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Research on Adaptive Predictive Control Algorithm for Autonomous Driving

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Abstract: *Autonomous vehicles hold significant promise for enhancing traffic safety, alleviating urban congestion, and reducing energy consumption. This study proposes an adaptive Model Predictive Control (MPC)-based trajectory tracking controller to address the issue of increased tracking errors caused by vehicle kinematic parameter variations due to changing speeds in autonomous driving. The controller employs polynomial fitting to adaptively adjust control parameters within the prediction horizon based on varying vehicle speeds, ensuring high-precision trajectory tracking in diverse and complex environments. Multi-scenario simulation results on the Carsim, MATLAB, Simulink co-simulation platform demonstrate that the proposed controller effectively improves control performance under different speeds and prediction horizons. Compared to traditional MPC methods, the controller exhibits enhanced stability and accuracy in complex driving scenarios. The experimental results validate the effectiveness of the proposed approach, providing a novel perspective for adaptive control strategies in the field of autonomous driving. Furthermore, this research investigates the impact of varying prediction horizons on controller performance, specifically analyzing the trade-off between tracking accuracy and computational load. The adaptive strategy demonstrates a capability to dynamically adjust the prediction horizon in response to real-time driving conditions, ensuring both robust tracking and efficient computational performance. By minimizing lateral and heading errors, the proposed controller enhances overall vehicle stability and responsiveness. This study contributes to the advancement of autonomous driving by offering a practical and adaptable control solution for trajectory tracking.*

Keywords: *Model Predictive Control, Autonomous Driving, Trajectory Tracking*

1. Introduction

With the rapid advancement of artificial intelligence and automation technologies, autonomous driving has emerged as a research hotspot and frontier in the global automotive industry. Autonomous vehicles demonstrate immense potential in enhancing road safety, alleviating urban traffic congestion, and significantly reducing energy consumption, garnering widespread attention for their long-term development prospects[1]. Among the critical components of autonomous driving technology, designing efficient, reliable, and precise controllers to achieve autonomous vehicle control under complex environments is of paramount importance.

Currently, widely adopted control algorithms in autonomous driving[2] include Linear Quadratic Regulator (LQR), Dynamic Programming (DP), Proportional-Integral-Derivative (PID), and Model Predictive Control (MPC). Liu Fuhua[3] and his team developed a preview strategy with an autonomously adjusted weighting matrix and an LQR-optimized regulator, combined with feedforward control, effectively managing lateral motion parameters of intelligent vehicles. However, this approach is limited to path-tracking deviations within 0.3 meters, struggling to adapt beyond this range. Zhou Huizi[4] et al. focused on obstacle-avoidance dynamic path planning, proposing a real-time algorithm based on known vehicle initial position, velocity, orientation, and obstacle locations. Yet, its primary drawback lies in addressing only static obstacles, lacking effective strategies for dynamic ones, potentially posing safety risks in real-world dynamic scenarios. Farag W et al. [5] introduced a PID controller supporting trajectory control in autonomous vehicles, validated through extensive simulations under challenging conditions like sharp turns. Nevertheless, traditional PID controllers exhibit limitations in handling variable coupling, compromising precision and stability in multivariable scenarios.

These algorithms face constraints in managing dynamic conditions. Many are suited only to specific static scenes or limited environments, lacking flexibility when dynamic strategy adjustments are required.

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As an advanced control approach, MPC stands out by flexibly incorporating multiple constraints and ensuring optimal system performance through real-time prediction and adjustment [6]. Thakur Mugdha Basu et al.[7] proposed an adaptive control scheme integrating fast nominal MPC with a model reference adaptive control strategy in a cascaded architecture, achieving robust and computationally efficient trajectory tracking under uncertain conditions, validating its effectiveness. Wang Yin et al.[8] developed an adaptive trajectory tracking strategy that optimizes the prediction horizon based on vehicle speed, significantly enhancing tracking accuracy and stability on low-adhesion surfaces during variable-speed driving. However, the prediction horizon, derived from fitting four data points with a cubic polynomial, suffers from limited data, potentially reducing adaptability and precision in complex road conditions. Vivek B et al.[9] introduced a robust tube-based MPC framework for emergency obstacle-avoidance steering, effectively integrating path planning and tracking. Yet, at low longitudinal speeds, this method covers shorter path distances within the same timeframe, with conservative steering adjustments failing to adapt to current speed states, thus limiting emergency responsiveness, particularly in challenging road scenarios.

