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A Model Predictive-based Approach for Longitudinal Control in Autonomous Driving with Lateral Interruptions

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***Abstract*—The longitudinal control of an autonomous vehicle usually suffers from lateral interruptions, such as the cutting in/out of the lead vehicle, deteriorating its performance and even endangering driving safety. To address this problem, we present a model predictive-based approach for longitudinal control in autonomous driving by taking the lateral interruptions into account. First, a virtual lead vehicle scheme is introduced to predict the future behavior of the actual lead vehicle. By following the virtual lead vehicle rather than the actual lead vehicle, the control of the host vehicle is simplified to keep a proper following gap problem. Then, a strategic car-following gap (CFG) model, generated from highway naturalistic driving data, is employed to describe the safety hazard and the probability of cut-ins by other vehicles. A model predictive controller, incorporating the strategic CFG model as well as the acceleration and jerk limitations in the objective function, is designed for the longitudinal control of the host vehicle. Solving the optimal control problem can not only smooth the oscillation and overshoots caused by the lateral interruptions but also reduce the probability of cut-ins from the adjacent lanes. The proposed approach is simulated and validated through some predefined test scenarios in CarSim software.**

***Keywords*—Model predictive control; Autonomous driving; Virtual lead vehicle; Strategic car-following gap model**

I. INTRODUCTION

The last decade has seen significant achievements in the field of autonomous driving and the autonomous velocity control is one of the most widely commercialized technologies (e.g., adaptive cruise control, autonomous emergency braking). Typically, these longitudinal control systems consist of two control modes: velocity cruise control and relative distance control. Existing applications have demonstrated stable and reliable performance according to the surrounding situation: keeping an appropriate relative distance to the lead vehicle when a lead vehicle exists, otherwise, tracking the desired speed [1].

However, more and more damages, injuries, and deaths, in the accidents related to the autonomous driving have exposed some critical challenges for autonomous velocity control with lateral interruptions. Firstly, the existing velocity control systems mainly focus on keeping safety in the longitudinal direction, but in the reality scenarios, they are frequently affected by lateral interruptions such as lane changing and cut-ins from adjacent lanes. Consequently, the host vehicle usually will brake or accelerate abruptly, leading to unnecessary deceleration or acceleration that is greatly bad for eco-driving and traffic efficiency. Moreover, the speed oscillation and overshoots caused by the lateral interruptions would put the autonomous vehicle into a dangerous situation. Secondly, the lateral interruptions arose a dilemma that is typically faced by host vehicle when following a preceding vehicle on a highway: leaving a sufficient car-following gap (CFG) poses an opportunity for other vehicles to cut-in while shortening the gap increases the likelihood of running into a crash. Therefore, it is important for the host vehicle to maintain proper CFGs that ensure safety distances in the longitudinal direction and, meanwhile, avoiding cut-ins from the lateral direction. Hence, it is needed to take the lateral interruptions into consideration when designing a longitudinal controller for autonomous vehicles.

Developing such approaches will not only improve the performance of longitudinal controller in autonomous driving, by promoting smooth traffic flow with increased safety and reduced fuel consumption and emissions, but can also be further used as an advanced safety technique in advanced driver-assistance systems (ADAS) and intelligent transportation systems (ITS).

A. Related works

A few methods have been proposed in the literature to address these challenges of lateral interruptions. To improve the transient performance when switching from one control model to another caused by the cutting in/outs of lead vehicles, a virtual lead vehicle is introduced in [2, 3]. Instead of following the actual lead vehicle, the host vehicle follows a virtual lead vehicle whose position and speed converge smoothly to those of the actual lead vehicle. This virtual lead vehicle makes the switching between the speed control mode and the distance control mode unnecessary. In addition, the motion of the host vehicle can be smoothly controlled to mitigate the overreacts to the cutting in/outs of the lead vehicle. Owing to the real-time ability, two different linear quadratic regulators (LQR) are designed for the virtual lead vehicle and the host vehicle, respectively. However, this virtual lead vehicle scheme has some drawbacks that impede its further application. Firstly, the fact that the performance of host vehicle controller depends on the performance of the virtual lead vehicle controller affects the system stability and increase the system complexity. Secondly, the dynamic characteristics of the host vehicle, such as the acceleration and jerk constraints, were not considered during the optimization.

