



Article

# Research on Intelligent Platoon Formation Control Based on Kalman Filtering and Model Predictive Control

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**Abstract:** Recently, the intelligent platoon has attracted a lot of attention in both academic and industrial research. For each intelligent platoon, all vehicles drive sequentially in a line, which helps to improve fuel economy and road capacity. Consider two adjacent vehicles in the intelligent platoon, and there is no mechanical boundary between them. However, an intelligent platoon may still suffer from the issues of poor vehicle-following performance during the process of vehicle-following, especially when it obtains its own position and other parameters inaccurately. To address this issue, this paper proposes a model predictive control method based on an improved version of Kalman filtering, aiming to enhance the anti-interference capacity of intelligent platoons in scenarios where the following vehicles have acquired inaccurate parameters resulting from environmental disturbances and sensor noise. Firstly, this paper establishes a three-degree-of-freedom single-track model for the following vehicle, conducting dynamic analysis of its lateral, longitudinal, and yaw movements. Then, this paper develops a horizontal and longitudinal formation driving control frame of the intelligent vehicle platoon. Moreover, this paper also has employed Kalman filtering for interference reduction of state parameters and designs an improved model predictive controller. The proposed scheme is verified and evaluated through a joint simulation within Carsim and MATLAB/Simulink, and the results demonstrate that the longitudinal following error is reduced by 37% and the lateral following error is reduced by 51% compared to traditional algorithms, effectively improving the stability of intelligent vehicle platoons during following driving.

**Keywords:** Kalman filtering; model predictive control; external disturbance; collaborative driving



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## 1. Introduction

In recent years, with the continuous development of intelligent transportation system, there has been a growing interest in research on intelligent vehicle platooning. An intelligent vehicle platoon consists of several interconnected vehicles that optimize their driving strategies through information exchange and sharing, enabling them to maintain high velocities and small gaps between vehicles [1–4]. The control of intelligent vehicle platoon driving involves the interaction between preceding and following vehicles. Improper control of any individual intelligent vehicle can lead to increased overall lateral and longitudinal driving errors in the platoon, resulting in decreased platoon stability and potential safety hazards. Furthermore, current research on formation control of intelligent vehicle platoons only considers the longitudinal motion of vehicles, neglecting the influence of lateral motion on longitudinal motion. This paper comprehensively considers both the lateral and longitudinal motions of intelligent vehicle platoons to control the formation of vehicles and ensure platoon stability. Currently, the mainstream approaches for controlling the formation driving of intelligent vehicle platoons can be classified into three categories: sliding mode control, model predictive control, and neural network-based methods.

- (1) Sliding mode control: The main principle is that the system continuously changes according to the current operating state, causing the system to move according to

the predetermined trajectory and reach the sliding surface in a limited time, reducing the platoon driving difference and controlling it within the specified range [5]. Negash N. M. et al. [6] explored the problem of optimal velocity tracking of the vehicle platoon, modeled the automatic driving system by using the human-like prediction vehicle following model, and proposed a sliding mode control method based on adaptive radial basis function neural network. Through simulation analysis, the platoon stability of the vehicle platoon system was ensured. Gao Z. et al. [7] investigated the problem of vehicle platoon following control with actuator saturation, dynamic uncertainty and unknown disturbance. Based on the saturation function and fixed-time performance function of the Gaussian difference function, an adaptive fixed-time sliding mode control scheme was proposed to ensure that the vehicle platoon following difference converged to a steady state within a fixed time. Boo J. et al. [8] proposed a robust bidirectional longitudinal platoon control method based on integral sliding mode control for vehicles with unknown acceleration and unknown matching disturbance. The finite time robust estimator was used to estimate the acceleration and unknown matching disturbance of adjacent vehicles, and the disturbance compensation was carried out, effectively improving the performance of platoon following control. This method can overcome the uncertainty of the system and has strong robustness to external disturbances. However, when the trajectory of the system reaches the sliding mode surface, it is difficult to strictly follow the equilibrium point of the sliding mode surface, and the system is prone to jitter.

- (2) Model predictive control: This model establishes a prediction model based on the current state of the control object, predicts the future output value of the control object, and then corrects it based on feedback to achieve the optimal control effect [9]. Luo Q. et al. [10], aiming at the control problem of heterogeneous platoon affected by perturbations and modeling differences, proposed an improved model prediction controller, which used a particle swarm optimization algorithm with an  $H_\infty$  performance index of augmenting difference system to optimize the gain in the integrated control strategy, effectively reducing the platoon following difference. Hu X. et al. [11] proposed a distributed MPC scheme to solve the problems of model uncertainty, external interference and time delay existing in platoon control, which carried out unbiased estimation of system state and disturbance, eliminated vehicle following difference, and ensured the stability of platoon following. Ju Z. et al. [12] proposed a distributed stochastic MPC algorithm for vehicle platoon, aiming at the performance of vehicle platoon following control. Under the condition that vehicle driving is full of uncertainties, the algorithm transformed the stochastic MPC problem into a deterministic problem through constraint tightening. Through simulation analysis, the algorithm ensured the stability of vehicle platoon difference convergence. This type of method can explicitly handle the constraints of the controlled system and has the advantage of performance optimization, but its complex computational complexity can affect the timeliness of the system.
- (3) Neural network control: This involves statistical analysis of platoon trajectory data, mining relevant driving behavior patterns, establishing corresponding fitting relationships, and achieving effective control of vehicle formation [13]. Huang J. et al. [14] proposed a vehicle platoon following control strategy based on adaptive neural network algorithm. This method uses adaptive neural network to estimate the nonlinear terms in the vehicle model and compensates the control input with the estimated value, effectively improving the vehicle platoon following performance. Wu Z. et al. [15] aiming at the problem that it is difficult to control nonlinear vehicle platoon following due to measurement differences and environmental interference, applied radial basis function neural network to approximate the nonlinear function, and designed an adaptive distributed controller by using reverse step control method to ensure the consistency of vehicle formation following. An J. et al. [16] solved the distributed adaptive singular free fixed time neural network tracking control problem for vehicle

platoon with model uncertainty. They used adaptive neural networks and  $H_\infty$  control theory to deal with unknown nonlinearity and mismatched complete disturbances in third-order vehicle dynamics. The effectiveness of the proposed algorithm for platoon following control was verified through simulation experiments. Such methods can learn from data sets, extract model features, solve nonlinear problems, and have a certain generalization ability, but their data demand is large, training equipment and time costs are high, and the application threshold is high.

