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Research Article

Research on Local Dynamic Path Planning Method for Intelligent Vehicle Lane-Changing

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A local dynamic path planning method is proposed to compensate for the lack of consideration of the movement state of surrounding vehicles, the poor comfort, and the low traffic efficiency when the existing vehicle changes lanes automatically. Firstly, the cubic polynomial is predefined, and the optimal track path is solved. According to the real-time information of environment perception, the model is continuously modified by acquiring real-time information in the course of path planning, and the regional safety of the vehicle is realized. The Carsim and simulink simulation results and actual vehicle verification show that, compared with the traditional nondynamic research method, this method can effectively solve the problem that the vehicle speed variation and the sudden intrusions of the vehicle leading to the compulsory operation of the vehicle during the course of lane-changing. The safety is also improved. In order to ensure the vehicle comfort and stability, the lane-changing time is shortened by 20%, and the efficiency of lane-changing is improved obviously.

1. Introduction

According to the data analysis of traffic accident research in Germany, in rear-end accidents, 80 percent of drivers did not use lane-changing method to avoid collisions. Among them, 24% of accidents can be avoided by changing lanes [1]. In order to reduce the traffic accidents caused by changing lanes, scholars at home and abroad have done a lot of research on it [2].

In [3], the researchers used the fusion of deterministic algorithm and nondeterministic algorithm with neural network to solve the obstacle avoidance problem of mobile robot and carried out computer simulation. However, little consideration was given to the dynamic environment and the experimental results of the actual physical model were not given. In [4], a hybrid Fuzzy-WDO algorithm was proposed to solve the navigation and collision avoidance problems of mobile robots in unknown static and dynamic environments. The simulation results were favourable, but the actual experimental results were not given. In [5], the research on motion planning of wheeled robots with various heuristic techniques was summarized in the past twenty years, and the solutions to key problems were shared. However, it was difficult for these methods to find the optimal solution due to the large amount of calculation. The trapezoidal acceleration model is used to design the track changing path in the process of track lane-changing. This method only considered the kinematics and dynamics of the vehicle itself and did not consider the influence of the surrounding vehicle on tracking lane changes, and the change model was not flexible [6–9]. In [10–12], considering the dynamic target position and road boundary, the artificial potential energy field was used to plan the road, and the simulation was carried out, and the simulation results were satisfactory. But the artificial potential energy field model could not solve the problems of local minima and the target could not reach. It could only be used in special scenarios but not in most cases. The local path planning based on polynomial in literature [13, 14] could satisfy the situation that there was only one stationary vehicle in front of the track changing process without considering the influence of other vehicle state changes during the course of lane-changing. The existing research based on polynomial track path method was only calculated at the starting point of lane change, and it can not guarantee the safety of whole process. At present, the research of static path planning is mainly aimed at two vehicles with zero heading angle in the same straight lane, ignoring the influence of environmental conditions, so the practicability is not high [15]. At present, dynamic path planning mainly relies on empirical formula [16, 17], which makes it difficult to obtain the optimal path and inflexible lane-changing model.

To sum up, the dynamic and complex environment in most of relevant research was rarely studied. The method used was generally less flexible. Security acceptability was considered to be more important. The influence of comfort and traffic efficiency combination was seldom considered. It was difficult to cope with complex road conditions such as sudden break-in and rapid speed change, which is one of the main causes of rear-end accidents. If these factors are not taken into account, vehicle of only the minimum safe distance model will not be secured. In view of the automatic lane-changing without considering the vehicle motion state variation around itself, the technology of using the telematics to share data and sensors to obtain real-time information of the outside world constantly replans the path. This paper presents an objective function based on the maximum longitudinal acceleration and lane change time in a networked vehicle environment. By using the cubic polynomial model, the constraint conditions and the objective function are solved to obtain the dynamic optimal trajectory model. Finally, the algorithm is verified by the joint simulation of Carsim and simulink. The results show that the method is feasible and solves the problems of incompatibility of comfort and traffic efficiency and not taking the variation of the surrounding vehicle state into account.

2. Dynamic Automatic Lane-Changing Strategy

Car networking intelligent vehicles perceive the driving environment through car networking and sensors, which include millimeter wave radar, GPS, camera, and lidar to obtain information. These raw data are fused in "sensor data fusion module", and the vehicle network transceiver unit receives real-time information of vehicle network to obtain dynamic and static obstacle information. According to the real-time information of obstacles, the system plans out a safe, comfortable, and efficient track and then tracks the footprint. The real-time data of the vehicle network can replan the path according to the metabolic information of the environment around the vehicle. The specific policy flow is shown in Figure 1.

