Eurasia Journal of Science and Technology
Print ISSN: 2663-1024
Online ISSN: 2663-1016
DOI: https://doi.org/10.61784/ejst3097

ADAPTIVE CRUISE CONTROL CONSIDERING THE VARIABILITY OF THE LEADING VEHICLE'S DRIVING CONDITIONS

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Abstract: Due to the complex and variable driving conditions of the leading vehicle, it is difficult to control the distance between vehicles when following, resulting in poor driving comfort and safety. Based on this, this paper proposes an adaptive cruise control considering the variable driving conditions of the leading vehicle. Firstly, the longitudinal dynamics model of the self-vehicle is established using the Carsim software. Then, a safety distance model considering the speed of the vehicle in front is established, and the tracking control of the self-vehicle to the leading vehicle is realized based on model predictive control (MPC). Finally, the following vehicle simulation experiments are completed under different driving conditions of the leading vehicle. The results show that the adaptive cruise control strategy based on the improved safety distance model can achieve comfortable and safe following under different driving conditions of the leading vehicle.
Keywords: Adaptive cruise control; Model predictive control; Dynamics model; Safety distance model

1 INTRODUCTION

With China's vigorous efforts to liberate and develop productive forces, the living standards of the people have been continuously improving, and the number of cars purchased has been increasing. This has also led to many automobile traffic accidents. According to the survey, among a large number of automobile traffic accidents, those caused by rear - end collisions account for a relatively large proportion[1]. To solve this problem, experts and scholars at home and abroad have invested a great deal of energy. Adaptive Cruise Control (ACC) has received extensive attention due to its good performance in following - vehicle driving[2-5].

In terms of foreign research, Yang et al proposed a monocular - vision - based structure[6], TheNeoNet, structure, TheNeoNet, to improve the accuracy of speed estimation. On this basis, the soft Actor - Critic method was adopted to further optimize the vehicle - following strategy, achieving an improvement in the safety and comfort of the vehicle - following strategy and having good adaptability to various driving and following - vehicle scenarios. Chen et al proposed a multi - mode - switching - based intelligent vehicle multi - objective adaptive cruise control method based on a hierarchical control structure[7], fuzzy control theory, variable - spacing strategy, and particle swarm optimization algorithm, achieving an improvement in the driving safety, comfort, and fuel economy of the vehicle during cruising under multiple working conditions. Hu et al proposed a hierarchical adaptive cruise control strategy for vehicles[8]. The upper - layer controller calculates the expected vehicle output acceleration based on model predictive control and switches between speed and spacing control according to the driving conditions. The lower - layer controller uses the brake/throttle opening switching model, the inverse brake control model, and the inverse throttle opening model to obtain the expected throttle opening and brake pressure of the vehicle, thus achieving accurate and safe tracking of the target vehicle under different driving conditions. Chen et al proposed a model - predictive - control - based vehicle - following scheme based on the continuous comprehensive variable time - headway (CSVTH) model[9]. Compared with the existing three time - headway model - predictive - control - based vehicle - following schemes, the proposed CSVTH scheme has an economic improvement of 22.7%, a vehicle - following performance improvement of 38.8%, and a comfort improvement of 15.3%.

In terms of domestic research, He Liyang et al proposed a vehicle adaptive cruise control strategy based on model predictive control and improved active disturbance rejection control[10], which effectively weakened the impact on system control caused by changes in the vehicle itself or the external environment and improved the vehicle's adaptability and stability in following vehicles under different driving conditions. An Tingyu et al established an adaptive cruise control algorithm capable of predicting the acceleration of the vehicle in front based on a temporal convolutional network[11], effectively reducing the tracking error of the speed of the vehicle in front and the following - response time during the vehicle - following process. Li Shengqin et al proposed a hierarchically - designed adaptive cruise control strategy[12]. The upper - layer controller calculates the expected vehicle output acceleration based on the model predictive control algorithm, and the lower - layer controller calculates the expected vehicle torque based on the inverse longitudinal dynamics model, thus achieving stable and safe tracking of the target vehicle under multiple working conditions. Gu Zhiqiang et al proposed a multi - mode - switching control strategy based on fuzzy logic[13]. When the driving conditions of the vehicle in front are changeable, the ego - vehicle can achieve a smooth switch of the following - vehicle mode, effectively improving the accuracy of following - vehicle control.

