Time-Domain Predictable Trajectory Planning for Autonomous Driving Based on Internet of Vehicles

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Abstract. For the polynomial lane change method, the lane change trajectory is planned only at the initial time, and it cannot cope with the problem that other traffic participants enter the driving environment during the lane change process. This paper decomposes the polynomial lane change method into lateral displacement planning and longitudinal velocity planning. The Pontryagin minimum principle is used to solve the optimal lane change duration meeting the requirements of different driving conditions, and the polynomial method is used to plan the lateral displacement trajectory. In the longitudinal direction, the variable acceleration motion equation is used to describe the trajectory, so as to establish a prediction model, the real-time driving environment information is obtained through the internet of vehicles to realize the speed rolling optimization, the trajectory dynamic planning is carried out during the driving process, and the slack variable is introduced to solve the problem that the vehicle suddenly increases speed beyond the constraint range. Through Matlab/Simulink and Prescan co-simulation verification, the trajectory planned in this paper not only meets the requirements of comfort and lane change efficiency, but also has better avoidance capabilities for other traffic participants and is easy to follow in real vehicles.

Keywords: Quintic polynomial · Path planning · Model predictive control · Internet of Vehicles

1 Introduction

In recent years, lane change of autonomous driving has become a hot research topic for scholars at domestic and foreign [1]. The development of 5G communication technology has greatly improved the communication ability between vehicles and the surrounding traffic environment [2], thus enabling vehicles to better cope with the complex driving environment and providing a great guarantee for vehicles to plan a safe and efficient lane change trajectory in real time.

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Curve-fitting path planning method is often used in the field of intelligent vehicles [3]. By giving the vehicle starting point and ending point, a trajectory with continuous curvature, satisfying comfort and dynamic constraints is generated [4]. Among them, arcs, Bessel curves and polynomial functions are commonly used [5]. Literature [6] realized trajectory planning by using geometric features of circular arc curve, but curvature discontinuity would appear at the end of circular arc, which would affect the stability of the car body. In Literature [7], Bezier curve is used for path planning, and the obstacle avoidance function is realized on electric vehicles. However, it is difficult to select control points for path planning based on Bezier curve. In contrast, for polynomial functions, these problems can be reduced by adjusting the order of the polynomial to achieve the desired performance. Literature [8] proposes a quintic polynomial automatic lane change model, and analyzes the key variables that affect the performance of lane change, thus generating the optimal lane change trajectory. However, only the state information of the starting and ending points is considered.

Combining the above problems, this paper considers that the planned trajectory satisfies performance indicators such as comfort, safety, lane change efficiency, etc., and uses the Pontryagin principle of minimum to solve the lateral displacement corresponding to the optimal lane change duration. Through the model predictive control method, the longitudinal speed is optimized by rolling to cope with the situation of other traffic participants in the driving process, so as to achieve dynamic path planning. Matlab/Simulink and Prescan co-simulation were used to verify the two driving conditions of free lane change and active lane change by traffic participants.

2 Trajectory Planning

In this paper, the current state (position, speed, acceleration) of the lane change vehicle, environmental information and the state of other traffic participants are collected through the Internet of Vehicles and sensors that include 5G communication technology. During lane change, the vehicle is driving on the road in a longitudinal variable acceleration motion. In order to ensure that the lateral displacement is continuous and the curvature is smooth during the lane change process, a quintic polynomial is used to describe the lateral displacement trajectory. Combining the initial state displacement, velocity and acceleration of the lateral movement are all zero, the end state velocity and acceleration are zero, and the end displacement is the distance between the center lines of the two lanes, and the lane change trajectory model is obtained as:

$$\begin{cases} x(t) = x_{t_0} + v_{x_{t_0}} t + \frac{1}{2} a_{x_t} t^2 \\ y(t) = \frac{6y_{t_f}}{t_f^5} t^5 - \frac{15y_{t_f}}{t_f^4} t^4 + \frac{10y_{t_f}}{t_f^3} t^3 \end{cases} \tag{1}$$

Where, $x(t)$, x_{t_0}, $v_{x_{t_0}}$, a_{x_t} respectively represent the displacement at time t, the displacement at initial time, the initial velocity and the acceleration at time t in longitudinal motion; $y(t)$ is the lateral displacement at the end of lane change. t, t_f are lane change time and lane change duration respectively.

