

Automated Driving Control in Safe Driving Envelope Based on Probabilistic Prediction of Surrounding Vehicle Behaviors

Junyung Lee, Beomjun Kim, Jongsang Seo, and Kyongsu Yi
Seoul National Univ

Jihyun Yoon and Bongchul Ko
Hyundai Motors

ABSTRACT

This paper presents an automated driving control algorithm for the control of an autonomous vehicle. In order to develop a highly automated driving control algorithm, one of the research issues is to determine a safe driving envelope with the consideration of probable risks. While human drivers maneuver the vehicle, they determine appropriate steering angle and acceleration based on the predictable trajectories of the surrounding vehicles. Therefore, not only current states of surrounding vehicles but also predictable behaviors of that should be considered in determining a safe driving envelope. Then, in order to guarantee safety to the possible change of traffic situation surrounding the subject vehicle during a finite time-horizon, the safe driving envelope over a finite prediction horizon is defined in consideration of probabilistic prediction of future positions of surrounding vehicles. A model predictive control (MPC) approach is used to determine appropriate steering angle and acceleration to control the vehicle satisfying the safe driving envelope over a finite prediction horizon. If a dynamics model which integrates a longitudinal motion and a lateral motion is used to determine the control inputs, a nonlinear optimization problem should be solved at each time step. However, a computational burden to solve a nonlinear MPC problem is a critical barrier for its implementation. Therefore a parallel architecture which decides a desired steering angle and a desired longitudinal acceleration separately is designed to reduce a computational burden. The effectiveness of the proposed control algorithm is evaluated via computer simulations.

CITATION: Lee, J., Kim, B., Seo, J., Yi, K. et al., "Automated Driving Control in Safe Driving Envelope Based on Probabilistic Prediction of Surrounding Vehicle Behaviors," *SAE Int. J. Passeng. Cars – Electron. Electr. Syst.* 8(1):2015, doi:10.4271/2015-01-0314.

INTRODUCTION

In recent years, the interest of automotive industry changes from the passive safety system to the active safety system and, by extension, automated driving system due to advances in sensing technologies. For example, active safety applications, such as vehicle stability control (VSC), adaptive cruise control (ACC), lane keeping assistance (LKA) and lane change assistance (LCA) system, have been extensively researched [1, 2, 3, 4, 5]. In order to enhance safety and achieve zero fatalities, many researches have been undertaken to integrate individual active safety systems for the development of an automated driving system.

In developing an automated driving system which is required to operate in a wide operating region and limit the set of permissible states and inputs, MPC approach has been used widely because of its capability to handle system constraints in a systematic way [6], [7]. MPC approach uses a dynamic model of the plant to predict the future states of the system and determines optimal control sequences at each time step to minimize a performance index while satisfying constraints based on the predicted future states [8]. The first term of this optimal control sequences is applied to the system. At next time step, new optimal control sequences is calculated over a shifted

prediction horizon. In [9], Falcone et al. present a MPC based active steering controller for tracking the desired trajectory as close as possible while satisfying various constraints. In this research, it is assumed that the desired trajectory over a finite prediction horizon is known. Erlien et al. use a safe driving envelope which means a safe region of states in which the system should be constrained [10], [18]. In this research, the safe driving envelope consists of a stable handling envelope to ensure vehicle stability and an environmental envelope to constrain the position states for the collision avoidance. The environmental envelope is defined based on the current states of surrounding environment of the subject vehicle.

In order to develop a highly automated driving system, the research issues can be classified into two things. One of the issues is to determine a safe driving envelope with the consideration of probable risks. Human drivers maneuver the vehicle predicting possible surrounding vehicle's trajectories. Therefore, not only current states of surrounding environment of the subject vehicle but also predicted behaviors of surrounding environment should be considered to control the vehicle autonomously [11]. Furthermore, since probable

behaviors of the surrounding vehicles should be considered to prevent a potential collision accident in the future, a probabilistic prediction is required [12].

