Journal of Research in Science and Engineering (JRSE)
ISSN: 1656-1996 Volume-7, Issue-3, March 2025
DOI: 10.53469/jrse.2025.07(03).08

Intelligent Vehicle Path Tracking Control Based on Model Predictive Control

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Abstract: ***With the rapid development of intelligent transportation system, the path tracking control of intelligent vehicles has become one of the key technologies. In this paper, the path tracking method of intelligent vehicles based on model predictive control (MPC) is studied deeply. Firstly, the control law for adaptive adjustment of the optimal time domain is designed based on the two-degree-of-freedom vehicle dynamics model and the model control algorithm. Next, the MPC trajectory tracking controller is built based on the error characteristics of the actual front wheel angle and the predicted front wheel angle. Finally, the results of Matlab/Simulink and Carsim joint simulation show that the MPC has significant advantages compared with the traditional PID controller in terms of path tracking accuracy, stability, and adaptability to complex road conditions, etc., which provides theoretical support for the further optimization of the path tracking technology of intelligent vehicles.***

Keywords: Intelligent vehicle, Path tracking, Model predictive control, Dynamics model, Optimization**.**

1. Introduction

In recent years, intelligent transportation systems (ITS) have attracted wide attention as an effective means to alleviate traffic congestion, improve driving safety and reduce energy consumption [1]. As a core component of ITS, one of the key technologies of ITS is accurate path tracking control. Whether autonomous driving tracks on structured roads or assisted driving helps drivers keep a given route, they all rely on reliable path tracking algorithms [2].

Compared with traditional rule-based optimization methods, learning-based autonomous vehicle control algorithms can cope with more complex and real-time changing driving scenarios, including end-to-end learning of driving behavior based on human driver behavior data and learning for improving the accuracy or parameter adjustment of predictive models. Liu Zhiqiang [3] and Zhang Qing proposed an intelligent vehicle trajectory tracking control strategy based on adaptive time-domain parameters. A linear time-varying MPC controller was established and dynamic constraints were added to design an adaptive time-domain parameter controller. Hind Laghmara [4] proposed a global obstacle avoidance control framework for autonomous vehicles, which consists of three modules: perception module, planning module and control module. Obstacles are identified in perception module based on belief mesh occupancy, obstacle avoidance trajectory is designed in trajectory planning module based on parametric Sigmoid function curve, and finally a lateral controller with feedforward and robust feedback is designed to complete vehicle trajectory tracking. Pei Yulong [5] and Zhang Chenxi designed an MPC controller with adaptive sampling period and predictive time domain. Through joint simulation platform experiments, it is proved that the controller has higher path tracking control accuracy and better vehicle stability at different vehicle speeds. Miao Baorui and Han Chao designed a two-layer adaptive model predictive controller (MPC), established an obstacle avoidance planning controller and a path tracking controller, and proposed an adaptive path tracking control strategy according to the relationship between prediction time domain and vehicle speed in MPC algorithm. Wang Mingliang [6] proposed a low complexity vehicle dynamics model, analyzed vehicle lateral stability by using phase plane and proposed envelope constraint method, designed MPC control system based on improved vehicle dynamics model, introduced fast solver to realize high speed solution, verified the performance of control system by joint simulation platform and real vehicle test. NadaAwad [7] introduces an integrated path tracking control strategy based on multiple-input multiple-output linear model predictive control (LMPC) and fuzzy logic switching systems. Simulation results show that the tracking performance of the designed tracking controller is better than that of linear quadratic Gaussian (LQG) tracking controller on different paths. Xie Rui [8] and Liu Guangmin presented a MPC model with variable prediction time domain based on particle swarm optimization (PSO) algorithm. PSO algorithm was used to calculate the optimal prediction time domain and applied to MPC controller model. Through MATLAB comparative analysis, it was proved that the improved model could improve the trajectory tracking accuracy.

To sum up, traditional path tracking control methods such as PID control, although simple in structure and easy to implement, are often limited in the face of complex and variable road conditions, vehicle parameter uncertainty and system nonlinearity. MPC can predict the future system state based on predictive model, solve optimal control sequence through online rolling optimization, and use feedback correction to deal with model mismatch and disturbance. The controller parameters and vehicle parameters have a great influence on the accuracy of MPC tracking control. Therefore, for the optimal time-domain problem of different vehicle speeds, a steering-compensated MPC trajectory tracking controller is designed by using a two-degree-of-freedom vehicle dynamics model and based on the optimal control law in both speed and time domains. The effectiveness and stability of the trajectory tracking are verified by the joint simulation of Matlab/Simulink and CarSim at different vehicle speeds.

2. Model Predictive Control Principle

2.1 Prediction Model

Predictive models are the basis of MPC and are used to describe the future dynamic behavior of the system. Common predictive models include linear time-invariant (LTI) models, linear parameter variation (LPV) models, and nonlinear models. For intelligent vehicle path tracking, simplified kinematic or dynamic models of the vehicle are usually established under certain assumptions [9]. For example, based on the bicycle model, considering the longitudinal speed, lateral speed, yaw rate and other state variables of the vehicle, combined with the tire model and vehicle geometric parameters, the vehicle motion is characterized in the form of state space equations [10]:

$$\dot{x} = f(x,u) \tag{1}$$

Where x is the state vector, u is the control input vector, and f is a nonlinear function. In practical applications, the nonlinear model is often linearized to solve optimization problems, such as discrete linear time-varying (LTV) models [11]:

$$x_{k+1} = A_k x_k + B_k u_k \tag{2}$$

Where x_k and u_k are the state and control variables at k time respectively, and A_k and B_k are the corresponding coefficient matrices, which are determined by the current state and system parameters.