Trajectory planning meets the needs of comfort, safety, and efficiency. Among them, comfort is characterized by $|a_x| \leq a_{x_{\max}} (a_{x_{\max}} = 0.4g)$, $|a_y| \leq a_{y_{\max}} (a_{y_{\max}} = 0.4g)$; efficiency is characterized by $0 \leq t \leq t_f (t_f \leq 5)$; and safety is characterized by $0 < y(t) < y_{t_f} (0 < t < t_f), 0 < v_x(t) < v_{x_{\max}} (0 < t < t_f)$.

According to the lane change trajectory model, the lateral trajectory is determined by the duration of the lane change and the end lateral displacement. The terminal lateral displacement is determined by the distance between the centerlines of the two lanes, and the lane width is 3.75 m according to the international standard [9]. The lane change duration is often set by empirical values, which is uncertain [10]. In this paper, combining the lateral boundary conditions and comfort requirements, the lane change duration should be greater than 2.35 s, and the lane change duration is a variable. Taking safety, comfort and lane change efficiency as the objective function, establish a lateral trajectory optimization model:

$$\begin{array}{l} \min C = w_j \frac{1}{t_f} \int_0^{t_f} j_y^2 dt + w_t t_f \\ s.t. \left\{ 0 \leq y(t) \leq 3.75, \left| a_y \right| \leq a_{y_{\max}} \left(a_{y_{\max}} = 0.4g \right), 2.35 \leq t \leq 5 \right. \end{array} \tag{2}$$

Where ω_j, ω_t represents the weight; j_y is the lateral jerk, which represents the rate of change of acceleration, obtained by taking the third derivative of lateral displacement.

The objective function is solved by Pontryagin's minimum principle [11, 12], and the optimal lane change duration is substituted into the lateral trajectory function.

3 Longitudinal Speed Rolling Optimization

In the process of lane change, due to the use of 5G communication technology, vehicles can receive and send information about the surrounding environment in real time. When other traffic participants are involved and may cause a collision, the lane change vehicles adjust the current planned path by rolling optimization of longitudinal speed.

This article quotes the double integrator in the literature [13] to derive the Eq. (1) longitudinal equation as the longitudinal motion model:

$$\begin{cases} x_t = x_0 + v_{x_{t_0}} t + \frac{1}{2} a_{x_t} t^2 \\ v_{x_t} = v_{x_{t_0}} + a_{x_t} t \end{cases} \tag{3}$$

Where, x_t represents the longitudinal displacement of the vehicle at time t; v_{x_t} represents the longitudinal velocity at time t.

The method discretization is carried out by the Taylor formula method, so that $a_x(k) = a_x(k-1) + \Delta a_x(k-1)$ obtains the discretization model:

$$\begin{array}{l} x(k+1) = x(k) + v_x(k) \cdot H + \frac{1}{2} a_x(k-1) \cdot H^2 + \frac{1}{2} \Delta a_x(k-1) \cdot H^2 \\ v_x(k+1) = v_x(k) + a_x(k-1) \cdot H + \Delta a_x(k-1) \cdot H \\ a_x(k) = a_x(k-1) + \Delta a_x(k-1) \end{array} \tag{4}$$

Where, H = 0.01 s is the sampling interval; x, v_x, a_x is the state quantity, Δa_x is the control input quantity, and $\Delta a_x(k-1)$ represents the incremental longitudinal acceleration of the vehicle at the moment k − 1.