Recent work has shown that model predictive control (MPC) can be used to enforce multiple safety constraints for autonomous vehicles[4-7]. The acceleration and the jerk constraints, as well as the states bounds, are incorporated in a cost function to evaluate each potential input trajectories in terms of driving safety, fuel efficiency and ride comfort.

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To the dilemma of maintaining a proper CFG when following a lead vehicle, many car-following models have been developed, and they can mainly be classified as follows: GHR model [8, 9], psychophysical or action point models[10], fuzzy logic-based models[11], and constant time-headway models [3, 12]. Nowadays, the constant time-headway models have gained acceptance for its simplicity and string stability. This model mainly focuses on keeping safety distances which are the minimum distance such that a collision would be avoidable if the lead vehicle behaves 'unpredictably' [13]. Nevertheless, this model couldn't handle the lateral interrupts caused by the cutting in vehicles. As a matter of fact, some studies have verified that the host vehicle's perception of risk is affected by multiple vehicles in front [14, 15], hence it is significant to consider the effect of vehicles cutting in from adjacent lanes. Addressing this problem, a strategic CFG model is proposed to represents the probability of rear-end collision without cut-ins and the likelihood of cut-ins by surrounding vehicles [16]. The strategic CFG model, generated using highway naturalistic driving data, is incorporated in an overall objective function. By finding the optimal solution of the overall objective function, the strategic CFG is realized. However, one drawback of this strategic CFG model is the nonlinearity and nonconvexity, which require a lot more calculation efforts in the optimization. In addition, the acceleration and jerk constraints of the host vehicle were not applied in the optimization.

B. Contributions

This paper presents a model predictive based approach for longitudinal control in autonomous driving with lateral interruptions. First, a new virtual lead vehicle scheme is introduced to handle control mode switching problem caused by the lateral interruptions. A two-level Kalman filter and a gradual reduction acceleration model is employed to predict the future behavior of the virtual lead vehicle. Then, an MPC based longitudinal controller is designed to smooth the oscillation and overshoots caused by the lateral interruptions.

Another contribution of this paper is the integration of the strategic CFG model in the cost function of the MPC controller. By approximating the nonlinear and nonconvex functions of the strategic CFG model with convex quadratic functions, the proposed MPC controller is converted to a quadratic optimal problem that can be solved with lower computational cost. Therefore, finding the optimal solution to the quadratic optimal problem is to seek the strategic CFG that ensures driving safety in the longitudinal direction, meanwhile, mitigates the probability of cut-ins from the adjacent lanes.

The remainder of the paper is organized as follows. Section II introduces the virtual lead vehicle scheme. Section III presents the strategic CFG model and the MPC based longitudinal controller for the host vehicle. Section IV shows the simulations results and discussion. Conclusions are drawn in Section V.

II. VIRTUAL LEAD VEHICLE SCHEME

Fig. 1 illustrates the proposed virtual lead vehicle scheme, in which the host vehicle follows the virtual lead vehicle with a CFG in the absence of the actual lead vehicle. For example,