In this research, we focus on designing an automated control algorithm which considers probable behaviors of the surrounding vehicles. In order to accomplish this objective, a safe driving envelope which describes the safe driving condition over a finite prediction horizon is defined in consideration of probabilistic prediction of future states of surrounding environment. Then MPC problem is formulated to determine a desired steering angle and desired longitudinal acceleration while maintaining the subject vehicle into the safe driving envelope. If a dynamics model which integrates a longitudinal motion and a lateral motion is used to determine the control inputs, a nonlinear optimization problem should be solved at each time step. However, a computational burden to solve a nonlinear MPC problem is a critical barrier for its implementation [9]. In order to obtain the desired steering angle and desired longitudinal acceleration while reducing a computational burden, a parallel architecture which decides the desired steering angle and desired longitudinal acceleration separately is designed. The effectiveness of the proposed control algorithm is evaluated via computer simulations.

This paper is structured as follows: Section II presents an overall architecture of the proposed automated driving control algorithm. In Section III, vehicle dynamics model used in this research is described briefly. Section IV describes a determination of the safe driving envelope based on the probabilistic prediction. Then MPC problem is formulated in Section V. Section VI shows the simulation results to evaluate the proposed algorithm. Then the contribution of this research and introduction of future works are summarized in Section VII.

OVERALL ARCHITECTURE

Figure 1 shows the overall architecture of the proposed automated driving control algorithm, which is organized as a hierarchical architecture consisting of three layers. In the integrated perception layer, states of the subject vehicle and surrounding vehicle are estimated using measurements from various measurements via exterior sensors, such as vision and radar sensors. Then the probable behaviors of the surrounding vehicles are predicted based on the assumption that the behavior of a surrounding vehicle would varies in the reasonable ranges. Using the estimated states of the subject vehicle and the ranges of probable behaviors of the surrounding vehicles over a finite prediction horizon, a desired motion or desired driving mode of the subject vehicle is determined in the risk management layer. On an auto road, the required driving mode could be approximately classified into lane keeping and lane change mode. After the determination of the desired driving mode, the safe driving envelope is defined based on the desired motion. Then the controller is designed to determine the desired longitudinal acceleration and the desired steering angle. Using MPC approach, the desired control inputs are determined to improve safety and ride comfort while satisfying constraints of states and inputs.

DYNAMICS MODEL

Lateral Dynamics Model

A classic bicycle model is usually used to design a lateral control law [3], [6]. However, since an automated driving system should operate in a wide operating region, a classic bicycle model which assumes small slip angles of tires could not be suitable as a predictive model. On the other hand, if we use a nonlinear tire model to build a dynamic model, a nonlinear optimization problem should be solved at each time step. However, a computational burden to solve a nonlinear MPC problem is a critical barrier for its implementation [9]. In order to cope with this drawback, we apply a saturated linear tire model to reflect a tire saturation characteristic [13]. Then the bicycle model could be modified as follows:

$$\begin{bmatrix} \dot{\beta} \\ \dot{\gamma} \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} \beta \\ \gamma \end{bmatrix} + \begin{bmatrix} b_1 \\ b_2 \end{bmatrix} \delta_f \quad (1)$$

$$\begin{aligned} a_{11} &= -\frac{2k_{af}C_f + 2k_{ar}C_r}{mv_x}, a_{12} = -1 + \frac{-2k_{af}C_f l_f + 2k_{ar}C_r l_r}{mv_x^2}, \\ a_{21} &= \frac{-2k_{af}C_f l_f + 2k_{ar}C_r l_r}{I_z}, a_{22} = -\frac{2k_{af}C_f l_f^2 + 2k_{ar}C_r l_r^2}{I_z v_x}, \\ b_1 &= \frac{2k_{af}C_f}{mv_x}, b_2 = \frac{2k_{af}C_f l_f}{I_z} \end{aligned} \quad (2)$$

where, β is side slip angle of the vehicle and γ is yaw rate. k_{af} and k_{ar} are the cornering stiffness adjustment coefficients to reflect a tire saturation characteristic. These adjustment coefficients are assumed to be known exactly in this research.

