Intelligent Vehicle Path Tracking Control Based on Improved MPC and Hybrid PID

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ABSTRACT In this study, to improve the accuracy of path tracking in intelligent vehicles, we propose an intelligent vehicle path-tracking control method based on improved model predictive control (MPC) combined with hybrid proportional-integral-derivative (PID) control theory. In the lateral control, a constraint on the side deflection of the front wheel is added based on traditional MPC and a relaxation factor is introduced to improve the stability of vehicle control for the driving stability. In longitudinal control, a hybrid PID controller is designed for different road conditions to improve the accuracy of control of vehicle speed. We present the results of a co-simulation using Carim and MATLAB/Simulink and a test with a sample vehicle, which show that the proposed path tracking controller can greatly improve the path tracking accuracy and stability of an intelligent vehicle. The model-based prediction, rolling optimization solution, feedback control, and the addition of a constraint on the side deflection of the front wheel as well as a relaxation factor can ensure the lateral driving stability of an intelligent vehicle. The proposed approach achieved a lateral error of less than 1%, and the yaw angle was controlled within 4°. The longitudinal speed control based on hybrid PID controller can improve the response speed of the system and meet the real-time requirements of vehicle driving.

INDEX TERMS Automobile engineering, hybrid PID control, model predictive control, path tracking, co-simulation.

I. INTRODUCTION
Path tracking control is the most important technology in autonomous systems designed to drive intelligent vehicles. Path tracking control enables intelligent vehicles to drive accurately, quickly, and safely in accordance with a path planned by higher-level control [1]. Many control theories have been developed to perform path tracking control in automated systems designed to drive intelligent vehicles, the most important of which include preview control (a form of model predictive control (MPC)) [2], fuzzy control [3], LQR control [4], PID control [5], and model predictive control [6].

Ruo-Chen et al. [7] proposed a preview MPC path tracking method combining a visual preview model and MPC theory, which improved tracking accuracy overall. However, its performance was inconsistent under different road conditions and driving speeds. Tang et al. [8] used kinematic MPC to deal with road curvature disturbance, along with yaw rate PID feedback control to eliminate uncertainty and modeling errors and a vehicle sideslip angle compensator to correct motion model prediction. The robustness of this method to time delay was average. Shuo et al. [9] proposed the MPC-Fuzzy control strategy, which reduced the amount of computation required along with the steering error between the tracking accuracy and controller, but failed to make corresponding improvements in longitudinal tracking. Lin et al. [10] proposed a control algorithm combining MPC and fuzzy PID control, which was designed to solve the problem of rapid vehicle response owing to complex path tracking and stability control models, but did not consider all relevant aspects of vehicle dynamics. In terms of the effect of an MPC objective function on performance. A controller based on a combination of MPC...
and LQR controls has also been proposed [11]. The controller is capable of performing tracking control in multiple modes; however, it selects a control mode only according to the path curvature, without considering the effects of different road conditions and driving speeds. Chen et al. [12] compared the tracking performance of LMPC-based controllers using models of different complexities for MPC-based path tracking, but did not apply a time-varying speed reference and did not consider the impact on lateral and longitudinal control of the vehicle. An adaptive MPC controller has also been proposed [13]. Although it was designed to automatically adjust the time domain, its verification model cannot adapt to variations in working conditions under high speed and large lateral acceleration. Zeng et al. [14] proposed a speed control method for FWIA electric vehicles based on the MPC algorithm. The adaptability and robustness of the speed control method were guaranteed under different speed conditions and external disturbances. However, the tracking performance of the method at high speeds has not been effectively verified. Based on nonlinear model predictive control (NMPC), Liu et al. [15] proposed a vehicle path tracking control based on a variable predictive time domain and speed, which improved vehicle path tracking performance, but the associated kinematics model only considers low-to-medium speed conditions. Liu et al. [16] proposed an MPC method for path tracking in autonomous surface vehicles based on adaptive line-of-sight (LOS) guidance to improve the reference path tracking accuracy. However, problems of real-time operation and robust optimization for practical applications were ignored. Chen et al. [17] proposed a control mode that combined MPC and PID, which shortened the tracking time on the entire path. However, when the vehicle passed through the deceleration zone, the driving wheels left the ground for a short time. This resulted in a sudden loss of speed, leading to unstable longitudinal control accuracy. Mata et al. [18] implemented an MPC method based on a simple linear single-track model with nominal longitudinal velocity, considering the lateral and directional errors of the target trajectory to ensure correct path tracking, but did not analyze the tracking performance of the vehicle under different actual road conditions. Dong et al. [19] developed a single-neuron adaptive PID control system based on an established vehicle kinematics model and electric power steering model. Although the results of a simulation showed that the method improved the vehicle’s path tracking accuracy, the process from data input to data processing and acquisition of PID values based on an adaptive PID control algorithm was time-consuming. Moreover, intelligent vehicles adhere to rigorous requirements to ensure real-time performance; therefore, the performance of this method was not ideal for real vehicle tests. Xie et al. [20] proposed the use of yaw moment information for tracking bias compensation and coordinate vehicle stability control, and used MPC to calculate the steering angle of the front wheels and to control the vehicle along a reference path through automatic steering. However, the torque distribution in this study was simplified, and the tires of the vehicle were not fully utilized to distribute the yaw moment. Goli and Eskandarian [21] optimized tracking stability and tracking time in the process of path tracking and used a multi-objective optimization method to set the parameter value. Although the complexity of the process of manually adjusting the parameters was reduced, the performance of this method in path tracking was poor under complex road conditions.