Equation (4) is transformed into matrix form, and the prediction model in this paper is described as follows:

$$X = T_x \Delta A + B_x, V = T_v \Delta A + B_v, A = T_a \Delta A + B_a \tag{5}$$

Where, the state matrices X, V, A and control input matrix ΔA are as follows:

$$\begin{aligned} X &= [\, x(k+1) \quad x(k+2) \quad \cdots \quad x(k+p) \,]^T_{1\times p} \\ V &= [\, v_x(k+1) \quad v_x(k+2) \quad \cdots \quad v_x(k+p) \,]^T_{1\times p} \\ A &= [\, a_x(k-1) \quad a_x(k) \quad \cdots \quad v_x(k+p-2) \,]^T_{1\times p} \\ \Delta A &= [\, \Delta a_x(k-1) \quad \Delta a_x(k) \quad \cdots \quad \Delta v_x(k+p-2) \,]^T_{1\times p} \end{aligned}$$

The control input matrix ΔA and its coefficient matrix T_x, T_v, T_a are:

$$T_x = \begin{bmatrix} \frac{H^2}{2} & 0 & \cdots & 0 \\ 2H^2 & \frac{H^2}{2} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ \frac{p^2 H^2}{2} & \frac{(p-1)^2 H^2}{2} & \cdots & \frac{H^2}{2} \end{bmatrix}_{p\times p} \quad T_v = \begin{bmatrix} H & 0 & \cdots & 0 \\ 2H & H & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ pH & (p-1)H & \cdots & H \end{bmatrix}_{p\times p}$$

$$T_a = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 1 & 1 & \cdots & 0 \\ \vdots & \vdots & \ddots & 0 \\ 1 & 1 & \cdots & 1 \end{bmatrix}_{p\times p}$$

The other parameter matrices are:

$$B_p = \begin{bmatrix} p_x(k) \\ p_x(k) \\ \vdots \\ p_x(k) \end{bmatrix}_{p\times 1} + \begin{bmatrix} Hv_x(k) \\ 2Hv_x(k) \\ \vdots \\ pHv_x(k) \end{bmatrix}_{p\times 1} + \begin{bmatrix} \frac{1}{2}H^2 a_x(k-1) \\ 2H^2 a_x(k-1) \\ \vdots \\ \frac{p^2}{2}H^2 a_x(k-1) \end{bmatrix}_{p\times 1}$$

$$B_v = \begin{bmatrix} v_x(k) \\ v_x(k) \\ \vdots \\ v_x(k) \end{bmatrix}_{p\times 1} + \begin{bmatrix} Ha_x(k-1) \\ 2Ha_x(k-1) \\ \vdots \\ pHa_x(k-1) \end{bmatrix}_{p\times 1} \quad B_a = \begin{bmatrix} a_x(k-1) \\ a_x(k-1) \\ \vdots \\ a_x(k-1) \end{bmatrix}_{p\times 1}$$

In this paper, the relative minimum safety distance of the workshop is set to 2 m. During the lane change process, when other traffic participants enter, the area outside this area is a safe driving area. During the dynamic trajectory planning, the lane change vehicle must drive strictly at The safe driving area is the target, and the trajectory curve is smooth during the lane change. In view of the possible problem that the acceleration exceeds the maximum acceleration constraint caused by the sudden increase in the lane change, the slack variable S is introduced in this paper, and the slack variable S is introduced to solve the problem while slack The minimum variable is the goal; at the end of the lane change, the vehicle is driven at a constant speed in the target lane, so the speed is set as the speed of the target lane, and the acceleration at the end is 0. Considering the above conditions, the following objective function is designed:

$$\min_{\Delta A,S} \omega_1 (X - X_f)^T (X - X_f) + \omega_2 (V - V_f)^T (V - V_f) + \omega_3 A^T A + \omega_4 \Delta A^T \Delta A + \omega_5 S^T S \tag{6}$$

Where, X_f, V_f, S represent the displacement matrix and velocity matrix at the end time and the slack variable matrix respectively; $\omega_1, \omega_2, \omega_3, \omega_4, \omega_5$ represents the weight and $X_f = \begin{pmatrix} x_f & \cdots & x_f \end{pmatrix}^T_{1\times p}$, $V_f = \begin{pmatrix} v_f & \cdots & v_f \end{pmatrix}^T_{1\times p}$, $S = \begin{pmatrix} s_1 & s_2 & \cdots & s_p \end{pmatrix}^T_{1\times p}$.