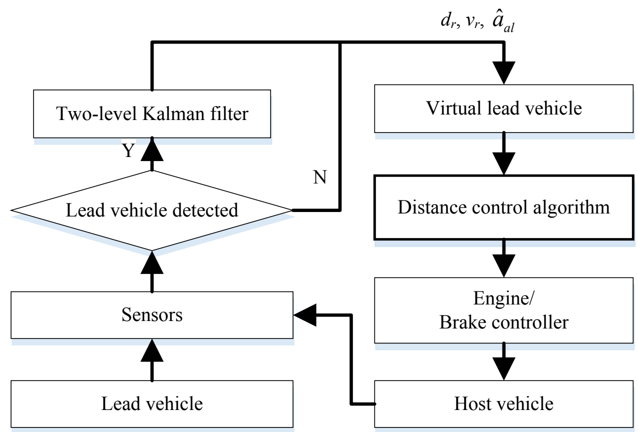


Fig. 1 Block diagram of the virtual lead vehicle scheme

when the lead vehicle cuts out and there is no lead vehicle detected, instead of switching to velocity control mode, the host vehicle remains in the distance control mode to follow a virtual lead vehicle. In this case, the velocity and acceleration of the virtual lead vehicle are set to be the desired speed and zero, respectively. In contrast, when a lead vehicle is detected, such as lead vehicle cuts in from adjacent lane, the position, velocity and acceleration of the virtual lead vehicle are set to be those of the actual lead vehicle. The relative distance and velocity of the actual lead vehicle are measurable through millimeter-wave radar. However, the acceleration of the actual lead vehicle is unknown. Some solutions simply considered the acceleration as a negligible disturbance or a constant value over the prediction horizon [17]. However, treating the acceleration as a disturbance means ignoring this valuable piece of data, which could be fatal when the lead vehicle brakes emergently. Also, choosing a fixed predicted acceleration can result in unrealistically very high or low speeds over long horizons.

An accurate relative acceleration estimation method based on two-level Kalman filter is proposed to overcome the problem, as shown in Fig. 2. First, the relative acceleration is estimated by using the first level Kalman filter. The vehicle relative motion model and the observation equations are written as

$$\begin{aligned} \boldsymbol{X}_1(k) &= \boldsymbol{A}_1\boldsymbol{X}_1(k-1)+\boldsymbol{B}_1\hat{\boldsymbol{a}}_{al}(k-1)+\boldsymbol{W}_1(k-1) \\ \boldsymbol{Z}_1(k) &= \boldsymbol{H}_1\boldsymbol{X}_1(k)+\boldsymbol{V}_1(k) \end{aligned} \tag{1}$$

where $\boldsymbol{A}_1=\begin{bmatrix}1 & T_s & T_s^2/2\\ 0 & 1 & T_s\\ 0 & 0 & 1\end{bmatrix}$, $\boldsymbol{B}_1=\begin{bmatrix}0\\ 0\\ T_s/\tau_1\end{bmatrix}$, and $\boldsymbol{H}_1=\begin{bmatrix}1 & 0 & 0\\ 0 & 1 & 0\end{bmatrix}$; $\boldsymbol{X}_1=\begin{bmatrix}d_r' & v_r' & a_{al}'\end{bmatrix}^T$ is system state vector and $\boldsymbol{Z}_1=\begin{bmatrix}d_r & v_r\end{bmatrix}$ is the observation vector. $\boldsymbol{W}_1$ and $\boldsymbol{V}_1$ are the state and measurement noises; d_r', v_r' and a_{al}' are the relative position, speed, and acceleration of the lead vehicle to the host vehicle, respectively; $\hat{a}_{al}(k-1)$ is the estimation of relative acceleration from the previous solution; d_r and v_r are the measured relative position and speed of the lead vehicle to the host vehicle, obtained by millimeter-wave radar; T_s is the time period; and τ_1 is the time constant of relative acceleration.

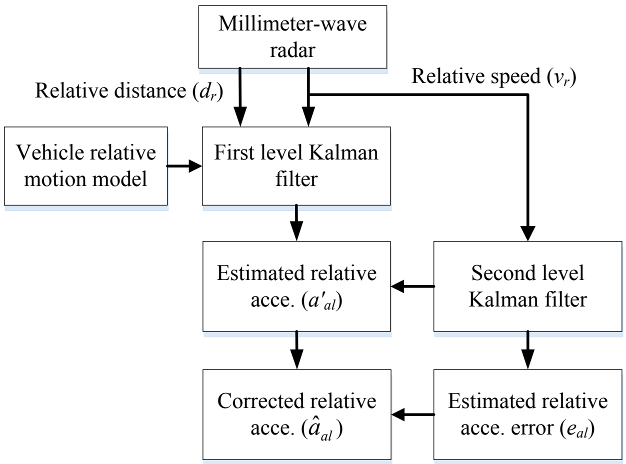


Fig. 2 Flow chart of two-level kalman filter for relative acceleration

The preliminary estimated relative acceleration a'_{al} and the relative speed is employed to estimate the relative acceleration error ($\boldsymbol{e}$) by using the second level Kalman filter. The system state-space model and the observation equations are written as

$$\begin{aligned} \boldsymbol{X}_2(k) &= \boldsymbol{A}_2\boldsymbol{X}_2(k-1) + \boldsymbol{B}_2 a'_{al}(k) + \boldsymbol{W}_2(k-1) \\ \boldsymbol{Z}_2(k) &= \boldsymbol{H}_2\boldsymbol{X}_2(k) + \boldsymbol{V}_2(k) \end{aligned} \tag{2}$$

