



A variable weight adaptive cruise control strategy based on lane change recognition of leading vehicle

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ABSTRACT

The traditional adaptive cruise system is responsible for delay in recognizing the cut-in/cut-out behaviour of front vehicle, and there is significant longitudinal acceleration of the vehicle fluctuation leading to reduced driver's comfort level and even dangerous situation. In this paper, the next generation simulation data set and back propagation (BP) neural network are used to train the vehicle lane change recognition model to recognize the lane change behaviour of the preceding vehicle. The higher controller adopts variable weight linear quadratic optimal control to adjust the weight parameters according to the recognition results of front vehicle to reduce the fluctuation of vehicle acceleration. The lower layer adopts fuzzy proportional-integral-derivative (PID) control to follow the expected acceleration and builds the vehicle inverse dynamic model. Through CarSim/Simulink co-simulation, the results show that, under the cut-in or cut-out and working conditions, the behaviour of the leading vehicle can be recognized, following target can be switched in advance, weight parameters can be adjusted and the large fluctuation of longitudinal acceleration can be reduced.

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Adaptive cruise control; lane change intention recognition of leading vehicle; layered control; weight adjustment strategy

1. Introduction

Adaptive cruise control (ACC) system is an advanced auxiliary driving system developed with the foundation of the steady speed cruise, which can obtain the information of front vehicle speed and distance. With the data available from sensors and based on the application algorithm, the controlling behaviour of the vehicle remains stable with front car by significantly reducing the fatigue of the drivers [1]. In case of the adaptive cruise system, the main task of target identification is to select the main purpose of vehicle tracking and to carry out the acceleration control of vehicle based on the motion status information of the main target. When the vehicle at the front cuts into or cuts out of the main lane, an ACC system should have necessary or even advance response capability [2]. In this process, ACC vehicles may have challenges of late braking and excessive braking [3]. Therefore, managing to identify and respond to the behaviour of vehicles in front in advance is of great significance to improve the performance of the ACC system.

Many scholars have carried out in-depth research on the ACC system. Gao et al. [4] designed an ACC system that can identify driver online requirement to meet the needs of different driving modes. Liu et al. [5] proposed a new safe distance model based on the analysis of real driving test data to optimize the safety and comfort economy of the ACC system. In terms of control algorithms, there are several methods such as PID

control, optimal control, model predictive control and other commonly used control algorithms [6]. Yang et al. [7] proposed ACC algorithm combining model predictive control and active disturbance rejection control by adopting hierarchical control algorithm. However, the online optimization process of model predictive control algorithm needs repeated optimization calculation, and the calculation cost is high, so it is difficult to ensure the real-time requirements of the system [8,9]. Xu et al. [10] proposed a control strategy based on optimal control in which adaptive cruise and lane keeping system can run simultaneously. Due to the complexity of actual traffic, linear quadratic optimal (LQR) control with fixed weight coefficient is unable to meet the performance requirements of the ACC system. Based on this, a variable weight LQR control algorithm is proposed to solve the expected follow acceleration in real time.

ACC system mostly adopts the hierarchical control structure. The upper control algorithm produces the desired acceleration required for safe follow according to the current driving environment. The lower controller switches control through throttle and brake, so that the actual acceleration of the vehicle can track the expected acceleration of the upper controller [11]. However, due to the vehicle's own nonlinear and external interference factors, the lower controller has poor robustness and the control effect is difficult to achieve the desired effect [12]. Therefore, fuzzy PID control is used in the lower layer as described in this paper, so that

the actual acceleration can quickly and stably follow the expected acceleration.

Currently, most studies on the ACC system are only able to control the vehicle target in the main lane, and the following target can only be replaced when the vehicle in the adjacent lane completely cuts into or cuts out of the main lane [13]. This leads to the phenomenon of lag in cutting recognition of the front vehicle, increasing the driver's sense of panic and excessive braking reduces ride comfort. Therefore, the ACC system based on cut-in vehicle recognition has important practical significance. Moon et al. [14] calculated the lane change probability of leading vehicle through the fuzzy controller to perform the target fusion of leading vehicle. Chen et al. [15] proposed a method to identify and quantify the possibility of vehicle access. Lane changing behaviour of vehicles has certain regularity. In the recent years, many scholars use machine learning methods to identify lane changing behaviour of vehicles. Zeisler et al. [16] used the information collected by sensors to predict the cut-in behaviour of surrounding vehicles using Bayesian network. Díaz-Álvarez et al. [17] used artificial neural network to build the lane change decision model. Remmen et al. [18] used machine learning algorithms such as support vector machines to identify the cutting vehicles. Jin et al. [19] proposed a lane changing behaviour decision-making model based on the Gauss mixture hidden Markov model. In addition, Do et al. [20] proposed different lane changing behaviour models based on various scenarios.

Through analysis, it is found that most of the existing studies have the following limitations. First, the prediction time is delayed, the information source is single, and the lane changing behaviour of drivers cannot be fully characterized, and the prediction accuracy is low. Second, most of the test data are obtained by driving simulators, which are very different from the real environment and the driver's psychological state. Based on this, in this paper, next generation simulation (NGSIM) data set of American expressways is used to train the lane change recognition model of the vehicle ahead using BP neural network.

Aiming at the above problems, a variable weight ACC strategy based on lane changing behaviour recognition of the vehicle ahead is proposed in this paper. The main contributions are summarized as follows:

- (1) The lane changing characteristics of vehicles are extracted using NGSIM data set, and the vehicle lane changing recognition model is obtained using BP neural network offline training. According to the information collected by sensors, the lane changing behaviour of the vehicle in front is identified online. The results show that the trained model can accurately identify the lane changing

condition of the vehicle in front, switch to follow the main target in advance and reduce the driver's discomfort caused by the sudden jump of the main target.

- (2) According to different driving conditions of the vehicle in front, the weight coefficient adjustment strategy of the LQR control algorithm is designed. Compared with the fixed weight algorithm, the proposed control algorithm can adjust the objective function in real time and reduce the fluctuation of acceleration. This makes ACC control more in line with the driver's decision-making process and improves driving safety and riding comfort.
- (3) The design details of the ACC system which is provided in this paper adopt a hierarchical control structure, and the upper layer adopts LQR control to obtain the expected acceleration considering relative velocity, relative distance and self-acceleration. In order to avoid time-varying vehicle parameters and external interference, fuzzy PID control is adopted in the lower layer to make the actual acceleration track the expected acceleration quickly and accurately.

The rest of this paper is organized as follows. Section 2 introduces the overall design framework of the ACC system. Section 3 introduces how to train the lane changing recognition model based on BP neural network using NGSIM data set. The ACC layered control algorithm and weight adjustment strategy are introduced in Section 4. In Section 5, details of the simulation analysis and comparison experiments carried out to verify the effectiveness of the control strategy are provided. Finally, the summary of the main conclusions is provided in Section 6.

2. Overview of the ACC system

The overall design framework of the ACC system is shown in Figure 1. The speed, acceleration, and position information of the leading vehicle can be calculated based on the relative distance and speed between the main vehicle and the leading vehicle information collected by the sensor. Based on the vehicle lane changing data available from US highway data set NGSIM, the vehicle lane changing recognition model was obtained by offline training with BP neural network, in order to identify the lane changing condition of the previous vehicle online. The ACC strategy adopts layered control, and the upper layer adopts variable weight LQR control algorithm, which adjusts weight parameters according to different driving conditions of the vehicle in front. The lower layer adopts fuzzy PID control to avoid the influence of external interference and vehicle parameter consolidation which makes the actual acceleration difficult to track the expected acceleration quickly and accurately. In order to avoid vehicle

