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Development of an Integrated Driving path Estimation Algorithm for ACC and AEBS Using Multi-sensor Fusion

ACC/AEBS용 센서 퓨전을 통한 주행경로 추정알고리즘

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이 동 우

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Abstract

Development of an Integrated Driving path Estimation Algorithm for ACC and AEBS Using Multi-sensor Fusion

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This paper presents an integrated driving path estimation algorithm for adaptive cruise control system and advanced emergency braking system using multi-sensor fusion. This algorithm is developed to predict the ego-vehicle's path accurately and to improve the performance of primary target detection using the predicted path of the ego-vehicle. The path prediction consists of two prediction process; vehicle states based prediction and vision data based prediction. For application to dynamic maneuvering situations, the driving mode index which allows a detection of the driver maneuver intention is proposed. In accordance with the driving mode, the two types of driving path information are integrated finally. The proposed driving path estimation algorithm has been investigated via closed-loop simulation. It has been shown that the proposed driving path estimation algorithm enhance the capabilities of adaptive cruise control and advanced emergency braking system functions by providing the ego-vehicle's path accurately, especially in dynamic maneuvering situation.

Keywords: Driving path, Sensor fusion, Vision sensor, Adaptive cruise control, Advanced emergency braking system

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Contents

List of Tables

List of Figures

Nomenclatures

u	: longitudinal velocity
v	: lateral velocity
γ	: yaw rate
m	: vehicle mass
I_z	: yaw moment of inertia
C_f	: front wheel cornering stiffness
C_r	: rear wheel cornering stiffness
δ_f	: front wheel steering angle
l_f	: distance from vehicle center of gravity to front axle
l_r	: distance from vehicle center of gravity to rear axle
a_x	: longitudinal acceleration of vehicle
Q	: covariance matirix
R	: covariance matirix
P	: covariance matirix
K	: Kalman gain
x_{ref}	: vehicle's longritudinal position
y_{ref}	: vehicle's lateral position
θ_{ref}	: vehicle's heading angle
γ_{des}	: desired yaw rate
κ_{vision}	: road curvature from vision sensor
θ_r	: heading angle error
t_0	: initial time of integral
t_f	: final time fo integral
δ_{ss}	: steady state steering angle

κ	: road cuvature
$I_{LC}(k)$	: driving mode index at k-th step
ρ	: forgetting factor
δ_k	: steering angle at k-th step
I_{Th}	: predefined threshold of driving mode index
$I_{Longitudinal}$	: longitudinal index
TTC^{-1}	: inverse time to collision
$TTC^{-1}{}_{th}$	: inverse time to collision threshold
x	: warning index
R	: relative distance
d_b	: braking distance
d_w	: warning distance
$\dot{R}$	: relative velosity

Chapter 1. Introduction

1.1 Research Background

An advanced driver assistance system (ADAS), of which research is in progress, controls the vehicle and warns the driver by visual, sound, or haptic signals, depending on the application. Adaptive cruise control (ACC) system and advanced emergency braking system (AEBS) are included in ADAS. In such systems, it is important to estimate reliably a driving path of ego-vehicle as the driving path is used by the target selection process to determine whether the objects that are detected by the radar are in the path of ego-vehicle or not.

The conventional way of driving path estimation is based only on on-board sensor and Kalman filter using vehicle dynamics (Lin et al., 2000). However, when the vehicle is performing complex maneuvers (e.g. lane change, overtaking) its usefulness becomes questionable and additional parameters such as lane information and the driver intention should be taken into account. AEBS and next-generation ACC systems use additional sensors and information fusion techniques (Jung et al., 2009). In order to estimate the road geometry more reliably, there has been much effort. Vision sensors, which can detect lanes, are utilized for driving path estimation based on lane trackers (Zotomor and Franke, 1997). Moreover, during recent years, digital map contribution toward road geometry estimation is broadly accepted. Information fusion techniques to complement the vehicle dynamics based path estimate and predict changes in the curvature of the road ahead using a digital map and a GPS receiver and forward looking vision sensors (NHTSA, 2003; Swartz, 2003; Tsogas et al., 2011). A fusion for lane estimation takes place using line markings detected by a vision sensor, information derived from a digital map (Klotz et al., 2004). In addition, a fuzzy logic enhanced Kalman filter was discussed to fuse the information from machine vision, laser radar, inertial measurement unit, and speed sensor, including a comparison between guiding a vehicle using the sensors independently and using fusion (Subramanian et al., 2009).

