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

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Abstract—**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 improve primary target detection rate. The path prediction is consisted of two prediction process; one is based on vehicle states and the other is based on vision data. For application to dynamic maneuvering situation, 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-vehicles path accurately, especially in dynamic maneuvering situation.**

Keywords-Driving path; Sensor fusion; Vision sensor; Adaptive cruise control; Advanced emergency braking system

I. Introduction

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 [1]. 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. 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 [2]. 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 [3-5]. A fusion for lane estimation takes place using line markings detected by a vision sensor, information derived from a digital map [6]. In [7] 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.

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. In [8] the determination of accurate path of ego-vehicle, especially while maneuvering, using the situation model to detect maneuvers. 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" as it is indicated in [8].

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 II, there is a description of the mathematical tools used to predict the driving path based on vehicle dynamics. In section III, a short presentation of driving path prediction based on vision sensor including the heading angle compensation. In section IV, 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 V. Results about the performance and the evaluation of the algorithm are presented in Section VI. The paper's conclusions are given in Section VII.

II. 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 Fig. 1.

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.

A. Vehicle Model

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

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

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:

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

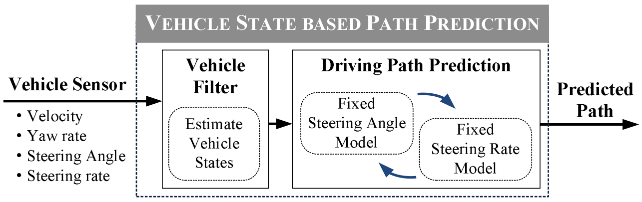

Figure 1. The Overall Structure of the Vehicle States based Path Prediction

B. Estimation Schemes

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

$$x = \begin{bmatrix} u & a_x & v & \gamma & \delta_f & \dot{\delta}_f \end{bmatrix}^T \qquad (3)$$

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 2^{nd} order linear Gauss Markov process model:

$$\begin{aligned} \dot{x} &= Fx + \Gamma w \\ z &= Hx + v \end{aligned} \qquad (4)$$

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

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

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 (4) consists of following two differential equations, one for the estimated state $\hat{x}$ and one for the error covariance P:

$$\begin{aligned} \dot{\hat{x}} &= F\hat{x} + K\left(z - H\hat{x}\right) \\ \dot{P} &= FP + PF^T + Q - PH^T R^{-1} HP \end{aligned} \qquad (6)$$

where Kalman gain K is given by:

$$K = PH^T R^{-1} \tag{7}$$

C. 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 [9] to assume that the steering angle is fixed and the velocity remains constant in future period of time. 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 (1):

$$\begin{bmatrix} \dot{x}_{ref} \\ \dot{y}_{ref} \\ \dot{v} \\ \dot{\gamma} \\ \dot{\theta}_{ref} \end{bmatrix} = \begin{bmatrix} u & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & u \\ 0 & 0 & \frac{2}{m}\left(\frac{C_f + C_r}{u}\right) & \frac{2}{m}\left(\frac{l_f C_f - l_r C_r}{u}\right) - u & 0 \\ 0 & 0 & \frac{2}{I_z}\left(\frac{l_f C_f - l_r C_r}{u}\right) & \frac{2}{I_z}\left(\frac{l_f^2 C_f + l_r^2 C_r}{u}\right) & 0 \\ 0 & 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} 1 \\ y_{ref} \\ v \\ \gamma \\ \theta_{ref} \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ -\frac{2C_f}{m} \\ -\frac{2l_f C_f}{I_z} \\ 0 \end{bmatrix} \underline{\delta}_f \tag{8}$$