The advantage of the MPC algorithm is that it can deal with constraints explicitly and solve linear or nonlinear problems with constraints online by predicting the future state of the system. With the improvement of on-board computer computing power, the calculation delay problem can be better solved. Therefore, the MPC algorithm has great potential for application in intelligent vehicle platoon decision-making and control. The above lists the current applications of three mainstream methods in the control of intelligent vehicle platoons, but there is a lack of research on the problem that the following vehicle obtains its own parameters inaccurately due to the influence of sensor noise and environmental disturbance during the driving process of the intelligent vehicle platoon, thus affecting the driving effect of intelligent vehicle platoon. In this paper, an improved model prediction controller based on Kalman filtering is designed to solve this problem. In this paper, interference signals caused by sensor noise and environmental interference are converted into noise consistent with Gaussian distribution, and noise reduction is carried out through Kalman filtering. The state parameters after noise reduction are input to the model prediction controller to calculate the expected Angle and vehicle velocity and control the intelligent vehicle platoon to follow. To solve the driving control problem of horizontal and longitudinal formation of intelligent vehicle platoon, this paper proposes an improved model prediction controller based on Kalman filtering. In Section 2, the three-degree-of-freedom model of intelligent vehicle platoons is derived based on the single-track model and nonlinear tire model, and a transverse and longitudinal control framework for the intelligent vehicle platoon is proposed. Section 3 uses Kalman filtering to denoise the system state parameters, designs an improved model predictive controller, and obtains the objective function and constraint conditions of this paper through analysis. Section 4 uses Carsim and MATLAB/Simulink joint simulation to compare with traditional control algorithms and verify the effectiveness of the algorithm proposed in this paper. Section 5 summarizes the work presented in this paper.

## 2. System Model

### 2.1. Problem Description

Consider an intelligent vehicle platoon composed of four intelligent connected vehicles driving along the expected trajectory with the expected distance between vehicles on the road. Among them, the intelligent vehicle platoon includes one leading vehicle and three following vehicles. The trajectory of the lead vehicle is predetermined, and the following vehicle tracks the driving trajectory of the preceding vehicle. Assuming that each vehicle in the intelligent vehicle platoon is equipped with onboard sensing devices and wireless signal transmission devices, all of them can detect the driving status information of surrounding vehicles and obtain the driving trajectory of the preceding vehicle through the wireless signal transmission device. The problem of collaborative control of intelligent vehicle platoon can be transformed into the problem of controlling the lateral steering angle and longitudinal acceleration of the following vehicles in the intelligent vehicle platoon. The following vehicles develop driving strategies based on their current driving status, adjust the steering angle and longitudinal acceleration, track the driving trajectory of the preceding vehicle, and send this information to the following vehicle. The following vehicle repeats this process until the end of platoon.

## 2.2. Intelligent Vehicle Platoon Monorail Model

In order to investigate the horizontal and vertical cooperative control of intelligent vehicle in the process of driving, this paper establishes a single-track model to study the following vehicle dynamics of intelligent vehicle platooning system [17,18]. Assume that at a certain moment, the front and rear vehicles of the intelligent vehicle platoon are in a stable state, ignoring the role of suspension and its impact on vehicle motion and the absence of wheel load transfer, the wheels of the same axis are concentrated on a single wheel located in the center of the front or rear axle, and any following vehicle in the intelligent vehicle platoon is taken and its monorail model is established, as shown in Figure 1.

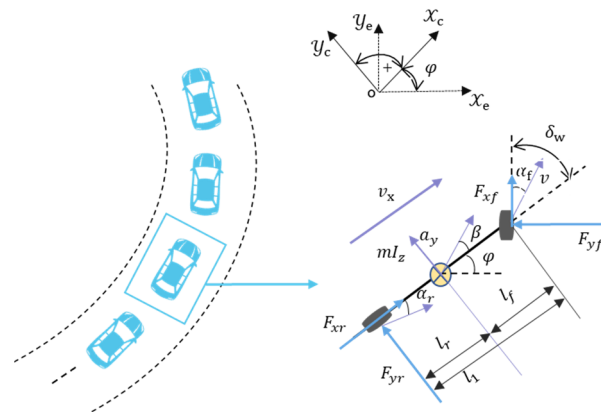


**Figure 1.** Monorail model of following vehicle.

Considering the lateral, longitudinal, and yawing motion of the following vehicle, taking a following vehicle as an example, the mass and yaw moment of inertia of  $m$  and  $I_z$  are respectively obtained.  $\dot{\varphi}$  is the yaw angle velocity of the following vehicle;  $\delta_w$  is the front wheel angle of the following vehicle;  $v_y$  and  $v_x$  are the lateral and longitudinal velocities at the center of mass of the following vehicle, respectively.  $\ddot{x}$  and  $\dot{x}$  are the longitudinal acceleration and velocity of the following vehicle, and  $\ddot{y}$  and  $\dot{y}$  are the lateral acceleration and velocity of the following vehicle, respectively.  $F_{yf}$  and  $F_{yr}$  are the lateral forces on the front and rear wheels of the following vehicle respectively, and  $F_{xf}$  and  $F_{xr}$  are the longitudinal forces on the front and rear wheels of the following vehicle, respectively.  $l_f$  and  $l_r$  are the distances from the center of mass of the following vehicle to the front and rear axes respectively. Through dynamic analysis, the intelligent vehicle's 3-DOF model can be obtained as follows: (1)–(3):

Longitudinal motion:

$$m(\ddot{x} - \dot{y}\dot{\varphi}) = F_{xf}\cos\delta_w - F_{yf}\sin\delta_w + F_{xr} \quad (1)$$

Lateral motion:

$$m(\ddot{y} + \dot{x}\dot{\varphi}) = F_{xf}\sin\delta_w + F_{yf}\cos\delta_w + F_{yr} \quad (2)$$