The aforementioned methods can be used for ACC and AEBS, when the vehicle is not performing complex maneuvers. However, if the ego-vehicle is overtaking or carries out a lane change, there will be a non-zero curvature even if the real curvature is zero in case of straight road driving as the driver intention is not taken into consideration. The determination of ego-vehicle's path, especially while maneuvering, using the situation model to detect maneuvers was proposed (Polychronopoulos et al., 2007). It is based on the current estimation of the lateral speed and a predefined threshold and it was shown that it possible to predict the path of the ego-vehicle more accurately in a dynamic maneuvering situation than conventional way. On the other hand, more efficient algorithms should be investigated for the "maneuver detection".

1.2 Research Overview

This paper presents driving path estimation based on vehicle dynamics and vision sensor considering the driver intention more efficiently. In order to detect driver maneuver, driving mode index, which is calculated from steering behavior, is proposed. In accordance with the driving mode, which is determined by driving mode index, the driving paths from vehicle dynamics and vision sensor are fused into ultimate driving path. An advantage of the fusion algorithm is the fact that it can detect the driver intention and provide reliable path prediction information in dynamic maneuver situation. Consequently, the goal of this path estimation algorithm is to enhance the capabilities of ACC and AEBS, especially in dynamic maneuvering situation such as lane change, entering a curve.

The paper is organized as follows: in Section 2, there is a description of the mathematical tools used to predict the driving path based on vehicle dynamics. In section 3, a short presentation of driving path prediction based on vision sensor including the heading angle compensation. In section 4, details are given on how driving mode is determined considering the driver intention. The information fusion technique to combine the multi-source information described above is presented in Section 5. Results about the performance and the evaluation of the algorithm are presented in Section 6. The paper's conclusions are given in Section 7

Chapter 2. Driving Path Prediction based on Vehicle States

A path prediction based on vehicle states comprises two linked steps. The overall structure of this prediction algorithm is shown in Figure 2.1.

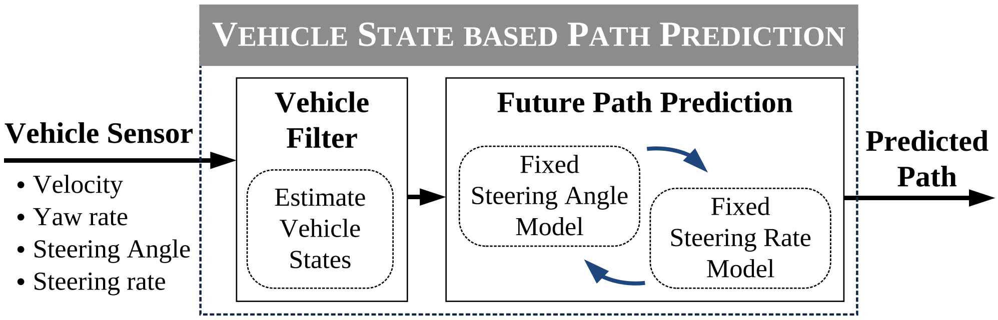


Figure 2. 1. The overall structure of the vehicle states based path prediction

The first step is vehicle filter. This filter estimates present vehicle states from vehicle sensor signals under Gaussian noise assumption. The following step is a driving path prediction. The driving path is predicted by estimated vehicle current states and assumed dynamic models. Two different dynamic models are used for adaptation to various driving situations in this research.

2.1 Vehicle Model

The 2 DOF bicycle model shown below is used for the vehicle states estimation and driving path prediction.

$$\begin{bmatrix} \dot{v} \\ \dot{\gamma} \end{bmatrix} = \begin{bmatrix} \frac{2}{m}\left(\frac{C_f + C_r}{u}\right) & \frac{2}{m}\left(\frac{l_f C_f - l_r C_r}{u}\right) - u \\ \frac{2}{I_z}\left(\frac{l_f C_f - l_r C_r}{u}\right) & \frac{2}{I_z}\left(\frac{l_f^2 C_f + l_r^2 C_r}{u}\right) \end{bmatrix} \begin{bmatrix} v \\ \gamma \end{bmatrix} + \begin{bmatrix} -\frac{2C_f}{m} \\ -\frac{2 l_f C_f}{I_z} \end{bmatrix} \delta_f \tag{2.1}$$

