)^2}{a}\right) \tag{4.15}$$

Based on the active safety intervention moment, a crossing point, an intervention margin has been derived and it divides risk assessment plane as two areas. Before collision risk and reaction time are intersected together, blue area, it is safe (normal) driving mode. On the other hand, the red area means emergency or abnormal driving mode. The active safety control has to intervene at the crossing point which is a best trade off moment.

Chapter 5

Performance Evaluations

This section describes the effectiveness of V2V communication on the vehicle predictions and control for application to prevent frontal collision of automated vehicle. In section 5.1, V2V communication information is fused with radar sensor and its effects are investigated on the response of automated vehicle control. Simulations for the human-centered risk assessment are conducted with the V2V communication. The risk assessment performance is evaluated with the host vehicle perception only and the controlled host vehicle. Vehicle tests are conducted on the Seoul National University campus inner circular road. And the test results are discussed by comparing the results of simulations

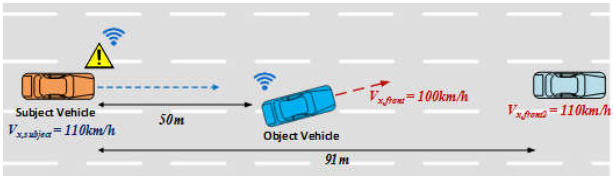
5.1 Simulations: MPC based Automated Vehicle Control

Model Predictive Control (MPC) based automated vehicle control algorithm consists of longitudinal and lateral vehicle model [Seo15]. Considering the error dynamics and first-order delay acceleration dynamics, a longitudinal model is designed with the input of host vehicle longitudinal acceleration. The lateral model is formulated considering vehicle dynamics derived by an extended bicycle model with control input of host vehicle front steering angle. The control algorithm is investigated and verified by [Seo15], further explanations will not be provided since this thesis focuses on the effects of V2V communication when using existing automated vehicle controller.

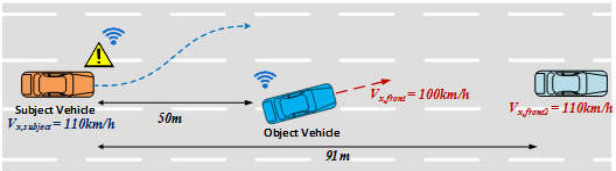
5.1.1. Effects of V2V Communication on the Controller

For the two simulations in Figure 5.1, initially the subject vehicle is cruising at certain speed. Then a vehicle in adjacent lace, object vehicle, cuts in between the two vehicles. In subject vehicle deceleration scenario in Figure 5.1-(a), the object vehicle cuts in the lane with the speed of 100kph, the MPC controller of the subject vehicle commands the subject vehicle to brake.

The other simulation scenario in Figure 5.1-(b) is constructed by decelerating and overtaking the unexpected cut-in vehicle as shown in Figure 5.1-(b). In this scenario, initially subject vehicle (orange) is cruising at 110kph. Then the object vehicle suddenly cuts in between the two vehicles with the speed of 100kph.



(a) Subject vehicle deceleration



(b) Subject vehicle lane change

Figure 5.1. Simulation Scenarios

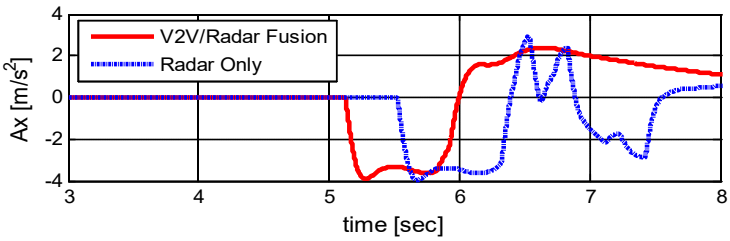
Without V2V communication, the radar only using vehicle would detect the cut-in vehicle when the object vehicle passes the lane border. The MPC controller then commands the vehicle to brake, often abruptly, and to change the lane suddenly.

With the aid of V2V communication system, the cut-in vehicle transmits the exact information such as yaw rate, longitudinal velocity and acceleration to the subject vehicle at the instant it starts to cut in from the center of the of the adjacent lane. The V2V communication system allows the subject vehicle to have 2-3seconds to slow down and to change the lane by making space for the cut-in vehicle.

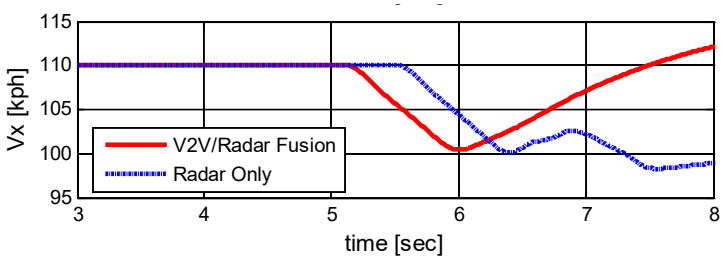
In order to show the effectiveness of the proposed V2V and radar sensor fusion algorithm, simulation results are compared with conventional ADAS system which is radar only using algorithm.

In subject vehicle deceleration scenario in Figure 5.1-(a), the cut-in happens at 4.8 seconds for both radar only and V2V/radar fusion cases. As shown in Figure 5.2–(a) and –(b), the radar only using vehicle detects the cut-in vehicle shortly after 0.7 second, and then the controller applies a hard brake of approximately –4.0 m/s2 to slow down by providing evasive steering maneuver. On the other hand, in Figure 5.2-(a) and –(b), because of the V2V communication, the response time of V2V/radar fusion vehicle is 0.5 seconds faster than that of the radar only by remarkably reducing the sharp notch in Figure 5.2-(a) and this also provides better ride quality.