Yaw motion:

$$I_z\ddot{\varphi} = (F_{xf}\sin\delta_w + F_{yf}\cos\delta_w)l_f - l_rF_{yr} \quad (3)$$

$\alpha_f$  and  $\alpha_r$  are the side declination angles of the front and rear wheels of the following vehicle, respectively. It is assumed that the side declination angles are small, so the trigonometric function in the equation is approximated. The side declination angles of the front and rear wheels of the following vehicle can be obtained through the analysis of the single track model as shown in Equations (4) and (5):

$$\alpha_f = \delta_w - \frac{\dot{y} + \dot{\varphi}l_f}{\dot{x}} \quad (4)$$

$$\alpha_r = \frac{\dot{\varphi}l_r - \dot{y}}{\dot{x}} \quad (5)$$

In order to solve the longitudinal force and lateral force on the front and rear axles of the following vehicle, this paper uses the *Pacejka* tire model [19,20]. When the steering angle and slip rate of the following vehicle are small, the longitudinal force and lateral force on the vehicle tire are as shown in Equation (6):

$$\begin{cases} F_{xf} = C_{xf}s_f \\ F_{yf} = C_{yf}\alpha_f \\ F_{xr} = C_{xr}s_r \\ F_{yr} = C_{yr}\alpha_r \end{cases} \quad (6)$$

In the equation,  $C_{xf}$  and  $C_{xr}$  are the longitudinal stiffness of the tires before and after the following vehicle, and  $C_{yf}$  and  $C_{yr}$  are the transverse stiffness of the tires before and after the following vehicle, respectively.  $s_f$  and  $s_r$  are the slippage ratio of the tires before and after the following vehicle respectively.

When the following vehicle is controlled in the intelligent vehicle platoon, its reference trajectory is the inertial coordinate system, and the relationship between the inertial coordinate system and the body coordinate system is shown in Equations (7) and (8):

$$\begin{cases} \dot{X} = \dot{x}\cos\varphi - \dot{y}\sin\varphi \\ \dot{Y} = \dot{x}\sin\varphi + \dot{y}\cos\varphi \end{cases} \quad (7)$$

$$\begin{cases} \ddot{X} = \ddot{x}\cos\varphi - \ddot{y}\sin\varphi - \dot{Y}\dot{\varphi} \\ \ddot{Y} = \ddot{x}\sin\varphi + \ddot{y}\cos\varphi + \dot{X}\dot{\varphi} \end{cases} \quad (8)$$

Combine Equations (4)–(8) and arrange Equations (1)–(3) into Equations (9)–(11):

$$m\ddot{x} = m\dot{y}\dot{\varphi} + C_{xf}s_f - C_{yf}\delta_w \left( \delta_w - \frac{\dot{y} + \dot{\varphi}l_f}{\dot{x}} \right) + C_{xr}s_r \quad (9)$$

$$m\ddot{y} = -m\dot{x}\dot{\varphi} + C_{xf}s_f\delta_w + C_{yf} \left( \delta_w - \frac{\dot{y} + \dot{\varphi}l_f}{\dot{x}} \right) + C_{yr} \frac{\dot{\varphi}l_r - \dot{y}}{\dot{x}} \quad (10)$$

$$I_z\ddot{\varphi} = \left[ C_{xf}s_f\delta_w + C_{yf} \left( \delta_w - \frac{\dot{y} + \dot{\varphi}l_f}{\dot{x}} \right) \right] l_f - C_{yr}l_r \frac{\dot{\varphi}l_r - \dot{y}}{\dot{x}} \quad (11)$$

Since the longitudinal acceleration in this paper is a control quantity, Equation (9) is updated and corrected, as shown in Equation (12):

$$m\ddot{x} = ma_x \quad (12)$$

This text analyzes the three motion directions of the following vehicle in combination with the model established above and defines the system state variable as  $\zeta$  and the input quantity as  $u$ , as shown in Equation (13):

$$\begin{cases} \zeta = (\dot{x}, \dot{y}, \varphi, \dot{\varphi}, X, Y, \dot{X}, \dot{Y}) \\ u = (a_x, \delta_w) \end{cases} \quad (13)$$

In the Equation, the control variables are, respectively, the acceleration of the following vehicle and the front wheel angle  $a_x$  and  $\delta_w$ . The nonlinear Equation of state of the intelligent vehicle platoon system is integrated, as shown in Equation (14):

$$\begin{cases} \dot{\zeta} = f(\zeta, u) \\ \eta = h(\zeta) \end{cases} \quad (14)$$

where  $\eta$  is the output.

### 2.3. Control Framework

The following control framework is proposed in this paper to address the issue of horizontal and vertical cooperative control of intelligent vehicle platoons, as shown in Figure 2. The driving trajectory and velocity of the lead vehicle are predetermined values, the driving track of the leading vehicle is obtained by following the driving vehicle, and the reference track of the leading vehicle is tracked. In order to mitigate the influence of external driving disturbance on the accuracy of self-vehicle parameters obtained by the following vehicle and improve the control performance of the model prediction controller, a Kalman filter is employed to estimate and compensate for system state parameters affected by external disturbances. The estimated actual system state parameters under external disturbance are then fed into the model predictive controller. The model prediction controller optimizes and solves the optimal acceleration and steering angle according to the system state parameters, objective function, and constraint conditions and inputs them into the prediction model. Through model feedback and intra-team communication interaction information, the solution process is cyclically optimized and feedback-corrected to realize the control of horizontal and longitudinal driving difference of the intelligent vehicle platoon.

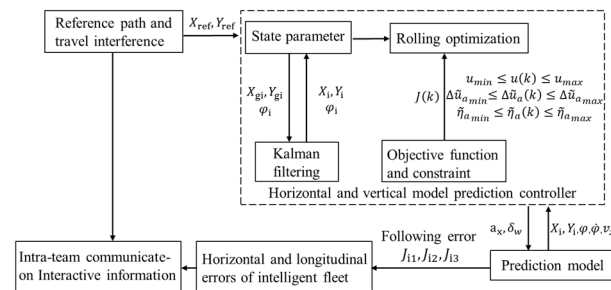


Figure 2. Intelligent vehicle platoon driving control framework.