3. Dynamic Trajectory Planning

3.1. Establishment of Lane-Changing Model. In order to ensure the smooth continuity of track curvature and variation rate, the cubic polynomial method is used to define the path. The cubic polynomial curve itself accords with the practical operation habits of the driver. Therefore, this paper uses cubic polynomials to define the path, as shown in

$$y(x) == a_0 + a_1 x + a_2 x^2 + a_3 x^3 \tag{1}$$

where y and x represent the longitudinal and horizontal positions of the main vehicle and a_0, a_1, a_2, a_3 represent the polynomial coefficients, respectively.

In the coordinate system set-up in Figure 2, the origin of the coordinate is the position of the center of vehicle mass, of which θ_i is instantaneous yaw angle, t is point of lane change, τ is total lane change time, and x_τ is the distance of lane change. W is a distance between two-lane centerline. Figure 2 shows that the initial and end states of the vehicle when changing lanes need to meet the following conditions:

$$\begin{aligned} y(0) &= 0, \\ y(0)' &= \tan\theta_i, \\ y(x_\tau) &= W \\ y(x_\tau)' &= 0 \end{aligned} \tag{2}$$

By substituting the boundary condition (2) with the upper formula (1), the path of the lane change can be obtained as follows:

$$\begin{aligned} y(x) = \tan\theta_i x &+ \frac{3W - 2x_\tau \tan\theta_i}{(x_\tau)^2} x^2 \\ &+ \frac{x_\tau \tan\theta_i^2 - 2W}{(x_\tau)^3} x^3 \end{aligned} \tag{3}$$

where θ_i and W are detected to known variables per second in real time by cars and the main trajectory depends on the longitudinal position x_τ.

3.2. Establishment of the Optimal Lane-Changing Objective Function under the Condition of Vehicle Networking. The research shows that acceleration is the main reason of affecting comfort, so if we want to consider comfort, we must consider acceleration. In addition, the change time not only affects the traffic efficiency, but also affects the whole traffic operation. The shorter the change time, the higher the traffic efficiency and the less the impact on the whole traffic operation. The path and the corresponding curvature of the general polynomial lane change curve are shown in Figure 3. It can be seen that the maximum curvature is at the starting point and the terminating point in the course of lane-changing. Longitudinal acceleration at the end of lane-changing a_τ may be expressed as

$$a_\tau = (u_\tau)^2 K(x_\tau) \tag{4}$$

where u_τ is transverse velocity at the end of lane-changing. The curvature of the end point of lane-changing $K(x_\tau)$ can be expressed as

$$K(x) = \left| \frac{y''}{\left(1 + y'^2\right)^{3/2}} \right| \tag{5}$$

where y' and y'' are the first and second derivatives of the lane-changing trajectory equation, respectively.

So the longitudinal acceleration a_τ at the end point is relatively large. Therefore, an objective function J, which can reduce the longitudinal acceleration and the lane-changing