In subject vehicle lane change scenario in Figure 5.4-(b), the cut-in happens at 4.8 second for both radar only and V2V/radar fusion cases. As shown in



(a) Subject vehicle deceleration



(b) Subject vehicle lane change

Figure 5.2 Simulation results for Subject vehicle deceleration

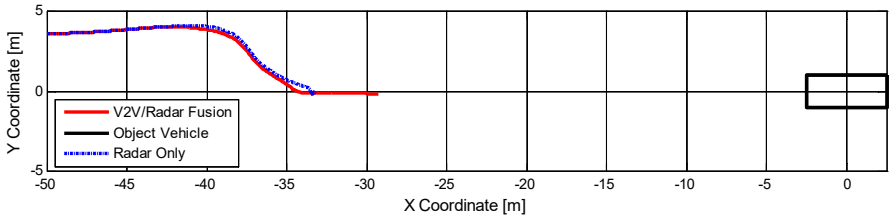
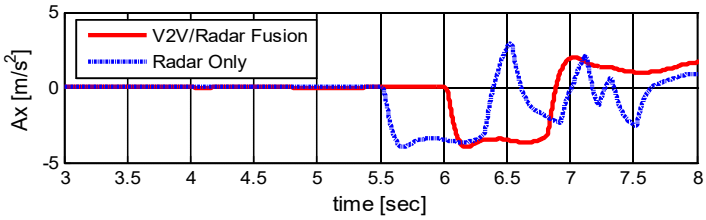
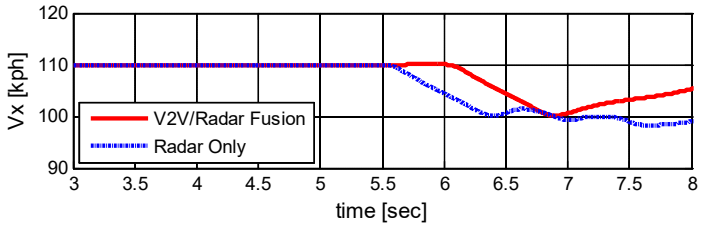


Figure 5.3. Relative trajectories of subject vehicle deceleration with respect to object vehicle

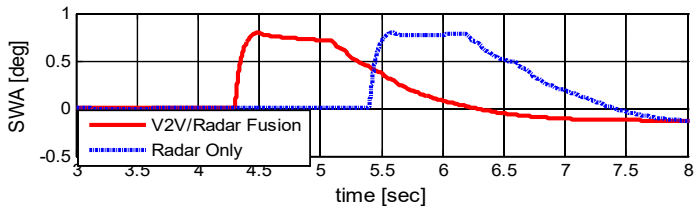
Figure 5.4 –(a) and –(b), the radar only using vehicle detects the cut-in vehicle shortly after 0.6 second, and then the controller applies a hard brake of approximately –3.8 m/s^2 to slow down by providing evasive steering maneuver. On the other hand, in Figure 5.4-(a) and –(b), because of the V2V communication, the V2V/radar fusion vehicle responds 0.5 seconds before the object vehicle cuts in by providing evasive steering maneuver for the enhancement of safety. Since the V2V/radar fusion brakes much less than the radar only using vehicle and the sharp notch in Figure 5.4-(a) disappears remarkably. When the subject vehicle maneuvers, the desired steering control input by the proposed V2V/radar fusion algorithm is smaller than that by the algorithm based on radar only using as shown in Figure 5.4-(c). Therefore the lateral acceleration which is one of the key factors that influence the ride comfort is smaller in the case of V2V/radar fusion as shown in Figure 5.4-(d). After this brake, the velocity of the V2V/radar fusion vehicle resumes to a cruising speed, and the acceleration then goes back to the normal value in Figure 5.4-(a) and –(b)



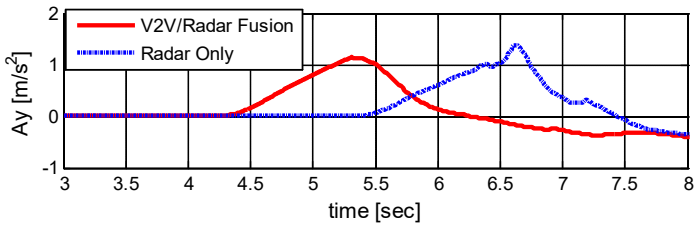
(a) Longitudinal acceleration



(b) Longitudinal velocity



(c) Desired steering wheel angle (SWA)



(d) Lateral acceleration

Figure 5.4 Simulation results for Subject vehicle deceleration

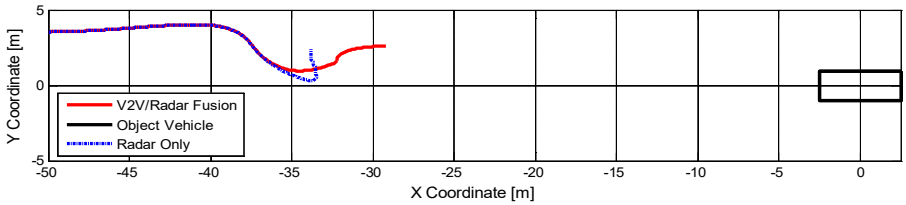


Figure 5.5 Relative trajectories of subject vehicle deceleration

with respect to object vehicle

As can be seen in Figure 5.4 –(a) and (c), the V2V communication helps save large amount of control effort, which means more safety for the vehicle, and less discomfort for the passenger. Figure 5.3 and 5.5 are the relative trajectories of subject vehicle with respect to the object vehicle at the origin. It can be clearly seen in Figure 5.3 and 5.5 that vehicle trajectory is smoothed in the case of V2V/radar fusion, and it is expected to minimize influence of traffic flow. The reason lies in two facts. First is that the subject vehicle receives the object vehicle's warning message in advance, thus it can brake much earlier and more gently than radar only using vehicle. Second is when the object vehicle cuts-in, the V2V/radar fusion subject vehicle maneuvers much earlier than radar only, the subject vehicle does not need to brake hard for safety and it resumes to desired set speed, 110kph, as it has (is supposed) to do in conventional adaptive cruise control (ACC) scheme which can be seen in Figure 5.4-(b).