where, u and v are the vehicle longitudinal and lateral velocities, γ is the yaw rate, m is the vehicle mass and I_z is the yaw moment of inertia. C_f and C_r are front and rear wheel cornering stiffness, respectively. δ_f is the front wheel steering angle, and l_f and l_r are the distance from vehicle center of gravity to front and rear axles. Above conventional model can be extended as following by considering δ_f as a new state variable and introducing $\dot{\delta}_f$ as a new input variable which means a steering rate

$$\begin{bmatrix} \dot{v} \\ \dot{\gamma} \\ \dot{\delta}_f \end{bmatrix} = \begin{bmatrix} \frac{2}{m}\left(\frac{C_f + C_r}{u}\right) & \frac{2}{m}\left(\frac{l_f C_f - l_r C_r}{u}\right) - u & -\frac{2C_f}{m} \\ \frac{2}{I_z}\left(\frac{l_f C_f - l_r C_r}{u}\right) & \frac{2}{I_z}\left(\frac{l_f^2 C_f + l_r^2 C_r}{u}\right) & -\frac{2 l_f C_f}{I_z} \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} v \\ \gamma \\ \delta_f \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \dot{\delta}_f \tag{2.2}$$

2.2 Estimation Schemes

The Kalman-Bucy filter is used to track the present dynamic states from the vehicle sensor output. The state vector is defined as following:

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

where, a_x is the vehicle longitudinal acceleration. Assuming that the derivatives of the longitudinal acceleration and steering rate can be considered as the process noise, the state equations are given by following form based on above 2 DOF bicycle model and 2nd order linear Gauss Markov process model.

$$\begin{aligned} \dot{x} &= Fx + \Gamma w \\ z &= Hx + v \end{aligned} \tag{2.4}$$

$$F = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \frac{2}{m}\left(\frac{C_f + C_r}{u}\right) & \frac{2}{m}\left(\frac{l_f C_f - l_r C_r}{u}\right) - u & -\frac{2C_f}{m} & 0 \\ 0 & 0 & \frac{2}{I_z}\left(\frac{l_f C_f - l_r C_r}{u}\right) & \frac{2}{I_z}\left(\frac{l_f^2 C_f + l_r^2 C_r}{u}\right) & -\frac{2 l_f C_f}{I_z} & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$\Gamma = \begin{bmatrix} 0 & 0 \\ 1 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 1 \end{bmatrix} \quad H = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \quad w \in R^2 \quad v \in R^5 \tag{2.5}$$

The process noise and measurement noise are assumed to be white with unknown covariance matrices Q and R. As a result, the filter for the state space model shown in Eq 2.4 consists of following two differential equations, one for the estimated state $\hat{x}$ and one for the error covariance P.

$$\begin{aligned} \dot{\hat{x}} &= F\hat{x} + K(z - H\hat{x}) \\ \dot{P} &= FP + PF^T + Q - PH^T R^{-1} HP \end{aligned} \tag{2.6}$$

And kalman gain K is given as Eq 2.7.

$$K = PH^T R^{-1} \tag{2.7}$$

2.3 Driving Path Prediction

Vehicle path is determined by the complex interaction between human driver and the vehicle dynamics. To predict the driving trajectory of the vehicle, it is a common practice to assume that the steering angle is fixed and the velocity remains constant in future period of time (Lio and Ulsov, 1995). But this assumption is not true in many real cases. A typical example is curve entry or curve exit. When the driver enters the curved road or exits from the curved road, the steering angle tends to varies linearly rather than fixed. Therefore this study considered the assumption that the steering rate and the velocity remain constant in addition to fixed steering angle assumption. When the steering angle is assumed to have the fixed value $\underline{\delta}_f$, the dynamic model to predict the path is given by following form from Eq 2.1,

$$\begin{bmatrix} \dot{x}_{ref} \\ \dot{y}_{ref} \\ \dot{v} \\ \dot{\gamma} \\ \dot{\theta}_{ref} \end{bmatrix} = \begin{bmatrix} u & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & u \\ 0 & 0 & \frac{2}{m}\left(\frac{C_f + C_r}{u}\right) & \frac{2}{m}\left(\frac{l_f C_f - l_r C_r}{u}\right) - u & 0 \\ 0 & 0 & \frac{2}{I_z}\left(\frac{l_f C_f - l_r C_r}{u}\right) & \frac{2}{I_z}\left(\frac{l_f^2 C_f + l_r^2 C_r}{u}\right) & 0 \\ 0 & 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} 1 \\ y_{ref} \\ v \\ \gamma \\ \theta_{ref} \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ -\frac{2C_f}{m} \\ -\frac{2 l_f C_f}{I_z} \\ 0 \end{bmatrix} \underline{\delta}_f \qquad (2.8)$$

where, x_{ref} , y_{ref} and θ_{ref} denote the vehicle's position and heading angle in current (*t=0*) body coordinates.