## 3. Controller Design

### 3.1. Prediction Model

The intelligent vehicle platoon system investigated in this paper is a nonlinear system, which can give rise to intricate nonlinear constraints that impact the real-time performance and stability of vehicle control. In this paper, the approximate linearization method is employed to linearize Equation (14) and depict the nonlinear system as a linear system for analysis, as shown in Equation (15):

$$\begin{cases} \dot{\zeta}_t = B_t \zeta_t + E_t u_t \\ \eta_t = G_t \zeta_t \end{cases} \quad (15)$$

where  $B_t$  is the constant matrix related to vehicle parameters,  $E_t$  is the nonlinear input part of the intelligent vehicle platoon Equation of state,  $G_t$  is the output variable constant matrix, as shown in Equations (17)–(19) for details, and  $u_t$  is the input parameter of the intelligent vehicle platoon.

During platoon driving, the inevitable presence of input and measurement disturbances can adversely affect the estimation of system variable parameters, leading to a reduction in the control effectiveness of the platoon. This paper considers these perturbations and employs the Euler method for discretizing Equation (15), as described in Equation (16):

$$\begin{cases} \zeta(k+1) = B(k)\zeta(k) + E(k)u(k) + \omega(k) \\ Z(k) = H(k)\zeta(k) + v(k) \\ \eta(k) = G(k)\zeta(k) \end{cases} \quad (16)$$

$$B_t = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \frac{C_{yf}(\dot{y} + \dot{\phi}l_f) - C_{yr}(\dot{\phi}l_r - \dot{y})}{m(\dot{x})^2} - \dot{\phi} & -\frac{C_{yf} + C_{yr}}{m\dot{x}} & 0 & \frac{C_{yr}l_r - C_{yf}l_f}{m\dot{x}} - \dot{x} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ \frac{C_{yf}l_f(\dot{y} + \dot{\phi}l_f) + C_{yr}l_r(\dot{\phi}l_r - \dot{y})}{I_z(\dot{x})^2} & \frac{C_{yr}l_r - C_{yf}l_f}{I_z\dot{x}} & 0 & -\frac{C_{yf}l_f^2 + C_{yr}l_r^2}{I_z\dot{x}} & 0 & 0 & 0 & 0 \\ 1 & -\phi & -\dot{y} & 0 & 0 & 0 & 0 & 0 \\ \phi & 1 & \dot{x} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & -\ddot{y} & -\dot{Y} & 0 & 0 & 0 & -\dot{\phi} \\ 0 & 0 & \ddot{x} & \dot{X} & 0 & 0 & \dot{\phi} & 0 \end{bmatrix} \quad (17)$$

$$E_t = \begin{bmatrix} 1 & 0 \\ 0 & \frac{C_{xf}s_f + C_{yf}}{m} \\ 0 & 0 \\ 0 & \frac{C_{xf}s_f l_f + C_{yf}l_f}{I_z} \\ 0 & 0 \\ 0 & 0 \\ 1 & 0 \\ \phi & 0 \end{bmatrix} \quad (18)$$

$$G_t = \begin{bmatrix} 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \end{bmatrix} \quad (19)$$

$$H(k) = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \quad (20)$$

where  $B(k) = I + TB_t$ ,  $E(k) = TE_t$ ,  $G(k) = G_t$ ,  $T$  is the sampling time, and  $H(k)$  is the observation matrix.  $\omega(k)$  and  $v(k)$  are process noise and measurement noise, respectively; the two are independent of each other and accord with normal distribution. The process noise covariance of  $Q(k) = E[\omega(k)\omega(k)^T]$ , and the measurement noise covariance  $R(k) = E[v(k)v(k)^T]$ . The initial state value of the system is  $x(0)$ , and the initial covariance matrix is  $\rho_0$ . This paper calculates the estimated state according to the Kalman filter, as shown in Equation (21):

$$\begin{cases} \hat{\zeta}(k+1|k) = B(k)\hat{\zeta}(k) + E(k)u(k) \\ q(k+1) = \hat{Z}(k+1) - H(k)\hat{\zeta}(k+1|k) \\ \hat{P}(k+1|k) = B(k+1)P(k|k)B(k+1)^T + Q(k) \\ K(k+1) = \frac{\hat{P}(k+1)H(k+1)^T}{H(k+1)\hat{P}(k+1|k)H(k+1)^T + R(k)} \\ \hat{\zeta}(k+1|k+1) = \hat{\zeta}(k+1|k) + K(k+1)q(k+1) \\ P(k+1) = (I - K(k+1)H(k+1))\hat{P}(k+1|k) \\ \hat{\zeta}(k+1|k+1) = \hat{\zeta}(k+1|k) + K(k+1)q(k+1) \end{cases} \quad (21)$$

where  $q$  is the difference between the observed and predicted values of the system,  $\hat{P}$  is the predicted value of the system covariance,  $K$  is the Kalman gain, and  $P$  is the updated value of the system covariance. After de-perturbation, the state parameter value shown in Equation (21) is finally obtained and input to the controller.

In the process of tracking the vehicle in front, the system needs to predict the decision-making behavior of the vehicle within the specified prediction interval and reduce the

difference between the predicted value and the target value. Due to the mechanical constraints of the vehicle itself, the changes in the control quantity before and after the time cannot be too big, so the change increment of the control quantity needs to be constrained. This paper establishes a new state Equation based on Equation (16), selects  $\Delta u$  as the new control variable, and adds  $u(k-1)$  to the system state variable, as shown in Equation (22):

$$\begin{cases} \tilde{\zeta}(k+1) = \tilde{B}(k)\tilde{\zeta}(k) + \tilde{E}(k)\tilde{u}(k) \\ \tilde{\eta}(k) = \tilde{G}(k)\tilde{\zeta}(k) \end{cases} \quad (22)$$

where

$$\begin{cases} \tilde{\zeta}(k) = \begin{bmatrix} \hat{\zeta}(k) \\ u(k-1) \end{bmatrix} \\ \tilde{u}(k) = \Delta u(k) = u(k) - u(k-1) \\ \tilde{B}(k) = \begin{bmatrix} B(k) & E(k) \\ 0_{1 \times 8} & I \end{bmatrix} \\ \tilde{E}(k) = \begin{bmatrix} E(k) \\ I \end{bmatrix} \\ \tilde{G}(k) = [G(k) \quad 0] \end{cases} \quad (23)$$