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 (2):

$$\begin{bmatrix} \dot{x}_{ref} \\ \dot{y}_{ref} \\ \dot{v} \\ \dot{\gamma} \\ \dot{\theta}_{ref} \\ \dot{\delta}_f \end{bmatrix} = \begin{bmatrix} u & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & u & 0 \\ 0 & 0 & \frac{2}{m}\left(\frac{C_f + C_r}{u}\right) & \frac{2}{m}\left(\frac{l_f C_f - l_r C_r}{u}\right) - u & 0 & -\frac{2C_f}{m} \\ 0 & 0 & \frac{2}{I_z}\left(\frac{l_f C_f - l_r C_r}{u}\right) & \frac{2}{I_z}\left(\frac{l_f^2 C_f + l_r^2 C_r}{u}\right) & 0 & -\frac{2l_f C_f}{I_z} \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} 1 \\ y_{ref} \\ v \\ \gamma \\ \theta_{ref} \\ \delta_f \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 1 \end{bmatrix} \underline{\dot{\delta}}_f \tag{9}$$

III. 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 Fig.2. 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.

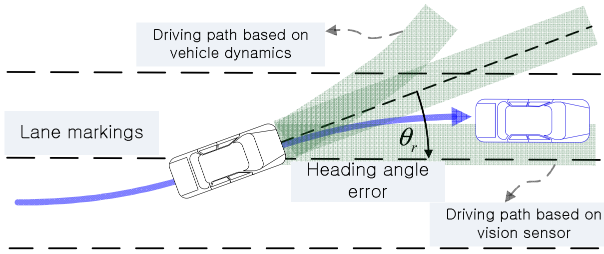

Figure 2. The Driving paths based on vehicle dybamics and vision sensor

A. Heading Angle Error Compensation

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:

$$\gamma_{des} = u \cdot \kappa_{vision} \tag{10}$$

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:

$$\theta_r = \int_{t_0}^{t_f} (\gamma - \gamma_{des})\, dt \tag{11}$$

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 [10].

B. Characteristics of road geometry based on vision sensor

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, while the driving path based on vehicle dynamics is inconsistent with the real geometry of the road.

IV. DRIVING MODE DECISION FROM DRIVER INTENTION

A. Driving mode index

To detect the intention of the lane change with a steering behavior, the steering behavior index is proposed in [11] and it presents a brief way to recognize the intention. 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 [12].

$$\delta_{ss} = \left(l_f + l_r + \frac{mV_x^2 \left(l_r C_{\alpha r} - l_f C_{\alpha f} \right)}{2C_{\alpha f} C_{\alpha r} \cdot \left(l_f + l_r \right)} \right) \cdot V_x \cdot \kappa \qquad (12)$$

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.

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

$$I_{LC}(k+1) = \rho \cdot I_{LC}(k) + \left(\delta_k - \delta_{ss} \right) \cdot \dot{\delta}_k \cdot T \qquad (0 < \rho < 1) \qquad (13)$$

$$I_{LC}(k) = T \cdot \sum_{p=1}^{p=k} \rho^{k-p} \cdot \left(\delta_p - \delta_{ss} \right) \cdot \dot{\delta}_p \qquad (14)$$

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.

B. Drving 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.

$$\begin{aligned}
&if\ I_{LC}(k) > I_{Th}\ \&\ \delta_f < 0, \\
&\qquad \text{then driving mode} = \text{"lane change"(right)} \\
&if\ I_{LC}(k) > I_{Th}\ \&\ \delta_f > 0, \\
&\qquad \text{then driving mode} = \text{"lane change"(left)} \\
&if\ I_{LC}(k) < I_{Th}, \\
&\qquad \text{then driving mode} = \text{"lane keeping"}
\end{aligned} \qquad (15)$$

V. 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 Fig.3. 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

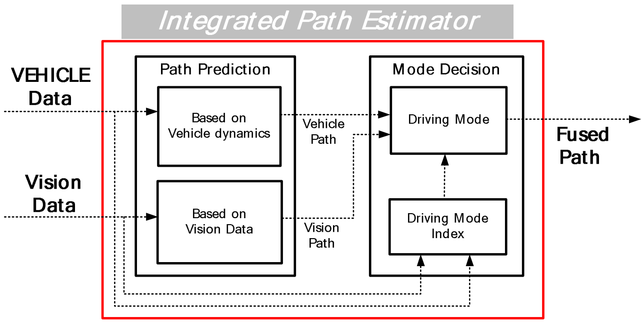

Figure 3. The ovetrall structure of the integrated path estimator

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.