When the steering rate is assumed to have fixed value $\underline{\dot{\delta}}$, the extended dynamic model is given by following form from Eq 2.2.

$$\begin{bmatrix} \dot{x}_{ref} \\ \dot{y}_{ref} \\ \dot{v} \\ \dot{\gamma} \\ \dot{\theta}_{ref} \\ \dot{\delta}_f \end{bmatrix} = \begin{bmatrix} u & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & u & 0 \\ 0 & 0 & \frac{2}{m}\left(\frac{C_f + C_r}{u}\right) & \frac{2}{m}\left(\frac{l_f C_f - l_r C_r}{u}\right) - u & 0 & -\frac{2C_f}{m} \\ 0 & 0 & \frac{2}{I_z}\left(\frac{l_f C_f - l_r C_r}{u}\right) & \frac{2}{I_z}\left(\frac{l_f{}^2 C_f + l_r{}^2 C_r}{u}\right) & 0 & -\frac{2 l_f C_f}{I_z} \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} 1 \\ y_{ref} \\ v \\ \gamma \\ \theta_{ref} \\ \delta_f \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 1 \end{bmatrix} \underline{\dot{\delta}}_f \quad (2.9)$$

Chapter 3. Vision Sensor based Road Geometry Estimation

The vision sensor provides curvature of the road in ahead of the ego-vehicle which is estimated by means of and image processing module on itself. However, there is problem of heading angle error for direct use of the curvature from vision sensor when the vehicle is performing lane change maneuver as shown in Figure 3.1. On the other hand, when the vehicle is performing lane keeping maneuver, the heading angle error is close to zero as the heading of vehicle is corresponding to lane markings.

3.1 Heading Angle Error Compensation

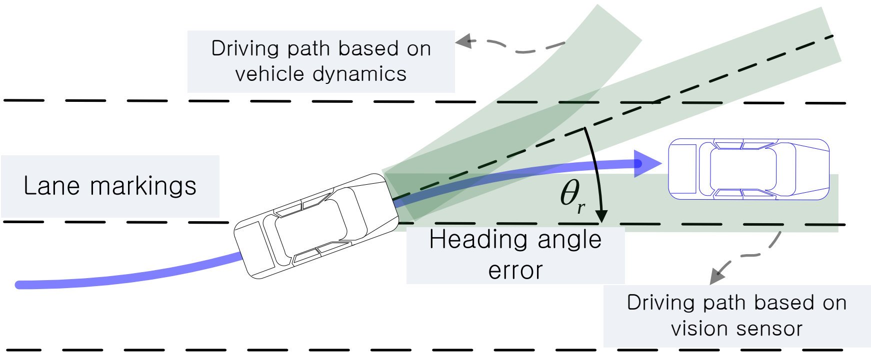


Figure 3. 1. Driving Path based on Vehicle Dynamics and Vision Sensor

From the road curvature obtained from the vision sensor, the desired yaw rate to follow the road geometry can be calculated as following under the assumption of steady-state cornering:

$$\gamma_{des} = u \cdot \kappa_{vision} \tag{3.1}$$

where, κ_{vision} is the road curvature from vision sensor. Then the heading angle error is represented as the integration of differences between desired yaw rate and ego-vehicle's yaw rate as following:

$$\theta_r = \int_{t_0}^{t_f} \left(\gamma - \gamma_{des}\right) dt \tag{3.2}$$

where, θ_r denotes the heading angle error. The initial time t_0 and final time t_f of the integral are determined by lateral offset information from the vision sensor. When the lateral offset from the road center exceeds threshold value, integration procedure starts and ends if lateral offset is less than threshold for some period of time. The calculated heading angle error can be compensated using simple rotation transformation

(Li and Jilkov, 2003)

3.2 Characteristics of Road Geometry Based on Vision Sensor

To analyze the characteristic of road geometry based on vision sensor, vision sensor data in real road manual driving situation is collected. A data collection vehicle is constructed as shown Figure 3.2.