Set the prediction time domain and control time domain of the MPC controller to  $N_p$  and  $N_c$ , and specify  $N_p > N_c$ . Specifying that the current moment is  $k$  and the initial moment state  $\tilde{\zeta}(k)$  can be obtained by sensor measurement or state estimation. Equation (22) can be written in the following form, as shown in Equation (24):

$$\tilde{\eta}_a(k) = \psi(k)\tilde{\zeta}_a(k) + \Phi(k)\Delta\tilde{u}_a(k) \quad (24)$$

where  $\tilde{\eta}_a(k)$ ,  $\psi$ ,  $\Phi$ ,  $\Delta\tilde{u}_a(k)$  See Equations (25)–(28) for details:

$$\tilde{\eta}_a(k) = \begin{bmatrix} \eta(k+1|k) \\ \eta(k+2|k) \\ \vdots \\ \eta(k+N_c|k) \\ \vdots \\ \eta(k+N_p|k) \end{bmatrix}_{N_p \times 1} \quad (25)$$

$$\psi(k) = \tilde{G}(k) \begin{bmatrix} \tilde{B}(k) \\ \tilde{B}^2(k) \\ \vdots \\ \tilde{B}^{N_p}(k) \end{bmatrix} \quad (26)$$

$$\Phi(k) = \tilde{G}(k) \begin{bmatrix} \tilde{E}(k) & 0 & \cdots & 0 \\ \tilde{B}(k)\tilde{E}(k) & \tilde{E}(k) & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{B}^{N_c-1}(k)\tilde{E}(k) & \tilde{B}^{N_c-2}(k)\tilde{E}(k) & \cdots & \tilde{E}(k) \\ \tilde{B}^{N_c}(k)\tilde{E}(k) & \tilde{B}^{N_c-1}(k)\tilde{E}(k) & \cdots & \tilde{B}(k)\tilde{E}(k) \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{B}^{N_p-1}(k)\tilde{E}(k) & \tilde{B}^{N_p-2}(k)\tilde{E}(k) & \cdots & \tilde{B}^{N_p-N_c}(k)\tilde{E}(k) \end{bmatrix} \quad (27)$$

$$\Delta \tilde{u}_a(k) = \begin{bmatrix} \Delta u(k) \\ \Delta u(k+1) \\ \vdots \\ \Delta u(k+N_c-1|k) \end{bmatrix}_{N_c \times 1} \quad (28)$$

### 3.2. Objective Function

In this paper, the trajectory of the lead vehicle is provided, so only the objective function is designed for the following vehicle. To accomplish cooperative driving among intelligent vehicle platoons and ensure that an intelligent vehicle platoon keeps the desired distance along the desired trajectory, the objective function designed in this paper is as follows:

- (1) One of the main objectives of the longitudinal driving control of the intelligent vehicle platoon is to maintain the desired longitudinal workshop distance and ensure that the following difference is as small as possible. This control objective is achieved by solving the objective function  $J_{i1}$ , as shown in Equation (29):

$$J_{i1} = \sum_{j=1}^{N_p} \|X_i(k+j|k) - X_{i-1}(k+j) - D_{des}\|^2 \quad (29)$$

where  $X_i$  is the longitudinal position of the  $i$  following vehicle in the intelligent vehicle platoon, and  $D_{des}$  is the expected workshop distance. Compared with the fixed interval strategy, the constant interval strategy is more conducive to improving the driving safety of the following vehicle. Therefore, the constant interval strategy is adopted in this paper to set the expected workshop distance, and the expected workshop distance can be described as Equation (30):

$$D_{des} = C + hv_x \quad (30)$$

where  $D_{des}$  is the expected workshop distance,  $C$  is the safe distance,  $h$  is the front time distance,  $v_x$  is the longitudinal velocity.

- (2) In order to ensure the driving effect of the vehicle following, it is necessary to control the velocity of the following vehicle so that the velocity of the following vehicle is as consistent as possible with the velocity of the leading vehicle. This control goal is achieved by solving the objective function  $J_{i2}$ , as shown in Equation (31):

$$J_{i2} = \sum_{j=1}^{N_p} \|v_i(k+j|k) - v_{i-1}(k+j)\|^2 \quad (31)$$

- (3) The main objective of lateral driving control of the intelligent vehicle platoon is to minimize the difference between current lateral driving position of the following vehicle and the lateral position of the reference trajectory, and to ensure that the yaw angle difference is as small as possible, This control goal is achieved by solving the objective function  $J_{i3}$ , as shown in Equation (32):

$$J_{i3} = \sum_{j=1}^{N_p} \|Y_i(k+j|k) - Y_{ref}(k+j|k)\|^2 + \sum_{j=1}^{N_p} \|\varphi_i(k+j|k) - \varphi_{ref}(k+j|k)\|^2 \quad (32)$$

where  $Y_i$  is the lateral position of the  $i$  following vehicle in the intelligent vehicle platoon,  $Y_{ref}$  is its reference position,  $\varphi_i$  is the yaw angle of the  $i$  following vehicle, and  $\varphi_{ref}$  is its reference yaw angle.

By integrating the above three objective functions, the objective function of this paper can be obtained as shown in Equation (33):

$$\min J_i \left\{ \tilde{\zeta}_a(k), \Delta \tilde{u}_a(k) \right\} = \min \{J_{i1} + J_{i2} + J_{i3}\} \quad (33)$$

It is converted into a quadratic objective function. In order to avoid the situation of no solution under constraints, relaxation factors are added, as shown in Equation (34):

$$J(k) = \sum_{j=1}^{N_p} \left\| \eta(k+j|k) - \eta_{ref}(k+j|k) \right\|^2 \tilde{Q} + \sum_{j=1}^{N_c} \left\| \Delta u(k+j|k) \right\|^2 \tilde{R} + \check{\rho} \varepsilon^2 \quad (34)$$

where  $\tilde{Q}$  and  $\tilde{R}$  are output weight matrix and input weight matrix, respectively.  $\tilde{Q} = \text{diag}(Q_{\Delta x}, Q_{\Delta v}, Q_{\Delta y}, Q_{\Delta \varphi})_{N_p}$ ,  $Q_{\Delta x}$ ,  $Q_{\Delta v}$ .