where $\boldsymbol{A}_2 = \begin{bmatrix} 1 & -T_s \\ 0 & 1 \end{bmatrix}$, $\boldsymbol{B}_2 = \begin{bmatrix} T_s \\ 0 \end{bmatrix}$ and $\boldsymbol{H}_2 = \begin{bmatrix} 1 \\ 0 \end{bmatrix}^T$, $\boldsymbol{X}_2 = \begin{bmatrix} v_r \\ e \end{bmatrix}$ is the system state vector and $\boldsymbol{Z}_2 = v_r$ is the observation vector; $\boldsymbol{W}_2$ and $\boldsymbol{V}_2$ are the uncorrelated and gaussian noises for state and measurement. Therefore, an accurate and reliable relative acceleration is obtained by

$$\hat{a}_{al} = a'_{al} + e \tag{3}$$

As the Kalman filter theory has been fully developed, the detailed estimation equations are not presented in this paper. Based on this corrected estimation of relative acceleration, we employ a gradual reduction acceleration model to predict the future behaviors of the virtual lead vehicle. This model assumes the estimated acceleration decrease exponentially over the prediction horizon [18].

$$a_{vl}^{p}(k) = e^{-\lambda k T_s}\hat{a}_{al} \tag{4}$$

where $a_{al}^{p}(k)$ is the predicted acceleration, and λ is a positive number that defines the sharpness of reduction.

III. MPC BASED LONGITUDINAL CONTROLLER

To facilitate MPC based formulation, Fig. 3 illustrates a scene of car-following. The host vehicle is following another lead vehicle in the inner lane, while a third vehicle in the adjacent lane is seeking the opportunity to cut in. v_h, and a_h are the longitudinal speed and acceleration of the host vehicle, respectively.

A. Strategic CFG Model

To weigh the two competing goals (i.e., ensuring longitudinal safety and avoiding cut-ins), a strategic CFG model with two potential field functions is employed. One function named the hazard index (*HI*) represents the safety hazard host vehicle faced by using the probability of rear-end collision without cut-ins. The other function called the cut-in probability (*CIP*) reflects the likelihood of cut-ins by surrounding vehicles. According to [16], the two potential functions are formulated as

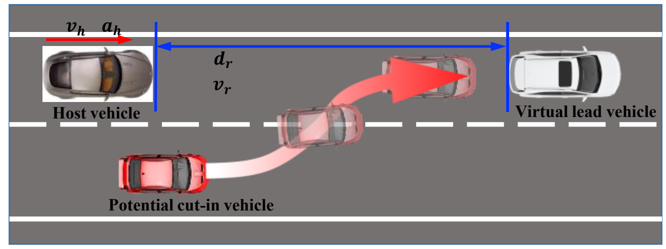
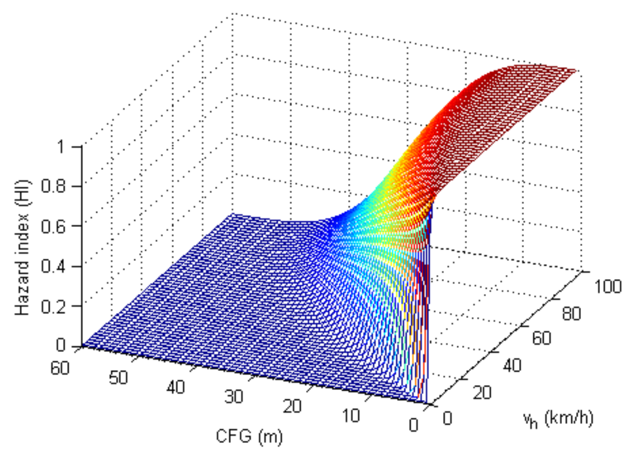