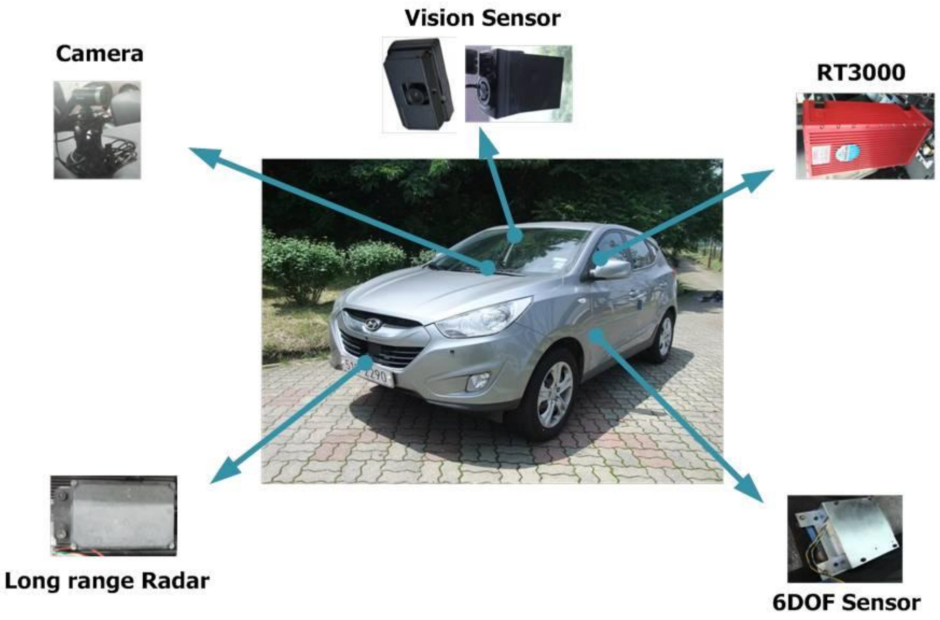


Figure 3. 2. The Data Collection Vehicle

Vision sensor measures the road curvature based on the lane marking of the road. The GPS-based device, RT3000, is used to measure the reference of the driving path. To analyze the vision sensor based road curvature, the vehicle stated based curvature is compared with vision sensor based road curvature. Figure 3.3 shows lane change maneuvering situation in straight road and Figure 3.4 shows the comparison between the vehicle state based road curvature and the vision sensor based road curvature.

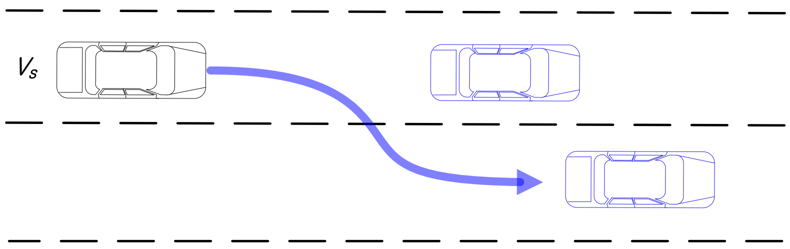


Figure 3. 3. Lane change maneuvering situation

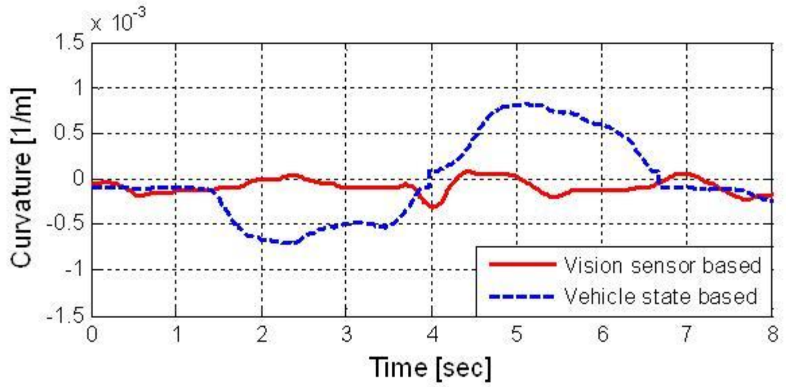


Figure 3. 4. Curvature data in lane change maneuvering situation

As the vision sensor estimates the road curvature based on the lane markings of the road, it is clearly different from predicted vehicle path based on vehicle states when the vehicle is performing lane change maneuver. The driving path based on vision sensor approximately corresponds to the real geometry of the road which is almost zero, while the driving path based on vehicle dynamics is inconsistent with the real geometry of the road. As the target loss can be occurred using the driving path which is based on vehicle dynamics in lane change maneuvering situation, there is advantage to use the vision sensor based road curvature for driving path prediction, in case of lane change driving situation.

