

Probabilistic and Holistic Vehicle States Prediction with Enhanced Driver Model and Application to Smart Cruise Control Systems

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ABSTRACT

This paper presents a probabilistic vehicle states prediction algorithm by using multi-sensor fusion. The system inputs come in two main varieties: 1) vehicle sensor signal, such as steering angle, longitudinal velocity, longitudinal acceleration and yaw rate and 2) vision sensor signal, such as curvature, slope and distance to lane mark. From these inputs, the algorithm presents the time series prediction of future vehicle states and the corresponding covariance matrixes for the pre-defined future time horizon.

The probabilistic states prediction algorithm consists of two sequential parts. The first part is the estimation part which contains a vehicle filter which estimates current vehicle states and a road filter which approximates the road geometry. The second part is prediction part which consists of a path following model generating future desired yaw rate which acts as a virtual measurement and a vehicle predictor which predicts future vehicle states by maximum likelihood filtering method.

The proposed algorithm has been investigated via test data based closed loop simulation with Smart Cruise Control (SCC) system. Compared to two kind of existing path prediction methods; a fixed yaw rate assumption based method and a lane keeping assumption based method, it has been shown that the states prediction performance can be significantly enhanced by the proposed prediction algorithm. And this enhancement of prediction performance led to capabilities improvement of driver assistance functions of SCC by providing accurate predictions about the future driving environment.

INTRODUCTION

Recently, numerous Advanced Driver Assistant Systems (ADAS) have been developed and commercialized for the driver's safety and handling enhancement. A smart cruise control (SCC) system which maintains the safe distance from the preceding vehicle has been introduced to the market and next-generation SCC which can assist driver in obstacle avoidance situation is in progress. And a lane keeping assistance system (LKAS) which prevents an unintended lane departure and guide a vehicle into the lane

boundary have been developed. Such systems have been identified to enhance road safety effectively through numerous field tests [1]. In those systems, a reliable prediction for the ego-vehicle's future states should be available for threat assessment and decision-making functions.

The conventional driver assistant systems introduced in the market predict the vehicle's future path based on a fixed circular motion assumption, or a fixed steering angle assumption [3], [4]. However, this method is not sufficient to ensure a correct assignment of the vehicle's future path [2]. The inadequacy of the conventional path prediction method causes wrong threat assessment or wrong decision-making in the corresponding driver assistant system.

Subsequently, some modifications have been suggested. One approach combines a fuzzy rule and finite-state machines to capture all possible driving maneuver sequences [24]. However, this approach has been evaluated only for turn maneuvers. Another approach classifies the maneuver type from current vehicle information such as turn light, brake pedal, etc. and predicts the future path by building various situation models [21]. However, this approach has not been evaluated for dynamic maneuver situation (e.g. lane change).

As the various sensors have been introduced to vehicles, some additional information such as lane marking, GPS based map data have been taken into account. As a part of such effort, the vision sensors, which can detect lanes, are utilized for driving path prediction based on lane trackers [10]. Furthermore, during recent years, digital map contribution toward road geometry estimation is broadly proposed [2], [11]. However, path prediction method which is fully dependent on road geometry still brings a number of problems when the vehicle's motion and the road geometry do not coincide (e.g., lane change or overtake situation) or the road information do not exact.

In short, the vehicle motion based path prediction method is not suitable for a long term prediction because of divergence of prediction error. And the road geometry based path prediction method might not perform well in dynamic maneuvering situations such as lane change or overtake driving. Consequently, two information, the

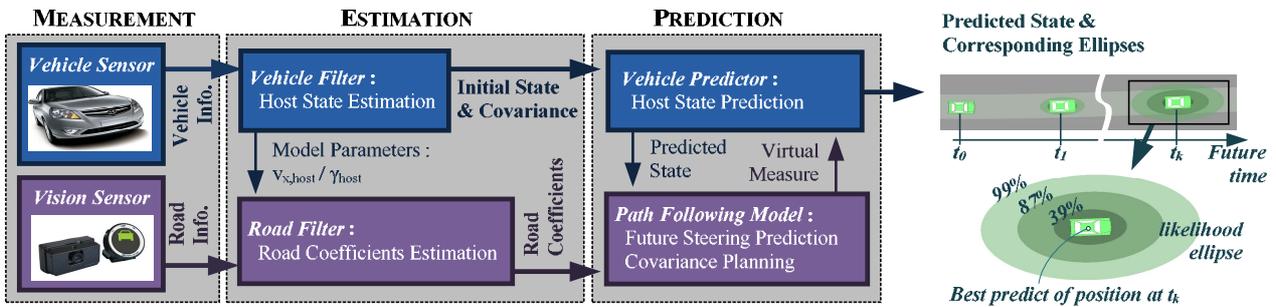


Figure 1. Architecture of a probabilistic and holistic states prediction

vehicle states and the road, should be fused properly and reasonably to make the most out of relative merits of each measure.

