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Algorithm and Implementation of Vehicle Trajectory Tracking Based on Vehicle Three-Degree-of-Freedom Dynamics MPC

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Abstract. Against Amid the rapid development of autonomous driving tech, trajectory tracking – a key link between decision-making and execution layers – directly impacts autonomous vehicle safety and stability. The traditional 2-DOF vehicle dynamic model used in MPC lacks accuracy and practicality, as it only accounts for basic motion scenarios while ignoring multi-variable coupling and complex constraints.To address this, this paper builds a 3-DOF vehicle dynamic model covering longitudinal displacement, yaw angle, lateral velocity, and yaw rate, better reflecting the coupling of the vehicle's longitudinal, lateral, and yaw motions. First, the Euler method discretizes the continuous model to establish a discrete state-space expression. Then, an MPC controller is designed: a dual-objective optimization function (combining state weight matrix Q and control weight matrix R) for "trajectory tracking accuracy-control input smoothness" is defined, and physical constraints like front-wheel steering angle and its rate of change are introduced to convert the control problem into a quadratic programming one. Finally, rolling optimization enables dynamic tracking and real-time correction of the reference trajectory.MATLAB simulations (S-shaped reference trajectory, real-vehicle-like parameters: 1573kg mass, 8000N/rad front/rear axle cornering stiffness; key MPC parameters: 20-step prediction horizon, 10-step control horizon, 0.05s sampling time) show high overlap between the proposed model's actual and reference trajectories. Lateral position tracking error stabilizes between -0.16m and 0.16m (well below the 0.3m autonomous driving safety threshold), and the front-wheel steering angle (control input) is highly smooth, free from traditional control's "chattering". In short, the 3-DOF MPC trajectory tracking algorithm has good dynamic response and control accuracy, meeting autonomous driving scenario needs.

Keywords: Intelligent Vehicles, MPC Dynamic Model, Quadratic Programming, Trajectory Tracking

1. Introduction

1.1. Research background and significance

In the current era of rapid iteration of intelligent technologies, autonomous driving has become a core direction reshaping the field of transportation [1]. As a key execution link in autonomous driving systems, trajectory tracking directly determines whether a vehicle can travel safely and

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accurately according to the planned path. Furthermore, it affects the implementation effect of path planning [2-3], the accuracy of trajectory prediction for surrounding vehicles and pedestrians, and even the operational safety of the entire traffic scenario. It can be said that trajectory tracking is an important bridge connecting the decision-making layer and the execution layer of autonomous driving. If this link has problems such as insufficient accuracy or delayed response, it will be difficult to achieve reliable application of autonomous driving even if the path planning algorithm is perfect [4-5].

Traditional vehicle control methods, such as Proportional-Integral-Derivative (PID) control and sliding mode control [6], have certain feasibility when dealing with simple working conditions or single constraint conditions. However, their limitations have become increasingly prominent in the complex practical scenarios faced by autonomous driving [7]. For example, PID control relies on the linear characteristics and accurate model of the system. When the vehicle is in dynamically changing scenarios such as high-speed steering and sudden changes in road surface adhesion coefficient, it is prone to problems such as overshoot, oscillation, or increased steady-state error. Although sliding mode control has strong robustness to parameter perturbations and external disturbances, it often has a "chattering" phenomenon, which leads to unstable control inputs and makes it difficult to meet the requirements of vehicle driving smoothness. These traditional methods are difficult to achieve high-precision trajectory tracking under multi-constraint conditions (such as steering angle limits, longitudinal speed limits, tire cornering characteristics constraints, etc.) and cannot adapt to the strong coupling and multi-variable dynamic system characteristics of autonomous driving vehicles [8-9].