To solve the above problems, in this study, we propose an intelligent path tracking control method based on an improved MPC and hybrid PID. The main contributions of this study are as follows.

1) The objective function of the vehicle model predictive control is set based on a model of vehicle kinematics and dynamics, and the prediction model is improved in real time using the feedback correction characteristics of MPC. Then, the established objective function is solved according to the improved model to obtain the optimal value for the angle of the front wheels.

2) In the lateral control, a constraint is added on the sideslip angle of the front wheels, and a relaxation factor is introduced to ensure the stability of the lateral control. In the longitudinal control, a hybrid PID controller is designed for different road conditions to ensure the accuracy, stability, and real-time operation of the longitudinal control of an intelligent vehicle.

3) Finally, a co-simulation and real-vehicle experiment were carried out using CarSim and MATLAB/Simulink software. The research results show that precise control of intelligent vehicle path tracking can be achieved under different road conditions and speeds. The lateral error was less than 1%, and the yaw angle was controlled within $-4^\circ$ to $2^\circ$. Moreover, the computation time of the program was shorter, and it exhibited better real-time performance in path tracking. Overall, the improved MPC and hybrid PID methods reduced the calculation time of the program and improved its real-time path-tracing performance compared to prior methods.

II. ESTABLISHING A MODEL OF THE VEHICLE

The establishment of a vehicle kinematics model and a dynamics model is the basis for the analysis and research of the intelligent vehicle control system and the design of the controller [22]. A vehicle kinematics model is established based on the position of an intelligent vehicle in space and the current driving speed and other geometric variable changes over time. In contrast, the vehicle dynamics model describes the state and the physical laws affecting the motion of intelligent vehicles from the mechanical perspective, including a physical model and model composed of differential equations.

A. VEHICLE KINEMATICS MODEL

Kinematics is used to study the motion change law of a vehicle from a geometric perspective, including the change in vehicle speed and position variables with time in space. To meet the geometric constraints of vehicle driving and improve the reliability of the path tracking control, a kinematics model of the intelligent vehicle must be established.
In this work, we used a 3-DOF kinematic model of the entire vehicle, as shown in Fig. 1.

In Fig. 1, \((X_f, Y_f)\) and \((X_r, Y_r)\) are the center coordinates of the front and rear axles of the intelligent vehicle in the geodetic coordinate system, respectively. \(l\) is the wheelbase, \(\delta_f\) is the front wheel steering angle of the intelligent vehicle, \(\varphi\) is the yaw angle, \(v_f\) and \(v_r\) are the speeds of the front and rear axle centers of the intelligent vehicle, respectively.