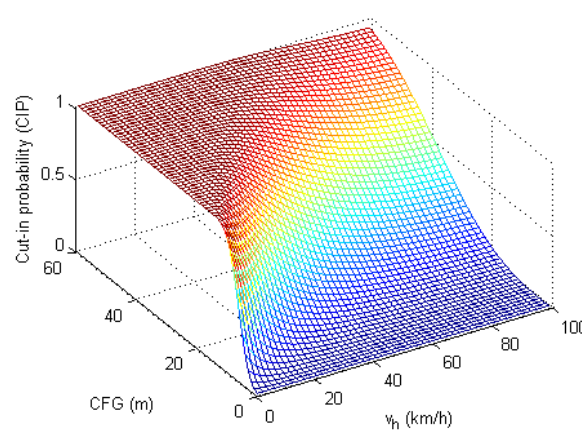
Fig. 3 Steady-state car-following with potential cut-in vehicle

$$\begin{aligned} HI &= e^{-\left(d_r / a_{NCI}\right)^{b_{NCI}}} \\ CIP &= 1 - e^{-\left(d_r / a_{CI}\right)^{b_{CI}}} \end{aligned} \tag{5}$$

where b_{NCI} and b_{CI} are shape parameters of the models without and with cut-ins, respectively, and their values are 3.44709 and 3.027836. a_{NCI} is the scale parameter of the model without cut-ins, and a_{CI} is the scale parameter of the model with cut-ins. a_{NCI} and a_{CI} are fitted and approximate highway naturalistic driving data, written as



(a) Figure of *HI*



(b) Figure of *CIP*

Fig. 4 Plot of the strategic CFG functions

$$
\begin{aligned}
a_{NCI} &= -0.0033v_h^2 + 0.6515v_h - 0.3184 \\
a_{CI} &= -0.0031v_h^2 + 0.6676v_h + 7.4344
\end{aligned} \tag{6}
$$

The comparison of *HI* and *CIP* in Fig. 4 reveals that longer CFG is needed to ensure safety while doing so the probability of cut-ins by other vehicles increases. Therefore, the strategic CFG model can be used to capture the effect of cut-ins.

B. Convex Quadratic Approximation

Due to the nonlinearity and nonconvexity of functions *HI* and *CIP*, they are computationally expensive to apply the strategic CFG model in a model predictive-based optimal control problem. However, their approximated quadratic convex problem can be solved noticeably faster. Thus, to reduce the calculation cost, *HI* and *CIP* are approximated by convex functions. As they can be represented as a function of f_*, with (d_r, v_h) being the variable, respectively. Here，the subscript * represents *HI* and *CIP*, respectively. These functions are then approximated by a quadratic function through the second order Taylor series. The norminal operation point is selected as the current point (d_{r0}, v_{h0}). This approximation is convex if both diagonal elements of the Hessian matrix are non-negative. If any diagonal element is negative, the function is linearized at the corresponding direction of the element, using only the first order Taylor series. The resulting function is a convex function convexified around the anticipated operating point [19]. The whole process is equivalent to an eigenvalue decomposition process that only keeps the positive eigenvalues. Henceforth, the resulted convex function is, written as (7), a close convex quadratic approximation of the original function around the nominal point, written as

$$
f_*(d_r, v_h) \approx f_*(d_{r0}, v_{h0}) + \nabla f_* \begin{bmatrix} d_r - d_{r0} \\ v_h - v_{h0} \end{bmatrix} + \frac{1}{2} \begin{bmatrix} d_r - d_{r0} \\ v_{hr} - v_{h0} \end{bmatrix}^T H \begin{bmatrix} d_r - d_{r0} \\ v_h - v_{h0} \end{bmatrix} \tag{7}
$$

where ∇f and $\boldsymbol{H}$ are the modified gradient and Hessian of function f_*. They can be written as

$$
\begin{aligned}
\nabla f_*(d_r, v_h) &= \begin{bmatrix} \dfrac{\partial f_*(d_{r0}, v_{h0})}{\partial d_r} & \dfrac{\partial f_*(d_{r0}, v_{h0})}{\partial v_h} \end{bmatrix} \\
\boldsymbol{H}(d_r, v_h) &= \begin{bmatrix} \dfrac{\partial^2 f_*(d_{r0}, v_{h0})}{\partial {d_r}^2} & \dfrac{\partial^2 f_*(d_{r0}, v_{h0})}{\partial d_r \partial v_h} \\ \dfrac{\partial^2 f_*(d_{r0}, v_{h0})}{\partial v_h \partial d_r} & \dfrac{\partial^2 f_*(d_{r0}, v_{h0})}{\partial {v_h}^2} \end{bmatrix}
\end{aligned} \tag{8}
$$

The modified gradient equals the original function's gradient and the modified Hessian matrix is the closest positive definite matrix to the original function's Hessian matrix in terms of Frobenius norm [20]. Using the resulted approximations, the optimal control problem is transformed into a convex quadratic optimization problem.