From the above research, it can be seen that the current adaptive cruise control strategy is no longer only satisfied with studying the vehicle - following control under ideal conditions but also takes into account the variability of the driving conditions of the vehicle in front. Based on this, this paper proposes an adaptive cruise control considering the variability of the driving conditions of the vehicle in front. First, the longitudinal dynamics model of the ego - vehicle is built using Carsim software. Then, a safety inter - vehicle distance model considering speed is established, and the acceleration control of the ego - vehicle is achieved based on model predictive control (MPC). Next, the tracking control of the vehicle in front is completed according to the inverse longitudinal dynamics model of the ego - vehicle. Finally, vehicle - following simulation experiments are completed under different driving conditions of the vehicle in front. The results show that the adaptive cruise control strategy established based on the improved safety inter - vehicle distance model proposed in this paper can achieve comfortable and safe vehicle - following under different driving conditions of the vehicle in front.

2 ESTABLISHMENT OF VEHICLE DYNAMICS MODEL

The driving process of an automobile is complex and changeable. Different driving environments will lead to different driving behaviors of drivers. As one of the solutions for vehicle - following control, the adaptive cruise control strategy can effectively cope with different driving environments. In this paper, Carsim software is used to build the longitudinal dynamics model of the ego - vehicle to achieve the tracking control of the vehicle in front, enabling the ego - vehicle to follow the vehicle in front safely and comfortably[14]. The main interface of Carsim software for modeling is shown in Figure 1. The modeling process mainly consists of three parts: simulation conditions, solver, and vehicle parameter setting. After setting these three parts, a simulation experiment can be carried out to obtain the simulation results of the target vehicle under different working conditions[15].

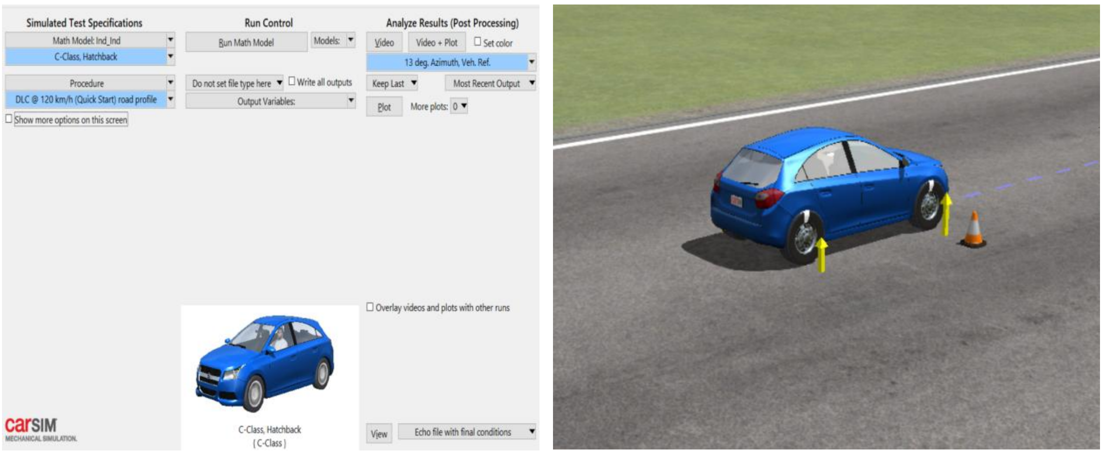

Figure 1 Main Interface of Carsim Modeling

This paper takes electric vehicles as the research object, establishes a vehicle model using some parameters of the Tesla Model 3 as the research vehicle parameters, and conducts adaptive cruise control simulation tests. Table 1 shows some parameters set in this model. In terms of layout, the rear-mounted rear-wheel drive scheme is adopted as the vehicle's driving mode.