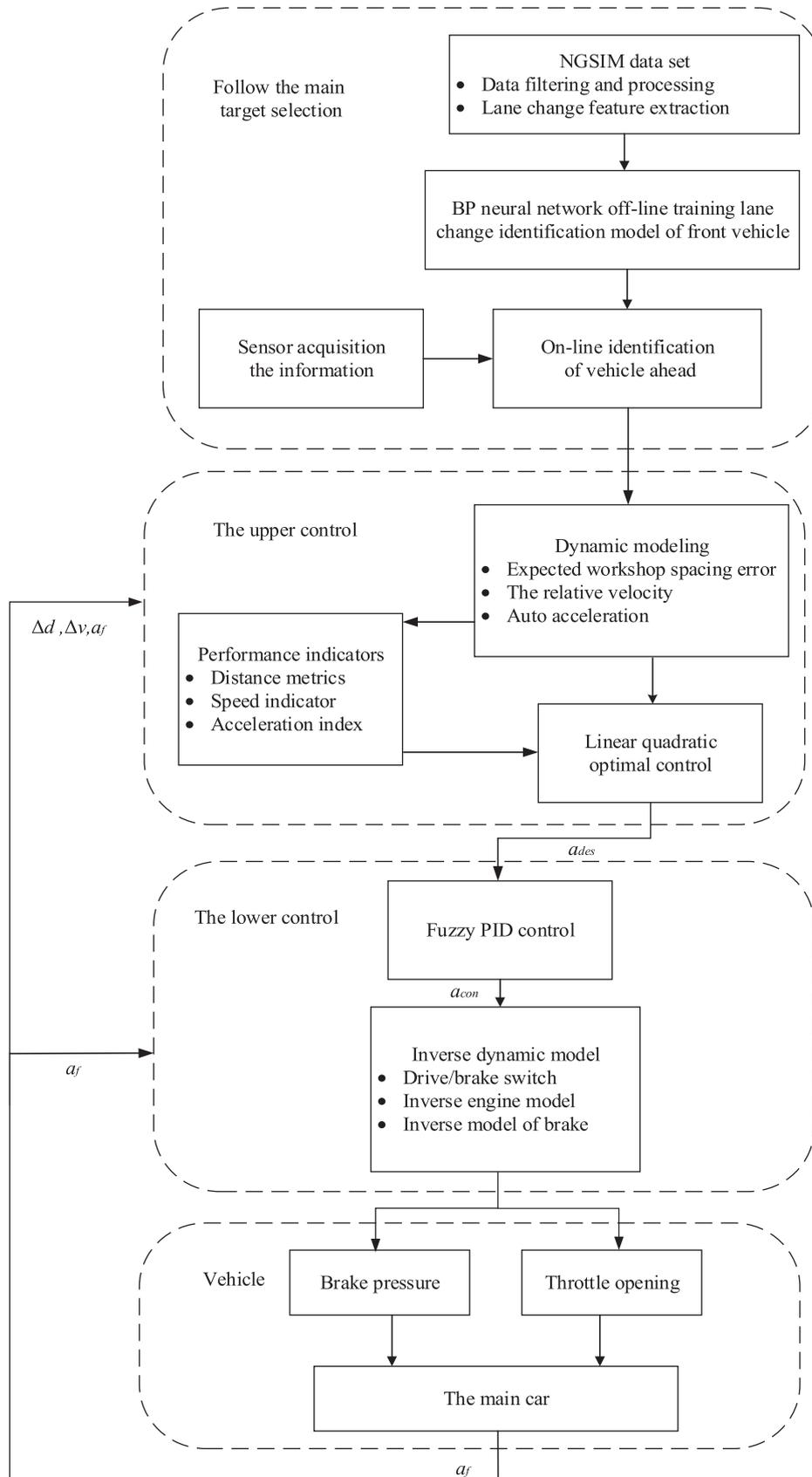


Figure 1. Overview of the ACC system.

accelerating and braking simultaneously, the braking and driving switching logic is designed. In addition, the corresponding throttle opening and braking master cylinder pressure are obtained through the vehicle

inverse dynamics model. After acting on the main vehicle, the feedback adjustment is performed continuously according to the vehicle state at the next moment, so as to realize the function of the ACC system.

3. Introduction to recognition of front vehicle lane changing behaviour

Since there is no communication between the front and rear vehicles, for the rear vehicles, the intention of front vehicle's behaviour cannot be directly known, but the motion state parameters of the front vehicle can be calculated through the relative motion relationship of the surrounding vehicles detected by the sensor. The traditional adaptive cruise main target selection algorithm only controls the main target vehicle in the main lane. In order to accurately follow the main target and to reduce the discomfort feeling of the driver, the NGSIM data set is selected to extract the lane changing characteristic parameter of driving vehicles. Driving behaviour intention is divided into three types: lane change left, lane change right, and lane keep. The lane changing behaviour recognition was established based on the BP neural network model.

3.1. Lane change feature selection

Figure 2 shows the analysis of driving behaviours such as lane keeping and left-right lane changing when the vehicle is driving on a straight road. When the vehicle is in lane keeping state, its lateral movement will not have a large range, instead only a small change, and it will not appear a fixed movement state in a certain direction. In the process of lane change, the movement of vehicles in the lateral direction has an obvious trend

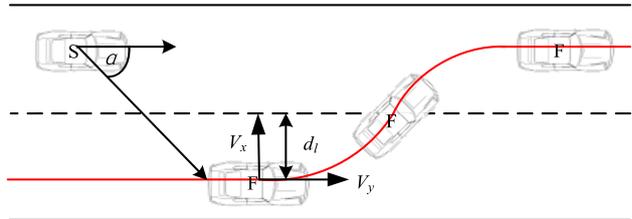


Figure 2. Schematic diagram of vehicle lane change.

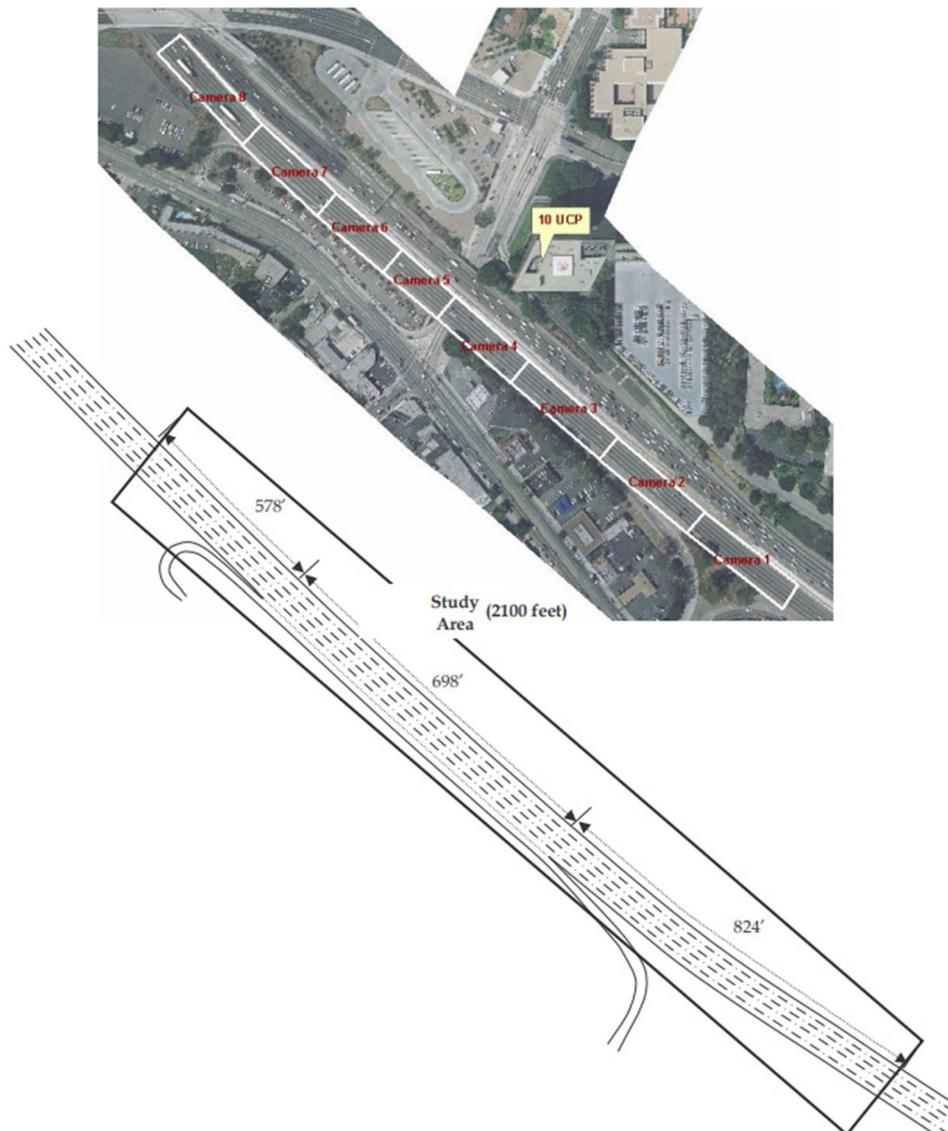


Figure 3. NGSIM dataset study area.

of change. Therefore, the change rule of vehicles in the lateral direction can well distinguish lane keeping and lane change on the left and right, and the physical quantity related to the lateral movement can also be used as the observation variable to characterize lane change behaviour. Based on the above analysis, the distance between the vehicle in front and the left lane line of original lane, the lateral velocity and the longitudinal velocity of the vehicle in front were selected as the observation variables, among which the distance between the vehicle and the left lane line was the most significant parameter. The three observation variables of the model are respectively described as lateral velocity of the leading vehicle V_x , the longitudinal velocity of leading vehicle V_y , and the distance between the front vehicle centre and the lane line on the left side of the initial lane d_l .

3.2. Data set selection and processing

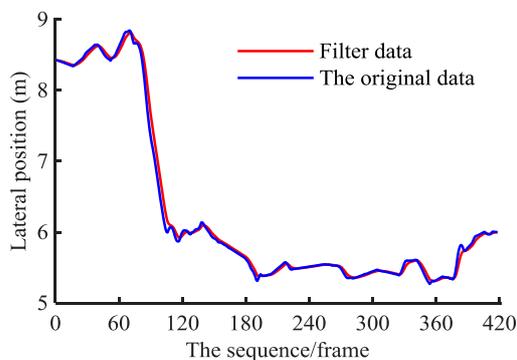
In this paper, the vehicle trajectory data of US-101 provided by the NGSIM project of the Federal Highway Administration of the United States is selected as the research data [21]. This project uses the camera to sample every 0.1 s and obtains the vehicle trajectory data through video software processing, such as vehicle acceleration, speed, lane, and so on. Therefore, this data set is used in this paper to study the vehicle lane change recognition model, and the NGSIM data set to study the road section area as shown in Figure 3.

Table 1. Width of lanes in US-101.

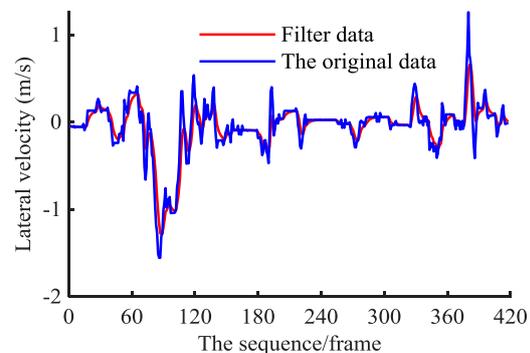
Lane number	Left lane line position (m)	Position of right lane line (m)	Lane width range (m)
1	0	3.75	3.58–3.75
2	3.58	7.45	3.39–3.97
3	7.14	11.03	3.38–3.89
4	10.83	14.79	3.54–3.96
5	14.57	18.45	3.34–3.88

In this study, vehicles in the NGSIM data set were selected as the research object to analyze their lane change characteristics. In order to avoid the influence of forced lane change behaviour and to obtain data on vehicles on and off the ramp, the data of lanes 1–5 were selected for this study. Table 1 shows the data on width of lanes in US-101 [22]. According to the lane width and the distance between the head centre and the left edge of the section, the distance between the vehicle and the lane line on the left side of the initial lane can be obtained.