$Q_{\Delta y}$ ,  $Q_{\Delta \varphi}$  is the weight factor for the longitudinal distance error, vehicle velocity error, lateral position error, and yaw angle error of the following car and the preceding car, respectively.  $\tilde{R} = \text{diag}(R, R \cdots R)_{N_c}$  was calculated by the controller to obtain the weight coefficient of expected angle of following vehicle and velocity,  $\check{\rho}$  is the weight factor, and  $\varepsilon$  is the relaxation factor.

### 3.3. Optimization Solution

Substitute Equation (24) into Equation (34) to obtain Equation (35):

$$J(k) = \left[ \tilde{\eta}_a(k) - \tilde{\eta}_{ref}(k) \right]^T \tilde{Q} \left[ \tilde{\eta}_a(k) - \tilde{\eta}_{ref}(k) \right] + \Delta \tilde{u}_a(k)^T \tilde{R} \Delta \tilde{u}_a(k) + \check{\rho} \varepsilon^2 \quad (35)$$

The output difference in the prediction time domain is expressed as Equation (36):

$$M(k) = \psi \tilde{\zeta}_a(k) - \tilde{\eta}_{ref}(k) \quad (36)$$

By substituting Equation (36) into Equation (35), the updated objective function can be obtained as shown in Equation (37):

$$J_i \left\{ \tilde{\zeta}_a(k), \Delta \tilde{u}_a(k) \right\} = \left[ \Delta \tilde{u}_a(k)^T, \varepsilon \right]^T L_t \left[ \Delta \tilde{u}_a(k)^T, \varepsilon \right] + N_t \left[ \Delta \tilde{u}_a(k)^T, \varepsilon \right] + S_t \quad (37)$$

where  $L_t = \begin{bmatrix} \Phi(k)^T \tilde{Q} \Phi(k) & 0 \\ 0 & \check{\rho} \end{bmatrix}$ ,  $N_t = \begin{bmatrix} 2M(k)^T \tilde{Q} \Phi(k) & 0 \end{bmatrix}$ ,  $S_t = M(k)^T \tilde{Q} M(k)$ ,  $S_t$  is constant at time  $k$ ,  $\Omega = \left[ \Delta \tilde{u}_a(k)^T, \varepsilon \right]$ , then Equation (37) can be updated to Equation (38):

$$J(k) = \frac{1}{2} \Omega^T L_t \Omega + N_t \Omega \quad (38)$$

The optimal control incremental input is obtained by solving the following optimization problems; for details, see Equation (39):

$$\begin{aligned} \min_{\Omega} J(k) &= \frac{1}{2} \Omega^T L_t \Omega + N_t \Omega \\ \text{s.t. } u_{\min} &\leq u(k) \leq u_{\max} \\ \Delta \tilde{u}_{a\min} &\leq \Delta \tilde{u}_a(k) \leq \Delta \tilde{u}_{a\max} \\ \tilde{\eta}_{a\min} &\leq \tilde{\eta}_a(k) \leq \tilde{\eta}_{a\max} \# \end{aligned} \quad (39)$$

The quadratic programming process solved by MATLAB is shown in Figure 3:

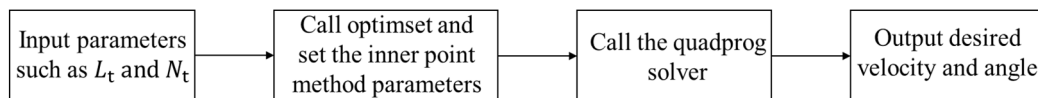


**Figure 3.** Solving process.

The constraint conditions in the Equation are control quantity, control increment, and output quantity within their respective prescribed ranges. The optimal control increment obtained in the control time domain is expressed as Equation (40):

$$\Delta \tilde{u}_a(k)^* = \begin{bmatrix} \Delta u(k)^* \\ \Delta u(k+1)^* \\ \vdots \\ \Delta u(k+N_c-1|k)^* \end{bmatrix}_{N_c \times 1} \quad (40)$$

According to the basic principle of MPC, the first optimal control increment obtained by the solution is input to the system, then the first control quantity can be expressed as Equation (41):

$$u(k) = u(k-1) + \Delta u(k)^* \quad (41)$$

The optimal control quantity obtained from the above Equation will act on the system to control the driving of the following vehicle and then cycle the above solution process until the optimal control quantity is solved at the next time.

## 4. Simulation Analysis

### 4.1. Simulation Parameter Setting

To verify the effectiveness of the improved MPC based on Kalman filtering, this paper uses Carsim and MATLAB/Simulink to build an intelligent vehicle platoon driving control model with a road slip rate of 0.8. The simulation scene is depicted in Figure 4, while Table 1 presents the vehicle parameters and Table 2 provides the control parameters.



**Figure 4.** Simulation scene.

**Table 1.** Vehicle parameters.

| Parameter Name                             | Value  | Unit              |
|--------------------------------------------|--------|-------------------|
| Vehicle mass                               | 1270   | kg                |
| Distance from center of mass to front axis | 1015   | mm                |
| Front and rear axle distance               | 2910   | mm                |
| Body height                                | 1610   | mm                |
| Height of center of mass                   | 540    | mm                |
| Tyre radius                                | 325    | mm                |
| Moment of inertia about the z axis         | 1536.7 | kg/m <sup>2</sup> |

The lead vehicle's initial position is set at 30 m, while the three following vehicles have initial longitudinal positions of 20 m, 10 m, and 0 m, respectively, all vehicles in the team

have an initial velocity of 5 m/s, and the simulation duration is designed to last for 30 s; during this time period, the velocity  $v_1$  of the lead vehicle changes as follows:

$$v_1 = \begin{cases} 5, & 0 \leq t \leq 5 \\ 5 - 0.4(t - 5), & 5 \leq t \leq 10 \\ 3 + 2.3(t - 10), & 10 \leq t \leq 13 \\ 10, & 13 \leq t \leq 30 \end{cases} \quad (42)$$

where, the unit of vehicle velocity  $v_1$  is m/s, and the unit of time  $t$  is s.