In order to control the vehicle in the lateral direction, the modified bicycle model is combined with the error dynamics which describes error with respect to a road. Therefore, the complete model used to design a MPC controller is defined as shown in (3) and a diagram of the vehicle model is depicted in Figure 2.

$$\dot{x}_{lat} = A_{lat}x_{lat} + B_{lat}u_{lat} + F_{\rho,lat}\rho_{ref} \quad (3)$$

$$A_{lat} = \begin{bmatrix} a_{11} & a_{12} & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 \\ 0 & 1 & 0 & 0 \\ v_x & 0 & v_x & 0 \end{bmatrix}, B_{lat} = \begin{bmatrix} b_1 \\ b_2 \\ 0 \\ 0 \end{bmatrix}, F_{\rho,lat} = \begin{bmatrix} 0 \\ 0 \\ -v_x \\ 0 \end{bmatrix} \quad (4)$$

where, the state vector is $x_{lat} = [\beta \ \gamma \ e_\psi \ e_y]^T$, the control input is $u_{lat} = \delta_{f,des}$, e_ψ is the orientation error of the vehicle with respect to the road, e_y denotes the lateral offset with respect to the center line of the lane, and ρ_{ref} is the road curvature.

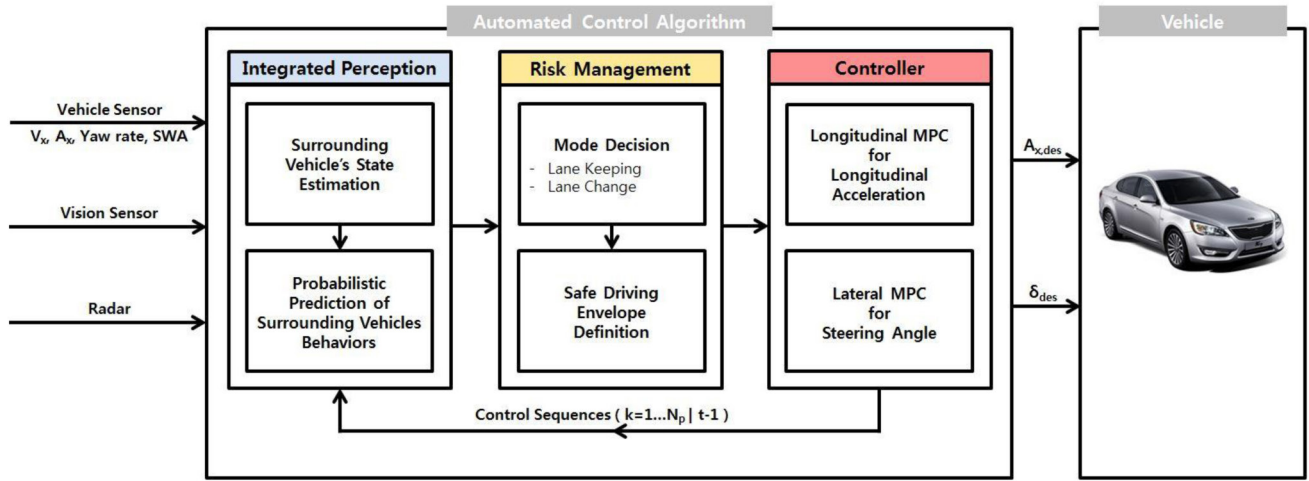


Figure 1. Overall architecture of the proposed automated driving control algorithm

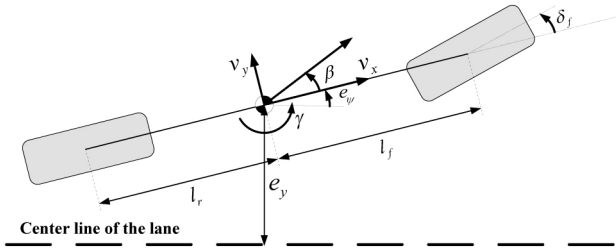


Figure 2. Diagram of lateral dynamics model

In order to solve a receding horizon optimization problem, the continuous differential equation (3) should be transformed into discrete difference equation. Based on the assumption of zero-order hold (ZOH) method for the control input u_{lat} , (1) can be converted as follows:

$$x_{lat}(k+1) = A_{lat,d}x(k) + B_{lat,d}u(k) + F_{\rho,lat,d}\rho_{ref}(k) \quad (5)$$

$$A_{lat,d} = e^{A_{lat}T_s}, B_{lat,d} = \left(\int_0^{T_s} e^{A_{lat}\tau} d\tau \right) B_{lat}, F_{\rho,lat,d} = \left(\int_0^{T_s} e^{A_{lat}\tau} d\tau \right) F_{\rho,lat} \quad (6)$$

where, T_s is the sampling time.

Longitudinal Dynamics Model

In designing a longitudinal dynamics model of the subject vehicle, an actuator delay between the desired longitudinal acceleration and the response of the actual longitudinal acceleration is considered as follows [13]:

$$a_x = \frac{1}{\tau_{ax}s + 1} a_{x,des} \quad (7)$$

where, τ_{ax} is a time-constant chosen as 0.4 sec based on the analysis of the vehicle test platform.

In this research, two variables, such as distance error Δd and relative speed Δv_x , are used to define the inter-vehicle dynamics.

$$\begin{aligned} \Delta d &= C_x - C_{x,des}, C_{x,des} = \tau_h \cdot v_x + C_{x,safe} \\ \Delta v_x &= v_{x,target} - v_x \end{aligned} \quad (8)$$

where, C_x and $C_{x,des}$ are the actual clearance and desired clearance between the subject vehicle and the target vehicle respectively, τ_h indicates the time gap, $C_{x,safe}$ is the minimum safety longitudinal clearance and $v_{x,target}$ is the longitudinal velocity of the target vehicle. In this research, in order to embrace driving characteristics of all of the drivers, the time gap, τ_h , is chosen as 1.36 sec which is the mean value of time gap for collected driving data in steady-state following situation [19]. Furthermore the minimum safety longitudinal clearance, $C_{x,safe}$, is chosen as 2 meters which is identical with the mean value of the clearance at the zero speed for all of the drivers [19]. The method how to select the target vehicle among the surrounding vehicle would be described in Section IV.

The derivative of the equation (8) could be derived as shown in equation (9).

$$\begin{aligned} \Delta \dot{d} &= \Delta v_x - \tau_h \cdot a_x \\ \Delta \dot{v}_x &= a_{x,target} - a_x \end{aligned} \quad (9)$$

Combining equation (7) and equation (9), the longitudinal dynamics model could be described as follows:

$$\dot{x}_{long} = A_{long}x_{long} + B_{long}u_{long} + F_{long}a_{x,target} \quad (10)$$

$$A_{long} = \begin{bmatrix} 0 & 1 & -\tau_h \\ 0 & 0 & -1 \\ 0 & 0 & -1/\tau_{ax} \end{bmatrix}, B_{long} = \begin{bmatrix} 0 \\ 0 \\ 1/\tau_{ax} \end{bmatrix}, F_{long} = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} \quad (11)$$

where, the state vector is $x_{long} = [\Delta d \ \Delta v_x \ a_x]^T$ and the control input is $u_{long} = a_{x,des}$.

As similar as the lateral dynamics model, the discretization of the continuous state [equation \(10\)](#) is conducted through the ZOH method as follows:

$$x_{long}(k+1) = A_{long,d}x_{long}(k) + B_{long,d}u_{long}(k) + F_{long,d}a_{x,target}(k) \tag{12}$$

$$A_{long,d} = e^{A_{long}T_s}, B_{long,d} = \left(\int_0^{T_s} e^{A_{long}\tau} d\tau \right) B_{long}, F_{\rho,long,d} = \left(\int_0^{T_s} e^{A_{long}\tau} d\tau \right) F_{\rho,long} \tag{13}$$

SAFE DRIVING ENVELOPE DECISION

In this research, a safe driving envelope is defined as the combination of an environmental envelope and a stable handling envelope. In order to define the environmental envelope to ensure safety of the vehicle during a finite prediction horizon, not only current states of traffic situation surrounding the subject vehicle but also probable future states of that are considered simultaneously. As mentioned in Introduction, human drivers monitor surrounding environment and predict the future states of surrounding environment based on the current states of that. Then drivers maneuver the vehicle in the consideration of the states of surrounding environment during a finite prediction horizon. Therefore, if the environmental envelope is defined based on the probabilistic prediction, we can develop an automated driving control algorithm which reflects human driver's driving characteristics with an acceptable ride comfort.