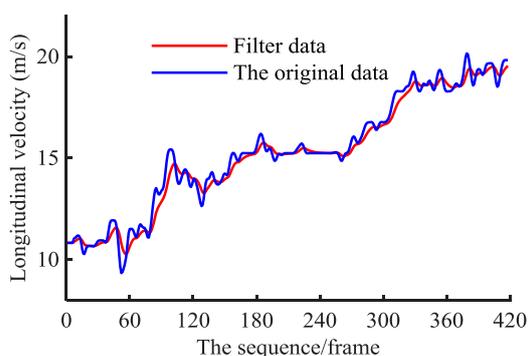
The original NGSIM data is not filtered and has certain measurement error and noise. In order to reduce the influence of error, the Kalman filtering is adopted to process the vehicle trajectory data. Since the vehicle speed in the NGSIM data set is the speed in the driving direction, the longitudinal and transverse velocity data of vehicle cannot be obtained. Therefore, the changing rates of the horizontal and vertical coordinates of the vehicle can be obtained. Figure 4(a) shows the transverse displacement fitting curve of No. 543 vehicle processed by Kalman filter, Figure 4(b) shows the



(a) Fitting curve of vehicle lateral displacement



(b) Fitting curve of vehicle lateral velocity



(c) Fitting curve of vehicle longitudinal velocity

Figure 4. Kalman filtering results for vehicle no. 543.

transverse velocity fitting curve, and Figure 4(c) shows the longitudinal velocity fitting curve. As it is evident from these results, the transverse displacement data has no obvious change after filtering, while the transverse velocity and longitudinal velocity data smooth the fluctuation of data change after filtering and still reflect the driving behaviour characteristics of vehicles while changing lanes. Therefore, the filtered data is replaced with the original data.

After filtering the data, in order to train the lane changing recognition model of the leading vehicle and extract the lane changing data, it is necessary to retrieve the ID of the lane changing vehicle. Combined with the data screening method proposed by Yang et al. [23], the vehicle movement trajectory data within 5 s before and after the time when the vehicle centre crosses the lane line is extracted for this research. It can guarantee to cover the whole process of vehicle lane change. To extract the characteristic parameters of vehicle lane change trajectory, it is necessary to find the starting point and end point of vehicle lane change. In this paper, the time when the lateral velocity of vehicle is greater than 0.2 m/s proposed by Wang et al. [24] is adopted as the beginning of vehicle lane change time. Through data screening, some unconventional lane changing data are excluded, such as continuous lane changing data and data obtained from the lane changing to the target lane and then returning to the lane immediately. Only a single lane changing scenario is considered. A set of vehicle trajectory data includes lane keeping and vehicle lane changing. The data sample in the vehicle holding state is added with a digital label 0, the data sample in the left lane changing state is added with a digital label 1, and the data sample in the right lane changing state is added with a digital label 2.

3.3. Lane change recognition of leading vehicle based on BP neural network

The method of vehicle lane changing condition recognition based on feature extraction combined with classification algorithm has been proved to have good feasibility and practicability [25]. In this paper, BP neural network is used to train lane changing intention recognizer based on vehicle lane changing data collected

from actual road, and it is used to recognize lane changing condition online. According to the surrounding vehicle information obtained by the sensor, the specified characteristic parameters are extracted from the data and input into the trained recognition algorithm to output the real-time driving condition category. Considering the driving characteristics of vehicles, driving intention is divided into three categories: left lane changing, right lane changing, and lane keeping. Based on the corresponding driving behaviour characterization parameters, a lane changing intention recognition model of the vehicle in front is established. The working process of lane changing recognition is shown in Figure 5.

BP neural network usually includes input layer, hidden layer, and output layer, which is often used to deal with classification and nonlinear prediction problems. This algorithm has strong nonlinear mapping and self-learning ability, which is conducive for improving the identification accuracy [26]. The designed vehicle lane changing condition recognition network structure is shown in Figure 6. After the correlation analysis between characteristic parameters and lane changing conditions, the longitudinal velocity, lateral velocity, and the distance between the head centre and the left

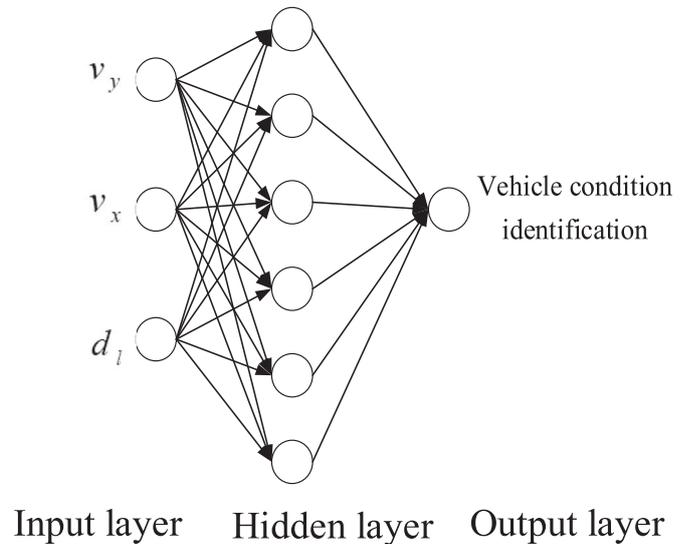


Figure 6. BP neural network structure for vehicle condition recognition.

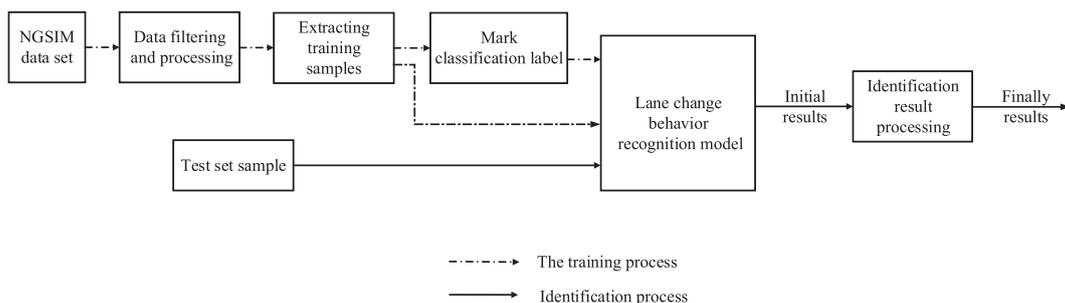
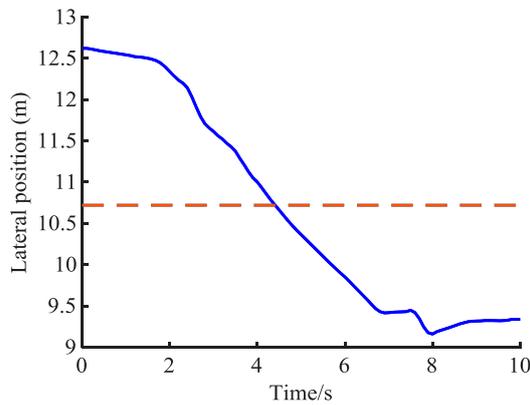
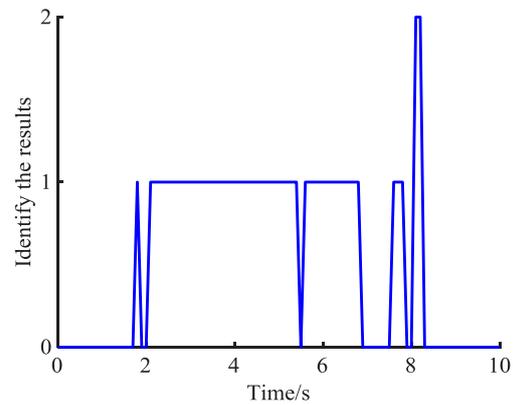


Figure 5. Lane change identification workflow.



(a) Lateral position of vehicle



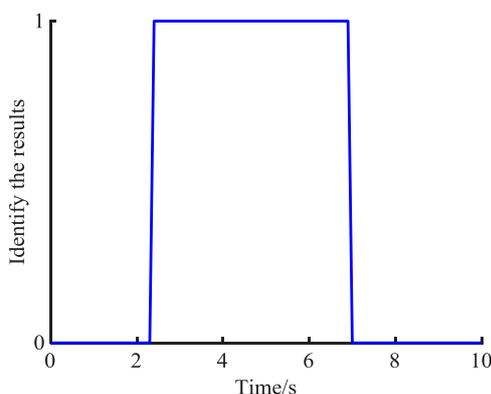
(b) Initial vehicle recognition results

Figure 7. Lane change identification.

lane line of the original lane were selected as the input parameters to the neural network, and the number of neurons in the input layer was 6. Considering the recognition accuracy and network complexity, one hidden layer is adopted, and the number of neurons is 6. The output of the output layer is the matching type of vehicle working condition, and the number of neurons is one.

After data screening and processing, a total of 22,900 groups of sample data is obtained. There are 9449 groups of lane keeping status data, 7186 groups of left lane change status data, and 6265 groups of right lane change status data. The sample data were randomly divided into training set and test set in a ratio of 5:1. The lane changing behaviour recognizer obtained was tested using the test set. The lateral position of a group of ID826 left lane changing vehicles was shown in Figure 7(a), and the recognition results were shown in Figure 7(b) when the vehicles approach the lane changing point.