C. MPC Formulation

The convex quadratic approximated strategic CFG model, as well as limitations on acceleration and jerk, are incorporated in the cost function of the MPC controller. The MPC problem is formulated as (9) to seek the strategic CFG, fuel economy and ride comfort.

$$
\begin{aligned}
\min_{a_{des}, \varepsilon} \; J = \sum_{k=0}^{Np} \gamma\left(f_{HI}(k) + f_{CIP}(k)\right) \quad & (a) \\
+ \left\|a_{des}(k)\right\|_\alpha^2 + \left\|a_{des}(k) - a_{des}(k-1)\right\|_\beta^2 \quad & (b) \\
+ \left\|\varepsilon(k)\right\|_\rho^2 \quad & (c) \\
\text{s. t.} \quad \boldsymbol{\xi}(k+1) = \boldsymbol{A}_h \boldsymbol{\xi}(k) + \boldsymbol{B}_1 a_{des}(k) + \boldsymbol{B}_2 a_{vl}^p(k) \quad & (d) \\
a_{\min} \le a_{des}(k) \le a_{\max} \quad & (e) \\
\left|a_{des}(k) - a_{des}(k-1)\right| \le j_{\max} \quad & (f) \\
\boldsymbol{H}\boldsymbol{\xi}(k) \le \boldsymbol{G} + \varepsilon(k) \quad & (g)
\end{aligned} \tag{9}
$$

where the variables to be optimized are the desired acceleration of the host vehicle (a_{des}) and the constraint slack variable ε. Tunable parameters in this optimization problem are α, β, γ, *and* ρ which establishes the trade-off between the strategic CFG model (9*a*) and a smooth acceleration input (9*b*), and the slack variable costs (9*c*).

(9*d*) is the state space model for host vehicle with the system state vector defined as $\boldsymbol{\xi} = \begin{bmatrix} d_r & v_r & v_h & a_h \end{bmatrix}^T$ with

$$
\boldsymbol{A}_h = \begin{bmatrix} 1 & T_s & 0 & -T_s^2/2 \\ 0 & 1 & 0 & -T_s \\ 0 & 0 & 1 & T_s \\ 0 & 0 & 0 & 1 - T_s/\tau_2 \end{bmatrix}, \; \boldsymbol{B}_1 = \begin{bmatrix} 0 \\ 0 \\ 0 \\ T_s/\tau_2 \end{bmatrix}, \text{ and } \boldsymbol{B}_2 = \begin{bmatrix} T_s^2/2 \\ T_s \\ 0 \\ 0 \end{bmatrix}.
$$

A first order system is employed to model the relationship between the actual acceleration (a_h) and the desired acceleration (a_{des}) of the host vehicle. τ_2 is the time constant for acceleration.

The convexity of the optimization problem allows for efficient real-time implementation. CVXGEN [21] generates a solver that is implemented on a single core of an i7 processor. The resulting controller is capable of solving the optimization problem for in less than 10 ms allowing for a controller execution rate of 20 Hz. At each execution of the controller, optimization problem (9) is solved to find an optimal sequence of desired accelerations. The optimal input for the first step, $a_{des}(0)$, is applied to the vehicle, and the optimization problem is re-solved at the next time step.

IV. Simulation and Results

A. Test Scenarios

Simulations of the proposed approach are conducted in the Simulink/CarSim environment. The vehicles used in the simulations are typical D-class sedan with default parameters from CarSim database. The controller parameters are shown in Table I. Several test scenarios are defined to evaluate the performance of the proposed car-following controller for autonomous driving. The host vehicle is commanded to stay in the current lane. And the relative distance defaults as 70m when no lead vehicle is detected.

Cut-in scenario: The host vehicle is driving at 72km/h. There is a lead vehicle on the same longitudinal position with the speed of 90km/h on the adjacent lane. The lead vehicle is commanded to cut-in after 5 s. The host vehicle should react smoothly to the cut-in and maintain a strategic CFG to avoid other cut-ins.