To satisfy this requirement of information fusion, there are few approaches to propose fusion method and describe its validity. One study proposed independent-parallel two predictions, current dynamics based and road geometry based, and a weighted manner combining method [2]. In this method, it gives more weight to the current dynamics based prediction at the beginning and reduces the weight in a linear sense. However, there is no mathematical description about this linear sense weighting fusion strategy. Other approaches which learns motion patterns by building a motion database have been presented [22], [23]. This method, however, has the drawback that many trajectories have to be stored in large databases and accessed online. Lin et al. [25] presented an approach using numerical integration of a linearized two degree-of-freedom vehicle handling model. However, it assumes constant steering wheel angle and highway speeds (80 km/h). Tsogas et al. [26] has defined various maneuver states and proposed a transition model from one maneuver to another by a state diagram. And Zong et al. [27] combine an Artificial Neural Network (ANN) and a Hidden Markov chain Model (HMM) in their integrated model to identify the driving intention and predict the maneuvering behavior of the driver. In these situation-classification based approaches, there are problems that every complicate situation cannot be predefined.

From a number of literature reviews, main concern in vehicle prediction area at the moment can be summarized as a reliable and reasonable sensor-fusion method for the path prediction. To the authors' knowledge, in addition to this requirement of sensor-fusion, two more requirements have to be concerned. One is that the real time evaluation of prediction error. When the prediction algorithm is utilized in driver risk monitoring function of various Advanced Driver Assistance Systems (ADAS), the evaluation of prediction uncertainty is essential to guarantee the performance of the assistance system. This cannot take place by existing methods because of their deterministic prediction process. And the other is the extension of size of predicted states. Only just future position, so called 'future path', is not sufficient enough to define the actual risk of the vehicle. Therefore more elements such as yaw angle, yaw rate, longitudinal velocity and acceleration, etc. have to be predicted reliably.

To satisfy these requirements of sensor-fusion, states

extension and uncertainty evaluation, a sensor fusion based probabilistic prediction method for holistic vehicle states is developed and proposed in this manuscript. The main idea of this study is that a prediction problem can be solved as a multi-stage of optimal estimation problem if we consider the road geometry as the measurement, as the future road geometry is exactly same with the current road geometry.

The algorithm consists of two sequential parts. The first part is the estimation part which contains a vehicle filter which estimates current vehicle states and a road filter which approximates the road geometry. The second part is prediction part which consists of a path following model generating future desired yaw rate which acts as a virtual measurement and a vehicle predictor which predicts future vehicle states by maximum likelihood filtering method.

The proposed algorithm has been investigated via closed-loop simulation with Smart Cruise Control systems. Compared to existing methods, it has been shown that the states prediction performance can be significantly enhanced by the proposed prediction algorithm and this enhancement of prediction performance led to capabilities improvement of driver assistance functions of ADAS by providing accurate predictions about the future driving environment.

PROBABILISTIC STATES PREDICTION

A probabilistic states prediction algorithm presents the quasi-best predicts of ego-vehicle's potential position and corresponding likely ellipses which are covering some given finite time horizon.

The system inputs come in two main varieties: 1) vehicle sensor signal, such as steering angle, longitudinal velocity, longitudinal acceleration and yaw rate and 2) vision sensor signal, such as curvature, slope and distance to lane mark. From these inputs, the proposed algorithm produces a time-series of predicts for vehicle position and corresponding likely ellipses.

Fig. 1 depicts the procedures of a probabilistic states prediction. As shown in the figure, the overall structure of this algorithm consists of 2 parts. The first part is the estimation part which contains a vehicle filter which estimates current vehicle states and a road filter which approximates road geometry. The second part is prediction part which consists of a path following model generating future desired yaw rate which acts as a virtual measurement and a vehicle predictor which predicts future vehicle states by maximum likelihood filtering method.

Estimation

In the estimation part, the vehicle's current dynamic states and the road geometry are estimated. The yaw acceleration and the longitudinal acceleration are very important factors to improve the prediction reliability than conventional method. However, the value of yaw acceleration is very difficult or expensive to measure directly. This value can be successfully estimated in real-time using measurements such as the steering angle, the yaw rate, the longitudinal velocity and the longitudinal acceleration which are available from existing vehicle sensors. And in an approximation of the road geometry, the road geometry is approximated as a 2nd order polynomials in present vehicle coordinate. In this approximation, the coefficients of polynomials can be calculated from road curvature, road slope and vehicle's lateral distance from the road center line and these values can be measured directly by an equipped vision sensor.