2.2 Rolling Optimization

At each sampling moment k, the MPC solves the control sequence for the next N_p steps based on a prediction model to optimize a predefined objective function $\{u_k, u_{k+1}, \cdots\}$. The objective function usually integrates the path tracking error, control input variations, etc, such as [12]:

$$J_k = \sum_{i=0}^{N_p-1} (e_{k+i}^T Q e_{k+i} + \Delta u_{k+i}^T R u_{k+i}) + (e_{k+N_p}^T P e_{k+N_p}) \tag{3}$$

Where e_{k+i} is the path tracking error vector at k+i moments, u_{k+i} is the control increment, and Q, R, P_{Np} are the weight matrices, which are used to weigh the tracking accuracy and control smoothness. Meanwhile, the optimization process needs to satisfy the physical constraints of the system, such as the maximum steering angle of the vehicle, steering angular velocity, and acceleration limits:

$$u_{\min} \leq u_{k+i} \leq u_{\max} \tag{4}$$

$$\Delta u_{\min} \leq \Delta u_{k+i} \leq \Delta u_{\max} \tag{5}$$

By solving this constrained optimization problem, the optimal control inputs u_k^* at the current moment are obtained and acted on the system.

2.3 Feedback Correction

Due to model uncertainty and external disturbances, the actual system state may deviate from the output of the prediction model, and the MPC uses the actual system state measured x_{k+1}^* by the sensors to correct the prediction model at the end of each cycle. A common method is to take the error as new information and correct the initial state of the prediction model at the next moment, to re-predict and optimize, and so on, continuously adapting to the actual working condition changes.

3. Intelligent Vehicle Modeling

3.1 Kinematic Model

The kinematic model describes the vehicle motion from the perspective of geometric relationship, ignoring the vehicle tire force, inertia and other dynamics, and is suitable for low-speed, small curvature path tracking scenarios [13]. As shown in Figure 1:

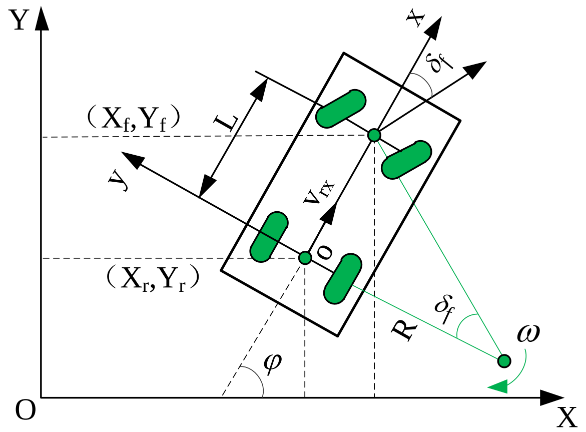


Figure 1: Vehicle Motion Model

The velocity at the center of the rear axle along the x-axis of the body coordinate system is:

$$v_{rx} = \dot{X}_r \cos(\phi) + \dot{Y}_r \sin(\phi) \tag{6}$$

The kinematic constraints on the anterior and posterior axes are (lateral equilibrium):

$$\begin{cases} \dot{X}_f \sin(\phi + \delta_f) \dot{Y}_f \cos(\phi + \delta_f) = 0 \\ \dot{X}_r \sin\phi - \dot{Y}_r \cos\phi = 0 \end{cases} \tag{7}$$

The relationship between the coordinates of the centers of the front and back axes is known from the geometric relationship:

$$\begin{cases} X_f = X_r + L\cos(\phi) \\ Y_f = Y_r + L\sin(\phi) \end{cases} \tag{8}$$

From v_{rx} and angular velocity, the vehicle steering radius and front wheel angle of rotation are obtained as:

$$\begin{cases} R = v_{rx}/\omega \\ \delta_f = \arctan(L/R) \end{cases} \tag{9}$$

In vehicle unmanned driving, the vehicle speed v_{rx} and the pendulum angular velocity are often used as control quantities, and the kinematics of the vehicle is modeled as:

$$\begin{bmatrix} \dot{X}_r \\ \dot{Y}_r \\ \dot{\phi} \end{bmatrix} = \begin{bmatrix} \cos(\phi) \\ \sin(\phi) \\ 0 \end{bmatrix} v_{rx} + \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \omega \tag{10}$$

where (x,y) is the vehicle position coordinate in the geodetic coordinate system, θ is the vehicle heading angle, v is the vehicle longitudinal velocity, β is the vehicle center-of-mass lateral deflection angle (approximated to 0 at low speeds), L is the vehicle wheelbase, and δ is the front wheel steering angle.

3.2 Kinetic Model

Considering the vehicle tires and ground forces, vehicle

inertia and other factors, the dynamics model can more accurately reflect the vehicle high-speed driving characteristics [14], as shown in Figure 2:

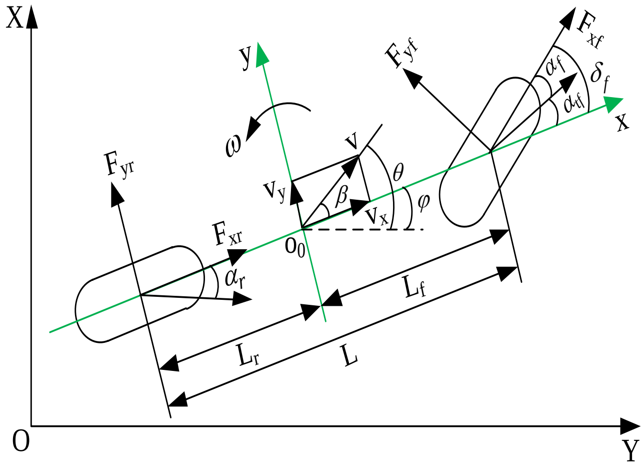


Figure 2: Vehicle dynamics model

A two-degree-of-freedom vehicle dynamics model is used, containing the vehicle longitudinal and lateral dynamics equations:

$$\begin{cases} m(\dot{V}_x - V_y\omega) = F_{xf}\,cos(\delta_f) - F_{yf}\,sin(\delta_f) + F_{xr} - F_{ftal} \\ m(\dot{V}_y + V_x\omega) = F_{xf}\,sin(\delta_f) + F_{yf}\,cos(\delta_f) + F_{yr} \\ I_Z\dot{\omega} = L_f(F_{xf}\,sin(\delta_f) + F_{yf}\,cos(\delta_f)) - L_rF_{yr} \end{cases} \tag{11}$$