5.2 Simulations:

Human-Centered Risk Assessment

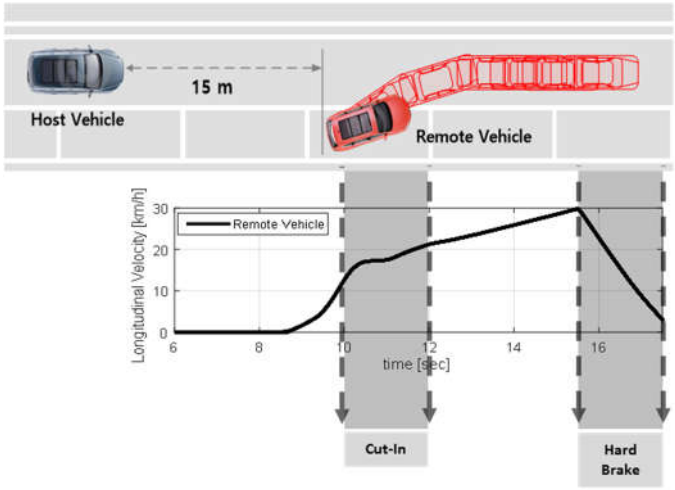
To validate the effectiveness of the vehicle to vehicle wireless communication for application to automated vehicles, simulations are conducted on the Matlab/Simulink, connected to Carsim8.02. The simulations are based on the human-centered risk assessment algorithm in order to show the effectiveness of an inter vehicle communication. A perception and a vehicle control performance are investigated on the human-centered risk assessment algorithm. The scenarios are given in Figure 5.6-(a) and (b), respectively.

5.2.1. Scenarios

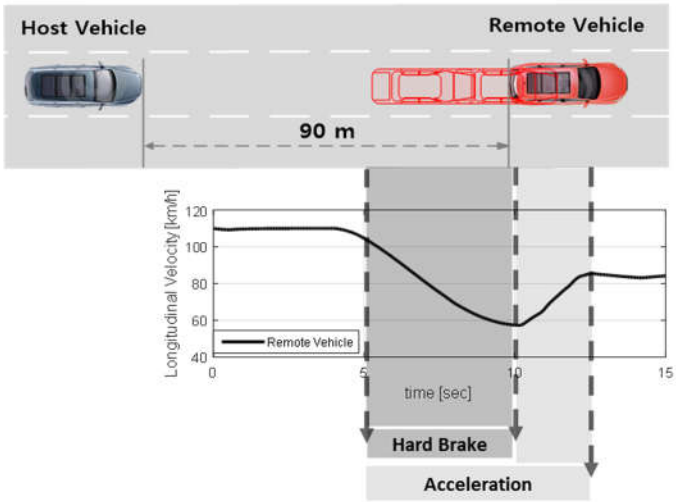
Two simulation studies are investigated in this paper. The first is the simulation of the parked remoted vehicle's sudden cut in and braking. And the second study is the simulation of the response of the host vehicle to the hard deceleration of the preceding remote vehicle on the highway.

In a parked remote vehicle cut-in and braking scenario, the host vehicle is driving at a constant velocity of 30 km/h and the remote vehicle is suddenly cutting in at 10 seconds with the range of 15 meters. After about 3 seconds, the remote vehicle applies hard brake of 0.35g, as illustrated in Figure 5.6-(a).

The effect of communication on the response of the autonomously cruising host vehicle to the braking and accelerating of preceding remote vehicle is investigated. The scenario is shown in Figure 5.6-(b). At the beginning, the host vehicle and the remote vehicle drive at 110kph with the range of 90 meters. The



(a) Parked Remote Vehicle Cut-in and Braking



(b) Remote Vehicle Braking on the Highway

Figure 5.6. Simulation Scenarios

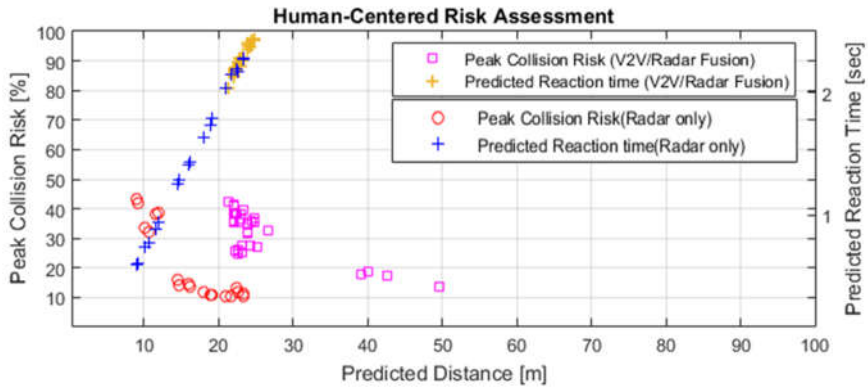
preceding remote vehicle starts sudden braking of 0.5g at 4.8 seconds and then accelerates at 10 seconds. The following host vehicle is expected to autonomously apply a proper brake or acceleration to maintain the desired

range.