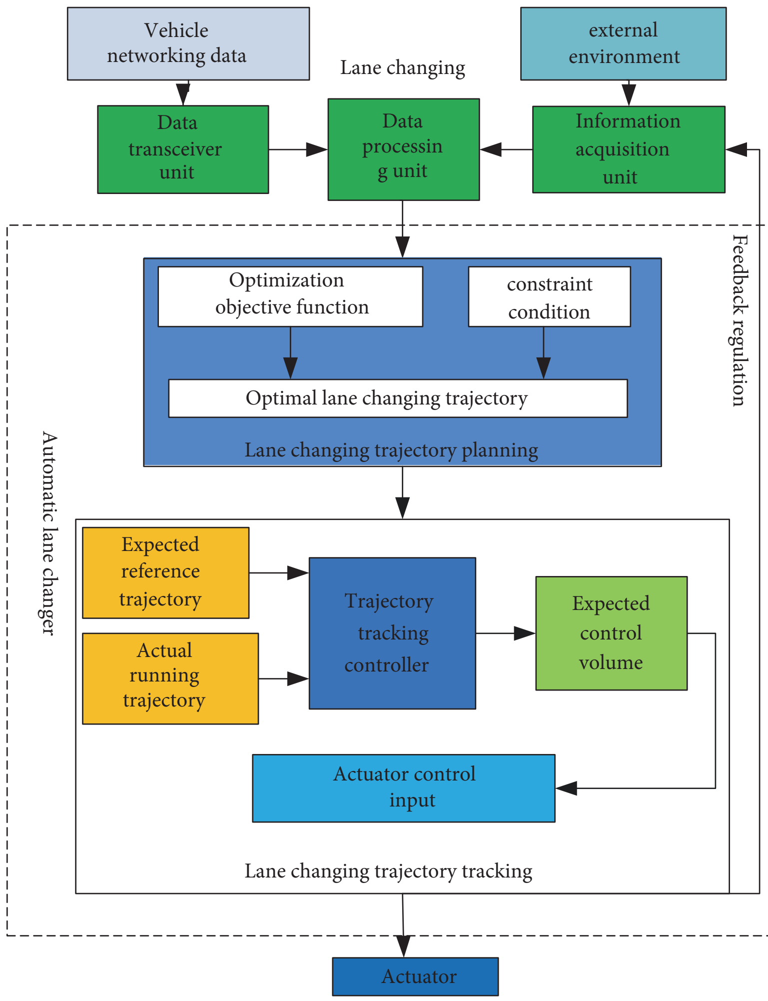

FIGURE 1: THE flow chart of automatic change of track under the condition of vehicle interconnection.

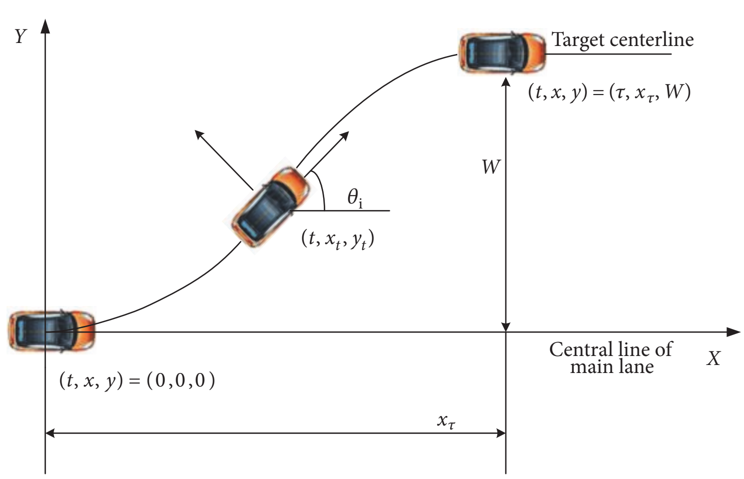

FIGURE 2: Vehicle track during the course of lane-changing.

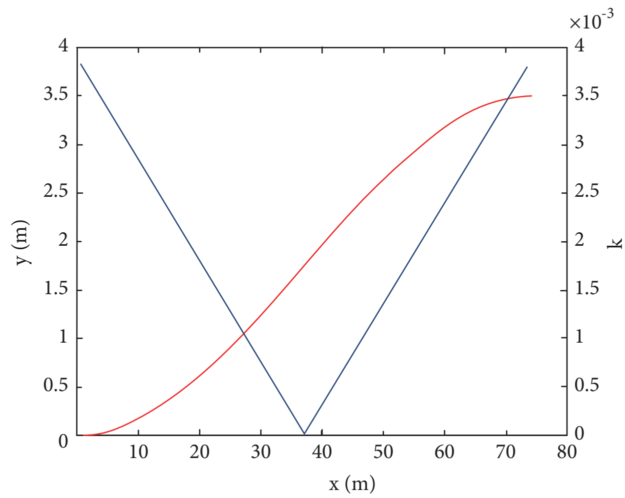

Figure 3: Trajectory and corresponding curvature change diagram.

time, is established to obtain the optimal lane-changing trajectory as shown in

$$J = \frac{a_\tau}{a_{\tau,\max}} + \frac{\tau}{\tau_{\max}} \tag{6}$$

where $a_{\tau,\max}$ is the maximum longitudinal acceleration in all lane-changing trajectories; $\tau_{\max}$ is the maximum lane-changing time for all lane-changing trajectories.