As shown in Figure 7, the leading car is in the right lane at the beginning and moves towards the main lane at 2 s and reaches the lane change point at 4.4 s. It can be seen from the initial recognition results that although the lane change results trained and recognized by BP neural network can roughly reflect the lane change situation of vehicles, there are many misidentification

**Figure 8.** Vehicle final recognition results.

results due to the limited representation of samples to the actual driving behaviour. Therefore, the recognition algorithm is set as follows: when the vehicle recognition detection is 0, if there are 4 detection 1 or 2 in the last 5 close near the lane change recognition model, the result is set as 1 or 2.

As shown in Figure 8, for the final results, the recognition accuracy is significantly increased, lane changing vehicles based on BP neural network training behaviour recognition model in 2.4 s decision after the beginning of the adjacent lanes vehicles into the driveway, as main target. This allows for earlier integration with the car in front of the adjacent lane with the car in front of its own lane. Although slight lag in identification results, but the time lag in the lane changing process can be neglected.

4. Hierarchical control strategy of the variable weight adaptive cruise system

4.1. Design of upper controller

The main purpose of the ACC system is to control the workshop spacing of two vehicles to ensure the safety of driving, and on this basis, it is optimized to meet the requirements of comfort, economy, and other multi-objectives [27]. In this paper, the upper controller is designed using LQR algorithm, and the longitudinal kinematic diagram of the two workshops is shown in Figure 9. The relative distance between the two vehicles is d , the expected distance of the following vehicle is d_{des} , and the error of the expected distance is Δd .

In consideration of the complexity and practical safety of the model, the calculation method provided in Ref. [28] of the expected car-following distance using the timing distance is applied. The calculation formula for calculation is as follows:

$$d_{des} = \tau_h * v_f + d_0, \quad (1)$$

where τ_h is the time interval between vehicles, v_f is the vehicle speed, and d_0 is the minimum safe distance.

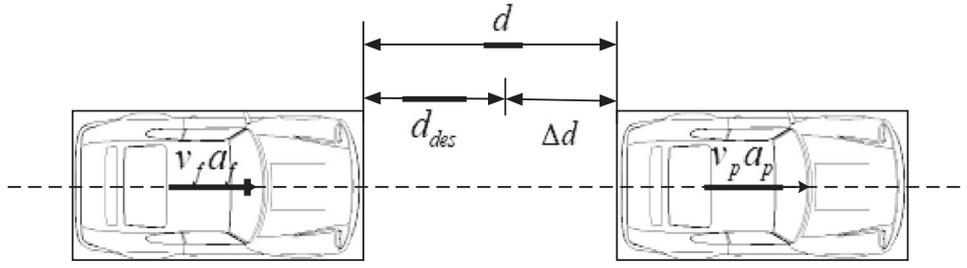


Figure 9. Vehicle spacing dynamics diagram.

The relationship between the actual acceleration and the expected acceleration of the main vehicle is regarded as the first-order inertial link:

$$a_f = \frac{1}{T_I s + 1} a_{des}. \quad (2)$$

Taking Δd , Δv , and a_f as state variables, a_f as control input, and a_p as system disturbance, the state equation can be obtained as follows:

$$\begin{aligned} \dot{\mathbf{x}} &= \mathbf{A}\mathbf{x} + \mathbf{B}u + \mathbf{G}v, \\ \mathbf{y} &= \mathbf{C}\mathbf{x}, \end{aligned} \quad (3)$$

where

$$\mathbf{x} = \begin{bmatrix} \Delta d \\ \Delta v \\ a_f \end{bmatrix}; \quad \mathbf{A} = \begin{bmatrix} 0 & 1 & -\tau_h \\ 0 & 0 & -1 \\ 0 & 0 & -1/T_I \end{bmatrix};$$

$$\mathbf{B} = \begin{bmatrix} 0 \\ 0 \\ K/T_I \end{bmatrix}; \quad \mathbf{G} = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix};$$

$$\mathbf{C} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix};$$

$$u = a_f; \quad v = a_p; \quad \tau_h = 1.5; \quad K_L = 1; \quad T_L = 0.5.$$

For the car-following system, the controlling strategy is to make the actual distance between the main vehicle and the leading vehicle approach to the expected distance, and the speed of the main vehicle approach to the speed of the leading vehicle. That is, the vehicle distance error Δd and the relative speed Δv are required to approach zero.

A control index function considering vehicle distance, relative speed, and main vehicle acceleration is established as shown in Equation (4):

$$J = \frac{1}{2} \int_0^{\infty} [q_1 \cdot \Delta d^2 + q_2 \cdot \Delta v^2 + q_3 \cdot a_f^2 + r \cdot u^2] dt, \quad (4)$$

where q_1 , q_2 , and q_3 are the weight coefficients of vehicle distance error, relative speed, and main vehicle acceleration, respectively; r is the weight coefficient limiting the jitter of the expected acceleration. Based on the LQR control theory, the minimum expected vehicle following acceleration of the index function J is sought.

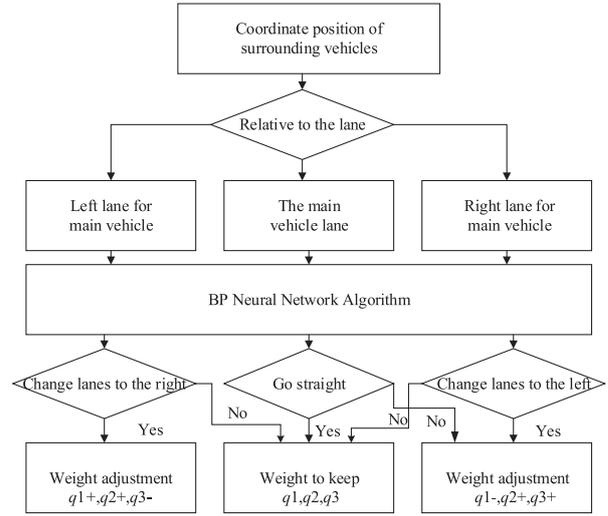


Figure 10. Weight adjustment strategy.

4.2. Weight adjustment strategy

Compared with the traditional fixed weight coefficient LQR algorithm, a variable weight coefficient LQR controller for the driving condition of the vehicle in front is designed in this paper, so as to reduce the influence of large fluctuation of longitudinal acceleration caused by following the main target switch. Weight adjustment strategies are designed for different lane changing conditions of the front vehicle, as shown in Figure 10. Based on the coordinate information of the surrounding vehicles obtained by the sensor, the lane of leading vehicle relative to the main vehicle was analysed, the lane changing condition of the vehicle was identified by using the BP neural network, and the weight parameters were adjusted. The setting of parameter adjustment rules is divided into three cases. The first is that the leading vehicle cuts out of the lane, and the main car switches to the vehicle farther down the lane. The second is that the side car cuts into the lane, and the main car recognizes the target and switches to the cutting vehicle. The third is that the leading vehicle stays in the main lane, and the main car recognizes the target unchanged.

In the LQR algorithm, the larger the values of q_1 , q_2 , and q_3 , the more significant the expected distance, velocity difference, and acceleration are in the performance function, and the larger the value of r , the more

important the control constraints are. In this paper, the values of q_1 , q_2 , and q_3 are adjusted, and r is selected as a fixed value. By analyzing the NGSIM data set and in combination with the practical situation of the road, it is found that cut into the main lane is usually due to vehicles in front and the vehicle speed is low, and lane changing the distance between car in left and the new target vehicle is greater than the expected distance, Δd positive, both relative velocity decreases, Δv is negative, should smooth deceleration. Therefore, q_2 and

q_3 should be larger, q_1 is small, and the parameter is adjusted for (q_{1-}, q_{2+}, q_{3+}) . When other lane to the main lane is generally slow down in turn into the main lane, lane changing the distance between the left in the car and the new target vehicle is less than expected, the relative velocity is smaller, Δd and Δv are negative, should slow down as soon as possible. Therefore, q_1 and q_2 should be larger, q_3 is relatively low, to avoid collision, and the parameter adjustment for (q_{1+}, q_{2+}, q_{3-}) . When the vehicle accelerates and cuts into the main

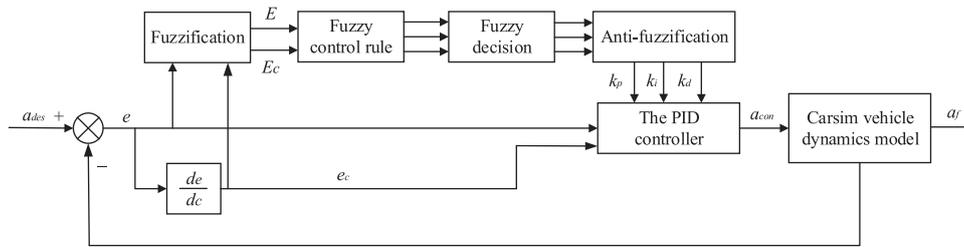


Figure 11. Fuzzy PID control principle.