According to the kinematic principles of vehicle motion, the speed at the center point \((X_r, Y_r)\) of the rear axle is given as

\[
V_r = \dot{X}_r \cos \varphi + \dot{Y}_r \sin \varphi
\]  

(1)

The following expression may be obtained according to the kinematic constraints of intelligent vehicles.

\[
\begin{align*}
\dot{X}_r \sin \varphi - \dot{Y}_r \cos \varphi &= 0 \\
\dot{Y}_r (\sin (\varphi + \delta_f) - \dot{Y}_f \cos (\varphi + \delta_f)) &= 0
\end{align*}
\]  

(2)

By combining equation (1) and equation (2), we obtain

\[
\begin{align*}
\dot{X}_r &= \dot{V}_r \cos \varphi \\
\dot{Y}_r &= \dot{V}_r \sin \varphi
\end{align*}
\]  

(3)

According to the geometric relationship between the front and rear wheels of an intelligent vehicle,

\[
\begin{align*}
X_f &= X_r + l \cos \varphi \\
Y_f &= V_r + l \sin \varphi
\end{align*}
\]  

(4)

By combining the above equations, the kinematic model of the intelligent vehicle can be obtained as follows.

\[
\begin{bmatrix}
\dot{X}_r \\
\dot{Y}_r \\
\dot{\varphi}
\end{bmatrix} =
\begin{bmatrix}
\cos \varphi \\
\sin \varphi \\
\tan \delta_f / l
\end{bmatrix}
\begin{bmatrix}
v_r
\end{bmatrix}
\]  

(5)

**B. VEHICLE DYNAMICS MODEL**

To ensure that the intelligent vehicle follows the path planned by the upper controller accurately, a vehicle dynamics model must be established [5]. Research on vehicle dynamics generally considers the stability of vehicle handling and the comfort of the driver. In this study, we investigate path tracking based on an improved MPC and hybrid PID control. We focus on handling the stability of intelligent vehicles, including the lateral and longitudinal dynamics as well as the yaw dynamics. The established model is shown in Fig. 2, which is a 3-DOF dynamic model that considers the transverse, longitudinal, and heading directions of the intelligent vehicle.

**C. OTHER RECOMMENDATIONS**

The balance equations of an intelligent vehicle along the \(x\), \(y\), and \(z\) axes can be obtained according to Newton’s second law, as given below.

\[
\begin{align*}
m \ddot{x} &= -m \ddot{\varphi} + 2F_{sf} + 2F_{sr} \\
m \ddot{y} &= -m \ddot{\varphi} + 2F_{fy} + 2F_{fr} \\
I_z \ddot{\varphi} &= 2aF_{sf} - 2bF_{fr}
\end{align*}
\]  

(6)

In equation (6) above, \(m\) is the mass of the intelligent vehicle, \(a\) and \(b\) are the distance between the center of mass of the intelligent vehicle and the front and rear axles, respectively, and \(I_z\) is the moment of inertia of the intelligent vehicle around the \(z\) axis.

The expressions of the longitudinal and lateral forces of the intelligent vehicle in the \(x\) and \(y\) axis directions are given as follows.

\[
\begin{align*}
F_{sf} &= F_f \cos \delta_f - F_{cf} \sin \delta_f \\
F_{fr} &= F_f \cos \delta_r - F_{cr} \sin \delta_r \\
F_{fy} &= F_f \sin \delta_f + F_{cf} \cos \delta_f \\
F_{fr} &= F_f \sin \delta_r + F_{cr} \cos \delta_r
\end{align*}
\]  

(7)

In equation (7) above, \(F_f\) and \(F_t\) denote the longitudinal force respectively received by the front and rear wheels, whereas \(F_{cf}\) and \(F_{cr}\) are similarly the transverse force.
received by the front and rear wheels, \( F_{f} \) and \( F_{r} \) are the force along the X axis received by the front and rear wheels, \( F_{f} \) and \( F_{r} \) are the force along the Y axis received by the front and rear wheels.