In summary, current control algorithms in the field of autonomous driving exhibit certain limitations in adaptability and flexibility, which affects their effectiveness in complex dynamic environments. Therefore, an adaptive MPC-based approach, capable of dynamically adjusting control strategies and effectively addressing vehicle kinematic parameter variations at different speeds, is particularly important. This research aims to develop a highly robust and accurate adaptive MPC trajectory tracking controller that enhances the trajectory tracking capability of autonomous vehicles in diverse road conditions by real-time monitoring and optimization of control inputs. This not only contributes to improving vehicle safety and driving comfort but also lays the foundation for the widespread application of autonomous driving technology in the future.

2. Research Methods

To address the issue of increased trajectory tracking errors caused by variations in vehicle kinematic parameters under different speeds, this study proposes an adaptive MPC trajectory tracking controller. By continuously monitoring and adapting to changes in vehicle dynamic characteristics, the controller employs advanced control algorithms and strategies to adjust control parameters online, ensuring high-precision trajectory tracking across a range of speeds and road conditions.

Subsequent sections will elaborate on the design process of this controller in detail. First, a vehicle kinematic model is established as the predictive foundation for the MPC framework. Next, the MPC controller is designed based on this kinematic model, achieving adaptive control by adjusting the prediction horizon. Finally, the physical constraints of the vehicle’s steering mechanism are considered to ensure the feasibility and practicality of the control inputs.

2.1 Establishment of the Kinematic Equations

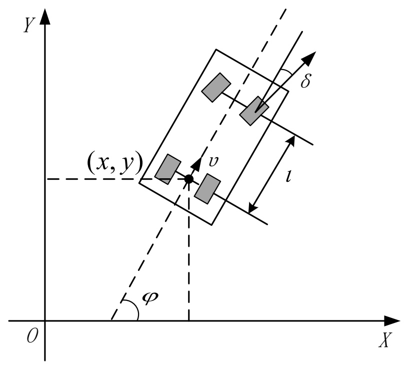

Figure 1 Vehicle Kinematic Model

To apply the vehicle kinematic model within the prediction stage of the controller, it is necessary to simplify the model as much as possible while ensuring that it accurately reflects the vehicle's kinematic characteristics, thereby reducing the computational complexity of the control algorithm. Therefore, the following idealizing assumptions are typically introduced when establishing the vehicle kinematic model:(1) The vehicle's vertical motion is neglected, assuming that the vehicle moves only in a twodimensional plane. (2) The front and rear wheels of the vehicle are assumed to have the same rotational speed and velocity, and the vehicle's motion can be simplified to that of a single wheel. (3) The vehicle's speed is assumed to be relatively low, and the steering angle is small, allowing for the approximation of linear motion. (4) The vehicle is assumed to follow a rigid body dynamic model. (5) The vehicle's movement and steering are assumed to be driven by the front wheels. The vehicle kinematic model is established based on the above assumptions, as shown in Figure 1.

Where (x, y) are the coordinates of the vehicle's rear axle center in the inertial coordinate system, v is the vehicle's velocity at the rear axle center, l is the wheelbase, δ is the front wheel steering angle, and φ is the vehicle's yaw angle.