In contrast, the Model Predictive Control (MPC) algorithm provides an ideal technical path for solving the problem of vehicle trajectory tracking by virtue of its unique "rolling optimization" mechanism and efficient multi-constraint handling capability [10]. The core logic of the MPC algorithm is as follows: first, by establishing a system model that conforms to the actual motion law of the vehicle, the system state changes within a period of time in the future (prediction horizon) are predicted based on the vehicle state at the current moment; then, combined with preset optimization objectives and physical constraints, the control problem is transformed into a solvable optimization problem, and the optimal control sequence for a period of time in the future is calculated [11-12]; finally, only the first control input in the control sequence is executed, and the above "prediction-optimization-execution" process is repeated at the next moment. Through real-time feedback and rolling optimization, the control strategy is dynamically corrected. This control method is naturally suitable for dynamic systems with strong coupling and multi-constraints such as vehicles. During the driving process of a vehicle, longitudinal motion, lateral motion, and yaw motion are interrelated and restricted by various factors such as tire grip, body structure, and driving speed. The MPC algorithm can fully integrate these dynamic characteristics and constraint conditions in the modeling stage and realize the coordinated balance of multiple objectives in the optimization process. For this reason, the MPC algorithm has gained wide attention and application in the field of vehicle trajectory tracking and has become one of the key technologies to improve the driving safety, stability, and accuracy of autonomous driving vehicles [13].

1.2. Research content

The first part involves establishing a three-degree-of-freedom (3-DOF) vehicle dynamics model and discretizing it. The second part focuses on designing an MPC controller by constructing a prediction model, defining the optimization objectives, and setting the constraints. The third part entails simulating the designed controller to validate its performance in curved trajectory tracking.

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2. Establishment and discretization of vehicle dynamic model

2.1. Model assumptions and parameter definitions

To balance the corresponding accuracy requirements and computational complexity [14], a three-degree-of-freedom model will be adopted. The establishment of this three-degree-of-freedom model needs to consider the dynamic changes of longitudinal displacement y, yaw angle φ, longitudinal velocity v_y , and yaw rate r. Additionally, real-world conditions should be taken into account, such as vehicle mass m, moment of inertia around the z-axis I_z distances from the front and rear axles to the vehicle's center of mass l_f and l_r respectively, cornering stiffness of the front and rear wheels c_f and c_r ,and front wheel steering angle δ_f .

2.2. Derivation of the three-degree-of-freedom vehicle dynamic model

Tire slip angle refers to the angle between the tire plane of the vehicle and its direction of motion. The formula for it is as follows:

$$\alpha_f = \delta_f - \frac{v_y + l_f r}{v_x} \tag{1}$$

$$\alpha_r = -\frac{v_y - l_r r}{v_x} \tag{2}$$

Based on the small angle assumption, the lateral force of the front wheel is $F_{yf} = -c_f\alpha_f$, and the lateral force of the rear wheel is $F_{yr} = -c_r\alpha_r$[15]. Subsequently, the lateral motion and yaw motion are established, starting with the lateral motion:

$$m\left(\dot{v}_y + \dot{v}_{xr}\right) = F_{yf} + F_{yr} \tag{3}$$

Next is the yaw motion:

$$I_z\dot{r} = l_f F_{yf} - l_r F_{yr} \tag{4}$$

Where $\dot{y} = v_y + v_x\varphi, \dot{\varphi} = r$ and. Subsequently, the state vector $x = [y, \varphi, v_y, r]^T$ and input $u = \delta_f$ are introduced. Furthermore, the state-space model $\dot{X} = A_c x + B_c u$ is introduced, where the state-space matrices

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$$A_c = \begin{bmatrix} 0 & v_x & 0 & 1 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & \frac{-c_f+c_r}{mv_x} & \frac{l_r c_r - l_f c_f}{mv_x} - v_x \\ 0 & 0 & \frac{l_r c_r - l_f c_f}{I_z v_x} & -\frac{l_f^2 c_f + l_r^2 c_r}{I_z v_x} \end{bmatrix}$$

$$B_c = \begin{bmatrix} 0 \\ 0 \\ \frac{c_f}{m} \\ \frac{l_f c_f}{I_z} \end{bmatrix}$$