**Table 2.** Control parameters.

| Parameter Name                | Range       | Unit             |
|-------------------------------|-------------|------------------|
| $v_x$                         | [2, 15]     | m/s              |
| $a_x$                         | [-5, 5]     | m/s <sup>2</sup> |
| $\delta_w$                    | [-20, 30]   | °                |
| $\Delta \tilde{u}_{a_x}$      | [-1.5, 1.5] | m/s <sup>2</sup> |
| $\Delta \tilde{u}_{\delta_w}$ | [-5, 5]     | °                |
| $C$                           | 6           | m                |
| $h$                           | 1           | -                |

In this paper, the communication topology of the vehicle platoon is the predecessor following. According to the guideline standard 2021-0135T-QC [21] in the construction of China's National Vehicle Networking Industry Standard System, when the vehicle transmits information unidirectionally, the communication delay should be less than 4 ms. In this paper, the corresponding simulation experiment parameters are set on the basis of the national standard, and the communication delay is set to 4 ms. In order to avoid the failure of the quadratic programming in this paper to solve the result in time, the sampling time in this paper is set to 0.1 s. Since the sampling time is much larger than the communication delay, the influence of communication delay on the queuing of intelligent vehicles is ignored in this paper.

Taking the intelligent vehicle 2 as an example, Figures 5 and 6, respectively, show the block diagram of the model predictive control system based on improved Kalman filtering and the block diagram of the PID control system. In the improved model predictive control system based on Kalman filtering, firstly, Gaussian noise is added into the information input by Carsim, and after noise reduction processing by Kalman filtering, the input of the model predictive controller is the longitudinal velocity of the front and rear vehicles, the longitudinal acceleration of the front and rear vehicles, the transverse displacement of the front and rear vehicles, the longitudinal displacement of the front and rear vehicles, and the yaw angle. The model prediction controller calculates the desired acceleration and angle of the output. The rotation angle directly acts on the vehicle and controls the lateral following of the vehicle. The acceleration is converted into the corresponding velocity, the actual distance between the vehicle and the vehicle in front is calculated, and the expected distance is calculated through the fixed time distance strategy for comparative analysis, so as to control the longitudinal following.

Figure 6 is the PID control system diagram; taking the second vehicle as an example, other vehicles are consistent with this. The input of PID controller is the longitudinal velocity of the front and rear vehicle, the longitudinal acceleration of the front and rear vehicle, the lateral displacement of the front and rear vehicle, the longitudinal displacement and the yaw angle. The outputs are angle and acceleration. Taking longitudinal follow drive as an example, the PID adjustment idea in this paper is to adjust P and I first, and then adjust D. The main observation is whether the desired acceleration calculated by the controller can keep the following vehicle running at the desired workshop distance, and the workshop distance is calculated using the constant interval strategy. When P is adjusted, it is adjusted from small to large. When the system is stable, the actual workshop distance is

stable with the expected workshop distance, and there is a certain error, but it is basically close to the expected workshop distance curve. Then I is adjusted from small to large, and the value of I is gradually increased until the actual workshop distance curve fits the expected workshop distance curve. Then observe the overshoot phenomenon of the system and slowly increase D until the overshoot is eliminated, at which time the PID adjustment is completed.

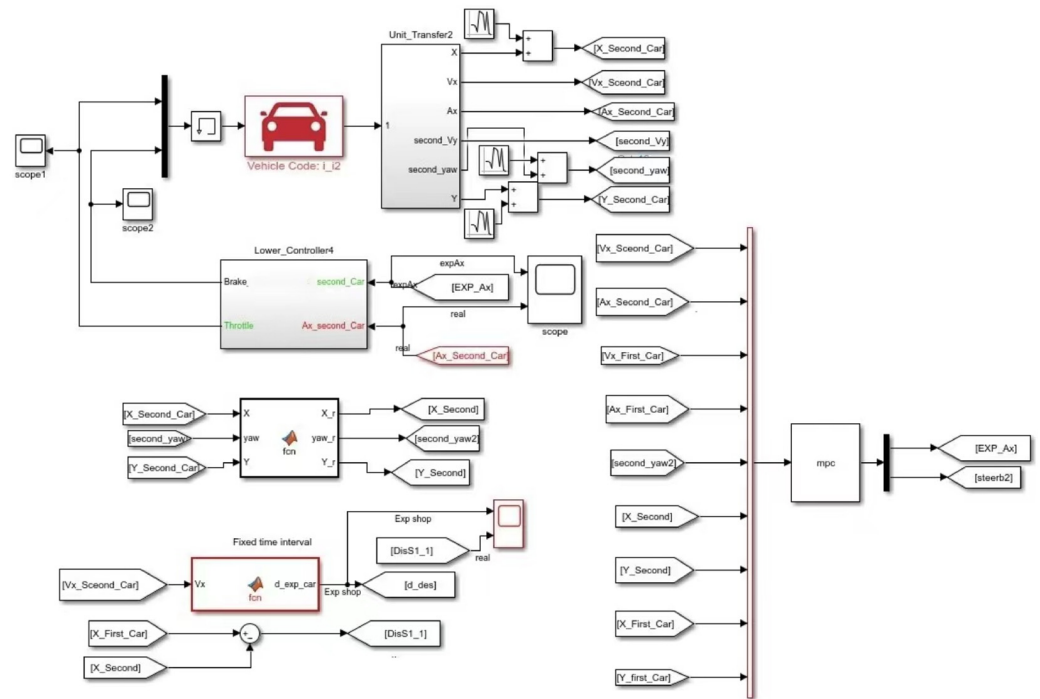


Figure 5. An improved model predictive control system diagram based on Kalman filtering.