Assuming that the lateral acceleration of an intelligent vehicle during driving is \( a_{y} \leq 0.4g \) and the tire force has a linear relationship with the sideslip angle, the longitudinal and lateral forces on the front and rear wheels of the intelligent vehicle are as follows.

\[
\begin{align*}
F_{f} &= C_{f} s_{f} \\
F_{r} &= C_{r} s_{r} \\
F_{f} &= C_{f} \left( b\dot{\phi} - \dot{y} \right) \\
F_{r} &= C_{r} \left( \delta - \dot{y} + a\dot{\phi} \right)
\end{align*}
\]

(8)

In equation (8) above, \( C_{f} \) and \( C_{r} \) are the longitudinal stiffness of the front and rear wheels, \( C_{f} \) and \( C_{r} \) are the cornering stiffness of the front and rear wheels, \( s_{f} \) and \( s_{r} \) are the slip rates when the front and rear wheels are rolling.

Assuming that the turning angles of the two front wheels of the intelligent vehicle are equally small, the lateral acceleration satisfies the assumption of a small wheel angle, and a linear relationship is satisfied. In this case, the following approximate relationship can be used.

\[
\begin{align*}
\sin \theta & \approx \theta \\
\tan \theta & \approx \theta \\
\cos \theta & \approx 1
\end{align*}
\]

Combining the above equations, the nonlinear dynamic model of an intelligent vehicle can be obtained as follows.

\[
\begin{align*}
\dot{X} &= \dot{x} \cos \phi + \dot{y} \sin \phi \\
\dot{Y} &= \dot{x} \sin \phi + \dot{y} \cos \phi \\
m\ddot{X} &= m\ddot{\phi} + 2 \left[ C_{f} s_{f} + C_{cf}(\delta_{f} - \dot{y} + a\dot{\phi}) + C_{r} s_{r} \right] \\
m\ddot{Y} &= -m\ddot{x} \dot{\phi} + 2 \left[ C_{cf}(\delta_{f} - \dot{y} + a\dot{\phi}) + C_{cr} b\dot{\phi} - \dot{\gamma} \right] \\
I_{\phi} \ddot{\phi} &= 2 \left[ aC_{cf}(\delta_{f} - \dot{y} + a\dot{\phi}) - bC_{cr} b\dot{\phi} - \dot{\gamma} \right]
\end{align*}
\]

(10)

III. CONTROLLER DESIGN

A. IMPROVED MPC CONTROLLER DESIGN

For nonlinear model predictive control problems, rapid optimization requires high controller performance, especially in the field of intelligent vehicles with high real-time requirements [23], [24]. To improve the speed of the optimization solution, most researchers believe that converting a nonlinear prediction model into a linear model to reduce complexity and improve the speed of the solution is more reasonable. The effects of the linear model are similar to that of a nonlinear MPC controller [25].

1) PREDICTIVE MODEL

Taking (10) as the nonlinear dynamic model of an intelligent vehicle, considering the real-time requirements of intelligent vehicles, the nonlinear dynamic model must be converted into a linear model.

The state variable of the reference system at any time is related to its state variable and control variable at a given time.

\[
\dot{\xi}_{\text{dyn}} = f_{\text{dyn}}(\xi_{\text{dyn}}, u_{\text{dyn}})
\]

(11)

where \( \xi_{\text{dyn}} \) is the state variable, and \( u_{\text{dyn}} \) is the control variable.

According to Taylor’s formula (12), high-order terms other than the first order can be omitted from equation (11) to obtain the linear time-varying equation (13).

\[
f(x) = f(a) + f^{(a)}(x-a) + \cdots + f^{(n)}(x-a)^{n} + R_{n}(x)
\]

(12)

\[
\dot{\xi}_{\text{dyn}} = A_{\text{dyn}}(t)\xi_{\text{dyn}}(t) + B_{\text{dyn}}(t)u_{\text{dyn}}(t)
\]

(13)

where:

\[
A_{\text{dyn}}(t) = \frac{\partial f_{\text{dyn}}}{\partial \xi_{\text{dyn}}} , \quad B_{\text{dyn}}(t) = \frac{\partial f_{\text{dyn}}}{\partial u_{\text{dyn}}}
\]

To achieve faster real-time control of the entire system, (13) must be discretized as follows.

\[
\begin{align*}
\xi(k+1 \mid t) &= \tilde{A}_{k,t}\xi(k \mid t) + \tilde{B}_{k,t}\Delta u(k \mid t) \\
\eta(k \mid t) &= \tilde{C}_{k,t}\xi(k \mid t)
\end{align*}
\]