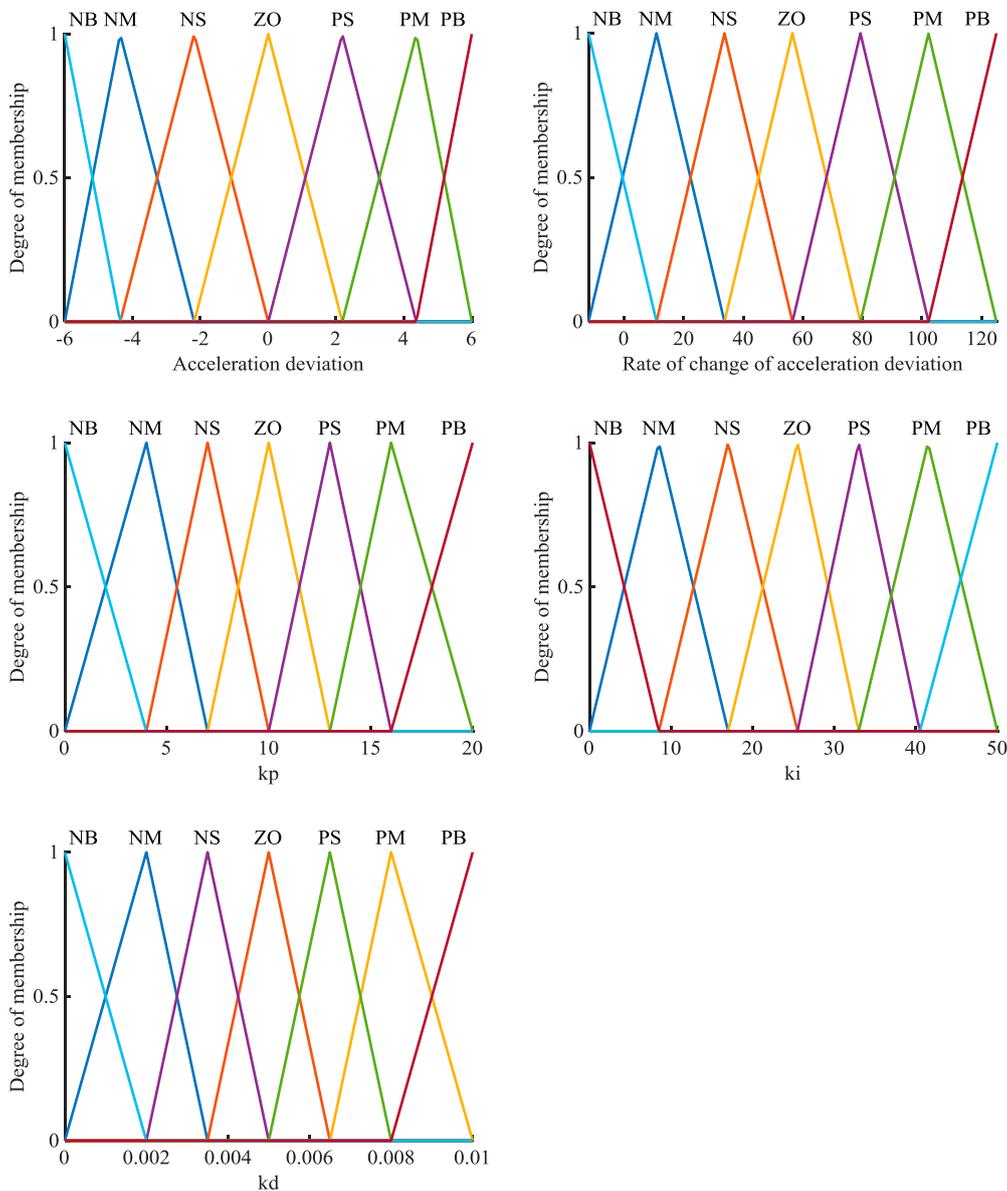


Figure 12. Membership function diagram.

lane, Δv is positive. For the sake of driving safety, the weighted value of q_{2+} is still adopted.

4.3. Lower controller design

Based on the strong nonlinear characteristics of the vehicle dynamics model, the precision of lower controller and the control performance are the precondition of the upper controller control functions. The actual road condition and of vehicles on the road are complicated, and because the engine in the vehicle dynamics and tyre model are showing strong nonlinear characteristics of conventional PID, it is difficult to achieve stable control effect. Fuzzy PID control, which can adjust PID parameters in real time through fuzzy rules, is suitable for nonlinear and time-varying control systems [29].

In order to make the actual acceleration track, the expected acceleration quickly and accurately, the lower controller adopts the fuzzy PID control principle in this study, and the fuzzy PID controller structure design block diagram is shown in Figure 11.

Deviation e is the difference between the expected acceleration a_{des} and the actual acceleration a_f of the vehicle; e_c is the deviation change rate; k_p , k_i and k_d are the three parameters of the PID controller; E and E_c are the input fuzzy values of the fuzzy controller,

respectively. To establish the inverse dynamic system with PID controller module connection, the Simulink is used, and CarSim for the joint simulation for vehicle dynamics system. Under the simulation environment, by trial and error method, PID parameters adjusted repeatedly, parameters to get ideal value rule is analyzed, and fuzzy controller is used to adjust parameters k_p , k_i and k_d .

In this paper, two-dimensional fuzzy control is used to realize real-time parameter tuning. Seven language variables are set, namely PB (positive large), PM (middle), PS (positive small), ZO (medium), NS (negative small), NM (negative medium), and NB (negative large). The output parameters are k_p , k_i and k_d . Set the input fuzzy set theory domain e as $[-n, n]$, e_c as $[-m, m]$, the output parameter a_{con} as $[-l, l]$, and the basic theory domain of e , e_c , and a_{con} as $[e_h, e_l]$, $[e_{ch}, e_{cl}]$, and $[e_{coh}, e_{col}]$, respectively. According to the fuzzy control theory, the quantization factor and the proportional factor can be worked out. The quantization factors k_e and k_{ec} are

$$k_e = \frac{2n}{e_h - e_l}, \quad (5)$$

$$k_{ec} = \frac{2m}{e_{ch} - e_{cl}}. \quad (6)$$

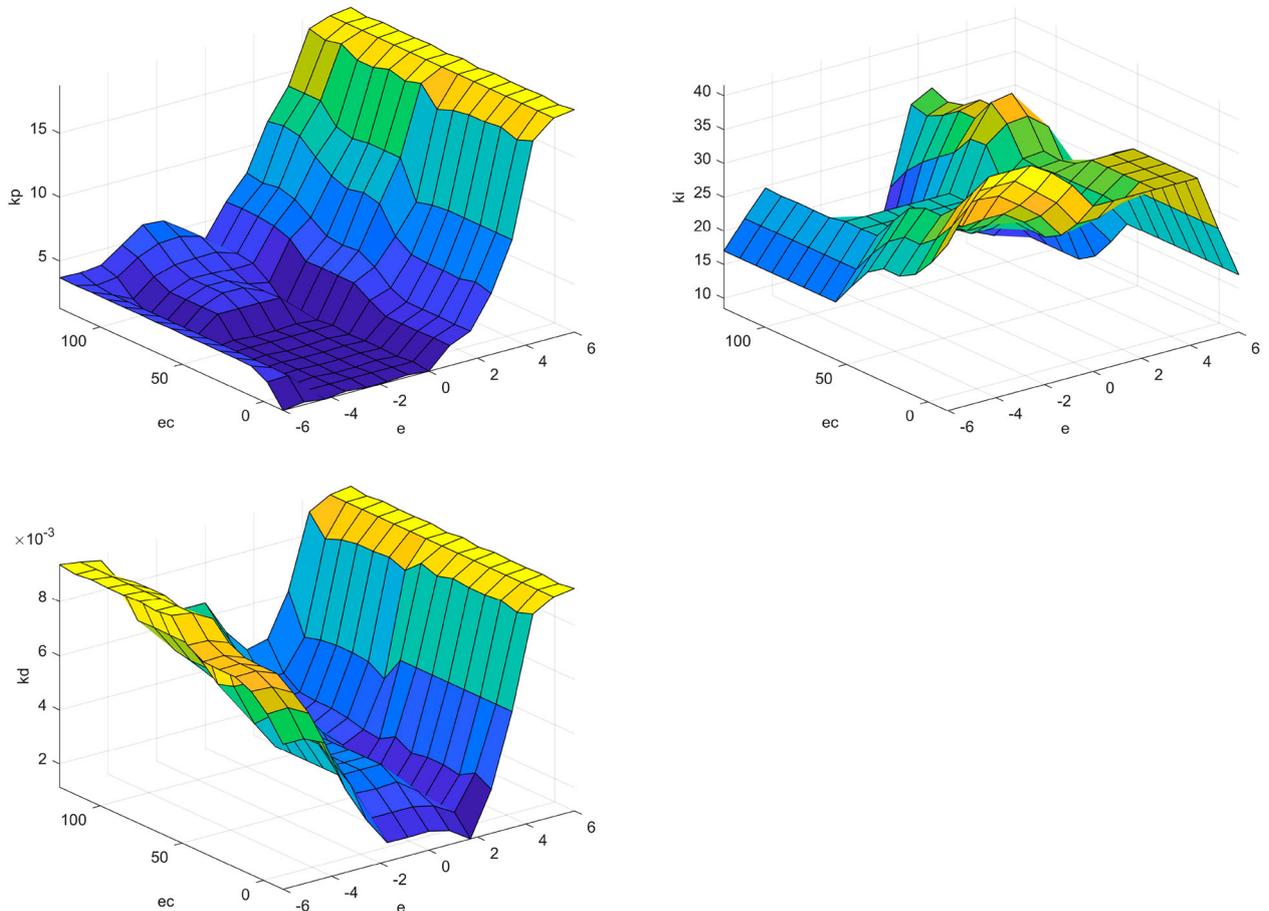


Figure 13. k_p , k_i and k_d output surface.

Table 2. Fuzzy rule table.