Where m is the mass of the vehicle, V_x and V_y are the longitudinal and lateral velocities, respectively, F_x is the longitudinal force, F_{yf} and F_{yr} are the lateral forces of the front and rear wheels, respectively, I_z is the inertia of the vehicle rotating around the z-axis, and L_f and L_r are the distances from the center of mass of the vehicle to the front and rear axes, respectively.

4. Design of MPC-based Path Tracking Control Strategy

4.1 Route Planning and Reference Track Generation

Before the path tracking, it is necessary to generate the reference trajectory through path planning algorithms, such as A algorithm, Dijkstra algorithm for global path planning, Dijkstra algorithm is based on the graph theory, traversing all the nodes from the starting point, calculating the shortest path to the target point, discretizing the map into a grid, and the weights of the edges between the nodes can be set to the distance, the cost of passage, etc. A algorithm based on the Dijkstra introduces a heuristic function to prioritize the search for the target direction node to improve the search efficiency. On the basis of Dijkstra, A algorithm introduces a heuristic function to prioritize the search for the target direction node and improve the search efficiency. Local path planning commonly used dynamic window method, artificial potential field method, dynamic window method according to the vehicle's current speed, acceleration limitations, search for feasible trajectories in the velocity space; artificial potential field method to build the gravitational force, repulsive force field to guide the vehicle to avoid obstacles, driving to the target. The generated reference trajectory is usually represented as a series of discrete points $\{x_r(k), y_r(k), k=0, 1, 2\}$ and contains information such as the angular curvature $\theta_r(k)$ curvature $\gamma_r(k)$ of the corresponding reference heading.

4.2 Objective Function Design

The objective function is designed to trade-off the path tracking accuracy with the control smoothness. In addition to the aforementioned tracking error and control increment terms, other penalties can be added as needed [15]. For example, to prevent the vehicle from deviating too much from the reference path, a weighted penalty is applied to the lateral deviation $e_y(k)$:

$$J_k = \sum_{i=0}^{N_p-1}[(e_{y,k+i}^2 + \rho\,\dot{e}_{y,k+i}^2)Q_1 + \Delta u_{k+i}^T R u_{k+i}] + e_{y,k+N_p}^2 P_{N_p} \tag{12}$$

Where ρ is a weighting coefficient that regulates the weight distribution of deviation and deviation change rate, and Q_1 focuses on lateral deviation control. In addition, if vehicle driving comfort is considered, the longitudinal acceleration $x(k)$ can be constrained and added to the objective function to induce a smooth change in the control inputs and to reduce the feeling of bumps for the vehicle occupants.

4.3 Constraint Setting

The constraints are formulated based on the physical characteristics of the vehicle and driving safety requirements. In addition to the basic constraints such as steering angle, steering angular velocity, acceleration, etc, the tire adhesion limit constraints also need to be considered to prevent the vehicle from slipping out of control when steering at high speed [16]. According to the elliptic model of tire-ground friction, the combined lateral and longitudinal forces should be satisfied:

$$(\frac{F_y}{F_{y,max}})^2(\frac{F_x}{F_{x,max}})^2 \tag{13}$$

Where $F_{y,max}$ and $F_{x,max}$ are the tire lateral and longitudinal maximum adhesion force, respectively, related to the road surface adhesion coefficient and vertical load. In the optimization solution process, it is ensured that the control input and vehicle state are always in the feasible domain to guarantee the driving safety and stability.

4.4 Vehicle Error Tracking Model

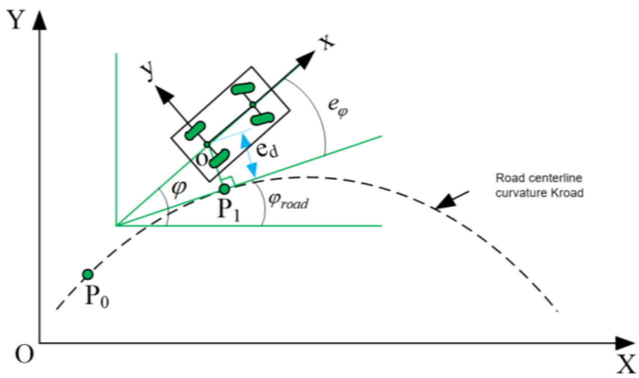


Figure 3: Vehicle error tracking model

The point P_1 moves along the centerline of the road as shown in Figure 3 [17]:

$$\dot{S} = \frac{1}{1-K_{road}e_d}[V_x \cos(e_\phi) + V_y \sin(e_\phi)] \tag{14}$$

The vehicle tracking error equation is:

$$\begin{cases} \dot{e}_\phi = \dot{\phi} - K_{road}\dot{S} \\ \dot{e}_d = V_x \sin(e_\phi) + V_y \cos(e_\phi) \end{cases} \tag{15}$$

Neglecting the lateral velocity V_y and adopting a small angle assumption for the transverse pendulum angular deviation e_φ, so that $sin(e_\varphi)=e_\varphi$, $cos(e_\varphi)=1$, $K_{road}*e_d=0$, combined with the transverse pendulum angular velocity equation, and so that $tan(\delta_f)=\delta_f$ there is an error tracking model as:

$$\begin{bmatrix} \dot{e}_\phi \\ \dot{e}_d \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ V_x & 0 \end{bmatrix} \begin{bmatrix} e_\phi \\ e_d \end{bmatrix} + \begin{bmatrix} \frac{V_x}{L} \\ 0 \end{bmatrix} \delta_f - \begin{bmatrix} \frac{V_x}{L} \\ 0 \end{bmatrix} \delta_{fref} \tag{16}$$