Based on the kinematic model in Figure 1, the vehicle kinematic equations are established as shown in Equation (1):

$$\begin{cases} \dot{x} = v\cos\varphi \\ \dot{y} = v\sin\varphi \\ \dot{\varphi} = \dfrac{v\tan\delta}{l} \end{cases} \Rightarrow \begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{\varphi} \end{bmatrix} = \begin{bmatrix} v\cos\varphi \\ v\sin\varphi \\ \dfrac{v\tan\delta}{l} \end{bmatrix} \tag{1}$$

2.2 Adaptive MPC Controller Design

Based on the vehicle kinematic equation, the state variables are selected as $X = \left[x, y, \varphi\right]^T$, and the control input is selected as $u = \left[v, \delta\right]^T$. The vehicle kinematic equations are then expressed as a set of nonlinear kinematic differential equations, i.e.,

$$\dot{X} = f\left(X, u\right) \tag{2}$$

Although control methods based on nonlinear prediction models are accurate and consistent with actual principles, their complex computational processes increase the computational burden, making it difficult to guarantee real-time performance and stability during long-term operation. Therefore, utilizing a linearized prediction model for trajectory tracking control design not only simplifies the solving process and reduces the computational burden but also ensures the practical application effectiveness of the control system. By linearizing the model, it can be expressed in the form shown in Equation (3):

$$\begin{aligned} \dot{\tilde{X}} &= \begin{bmatrix} \dot{x} - \dot{x}_r \\ \dot{y} - \dot{y}_r \\ \dot{\varphi} - \dot{\varphi}_r \end{bmatrix} = \begin{bmatrix} 0 & 0 & -v_r \sin\varphi_r \\ 0 & 0 & v_r \cos\varphi_r \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} x - x_r \\ y - y_r \\ \varphi - \varphi_r \end{bmatrix} + \begin{bmatrix} \cos\varphi_r & 0 \\ \sin\varphi_r & 0 \\ \dfrac{\tan\delta_r}{l} & \dfrac{v_r}{l\cos 2\delta_r} \end{bmatrix} \begin{bmatrix} v - v_r \\ \delta - \delta_r \end{bmatrix} \\ &= A\tilde{X} + B\tilde{u} \end{aligned} \tag{3}$$

After discretization, the model's output within the prediction horizon N_p can be represented as shown in Equation (4):

$$Y = \psi\tilde{X} + \Theta\Delta U + \Gamma\Phi + \Lambda \tag{4}$$

Where ψ、Θ、Γ are coefficient matrices related to the system dynamics, control input, and system constraints, respectively; ΔU is the change in the control input; Φ is a quantity related to system constraints; and Λ is a term associated with the constraints of the optimization problem.

To achieve trajectory tracking of the vehicle and simultaneously obtain the optimal solution, generating the optimal control input, the objective function is designed as shown in Equation (5):

$$J_{\min}\left(\tilde{X}(t),u(t-1),\Delta U(t),\varepsilon\right)=\sum_{i=1}^{N_p}\|\eta|t+i|t)-\eta_{ref}|t+i|t)\|Q^2+$$
$$\sum_{i=0}^{N_c-1}\|\Delta u(t+i)|t\|R^2+\sum_{i=0}^{N_c-1}\|u(t+i|t\|s^2+p\varepsilon^2 \tag{5}$$

Where N_p and N_c are the prediction horizon and control horizon, respectively. Q,R,s and p are the weighting coefficients for the tracking error, control increment, control input, and slack variable, respectively. The first term in the objective function ensures that the actual vehicle trajectory tracks the desired trajectory. The second term regulates the magnitude of the control input changes to prevent large fluctuations that could cause oscillations. The third term regulates the rate of change of the control input. The last term uses soft constraints to avoid infeasible solutions, generating a suboptimal solution as the best possible solution. Directly solving for the optimal solution consumes a significant amount of computation time and increases the controller's burden. Therefore, it needs to be transformed into a standard quadratic programming (QP) form to facilitate solving.