VI. Simulation Result

In this section, the performance of the proposed driving path estimation algorithm is investigated via a closed-loop simulation. 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 the collected driving data in a real road.

Test scenarios were determined to explore the performance 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.

A. Lane change driving situation

The simulation situation is lane change driving as shown in Fig.4

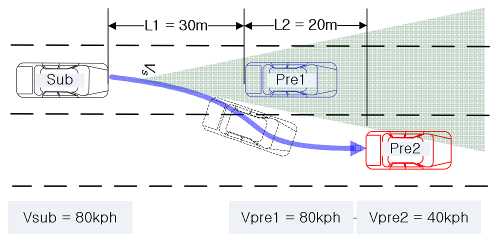

Figure 4. Lane change driving situation in multi-vehicle

To monitor evaluation the logitudinal motion related to the collision, the longitudinal index $I_{Longitudinal}$ is introduced in [13]. The longitudinal index indicates the collision potentialities.

$$I_{Longitudinal} = \max\left(\frac{|x_{\max} - x|}{|x_{\max} - x_{th}|}, \frac{|TTC^{-1}|}{|TTC_{th}^{-1}|} \right) \qquad (15)$$

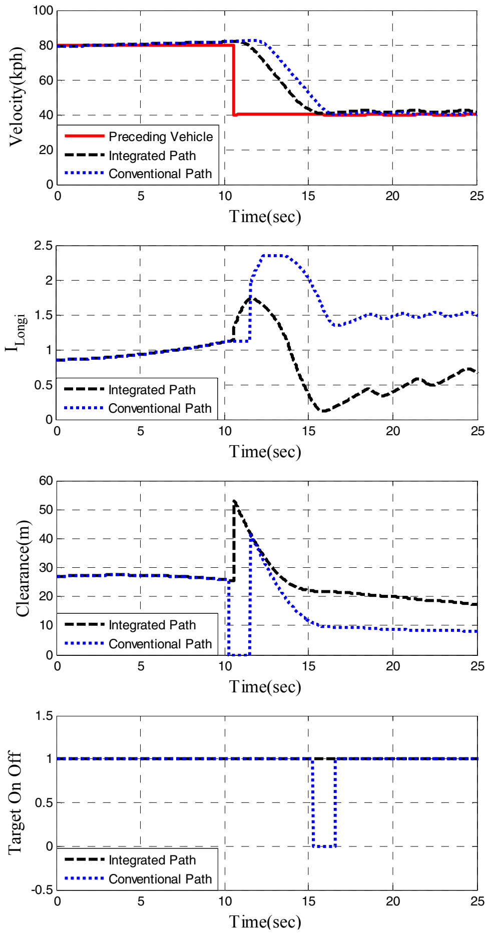

Figure 5. Simulation results of a lanechange driving in multi-vehicle

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 algorithm. As a result, the maximum of longitudinal index decreased which means the decrease of collision potentialities.

B. *Entering and exiting a curve situation*

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

TABLE I. COMPARISON OF CONVENTIONAL AND FUSION MODELS IN CURVED ROAD

Type	**Time gap (sec)**	**Road Center Error (m·sec)**	
		Conventional model	***Fusion model***
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

VII. CONCLUSION

This paper presents a novel method that is used to calculate the path of the ego-vehicle in a dynamic situation adaptive way. It was shown that it is possible to predict the intention of the driver and estimate the path reliably. Therefore, safety-critical applications, such as an ACC and an AEBS, can predict driving path recognizing the exact position of the vehicle ahead in front. Especially, the proposed path estimation algorithm enhances the capabilities of ACC and AEBS in dynamic maneuvering situation to change the lane, entering and exiting the curve.

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