5. Simulation Experiment

5.1 Simulation Environment Construction

Carsim and Simulink joint simulation platform, Carsim provides high-precision vehicle dynamics model, covering a variety of car models, tire models, road parameters, can realistically simulate the vehicle driving process. The vehicle powertrain option is four-wheel drive (4-wheel drive). The actual mass of the vehicle as a whole is 4 times the reference vertical force of a single tire, here 'M total = 4*5393.6/9.81 Kg'.The braking force is set to be continuously 0 Mpa. AT automatic gear shift, no steering, the initial position of the vehicle in the geodetic coordinate system is set to be (0, 0), and the initial steering angle is 0 degreesThe vehicle speed signal, left and right wheel steering angle signals are selected as input signals to the Carsim model.The longitudinal vehicle speed, front wheel steering angle, transverse angular velocity, lateral velocity, slip rate of the (left front, right front, left rear, right rear) four wheels and the longitudinal and transverse coordinates are selected sequentially as the output signals of the Carsim model.

Simulink is used to build MPC controllers, path planning module, etc., as shown in Fig.4.

Simulink builds the MPC model, including the control signal area, signaling area, result area and Simulink area.

The simulation parameters are shown in Table 1:

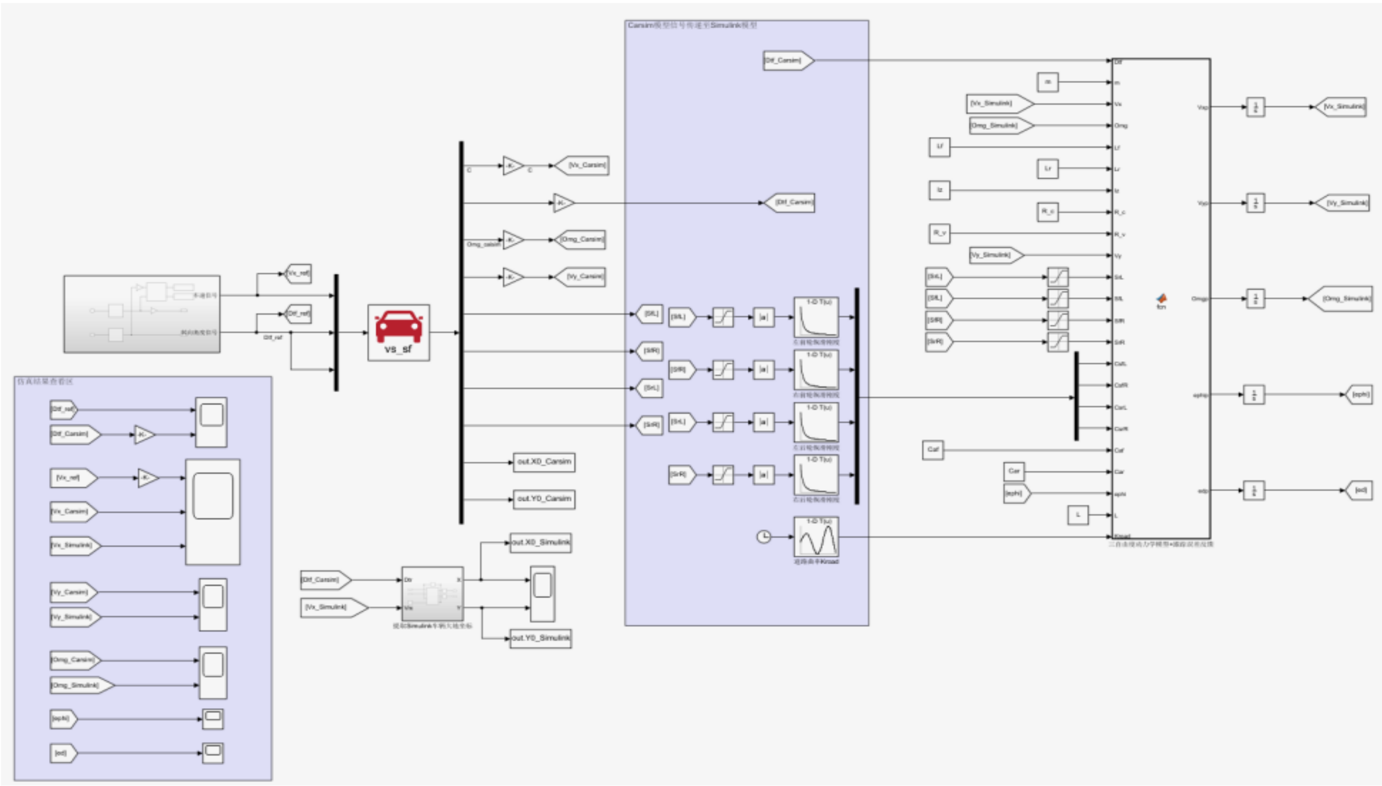


Figure 4: Carsim-Simulink co-simulation to validate models

Table 1: Simulation parameters

Parameters	Notation	Numerical value	Parameters	Symbol	Numerical value
Inertial frame	XOY		Longitudinal velocity at reference point	V_x	m/s
Car-body coordinate system	xoy		Lateral velocity at reference point	V_y	m/s
Front and rear wheelbase	L	m	Swing angle deviation	e_φ	rad
Yaw angle	φ	rad	lateral error	e_d	m
Front wheel angle	δ_f	rad	Front axle longitudinal force	F_{xf}	N