$e_c \setminus e$	PID						
	NB	NM	NS	ZO	PS	PM	PB
NB	NB, PS, PS	NB, ZO, PM	NM, ZO, PM	NM, NS, PB	NM, NS, PB	NM, NS, PB	NM, NS, PB
NM	NB, PM, PS	NB, PS, PM	NB, PS, PM	NB, ZO, PB	NB, ZO, PB	NB, ZO, PB	NM, ZO, PB
NS	NB, PM, NM	NB, PS, NS	NB, ZO, NS	NB, ZO, NS	NM, ZO, ZO	NM, NS, ZO	NS, NS, PS
ZO	NB, PS, NM	NB, ZO, NS	NB, ZO, NS	NB, ZO, NS	NB, ZO, ZO	NM, NS, ZO	NM, NM, PS
PS	NM, PS, PB	NM, PS, NB	NM, PS, NB	NS, PS, NB	NS, PM, NM	ZO, PM, NM	ZO, PB, NS
PM	PB, PS, PB	PB, PS, PB	PB, PS, PB	PB, ZO, PB	PB, ZO, PB	PB, NS, PB	PB, NM, PB
PB	PB, NS, PB	PB, NS, PB	PB, NS, PB	PB, NS, PB	PB, NM, PB	PB, NM, PB	PB, NB, PB

The scaling factor k_{acon} is

$$k_{acon} = \frac{a_{conh} - a_{conl}}{2l}. \tag{7}$$

The fuzzy set of language variables is described by a membership function. The input membership function adopts Gaussian membership function, and the output membership function adopts triangular membership function, as shown in Figure 12.

The essence of fuzzy control rules is to summarize the control experience obtained by experts in this field according to a large number of experiments, and then obtain the set of fuzzy conditional statements. The fuzzy rule table is formulated by referring to the summary of simulation experience of parameters at different times, as shown in Table 2.

Figure 13 shows the output surface viewer, which can intuitively show the corresponding relationship between the input and output of the three parameters k_p , k_i and k_d .

The designed fuzzy PID controller was joined with the vehicle inverse dynamics module, and the co-simulation was conducted with the vehicle dynamics system in Carsim to verify the control performance of the designed controller. The simulation condition is that the initial speed of the vehicle is set as 100 km/h, and the expected acceleration signals of step variation are set as -2 m/s^2 and -4 m/s^2 . The simulation time is 10 s. After simulation verification, the obtained vehicle acceleration curve is shown in Figure 14.

As can be seen from the simulation results, the control output of the actual acceleration in about 0.17 s to

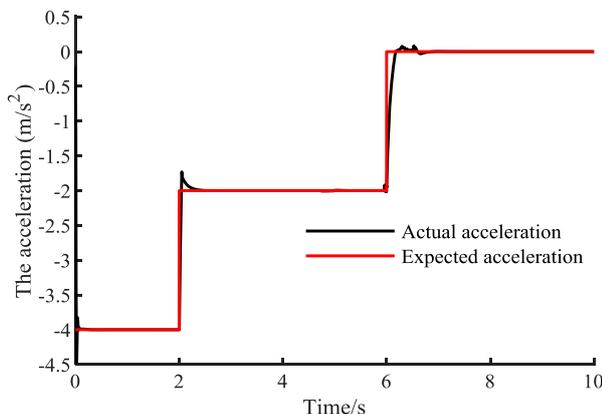


Figure 14. Ideal acceleration and actual acceleration of vehicle.

Table 3. Vehicle simulation parameters.

Dynamic parameter	Value	Dynamic parameter	Value
Vehicle quality (kg)	1374	Distance from the centre of mass to front axis (m)	1.159
The main reduction ratio	4.1	Distance from the centre of mass to rear axis (m)	1.678
Air density (kg m^3)	1.206	Transmission efficiency	0.9
Rolling resistance coefficient	0.02	Coefficient of ground adhesion	0.85
Air resistance coefficient	0.342	Tyre rolling radius (m)	0.325
Height of the centre of mass (m)	0.54	Windward area (m^2)	1.8

Table 4. Main parameters of LQR controller.

Parameter	Value
q_1, q_2, q_3	1, 3, 1
q_{1-}, q_{2+}, q_{3+}	0.5, 5, 1.5
q_{1+}, q_{2-}, q_{3-}	2.5, 5, 0.5
r	10

reach the desired acceleration has rapid response ability and is able to control the actual stable output to a desired acceleration. Moreover, this can steadily control the actual acceleration, and the simulation results show that controller has strong robustness.

5. Comparative analysis simulation

In order to verify the correctness of the algorithm proposed in this paper, the ACC system model and layered control algorithm based on BP neural network for lane change identification of leading vehicle are built in the Matlab/Simulink environment. Key parameters of LQR controller are obtained according to the methods mentioned in Refs. [30,31] and simulation test results were obtained. The simulation parameters of Carsim are shown in Table 3, and the key parameter settings of LQR controller are shown in Table 4.

In this study, two different scenarios are simulated, in which the main vehicle is always on road, but due to the different behaviours of the vehicle in front, the autonomous vehicle is adjusted accordingly to meet the control requirements. In order to better conform to the actual road scenario, the vehicle simulation environment is set according to the US-101 road environment. Trad-LQR is a LQR control method based on traditional target recognition, Pre-LQR is a LQR control method with fixed weight combined with BP neural

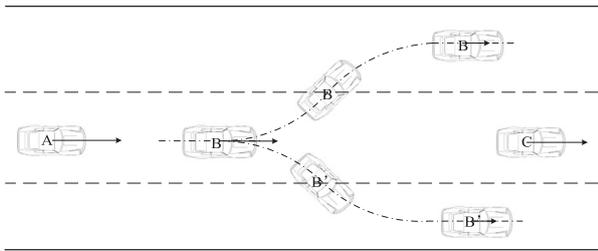


Figure 15. Schematic of the front car cut-out of the lane.

network, and Pre-VM-LQR is a LQR control method with variable weight (VM) combined with BP neural network.

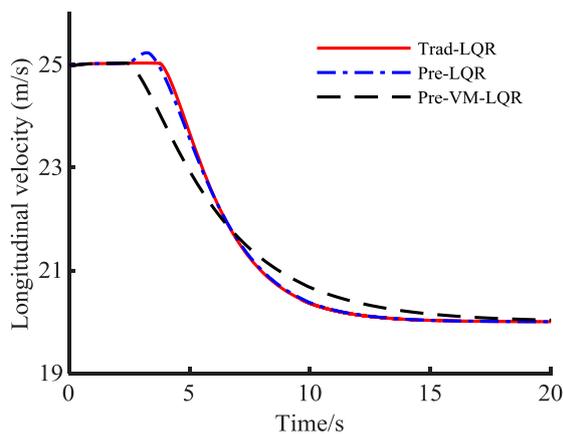
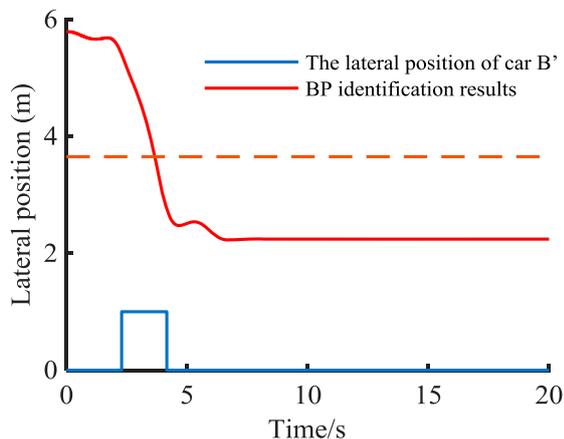
(1) The front vehicle cuts out of the lane

Figure 15 shows the schematic diagram of the leading car cutting out of the lane. The main car runs in the main lane, and the leading car changes lane to the right or left in the current lane for the cutting

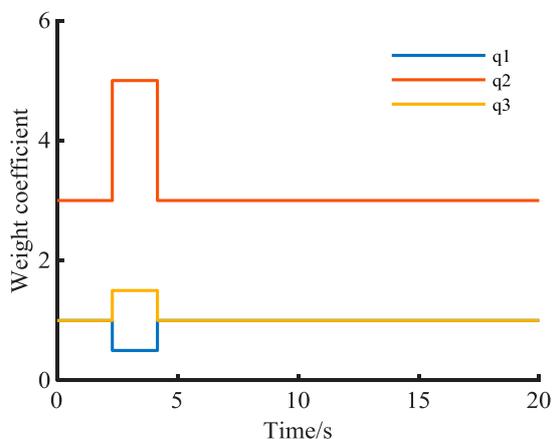
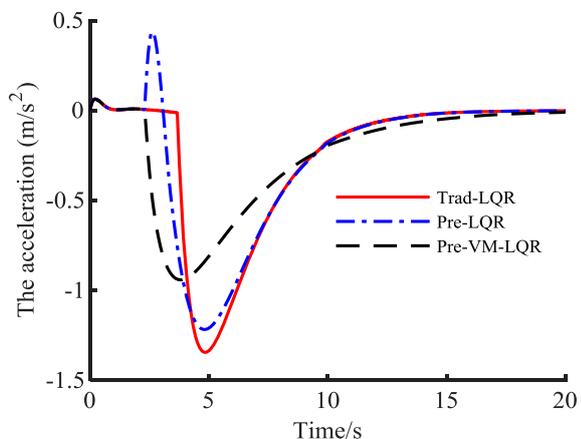
out condition of the leading car. Two different cut-out conditions are designed to verify the lane change behaviour recognition and the control strategy is proposed.