Chapter 4. Driving Mode Decision from Driver Intention

In this chapter, the driving mode index which can detect a driver's maneuvering intention is presented. On the other hand, the driving mode can be decided by driving mode index. The driving mode can be used to integrate of aforementioned two driving path to consider the driver's maneuvering intention.

4.1 Driving Mode Index

To detect the intention of the lane change with a steering behavior, the steering behavior index is proposed and it presents a brief way to recognize the intention (Lee and Yi, 2011). If the curvature of the road can be estimated or provided, the default value of the steering angle for negotiating a circular road can be calculated with a bicycle model. The steady state steering angle δ_{ss} for negotiating a circular road of curvature κ is given as follows (Rajamani, 2005).

$$\delta_{ss} = \left(l_f + l_r + \frac{mV_x^2 \left(l_r C_{\alpha r} - l_f C_{\alpha f} \right)}{2C_{\alpha f} C_{\alpha r} \cdot \left(l_f + l_r \right)} \right) \cdot V_x \cdot \kappa \tag{4.1}$$

When the driver has an intention to change the lane, the difference in steering angle between driver's steering angle and the steady state steering angle for negotiating a circular road of curvature κ is evident. In this paper, the curvature κ is estimated based on vehicle dynamics.

Based on the aforementioned approach, the steering behavior index to monitor the intention of driver can be defined as follows:

$$I_{LC}(k+1) = \rho \cdot I_{LC}(k) + \left(\delta_k - \delta_{ss}\right) \cdot \dot{\delta}_k \cdot T \qquad (0 < \rho < 1) \tag{4.2}$$

$$I_{LC}(k) = T \cdot \sum_{p=1}^{p=k} \rho^{k-p} \cdot \left(\delta_p - \delta_{ss}\right) \cdot \dot{\delta}_p \tag{4.3}$$

where, $I_{LC}(k)$ is the driving mode index at k-th step and ρ is the forgetting factor and T is the sampling time and δ_k is the steering angle at k-th step and $\dot{\delta}_k$ is the steering angle rate at k-th step. The steering angle rate signal is obtained by kalman filter using a steering angle measurement.

4.2 Driving Mode Decision

The driving mode is classified into two major driving mode; “lane keeping mode” and “lane change mode”. If the value of the driving mode index gets over a predefined threshold I_{th} , then it can be assumed that the vehicle is starting to change the lane toward neighboring lane as shown in Eq 4.6.

$$
\begin{aligned}
&if\ \ I_{LC}(k) > I_{Th}\ \ \&\ \delta_f < 0, && \text{then driving mode} = \text{"lane change"(right)} \\
&if\ \ I_{LC}(k) > I_{Th}\ \ \&\ \delta_f > 0, && \text{then driving mode} = \text{"lane change"(left)} \\
&if\ \ I_{LC}(k) < I_{Th}, && \text{then driving mode} = \text{"lane keeping"}
\end{aligned}
\tag{4.6}
$$

Chapter 5. Driving Path Estimation Algorithm

The two driving paths which are both estimated based on vehicle dynamics and vision data, respectively, are fused in accordance with the driving mode as shown in Figure 5.1. If the driving mode is "lane keeping mode", the driving path based on vehicle dynamics is used for fused path as it is reliable when the vehicle is not performing complex maneuvers. On the other hand, if the driving mode is "lane change mode", the driving path based on vehicle dynamics can't be reliably used for fused path as it is not corresponds to the real geometry of the road. Instead of the driving path based on vehicle dynamics, therefore, the driving path based on vision sensor is used for fused path when the driving mode is "lane change mode" as it is extracted from the lane geometry of the road.