3.3. Solution of Optimal Route-Changing Trajectory Model. Substituting formula (3) into formula (5) obtains

$$K(x) = \left| \frac{(6W - 4x_\tau \tan\theta_i)/x_\tau^2 + ((6x_\tau \tan\theta_i - 12W)/x_\tau^3)\, x}{\left\{1 + \left[\tan\theta_i + (6W - 4x_\tau \tan\theta_i)/x_\tau^2 + ((3x_\tau \tan\theta_i - 6W)/x_\tau^3)\, x^2\right]^2\right\}^{3/2}} \right| \tag{7}$$

and substitute $x = x_\tau$ into the upper form to get

$$K(x_\tau) = \left| \frac{2x_\tau \tan\theta_i - 6W}{x_\tau^2} \right| \tag{8}$$

From formulas (4), (6), and (8), we can get that

$$J = \frac{u_i^2}{a_{\tau,\max}} \left| \frac{2x_\tau \tan\theta_i - 6W}{x_\tau^2} \right| + \frac{\tau}{\tau_{\max}} \tag{9}$$

where real-time vehicle speed u_i is detected by sensors. The two variables x_τ and τ will be adjusted to control the optimal trajectory in response to the state changes of the surrounding vehicles. Minimizing the objective function will obtain these two parameters to solve the optimal lane-changing trajectory.

In reality, vehicle lane-changing needs to consider many constraints instead of simply solving a mathematical formula for trajectory planning. For example, the longitudinal velocity and acceleration cannot exceed the maximum value in the course of lane-changing. In terms of security, the key nodes of lane-changing can be constrained by the mature minimum safe distance model [18, 19].

As shown in Figure 4, the calculation formulas of the minimum safe distance $S_{(C,D)}$, $S_{(C,A)}$, and $S_{(C,B)}$ between C and D, B, and A are, respectively, given[18, 19].

$$S_{(C,D)} = \max\left\{ \int_0^t \int_0^\lambda \left[a_C(\tau) - a_D(\tau)\right] d\tau\, d\lambda\, t + \left[v_C(0) - v_D(0)\right] t \right\}; \quad \forall t \in \left[t_c, t_f\right], \tag{10}$$

$$S_{(C,A)} = \max\left\{ \int_0^t \int_0^\lambda \left[a_A(\tau) - a_C(\tau)\right] d\tau\, d\lambda\, t + \left[v_A(0) - v_C(0)\right] t \right\}; \quad \forall t \in \left[t_c, t_f\right], \tag{11}$$

$$S_{(C,B)} = \max\left\{ \int_0^t \int_0^\lambda \left[a_C(\tau) - a_B(\tau)\right] d\tau\, d\lambda\, t + \left[v_C(0) - v_B(0)\right] t \right\}; \quad \forall t \in \left[t_c, t_f\right] \tag{12}$$

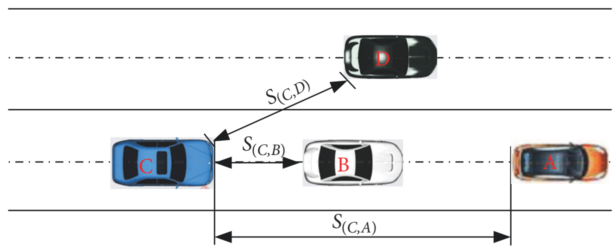

Figure 4: Change of track scenario.

where v_A, v_B, v_C, v_D are the speeds of each vehicle, respectively; a_A, a_B, a_C, a_D are the acceleration of each vehicle, respectively; t_c is the critical collision time between vehicles; t_f is the end of the lane change; τ and λ is integral variable.

The main constraint in the process of lane change is

$$|\ddot{x}(t)| < a_{x,\max} \tag{13}$$

$$|\ddot{y}(t)| < a_{y,\max} \tag{14}$$

$$0 < \dot{x}(t) < v_{x,\max} \tag{15}$$

$$0 < y(t) < W \tag{16}$$

$$S_{(C,D)} + d_0 < d_{(C,D)} \tag{17}$$

$$S_{(C,A)} + d_0 < d_{(C,A)} \tag{18}$$

$$S_{(C,B)} + d_0 < d_{(C,B)} \tag{19}$$

where $v_{x,\max}$ is the speed threshold of vehicle in longitudinal direction; d_0 is the minimum safe distance between vehicles; $d_{(C,D)}$, $d_{(C,A)}$, and $d_{(C,B)}$ are the actual distances from C to D, A, and B, respectively.