The objective function is transformed into a standard form as shown in Equation (6):

$$J_{\min}\left(\tilde{X}(t),u(t-1),\Delta U(t),\varepsilon\right)=\frac{1}{2}\begin{bmatrix}\Delta U_t\\ \varepsilon\end{bmatrix}^T H_t\begin{bmatrix}\Delta U_t\\ \varepsilon\end{bmatrix}+G_t\begin{bmatrix}\Delta U_t\\ \varepsilon\end{bmatrix}+P_t \tag{6}$$

Trajectory tracking is achieved by controlling the front wheel steering mechanism. Considering the actuation capabilities of the steering mechanism, the following constraints are imposed on the steering angle increment and the total input steering angle within each cycle, as shown in Equation (7):

$$\begin{bmatrix}\Delta U_{\min}\\ 0\end{bmatrix}\le\begin{bmatrix}\Delta U(0)\\ \varepsilon\end{bmatrix}\le\begin{bmatrix}\Delta U_{\max}\\ \varepsilon_{\max}\end{bmatrix} \tag{7}$$

Where $\Delta U_{\min}$ and $\Delta U_{\max}$ are the minimum and maximum input for the change in control input, and $\varepsilon_{\max}$ is the maximum limit of the error.

The optimal solution can be determined as:

$$\begin{cases}\Delta U(t)=\left[\Delta U(t),\Delta U(t+1),\ldots,\Delta U(t+N_c-1)\right]\\ u(t)=u(t-1)+\Delta u(t)\end{cases} \tag{8}$$

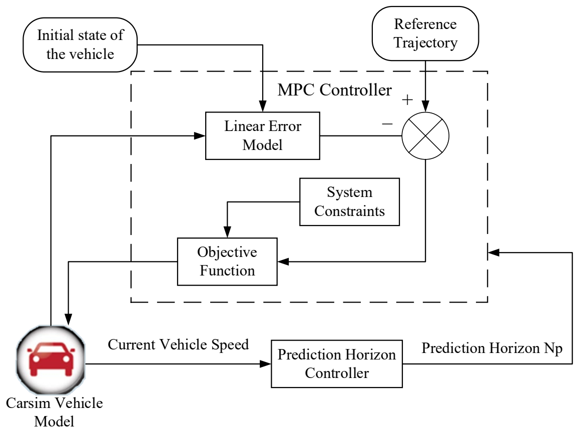

Figure 2 Adaptive MPC-Based Trajectory Tracking Controller

This study proposes an adaptive MPC-based vehicle trajectory tracking method, the flowchart of which clearly depicts the control framework, as shown in Figure 2. The process starts with the initial state of the vehicle and calculates the deviation between the current state and the reference trajectory using a linearized error model, providing an optimization target for the MPC controller. The MPC controller, combined with system constraints and the objective function, dynamically adjusts the prediction horizon based on the current vehicle speed and optimizes the control input (e.g., front wheel

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steering angle) to achieve high-precision trajectory tracking. The Carsim vehicle model is used to simulate the vehicle's dynamic response, and the controller's performance is validated through co-simulation.

3. Experiments and Results

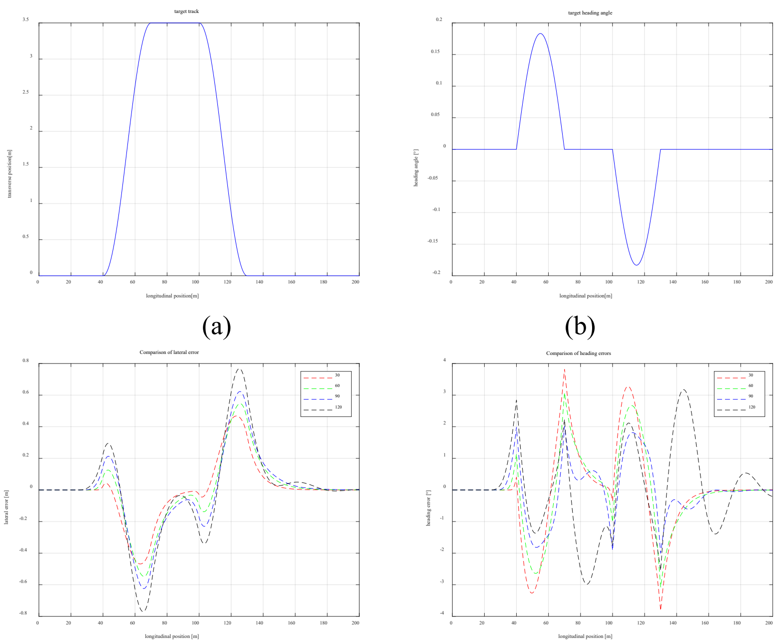
To comprehensively evaluate the performance of the proposed adaptive MPC framework for trajectory tracking in autonomous vehicles, this study conducted a systematic experimental analysis using the Carsim, MATLAB, and Simulink co-simulation platform. The experimental design aimed to investigate the impact of vehicle speed and prediction horizon (N_p) on trajectory tracking accuracy, and to quantify the controller's performance using two key metrics: lateral error and heading error. To ensure the authenticity and reliability of the simulation results, the experiment employed parameter configurations based on the vehicle kinematic model. The following table lists the main physical parameters of the vehicle used in the simulation experiments, as shown in Table 1. These parameters provide the foundational support for subsequent analysis.[10]