Vehicle Filter The Kalman filter is used to estimate present vehicle states such as longitudinal velocity, yaw rate, longitudinal acceleration and yaw acceleration from the vehicle sensor signals such as steering angle, yaw rate, longitudinal velocity and longitudinal acceleration under the assumption of the Gaussian white noise. As aforementioned, the state vector x is defined as following in order to represent the driver's intention and the vehicle's planar behavior:

$$x = [v \quad \gamma \quad a \quad \dot{\gamma}]^T \quad (1)$$

where v is the longitudinal velocity, γ is the yaw rate, a is the longitudinal acceleration and $\dot{\gamma}$ is the yaw acceleration. The measurement vector is defined as following to reflect the available sensor information.

$$z = [v \quad \gamma \quad a \quad \delta_f]^T \quad (2)$$

where δ_f is the front wheel steering angle. Assuming that the time derivatives of the longitudinal acceleration and the yaw acceleration can be considered as the process noise, the process model and measurement model are given by following form:

$$x[k+1] = F[k] \cdot x[k] + w[k] \quad (3)$$

$$z[k] = Hx[k] + v[k] \quad (4)$$

where

$$F = \begin{bmatrix} 1 & 0 & \Delta t & 0 \\ 0 & 1 & 0 & \Delta t \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & h_{42} & 0 & h_{44} \end{bmatrix}$$

$$h_{42} = \frac{2l_f^2 C_f + 2l_r^2 C_r}{2l_f C_f v} \quad h_{44} = \frac{I_z}{2l_f C_f}$$

where Δt is the sampling time which taken as 0.1 second in this study, I_z is the yaw moment of inertia, C_f and C_r are the front and rear wheel cornering stiffness, respectively

and l_f and l_r are the distances from vehicle's center of gravity to front and rear axles. Two elements in 4th row of measurement matrix are determined from the bicycle model which is most well-known lateral vehicle dynamics model. The process noise is assumed to be a white noise with associated covariance matrix, W . The measurement noise is also assumed to be a white noise with associated covariance, V . Note that measurement model, H , is time varying because there exist longitudinal velocity in the element of the matrix. Therefore, it should be re-calculated at each time step. With above process and measurement model, vehicle states are recursively estimated by using the Kalman filter which is a sequence of time and measurement update steps as following specific equations:

Time update

$$\begin{aligned} \bar{x}[k] &= F \cdot \hat{x}[k-1] \\ M[k] &= F \cdot P[k-1] \cdot F^T + W \end{aligned} \quad (5)$$

Measurement update

$$\begin{aligned} \hat{x}[k] &= \bar{x}[k] + K[k] \cdot (z[k] - H[k] \bar{x}[k]) \\ K[k] &= M[k] H[k]^T \cdot (H[k] M[k] H[k]^T + V)^{-1} \\ P[k|k] &= (I - K[k] H[k]) \cdot M[k] \end{aligned} \quad (6)$$

Road Filter Road geometry is the key factor effecting on driver's maneuverings, especially on steering behavior. Therefore, in this section, the method to describe the forward road geometry using the measurement of the vision sensor is discussed. As the first step of the description, the road geometry is defined in current vehicle body coordinate and approximated as the 2nd order polynomials. And secondly, its coefficients are estimated reclusively from the vision sensor measurements and prior estimate of vehicle states.

It is common practice to describe the forward road geometry by a 2nd order polynomial [7]. The relation between the host vehicle and the road center line can be described by two factors. One is a relative lateral position, e_y , and the other is a relative heading angle, e_θ . This is depicted in Fig. 7. With these two factors, the road geometry, which has the curvature radius R , can be approximated as following [6]:

$$\begin{aligned} y_r &= \frac{1}{2R} x^2 - \tan e_\theta \cdot x - e_y \\ &\equiv a_2 \cdot x^2 + a_1 \cdot x + a_0 \end{aligned} \quad (7)$$

where x is the down range distance and y_r is the lateral position of the corresponding road center in current body coordinates. As the vehicle drives with velocity v and yaw rate γ , the coefficients describing the road geometry change according to the motion of the vehicle. The discrete-time process model of the road geometry coefficients can be written in the following state-space form. Details of process modeling will be described in section B.1.

$$x_r[k+1] = F_r[k]x_r[k] + G_r u_r[k] + w_r[k] \quad (8)$$

where

$$x_r = \begin{bmatrix} a_2 \\ a_1 \\ a_0 \end{bmatrix} \quad u_r = \gamma \quad F_r = \begin{bmatrix} 1 & 0 & 0 \\ 2v\Delta t & 1 & 0 \\ 0 & v\Delta t & 1 \end{bmatrix} \quad G_r = \begin{bmatrix} 0 \\ -\Delta t \\ 0 \end{bmatrix}$$

A subscript ‘ r ’ is used to denote ‘of road geometry states’. The vision sensor provides full information of road state vector. Likewise with the vehicle states estimation, the Kalman filter is used for the estimation of road geometry coefficients. Note that the process model F_r is time varying because there exist longitudinal velocity in the element of the matrix. Therefore, it should be re-calculated at each time step by using the best estimate results of the vehicle filter. The yaw rate which is the system input of road geometry system model also uses the best estimate result of the vehicle filter. Hence the covariance of the process noise should be well-defined so that can represent the effect of the estimate error of the vehicle filter. As the result, road geometry coefficients are recursively estimated by using the Kalman filter which is a sequence of time and measurement update steps as following specific equations:

Time update

$$\begin{aligned} \bar{x}_r[k] &= F_r[k-1] \cdot \hat{x}_r[k-1] + G_r u_r[k-1] \\ M_r[k] &= F_r[k-1] \cdot P_r[k-1] \cdot F_r[k-1]^T + W_r \end{aligned} \quad (9)$$

Measurement update

$$\begin{aligned} \hat{x}_r[k] &= \bar{x}_r[k] + K_r[k] \cdot (z_r[k] - H_r \bar{x}_r[k]) \\ K_r[k] &= M_r[k] H_r^T \cdot (H_r M_r[k] H_r^T + V_r)^{-1} \\ P_r[k] &= (I - K_r[k] H_r) \cdot M_r[k] \end{aligned} \quad (10)$$

Prediction

In the part of prediction, it is assumed that the driver may maintain current behavior in the near future and keep the lane in the end. To implement this assumption, a path following model and a vehicle state predictor keep interacting with each other during the prediction processing. A path following model generates the desired yaw rate which consists of error state feedback term and road curvature feedforward term. The feedback and feedforward law is determined properly so that it can represent the human driver’s yaw behavior on the road. And a vehicle state predictor predicts the vehicle’s future potential position and its error covariance by linearized Kalman filtering with using the path following model based desired yaw rate as the virtual measurement.

Path Following Model The objective of a path following model is to develop a yaw control system for human-like lane keeping. To achieve this goal, it is useful to utilize a dynamic model in which the state variables are in terms of position and orientation error with respect to the road. The error state is defined in term of fixed coordinate under the assumption of traveling with constant

longitudinal velocity on a road of constant radius. Note that the error state is defined in inertial fixed coordinates not in body-fixed moving coordinates. By using the definition of the road geometry in section A.2, the position error can be defined as

$$e_y = p_y - \{a_2 \cdot p_x^2 + a_1 \cdot p_x + a_0 + w_{road} \cdot N(\text{current lane})\} \quad (11)$$

where w_{road} is the width of the road lane and N is the adjusting integer to represent the current lane. For example, if the vehicle changes the lane to the left one, N has the value of minus one. Under the small slip angle assumption, the time derivative of the position error can be defined as

$$\begin{aligned} \dot{e}_y &= \frac{d}{dt}(p_y) - (2a_2 \cdot p_x + a_1) \cdot \frac{d}{dt}(p_x) \\ &\equiv v \sin \theta - (2a_2 \cdot p_x + a_1) \cdot v \cos \theta \end{aligned} \quad (12)$$

where v is the longitudinal velocity and θ is the orientation. The orientation error and its time derivative can be defined as

$$e_\theta = \theta - \tan^{-1}(2a_2 \cdot p_x + a_1) \quad (13)$$

$$\begin{aligned} \dot{e}_\theta &= \dot{\theta} - \frac{d}{dt}\{\tan^{-1}(2a_2 \cdot p_x + a_1)\} \\ &= \gamma - \frac{1}{1 + (2a_2 \cdot p_x + a_1)^2} \cdot \frac{d}{dt}(2a_2 \cdot p_x + a_1) \\ &= \gamma - \frac{1}{1 + (2a_2 \cdot p_x + a_1)^2} (2a_2) \cdot \frac{d}{dt}(p_x) \\ &= \gamma - \frac{2a_2}{1 + (2a_2 \cdot p_x + a_1)^2} \cdot (v \cos \theta) \end{aligned} \quad (14)$$

Under the small road slope and small error assumptions, above time derivatives of error states can be simplified as follows:

$$\begin{aligned} \dot{e}_y &= v \sin \theta - (2a_2 \cdot p_x + a_1) \cdot v \cos \theta \\ &= v \cos \theta \cdot \{\tan \theta - (2a_2 \cdot p_x + a_1)\} \\ &\equiv v \cos \theta \cdot e_\theta \end{aligned} \quad (15)$$

$$\begin{aligned} \dot{e}_\theta &= \gamma - \frac{2a_2}{1 + (2a_2 \cdot p_x + a_1)^2} \cdot (v \cos \theta) \\ &\equiv \gamma - 2a_2 \cdot (v \cos \theta) \end{aligned} \quad (16)$$

If the yaw rate dynamics can be approximated as 1st order system which has the desired yaw rate as the system input, the state space model of tracking error variables is given by following equation.

$$\begin{aligned} \frac{d}{dt} \begin{bmatrix} e_y \\ e_\theta \\ \gamma \end{bmatrix} &= \begin{bmatrix} 0 & v \cos \theta & 0 \\ 0 & 0 & 1 \\ 0 & 0 & f \end{bmatrix} \cdot \begin{bmatrix} e_y \\ e_\theta \\ \gamma \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ -f \end{bmatrix} \gamma_{des} + \begin{bmatrix} 0 \\ -2v \cos \theta \\ 0 \end{bmatrix} a_2 \\ &\equiv F_e \cdot x_e + G_e \cdot \gamma_{des} + G_w \cdot a_2 \end{aligned} \quad (17)$$

We can see that first and second row of equation describe the road geometry coefficient process model under the assumption of fixed road curvature.