(14)

where:

\[
\tilde{A}_{k,t} = \begin{bmatrix} A_{k,t} & B_{k,t} \\ 0 & I_{m} \end{bmatrix} , \quad \tilde{B}_{k,t} = \begin{bmatrix} B_{k,t} \\ I_{m} \end{bmatrix}
\]

\[
\tilde{C}_{k,t} = \begin{bmatrix} C_{k,t} & 0 \end{bmatrix}
\]

\[
\Delta u(k \mid t) = u(k \mid t) - u(k-1 \mid t)
\]

Suppose that \( N_{p} \) and \( N_{c} \) are the prediction time domain and control time domain in the model predictive control, respectively, and the controller can predict the state variables of the system as follows.

\[
\dot{\xi}(t + N_{p} \mid t) = \tilde{A}_{t}^{N_{p}}\xi(t \mid t) + \sum_{i=0}^{N_{c}-1}B_{t}\Delta u(t \mid t) + \cdots + \tilde{A}_{t}^{N_{p}-N_{c}-1}B_{t}\Delta u(t + N_{c} \mid t)
\]

(15)

where \( \tilde{A}_{t}^{N_{p}} \) is the \( A_{t} \) matrix at time \( N_{p} \) and \( \tilde{A}_{t}^{N_{p}-N_{c}-1} \) is the \( A_{t} \) matrix at time \( N_{p} - N_{c} - 1 \).

2) ROLLING OPTIMIZATION SOLUTION

To allow an intelligent vehicle to track the path planned by the upper layer quickly and accurately, an objective function must be established. Because intelligent vehicles may encounter a sudden change in the control variable when driving, a relaxation factor must be added to the objective function. To this end, the objective function is established as follows.

\[
J(\xi(k), u(k - 1), \Delta U(k), \varepsilon)
\]
In equation (16) above, $\eta_{dyn}$ represents the controller output reference quantity, $\Delta u_{dyn}$ represents the control deviation increment, $\varepsilon$ represents relaxation factor $\rho$ represents the relaxation factor weight coefficient.

MPC exhibits excellent advantages when dealing with multiconstraint problems. Constraints can be added to the system control variable and control increment in each control step of the MPC controller.

$$u_{\min}(k + t) \leq u(k + t) \leq u_{\max}(k + t) \quad (17)$$

$$\Delta u_{\min}(k + t) \leq \Delta u(k + t) \leq \Delta u_{\max}(k + t) \quad (18)$$

where, $k = 0, 1, \ldots, N_C - 1$.

To accelerate the solving speed of the solver, the above optimization problem is converted into a quadratic programming problem as follows.

$$\begin{align*}
\text{min} & \quad J(\xi(t), u(t - 1), \Delta U(t), \varepsilon) \\
\text{s.t} & \quad U_{\min} \leq \Delta U(t) + U(t) \leq U_{\max} \\
& \quad \Delta U_{\min} \leq \Delta U(t) \leq \Delta U_{\max} \\
& \quad y_{\min} - \varepsilon \leq y_t \leq y_{\max} + \varepsilon \\
& \quad \varepsilon > 0
\end{align*}$$

(19)

In equation (19) above, $U_{\max}$ and $U_{\min}$ are respectively the maximum and minimum of the control variables, which corresponds to the boundary value of the front wheel rotation angle. $\Delta U_{\max}$ and $\Delta U_{\min}$ are the maximum and minimum of the control increment, which is the boundary value of the front wheel angle increment. $y_{\max}$ and $y_{\min}$ are the maximum and minimum output values of the constraint.

3) FEEDBACK CORRECTION

By solving (19) in each cycle of MPC control, a list of optimal control sequences in the time domain of MPC control can be obtained as follows.

$$\Delta U_t^* = \left[ \Delta u_t^*, \Delta u_{t+1}^*, \ldots, \Delta u_{t+N_C-1}^* \right]^T$$

(20)

According to the model predictive control theory, the first element of the optimal sequence in the control time domain is used as the input increment of the actual control to act on the entire system as follows.

$$u(t) = u(t - 1) + \Delta u_t^*$$

(21)

After the entire system enters the next cycle, the system continually loops the above process and predicts the output of the next time domain. After continuous rolling optimization of the system, the control sequence is updated until the search is completed, thus completing the path tracking of the intelligent vehicle.