Next, the model discretization operation is performed. First, the new matrices $A_d = I + A_c T, B_d = B_c T$ are introduced (where T is the sampling time). Subsequently, discretization is carried out, and the resulting outcome is [16]:

$$X(k+1) = A_d x(k) + B_d u(k) \tag{5}$$

3. MPC design

3.1. Basic principle of MPC

Using a discrete predictive model, the system states for the future N_p steps(prediction horizon) are predicted. According to the established optimization objective, a constrained problem is solved; based on this result, one control input from the optimization solution is implemented. At the next time step, the above operations are repeated. To describe the basic principle simply, it follows the sequence of prediction, optimization, feedback, and rolling optimization to achieve the target.

3.2. Recursive discrete equation

After establishing the relevant model, it is necessary to predict multiple subsequent steps (i.e., extend to high-dimensional states). Predicting only one step ahead is far from sufficient, so recursion is required to enable the prediction to extend to high-dimensional states. Regarding the recursive discrete equation, it can be calculated according to the following formula:

$$\hat{X} = \Phi x(k) + \Gamma v$$

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Wherein, $\Phi = \begin{bmatrix} A_d \\ A_d^2 \\ \vdots \\ A_d^{N_p} \end{bmatrix}, \Gamma = \begin{bmatrix} B_d & 0 & \cdots & 0 \\ A_d B_d & B_d & \cdots & 0 \\ \vdots & \vdots & \cdots & \vdots \\ A_d^{N_p-1} B_d & A_d^{N_p-2} B_d & \cdots & A_d^{N_p-N_c} B_d \end{bmatrix}$, where N_p is the prediction horizon and N_c is the control horizon.

3.3. Optimization objective function

As mentioned above, the principle of MPC requires solving constrained problems based on optimization objectives, which are related to control accuracy and the smoothness of control variables. Next, the optimization objective function will be introduced:

$$J = \sum_{i=1}^{N_p} \left\| x(k+ik) - x_{ref}(k+i) \right\|_Q^2 + \sum_{j=0}^{N_c-1} \left\| u(k+j) \right\|_R^2 \tag{6}$$

Wherein, $x(k+ik)$ represents the trajectory under the specified steps, while $x_{ref}(k+i)$ denotes the reference trajectory under the predetermined steps. Subsequently, the term $\sum_{j=0}^{N_c-1} \left\| u(k+j) \right\|_R^2$ stands for the corresponding predetermined control input. This optimization objective function comprehensively takes into account issues related to control accuracy (trajectory) and the smoothness of control variables. After sorting out the above expression, it can be transformed into:

$$J = \frac{1}{2} u^T H u + f^T u \tag{7}$$

According to the above context, the principle of Model Predictive Control (MPC) requires solving constrained problems based on optimization objectives. Now, parameter constraints will be imposed on the above expression, such as: $|\delta_f| \le \delta_{max}, \left|\dot{\delta}_f\right| \le \dot{\delta}_{max}$.

4. Simulation experiments and result analysis

4.1. Simulation parameters

For the determination of simulation parameters, they should be defined as close to the parameters of a real vehicle as possible. Here, a set of basic parameters are specified as follows:

m=1573kg, $I_z = 2873 kg \bullet m^2, l_f = 1.1m, l_r = 1.58m, c_f = c_r = 8000 N/_{nac}$.

The above are the vehicle parameters. In addition, the settings of MPC parameters are as follows: prediction horizon $T_s = 0.05s, N_p = 20, N_c = 10$, $Q = diag[10,10,5,5]$, $R = 0.1$. $v_x = 15 m/_s$,

the reference trajectory is selected as an S-shaped curve.

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4.2. Simulation results

4.2.1. Trajectory tracking

In Figure 1, it visually presents the fitting effect between the reference trajectory and the actual motion trajectory, where the red dashed line represents the preset S-shaped reference trajectory, and the blue solid line represents the actual motion trajectory of the vehicle under the control of the three-degree-of-freedom (3-DOF) MPC model. From the overall trend, the two trajectories show a high degree of overlap, which intuitively reflects that the proposed model has good basic performance in trajectory tracking.

