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Robust Autonomous Emergency Braking System for Vulnerable Road Users

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Abstract

Robust Autonomous Emergency Braking System for Vulnerable Road Users

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A robust autonomous emergency braking (AEB) algorithm for vulnerable road users (VRU) is studied. Autonomous emergency braking (AEB) is a system which helps driver to avoid or mitigate a collision using sensor information. After many kinds of AEB system is produced by automakers, researchers and automakers are currently focusing on VRU-related collisions. Vulnerable road users (VRU) usually defined as ‘non-motorized road users such as pedestrian and cyclist. Although VRU are relatively slower than vehicle, VRU related collisions should be prevented due to their fatalities. Therefore, many researchers are trying to develop a VRU-AEB.

In order to assess the risk of collision before it occurs, the motion of host vehicle and target VRU should be predicted. For this, dynamic models of host vehicle and target VRU is required.

In the case of host vehicle, in order to judge whether a driver can avoid a collision or not, driver’s evasive maneuver also should be predicted as well as normal driving maneuver. For this, the motion of the host vehicle is predicted using constant acceleration model. In the case of target VRU, since the identification between pedestrian and cyclist is difficult, safety performance of AEB should be guaranteed even if the type of the target is unclear. Therefore, the behavior of pedestrian and cyclist is described using a single constant velocity model.

These predicted information is then used to judge whether a collision is inevitable or not. If a driver cannot avoid a collision with pre-defined limits and safety margin, then the proposed AEB system is activated to decelerate the vehicle. To guarantee the robust safety performance of AEB system, measurement uncertainty and prediction uncertainty are also considered while defining the safety margin. To evaluate the safety performance of proposed AEB system, simulation study is conducted via vehicle simulation tool Carsim and MATLAB/Simulink. To investigate the robust safety performance of the proposed AEB system, simulation study is repeated 100 times with same traffic scenario with uncertainties. Performance of the proposed AEB system is compared with the deterministic AEB which is introduced in this work.

Keywords: Autonomous Emergency Braking System, Active Safety System, Driver Assistance System, Collision Avoidance, Sensor Uncertainty, Prediction Uncertainty

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Chapter 1

Introduction

1.1 Motivation

After passive safety systems such as airbag or seat belt were introduced, active safety systems have become one of the main issues. The main advantage of active safety system is that a collision can be prevented before it occurs. Therefore, many kind of active safety system such as forward collision warning system (FCWS), autonomous emergency braking system (AEBS) and lane keeping assistance system (LKAS). Especially, Autonomous emergency braking (AEB) is a system which helps drivers to avoid or mitigate a collision using an environmental information such as traffic situation. Since many of collisions are occurred by driver's distraction, AEBS system is very helpful to prevent this kinds of collisions. Since the first AEB system was produced in 2008 by Volvo, the target of AEB system is expanded from vehicle-to-vehicle collision to vehicle-to-'other road users' such as pedestrian and cyclist. Recently, AEB for Vulnerable Road Users (VRU) has become one of the main issues for researchers and automakers. VRU are defined as “non-motorized road users, such as pedestrians and cyclists as well as motor-cyclists”. Although the number of collisions related with VRU is smaller than other car to car collisions, it is important to mitigate or avoid car-to-VRU crashes due to their fatality.

Table 1.1.1 shows the number of vehicle-to-pedestrian accidents in Korea from 2005 to 2014. According to Table 1., the number of vehicle-to-pedestrian accident accounts for 21.95% of the number of total accident. Also, 36.88% of fatal accident was vehicle-to-pedestrian accident. This results shows that vehicle-to-pedestrian accidents easily lead to fatal accident rather than other accidents.

Table 1.1.2. shows the number of cyclist related collisions which were occurred by passenger cars, van, or commercial vehicles. The result shows that the number of total accident was reduced 1.03% annually on the average while the number of vehicle-to-cyclist collision was increased 5.61% every year.

As mentioned above, many of these accidents can be prevented or mitigated using autonomous emergency braking system.

Table 1.1.1 Vehicle-to-Pedestrian Accidents in Korea

Year	Number of Accident			Number of Fatal Accident		
	Total Accident	Vehicle-to-Pedestrian Accidents		Total Accident	Vehicle-to-Pedestrian Accidents	
			[%]			[%]
2005	214,171	46,594	21.76	6,376	2,457	38.54
2006	213,745	45,261	21.18	6,327	2,377	37.57
2007	211,662	44,857	21.19	6,166	2,232	36.20
2008	215,822	47,281	21.91	5,870	2,063	35.14
2009	231,990	49,665	21.41	5,838	2,047	35.06
2010	226,878	49,353	21.75	5,505	2,010	36.51
2011	221,711	49,701	22.42	5,229	1,998	38.21
2012	223,656	50,111	22.41	5,392	1,977	36.67
2013	215,354	49,130	22.81	5,092	1,928	37.86
2014	223,552	50,315	22.51	4,762	1,843	38.70
Average	219,854	48,227	21.95	5,656	2,093	36.88

* Reference: Traffic Accident Analysis System (TAAS) of Korea

Table 1.1.2 Vehicle-to-Cyclist Accidents in Korea

Year	Number of Accident			Number of Fatal Accident		
	Total Accident	Vehicle-to-Cyclist Accidents		Total Accident	Vehicle-to-Cyclist Accidents	
			[%]			[%]
2010	200,347	7,711	3.84	4,468	209	4.67
2011	195,243	8,257	4.22	4,202	177	4.21
2012	196,610	8,310	4.22	4,367	170	3.89
2013	187,651	8,091	4.31	4,080	161	3.94
2014	191,943	9,498	4.94	3,809	171	4.48
Average	219,854	48,227	21.95	5,656	2,093	36.88

* Reference: Traffic Accident Analysis System (TAAS) of Korea

1.2 Autonomous Emergency Braking System

– Global Trend

Although an autonomous emergency braking(AEB) system is only recently became popular, the first vehicle with AEB system was produced almost ten years ago. Since ‘City Safety’, the first type of AEB system, was introduced by Volvo in 2008, various kinds of AEB system were developed and produced by automakers. They can be classified according to the operation environment, actuation type, sensor configuration, and target of the system. Detailed information and some examples are shown in Figure 1.2.1.

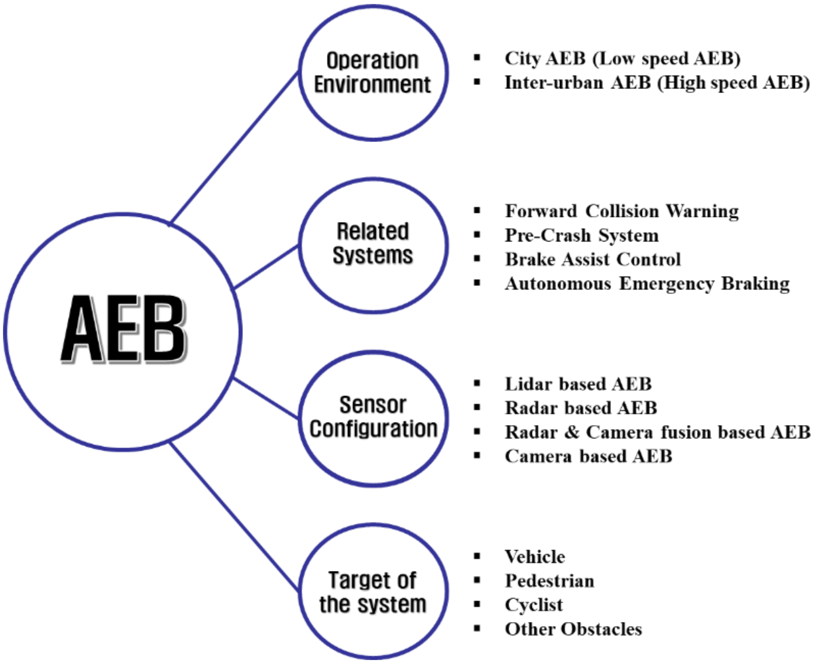


Figure 1.2.1 AEB system classification

Euro-NCAP (European New Car Assessment Programme) is providing information about produced AEB systems and their specifications. Information about previous AEB systems which were produced from 2008 to 2015 are shown in table 1.2.

Some of the earlier version of AEB systems, such as ‘City Safety (2010)’ of Volvo, ‘Active City Stop (2011)’ of Ford, ‘City Emergency Brake (2011)’ of VW, and ‘City Brake Control (2013)’ of FIAT, used short range lidar sensor to prevent a vehicle to vehicle collision in city environment. Since the range of the lidar was lower than 12m, they can be operated only in low speed driving condition lower than 30km/h.

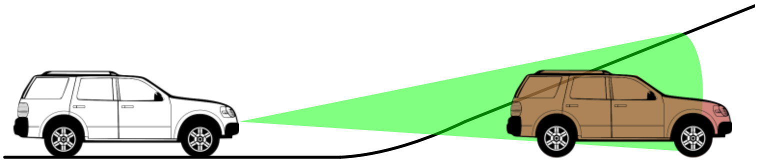
In order to prevent a collision in high speed driving condition, some AEB system started to use a radar sensor. ‘Collision Mitigation Brake System (2010)’ of Honda used the radar sensor with a range of 100m. ‘Collision Prevention Assist (2011)’ of Benz used the radar with a range of 80m. ‘PRE_SAFE BRAKE (2010)’ of Benz, ‘Forward Alert (2011)’ of Ford, and ‘Forward Collision Mitigation (2013)’ of Mitsubishi used the radar with a range of 200m. These systems can prevent or mitigate a collision in high speed condition. For example, ‘PRE_SAFE Brake (2010)’ of Benz can be operated with the speed from 30km/h to 250km/h. However, since they only used a radar sensor, it is difficult to distinguish a preceding vehicle with a slope in front of the vehicle, guardrail on curve or parked vehicle in other lane as shown in Figure 1.2.2.