Table 1 Vehicle Parameters

Parameter	Value
Curb weight	1760kg
Wheelbase	2875mm
Maximum power	194kw
Maximum torque	340N.m
Drag coefficient	0.22

3 ADAPTIVE CRUISE CONTROL STRATEGY

The overall flow of the adaptive cruise control strategy is shown in Figure 2, which consists of three parts: the safe inter-vehicle distance model, the MPC controller, and the inverse longitudinal dynamics model. First, the safe inter-vehicle distance model calculates the desired inter-vehicle distance based on the preceding vehicle information obtained from radar and cameras and the host vehicle information. Then, the MPC controller obtains the desired acceleration according to the desired inter-vehicle distance and the actual inter-vehicle distance obtained from radar and cameras. Finally, the inverse longitudinal dynamics model obtains the output torque of the vehicle based on the desired acceleration and the actual acceleration of the host vehicle, thereby realizing the control of the vehicle.

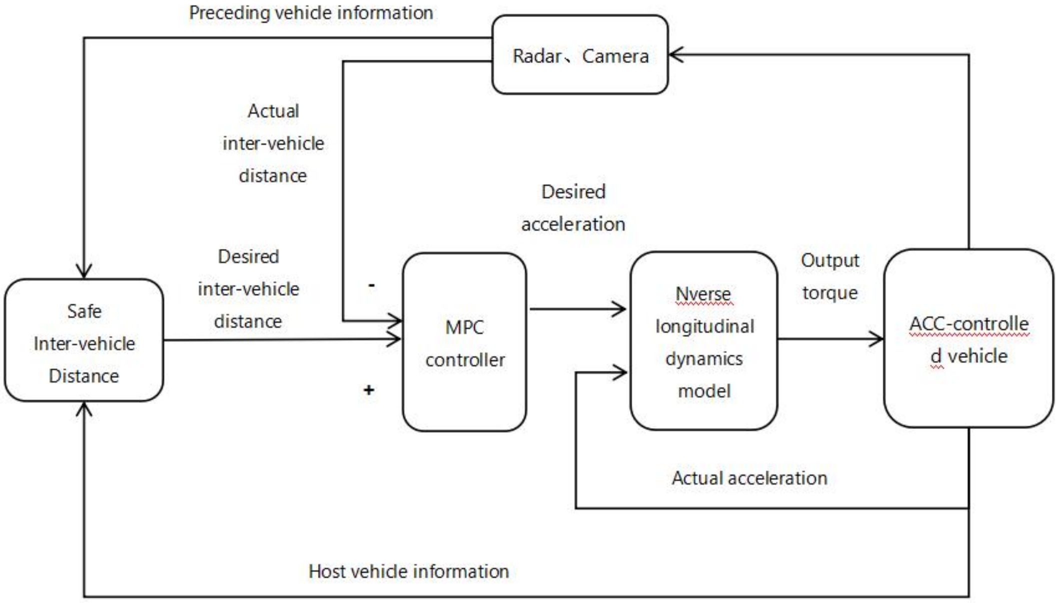

Figure 2 Overall Flow of Adaptive Cruise Control Strategy

3.1 Safe Inter-Vehicle Distance Model

The common safe inter-vehicle distance model in ACC strategies is an ideal inter-vehicle distance model, which does not consider the speed and acceleration of the preceding vehicle, but only the speed of the host vehicle, so that the inter-vehicle distance remains unchanged in a short time[16]. The specific formula is:

$$d_{exp}=v_{sel}t_1+d_{min} \tag{1}$$

Where: d_{exp} is the desired safe inter-vehicle distance between two vehicles; v_{sel} is the speed of the host vehicle; t_1 is the fixed inter-vehicle time headway, generally ranging from 1.5 to 2.0 s; d_{min} is the minimum safe inter-vehicle distance, generally ranging from 3 to 5 m.

In order to make the inter-vehicle distance model better adapt to different car-following conditions, this paper comprehensively considers the factors of the host vehicle speed and the preceding vehicle speed on the basis of the above common safe inter-vehicle distance. When the preceding vehicle speed v_{fro} is equal to the host vehicle speed v_{sel}, the host vehicle travels at a constant inter-vehicle distance; when $v_{fro} < v_{sel}$, the preceding vehicle speed is lower than that of the host vehicle, and the host vehicle needs to decelerate appropriately to increase the inter-vehicle distance to avoid collision; when $v_{fro} > v_{sel}$, the host vehicle should accelerate appropriately to reduce the following distance while ensuring safety. The specific formula is as follows:

$$d_{exp}=v_{sel}t_1+d_{min}-v_{rel}t_2+v_{sel}t_3^2 \tag{2}$$

Where t_2 and t_3 are constants greater than 0, and v_{sel} is the speed difference between the preceding vehicle and the host vehicle.