From the perspective of segmented performance: In the initial stage of the trajectory (travel distance of approximately 0–40 m), the deviation between the actual trajectory and the reference trajectory gradually narrows, and the tracking accuracy shows a steady improvement trend. This phenomenon stems from the "rolling optimization" mechanism of the MPC controller—at the initial moment, the controller quickly calculates the optimal control input, continuously corrects the vehicle's motion state, and makes the actual trajectory gradually approach the reference trajectory. In the second stage (40 m–67 m), affected by the curvature change of the S-shaped trajectory, the deviation between the actual trajectory and the reference trajectory slightly increases, and the tracking accuracy decreases to a certain extent. This is because during this stage, the vehicle needs to adjust the yaw angle and lateral velocity more frequently to adapt to the trajectory turning. However, when the model responds to continuous dynamic changes, there is a slight lag in the matching between short-term prediction and actual working conditions. In the final stage (67 m–73 m), the trajectory curvature tends to be stable, and the deviation between the actual trajectory and the reference trajectory remains within a small range with almost no fluctuation. This indicates that the controller has achieved stable control of the vehicle's motion state at this time, verifying the tracking reliability of the model under steady-state working conditions.

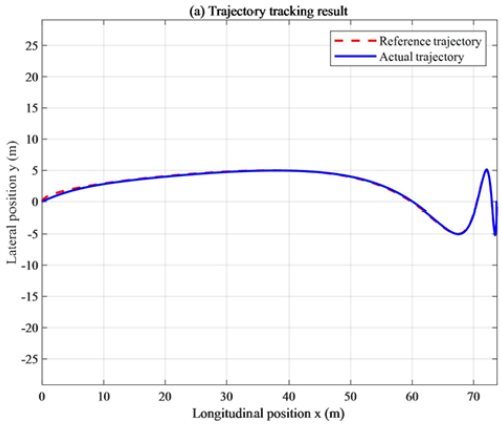

Figure 1. Comparison diagram of vehicle actual trajectory and S-shaped reference trajectory under the 3-DOF MPC model

In Figure 2 ,it focuses on the variation law of lateral position over time, where the red dashed line corresponds to the lateral position change of the reference trajectory, and the blue solid line corresponds to the lateral position change of the actual driving. It allows for further detailed analysis of the control accuracy in the lateral dimension during trajectory tracking.

From the overall trend, the variation trend of the actual lateral position is highly consistent with that of the reference lateral position, indicating that the model can accurately capture the lateral

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dynamic characteristics of the reference trajectory. However, slight deviations occur at key nodes such as the peaks and valleys of the trajectory: At the first peak (corresponding to time t1), the actual lateral position is slightly lower than the reference value, with a deviation range of approximately 0.05–0.08 m; at the first valley (corresponding to time t2), the actual lateral position is also slightly lower than the reference value, with a deviation range similar to that at the peak; at the second peak (corresponding to time t3), the deviation of the actual lateral position being higher than the reference value is more obvious, with a range of approximately 0.08–0.12 m. This deviation change is related to the curvature variation law of the S-shaped trajectory—the trajectory curvature at the second peak is larger, requiring higher lateral acceleration of the vehicle. During the calculation of lateral force and yaw moment by the model, it is slightly affected by the linearization assumption (small-angle assumption) of tire cornering characteristics, leading to a deviation between the actual lateral displacement and the reference value.

From the perspective of phase stability: During the period from the first peak to the first valley, the actual lateral position is always slightly higher than the reference value, but the deviation range remains basically stable (approximately 0.03–0.05 m), indicating that the controller has stable adjustment ability for lateral position during this stage; during the period from the first valley to the second peak, the reference lateral position is slightly higher than the actual value, and the deviation range also remains within a stable range (approximately 0.04–0.06 m). This further proves that the model has good stability in lateral position control, with only acceptable slight deviations at the points where the trajectory curvature changes suddenly.