In order to prevent a collision in various environmental conditions, automakers started to produce an AEB system with both radar and camera. With this kind of sensor configuration, they can be operated in both low speed and

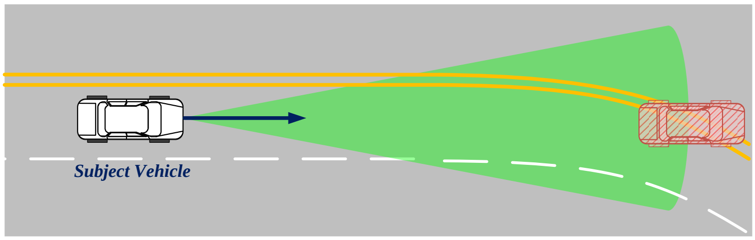
Table 1.2 Previous AEB Systems

Systems		Operation Condition	Objective	Sensor
Volvo	City Safety (2010*)	3.6-30 km/h	Vrel< 15km/h (CA)	10 m lidar
Honda	Collision Mitigation Brake System (2010*)	> 15 km/h	Hard Brake TTC = 1.0 sec	100 m radar
Benz	PRE_SAFE® Brake (2010*)	30 -200 km/h	Hard Brake TTC = 0.6 sec	200 m radar
	Collision Prevention Assist (2011*)	30 –250 km/h	when driver brakes	80 m radar
Ford	Forward Alert (2011*)	7 –180 km/h	When driver brakes	200m radar
	Active City Stop (2011*)	-30 km/h	Vrel < 15 km/h (CA)	7.6m lidar
VW	City Emergency Brake (2011*)	5 –30 km/h	Vrel < 20 km/h (CA)	10 m lidar
	Front Assist (2012*)	-30 km/h	CA braking	80 m radar One mono camera
		30 –200 km/h	Stationary object : no brake Moving traffic : partial brake and brake assistance	
Audi	Pre Sense Front (2012*)	-30 km/h	CA braking	80 m radar One mono camera
		30 –200 km/h	Stationary object : no brake Moving traffic : partial brake and brake assistance	
	Pre Sense Front Plus (2012*)	-200 km/h	CA braking under 30 km/h CM braking over 30 km/h	Two long range radars One mono camera
Skoda	Front Assistant (2013*)	-30 km/h	CA braking	80 m radar One mono camera
		30 –200 km/h	Stationary object : no brake Moving traffic : partial brake and brake assistance	
Mitsubishi	Forward Collision Mitigation (2013*)	-30 km/h	0.8g deceleration	200m radar
		30-180 km/h	0.6g deceleration	
FIAT	City Brake Control (2013*)	5-20 km/h	-10 m/s2 deceleration	10-12 m Lidar
		20-30km/h	-6 m/s2 deceelration	
BMW	Pedestrian Warning with City Brake Activation (2014*)	10-60 km/h	Warning Braking before the collision	Camera
Audi	Pre Sense City (2015*)	-40 km/h	CA braking	Camera
		40-85 km/h	CM braking	

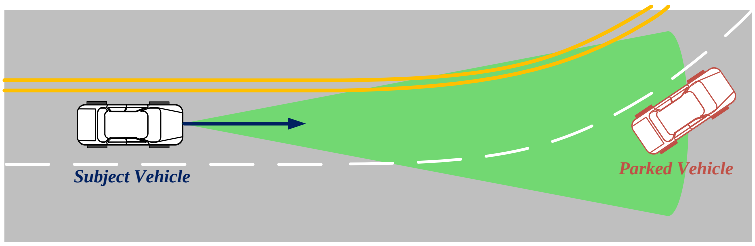
* Each system was tested by Euro-NCAP in the year shown



(a) a slope in front of the vehicle



(b) guardrail in curve



(c) parked vehicle in other lane

Figure 1.2.2 Radar based Inter-urban AEB - Limitation

high speed region. Also, with camera measured information, preceding vehicle can be distinguished with other objects. Therefore, these AEB system can be effectively operated in both city and inter-urban environment.

As a detection performance of camera is improved, some automakers started to produce camera-only-AEB systems. 'Pedestrian Warning with City Brake Activation (2014)' of BMW detects a pedestrian, warns driver, and decelerates the vehicle before collision. 'Pre Sense City (2015)' of Audi can avoid a collision with a speed lower than 40km/h and mitigate a collision with a speed from 40km/h to 85km/h.

Currently, many kinds of AEB systems are produced by automakers. They are trying to apply the AEB system to the various kind of vehicle models. Also, after Volvo introduced pedestrian safety system in 2010, named ‘Collision Warning with Full Auto Brake and Pedestrian Detection’, and cyclist safety system in 2013, named ‘Pedestrian and Cyclist Detection with full auto brake’ system, for the first time, many automakers are trying to expand the target of their AEB system to the cyclist.

Although a pedestrian/cyclist AEB system is already produced by automakers, many researchers are trying to improve the detection performance and safety performance of AEB system. In section 1.3, many kind of methodologies to assess the risk of collision is introduced.

1.3 Thesis Objectives and Outline

The aim of this work is a robust autonomous emergency braking algorithm for VRU which can deal with both types of VRU. For this, simple constant velocity model is used to describe the motion of VRU. Current state of target VRU is estimated based on the measured information from radar and camera sensors. And then, the future states of host vehicle and target VRU are predicted to judge whether a collision is inevitable or not. In order to describe the evasive maneuver of driver, it is assumed that the driver can avoid a collision only using braking or steering. In general cases, drivers can use steering, braking, accelerating or combination of them. However, combined motion in dangerous situation is difficult for common drivers. Hence, proposed algorithm assumes that braking or steering is the only option for driver to avoid a collision. In order to evaluate the performance of the proposed AEB algorithm, computer simulation was conducted using vehicle simulation software, CARSIM and MATLAB/Simulink.

Chapter 2

Previous Researches

Since an active safety system, such as forward collision warning, was introduced, many automakers and researchers are trying to guarantee the safety using advanced driver assistance system or automated driving system.

For this, a risk of collision should be assessed and predicted before a collision occurred. There were many kind of studies which are trying to assess a risk of collision for various systems. Some of them tried to assess a risk of collision simply in terms of time-to-collision (TTC) [Labayrade 2005], predicted minimum distance [Polychronopoulos 2004], or required deceleration [Karlsson 2004]. Hilenbrand proposed a multilevel collision mitigation approach with consideration about the tradeoff between many kind of collision risk indices such as time to collision (TTC), time to brake (TTB), time to kickdown (TTK), and time to steer (TTS). [Hillenbrand 2006] Tamke proposed a criticality assessment methodology for general road scene using time-to-x (TTX) criticality measures which contains time-to-collision, time-to-brake, time-to-steer. [Tamke 2011] Hilgert tried to measure collision risk using elastic bands with complex path planning frameworks which was inspired by the mobile robotics community. [Hilgert 2003] Berthelot proposed an estimation algorithm of the probabilistic distribution of time-to-collision index [Berthelot 2012] Kim propose a probabilistic threat assessment methodology with environment description and rule-based multi-traffic prediction for integrated risk management system. [B. Kim 2015]

However, it is difficult to express and measure the risk in general situation only using these kind of index based risk assessment methods. For this, other people tried to assess the risk of collision using pre-defined avoidance models. Brannstrom proposed a model based threat assessment which judges whether a driver can avoid a collision with one of pre-defined models. [Brannstrom 2010] They improved it to the decision-making algorithm to decide how to control the vehicle for collision avoidance [Brannstrom 2014] Proposed a trigger time calculation algorithm for emergency braking with consideration about all physically possible trajectories of the object and host vehicle. [Kaempchen 2009]

Also, there were some studies tried to assess the risk of collision using other various approaches. Damerow proposed a motion planning algorithm using risk-map based threat assessment and rapidly exploring random tree (RRT) [Damerow 2015] Kim proposed a collision detection algorithm in general road scenes using crash probabilities and an interactive multiple model (IMM) particle filter. [T. Kim 2014] Lafevre compared many kind of motion prediction and risk assessment methods for intelligent vehicle. [Lefevre 2014]

In order to assess the risk of collision, behavior of the target should be estimated and predicted. For example, Kim proposed a probabilistic and holistic prediction model of vehicle for integrated vehicle safety systems [B. Kim 2014] And then, they proposed a target state estimator using IMM and EKF for integrated risk management system [B. Kim 2015] Li tried to introduced many kind of target tracking method with various dynamic models [Li 2003] They also introduced many kind of target tracking method which are based on the multiple-model approach [Li 2005]

In the case of steering avoidance system or autonomous driving system, path planning for steering avoidance is also important. Volvo proposed a path planning for steering avoidance which minimize the lateral jerk of the host vehicle [Volvo 2014] Ferdinand proposed a trajectory planning algorithm for collision avoidance in urban area [Ferdinand 2016] Madas proposed and compared three kind of methods for path planning and obstacle avoidance: a state lattice planner, predictive constraint-based planning, and spline-based search tree. [Madas 2013]

In the case of intersection scenario, improved approach for motion prediction and risk assessment is required. Some studies tried to guarantee the safety using vehicle-to-vehicle or –infrastructure communication. Campos proposed an autonomous cooperative driving system with a velocity-based negotiator for intersection crossing. [Campos 2013] Other studies tried to assess the risk of collision in intersection scenarios for safety systems. Campos presented the probabilistic threat assessment and decision-making algorithm for emergency braking system. [Campos 2014] Maile improved the intersection movement assist (IMA) application to an intersection collision avoidance (ICA) based on dedicated short range communications (DSRC) [Maile 2015] Schildbach proposed a robust model predictive control strategy based intersection safety system without vehicle-to-vehicle or –infrastructure communication. [Schildbach 2016]

Additionally, there were various kind of studies which tried to assess the risk of collision or improve the performance of safety systems. Stellet analyzed a performance bounds of autonomous emergency braking systems considering sensor and prediction uncertainties. [Stellet 2016] Yang presented a threshold development methodology for active safety system in rear-end collision scenario. [Yang 2003] Sieber analyzed the perception and reaction time of driver using experimental data with cross traffic obstacle scenario. [Sieber 2016] Jula tried to analyze the initial minimum longitudinal spacing which is required to guarantee the safety during lane change/merge scenario. [Jula 2000] Lenz proposed a Monte Carlo Tree Search (MCTS) based cooperative combinatorial motion planning algorithm without inter vehicle communication. [Lenz 2016]

Meanwhile, there were also many kind of studies about the safety systems for vulnerable road users (VRU). In the case of pedestrian safety system, there were many kind of studies about pedestrian detection, modeling, model prediction and risk assessment.