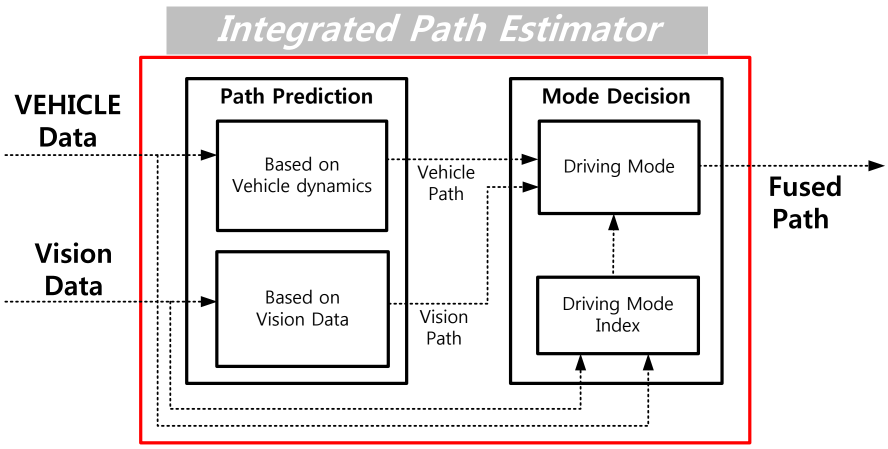


Figure 5. 1. The Overall Structure of the Integrated Path Estimator

Chapter 6. Simulation Results

In this section, the performance of the proposed driving path estimation algorithm is investigated via a closed-loop ACC simulation. The simulated subject vehicle is controlled by the ACC system with the integrated path estimation algorithm application and the simulation results is compared with the simulation results of ACC system to which the conventional path estimation algorithm is applied. And the effect of the path estimation algorithm to longitudinal safety control performance of ACC is also evaluated. To perform the closed-loop simulation in multi-sensor data, the vision sensor informations such as a lane width and road curvature are generated using real-road driving data.

Test scenarios were determined to explore the performance of the path estimation algorithm in the case of the ego-vehicle’s dynamic maneuvering. The three driving situations, which are a entering a curve, a exiting a curve and a lane change driving, are selected in this study. In these situations, a comparison of performance was shown between conventional way and proposed way of driving path estimation.

6.1 Lane Change Driving Situation

The simulation situation is lane change driving as shown in Figure 6.1. To monitor the longitudinal motion related to the collision, the longitudinal index $I_{longitudinal}$ is introduced (Cho et al., 2010). It is normalized value of warning index and inverse TTC(time to collision). The longitudinal index indicates the longitudinal collision potentiality.

$$I_{Longitudinal} = \max\left(\frac{|x_{\max} - x|}{|x_{\max} - x_{th}|}, \frac{|TTC^{-1}|}{|TTC_{th}^{-1}|} \right) \quad (6.1)$$

$$x = \frac{R - d_b}{d_w - d_b} \quad (6.2)$$

$$TTC^{-1} = \frac{\dot{R}}{R} \quad (6.3)$$

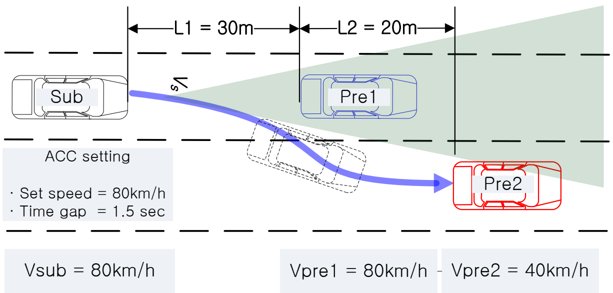
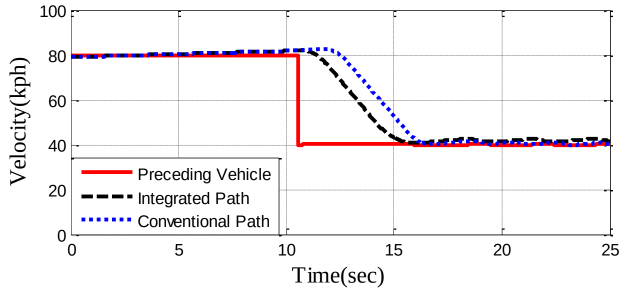
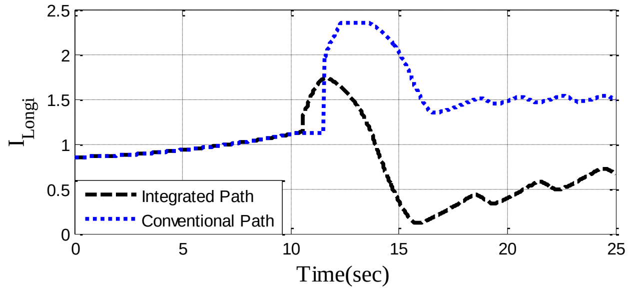


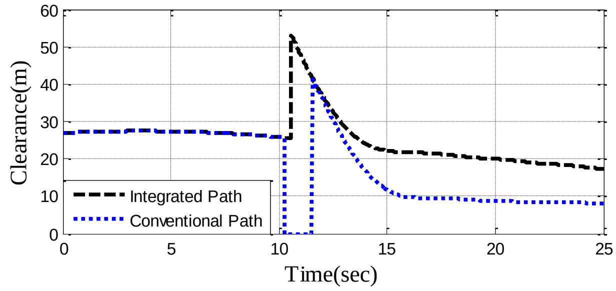
Figure 6. 1. Lane Change Driving Situation in Multi-Vehicle