4) CONSTRAINED OPTIMIZATION

The tire sideslip angle plays an important role in the characteristics of vehicle tires. The sideslip angle is the basis for studying vehicle handling and stability. Thus, it is necessary to calculate the constraint of the tire sideslip angle of the front and rear wheels according to the state quantity. This relationship is given as follows.

$$\alpha_f = \frac{\dot{\gamma} + a \dot{\phi}}{\dot{x}} - \delta_f$$

(22)

$$\alpha_r = \frac{\dot{\gamma} - b \dot{\phi}}{\dot{x}}$$

(23)

To ensure that the tire lateral force changes linearly, the maximum tire sideslip angle is limited to 5° on a road with large adhesion coefficient and 2° on a road with small adhesion coefficient.

B. DESIGN OF HYBRID PID CONTROLLER

Fig. 3 shows the principal diagram of the PID control system, where $r(t)$ is the expected input signal, $e(t)$ is the error signal after the system feedback, $u(t)$ is the control signal calculated by the PID algorithm, and $c(t)$ is the current actual output signal of the controlled object. The controlled object should operate in the state designed by the control algorithm. The differential equation of a traditional PID controller is expressed as follows [5].

$$u(t) = K_p e(t) + \frac{1}{T_i} \int_0^t e(t) dt + T_d \frac{de(t)}{dt}$$

(24)

$$e(t) = r(t) - c(t)$$

(25)

where the output $u(t)$ is the linear combination of the $e(t)$ proportion, integral, and differential, and $K_p, T_i$ and $T_d$ are the proportional coefficient, integral time constant, and derivative time constant, respectively.

Fig. 4 shows the PID control logic diagram. The difference between the actual speed and the reference speed of the driving wheel is used as the deviation input of the PID controller. Reset is defined as a state in which the torque is at zero or in the braking state. At the same time, the PID debug enable port is set. The Vehicle Spy 3 software product was used to adjust the PID value online through the CAN network to obtain the best PID value under various working conditions by the debug enable port.
Based on the principles outlined in Fig. 3 and the logic in Fig. 4, the designed hybrid PID controller is expressed as follows. Fig. 5 shows the actual operating conditions of the vehicle, including flat roads, uphill and downhill roads, and deceleration.

For the flat roads and high-speed, medium-speed, and low-speed driving, two numerical PID controllers were designed. The first PID values are 3, 0.3, and 0.1, respectively, which are applicable to intelligent vehicle conditions when the starting speed is less than 2 km/h; the driving wheel may be expected to stall with a slightly large torque, the actual vehicle speed to be far smaller than the target vehicle speed, and the torque to be excessively large, while the change in speed is slow. The second PID values are 0.3, 0.03, and 0.1, respectively, which are applicable to intelligent vehicle conditions when there is a small torque, excessively fast speed, and drastic changes in torque acceleration and speed.

To clearly illustrate the control logic for the two different PID values, we draw Figure 5 in two parts. Among them, Figure 5(a) shows the control logic diagram under the large PID value, and the output part is the part coupled with the small PID control logic, which corresponds to the input part in Figure 5(b). Figure 5(b) is the control logic diagram under the small PID value.

IV. SIMULATION ANALYSIS AND EXPERIMENTAL VERIFICATION

A. SIMULATION ANALYSIS

The simulation parameters were obtained from the parameters of an experimental prototype vehicle developed by the research group. The simulation parameters of the controller are presented in Table 1, the parameters of the vehicle dynamics model are listed in Table 2.

To highlight the performance of intelligent vehicle control based on the improved MPC and hybrid PID controllers, MPC controllers and the improved MPC and hybrid PID controllers were used to perform path tracking tests. The co-simulation diagram of the improved MPC, hybrid PID controller, and CarSim is shown in Fig. 6.