Condition 1: When the main car A at the initial time with speed 25 m/s followed the vehicle B' 40 m ahead of the main lane at A with constant speed of 25 m/s, it began to change lane to the adjacent lane on the left at about 1.85 s and reached the lane change point at 3.64 s. Car C at the front keeps a constant speed of 20 m/s, and the initial distance is 65 m from the car. The test results are shown below:

It can be seen from Figure 16 that the lane changing behaviour recognition model of the leading vehicle trained by BP neural network recognized the lane changing behaviour of the leading vehicle at 2.52 and 1.36 s earlier than the traditional adaptive cruise algorithm, and ACC could be switched to follow the target in advance. When the target switches to C, the expected spacing error $\Delta d = 13.6$ m and



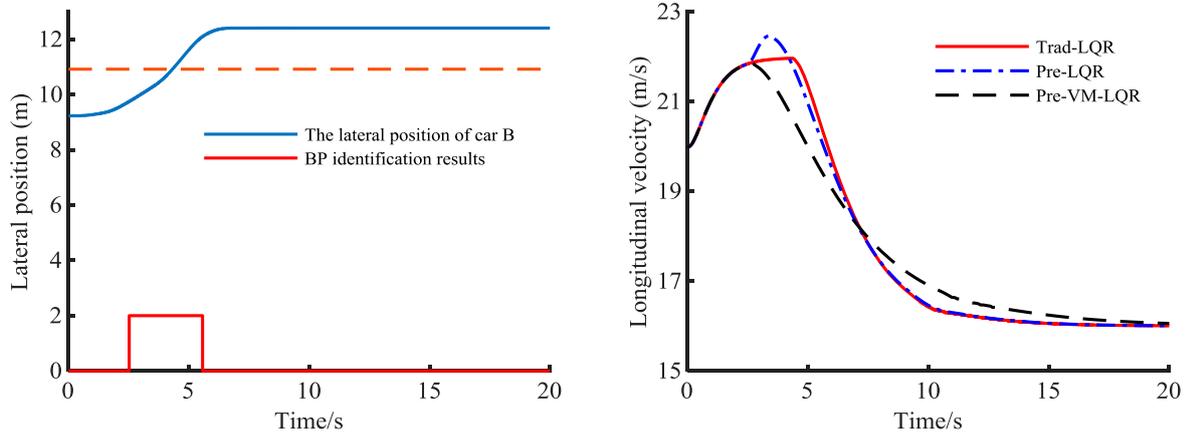
(a) Transverse position and recognition results (b) Longitudinal velocity of vehicles



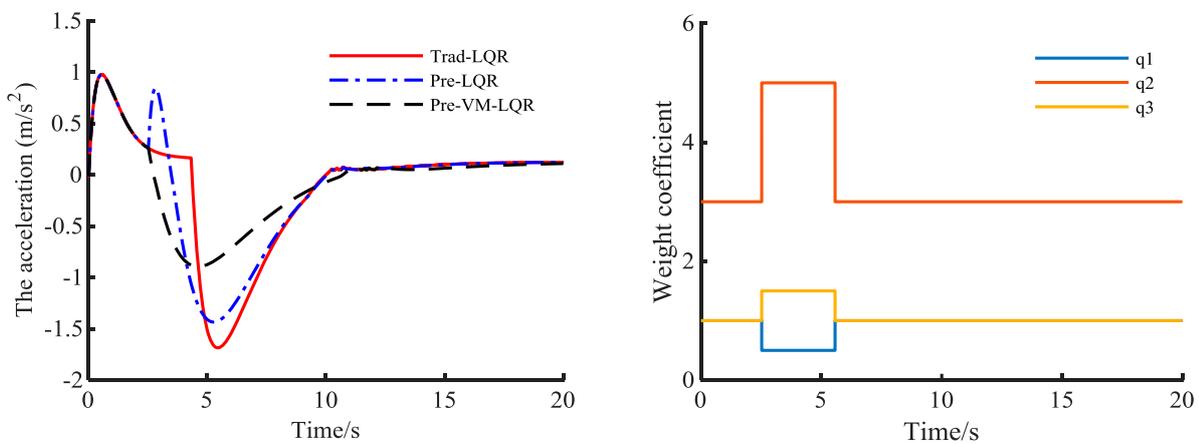
(c) Vehicle acceleration

(d) Weight coefficient

Figure 16. Comparison of the left cut-out simulation results of leading vehicle.



(a) Transverse position and recognition results (b) Longitudinal velocity of vehicles



(c) Vehicle acceleration

(d) Weight coefficient

Figure 17. Comparison of the right cut-out simulation results of leading vehicle.

the relative velocity $\Delta v = -5$ m/s. The fixed weight will cause a large fluctuation of acceleration. In this case, a steady deceleration is required, and the weight parameter should be adjusted as (q_{1-}, q_{2+}, q_{3+}) , as shown in Figure 16(d). From the simulation results, the maximum deceleration speed of Pre-VM-LQR is -0.94 m/s², which is about 29.85% lower than that of Trad-LQR and 22.31% lower than that of Pre-LQR. Results show that the vehicle lane changing intention recognition based on BP neural network as the main target selection method can benefit from a faster lane adjacent lane changing conditions to respond. Both fixed weight ACC and variable weight ACC can finally achieve the control effect, but variable weight ACC deviation value smaller, speed change more smoothly, can improve the riding comfort.

Condition 2: At the initial moment, main vehicle A follows vehicle B 35 m ahead of the main lane with speed of A being 20 m/s and keeps 22 m/s as the constant speed of A. At about 1.46 s, it starts to change lane to the right adjacent lane and arrives at the lane change

point at 4.25 s. Car C at the front keeps a constant speed of 18 m/s, and the initial distance is 70 m from the car. The test results are shown in Figure 17.

As can be seen from Figure 17, Pre-LQR recognizes the entry of a vehicle in an adjacent lane 1.68 s before the lane change point, and the deceleration peak is about -1.44 m/s², while Trad-LQR deceleration peak is -1.69 m/s². As shown in Figure 17(c), although Pre-LQR can operate the actuator in advance, the fixed weight coefficient LQR acceleration fluctuates significantly. When the target switches to C, the expected spacing error $\Delta d = 18$ m, the relative speed $\Delta v = -4$ m/s and the adjustment of variable weight coefficient is shown in Figure 17(d). The results show that the peak deceleration of Pre-VM-LQR is about -0.89 m/s², which is 47.33% lower than that of Trad-LQR, and the acceleration change is smoother and the overshoot is smaller. ACC vehicles can slow down in advance and reduce braking strength.

(2) Sidecar cuts into lane

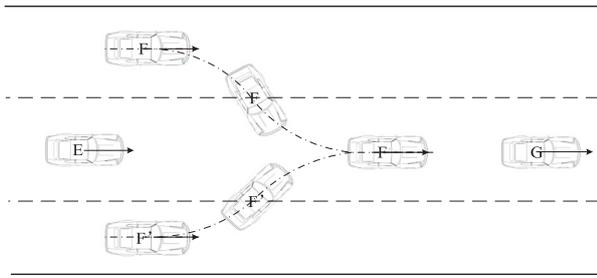


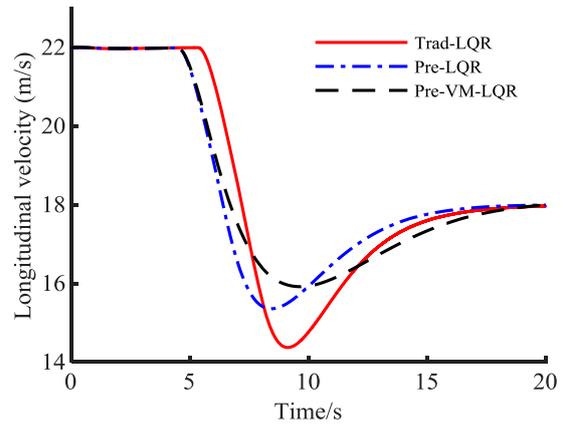
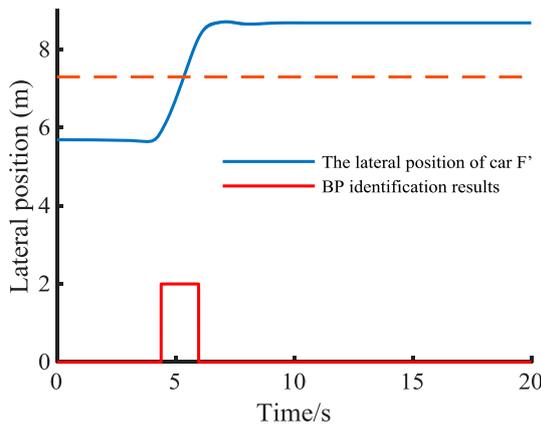
Figure 18. Diagram of side vehicle cut-in.

Figure 18 shows the schematic diagram of sidecar lane entry. The main car is driving in the main lane. When the car in front of the adjacent left lane changes lane to the right or the car in front of the adjacent right lane changes lane to the left, it is the sidecar lane entry condition. Two different cutting conditions are designed to verify the lane change behaviour recognizer and control strategy is proposed.