Rear Axis Center x-axis speed	V_{rx}	m/s	Rear axle longitudinal force	F_{xr}	N
Rear axle steering radius	R	m	Front axle lateral force	F_{yf}	N
Front Axis Center Inertial coordinates	(X_f,Y_f)	m	Rear axle lateral force	F_{yr}	N
Rear Axis Center Inertial coordinates	(X_r,Y_r)	m	Transverse angular velocity	ω	rad/s

5.2 Simulation Results Analysis

In this study, in order to comprehensively and accurately validate the intelligent vehicle path tracking control strategy based on Model Predictive Control (MPC), we choose the joint simulation platform of Carsim and Simulink to carry out in-depth investigation. Carsim, with its powerful vehicle dynamics modeling capability, can realistically simulate the actual motion state of the vehicle under various complex working conditions; Simulink provides a rich library of control algorithms and a flexible construction environment, which provides strong support for the realization and debugging of MPC control algorithms. The organic combination of the two allows us to highly reproduce the real vehicle driving scene in the virtual environment, so as to evaluate the MPC control effect in an all-round and multi-dimensional way. After a series of rigorous parameter setting, model building and multiple simulation runs, the simulation results shown in Figure 5 are finally obtained. The results intuitively and clearly present the comparison of the deviation between the actual trajectory and the preset trajectory of the vehicle in the intelligent vehicle path tracking process of MPC control, which lays a solid foundation for the subsequent analysis of the results and optimization of the strategy.

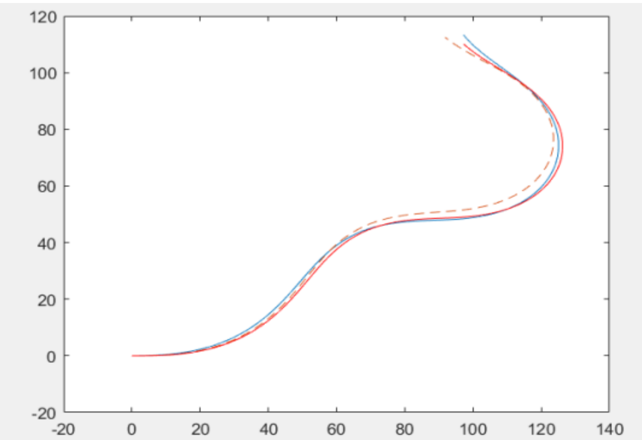
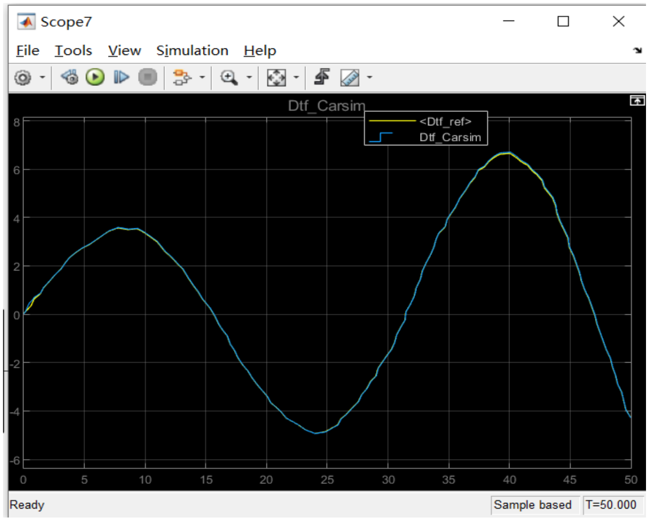
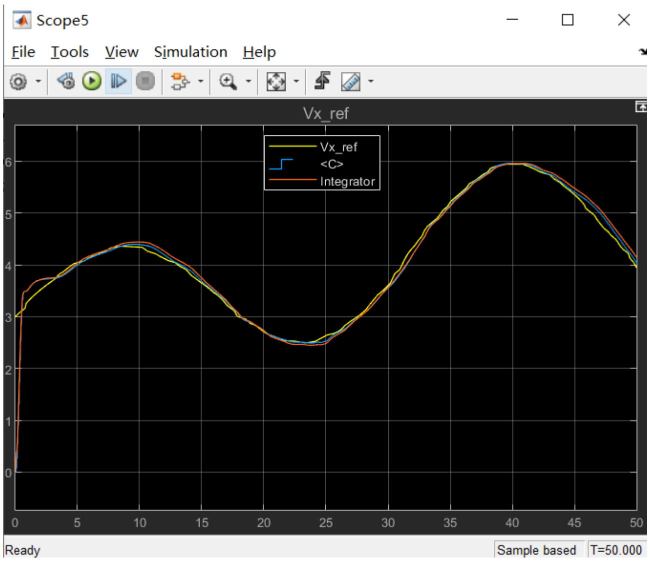