Table 1 Vehicle model parameters

Parameter Description	Value	Units
Vehicle quality	1650	kg
Moment of inertia of a vehicle	3200	Kg gm^2
Distance from the front axis to the center of mass	1.4	m
Distance from the posterior axis to the center of mass	1.6	m
Height of vehicle center of mass	0.53	m
Front Axle Width	1.58	m
Rear axle width	1.58	m
Effective rolling radius of tires	0.32	m

3.1 Influence of Vehicle Speed with Fixed Prediction Horizon Simulation Experiment

The first set of experiments evaluated the controller's performance at vehicle speeds of 30 km/h, 60 km/h, 90 km/h, and 120 km/h, with the prediction horizon fixed at N_p =29. Figures (a) and (b) illustrate the target trajectory and desired heading angle at 90 km/h, serving as a reference for subsequent error analysis. Figures (c) and (d) respectively show the lateral error and heading error at different vehicle speeds.[11]



(a) (b)

(c) (d)

Figure 3 Fixed prediction time domain Effect of vehicle speed

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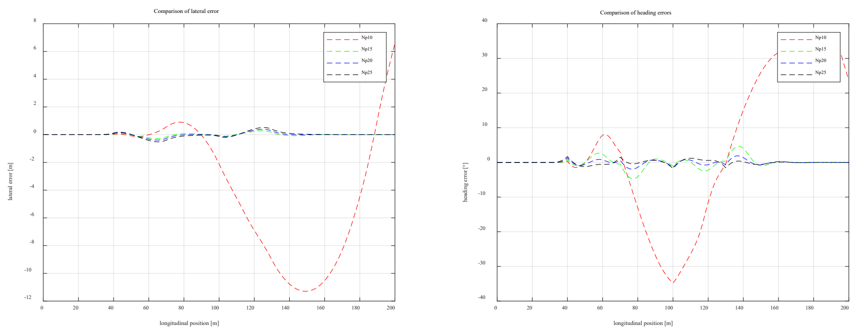
Figures 3 (a) and (b) depict the predefined trajectory and its corresponding heading angle used for tracking. The trajectory includes straight segments and curved segments, representing typical driving scenarios. The smooth variation of the heading angle indicates that this is a realistic path suitable for evaluating the controller's performance.

Figure 3(c) shows that the lateral error gradually increases with increasing vehicle speed. At 30 km/h, the lateral error is minimal, and the trajectory tracking closely aligns with the target path. As the vehicle speed increases to 60 km/h and 90 km/h, the error gradually increases, but the deviation remains within a relatively small range. At 120 km/h, the error further expands, and the deviation from the target trajectory becomes more pronounced. The error curve is smooth, with no obvious oscillations.

Figure 3(d) shows that the heading error exhibits different trends with changes in vehicle speed. At 90 km/h, the heading error is minimal, and the direction control closely matches the desired heading angle. When the vehicle speed is 30 km/h and 60 km/h, the heading error is slightly larger. At 120 km/h, the error significantly increases, and the deviation from the desired heading angle becomes more substantial. The error curve is stable around 90 km/h, with no significant oscillations.