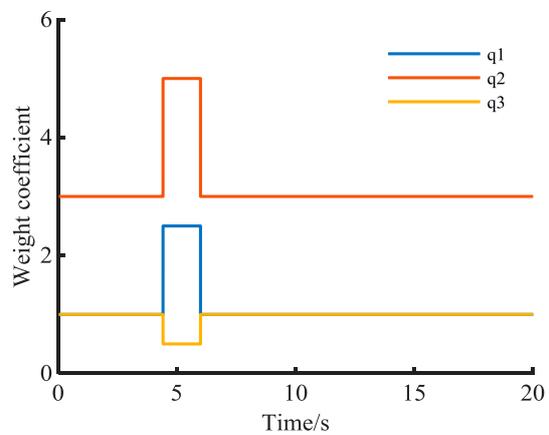
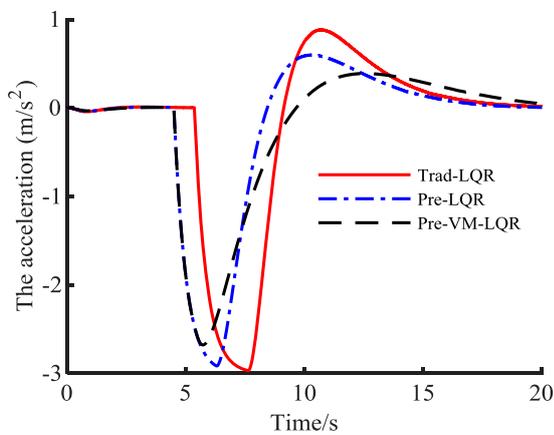
Condition 1: The main vehicle E at the initial moment with a speed of 22 m/s follows the vehicle G

40 m in front of the main lane, which keeps a constant speed of 22 m/s. F' car in the adjacent left lane runs at a constant speed of 18 m/s. The initial distance is 45 m from the car. It starts to change lane to the right at about 4.05 s and arrives at the lane changing point at 5.35 s. The test results are shown in Figure 19.

As it can be seen from Figure 19, the lane changing behaviour recognition model based on BP neural network training recognized the lane changing behaviour recognition model based on BP neural network training at 4.48 and 0.87 s earlier than the traditional adaptive cruise algorithm. When the target switches to F', the expected spacing error $\Delta d = -12.5$ m and the relative speed $\Delta v = -4$ m/s. In this case, it is necessary to slow down as soon as possible, adjust the value of the weighting parameter to (q_{1+}, q_{2+}, q_{3-}) , and the weight coefficient change curve is shown in Figure 19(d). According to Figure 19(c), the maximum deceleration rate of Trad-LQR is -2.96 m/s², the maximum deceleration rate of Pre-VM-LQR is



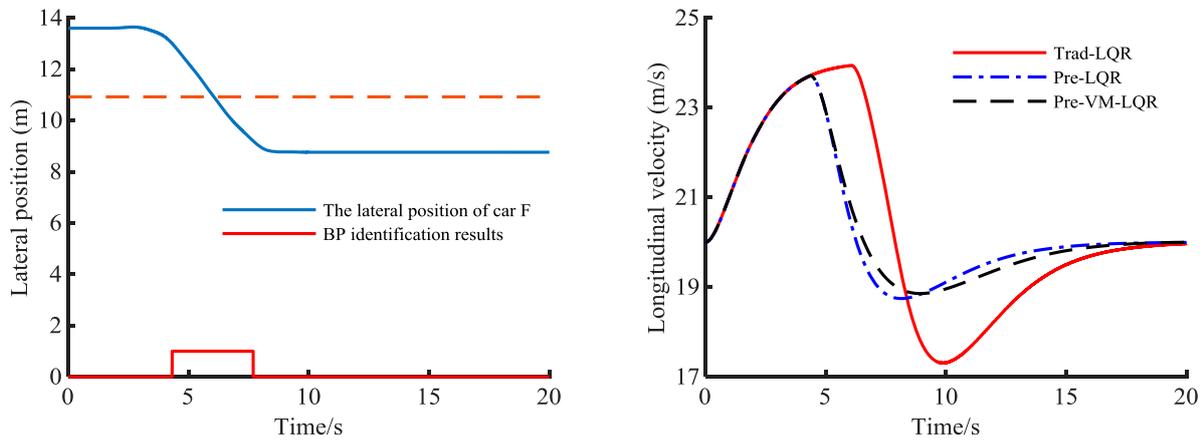
(a) Transverse position and recognition results (b) Longitudinal velocity of vehicles



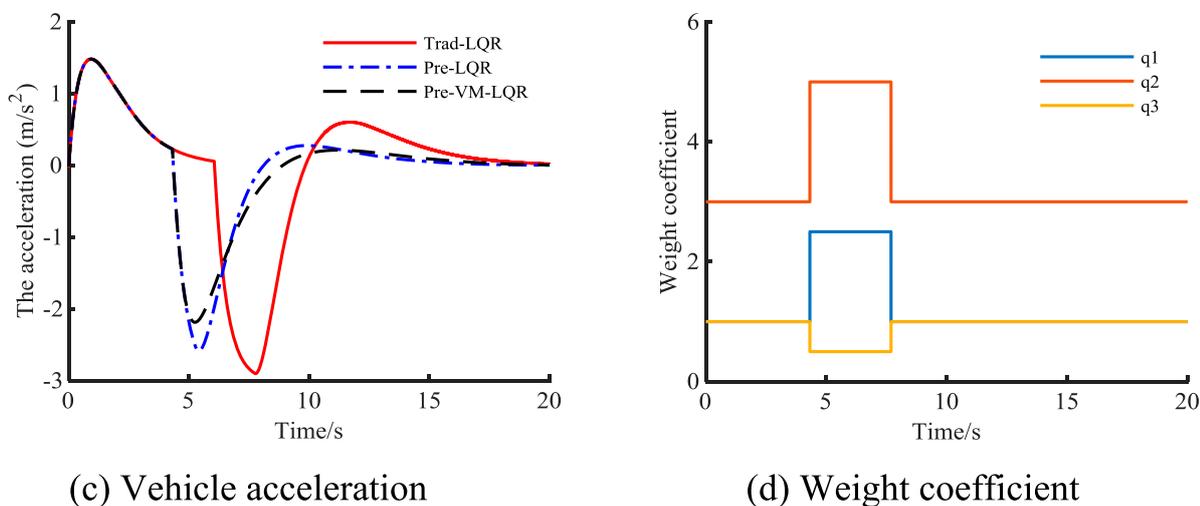
(c) Vehicle acceleration

(d) Weight coefficient

Figure 19. Comparison of right cut-in simulation results of side cars.



(a) Transverse position and recognition results (b) Longitudinal velocity of vehicles



(c) Vehicle acceleration

(d) Weight coefficient

Figure 20. Comparison of left cut-in simulation results of side cars.

-2.85 m/s^2 and the maximum deceleration rate of Pre-VM-LQR is -2.66 m/s^2 . By the time the leading car reached the lane change point, the Pre-VM-LQR vehicle had slowed down by about 5.45%. The results show that the BP neural network variable weight control strategy has less time in deceleration mode and can make ACC vehicle switch to follow the target earlier and avoid the phenomenon of forced movement of vehicles and reduce the fluctuation of acceleration. It cannot only reduce the impact on the comfort of the driver and passenger of the main vehicle but also improve the driving safety of the main vehicle and reduce the discomfort caused by the late switch of the main target.

Condition 2: The main vehicle E at the initial moment with the speed of 20 m/s follows the vehicle G which is located 30 m in front of the main lane and keeps 24 m/s uniform speed. Car F in the adjacent right lane ran at a constant speed of 20 m/s, and the initial distance was 40 m from the car. It began to change lanes to the right at about 3.18 s and arrived at the lane

changing point at 5.98 s. The test results are shown in Figure 20.

As can be seen from Figure 20, the Pre-LQR recognizes the entry of the vehicle in the adjacent lane 1.52 s before the lane change point, and the peak deceleration is about -2.18 m/s^2 , with gentle acceleration change and small overshoot. As shown in Figure 20(c), the peak value of Trad-LQR deceleration is -2.88 m/s^2 , and the peak value of Pre-LQR deceleration is -2.58 m/s^2 . When the target switches to C, the expected spacing error $\Delta d = -7.1 \text{ m}$ and the relative speed $\Delta v = -3.6 \text{ m/s}$. The adjustment of variable weight coefficient is shown in Figure 20(d). The results show that the peak deceleration of Pre-VM-LQR is 24.31% lower than that of Trad-LQR and 15.50% lower than that of Trad-LQR. The control strategy proposed in this paper can identify the cutting condition of the vehicle ahead earlier, avoid the phenomenon of forced movement of the vehicle and reduce the fluctuation of acceleration.

6. Conclusion

In this paper, a variable weight ACC control strategy based on BP neural network to identify the lane changing behaviour of the vehicle in front is proposed. The main purpose is to solve the problems of the ACC system being insensitive to the lane changing behaviour of the vehicle in front, braking too late or too fast. The lane changing characteristics of vehicles were extracted from NGSIM data set, and BP neural network was used to train the lane changing behaviour recognition model of the vehicle ahead offline. The lane changing behaviour recognition of the vehicle in front is integrated into ACC control strategy, and ACC vehicle is controlled before the vehicle arrives at the lane changing point. According to different working conditions of the vehicle in front, the weight coefficient adjustment strategy is designed to improve the LQR control algorithm. ACC system adopts hierarchical control strategy, and the lower controller adopts fuzzy PID control, so that the actual acceleration of the vehicle can follow the expected acceleration stably. In this paper, CarSim and Matlab/Simulink are used for co-simulation, and different experimental conditions are established to analyze and compare the proposed control strategy.

The simulation results show that under different lane changing conditions, lane changing recognizer can identify different lane changing behaviours in advance, and ACC vehicles can switch to follow the main target in advance. The variable weight LQR controller can adjust the weight coefficient according to different working conditions to avoid the occurrence of strength braking and even danger. This not only ensures the driving safety of driver but also ensures the riding comfort, and reduces the fear caused by the late switching of following the target.

Due to the limited experimental conditions, only simulation analysis is carried out in this study. If the subsequent conditions allow, further hardware-in-the-loop or real vehicle tests will be carried out to verify the control algorithm and to make the control strategy more accurate. The ACC system proposed in this paper only considers the longitudinal control of the vehicle, but for the actual driving process of the vehicle, such as turning, the lateral and longitudinal movement of the vehicle is inseparable. Therefore, in future studies, the influence of main target identification and lateral control of the ACC system on the system under curves will be comprehensively considered.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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