Figure 5: Vehicle trajectories in geodetic coordinates

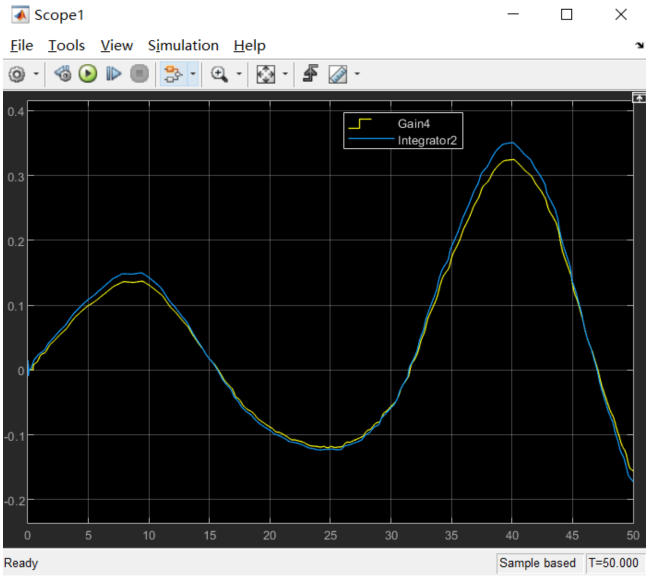
Under the complex simulation environment, through the precise setting of various parameters of the vehicle model and the simulation of different driving conditions, the simulation results based on the Carsim - Simulink joint platform strongly indicate that the vehicle equipped with the MPC controller shows excellent trajectory tracking performance throughout the entire driving process. In the face of a variety of complex road conditions, such as curves, lane changes, and paths with different curvatures, the vehicle is able to quickly and accurately adjust its own driving state by virtue of the powerful prediction and control capabilities of the MPC controller, so that the actual trajectory of the vehicle and the preset trajectory are highly consistent with each other. From the specific data, the vehicle trajectory deviation is always effectively controlled within a very small range in the continuous simulation time, which fully proves that the vehicle controlled by the MPC controller has an excellent tracking effect on the trajectory, and can provide a solid guarantee for the safe and stable driving of the intelligent vehicle.



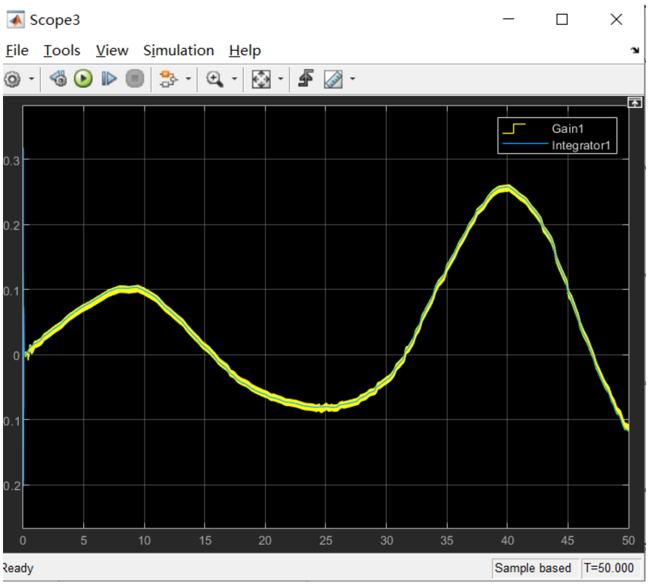
(a)



(b)



(c)



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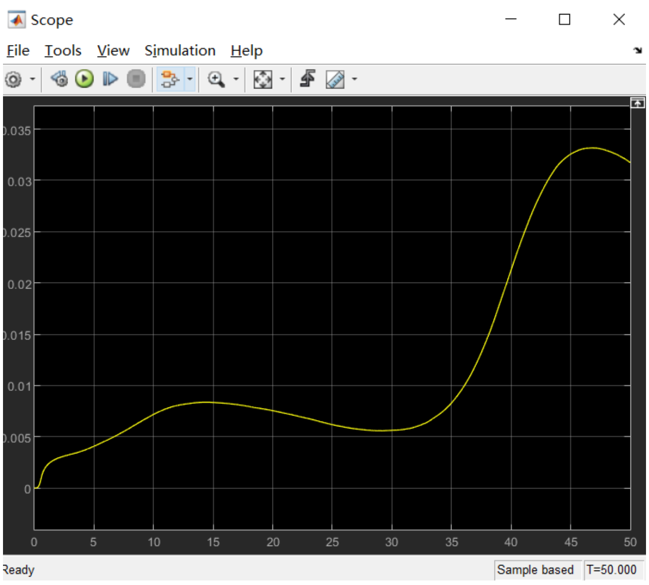
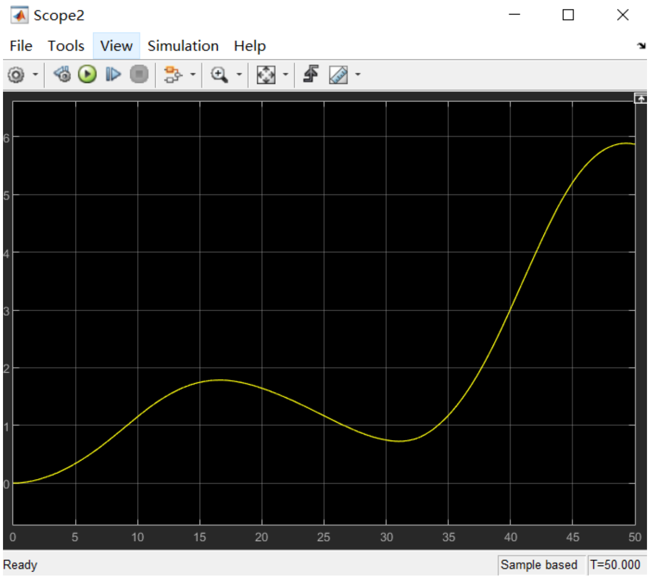


(e)



(f)

Figure 6: (a) Turning angle (b) Vertical speed (c) Lateral velocity (d) Swing angle (e) Angular error (f) Displacement error

After in-depth simulation experiments, the performance of the MPC controller is fully analyzed through the detailed analysis of multi-dimensional key data such as steering angle, longitudinal speed, lateral speed, traverse angle, angular error and displacement error. From the perspective of the core indicators of vehicle handling, the dynamic adjustment of the front wheel steering angle of the MPC controller always meets the needs of the vehicle during the whole operation process, and the maximum center of mass lateral deviation angle and the maximum traverse angle are strictly limited to the safe and reasonable constraints. This result not only demonstrates the MPC controller's effective control of the vehicle's dynamic stability, but also means that the vehicle is able to maintain a smooth driving attitude under complex road conditions.