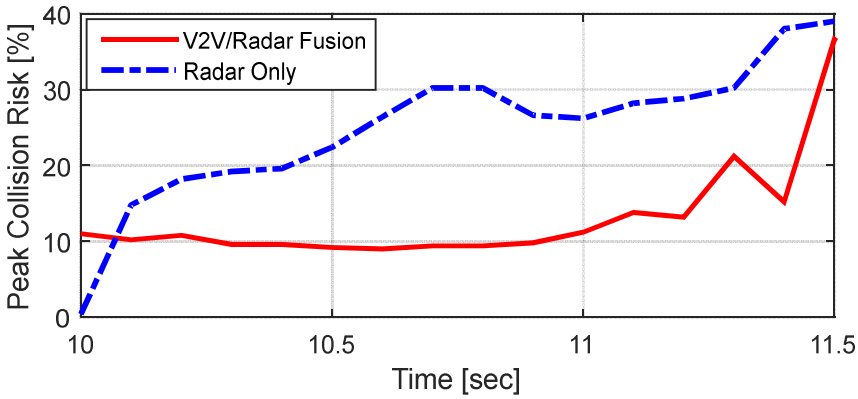
In a conventional radar only using active safety scheme, on-board radar is used to measure the distance between the host vehicle and the remote vehicle, and the distance is numerically differentiated to get the relative velocity. With V2V communication, whenever the remote vehicle brakes, it directly transmits the deceleration information to the host vehicle. The V2V/Radar fusion case, upon receiving the message, brakes strongly enough for safety while ensuring driver's comfort [Shin15]. In other words, response time is increased by replacing the sensor and computational delay with the reliable vehicular communication as described in Section II.

5.2.2. Effects of V2V Communication: Remote Vehicle Perception only with a Constant Host Vehicle Speed

The human-centered risk assessment algorithm consists of probabilistic threat assessment and decision of active safety intervention moment. The risk assessment algorithm derives peak (maximum) collision risk and most probable predicted collision distance from the threat vehicles ahead. Figure 5.7 and 5.8 present simulation results for the human-centered risk assessment of automated vehicle during which the parked remote vehicle is cutting in as described in Figure 5.6-(a). The host vehicle speed is constant for 30km/h whole period of simulation. The cut-in happens at 8.6 seconds for both V2V/Radar fusion and radar only cases. The radar only vehicle detects the cut-in remote vehicle at 10 seconds as seen in Figure 5.7-(b). On the other hand, in Figure 5.7-(b) because of the V2V communication, the V2V/Radar fusion vehicle already detects the



(a) Human Centered Risk Assessment



(b) Peak collision risk of the vehicles

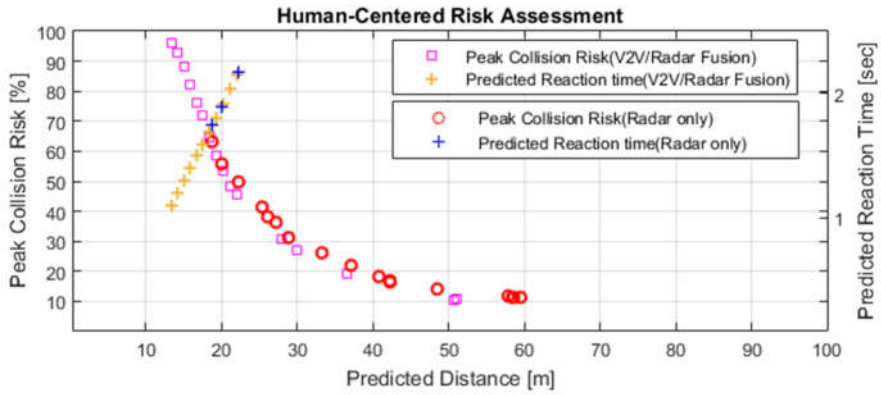
Figure 5.7. Simulation results for the parked vehicle cut-in scenario in Figure 5.6-(a)

risky situation much earlier with 10 percent of higher risk. The remote vehicle accelerates by 30 km/h during cut-in as shown in Figure 5.6-(a). Figure 5.7-(b) shows that human reaction time is still high enough by maintaining fairly low

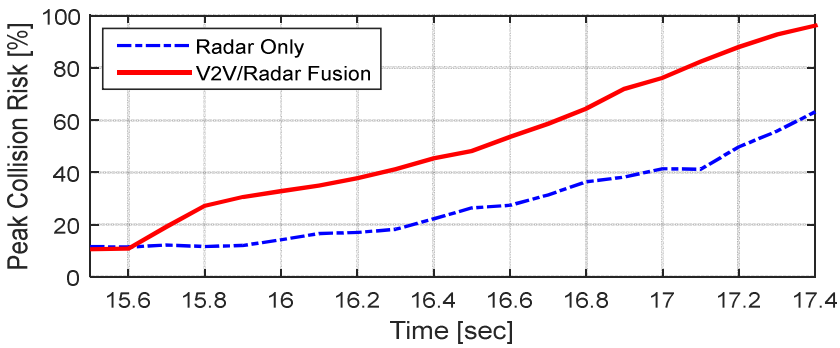
risk level. This means that active safety intervention moment does not exist. In Figure 5.7-(a), however, radar only case detect the risk when the vehicle is completely cutting-in and the risk keeps increasing although the remote vehicle accelerates. The active safety intervention moment, crossing point, is generated and human reaction time decreases as well in Figure 5.7-(a). Due to this, Figure 5.7-(a) and Figure 5.7-(b) demonstrate that the situation is still acceptable with the 21 percent of maximum collision risk difference compared to radar only case in Figure 5.7-(b). According to [Shin15], the reason is that more accurate and additional remote vehicle information such as longitudinal acceleration and yaw rate is sent to the host vehicle, V2V/Radar fusion algorithm has lower prediction uncertainty level than radar only case. This means that the V2V communication helps reduce the chances of overestimate issue as seen in Figure 5.7-(a).