The combined performance index optimization problem is subject to the following constraints:

$$X_{\min} < X < X_{\max}, V_{x_{\min}} < V_x < V_{x_{\max}}, A_{x_{\min}} < A_x < A_{x_{\max}} \tag{7}$$

For each step, the control input is the optimal solution obtained from the quadratic programming problem, and its first value is applied to the system, that is:

$$\Delta a^*(k) = \begin{pmatrix} 1 & 0 & 0 & \cdots & 0 \end{pmatrix}_{1\times k} \Delta A^*(k) \tag{8}$$

4 Simulation Analysis

This paper uses Matlab/Simulink to write the path planning algorithm program; In the prescan, a 300 m long, 3.75 m wide two-car straight lane in the same direction was established. The phantom vehicle without dynamic performance was taken as the ideal trajectory to verify the effectiveness of the algorithm. At the same time, a 2-DOF vehicle with a driver model was added to verify the tracking ability of the planned trajectory. All vehicles in the environment are equipped with radar and Internet of vehicles with 5G communications technology.

When lane change is free, as shown in Fig. 1, the optimal lane change duration is 5 s, the lateral displacement is 3.75 m, and the longitudinal displacement is 154.77 m, and the lane change trajectory is continuous and smooth. The longitudinal velocity was increased from 28 m/s to 32 m/s. During the lane change process, the longitudinal

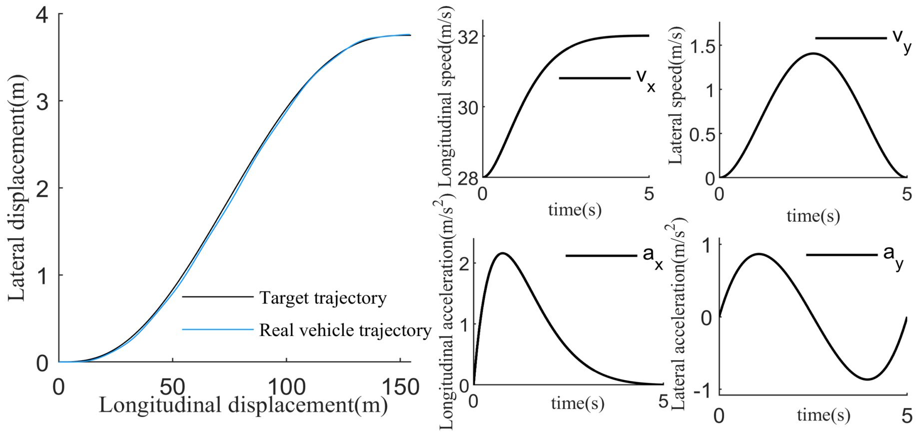

Fig. 1. Free lane change track and motion parameter diagram

velocity curve did not fluctuate repeatedly, which would not bring longitudinal compression force to passengers. The maximum lateral acceleration is 0.87 m/s^2, and the longitudinal acceleration is less than 0.4 g, which fully meets the requirements of comfort. Blue represents the 2-DOF vehicle trajectory, which is basically consistent with the target trajectory, indicating that the target trajectory is easy to follow.

When avoiding obstacles and changing lanes, this article mainly considers the collision between the vehicle in front of the current lane and the vehicle behind the target lane. In the scenario in Fig. 2, the initial distance between the vehicle in front of the current lane and the vehicle is 7.8 m, and the distance between the vehicle behind the target lane and the vehicle is 7.2 m. and the optimal lane change duration is calculated to be 3 s. All parameters meet the performance index requirements, and the trajectory is continuous and smooth without collision. The green trajectory is the trajectory of the vehicle with 2 degrees of freedom. It can be observed that the error with the target trajectory is small, which verifies that the trajectory is easy to follow.