TABLE I
MPC CONTROLLER PARAMETERS

Parameters	Value	Unit	Parameters	Value	Unit
Ts	0.05	ms	τ_1	0.2	s
$d_{r,min}$	1.5	m	τ_2	0.2	s
$v_{h,max}$	108	km/h	α	0.5	-
a_{min}	-5	m/s^2	β	0.1	-
a_{max}	1.5	m/s^2	γ	10	-
j_{max}	5	m/s^3	ρ	100	-
Np	30	-			-

Cut-out scenario: The host vehicle and the lead vehicle are driving at 72km/h on the current lane and the speed limit set to be 108km/h. The lead vehicle is commanded to change to the adjacent lane after 5 s. The host vehicle should smoothly speed up to the speed limit.

Cut-in with constant time headway scenario: In order to validate the strategic CFG model, a constant time headway model is applied in the longitudinal controller. The constant time is set to be 3 seconds. All the other settings are the same with the cut-in scenario.

Emergency cut-in scenario: The host vehicle is driving at the speed limit, 108km/h on the current lane without a lead vehicle and is commanded to stay in the current lane. There is a lead vehicle with the speed of 72km/h on the adjacent lane, commanded to cut-in after 5 s. The longitudinal distance between the preceding vehicle and the host vehicle is 90 m. This emergency for the host vehicle and it should response fast enough ensure safety.

B. Simulation Results

Simulation results and figures are given in this section. The step changes of relative distance (d_r) and relative speed (v_r) caused by the cut-ins/outs are shown in the upper plot of figures. The response of the host vehicle, e.g., the actual acceleration (a_h) and speed (v_h), are illustrated in the lower plot of figures. In addition, the desired acceleration (a_{des}) is also shown.

Fig. 5 and Fig. 6 shows the simulation results of lead vehicle cut-in and cut-out scenarios. It demonstrates that the cut-in and cut-out of the lead vehicles cause a step error in the following distance and speed of the host vehicle, which could lead to large velocity overshoot. Owing to the virtual lead vehicle scheme and the MPC based longitudinal controller, the acceleration and the jerk is smoother, thus the fuel efficiency and passenger comfort are improved.

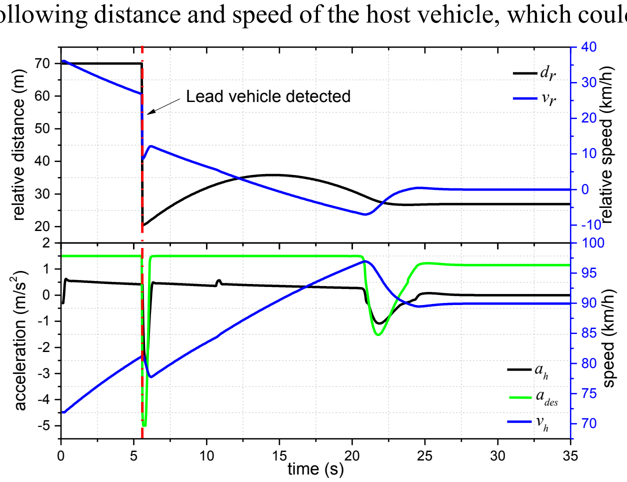


Fig. 5 Simulation results of cut-in scenario

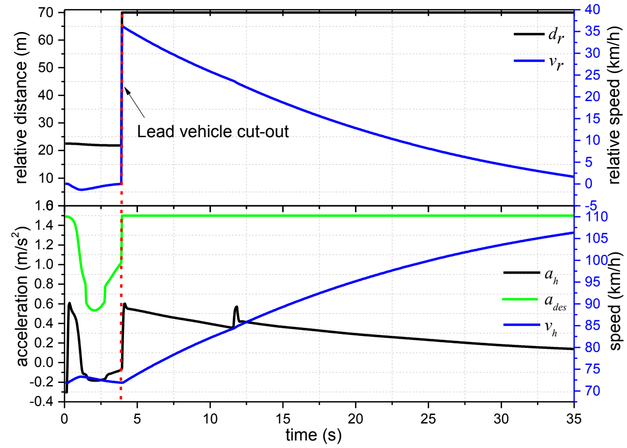


Fig. 6 Simulation results of cut-out scenario

Fig. 7 provides the simulation for the comparison cut-in scenario. The results demonstrate that the controller with strategic CFG model has a shorter car-following gap than that with the constant time headway model. Shorter following gap mitigates the probability of cut-ins from adjacent lanes.