Abramson proposed a frontal camera based pedestrian detection and impact prediction with pedestrian classifier, legs detector and a particle-filtering-based fusion system. [Abramson 2004] Simizu presented a pedestrian direction estimator which uses images from the frontal camera of vehicle. [Simizu 2003] Wakim proposed a markovian model to describe the pedestrian behaviors for pedestrian motion prediction. [Wakim 2004] Gavrila presented a field test result of vision-based pedestrian detection system with trajectory estimation, risk assessment, and driver warning. [Gavrila 2004] Gavrila also proposed a multi-cue vision based pedestrian detection and tracking system. [Gavrila 2007] Ferguson proposed a Gaussian process mixture model (DPGP) based pedestrian detection and motion prediction model. [Ferguson 2015] Also, pedestrian detection algorithms in other system structures were also studied. Antonini presented a discrete choice pedestrian behavior model for visual tracking system [Antonini 2004] Antonini also proposed a pedestrian walking behavior model using discrete choice model approach. [Antonini 2006]

Also, as many studies proposed pedestrian safety systems, there were studies trying to assess the effect of them. Chauvel and Edwards proposed an evaluation of the expected safety benefits of related systems such as autonomous emergency braking for pedestrian (AEB-P) [Chauvel 2013] [Edwards 2015] Gandhi introduced a various kind of pedestrian detection methodologies and pedestrian behavior model based motion prediction approaches. [Gandhi 2007] Habibovic used microscopic and macroscopic crash data to propose a guideline for the requirement of sensor, collision detection, and human-machine interface (HMI), which are a part of intersection safety system for car-to-vulnerable road user crashes. [Habibovic 2011] After the first pedestrian safety system of Volvo named 'Collision Warning with Full Auto Brake and Pedestrian Detection (CWAB-PD)' was produced, Coelingh tried to illustrate the theoretical and practical performance limitation of the system. [Coelingh 2010] Seiniger tried to investigate the changes and limitations of active safety system for vulnerable road user (VRU) based on the impact point of pedestrian and impact speed of vehicle from open loop simulation result. [Seiniger 2013] Themann assessed the impact of positioning and prediction uncertainties on the collision avoidance system for vulnerable road users. [Themann 2015]

Although the first pedestrian safety system was already produced, there were many studies which were trying to improve the performance of risk assessment algorithm in pedestrian accidents. Eidehall proposed a steering avoidance motion prediction based multi-target threat assessment for emergency braking system [Eidehall 2011] Savino proposed an inevitable collision states based triggering algorithm for motorcycle-to-Car autonomous emergency braking system. [Savino 2015] Roth proposed predicted probability distribution based risk assessment with consideration about driver awareness information from interior camera. [Roth 2016] Using these kind of risk assessment approaches, emergency braking systems for pedestrian crashes were also proposed. Westhofen introduced the pedestrian movement area based on a physiological model and proposed the movement area intersection based risk assessment in car-to-pedestrian collision scenarios which also consider about a realistic weighting of the movement area. [Westhofen 2012] On the other hand, autonomous systems with pedestrian collision avoidance were also introduced. Matsumi presented an autonomous driving system for pedestrian collision avoidance using a risk potential estimation approach. [Matsumi 2015]

In order to investigate the performance of these systems, Waizman developed a simulation model for vehicle-pedestrian road accident for implementation of pedestrian safety systems. [Waizman 2015]

Although many researches about pedestrian safety systems have been published, there were only few studies for cyclist safety system. In the case of cyclist safety system, while the behaviors of cyclists are similar with vehicles, it is difficult to distinguish a cyclist from a pedestrian because of its thin and tubular body frame. Although there were many studies trying to distinguish cyclist from pedestrian, performance of them are not still guaranteed. Therefore, AEB should be able to assess the risk of collision without VRU type identification. For this, Rosen has proposed an AEB system for VRU which uses exactly a same decision algorithm for both types of VRU. [Rosen 2013] The decision algorithm of Rosen activates the AEB only if VRU is in trigger area which represents the predicted path of the vehicle. As mentioned in Rosen's work, unwanted activations can be avoided with this approach. However, if the cyclist travels from the outside of the trigger area to the inside of it, AEB cannot be activated earlier enough to avoid a collision.

Chapter 3

Autonomous Emergency Braking Algorithm for Vulnerable Road Users

In this work, proposed AEB algorithm is activated if a collision is inevitable with the consideration about uncertainty level based safety distance. Inevitable collision state means the situation when collision occurs with any feasible maneuver of driver or within the physical limits. [Savino 2016] In this situation, AEB should be activated to avoid or mitigate the imminent collision.

To predict the future collision, it is assumed that VRU doesn't react to avoid a collision. This assumption is reasonable for short time-to-collision situations which also fits with target situation of AEB. Therefore, it is assumed that VRU cannot maneuver to prevent a collision. Also, simple constant speed model is used to describe the characteristics of pedestrian and cyclist using same dynamic model without target identification.

The motion of host vehicle is modeled using constant acceleration model. The longitudinal acceleration and yaw acceleration are very important factors to predict the future states of the vehicles. To use the yaw acceleration information, vehicle state estimator is used based on the measurement information from vehicle chassis sensors. Also, in order to judge whether the driver can avoid a collision or not, proposed algorithm assumes that braking or steering is the only option for driver to avoid or mitigate the collision. Driver's evasive maneuver is modeled using desired acceleration tracking model. To describe the characteristics of driver's evasive maneuver, driving data of 100 peoples is used. The schematic view of the propose AEB algorithm is shown in Figure 3.

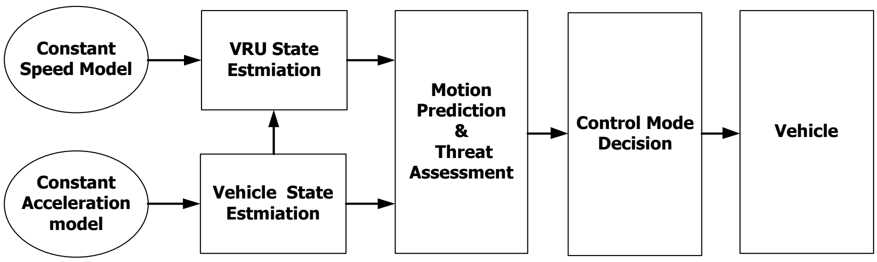


Figure 3. Schematic view of VRU AEB

Chapter 4

Host Vehicle Motion Prediction

In this section, future motion of host vehicle is predicted. For this, dynamic model of host vehicle is defined. In order to predict the evasive maneuver of a driver as well as the normal driving maneuver, constant acceleration model combined with acceleration tracking model is used. To predict the future position of host vehicle, velocity, yaw rate and longitudinal acceleration is measured using vehicle chassis sensors. Based on the measured information, the current state of host vehicle is estimated using simple integration model. The future motion of host vehicle is predicted using Taylor Method. Using the pre-defined dynamic models, the future position of vehicle can be predicted for each maneuver model of the driver in pre-defined prediction time horizon.

4.1 Host Vehicle State Estimation

In order to predict the future behavior of the host vehicle, vehicle velocity, yaw rate, and longitudinal acceleration is measured using vehicle chassis sensors. Then, a linear Kalman filter is used to estimate the longitudinal velocity, yaw rate, longitudinal acceleration and yaw acceleration. State vector x_{host} and measurement vector z_{host} of estimator can be defined as follows:

$$\begin{aligned} x_{host} &= \begin{bmatrix} v_x & \gamma & a_x & \dot{\gamma} \end{bmatrix}^T \\ z_{host} &= \begin{bmatrix} v_x & \gamma & a_x \end{bmatrix} \end{aligned} \tag{1}$$

where v_x : longitudinal velocity, γ : yaw rate, and a_x : longitudinal acceleration of vehicle.

Process model of the Kalman Filter can be expressed as follows:

$$\dot{\mathrm{x}} = \begin{bmatrix} \dot{v}_x \\ \dot{\gamma} \\ \dot{a}_x \\ \ddot{\gamma} \end{bmatrix} = A\mathrm{x} + B\mathrm{w} = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} v_x \\ \gamma \\ a_x \\ \dot{\gamma} \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 1 & 0 \\ 0 & 1 \end{bmatrix} \mathrm{w}, \quad \mathrm{w} \sim \begin{pmatrix} 0 & Q \end{pmatrix} \tag{2}$$

where Bw : process model uncertainty with proper dimension. The time derivatives of the longitudinal acceleration and yaw acceleration is assumed as a white noise.

In order to use a discrete Kalman Filter, Equation (2) should be discretized. For this, Taylor expansion method with second order is used. Vehicle process model and measurement model for state estimation can be expressed as follows:

Process model:

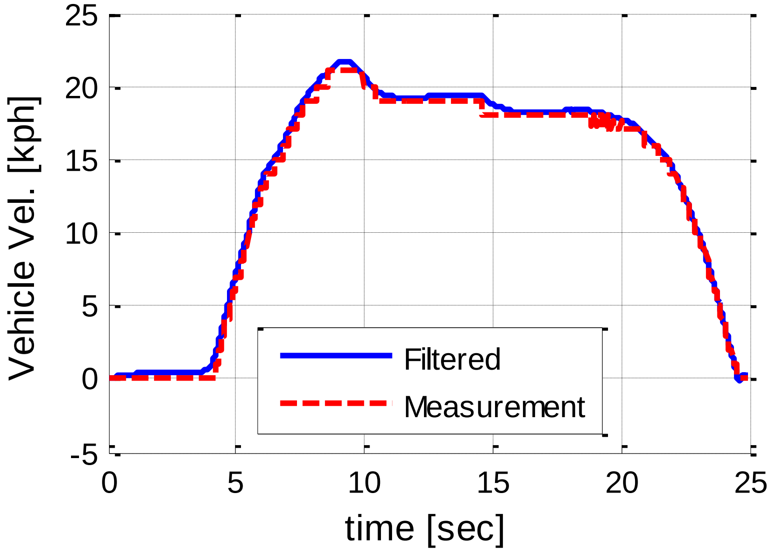
$$\mathrm{x}\left[k+1\right]=\left(I+A\Delta t+A^2\frac{\Delta t^2}{2}\right)\mathrm{x}\left[k\right]+\left(B\Delta t+AB\frac{\Delta t^2}{2}\right)\mathrm{w}\left[k\right]$$
$$=\begin{bmatrix}1&0&\Delta t&0\\0&1&0&\Delta t\\0&0&1&0\\0&0&0&1\end{bmatrix}\mathrm{x}\left[k\right]+\mathrm{w}_d\left[k\right] \quad (3)$$
$$where\ \ \mathrm{w}_d\left[k\right]\sim\left(0\ \ ,\ \ \left(B\Delta t+F_p\left[k\right]B\frac{\Delta t^2}{2}\right)Q\left(B\Delta t+F_p\left[k\right]B\frac{\Delta t^2}{2}\right)^T\right)$$
$$B=\begin{bmatrix}0&0&1&0\\0&0&0&1\end{bmatrix},\ F_p\left[k\right]=I+A\Delta t+A^2\frac{\Delta t^2}{2}$$

Measurement model:

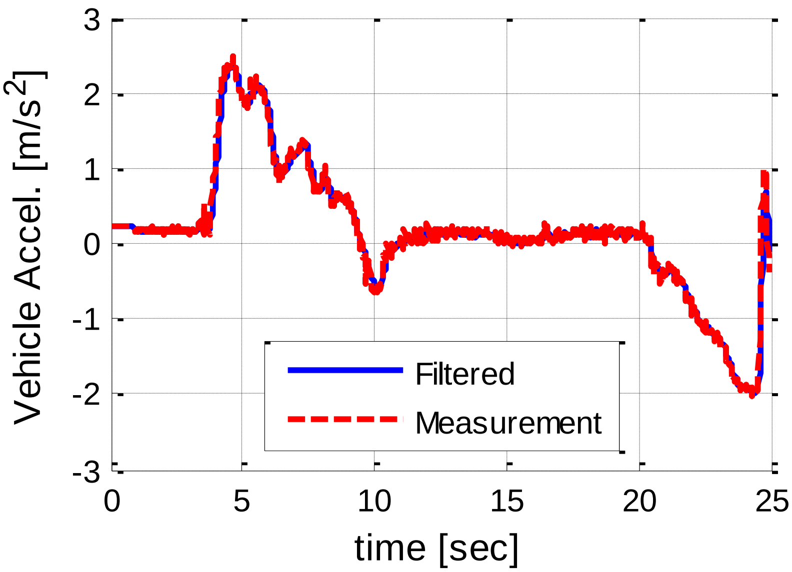
$$z\left[k\right]=H\mathrm{x}\left[k\right]+v\left[k\right]=\begin{bmatrix}1&0&0&0\\0&1&0&0\\0&0&1&0\end{bmatrix}\mathrm{x}+\mathrm{v}\left[k\right],\quad v\sim\left(0\quad V\right) \quad (4)$$

Proposed state estimator is evaluated using vehicle test data. The test result is shown in Figure 4.1.