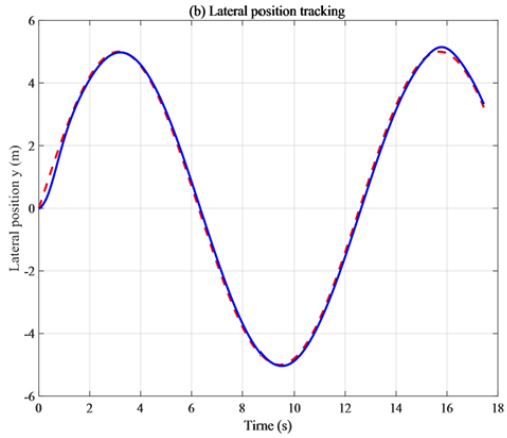

Figure 2. Comparison diagram of vehicle actual lateral position and reference lateral position variation with time

4.2.2. Error analysis

In Figure 3 ,ituses a red solid line to show the variation of lateral position tracking error over time, serving as a core basis for quantitatively evaluating the tracking accuracy of the model. The error variation can be divided into three key stages:

In the initial stage (t ≈ 0–0.45 s), the error shows a significant negative peak with a value of approximately -0.47 m. The main reason for this phenomenon is that the vehicle is in a stationary or low-speed state at the initial moment, with a certain deviation from the initial lateral position of the reference trajectory. Additionally, the controller needs to quickly output control signals (such as front wheel steering angle) to adjust the vehicle's attitude. During the short delay period of the control signal response, the error increases instantaneously. However, the error then converges

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rapidly—after t ≈ 0.45 s, the fluctuation range quickly narrows to between -0.16 m and 0.15 m, demonstrating the fast response capability of the MPC controller's "prediction-optimization-feedback" closed-loop mechanism. By real-time predicting the multi-step error in the future and continuously optimizing the control input, the error is quickly suppressed.

In the middle stable stage (t ≈ 0.45 s–t4, where t4 is the time close to the end of the trajectory), the error always fluctuates slightly within the range of -0.16 m to 0.15 m without obvious trend deviation. This indicates that the controller has established a stable lateral position control loop at this time, and the model has good ability to suppress lateral disturbances. In the later stage (t ≈ t4–t5), the error shows a small positive peak of approximately 0.16 m, which is related to the slight curvature adjustment at the end of the trajectory and belongs to a normal transition error under working conditions. Moreover, the peak duration is extremely short (approximately 0.1–0.2 s) before quickly returning to the stable range.

From the perspective of the overall error range, the lateral position tracking error during the entire experiment is basically maintained within -0.16 m to 0.16 m. This error range is far lower than the 0.3 m lateral safety error threshold in practical autonomous driving applications, fully verifying that the tracking accuracy of the model can meet the requirements of real-world scenarios.

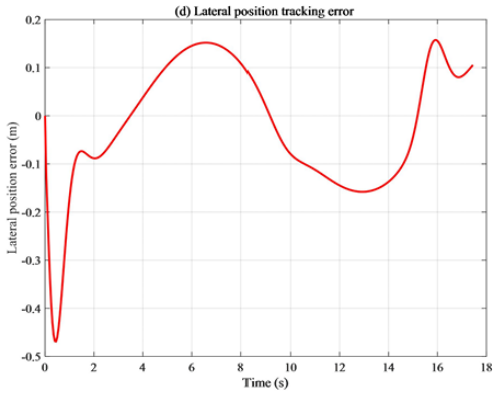

Figure 3. Curve diagram of vehicle lateral position tracking error variation with time

4.2.3. Control input analysis

In Figure 4 it uses a blue solid line to present the variation of the front wheel steering angle (control input) over time, enabling intuitive evaluation of the smoothness and response speed of the control signals output by the MPC controller. It serves as a key basis for verifying the engineering practicality of the model.