Assume that the human drivers determine the desired yaw rate by state feedback plus a feedforward tem that

attempts to compensate for the road curvature as following:

$$\begin{aligned}\gamma_{des} &= -Cx_e + \gamma_{ff} \\ &= -[c_1 \quad c_2 \quad c_3]x_e + \gamma_{ff}\end{aligned}\quad (18)$$

Similar to the road curvature, if the feedforward term is constant, the steady state is given by

$$\begin{aligned}\begin{bmatrix} e_y \\ e_\theta \\ \gamma \end{bmatrix}_{ss} &= -(F_e - G_e C)^{-1} \cdot \left(\begin{bmatrix} 0 \\ 0 \\ -f \end{bmatrix} \gamma_{ff} + \begin{bmatrix} 0 \\ -2v \cos \theta \\ 0 \end{bmatrix} a_2 \right) \\ &= \begin{bmatrix} \frac{1}{c_1} \cdot (\gamma_{ff} - 2a_2 v \cos \theta (c_3 + 1)) \\ 0 \\ 2a_2 v \cos \theta \end{bmatrix}\end{aligned}\quad (19)$$

Hence, we can see that the all error states can be made zero by appropriate choices of feedback gains and feedforward term. For example, the feedback gain can be determined by pole placement which is simulating the human driver's behavior characteristics. Then the feedforward term can be calculated directly from above feedback gain and estimated road curvature by equation (20).

$$\gamma_{ff} = 2a_2 v \cos \theta (c_3 + 1) \quad (20)$$

Vehicle Predictor In the prediction of the vehicle's future states, the only measurement available is the road geometry described in current body coordinate. As aforementioned, under the assumption that the driver may maintain current behavior in the near future and keep the lane in the end, the path following model based desired yaw rate is used as the virtual measurement while the prediction process. Consider the future vehicle system as the stochastic, multistage process described as following:

$$x_p[i+1] = f_p(x_p[i]) + w_p[i], \quad i = 0, \dots, N_p - 1 \quad (21)$$

where

$$x_p = [p_{x,p} \quad p_{y,p} \quad \theta_p \quad v_p \quad \gamma_p \quad a_p \quad \dot{\gamma}_p]^T$$

$$f_p(x_p) = x_p + [v_p \cos \theta_p \quad v_p \sin \theta_p \quad \gamma_p \quad a_p \quad \dot{\gamma}_p \quad -k_a a_p \quad -k_\gamma \dot{\gamma}_p]^T \cdot \Delta t$$

where N_p is the length of the pre-defined prediction time horizon and a subscript 'p' is used to denote 'predictive'. The longitudinal and yaw acceleration are assumed to be decayed with some time constants.

At each time step, as a noisy measurement of the true future yaw rate, desired yaw rate is evaluated by path following model. Let us suppose the measurement noise is also normal distributed, with zero mean. Hence a predictive measurement is linearly related to the predictive states by

$$\begin{aligned}z_p[i] &= H_p \cdot x_p[i] + v_p[i], \quad i = 0, \dots, N_p \\ &\equiv \bar{\gamma}_{des,p}[i] \\ &= -C \cdot \bar{x}_{e,p}[i] + \gamma_{ff,p}[i]\end{aligned}\quad (22)$$

Then the maximum likelihood predict of the future state is given by the following extended Kalman filtering. As an

example, a predict procedure at 1st future time step is depicted in Fig. 3-4.

Time update

$$\begin{aligned}\bar{x}_p[i] &= f_p(\hat{x}_p[i-1]) \\ F_p[i-1] &= \left. \frac{\partial f_p}{\partial x_p} \right|_{x_p=\hat{x}_p[i-1]} \\ M_p[i] &= F_p[i-1] \cdot P_p[i-1] \cdot F_p[i-1]^T + W_p\end{aligned}\quad (23)$$

Measurement update

$$\begin{aligned}\hat{x}_p[i] &= \bar{x}_p[i] + K_p[i] \cdot (z_p[i] - H_p \bar{x}_p[i]) \\ K_p[i] &= M_p[i] H_p^T \cdot (H_p M_p[i] + V_p[i])^{-1} \\ P_p[i] &= (I - K_p[i] H_p) \cdot M_p[i]\end{aligned}\quad (24)$$

Evaluation of Prediction Error Because the proposed prediction algorithm is based on stochastic filtering method, the covariance of prediction error can be evaluated at each time step as shown in equation (24). Furthermore, the eigenvalue and eigenvectors of the 2nd leading principal minor of P_p determine the likelihood ellipse around predictive position [19]. Using the square root of the eigenvalues as semi-axes, measured along the eigenvectors, we can sketch the 39 percent likelihood ellipse with center at most likely predictive position. The 87 percent likelihood ellipse is two times the size of the 39 percent ellipse in linear dimension and 99 percent is three times. This is depicted in Fig. 7. This analysis is very useful to visualize and compare the prediction performance in the view of accuracy and precision.