The outstanding performance of the MPC controller is further emphasized when focusing on typical vehicle speeds of up to 20m/s. At this speed, the MPC controller has an excellent control of the transverse direction of the vehicle. At this speed, the lateral deviation, a key measure of path tracking accuracy, was monitored and found to be a maximum of only 0.23 m. Compared to conventional control methods, which typically have a lateral deviation of more than 0.5m at the same speed, the MPC controller's lateral deviation is significantly lower. This data comparison strongly proves that the MPC controller has high path tracking accuracy and can accurately guide the vehicle along the preset trajectory, which greatly improves the safety and reliability of the intelligent vehicle traveling and provides solid data support and technical guarantee for the practical application.

5.3 Comparative Analysis

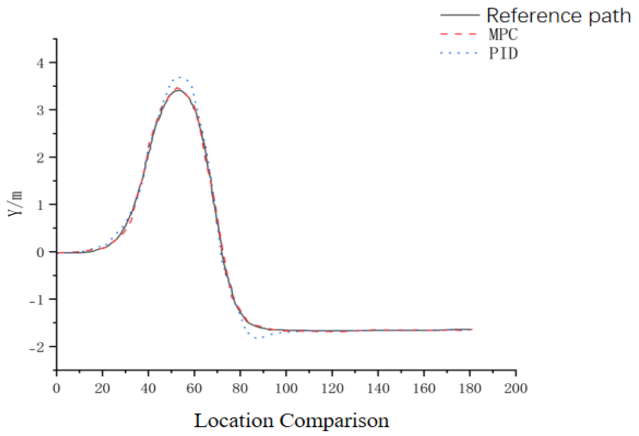


Figure 7: Comparison of MPC and PID control path tracking

In the process of vehicle driving, the curve driving condition is a key scene to test the performance of the controller. Based on the simulation results shown in Figure 7, the significant difference between the MPC controller and the PID controller under this condition can be clearly seen. When the vehicle is in the curve driving condition, the MPC controller shows excellent performance. Throughout the entire curve driving process, the actual trajectory of the vehicle closely matches the reference trajectory, as if it were being pulled by a precise navigation system. Through accurate statistical analysis of the data, we found that the average lateral deviation was always strictly controlled within ±0.1m, and the peak deviation was less than 0.2m, which means that the vehicle was able to maintain a very high driving accuracy in the curve, and followed the ideal path almost without deviation. On the contrary, the PID controller shows obvious deviations at the entrance and exit of the curve. At the entrance of the curve, due to the sudden change of the vehicle's driving state, the PID controller failed to make accurate adjustments in time, resulting in the vehicle began to deviate from the reference trajectory; and at the exit of the curve, the same because of the inability to quickly adapt to the transformation of the vehicle's driving state, further aggravating the deviation. According to the statistics, the average value of lateral deviation of the PID controller reached ±0.3m, and the maximum deviation was more than 0.5m. Such a large deviation not only affects the smoothness of the vehicle traveling, but also constitutes a potential threat to driving safety.

To explore the reasons behind, the MPC controller is based on an advanced prediction model, which is able to accurately predict the vehicle's driving state in the curve in advance and plan the optimal control sequence. In the face of the complexity of the curvature of the curve is constantly changing, it can quickly respond to timely adjustment of the vehicle's driving parameters, so as to ensure that the vehicle is stable and accurate along the reference trajectory. The PID controller, on the other hand, is mainly based on the current error control, with a certain lag characteristic. When the vehicle driving path changes rapidly, such as driving in a curve, the PID controller is difficult to capture these changes in time and quickly adjust the control strategy, so it is difficult to adapt to the changes in the complex path, resulting in a large deviation of the vehicle driving trajectory.

In summary, in the curved driving conditions, the MPC controller has obvious advantages over the PID controller by virtue of its unique control principle and excellent performance, providing a more reliable guarantee for the safe and stable driving of intelligent vehicles in complex road conditions.

Comparison of PID and MPC control of front wheel steering angle is shown in Figure 8.

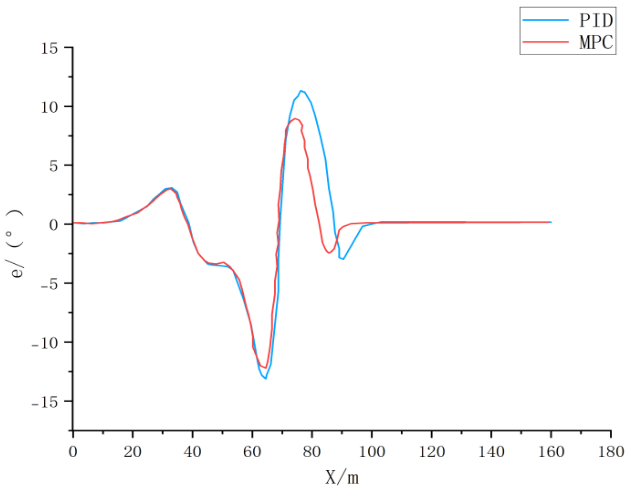


Figure 8: Comparison of PID and MPC control of front wheel steering angle

In the path tracking control system of intelligent vehicles, PID control and MPC control show very different characteristics when adjusting the front wheel steering angle. From the level of control principle, PID control mainly relies on the current error signal to adjust the front wheel steering angle according to the linear combination of proportional, integral and differential control roles, and its control logic is relatively simple and direct, but lacks the ability to predict the future state. On the other hand, MPC control is based on the vehicle dynamics model, through predicting the state of the vehicle in many future moments, and combined with the preset target trajectory, under a series of constraints, it optimally solves the optimal front-wheel steering angle control sequence at the current moment, and it has the advantages of forward-looking and global optimization.