At the initial moment (t ≈ 0 s), the front wheel steering angle undergoes a significant sudden change with a value of approximately 25°. This sudden adjustment is a necessary operation for the controller to address the initial deviation—at the initial moment, there is a deviation in position and attitude between the vehicle and the reference trajectory. To quickly reduce the deviation and start trajectory tracking, the controller needs to significantly adjust the front wheel steering angle to change the vehicle's yaw attitude and lateral motion direction, which aligns with the control requirement of "fast response". The duration of this adjustment process is extremely short (only about 0.8 s), after which the steering angle decreases rapidly and stabilizes. This proves that the controller has fast response capability, and the adjustment process does not affect the driving stability of the vehicle (no continuous oscillation).

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In the subsequent stable stage (from t ≈ 0.8 s to the end of the experiment), the front wheel steering angle is always maintained within a narrow range of 2.0° to 3.1° without obvious fluctuations, achieving extremely high smoothness of the control input. This phenomenon indicates that after the vehicle enters the stable tracking state, the controller only needs to output small-amplitude and smooth steering angle adjustment signals to maintain the vehicle's tracking of the reference trajectory. This avoids the "chattering" problem that may occur in traditional control methods (such as sliding mode control) and complies with the physical constraints of the actual vehicle steering system (steering angle change rate limit), verifying the engineering feasibility of the control input—it can not only meet the dynamic control requirements of the vehicle but also avoid excessive wear on the steering actuator.

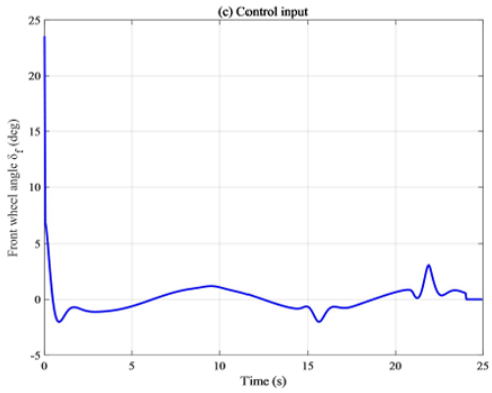

Figure 4. Curve diagram of front-wheel steering angle (control input) output by the MPC controller variation with time

5. Conclusions

5.1. Main conclusions

Focusing on the high-precision trajectory tracking needs of autonomous vehicles, this paper completed research on 3-DOF vehicle dynamic model construction, MPC controller design, and simulation verification. Compared with the traditional 2-DOF model, the constructed 3-DOF model introduces key state variables such as lateral velocity and yaw rate, accurately depicts the coupling of the vehicle's longitudinal, lateral, and yaw motions, conforms to real-vehicle dynamics, and enables stable state prediction in MATLAB after Euler discretization, laying a solid model foundation. The designed MPC controller balances trajectory tracking accuracy and control input smoothness through the "prediction-optimization-execution" rolling optimization mechanism: with rational settings of weight matrices Q (diag [10,10,5,5]) and R (0.1), the tracking error of the actual trajectory relative to the S-shaped reference trajectory is controlled between -0.16m and 0.16m, meeting autonomous driving safety requirements; the front-wheel steering angle completes the transition from 25° to a stable value within 0.8s and then stabilizes in the range of 2.0°–3.1°, avoiding excessive wear of the steering system. Meanwhile, in the curvature change stage (40m–67m) and stable curvature stage (67m–73m) of the S-shaped trajectory, the model can correct prediction deviations in real time without significant error expansion, and the deviation between the actual and reference trajectories is negligible, proving reliable tracking capabilities under both dynamic and steady-state working conditions.

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5.2. Limitations and future outlook

This research can only achieve high-precision tracking and control for specific trajectories, and cannot fully adapt to many unknown trajectory situations in reality. For future work, relevant parameters of adaptive models can be introduced to enable dynamic adjustments in more complex trajectories. Additionally, dynamic obstacles can be incorporated to better approximate real-life scenarios, and the solution efficiency of the MPC algorithm can be optimized. Finally, relevant deployments on actual vehicles can be implemented.

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