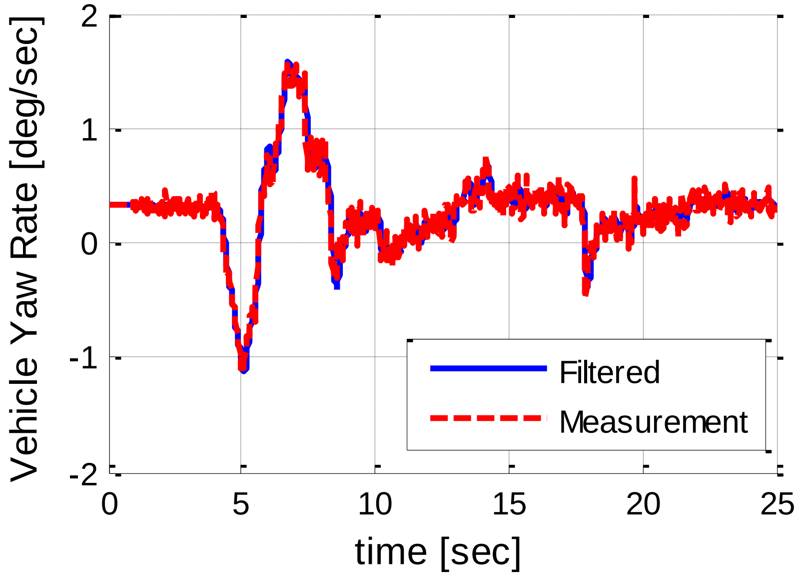
In order to estimate the state of vehicle precisely, rotational speed of each wheel can be used as a measurement. Using these information, vehicle speed and yaw rate can be estimated precisely. However, main target of AEB system is a prevention of unexpected collision in normal driving condition. Therefore, simple estimation model which is expressed above is used in this study.



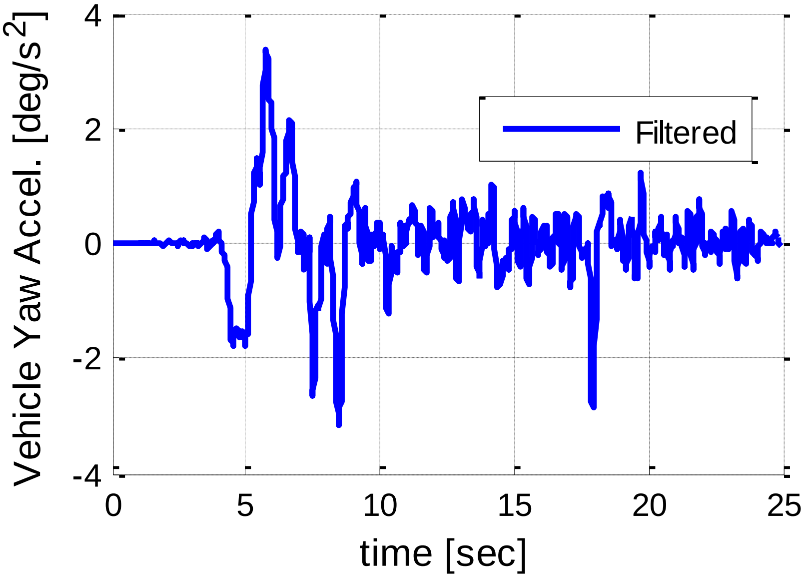
(a) Vehicle velocity



(b) Vehicle longitudinal acceleration



(c) Vehicle yaw rate



(d) Vehicle yaw acceleration

Figure 4.1. Vehicle state estimator – test result

4.2 Host Vehicle Evasive Maneuver Prediction

In order to judge whether the driver can avoid a collision or not, evasive maneuver of driver should be considered. In general cases, drivers can use steering, braking, accelerating or combination of them. However, since a combined motion in dangerous situation is difficult for common drivers, proposed algorithm assumes that braking or steering is the only option for driver to avoid the collision. In city driving condition, it is difficult to avoid a collision using acceleration due to limited acceleration. Therefore, only braking and steering maneuvers are considered for the proposed AEB algorithm.

To describe the future behavior of host vehicle using the constant acceleration model, prediction state vector $x_{host,p}$ can be defined as follows:

$$x_{host,p} = \begin{bmatrix} p_{x,p} & p_{y,p} & \theta_p & v_p & \gamma_p & a_p & \dot{\gamma}_p \end{bmatrix}^T \quad (5)$$

where subscript p : predicted, $p_{x,p}, p_{y,p}$: longitudinal and lateral position expressed in the current host vehicle local frame, θ_p, γ_p : heading angle and yaw rate, v_p, a_p : longitudinal velocity and acceleration

To judge whether the driver can avoid a collision or not, driver's evasive maneuver should be predicted. Steering or braking maneuver as well as the driver's constant acceleration model can be modeled using desired acceleration tracking model as follows:

$$\dot{x} = \begin{bmatrix} \dot{p}_{x,p} \\ \dot{p}_{y,p} \\ \dot{\theta}_p \\ \dot{v}_p \\ \dot{\gamma}_p \\ \dot{a}_p \\ \ddot{\gamma}_p \end{bmatrix} = \begin{bmatrix} v_p \cos\theta_p \\ v_p \sin\theta_p \\ \gamma_p \\ a_p \\ \dot{\gamma}_p \\ -\eta_a \left(a_p - a_{des}\right) \\ -\eta_{\dot{\gamma}}\dot{\gamma}_p - \eta_\gamma \left(\gamma_p - \gamma_{des}\right) \end{bmatrix} + B w_p \tag{6}$$

where subscript p : predicted, $p_{x,p}, p_{y,p}$: longitudinal and lateral position expressed in the current host vehicle local frame, θ_p, γ_p : heading angle and yaw rate, v_p, a_p : longitudinal velocity and acceleration, η_a : longitudinal acceleration tracking gain, η_γ yaw acceleration tracking gain, a_{des}, γ_{des} : desired longitudinal acceleration and yaw rate, and w_p : white noise with proper dimension. The derivatives of longitudinal acceleration and yaw acceleration are considered as a white noise.

To describe the characteristics of steering and braking maneuver, each acceleration tracking gain is pre-tuned. Also, constant acceleration motion of the driver can be described using equation (6) setting $a_{des} = a_p$ and $\gamma_{des} = \gamma_p$.

In this work, two kinds of acceleration levels are defined: nominal avoidance model and emergency avoidance model. Nominal avoidance model uses maximum acceleration of drivers in usual driving situation. However, emergency avoidance model uses maximum acceleration within physical limits.

To describe the characteristics of driver's evasive maneuver, driving data of 100 peoples is used which is shown in Figure 4.2. Although a vehicle can avoid a collision using maximum acceleration within physical limits, drivers only uses less than the half of them. According to Figure 4.2, drivers only uses 0.4g of acceleration for braking avoidance and 0.2g of acceleration for steering avoidance. Based on these information, the acceleration limitation of each level is shown in Table 4.2.

In the case of steering maneuver, maximum yaw rate is calculated using maximum lateral acceleration as follows:

$$\gamma_{\max} = \max(|\gamma|) = \frac{a_{lat,\max}}{v_p} \tag{7}$$

where $\gamma_{\max}$: maximum yaw rate, and $a_{lat,\max}$: maximum lateral acceleration.

In low speed driving condition, yaw rate is limited due to the maximum steering angle of the vehicle. The relation between steering wheel angle and yaw rate is as follows:

$$\delta_{\max} = \max(\delta) = GR \cdot \frac{L}{R_{\min}} = GR \cdot L \cdot \frac{\gamma_{\max}}{v_p} \tag{8}$$

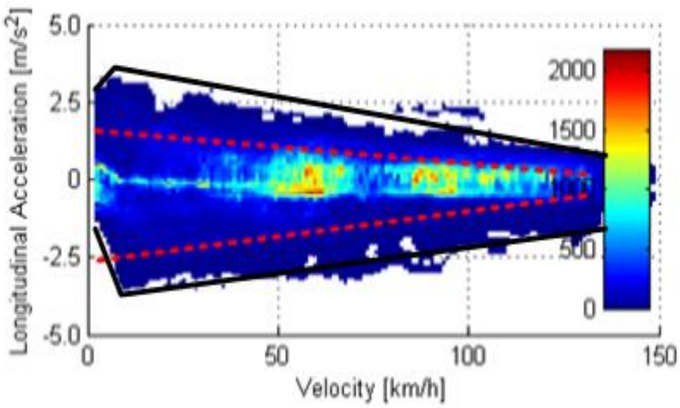
where $\delta_{\max}$: maximum steering angle, $R_{\min}$: minimum radius of curvature, GR : steering gear ratio, and L : vehicle length.

Using the equation (7) and (8), maximum yaw rate can be calculated as follows:

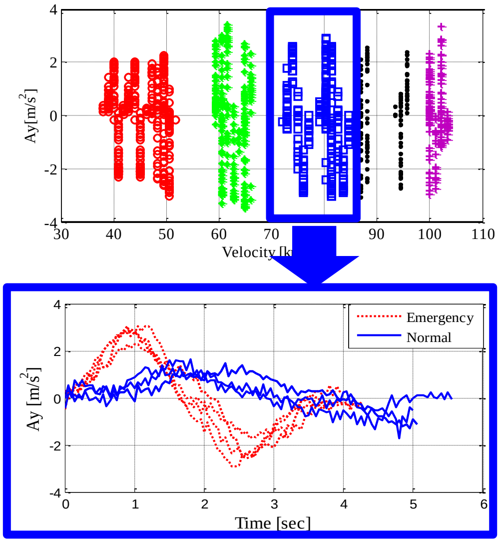
$$\gamma_{des} = \pm\gamma_{\max} = \pm\min\left(\frac{a_{lat,\max}}{v_p} \quad \frac{\delta_{\max} \cdot v_p}{GR \cdot L}\right) \tag{9}$$

Table 4.2. Maximum acceleration of evasive maneuver models.