Figure 5.8 is the simulation results for the sudden hard braking of 0.5g right after the remote vehicle is cutting in. Since the V2V/Radar fusion allows the host vehicle to contain more enriched remote information compared to radar only, collision risk of the remote vehicle because of sudden deceleration can be more accurately and reliably detected as seen in Figure 5.8-(b). Due to this, Figure 5.8-(a) and Figure 5.8-(b) show active safety intervention moment, crossing point, is detected much earlier with 40 percent of maximum collision risk difference at 17.1 seconds in Figure 5.8-(b). On the other hand, Figure 5.8-(a) describes the situation is still acceptable for driver because of fairly high enough human reaction time and the intervention point has not generated yet. From this simulation, V2V communication remarkably reduces the chances of

underestimate issue of the radar only case.



(a) Human Centered Risk Assessment

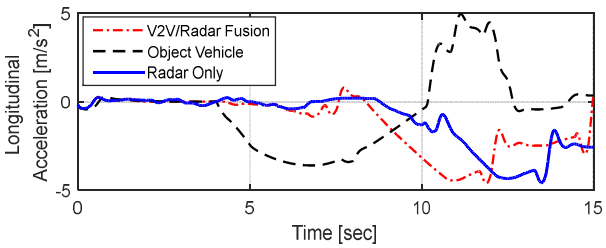


(b) Peak collision risk of the vehicles

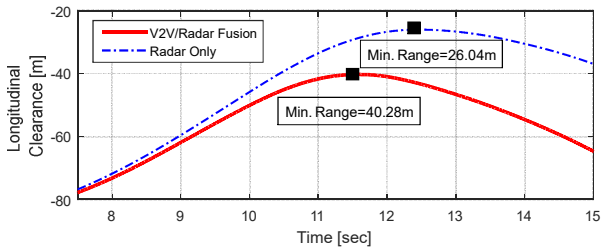
Figure 5.8. Simulation results for the cut-in vehicle braking scenario in Figure 5.6-(a)

5.2.3. Effects of V2V Communication: Controlled Host Vehicle

The human-centered risk assessment algorithm has been incorporated into a model predictive control (MPC) based longitudinal vehicle control in [26]. The objective of a longitudinal vehicle model is used and its objective is to maintain vehicle distance and adjust velocity to avoid the longitudinal collision. The state can be defined as three: clearance error, velocity error and longitudinal acceleration derived from the longitudinal model. The effect of communication on the response of host vehicle to the braking of preceding remote vehicle is studied. The scenario is shown in Figure 5.6-(b). The remote vehicle applies a hard brake of approximately 0.4g at 4.8 seconds and then accelerates again. As shown in Figure 5.9–(a), it can be seen that the V2V/Radar fusion vehicle brake response is 2 seconds earlier than the radar only case. Figure 5.9-(b) is the range, longitudinal clearance, between the host and the remote vehicle on the time domain. It can be clearly seen in Figure 5.9-(b) that the minimum range between two vehicles are extended by 14.24 meters because of V2V communication. Figure 5.10. shows that the simulation results confirm our belief that both collision risk and reaction time recover to safe region when the controller intervenes the system. Vehicular communication is of great benefit for the active safety control as shown in



(a) Longitudinal Acceleration of the vehicles

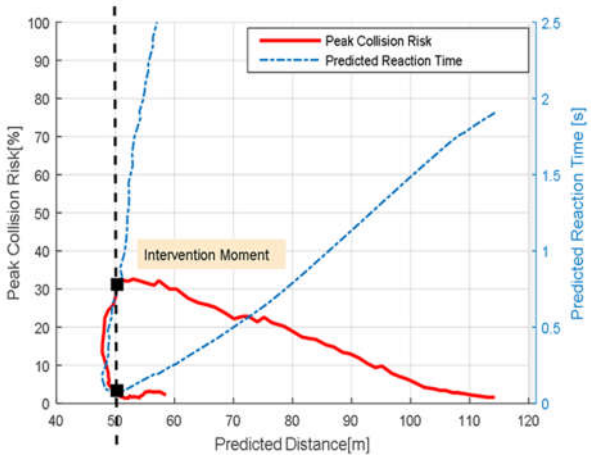


(b) Range of the vehicles

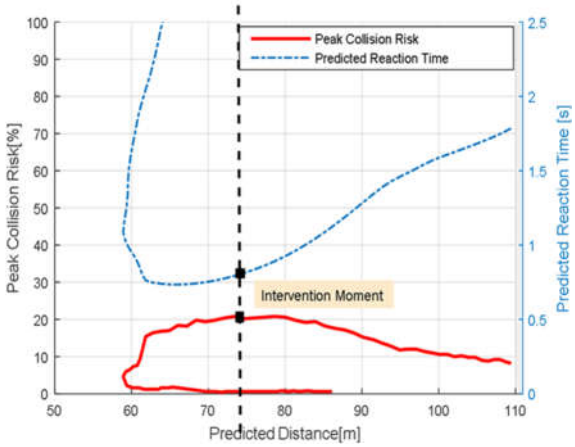
Figure 5.9. Simulation results for the host vehicle longitudinal control

Figure 5.10-(b) and (c). The longitudinal controller with radar only case does not fully guarantee the safety due to the fact that active safety intervention moment is 10 percent higher than its best intervention point. This means that predicted reaction time is only 0.1 second and predicted collision distance is 49 meters when the active safety intervenes the system.