4. Simulation and Experimental Verification

4.1. Simulation Scene Design and Analysis. In this paper, Carsim-simulink simulation is used to validate and compare the algorithms. Design multivehicle lane-changing scenario in software and determine the parameter value of PID controller which is $K_P = 0.125, K_I = 0.95, K_d = 0.01$。 Vehicle movement data in lane-changing scenes were obtained. The concrete joint simulation block diagram of PID control system for tracking lane change trajectory is shown in Figure 5.

As shown in Figure 6, a lane-change scene,one-way straight-line two-lane, has been set. There are three cars in the scene. Vehicle A is on the second lane at $x_2 = 40m$ and travels at $15m/s$. Vehicle B is on the second lane at $x_1 = 20m$ and travels at $20m/s$. Vehicle C is on the second lane at $x_0 = 0m$ and travels at $30m/s$. Among them, vehicle C is a main controlled vehicle for lane change and, to prevent collision, it changes lanes to the left and enters the fast lane.

As the vehicles change lanes to the left, the surrounding vehicles are not affected. The optimal trajectory utilized by formulas (3), (9), and (13)~(18) shown in Figure 7 and the parameters in Table 1 can be obtained.

When vehicle C changes lanes, leading vehicle A in the original lane also starts to change lanes to the right, while vehicle B runs at a speed of 20 m/s. The calculated safe distance between vehicle C and vehicle B should be more than 17.29m, and the safe distance between vehicle C and vehicle A should be more than 35m. In order to avoid collision, the existing lane-changing trajectory of vehicle C is replanned according to formula (3), formula (9), and formulas (13) ~ (19). As shown in Figure 9, the path of dynamic multiple planning keeps a safe distance between vehicle C, vehicle B, and vehicle A. Compared with the traditional nondynamic lane change route, the time of lane change is obviously shortened. In order to avoid collision with vehicle A, which suddenly changes lanes, vehicle C must first decelerate and increase the steering wheel angle to change lanes. The acceleration curves are shown in Figure 8.

According to the data in Figures 8 and 9 and Table 2, it can be seen that the maximum yaw angular velocity, front wheel yaw angle, and combined acceleration increased by 11.8%, 12.5%, and 21%, respectively. This is mainly due to the deceleration of the vehicle and the increase of the steering wheel angle when starting to change lanes, which will increase the comprehensive acceleration, but these values are within the constraints, and the vehicle still has good comfort and stability in the process of changing lanes. Compared with the traditional lane-changing method, the dynamic lane-changing strategy under the condition of vehicular network can not only effectively prevent collision in unexpected situations, but also shorten the lane-changing time by 20%. Therefore, the model can effectively improve the safety and efficiency of lane-changing.

4.2. Vehicle Validation. In order to verify the accuracy and validity of the optimal lane-changing model, a real vehicle is used to verify the model. The main assembly instruments of the test vehicle are shown in Figure 10.

In the following we show changing lanes in a three-lane area suitable for lane change and similar to the simulation scenario. Two experienced drivers drive vehicle A and vehicle C to change lanes at the same time. A driver drives vehicle B at uniform speed and collects the data of the test vehicle when changing lanes in actual road conditions. The experimental data acquisition is shown in Figure 11. This paper collects vehicle lane-changing data under real road conditions, and compares it with software simulation data to verify the accuracy of the lane-changing model established in this paper.