Models	Maneuver	
	Braking	Steering
Nominal avoidance model	0.4g	0.2g
Emergency avoidance model	0.8g	0.4g



(a) Longitudinal acceleration



(b) Lateral acceleration

Figure 4.2. Driver's acceleration distribution

Chapter 5

Target VRU Motion Prediction

In this section, the future motion of target VRU is predicted. As mentioned in chapter 1, type identification between pedestrian and cyclist is difficult using current systems. Therefore, performance of target prediction should be guaranteed irrespective of the performance of target identification. For this, proposed AEB system uses one dynamic model for both pedestrian and cyclist. To describe the motion of pedestrian and cyclist using a single model, a constant velocity model is used. In order to predict the future position of target VRU, relative position and relative longitudinal velocity of the target are measured using frontal camera and radar. Based on the measured information, relative position and relative velocity of the target is estimated using Kalman filter. For simplicity, 2-dimensional position and velocity relative to the vehicle are defined as the state of the target estimator. Using these estimated information, target states are predicted in pre-defined prediction time horizon. In order to judge a collision, predicted state of the target is defined on the global coordinate.

5.1 Target VRU State Estimation

In this work, the motion of VRU is modeled as a constant velocity model. Camera and radar are used to measure the relative position and velocity of target VRU. In order to formulate the VRU state estimator easily, position and velocity of VRU related to the host vehicle are considered as a state variable.

The states and the dynamic equations of VRU is defined and expressed as follows:

$$
\begin{gathered}
\mathrm{x}=\begin{bmatrix} p_{x,rel} & p_{y,rel} & v_{x,rel} & v_{y,rel} \end{bmatrix} \\
\dot{\mathrm{x}}=\begin{bmatrix} \dot{p}_{x,rel} \\ \dot{p}_{y,rel} \\ \dot{v}_{x,rel} \\ \dot{v}_{y,rel} \end{bmatrix}=\begin{bmatrix} v_{x,rel} \\ v_{y,rel} \\ -a_{host}+v_{y,rel}\cdot\gamma_{host}+p_{y,rel}\cdot\dot{\gamma}_{host} \\ -v_{x,rel}\cdot\gamma_{host}-p_{x,rel}\cdot\dot{\gamma}_{host} \end{bmatrix}+B\mathrm{w} \qquad (10) \\
where\ B=\begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 1 & 0 \\ 0 & 1 \end{bmatrix},\ \mathrm{w}=\begin{bmatrix} \mathrm{w}_{a_x} \\ \mathrm{w}_{a_y} \end{bmatrix}\sim\begin{pmatrix} 0 & Q_{VRU} \end{pmatrix}
\end{gathered}
$$

where $p_{i,rel}, v_{i,rel}$: relative position and velocity of VRU, subscript x/y : host vehicle local frame x/y axis, a_{host}, γ_{host} : host vehicle longitudinal acceleration and yaw rate, w_i : white noise which represents the derivatives of relative velocities.

Using the measured position and velocity information, the current states of VRU can be estimated using linearized Kalman filter. For this, equation (10) is discretized using Taylor method as follows:

$$
\begin{aligned}
\mathrm{x}[k+1] &= \mathrm{x}[k] + \Delta t \left.\frac{d\mathrm{x}}{dt}\right|_{\mathrm{x}[k]} + \frac{\Delta t^2}{2} \left.\frac{d^2\mathrm{x}}{dt^2}\right|_{x[k]} + h.\varnothing.t \\
&= \mathrm{x}[k] + \begin{bmatrix} v_{x,rel} \\ v_{y,rel} \\ -a_{host} + v_{y,rel} \cdot \gamma_{host} + p_{y,rel} \cdot \dot{\gamma}_{host} \\ -v_{x,rel} \cdot \gamma_{host} - p_{x,rel} \cdot \dot{\gamma}_{host} \end{bmatrix} \Delta t + \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} \frac{\Delta t^2}{2} + \mathrm{w}_d[k] \\
\textit{where} \;\; \mathrm{w}_d[k] &\sim \left(0 \;\; , \;\; \left(B\Delta t + F_p[k] B \frac{\Delta t^2}{2} \right) Q \left(B\Delta t + F_p[k] B \frac{\Delta t^2}{2} \right)^T \right) \qquad (11) \\
F_p[k] &= \left.\frac{\partial f_{VRU}}{\partial \mathrm{x}}\right|_{x=\hat{x}[k]}, \; B = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}^T \\
f_{VRU} &= \begin{bmatrix} v_{x,rel} \\ v_{y,rel} \\ -a_{host} + v_{y,rel} \cdot \gamma_{host} + p_{y,rel} \cdot \dot{\gamma}_{host} \\ -v_{x,rel} \cdot \gamma_{host} - p_{x,rel} \cdot \dot{\gamma}_{host} \end{bmatrix}
\end{aligned}
$$

Also, measurement model should be defined for Kalman filter. In this work, frontal camera and radar is used to estimate the state of target VRU. However, target identification process is performed in camera sensor, information from radar is fused with radar. Therefore, 2 kinds of situation can be happened.

1) Target is measured only by camera.
2) Target is measured by both camera and radar.

Measurement model of target state estimator should be designed for both cases. These measurement model can be expressed as follows:

Camera measurement only

$$
z[k] = H\mathrm{x}[k] + v[k] = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \mathrm{x} + \mathrm{v}[k], \;\; v \sim (0 \;\; V) \qquad (12)
$$

$$Camera \& Radar\ measurement$$

$$z[k]=H\mathrm{x}[k]+v[k]=\begin{bmatrix}1&0&0&0\\0&1&0&0\\0&0&1&0\\1&0&0&0\\0&1&0&0\end{bmatrix}\mathrm{x}+\mathrm{v}[k],\ \ v\sim\left(0\ \ V\right) \tag{13}$$

In order to investigate the proposed target state estimator, simulation study is conducted using vehicle test data. Simulation result of proposed target state estimator is compared with other 2 kind of target models. 'Model 1' considers the heading angle of the target VRU while 'Model 2' considers the heading angle and yaw rate of the target VRU. For simplicity, vehicle was stopped and the effect of vehicle motion is ignored.

State and process model of 'Model 1' is as follows:

$$\mathrm{x}=\begin{bmatrix}p_{x,rel} & p_{y,rel} & \theta_{rel} & v_{rel}\end{bmatrix}^T$$

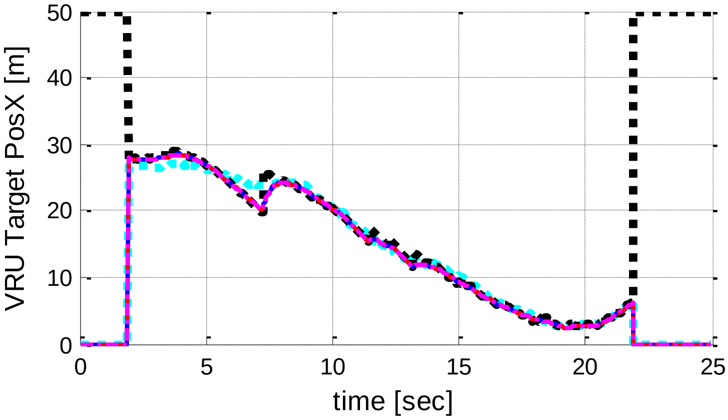
$$\dot{\mathrm{x}}=\begin{bmatrix}\dot{p}_{x,rel}\\ \dot{p}_{y,rel}\\ \dot{\theta}_{rel}\\ \dot{v}_{rel}\end{bmatrix}=\begin{bmatrix}v_p\cos\theta_p\\ v_p\sin\theta_p\\ 0\\ 0\end{bmatrix}+B\mathrm{w}_p\ \ ,\ where\ B=\begin{bmatrix}0&0\\0&0\\1&0\\0&1\end{bmatrix},\ \mathrm{w}_p=\begin{bmatrix}\mathrm{w}_{\dot{v}}\\ \mathrm{w}_{\gamma}\end{bmatrix} \tag{14}$$

State and process model of 'Model 2' is as follows:

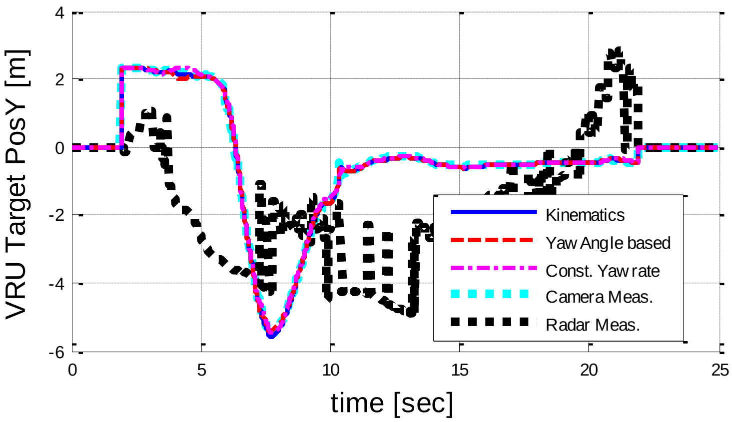
$$\mathrm{x}=\begin{bmatrix}p_{x,rel} & p_{y,rel} & \theta_{rel} & v_{re} & \gamma\end{bmatrix}^T,$$

$$\dot{\mathrm{x}}=\begin{bmatrix}\dot{p}_{x,rel}\\ \dot{p}_{y,rel}\\ \dot{\theta}_{rel}\\ \dot{v}_{rel}\\ \dot{\gamma}\end{bmatrix}=\begin{bmatrix}v_{rel}\cos\theta_{rel}\\ v_{rel}\sin\theta_{rel}\\ \gamma_{rel}\\ 0\\ 0\end{bmatrix}+B\mathrm{w}_p\ \ ,\ where\ B=\begin{bmatrix}0&0\\0&0\\0&0\\1&0\\0&1\end{bmatrix},\ \mathrm{w}_p=\begin{bmatrix}\mathrm{w}_{\dot{v}}\\ \mathrm{w}_{\dot{\gamma}}\end{bmatrix} \tag{15}$$

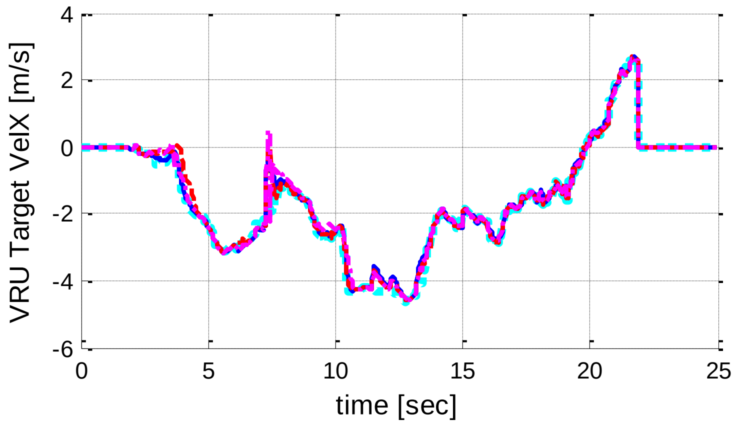
Test data based simulation result is shown in figure 5.1. Results shows that the performance of proposed target VRU state estimator is similar with other models in various scenarios. Based on these results, proposed target state estimator is used for simplicity.