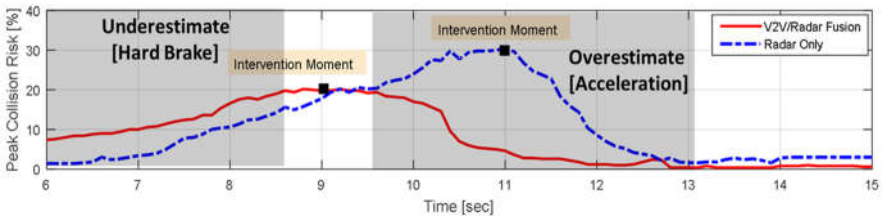
However, simulation for the V2V/Radar fusion case in Figure 5.10-(b) shows significant improvement in the risk assessment performance with the maximum 9 percent of peak collision risk difference. This results in faster intervention timing of controller and the active safety intervention moment is 11 percent lower than radar only case. The collision risk when the active safety system intervenes is 19.4 percent and is no greater than a best trade off moment. The predicted reaction time and distance are extended by 0.65 second and 10 meters, respectively. This means that it fully guarantees the safety compared to radar only case. Although a very conservative active safety system may be able to prevent all possible collisions, however, it will also be more likely disrupt the driver by applying the brakes at inappropriate times. It can be more improved by intervening the system at a best trade off moment. The predicted reaction time and distance are extended by 0.65 second and 10 meters, respectively.



(a) Radar only

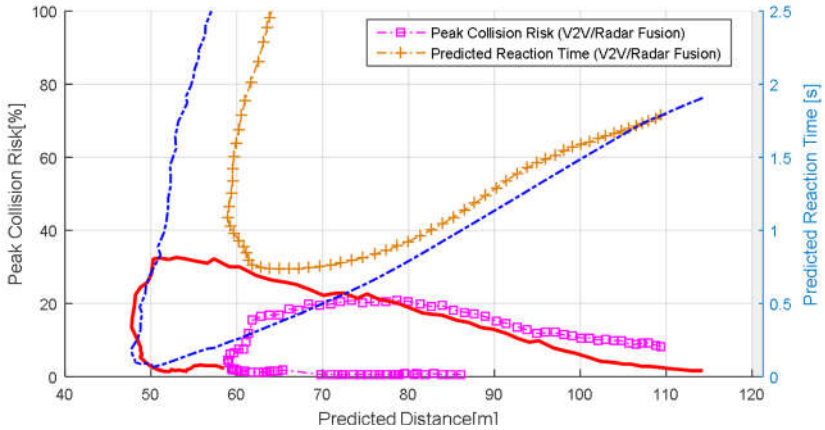


(b) V2V/Radar Fusion

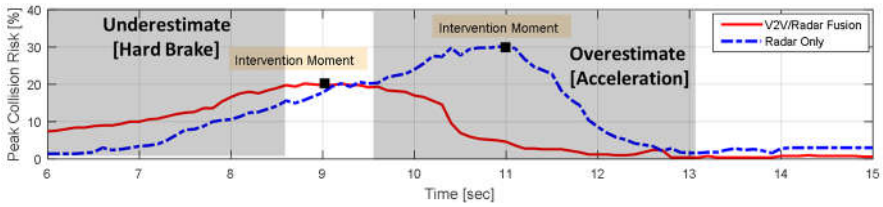


(c) Peak collision risk of the vehicles

Figure 5.10. Simulation results for the cut-in vehicle braking scenario in Figure 5.6-(b)



(a) Human Centered Risk Assessment: Combined View



(b) Peak collision risk of the vehicles

Figure 5.11. Simulation results for the cut-in vehicle braking scenario in Figure 5.6-(b) : Combined View

5.3 Vehicle Tests

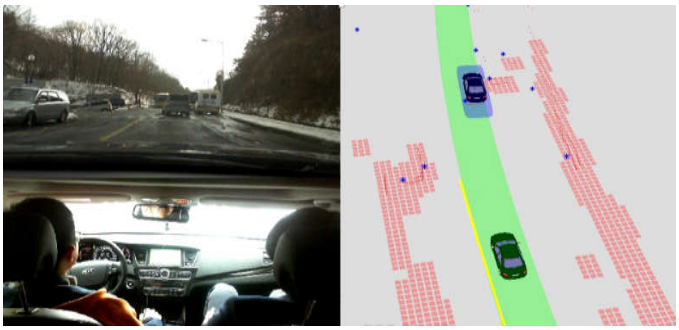
The developed human-centered risk assessment algorithm is implemented on the test vehicles. In order to show the effectiveness of the V2V communication on the human-centered risk assessment, vehicle tests are conducted on the real road with the scenario in Figure 5.11-(b) and (c). The maximum collision probability, and most probable predicted collision distance from the threat vehicles ahead are computed to decide active safety control intervention moment.

The V2V communication allows the vehicle to behave like human intelligence with enhanced risk prediction performance of both human and machine. Compared to conventional TTC or other active safety algorithm, the proposed active safety control algorithm takes into account driver's sensitivity, target uncertainty and useful remote vehicle information such as longitudinal acceleration and yaw rate.