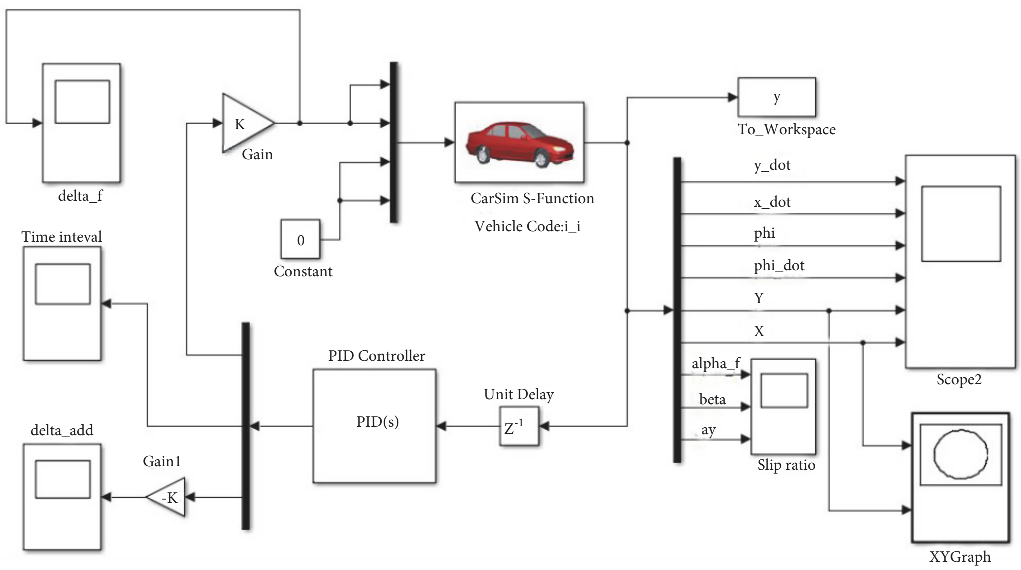

FIGURE 5: Joint simulation block diagram of PID control system with track tracking.

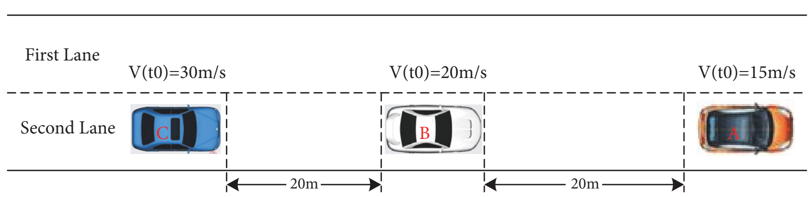

FIGURE 6: More than scene of vehicle cooperative lane change.

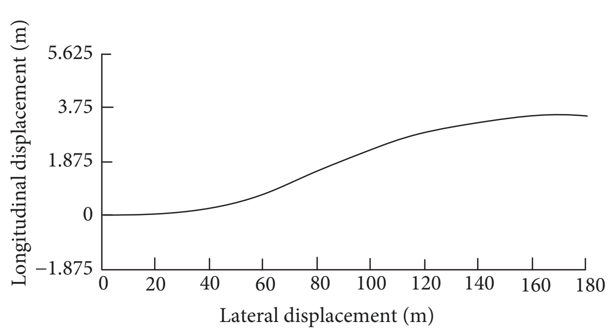

FIGURE 7: Optimal lane change trajectory.

TABLE 1: Change of track conditions for reference tracks.

main parameter	value	unit
Original Lane speed	20	m/s
Target Lane speed	30	m/s
Lane Width	3.75	m
Maximum Longitudinal Vehicle Speed	30	m/s
Maximum longitudinal acceleration	2.0	m/s^2
Maximum lateral acceleration	2.0	m/s^2

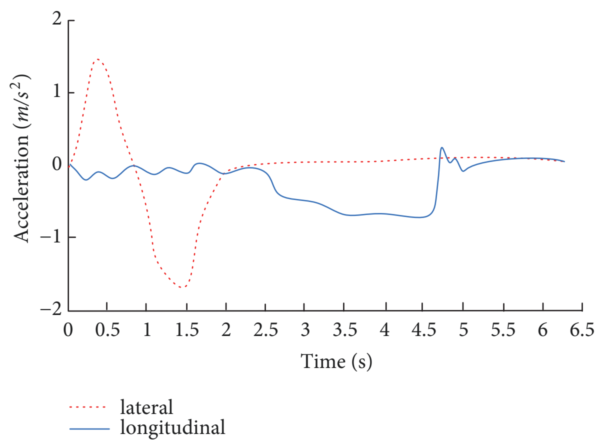

Figure 8: Longitudinal and transverse acceleration variation curve.

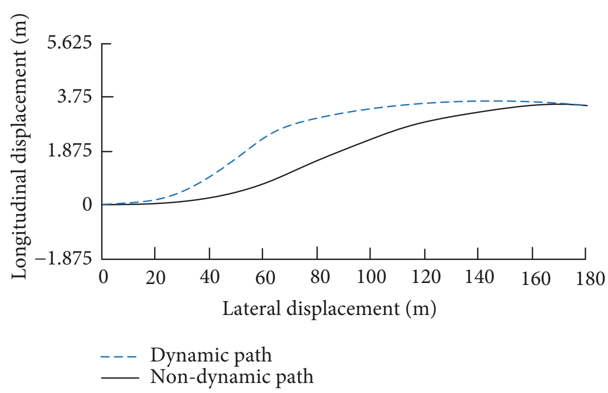

Figure 9: Comparison with traditional nondynamic.