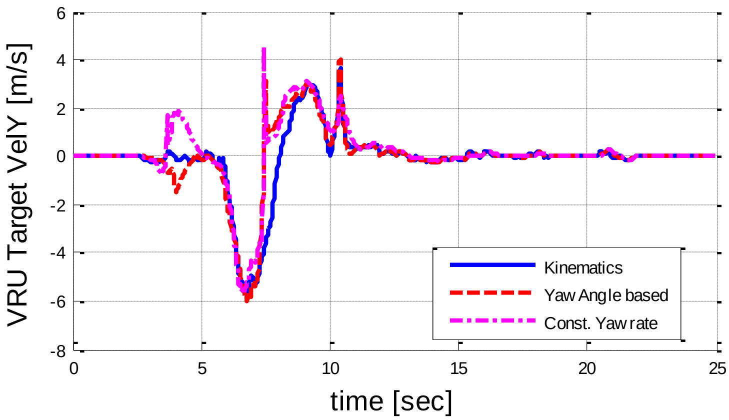
(a) Longitudinal position



(b) Lateral position



(c) Longitudinal velocity



(d) Lateral velocity

Figure 5.1. Target VRU state estimator – test result

5.2 Target VRU Motion Prediction

Target VRU is modeled as a constant velocity model. Their future position and velocity can be described in current local frame of vehicle. The prediction state vector of VRU is then expressed in fixed frame. The future states of VRU can be predicted using the simple dynamic equation:

$$\dot{\mathrm{x}}_p = \begin{bmatrix} \dot{p}_{x,p} \\ \dot{p}_{y,p} \\ \dot{v}_{x,\mathrm{p}} \\ \dot{v}_{y,p} \end{bmatrix} = \begin{bmatrix} v_{x,p} \\ v_{y,p} \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \mathrm{w}_{a_{x,p}} \\ \mathrm{w}_{a_{y,p}} \end{bmatrix} \tag{16}$$

where subscript p : predicted.

From the estimated current states of host vehicle and target VRU, the initial state vector $x_{p,0}$ for motion prediction can be calculated as follows:

$$\mathrm{x}_{p,0} == \begin{bmatrix} p_{x,\mathrm{p},0} \\ p_{y,p,0} \\ v_{x,\mathrm{p},0} \\ v_{y,\mathrm{p},0} \end{bmatrix} = \begin{bmatrix} p_{x,rel} \\ p_{y,rel} \\ v_{x,rel} + v_{host} - p_{y,rel} \cdot \gamma_{host} \\ v_{y,\mathrm{rel}} + p_{x,rel} \cdot \gamma_{host} \end{bmatrix} \tag{17}$$

where $p_{x,p,0}, p_{y,p,0}$: initial position of VRU, $v_{x,p,0}, v_{y,p,0}$: initial velocity of VRU, and subscript x,y : x/y axis of current local frame of the host vehicle.

Chapter 6

Threat Assessment

6.1 Collision Judgement

In this section, the potential threat between the host vehicle and target VRU is assessed. Based on the predicted information, it can be judged whether the host vehicle and target VRU will collide or not during the prediction time horizon. The schematic view of threat assessment is described in Figure 6.1.

In section 4&5, the following states were predicted:

$$\begin{aligned} \mathrm{x}_{host,j,p}\left[k\right] &= \left[\begin{matrix} p_{x,p} & p_{y,p} & \theta_p \end{matrix}\right]^T \\ \mathrm{x}_{tar,i,p}\left[k\right] &= \left[\begin{matrix} p_{x,tar} & p_{y,tar} \end{matrix}\right]^T \end{aligned} \tag{18}$$

where subscript i : target index, subscript j : host vehicle evasive maneuver model index, subscript p : predicted, k : prediction time step, $p_{x,p}, p_{y,p}$: predicted x, y position in current local frame of host vehicle.

Based on these states, relative future position of VRU with respect to the future position of host vehicle can be calculated as follows:

$$\mathrm{p}_{rel,p}\left[k\right]=\begin{bmatrix} p_{x,rel,i,j,p} \\ p_{y,rel,i,j,p} \end{bmatrix} = \begin{bmatrix} \cos\theta_p & \sin\theta_p \\ -\sin\theta_p & \cos\theta_p \end{bmatrix} \begin{bmatrix} p_{x,i,j,p}-p_{x,p} \\ p_{x,i,j,p}-p_{x,p} \end{bmatrix} \tag{19}$$

In order to activate the AEB before the collision became inevitable, safety area of host vehicle can be defined as follows:

$$D_{host}\left[k\right]=\left\{ \left(x,y\right) \middle| \begin{array}{c} \left|x\right|<\left(\frac{L}{2}+C_{longi}\right) \\ \& \left|y\right|<\left(\frac{t_w}{2}+C_{lat}\right) \end{array} \right\} \tag{20}$$

where L, t_w : vehicle length and width, C_{longi}, C_{lat} : longitudinal and lateral safety distance, and x/y : host vehicle local frame at predicted time step k.

Also, to judge whether the target VRU will collide with the host vehicle, two side edges of target VRU can be defined as shown in Figure 2(c). The position of the side edges of target VRU can be calculated as follows;

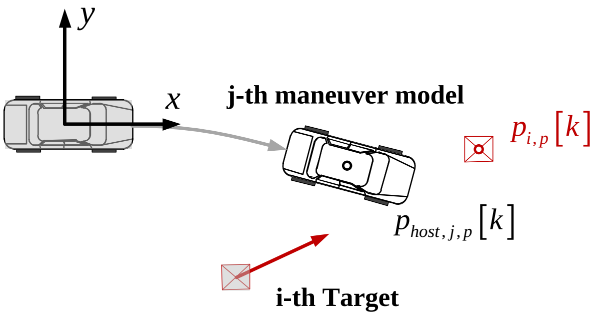
$$p_{rel,1\&2}=p_{rel,p}+\begin{bmatrix} \cos\theta_p & \sin\theta_p \\ -\sin\theta_p & \cos\theta_p \end{bmatrix} \begin{bmatrix} 0 \\ \pm\frac{w_{target}}{2} \end{bmatrix} \tag{21}$$

where w_{target} : measured width of target VRU.

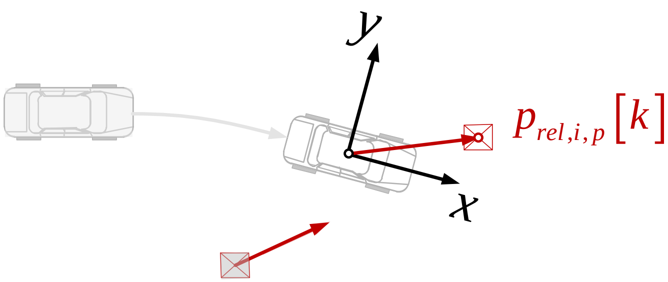
Using these information, it can be judged whether the j-th evasive maneuver model of host vehicle will collide with the i-¬th target at prediction time step k. In other words, if:

$$\mathrm{p}_{rel,i,j,1}\left[k\right]\in D_{host}\left[k\right] or\ p_{rel,i,j,2}\left[k\right]\in D_{host}\left[k\right] \tag{22}$$

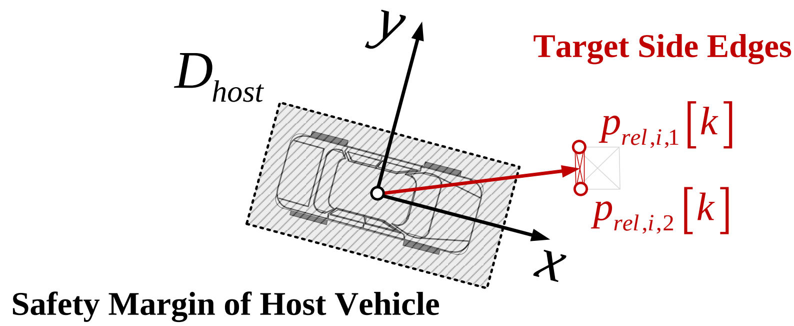
then, the j-th maneuver model of host vehicle is predicted to collide with the i-th target at time step k.



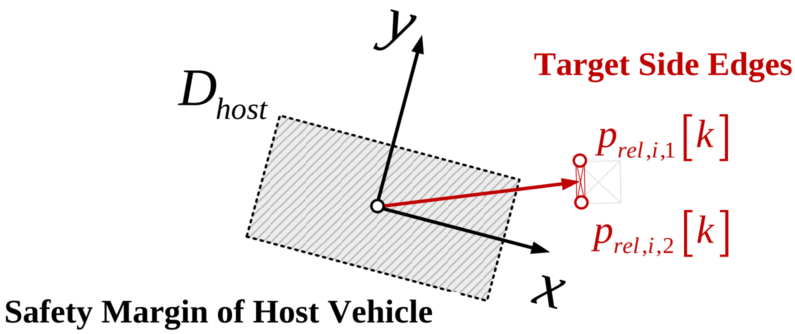
(a) Predicted information of host vehicle and target VRU



(b) Relative future position of VRU



(c) Safety margin of host vehicle



(d) Threat assessment

Figure 6.1. Schematic view of threat assessment

6.2 Safety Boundary for Collision Judgement

In order to guarantee the robust performance of the collision judgement, the value of safety margin is the most important factor. In this work, predicted uncertainty of the relative position between host vehicle and target VRU is considered to define the safety boundary.

In section 4&5, measurement noise and process noise are assumed as a white noise. Based on this assumption, uncertainties of the state information of host vehicle and target VRU can be estimated and expressed as a covariance matrix using linearized Kalman filter. Also, uncertainties of the state information of host vehicle and target VRU can be propagated during the prediction time horizon using Taylor method.