In terms of actual response speed, when the vehicle driving conditions change, the PID control reacts only according to the current error, and there is a certain lag. For example, when the vehicle turns at high speed, PID control may not be able to adjust the front wheel steering angle in time, resulting in a delayed vehicle response, it is difficult to quickly and stably into the corner driving state. On the contrary, MPC control can plan the control action in advance, and start to adjust the front wheel steering angle before the working condition changes, so that the vehicle can quickly and smoothly adapt to the new driving requirements.

From the actual control effect comparison, in complex road conditions, such as continuous curves and lane change scenarios, PID control of the vehicle front wheel steering angle adjustment is often not accurate enough, resulting in the actual trajectory of the vehicle and the preset trajectory deviation is large, affecting the stability and comfort of driving. In the MPC-controlled vehicle, the steering angle of the front wheels can be finely adjusted according to the real-time road conditions and the predicted driving state, and the actual driving trajectory of the vehicle closely matches the reference trajectory, which significantly improves the accuracy of the path tracking and the safety of the vehicle driving. Through a large number of simulation experiments and actual test data show that, under the same complex working conditions, the front wheel steering angle of MPC control can make the average value of vehicle lateral deviation reduced by about 5.5% compared with that of PID control, which fully proves that the MPC control has obvious superiority over the PID control in regulating the front wheel steering angle.

6. Result

This paper focuses on the in-depth study of intelligent vehicle path tracking based on model predictive control, elaborates the principle of MPC, constructs the kinematics and dynamics model of intelligent vehicle, designs the complete path tracking control strategy, and verifies the advantages of MPC compared with the traditional PID control in terms of accuracy, smoothness, and adaptability to complicated road conditions through simulation. With the feedback correction mechanism, real-time adjustment of the prediction model, the vehicle can still track the path well, speed fluctuation is small; PID control effect is significantly reduced, the path deviation increases, the vehicle attitude is unstable, indicating that the MPC has a stronger robustness to complex, uncertain environment. However, the application of MPC in intelligent vehicles still faces many challenges, such as modeling, computation, perception, and regulations. With the related technological breakthroughs and cross-field collaboration, MPC is expected to become the mainstream technology for intelligent vehicle path tracking, promote the maturity of the autonomous driving industry, and realize the vision of safe, efficient, and comfortable intelligent transportation.

References

[1] Yang Jiachen, Xi Meng, Wen Jiabao, et al. A digital twins enabled underwater intelligent internet vehicle path planning system via reinforcement learning and edge computing[J]. Digital Communications and Networks, 2024, 10(02):282-291.

[2] Xia Jia, Zheng Yanqun, Xie Binglei, et al. Research on optimal path planning method for intelligent vehicles based on improved particle swarm[J]. Mechanical Design and Manufacturing, 2025, (02):264-268.

[3] Liu Zhiqiang, Zhang Qing. Adaptive time-domain parametric MPC for intelligent vehicle trajectory tracking control [J]. Journal of Zhengzhou University (Engineering Edition), 2024, 45(01):47-53.

[4] Hind Laghmara, Mohamed-Taha Boudali, Thomas Laurain, et al. Obstacle Avoidance, Path Planning and Control for Autonomous Vehicles [C]. Intelligent Vehicles Symposium (IV). IEEE, 2019, 94(02):134-140.

[5] Pei Yulong, Zhang Chenxi, Fu Bohan, et al. Vehicle path tracking control based on adaptive sampling period and predictive time domain MPC [J]. Transportation Research, 2024, 10(3):46-55

[6] Wang Mingliang (2025). Research and implementation of unmanned vehicle trajectory fast tracking algorithm based on improved MPC[D]. Chang'an University, Xian.

[7] Nada Awad, Ahmed Lasheen, Mahmoud Elnaggar, et al. Model predictive control with fuzzy logic switching for path tracking of autonomous vehicles [J]. 2021, 34(01): 56-62.

[8] Xie Rui, Liu Guangmin, Zhu Fenghua, et al. Autonomous driving trajectory tracking control based on improved MPC[J]. Transportation Technology, 2023, 12(6): 494-501.

[9] Yinjian Sun (2015). Research on trajectory tracking control algorithm of unmanned vehicle based on model predictive control [D]. Beijing University of Technology, Beijing.

[10] Liu Chunzheng, Chen Zhihua, Ying Zhanfeng, et al. Research on trajectory tracking method of spherical robot based on MPC [J]. Journal of Weapons and Equipment Engineering, 2024, 45(7):290-297.

[11] Zhang Jiayu (2023). Research on Vehicle State and Traveling Trajectory Prediction Based on Machine Learning[D]. Beijing Jiaotong University, Beijing.

[12] Gao Xinqing, Ma Zhao, Liang Yingxi. Helicopter trajectory tracking control based on model predictive control [J]. Computer Simulation, 2021, 38(6):6.

[13] Liang Zhengtao, Zhao Kegang, Pei Feng, et al. MPC-based trajectory tracking algorithm for intelligent vehicles [J]. Machinery and Electronics, 2019, 36(01): 66-70.

[14] Wu Changshui, Gao Shaoyuan. Adaptive predictive time-domain parametric MPC vehicle trajectory tracking control[J]. Journal of Chongqing University of Technology (Natural Science), 2024, 38(2):99-108.

[15] Deng Tao, Li Xin. Research on the integrated control method of transverse and longitudinal motion of intelligent vehicles [J]. Journal of Chongqing Jiaotong University (Natural Science Edition), 2021, 40(04): 133-140.

[16] Hao Liang, Li Jinliang, Rong Tongkang, et al. Trajectory tracking of driverless vehicles based on MPC [J]. Automotive Practical Technology, 2017(20):3.

[17] Liang Zhongchao, Zhang Huan, Zhao Jing, et al. Trajectory tracking control of unmanned vehicle based on adaptive MPC [J]. Journal of Northeastern University: Natural Science Edition, 2020, 41(6):6.