3.2 MPC Controller

3.2.1 Vehicle kinematic model

The schematic diagram of the longitudinal motion between vehicles is shown in Figure 3, where a_{sel} and a_{fro} are the accelerations of the host vehicle and the preceding vehicle respectively, v_{sel} and v_{fro} are the speeds of the host vehicle and the preceding vehicle respectively, and the following definitions are made:

$$\begin{cases} \triangle d=d-d_{exp} \\ v_{rel}=v_{fro}-v_{sel} \end{cases} \tag{3}$$

Where $\triangle d$ is the difference between the actual inter-vehicle distance d and the safe inter-vehicle distance, and v_{rel} is the speed difference between the preceding vehicle and the host vehicle.

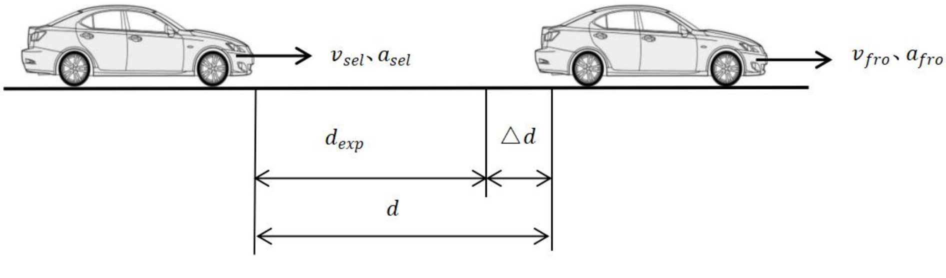

Figure 3 Schematic Diagram of Vehicle Longitudinal Motion

To eliminate the influence of time delay, a first-order inertial element is used to represent the relationship between the host vehicle acceleration a_{sel} and the desired acceleration a_{exp}:

$$a_{sel}=\frac{K_L}{T_L s+1}a_{exp} \tag{4}$$

Where: K_L is the system gain; T_L is the time constant; s is the Laplace operator.

Define the system state variables as $x(k)=[d(k),v_{sel}(k),v_{rel}((k),a_{sel}(k),j(k)]^T$, the system output vector as $y(k)=[\triangle d(k),v_{rel}((k),a_{sel}(k),j(k)]^T$, and $j(k)$ as the jerk of the host vehicle. Since it is difficult for sensors to accurately sense the acceleration of the preceding vehicle, and the acceleration of the preceding vehicle will affect the car-following control process of the host vehicle, the interference factor w(k) of the preceding vehicle acceleration is added to establish the following discrete state space equations:

$$x(k+1)=Ax(k)+Ba_{exp}(k)+Gw(k) \tag{5}$$

$$y(k)=Cx(k)-D \tag{6}$$

Where: A, B, and C are coefficient space matrices, where $A=\begin{bmatrix}1 & 0 & T_s & -0.5T_s^2 & 0\\ 0 & 1 & 0 & T_s & 0\\ 0 & 0 & 1 & -T_s & 0\\ 0 & 0 & 0 & 1-\frac{T_s}{\Upsilon} & 0\\ 0 & 0 & 0 & -\frac{1}{\Upsilon} & 0\end{bmatrix}$, $B=\begin{bmatrix}0\\0\\0\\\frac{T_s}{\Upsilon}\\\frac{1}{\Upsilon}\end{bmatrix}$, $G=\begin{bmatrix}0.5T_s^2\\0\\T_s\\0\\0\end{bmatrix}$, T_s is the time interval between the previous and current moments of the host vehicle, and Υ is the time constant, $C=\begin{bmatrix}1 & -t_1-t_3^2 & t_2 & 0 & 0\\ 0 & 0 & 1 & 0 & 0\\ 0 & 0 & 0 & 1 & 0\\ 0 & 0 & 0 & 0 & 1\end{bmatrix}$, $D=\begin{bmatrix}d_{min}\\0\\0\\0\end{bmatrix}$.