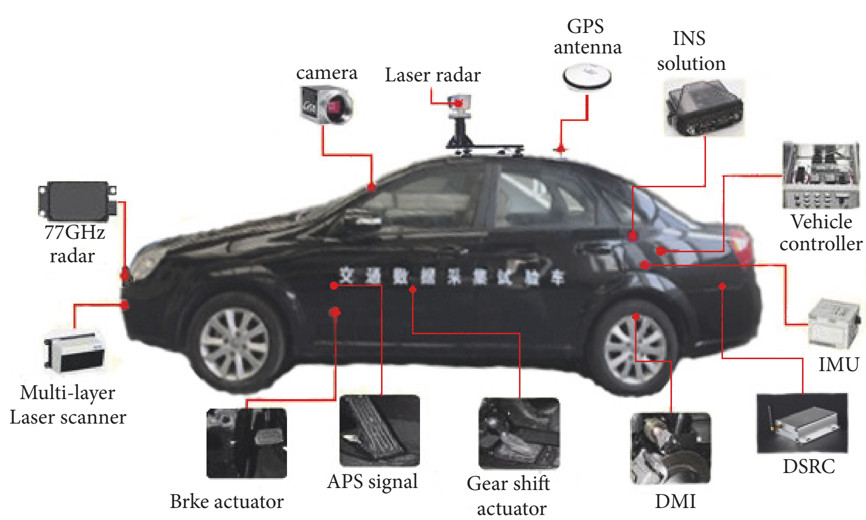

Figure 10: Test vehicles and data acquisition equipment.

The actual data of driver lane change are compared with the simulation data shown in Figures 12–16. It can be seen that the actual measured values of yaw angular velocity, front wheel deflection angle, center of mass side deflection angle, and lateral acceleration of lane-changing parameters are slightly delayed compared with the control values calculated by simulation. This is due to the inertia of the vehicle in motion, resulting in delay. Because the existence of steering clearance is not taken into account when establishing the model, the actual measured value of the

Table 2: Comparison of model parameters.

Whether dynamic process or not	No dynamic value	Dynamic value	unit
Longitudinal velocity	30	24	m/s
Maximum combined acceleration	1.7	2.3	m/s2
Maximum lateral acceleration	1.63	2.07	m/s2
Lane changing time	5.0	4.0	s
Maximum yaw angular velocity	7.5	8.5	deg/s
Front wheel yaw maximum	2.8	3.2	°

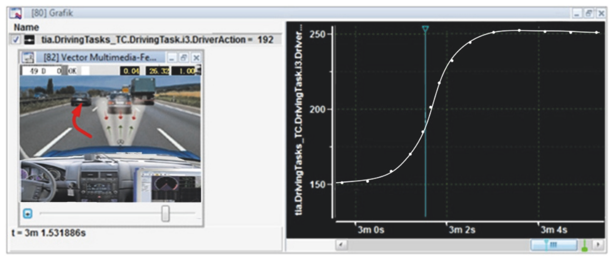

Figure 11: Data acquisition in collision avoidance experiment.

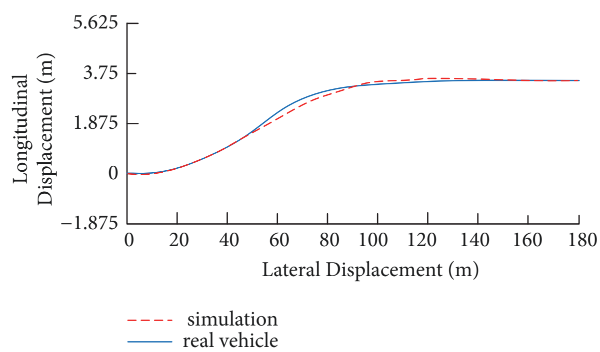

Figure 12: Comparison of vehicle planning trajectory and actual trajectory.