In order to find the uncertainty of related future position between host vehicle and target VRU, covariance matrices for the states of j-th maneuver model of host vehicle and k-th target VRU at prediction time step k can be expressed as $C_{host,j,k}$ and $C_{target,i,k}$. These two covariance matrices are expressed on the current local frame of host vehicle. These matrices can be expressed on the local frame of host vehicle at prediction time step k using rotational matrix as follows:

$$\begin{aligned} C_{host,rel,j,k} &= R_k C_{host,j,k} R_k^{\ T} \\ C_{target,rel,i,k} &= R_k C_{target,i,k} R_k^{\ T} \\ R_k &= \begin{bmatrix} \cos\theta_p(k) & \sin\theta_p(k) \\ -\sin\theta_p(k) & \cos\theta_p(k) \end{bmatrix} \end{aligned} \tag{23}$$

where θ_p : predicted yaw angle of host vehicle.

Since the predicted position of target VRU is expressed on the current local frame of host vehicle, it is independent from the future position of host vehicle. Also, if the situation is dangerous and AEB should be activated, distance between host vehicle and target VRU became relatively small. In this case, the effect from the vehicle speed and yaw rate to the target states is negligible. Therefore, future position of the host vehicle and target VRU can be assumed as an independent random variable. Using this assumption, relative future position of the host vehicle and target VRU can be considered as a new random variable as follows:

$$
\begin{aligned}
&p_{rel,p} \sim N\left(p_{rel,i,j,p}\left[k\right] \quad C_{rel}\right) \\
&p_{rel,i,j,p}\left[k\right] = \begin{bmatrix} p_{x,rel,i,j,p} \\ p_{y,rel,i,j,p} \end{bmatrix} \\
&C_{rel} = C_{host,rel,j,k} + C_{target,rel,j,k}
\end{aligned}
\tag{24}
$$

where $p_{rel,p}$: random variable which express the related future position between the j-th model of the host vehicle and i-th target VRU at prediction time step k, $p_{rel,i,j,p}$: predicted value of the related future position of target VRU with respect to the future position of host vehicle, and C_{rel} : covariance matric for the random variable $p_{rel,p}$.

In order to consider the uncertainty of the related future position of the host vehicle and target VRU, σ_{th} -sigma ellipse can be used as a safety boundary.

Here, we can define the σ_{th} as a tunable parameter. For simplicity, a rectangular region which covers the error-ellipse is used as a safety boundary. Figure 6.2 shows the shape and size of the safety boundary. In order to judge whether a collision is occurred or not, volume of the host vehicle and target

VRU also should be considered. Figure 6.2 shows a rectangular safety boundary which contains error-ellipses of each edge of the host vehicle. V_{mi} are the vectors of the major and minor axis of the error-ellipse. Based on Figure 6.2.2, C_{longi} and C_{lat} can be defined as follows:

$$\begin{aligned} C_{longi} &= \left|V_{m1} \cdot \hat{i}\right| + \left|V_{m2} \cdot \hat{i}\right| \\ C_{lat} &= \left|V_{m1} \cdot \hat{j}\right| + \left|V_{m2} \cdot \hat{j}\right| \end{aligned} \tag{25}$$

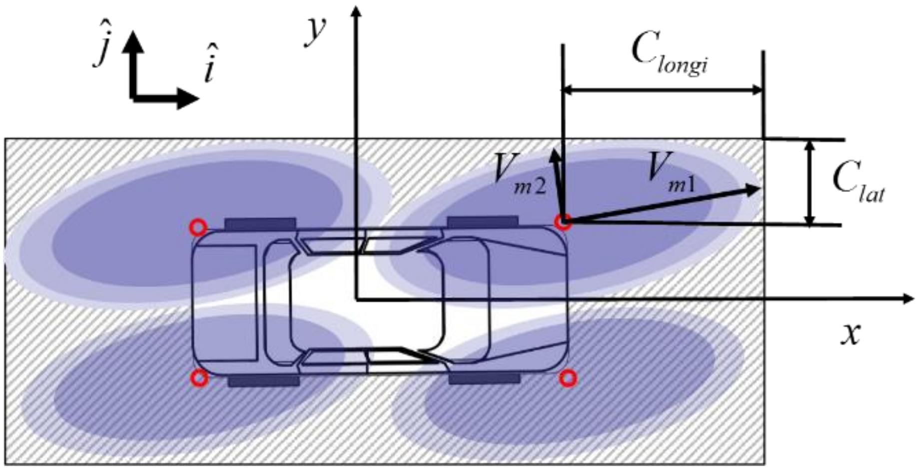


Figure 6.2. Safety boundary of host vehicle

6.3 Emergency Braking Mode Decision

To avoid the unnecessary interruption of driver's control authority, driver's possible evasive maneuver should be considered for AEB system. In this work, motions of host and target vehicles are assumed as follows:

1) Host vehicle can avoid or mitigate a collision only using steering or braking
2) Target vehicle maintain the current motion during prediction time horizon.

Based on these assumptions, driver's evasive maneuver models as well as the constant acceleration model can be predicted as Figure 6.3. As explained in the previous section, the threat of collision can be assessed for each maneuver model at each prediction time step. If driver cannot avoid the collision with any kind of models, AEB should be activated. In other words, if the collision became inevitable within the safety margin of host vehicle, AEB should be activated to avoid or mitigate the collision.

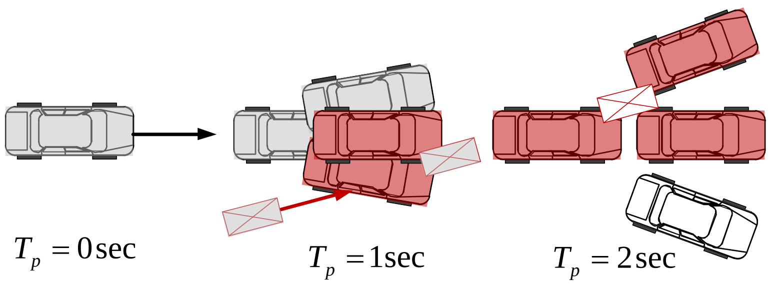


Figure 6.3. Mode decision of AEB system

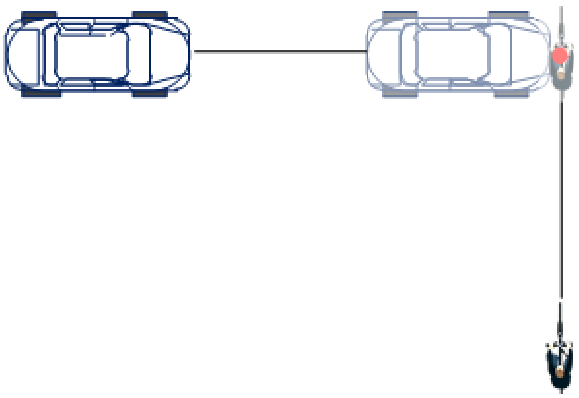
Chapter 7

Simulation Result

In order to evaluate the performance of the proposed AEB, simulation is conducted via vehicle simulation software Carsim and MATLAB/Simulink. To investigate the robust performance of the proposed algorithm, proposed robust AEB algorithm is compared with a deterministic AEB algorithm which uses constant size of safety boundary.

Test scenario of the simulation is expressed in Figure 7.1. In this simulation, the host vehicle is driving on the straight road while the cyclist is crossing from the front-right side of the host vehicle. The speed of the cyclist is 15km/h. It is assumed that the driver doesn't recognize a danger. Collision point of the host vehicle and target VRU is set to be the center of the front bumper of the host vehicle unless an AEB system is not activated.

In order to describe about uncertainty of camera sensor in simulation, camera test data in Figure 7.2 is used. Figure 7.2 shows the relation between measured



Test Scenario	Crossing cyclist without obstruction
Vehicle Speed	50km/h
Cyclist Speed	15km/h

Figure 7.1. Simulation scenario

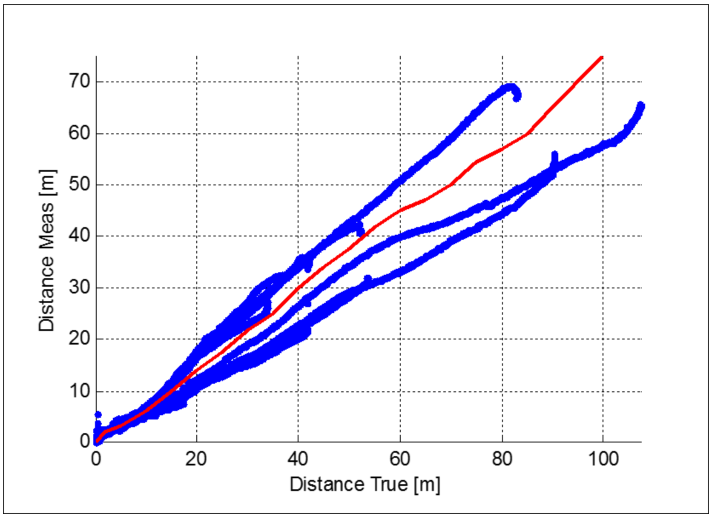
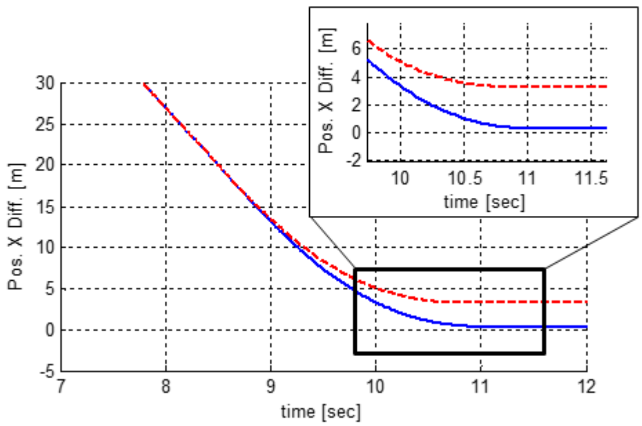


Figure 7.2. Camera data – measured distance vs. actual distance

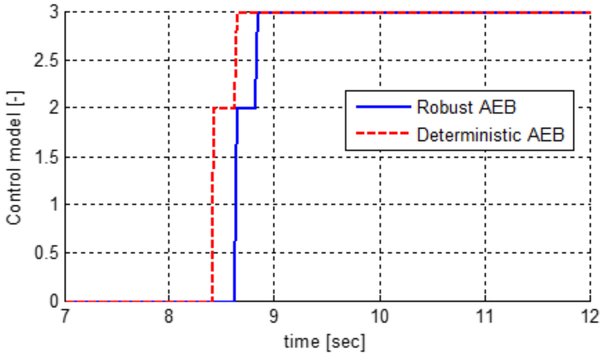
distance and actual distance. Blue line shows the measured data from the camera while red line shows the mean value of the measured results. Based on these results, 20% of camera uncertainty is described in the simulation. For comparison, two kinds of AEB system is simulated with same initial velocity and same sensor condition.