3.2.2 Controller design

Due to the uncertainty of vehicle parameters, there will be a certain deviation between the predicted value and the actual measured value. Therefore, to improve the accuracy of the system, the prediction error $e(k)$ is introduced to correct Equation 5, resulting in the prediction equation:

$$x(k+1|k)=Ax(k)+Ba_{exp}(k)+GW(k)+He(k) \tag{7}$$

Where: $e(k)=x(k)-x(k|k-1),H=diag(\mathrm{h}_1,\mathrm{h}_2,\mathrm{h}_3,\mathrm{h}_4,\mathrm{h}_5)$ is the correction matrix, and the value range of each element in H is (0, 1).

From Equations 5 and 7, the vehicle prediction model can be derived:

$$\begin{cases} X_p(k+N_p|k)=A_p x(k)+B_p A_{exp}(k+N_c)+G_p W(k+N_p)+H_p e(k)\\ Y_p(k+N_p|k)=C_p x(k)+F_p A_{exp}(k+N_c)+S_p W(k+N_p)+L_p e(k)-D_p\end{cases} \tag{8}$$

Where: N_p is the prediction horizon; N_c is the control horizon; $X_p(k+N_p|k)$and $Y_p(k+N_p|k)$ are the system state and output quantities from time k+1 to time $k+N_p$, respectively; A_p、B_p、G_p、H_p、C_p、F_p、S_p、L_p and D_p are all coefficient matrices of the prediction model; $A_{exp}(k+N_c)$ is the desired acceleration matrix; $W(k+N_p)$ is the system disturbance matrix.

During the MPC solution process, using hard constraints may result in no feasible solution[17]. To avoid this, this paper relaxes the hard constraints. Meanwhile, to prevent the constraint boundaries from expanding infinitely, a quadratic term of the slack factor is added to the objective function as a penalty. The objective function is established as follows:

$$\begin{gathered} J(k)=\sum_{i=1}^{N_p}[y_p(k+i|k)-y_{ref}(k+i|k)]^{\mathrm{T}}\times Q[y_p(k+i|k)-y_{ref}(k+i|k)]+\\ \sum_{i=1}^{N_p}a_{exp}{}^{\mathrm{T}}(k+i)Ra_{exp}(k+i)+\varepsilon^{\mathrm{T}}\rho\varepsilon \end{gathered} \tag{9}$$

$$\begin{cases} a_{min}+\varepsilon_1\delta_{min}^a\leq a_{sel}(k)\leq a_{max}+\varepsilon_1\delta_{max}^a\\ v_{min}+\varepsilon_2\delta_{min}^v\leq v_{sel}(k)\leq v_{max}+\varepsilon_2\delta_{max}^v\\ j_{min}+\varepsilon_3\delta_{min}^j\leq j(k)\leq j_{max}+\varepsilon_3\delta_{max}^j\\ a_{exp,min}+\varepsilon_4\delta_{min}^{a_{exp}}\leq a_{exp}(k)\leq a_{exp,max}+\varepsilon_4\delta_{max}^{a_{exp}}\end{cases} \tag{10}$$

Where:Q and R are weight coefficients; δ_{min}^a、δ_{min}^v、δ_{min}^j、$\delta_{min}^{a_{exp}}$ and δ_{max}^a、δ_{max}^v、δ_{max}^j、$\delta_{max}^{a_{exp}}$ are the slack coefficients for the upper and lower bounds of the system's hard constraints respectively; ε_1、ε_2、ε_3、ε_4 are slack factors; a_{min} and a_{max} are the minimum and maximum values of the host vehicle's acceleration respectively; v_{min} and v_{max} are the minimum and maximum values of the speed respectively; j_{min} and j_{max} are the minimum and maximum values of the jerk respectively; $a_{exp,min}$ and $a_{exp,max}$ are the minimum and maximum values of the control quantity respectively.