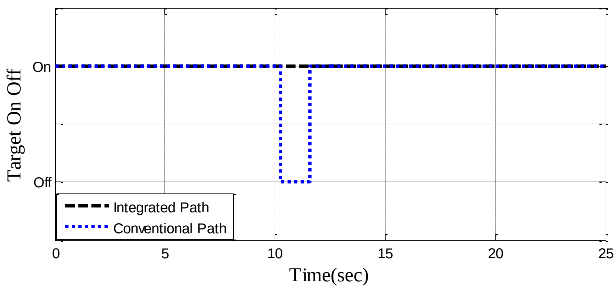
(a) Velocity



(b) Longitudinal Index



(c) Clearance



(a) Target On/Off Signal

Figure 6. 2. Simulation Results of a Lane Change Driving in Multi-Vehicle

The neighborhood vehicle which drives in low speed (40km/h) is detected with integrated path without target loss as the driver intention were taken into account, while there is target loss in case of the conventional path estimation algorithm as shown in Figure 6.2. As a result, the maximum of longitudinal index decreased which means the decrease of collision potentialities. Therefore it is shown that the control performance of the ACC system is enhanced in longitudinal collision control safety.

6.2 Entering and Exiting a Curve Situation

The results of the simulation in entering and exiting a curve situation are shown in Table 6.1. A road center error is the integration of the lateral distance between real center of the road and center of the predicted path during maneuvering. The fused path prediction algorithm reduces the road center error in entering and exiting a curve situation.

Table 6.1. Comparison of Conventional Path and Fused Path in Curved Road

Type	Time Gap (sec)	Road Center Error (m·sec)	
		Conventional Path	Fused Path
Entering a Curve	1	1.679	1.312
	2	4.952	3.723
	3	11.343	7.841
Exiting a Curve	1	1.838	1.501
	2	3.261	2.395
	3	5.042	3.114

Chapter 7. Conclusion

In this paper, a novel method for the prediction of the ego-vehicle's path in a dynamic situation has been presented. It was shown that it is possible to predict the intention of the driver and estimate the path reliably in dynamic maneuvering situation. As a result, the driving path prediction algorithm improved the longitudinal safety control performance of the ACC system, reducing a target loss time about 1.5sec and longitudinal collision potentiality. Therefore, the method can be applied to safety-critical applications, such as an ACC and an AEBS, allowing the application to predict driving path recognizing the exact position of the vehicle ahead in front, especially in dynamic maneuvering situation to change the lane, entering and exiting the curve.

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초 록

본 논문에서는 적응순항제어시스템 및 자동비상제동장치용 센서퓨전을 통한 주행경로 추정알고리즘을 제안하였다. 본 주행경로 추정알고리즘은 자차량의 주행경로의 예측 정확성을 향상시켜 최종적으로는 적응순항제어시스템 및 자동비상제동장치의 전방차량 타겟검지성능을 향상시키도록 한다. 본 주행경로 추정알고리즘은 두 가지 주행경로 추정방법을 통합하도록 구성된다. 첫번째는 차량의 상태변수기반의 주행경로 추정과정이며, 두번째는 카메라센서기반의 주행경로 추정방법이다. 특히, 차선변경이나 곡선로 진입상황과 같은 운전자의 조향입력이 있는 상황에서 주행경로 추정성능을 향상시키기 위하여 운전자의 차선변경 의도를 판단할 수 있는 주행모드 인덱스를 사용하였으며, 이를 통하여 두 가지 방법으로 추정한 주행경로를 통합하고 최종 주행경로를 생성한다. 본 알고리즘의 성능을 검증하기 위해 Carsim 및 MATLAB & Simulink 패키지를 활용하여 폐루프 시뮬레이션을 수행하였다. 본 논문에서 제안한 주행경로 추정방법으로 시뮬레이션을 수행한 결과, 차선변경상황 및 곡선로 진입상황에서 주행경로 추정성능이 향상되었음을 확인하였으며, 궁극적으로 적응순항제어시스템 및 자동비상제동장치의 안전도 제어 성능을 향상시킴을 확인하였다.

주요어: 주행경로, 비전센서, 적응순항제어, 자동비상제동장치, 센서퓨전

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