Fig. 7 is a simulation diagram of traditional MPC-controlled path tracing control. It may be observed from Fig. 7 that when the speed was 18 km/h, the intelligent vehicle achieved good path tracking performance, but when the speed increased to 36 km/h, the path tracking exhibited a significant deviation, which increased with the travel distance. According to the path tracking curve in Fig. 7, when the speed was 36 km/h, the intelligent vehicle did not turn until 37 m, which obviously lagged behind that of the reference path, leading to a deviation in path tracking. According to Figs. 8-9, under conditions of high vehicle speed, the intelligent vehicle exhibited poor lateral controllability, and even sideslip occurred in some cases.

As may be observed from Figs. 10 to 12, when the intelligent vehicle speed reached 54 km/h, controlling the steering of the intelligent vehicle became difficult owing to the high speed, and the vehicle sideslip angle, lateral speed, and lateral acceleration increased significantly, leading to a large deviation in path tracking. This result shows that traditional MPC controllers exhibit poor control performance and stability under high-speed working conditions. In summary, the path

FIGURE 4. PID control logic logic.
Figure 5.

(a) Large PID value control logic.

(b) Small PID value control logic.
TABLE 1. Controller simulation parameters.

| No. | Parameter                  | Value   |
|-----|----------------------------|---------|
| 1   | Simulation step size /s    | 0.02    |
| 2   | Weight matrix $Q$          | diag(200, 100, 100) |
| 3   | Weight coefficient $R$     | $5 \times 10^5$ |
| 4   | Weight coefficient $\rho$  | 1000    |
| 5   | Control time domain $N_c$/s| 15      |
| 6   | Prediction time domain $N_p$/s| 30     |

TABLE 2. Vehicle dynamics model parameters.

| No. | Kinetic model parameters | Numerical value |
|-----|--------------------------|-----------------|
| 1   | Vehicle mass $m$/kg      | 1026            |
| 2   | Distance between center of mass and front axle $a$/m | 0.8624 |
| 3   | Distance between the center of mass and the rear axle $b$/m | 1.0276 |
| 4   | Moment of inertia around z axis $I_z$/(kg·m²) | 2975 |
| 5   | Vehicle body length $L$/m | 2.8             |
| 6   | Front wheel cornering stiffness $C_f$/(N·rad⁻¹) | 46800 |
| 7   | Rear wheel cornering stiffness $C_r$/(N·rad⁻¹) | 42700 |
| 8   | Front and rear wheel slip rate $S_f$, $S_r$ | 0.2             |

Fig. 6 shows a simulation diagram of path tracking control based on the proposed improved MPC and hybrid PID algorithm control method. As shown in Fig. 6, when the speed of the intelligent vehicle was low at 18 km/h and 36 km/h, due to the addition of a front wheel deflection constraint and a relaxation factor in MPC control as well as the intervention of the hybrid PID, the accuracy of the path tracking was very high, with an error below 1%. When the speed was 54 km/h, the path tracing effect was slightly worse than at low speed. However, with the extension of time or the increase of driving distance, the tracing accuracy can also reach the accuracy at low speed.

As shown in Figs. 14–16, when the vehicle speed was 18 km/h, the intelligent vehicle exhibits a high lateral dynamic stability threshold owing to the low vehicle speed. At this point, the steering limit was high, which can ensure the flexibility of the intelligent vehicle and enhance its lateral control ability. As the vehicle speed increased, the slip angle, lateral speed, and lateral acceleration increased more obviously; however, according to the tracing trajectory in Fig. 14, it may be observed that the vehicle was still within the controllable range.
It may be observed from Figs. 17 to 18 that as the vehicle speed increased, the stability of the intelligent vehicle stability was reduced and along with the magnitude of the steering limit. However, compared with the traditional MPC control used in Figs. 8 and 9, the yaw angular velocity and yaw angle are both reduced, the driving stability of the intelligent vehicle was increased. Overall, it may be observed from these results that the respective use of the improved MPC and hybrid PID controllers for horizontal and vertical control achieved good results, which helped to improve the driving stability of the vehicle.