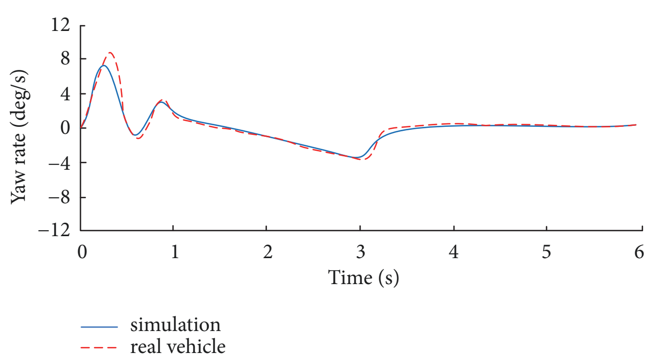

Figure 13: Vehicle yaw angular velocity curve.

front wheel deflection is larger than the simulated value. Even though there are slight errors between the measured and simulated values of some parameters in the course of lane-changing, the tracking error is less than 5% according to the coincidence degree of the simulation path and the actual lane-changing path. Therefore, the optimal dynamic lane-changing model of cubic spline curve established in this paper coincides with the actual lane-changing path. The lane-changing model proposed in this paper can effectively and quickly complete lane-changing.

5. Conclusions

In this paper, a local dynamic path planning strategy is proposed to overcome the disadvantages of traditional way, for example, poor comfort, long lane-changing time, and only

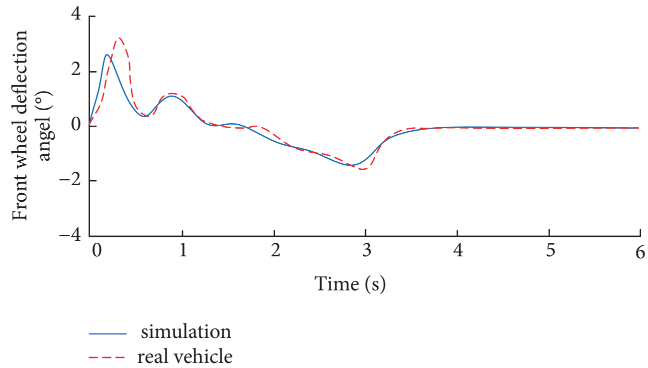

Figure 14: Vehicle front wheel angle diagram.

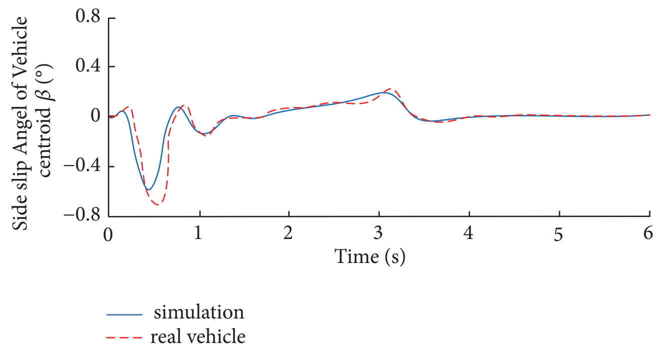

Figure 15: Side deflection curve of vehicle mass center.

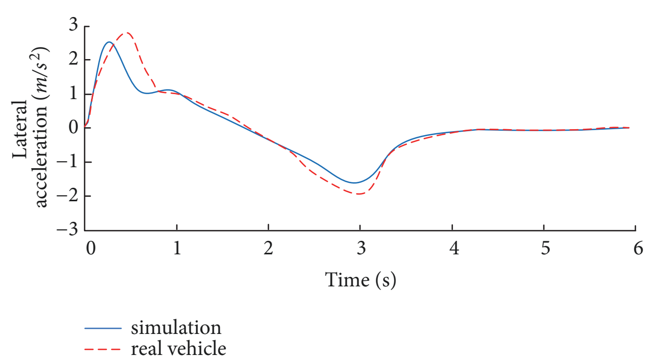

Figure 16: Vehicle lateral acceleration curve.

considering the starting point of lane-changing rather than the whole lane-changing process in the driving environment. The results of simulation and vehicle test show that the method is safe, reliable, and effective.

(1) Introducing the dynamic programming ability into the traditional cubic polynomial path planning method and improving the comfort and lane-changing efficiency, the dynamic optimal lane-changing trajectory is better by simulation and vehicle verification, and the tracking error is less than 5%.

(2) This method can effectively avoid emergencies and shorten the lane-changing time by 20%. Therefore, the model can effectively improve the security and efficiency of lane-changing.

(3) The research in this paper is based on a relative representative scenario. There are some more complex road conditions that have not been thoroughly considered, for example, how to change lane safely on scenes where pedestrians and motor vehicles are mixed. The following research will give the corresponding evaluation index and standard method.

Data Availability

All data included in this study are available upon request by contact with the corresponding author.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

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