3.3 Inverse Longitudinal Dynamics Model

The key to longitudinal control lies in accurately obtaining the required torque of the host vehicle under different working conditions. Assuming that the vehicle is driving on a horizontal road surface, when the vehicle acceleration is known, the required torque of the vehicle can be derived inversely according to the longitudinal dynamics, specifically as follows:

$$
\begin{cases}
F_j = F_q - F_f - F_w \\
a_{exp} = \frac{1}{m\beta}\left(\frac{T_{exp} i_c \mu}{r} - mgf - \frac{1}{2} C_D A \rho v_{sel}^2\right) \\
F_q = \frac{T_{exp} i_c \mu}{r} \\
F_f = mgf \\
F_w = \frac{1}{2} C_D A \rho v_{sel}^2 \\
F_j = m\beta a_{exp}
\end{cases} \tag{11}
$$

Where: m is the total mass of the vehicle; β is the conversion coefficient of the vehicle's rotating mass; T_{exp} is the total expected torque of the motor; i_c is the total transmission ratio; μ is the motor efficiency; r is the wheel radius; f is the tire rolling friction coefficient; C_D is the air resistance coefficient; A is the windward area; and ρ is the air density.
The expected torque of the motor can be obtained from Equation 11:

$$
T_{exp} = \frac{r[m(\beta a_{exp} + gf) + \frac{1}{2} C_D A \rho v_{sel}^2]}{i_c \mu} \tag{12}
$$

4 SIMULATION VERIFICATION

Co-simulations were conducted using Carsim and Matlab/Simulink to verify the effectiveness of the control strategy designed in this paper under three working conditions: constant speed, deceleration, and acceleration. Figures 4, 5, and 6 show the simulation results of the host vehicle and the preceding vehicle under the corresponding working conditions, respectively.

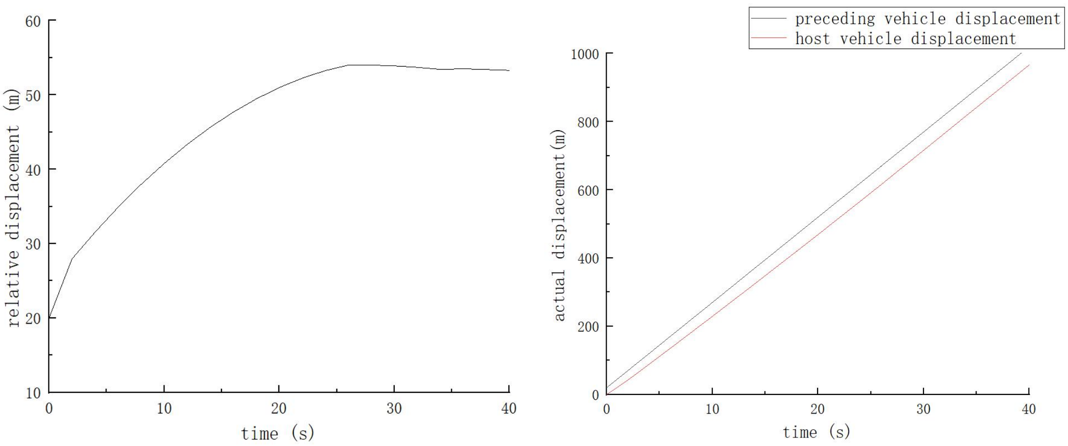

Figure 4 Simulation Setup for the Preceding Vehicle under Constant Speed Condition