Before the simulation, each AEB system is tuned to avoid a collision with proper values of tunable parameter: σ_{th} for robust AEB and constant C_{longi} and C_{lat} for deterministic AEB. These parameters are tuned to the value that each AEB system can avoid the collisions for the proposed simulation scenario.

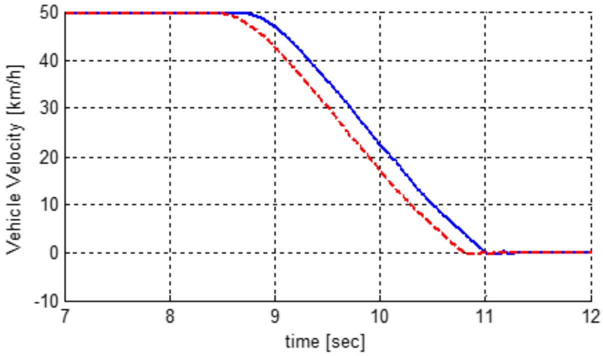
Simulated result is shown in Figure 7.3. Figure 7.3 shows that the final clearance of deterministic AEB system is longer than that of proposed AEB system which means proposed AEB system is activated more effectively.



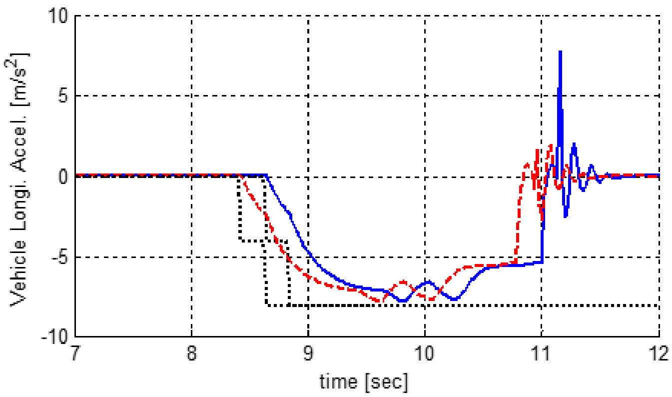
(a) Longitudinal distance



(b) Control mode of AEB systems



(c) Vehicle velocity



(d) Vehicle acceleration

Figure 7.3. Simulation result

However, robust performance of proposed AEB system cannot be shown only using this one simulation result. Therefore, to analyze the performance of AEB system, simulation is conducted 100 times and the speed of host vehicle is randomly selected between 20km/h and 60km/h. For each simulation, two kinds of AEB system is simulated with same initial velocity and same sensor condition. Also, to compare the performance of each AEB system effectively, minimum distance between vehicle and target VRU is defined as a comparative criterion. Definition of 'minimum distance', $c_{\min}$ is expressed in Figure 7.4. If a collision is occurred, minimum distance' became negative. If the value of

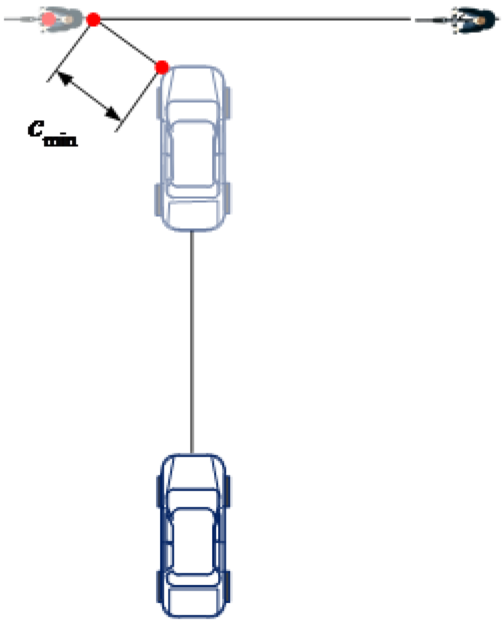


Figure 7.4. Definition of 'minimum clearance

minimum distance is too large, it can be said that the AEB system decelerate the vehicle earlier than required.

The simulation result is shown in Figure 7.5 and Table 7. The blue line in the Figure 7.5 shows the normal distribution which fits the result from robust AEB. Likewise, the red line shows the normal distribution which fits deterministic AEB result. As shown in Figure 7.5, no collision is occurred for both type of AEB system. However, deterministic AEB system shows larger minimum distance and wider distribution.

For better comparison, mean and variance of the minimum distance distribution of each AEB system is shown in Table 7. Since the variance of proposed AEB (robust AEB) is smaller than that of deterministic AEB system, proposed AEB system can be tuned to have smaller mean value of minimum distance which means that the proposed AEB system can be activated more effectively than deterministic AEB system.

Although both AEB system avoid a collision successfully, proposed AEB system shows robust performance for various initial speed and various sensor condition.

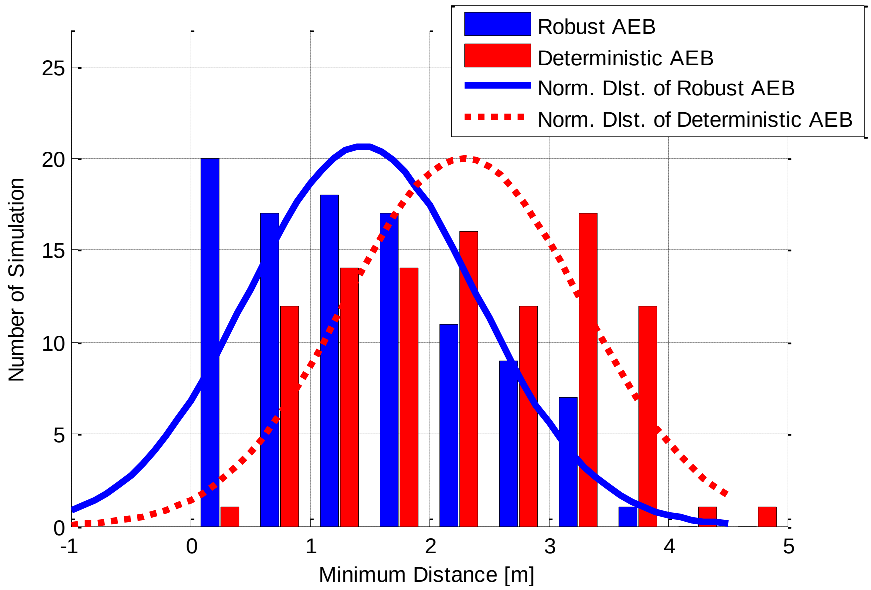


Figure 7.5. Simulation result – Robust AEB vs. Deterministic AEB

Table 7. Simulation Result – Robust AEB vs. Deterministic AEB

	Robust AEB	**Deterministic AEB**
Mean	1.44	2.29
Variance	093	0.99
Standard Deviation	0.96	0.99
Number of Crash	0/100	0/100

Chapter 8

Conclusion

In this work, robust autonomous emergency braking (AEB) algorithm for vulnerable road users is proposed. In order to guarantee the safety performance without target type identification, a single constant velocity model was used for both cyclist and pedestrian. Also, to describe the evasive maneuver of the driver, constant acceleration model is used. Based on the estimated information, future behaviors of host vehicle and target VRU are predicted. These information is then used to assess the risk of collision.

The performance of proposed robust AEB is evaluated via computer simulation using MATLAB/Simulink and vehicle simulation tool Carsim. In order to verify the robust performance of the proposed AEB, proposed algorithm is compared with the result of deterministic AEB algorithm which only uses constant safety margin. The simulation is repeated in crossing cyclist scenario with various speed of host vehicle. It was shown that the proposed AEB shows robust performance.

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초 록

교통약자 대상 강건 비상제동장치 개발

본 연구는 교통약자를 대상으로 하는 자동비상제동 알고리즘을 개발하고자 진행된 연구이다. 자동비상제동장치란 센서로부터 얻은 환경정보를 기반으로 운전자가 예상하지 못한 사고를 회피하거나 사고의 피해를 완화할 수 있도록 차량을 제동해주는 장치이다. 이러한 자동비상제동장치가 점차 양산되고 보급되기 시작한 이후 사람들은 이러한 자동비상제동장치를 이용하여 교통 약자와 관련된 사고까지 예방하기 위한 노력들을 수행하고 있다. 교통 약자는 일반적으로 '보행자, 자전거 등의 원동기를 장착하지 않은 도로 사용자'로 정의된다. 교통 약자는 비록 그 속도가 차량에 비해 느리지만, 실제 사고가 발생할 경우 그 피해가 커질 우려가 있다. 따라서 이러한 교통 약자와 관련된 사고를 줄이기 위한 노력이 필요하다.

사고가 발생하기 이전에 위험을 인지하기 위해서는 자차량 및 대상 교통 약자의 거동을 예측할 필요가 있다. 이를 위해서는 자차량 및 교통 약자의 거동을 모사할 수 있는 동역학 모델이 필요하다.

차량의 경우 운전자가 사고를 회피할 수 있는지 확인하기 위해서는 실제로 운전자가 사고를 회피할 때 일반적으로 사용하는

회피 거동에 대한 모사 역시 필요하다. 이를 위하여 자차량의 거동은 등가속도 모델을 이용하여 표현하였다. 또한 교통 약자의 경우 보행자와 자전거를 구분하는데 한계가 있기 때문에 대상 교통 약자의 종류 구분 없이 안전 성능을 확보할 수 있어야 한다. 따라서 보행자 및 자전거의 거동은 동일한 등속 직선 운동 모델을 이용하여 표현하고자 하였다.

이렇게 예측된 정보들을 바탕으로 운전자가 사고를 회피할 수 있는지 판단하고자 하였다. 만약 운전자가 사고를 회피하고자 할 때 일정 수준의 안전거리를 확보하지 못할 경우 자동비상제동장치가 작동하여 차량을 제동하도록 하였다. 이 때 자동비상제동장치의 강건 성능을 확보하기 위하여 측정 시에 발생하는 불확실성 및 정보 예측 시에 발생하는 불확실성을 고려하여 안전 거리를 정의하였다. 이렇게 개발된 자동비상제동장치의 성능을 확인하기 위하여 차량 시뮬레이션 툴인 Carsim과 MATLAB/Simulink를 기반으로 시뮬레이션 평가를 수행하였다. 이 때 개발한 자동비상제동장치의 강건 성능을 검증하기 위하여 시뮬레이션을 동일 시나리오에 대해 100회 반복 수행 하였으며, 비교를 위하여 불확실성을 고려하지 않은 자동비상제동장치를 함께 평가하였다.

주요어: 자동비상제동장치, 능동 안전 시스템, 운전자보조시스템, 사고 회피, 센서 불확실성, 예측 불확실성

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