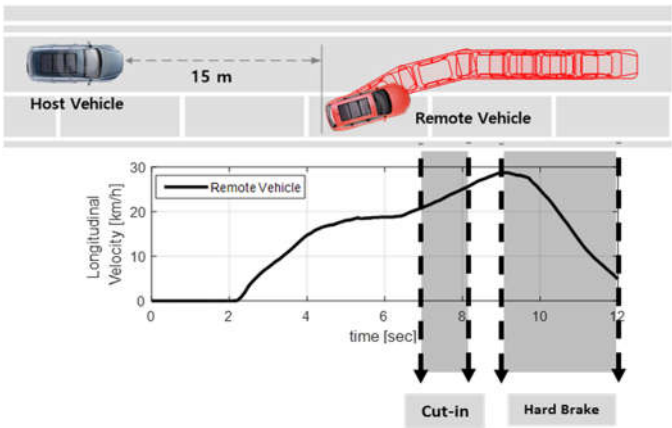
5.3.1 Test Vehicle Configuration and Scenario

Figure 5.12-(a) shows the host vehicle and remote vehicles used in this study. The host vehicle is equipped with a front-radar, wheel speed sensors, and a V2V communication (DSRC) device, etc. Since this paper focuses on the risk assessment for active safety system, additional details about the test vehicles' system have been omitted. The test scenario is the parked vehicle cut-in and sudden hard brake of 0.35g with the 15 meters of initial longitudinal clearance as shown in Figure 5.12-(b). The host vehicle speed is constant for 30 km/h and

(a) Configurations of the host vehicle and the remote vehicle



(b) Front view of the driver



(c) Preceding remote vehicle longitudinal velocity

Figure 5.12. Vehicle test set-up and scenario

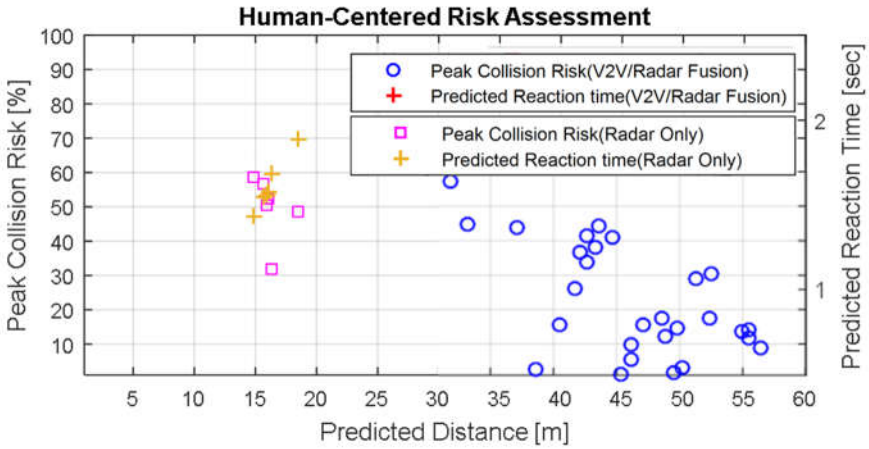
the remote vehicle is suddenly cutting in at 2 seconds with the range of 15 meters as seen in Figure 5.12-(b) and (c). After then, the remote vehicle applies

hard brake of 0.35g, as illustrated in Figure 5.12-(c).

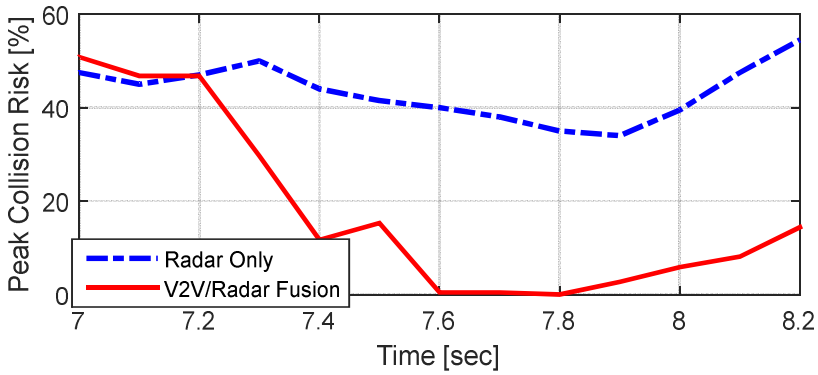
5.3.2 Implementation and Evaluation

Figure 5.13 and 5.14 present a vehicle test results for the proposed V2V/Radar fusion and radar only algorithm when the remote vehicle is cutting in from the parking spot with the 15meteres of initial longitudinal clearance as described in Figure 5.12. Since more enriched and accurate remote vehicle state information is processed from the V2V/Radar fusion algorithm, it significantly reduces the chances of inaccurate estimation issue as seen in Figure 5.13. As shown in Figure 5.13-(a), the active safety control intervention moment, a crossing point, does not exist and this means that it is safe driving mode. The test results in Figure 5.13 are fairly well matched with the simulation results in Figure 5.7 by reducing the chances of overestimate. The V2V communication can be beneficial to avoid overestimate issue which allows to design an unobtrusive algorithm which prevents all possible collisions.