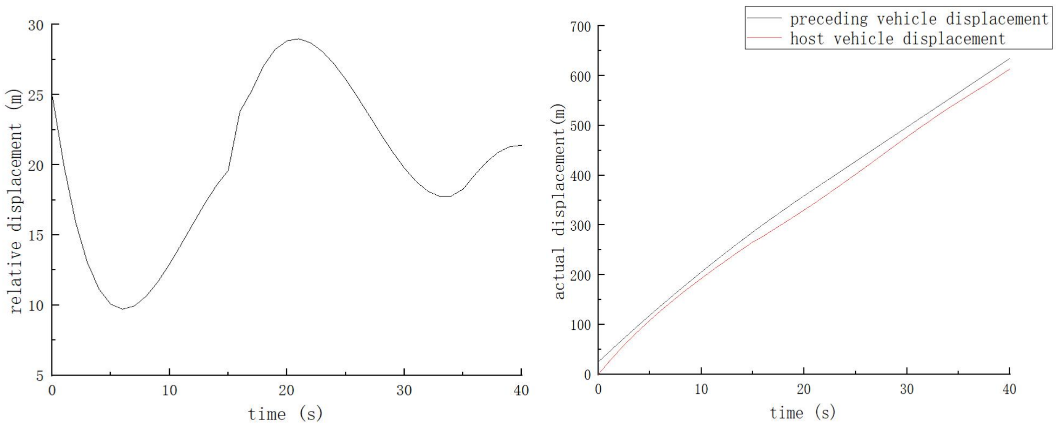

Figure 5 Simulation Setup for the Preceding Vehicle under Deceleration Condition

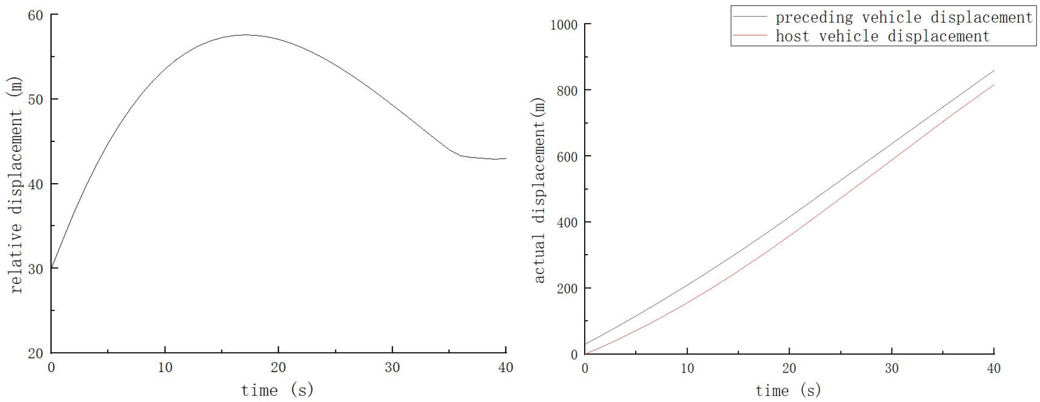

Figure 6 Simulation Setup for the Preceding Vehicle under Acceleration Condition

The simulation setup for the constant-speed condition is shown in Figure 4. At the start of the simulation, the distance between the preceding vehicle and the host vehicle is 20 meters. The preceding vehicle travels at a constant speed of 90 km/h, and the host vehicle follows at 75 km/h. To ensure effective following and improve road utilization, the host vehicle starts to accelerate. Since acceleration takes time, the inter-vehicle distance increases during this period. As the host vehicle's speed approaches that of the preceding vehicle, its acceleration gradually decreases, maintaining the distance between the two vehicles within a safe range.

The simulation setup for the deceleration condition is shown in Figure 5. At the beginning of the simulation, the preceding vehicle and the host vehicle are 25 meters apart. The preceding vehicle uniformly decelerates from 70 km/h to 50 km/h, while the host vehicle follows at 90 km/h. At this point, the sensors detect that the preceding vehicle is decelerating, and the actual inter-vehicle distance is much smaller than the desired safe distance, so the host vehicle starts to decelerate. The inter-vehicle distance first decreases and then increases, with a minimum distance of 9.7 meters, which well ensures the safety between the vehicles.

The simulation setup for the acceleration condition is shown in Figure 6. At the start of the simulation, the distance between the preceding vehicle and the host vehicle is 30 meters. The preceding vehicle is traveling at 60 km/h, and the host vehicle at 48 km/h. The preceding vehicle uniformly accelerates to 80 km/h. The host vehicle, recognizing that the preceding vehicle is accelerating and that its own speed is lower, also starts to accelerate, leading to an increase in the inter-vehicle distance. When the preceding vehicle begins to travel at a constant speed, the host vehicle gradually decelerates, causing the inter-vehicle distance to decrease and stabilize. The inter-vehicle distance shows a good response to changes in vehicle speed.

5 CONCLUSIONS

In this paper, the longitudinal dynamics model of the host vehicle is built using Carsim software. Then, a safe inter-vehicle distance model considering speed is established, and the acceleration control of the host vehicle is realized based on model predictive control (MPC). Furthermore, the tracking control of the preceding vehicle is completed according to the inverse longitudinal dynamics model of the host vehicle. Finally, co-simulations using Carsim and Matlab/Simulink are conducted to complete the car-following experiments under three working conditions of the preceding vehicle. The results show that the adaptive cruise control strategy proposed in this paper, which is based on the improved safe inter-vehicle distance model, can achieve comfortable and safe car-following under different driving conditions of the preceding vehicle.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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