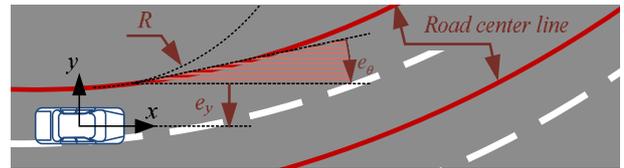


Figure2. Relationship between the host vehicle and the road center line

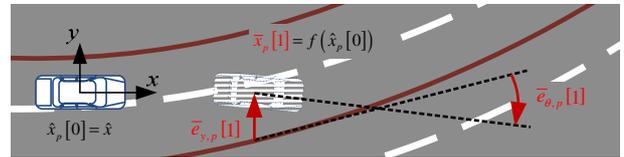


Figure3. Time-update-predicted host vehicle states and the relative error states with respect to road geometry defined on current body coordinate

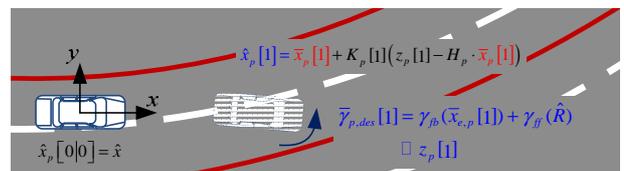


Figure4. Measurement-update-predicted host vehicle states where the predicted desired yaw rate to keep the lane is defined as virtual measurement

TESE DATA BASED CLOSED-LOOP SIMULATION WITH SMART CRUISE CONTROL SYSTEM

To validate the applicability of the proposed algorithm and to evaluate the performance enhancement induced by the algorithm in perception module of Advanced Driver Assistance System, simulation study has been conducted by using the commercial vehicle software Carsim and Matlab/Simulink. As the objective of the simulation is to investigate the induced performance enhancement of the target selection module in SCC by proposed algorithm compared to conventional methods, a scenario is selected as a lane change driving situation with presence of target vehicle on the new lane. Based on a collected real-road driving data, a driving scenario is re-constructed in computer simulation. The comparisons with the conventional Fixed Yaw Rate Model (FYRM) and Lane Keeping Model (LKM) are presented in this section. FYRM is the model which predicts the vehicle future states under the assumption of fixed current yaw rate and LKM based prediction assumed that the driver may keep the current lane which has no consideration of vehicle states is also applied and compared.

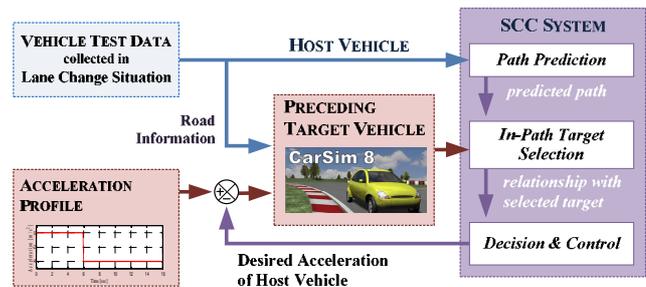
Simulation Environment

A primary target detection performance was evaluated by a simulation on an asphalt road in lane change driving situation. In the case of the ego-vehicle, a collected test data in lane change situation is applied as open-loop inputs. Since a simulation was conducted to evaluate target detection performance and associated SCC functions, a preceding vehicle which drives on the new lane set to keep constant velocity and start decelerating with deceleration level of 4 m/s^2 after the time that the ego vehicle starts its lane changing. For simulating the closed loop feedback response of the SCC system, the desired longitudinal acceleration command from the SCC system has been applied and added to the preceding vehicle's pre-defined acceleration profile with negative value. This is equivalent with general closed-loop simulation in longitudinal relative behavior between both vehicles.

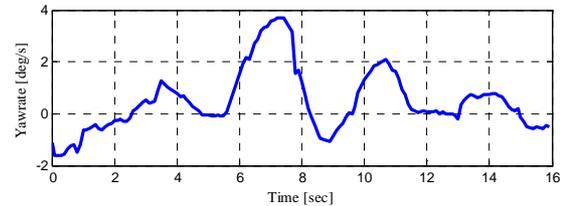
The description of the simulation is summarized in Fig. 5. As shown in the figure, the host vehicle starts its lane changing at 6 sec. And at the same time, the virtual preceding vehicle on the new lane is set to start decelerating by open-loop acceleration profile as shown in Fig. 5-(g). The perception module of SCC system which is appointed to do path prediction is replaced by each conventional and proposed prediction algorithm and comparative analysis is conducted in the view of the performance of SCC.