Figure 3 is measured by the Internet of Vehicles and radar containing 5G communication technology. From the beginning of the lane change to 1.42 s, the relative distance between the lane change vehicle and the two vehicles is continuously decreasing, and the lane change vehicle drives out of the current lane in 1.42 s relative to the preceding vehicle. The distance becomes zero. Prior to this, the minimum driving relative distance between the two vehicles was 2.4 m. After 2.3 s, the speed of the lane change vehicle was close, and the relative distance of 2.97 m was always maintained with the vehicle behind the target lane.

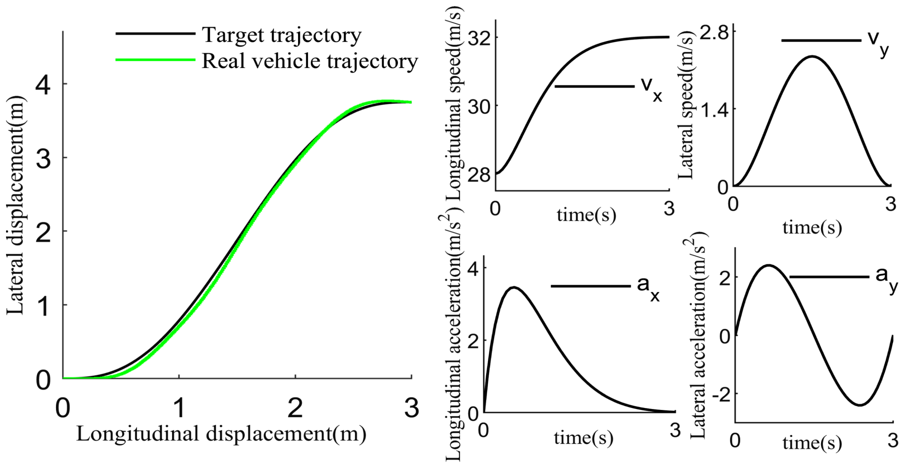

Fig. 2. Obstacle avoidance and lane change trajectory and motion parameter diagram

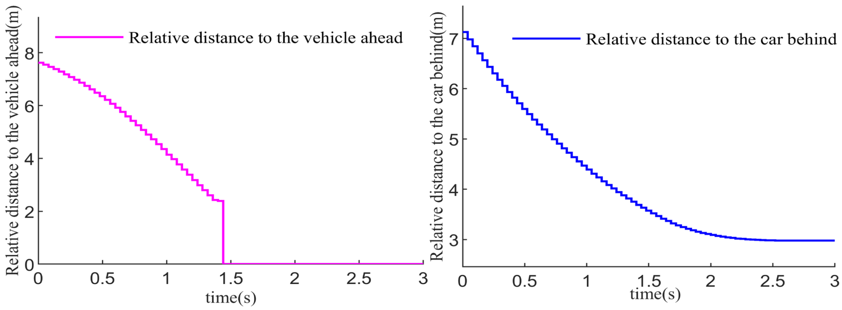

Fig. 3. Relative distance to other traffic participants in two lanes

5 Conclusion

This paper aims at the quintic polynomial lane change method, which cannot cope with the problem of other traffic participants entering during the lane change process. Combined with the horizontal two-point boundary conditions, the unknown coefficients of the horizontal quintic polynomial are solved to establish a lane change trajectory model. The Pontryagin minimum principle is used to find the optimal lane change duration, and the acceleration change in the next 5 s is predicted at the current moment through the prediction model, and the first set of values is applied to the next sampling interval for rolling optimization. Using Matlab/Simulink to program the algorithm, two lane change driving conditions are established in prescan for co-simulation. The results show that the algorithm planned in this paper guarantees the safety of the vehicle under the premise of comfort and lane change efficiency. Other vehicles entering during the lane change have good evasion capabilities. The addition of a 2-degree-of-freedom vehicle model verifies that the planned trajectory is easy to follow in the two working conditions.

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