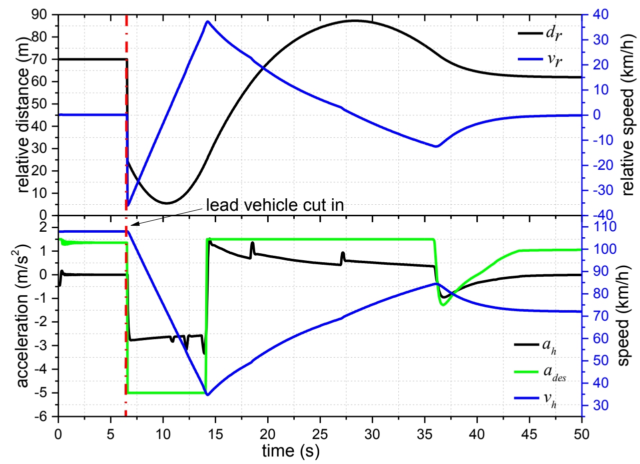


Fig. 7 Simulation results of comparison scenario for cut-in

Fig.8 illustrates the simulation results of emergency cut-in scenario. As shown in the figure, the acceleration is constrained by the acceleration and the jerk constraints. The results also show that the host vehicle response fast enough to adjust its relative distance and speed accordingly to avoid rear-end collision. Note that although the a_{des} remains constant, there are blips in the host vehicle acceleration, which are most likely a result of powertrain interrupts during gear-shift.

In summary, the virtual lead vehicle scheme smooths the motion of the host vehicle when the lead vehicle cuts out or if a new lead vehicle cuts in from an adjacent lane. The car-following gap is shorter than the controller with constant time headway model, which could reduce the probability of cut-ins. In the meanwhile, the proposed approach could ensure driving safety in emergency scenarios.

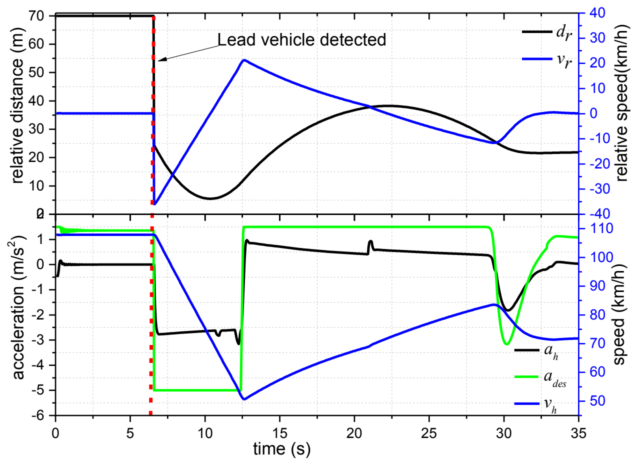


Fig. 8 Simulation results of emergency cut-out scenario

V. Conclusion

This paper presents a model predictive based longitudinal controller for autonomous driving taking lateral interruptions into account. A two-level Kalman filter is used to estimate the relative acceleration of the actual lead vehicle to the host vehicle. A virtual lead vehicle scheme is introduced to predict the future evolution of the actual lead vehicle. Then, a strategic CFG model is employed to account for the safety hazard and the probability of cut-ins, respectively. An MPC-based controller, incorporating the strategic CFG model in the cost function, is designed to find the optimal CFG. By approximating the nonlinear and nonconvex functions of the strategic CFG model with convex quadratic functions, the proposed MPC longitudinal controller is converted to a quadratic optimal problem for the real-time application. The proposed approach is simulated in CarSim software and tested by some predefined scenarios.

Future work will be focused on developing a human-like autonomous driving scheme, in which naturalistic driving data based personalized driver model and the MPC based longitudinal controller are combined together. Further validation of the proposed approach by experimental results also needs to be done.

Appendix

Videoes for simulations in this paper are available at: https://www.youtube.com/watch?v=e0E5mzmZEfM.

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