3.2 Influence of Different N_p at Constant Vehicle Speed Simulation Experiment

The second set of experiments evaluated the impact of the prediction horizon N_p on tracking performance at a constant vehicle speed of 90 km/h. The tested N_p values were 10, 15, 20, and 25. Figures 4 (a) and (b) respectively show the lateral error and heading error.



(a) (b)

Figure 4 Effects of predicting the time domain at fixed vehicle speeds

Figure 4(a) shows that when N_p = 10, the lateral error significantly increases, the system becomes unstable, and the trajectory deviates severely from the target path. As N_p increases from 15 to 25, the lateral error gradually decreases: at N_p = 15, the error improves; at N_p = 20 , the error further decreases, and the trajectory's alignment with the target path improves; at N_p = 25, the error continues to decrease, approaching the target path.

Figure 4(b) shows that the trend of the heading error with changes in N_p is consistent with that of the lateral error. When N_p = 10, the heading error is large, the system becomes unstable, and the direction deviation significantly deviates from the desired heading angle. As N_p increases from 15 to 25, the heading error gradually decreases: at N_p = 15, the error begins to converge; at N_p = 20, the direction control improves; at N_p = 25, the error is slightly larger than at N_p = 20.

For the simulation analysis targeting the impact of vehicle speed on trajectory tracking control, the prediction horizons at different speeds were extracted. These data serve as a reference for the design of the prediction horizon controller. Under low-speed conditions, employing a small prediction horizon can achieve satisfactory control performance. Conversely, under high-speed conditions, increasing the prediction horizon can enhance the stability of vehicle trajectory tracking. However, excessively increasing the prediction horizon may lead to a higher computational burden on the controller, thereby

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compromising real-time performance and introducing potential safety risks. Therefore, considering the accuracy, stability, and real-time requirements of the controller under high-speed scenarios, this study sets the minimum prediction horizon to 8 and the maximum to 20. A polynomial was fitted in MATLAB and rounded to obtain the specific control law for the prediction horizon as follows:

$$\begin{cases} N_p = 8, v < 36 \\ N_p = 20, v > 120 \\ N_p = -0.00004v + 0.012vx - 0.7v + 20, 36 < v < 120 \end{cases} \tag{9}$$

3.3 Adaptive Prediction Horizon Control Performance Analysis

Based on the results from Sections 3.1 and 3.2, an adaptive prediction horizon control strategy was implemented. This strategy adjusts the prediction horizon dynamically based on the vehicle's speed, using Equation (9) derived from polynomial fitting of experimental data in MATLAB. The goal is to balance tracking accuracy, stability, and real-time performance, particularly at higher speeds. The minimum prediction horizon was set to 8, and the maximum was set to 20.

4. Conclusions

In conclusion, the experimental results show that the adaptive MPC controller significantly improves trajectory tracking accuracy, particularly at higher speeds, by dynamically adjusting the prediction horizon. It outperforms traditional MPC approaches, offering higher stability and precision in complex conditions. The proposed method demonstrates superior performance in various road conditions, outperforming traditional algorithms, which struggled in high-speed scenarios. This confirms the effectiveness of the adaptive prediction horizon approach in enhancing stability and reducing computational burdens.

The adaptive MPC controller developed in this study demonstrates excellent trajectory tracking accuracy and stability under varying vehicle speeds and prediction horizons. Notably, the controller's performance significantly surpasses that of traditional algorithms, especially in complex driving scenarios. The experimental analysis identified the significant influence of vehicle speed and prediction horizon on control performance and effectively evaluated the controller's adaptability under various conditions. Furthermore, the proposed control strategy, through real-time adjustment of the prediction horizon, enables the maintenance of good tracking accuracy and response speed even on road surfaces with low adhesion coefficients. Future research could further optimize the selection strategy for the prediction horizon to seek a more reasonable balance between control accuracy and computational efficiency, thereby promoting the practical application of autonomous driving technology.

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