Figure 5.14 is the test results for the host vehicle's sudden hard braking of 0.35g right after the remote vehicle is cutting in from the parking spot as seen in Figure 5.12-(c). With the V2V communication in Figure 5.14-(a), sudden deceleration of the remote vehicle can be more accurately and reliably detected compared to radar only in Figure 5.14-(a). Thus it can be seen that the active safety intervention moment, a crossing point, is detected much earlier and the maximum collision risk difference is 40 percent in Figure 5.14-(b). Figure 5.14-(a) and (b) show that the V2V communication significantly reduces the chances



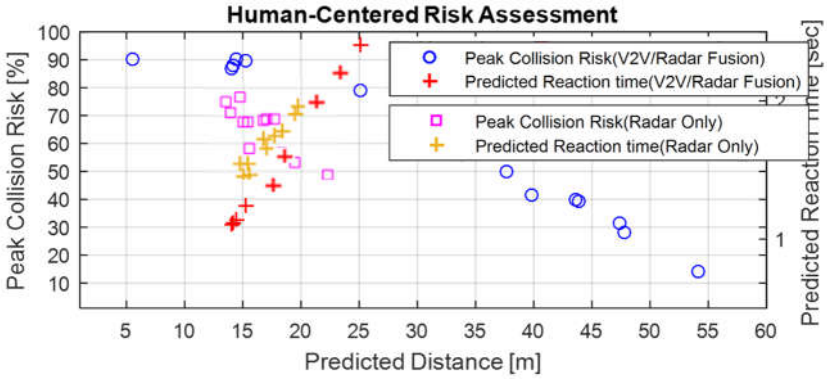
(a) Radar only



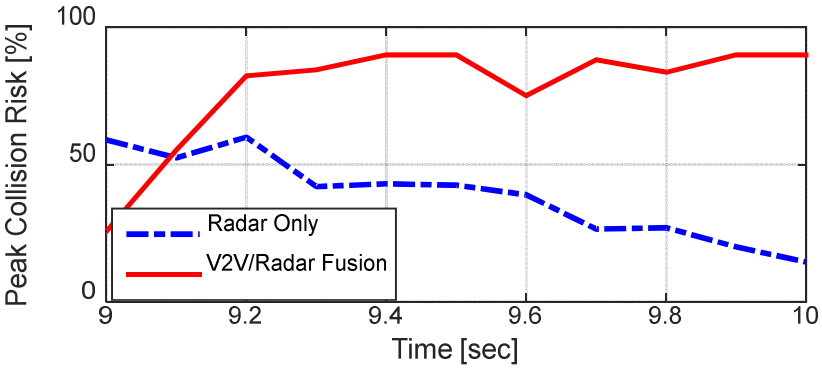
(b) Peak collision risk of the vehicles

Figure 5.13. Vehicle test results for the parked vehicle cut-in scenario in Figure 5.12-(c)

of underestimate issue compared to the radar only in Figure 5.14-(a). And it can be known that the result is fairly well aligned with the simulation result in Figure 5.8.



(a) Radar only



(c) Peak collision risk of the vehicles

Figure 5.14. Vehicle test results for the cut-in vehicle braking scenario in Figure 5.12-(c)

Chapter 6

Conclusion

An autonomous vehicle front collision avoidance algorithm has been developed using vehicular wireless communication and ADAS sensors. A human-centered risk assessment has been presented using probabilistic threat vehicle prediction and predicted human reaction time. The proposed human-centered risk assessment algorithm with the V2V communication can enhance the safety of vehicles with proper intervention timing. Since a vehicle-to-vehicle wireless communication (V2V communication) provides more enriched remote vehicle object information and prediction results, a host vehicle is able to overcome uncertainty over any deceleration of the remote vehicle. In order to decide active safety control intervention moment, a collision risk and a human reaction time are computed. It was shown from both simulations and vehicle tests that the active safety intervention decision and vehicle control performance are significantly enhanced with the V2V communication. And this makes active safety system of automated vehicle to have more human-like driving intelligence. Implementation and tests of the human-centered risk assessment algorithm for automated driving vehicles is the topic of our future research.

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초 록

차량간 통신을 이용한 지능형 자동차의 전방차량 위험판단 기법

본 학위논문에서는 차량간 통신을 이용한 지능형 자동차의 전방차량 위험판단 기법 개발에 대해서 서술하고 있다. 차량간 통신 모듈은 기존 운전자 지원 시스템에서 널리 활용되고 있던 환경센서와의 융합을 통해 전방차량의 움직임을 정확히 예측하는데 이용된다. 예측된 전방차량의 상태변수 및 거동을 기반으로 충돌확률 및 인간의 인지-반응시간이 전 주행속도구간에서 결정된다. 실시간 계산된 예측 충돌위험도 및 인간의 반응시간을 이용하여 보다 적절한 시기에 능동안전시스템의 개입 시점을 도출하였고, 이를 통하여 시스템에 대한 운전자의 수용성을 증대시킬 수 있다. 따라서 본 논문에서 제안하고 있는 지능형 자동차의 인간중심 위험 평가 및 판단 알고리즘은 기존 환경센서인 레이다 뿐만아니라 전방 차량에서 보내오는 통신 정보를 융합하여 충돌회피 시스템의 성능을 향상 및 확장시켰다. 실험결과 및 컴퓨터 시뮬레이션을 통해 차량간 통신을 이용한 지능형 자동차의 인간중심 위험평가 및 판단의 성능을 입증하였다. 고속도로 및

도심저속상황에서의 능동안전시스템의 개입시점을 정확히 판단하고, 자율주행 차량 및 지능형 자동차의 안전을 보장 하는데 효과적임을 확인하였다.

본 논문에서 개발한 차량간 통신을 이용한 전방차량 위험판단 알고리즘은 차량이 주행하는 전속도 구간에서 충돌 위험도 및 인간의 반응시간을 정확히 예측하여 능동안전 시스템 개입 성능을 향상시킴으로써 지능형 자동차 제어 분야에 기여한 바, 박사학위 논문으로 가치가 충분하다고 판단된다.

주요어: 차량간 통신, 지능형 교통시스템 (ITS), 자율주행 자동차, 능동안전 시스템, 운전자 지원시스템, 충돌회피, 인간기계상호작용, 충돌위험평가

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