Probabilistic Prediction of Surrounding Vehicle's Behavior

One of common approach to predict the future states of traffic situation surrounding the subject vehicles is a deterministic prediction which assumes that the surrounding vehicles maintain its current movement during a finite prediction horizon. This approach ignores the probability of all possible movements of surrounding vehicles.

In order to predict reasonable ranges of the future states of surrounding vehicles, driving data is collected on test track and real road to analyze the probabilistic movement characteristics of the vehicle [15]. Furthermore it is assumed that the vehicle keeps the lane or change one lane at a time, not two or more lanes at a time [14]. It means that the surrounding vehicles which would change the lane are assumed to keep the relevant lane in the far-off future. For the implementation of this assumption, a path-following model is designed while interacting with a vehicle state predictor during one cycle of the prediction process. In the vehicle state predictor, the vehicle's probable position and its error covariance over a finite prediction horizon are predicted by Extended Kalman Filter (EKF) using the desired yaw rate obtained by the path-following model as the virtual measurement.

[Figure 3](#) depicts the overall architecture of probabilistic prediction of surrounding vehicles. Using measurements from the various sensors, such as vehicle sensor, radar and vision sensor, the range of the predicted states with corresponding uncertainty is determined as shown in [Figure 3](#). p_x is the longitudinal position of the vehicle, p_y is the lateral position of the vehicle, N_p denotes the length of the prediction horizon, and subscript 'j' means the j-th objects. In predicting the position of the surrounding vehicle, it is assumed that the size of the object is equivalent to the subject vehicle.

The overall procedure of probabilistic prediction is depicted in [Figure 4](#). In brief, the prediction of the surrounding vehicle's future states and the correction of the predicted future states by a path-following model are conducted successively during one cycle of the prediction process. The ellipse in [Figure 4](#) indicates the predicted probable range of the center gravity of the vehicle at the prediction time. As shown in [Figure 4](#), the size of the ellipse increases as the prediction time is going to be far. A detailed description on the computational procedures to predict the probabilistic range of future states during a finite prediction horizon is described concretely in [12].

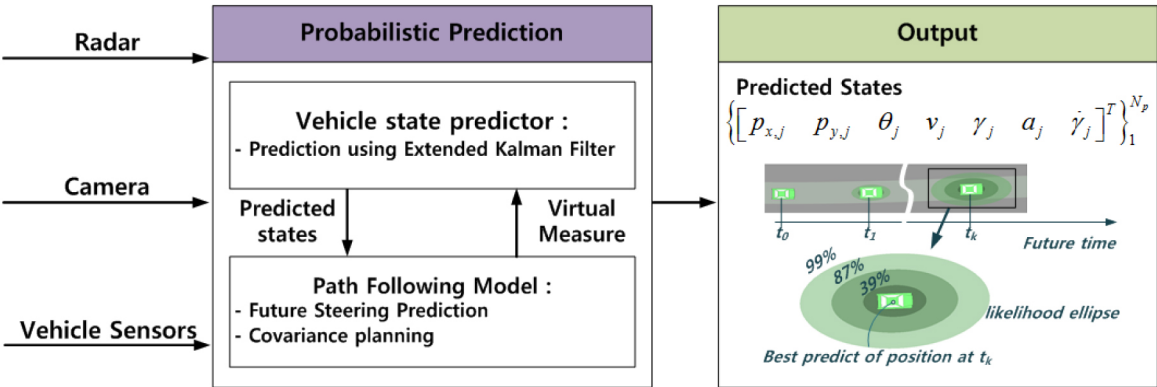


Figure 3. Overall architecture of probabilistic prediction