Simulation Results

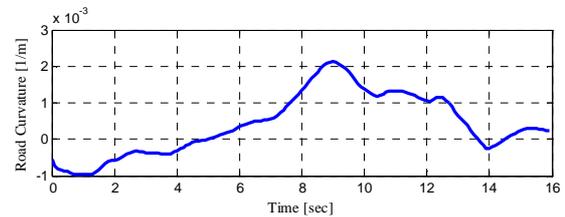
The simulation results are given in Fig. 6-9. The results have shown the some important performance difference and corresponding improvement of safety and convenience functions. In case of the FYRM based simulation which is denoted by dotted blue line, we can see that target loss has



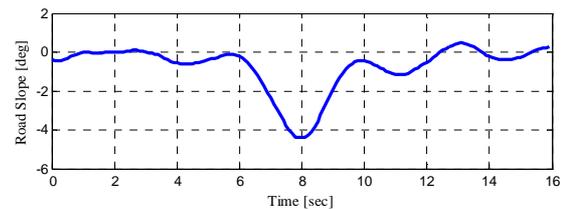
(a) Structure of the simulation



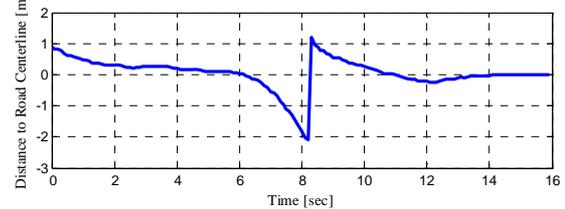
(b) Test data of the yaw rate of the host vehicle



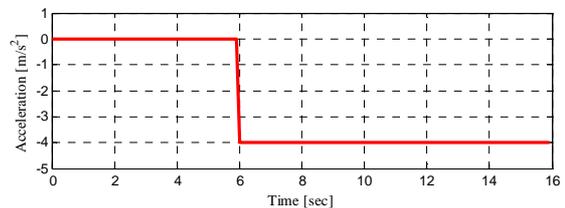
(c) Test Data of the road curvature



(d) Test Data of the relative road slope to host vehicle



(e) Test Data of the distance to road centerline of host vehicle



(f) Open-loop acceleration profile of preceding vehicle

Figure 5. Closed loop simulation environment based on real vehicle test data

occurred frequently as shown in Fig. 8-(b). The first target loss is caused by the miss-predicted path which veers off to the lane change direction as depicted in Fig. 6-(b). And the second target loss is caused by miss-predicted path which veers off to the lane correct direction which is depicted in Fig. 7-(b). Because of these two times of target loss, SCC system with FYRM based prediction module cannot

maintain the safe distance from the preceding vehicle and used oddly severe deceleration which may cause the driver inconvenience.

In LKM based case, there is no target loss but target detecting delay problem has been shown. The reason of this delay problem is that the LKM based path prediction method does not change the pursuing lane until the center of mass cross the boundary of the lane. Because of this target detecting delay problem, SCC system started deceleration late and used oddly severe deceleration to maintain the safety distance and cause the driver inconvenience. Note that in case of LKM, prediction error covariance cannot be evaluated because of non-realistic trust in path following model.

At last, in case of the proposed algorithm, the primary target vehicle which drives on the new lane is detected without target loss and detecting delay. As a result, the starting point of longitudinal deceleration of the ego-vehicle is moved forward almost 1 second compared to LKM based SCC system and retain more safety distance with smaller level of deceleration compared to FYRM based SCC system. Therefore it is shown that the control performance of the SCC system is enhanced in two important viewpoints; the longitudinal collision control safety and the convenience of the driver.

CONCLUSION

A novel method for the prediction of the ego-vehicle's states has been presented. This algorithm is developed to predict the ego-vehicle's states accurately and improve the performance of perception and risk assessment module in Advanced Driver Assistance Systems (ADAS). The probabilistic states prediction algorithm consists of two sequential parts. The first part is the estimation part which contains a vehicle filter which estimates current vehicle states and a road filter which approximates the road geometry. The second part is prediction part which consists of a path following model generating future desired yaw rate which acts as a virtual measurement and a vehicle predictor which predicts future vehicle states by maximum likelihood filtering method.

The proposed algorithm has been investigated via vehicle tests data based closed loop simulation with perception module of SCC. It has been shown that the states prediction performance can be significantly enhanced by the proposed prediction algorithm, especially in curve entry, exit and lane change driving situations and the enhancement of prediction performance led to capabilities improvement of driver assistance functions of ADAS by providing accurate predictions about the future driving environment.

The proposed algorithm can be utilized in perception modules of advanced driver assistance systems such as Emergency Driving Support (EDS) system, Advanced Emergency Braking System (AEBS), side-crash prevention system, Advanced Lane Change Assistance (ALCA) system and expected to enhance the vehicle safety in various driving situations