**B. ANALYSIS OF A TEST WITH A REAL VEHICLE**

To verify the path tracking performance of the improved MPC and hybrid PID controllers at different speeds and under different road conditions, a test sample vehicle was developed, as shown in Fig. 19. A single-line lidar was used for collision avoidance, a 16-line lidar was used for scanning and path tracking, and the CAN repeater ensured CAN network stability between the chassis and the industrial computer. The improved MPC and hybrid PID algorithm (adding the front wheel sideslip angle constraint and introducing the relaxation factor) were integrated into an industrial computer. The bottom controller was developed based on a DSP28335 control board, as shown in Fig. 20. Fig. 21 shows the actual path tracking of the intelligent vehicle under conditions of up and down slopes, flat roads, and speed bumps.

Fig. 22 shows the processed radar point cloud image. The red dot in the figure is the starting point and the yellow dot is the end point. Fig. 23 shows the vehicle torque feedback signal.

It may be observed from Fig. 22 that better path tracking performance was achieved in speed bumps and flat roads, regardless of whether the intelligent vehicle was at high, medium, or low speeds. When driving at medium and high speeds, the working scanning range of 16-line lidar is $270^\circ$ in the horizontal forward direction and $\pm 15^\circ$ in the vertical direction, a slight deviation appeared in the matching with the surrounding environment map on ascending and
descending slopes, and the tracing accuracy was reduced to some extent. As shown in Fig. 23, the torque feedback value of the in-wheel motor was transmitted to the industrial computer through the CAN network. According to the change in the torque value of the driving motor in the upward and downward slopes, the industrial computer adjusts the front wheel side constraint through MPC to limit the lateral movement of the intelligent vehicle and uses the added relaxation factor to improve the stability of the lateral control. In longitudinal control, the industrial computer uses the hybrid PID algorithm to quickly adjust the control parameters according to the road conditions, the change in the torque value of the driving motor, and the difference between the actual vehicle speed and the target vehicle speed; thus, the intelligent vehicle gradually approaches and coincides with the reference path.
FIGURE 21. Experimental setting with of various road conditions.

FIGURE 22. Map of experimental point cloud for the actual vehicle.

V. DISCUSSION

The proposed algorithm combines the advantages of MPC and PID theory, optimizes them, and designs a path tracking control method with good real-time performance and high control stability. Firstly, in the lateral control, MPC obtains the prediction error by comparing the predicted value of the model with the output measurement value, and then optimizes the predicted value of the model in a limited time domain according to the prediction error and continues to move forward to obtain a more accurate prediction model. The prediction model is improved by combining the feedback correction characteristics of MPC, and the stability of the lateral control is ensured by adding the front wheel slip angle constraints and relaxation factors. In the longitudinal control, according to different working conditions, the hybrid PID controller is designed according to the road conditions. When the driving wheel stalls and the torque is slightly larger, the actual vehicle speed is far from the target vehicle speed, and the torque excessively large and the speed changes slowly, a small PID value controller is used.

In the working conditions of low torque and excessively fast rotation speed, where the changes in torque acceleration and speed are abrupt, a large PID value controller is used. The targeted setting of the PID controller can ensure the stability of the longitudinal control, real-time vehicle tracking, and stability. Simultaneously, CarSim and MATLAB/Simulink were used for co-simulation to verify the effectiveness of the algorithm.

VI. CONCLUSION

To address the path tracking problem in the automatic driving of intelligent vehicles, in this study, we have proposed a control method based on an improved MPC and hybrid PID. The effectiveness of the algorithm was verified through simulations and real vehicle tests. We have drawn the following conclusions based on the results.

1. Model-based prediction, rolling optimization solution, feedback control, and the addition of front wheel sideslip angle constraints and relaxation factors can improve the stability of intelligent vehicles in lateral driving; the lateral error was less than 1%.

2. The proposed hybrid PID controller can realize longitudinal speed control of an intelligent vehicle, improve the response speed of the system, and improve the real-time performance of path tracking. When the vehicle speed is greater than 18 km/h and less than 54 km/h, the yaw angle is deliberately controlled within $-4^\circ$ to $2^\circ$, which can improve the driving safety of intelligent vehicles.

3. The proposed controller based on the improved MPC and hybrid PID can ensure that an intelligent vehicle tracks the target path quickly and stably under medium and low speeds and various complex working conditions, and exhibited higher path tracking accuracy than prior methods.

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