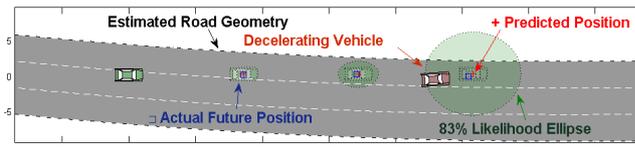
ACKNOWLEDGMENT

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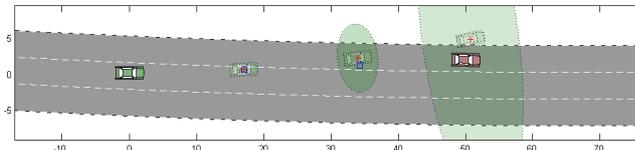
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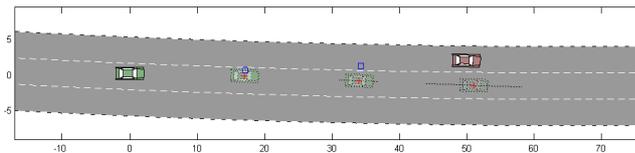
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(a) Proposed method based prediction

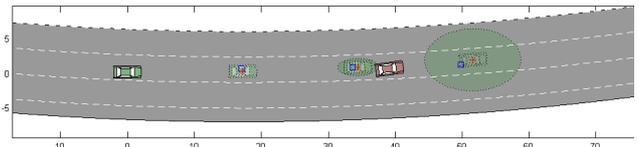


(b) Fixed Yaw Rate Model based prediction

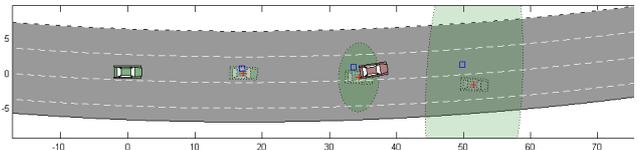


(c) Lane Keeping Model based prediction

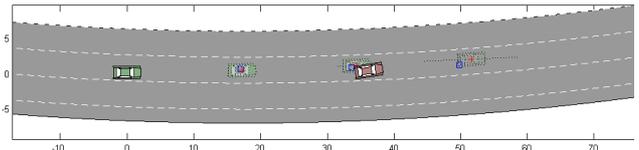
Figure. 6 Comparison of prediction results for 3 second of future time between the conventional and proposed method while lane change driving



(a) Proposed method based prediction

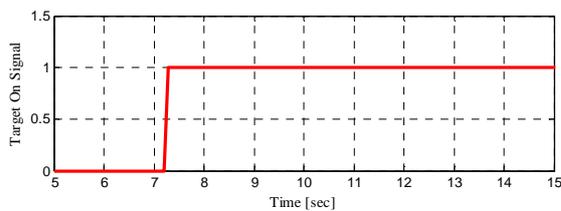


(b) Fixed Yaw Rate Model based prediction

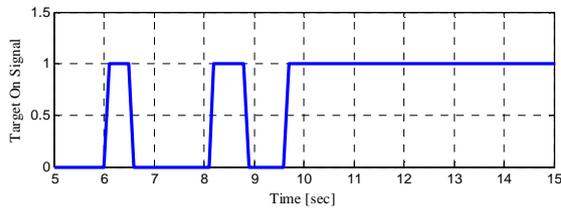


(c) Lane Keeping Model based prediction

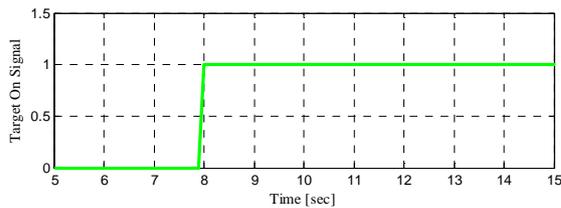
Figure. 7 Comparison of prediction results for 3 second of future time between the conventional and proposed method while lane correct driving



(a) Target detecting signal with proposed algorithm

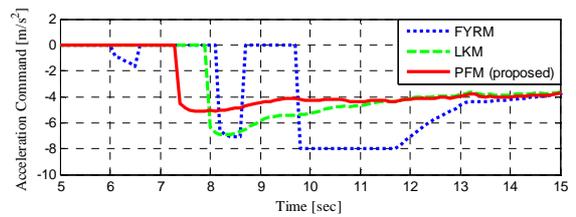


(b) Target detecting signal with fixed yaw rate model

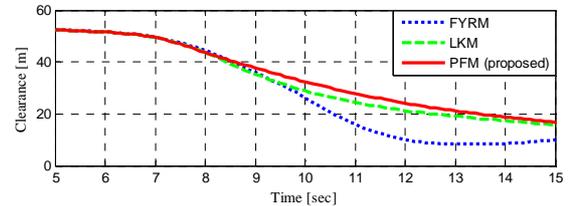


(c) Target detecting signal with lane keeping model

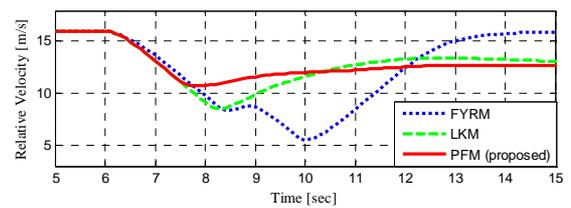
Figure. 8 Comparison of the target detecting performance



(a) Desired acceleration command of each method



(b) Clearance of each method



(c) Relative velocity of each method

Figure. 9 Comparison of the control results with SCC