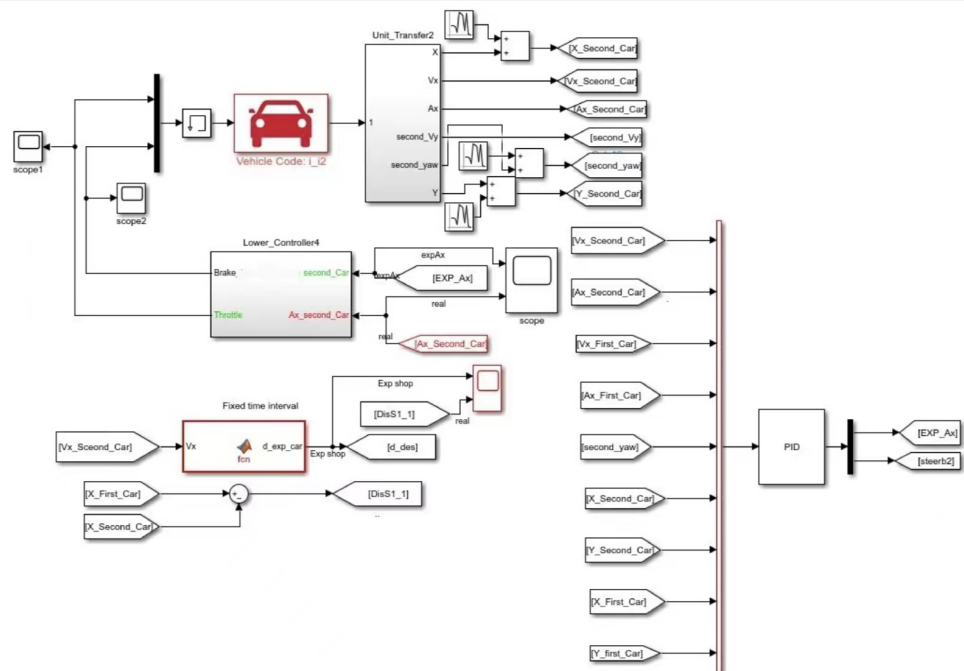


Figure 6. PID control system diagram.

#### 4.2. Controller Performance Analysis

In order to validate the controller's performance, this section conducts a joint simulation experiment on the horizontal and longitudinal driving of the platoon under the curve scene, and verifies the effectiveness of the controller designed in this paper on the control of the horizontal and longitudinal driving of the platoon by comparing the control effect with that of the traditional control method PID. Figure 7 is the simulation result of this paper.

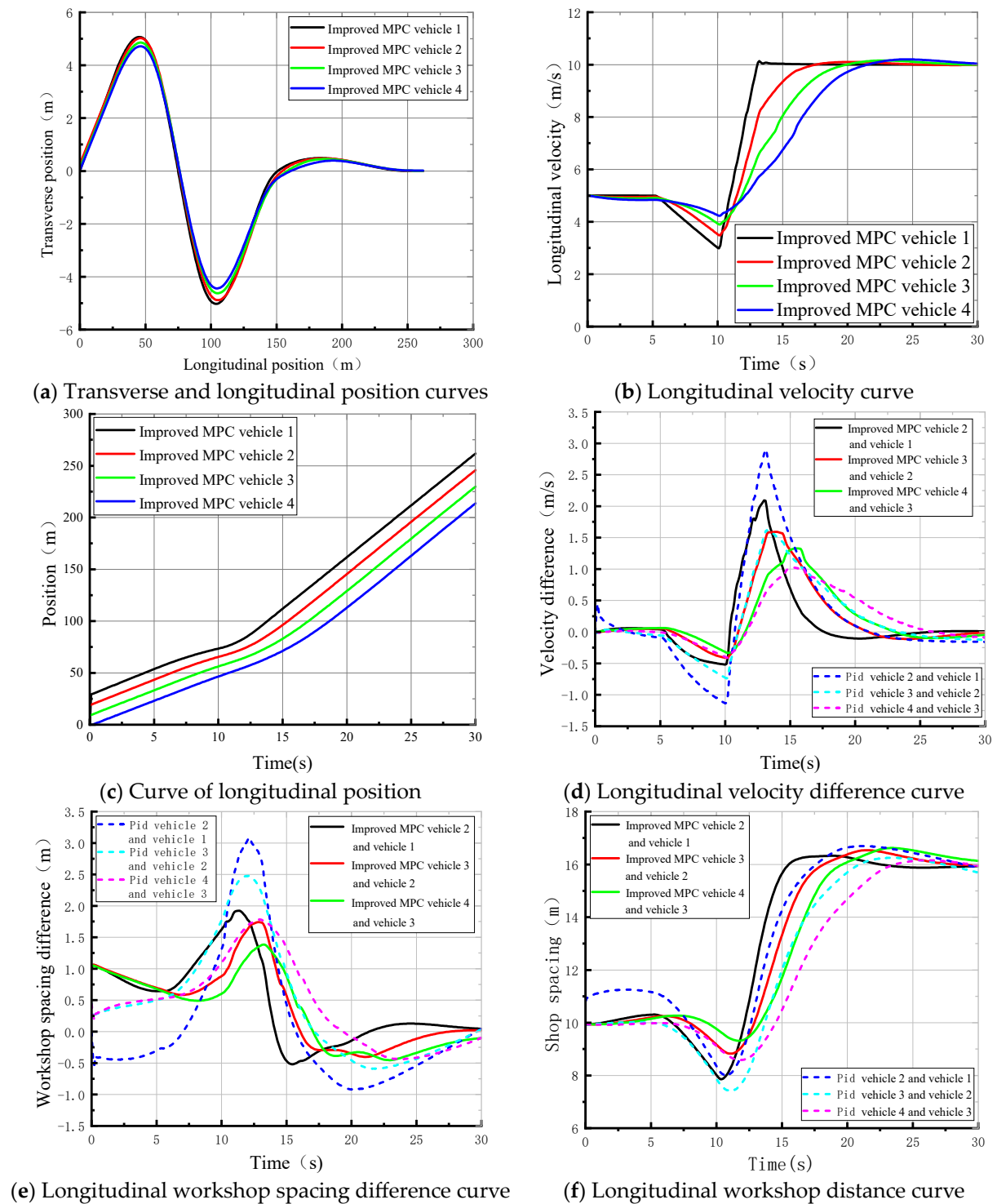


Figure 7. Cont.

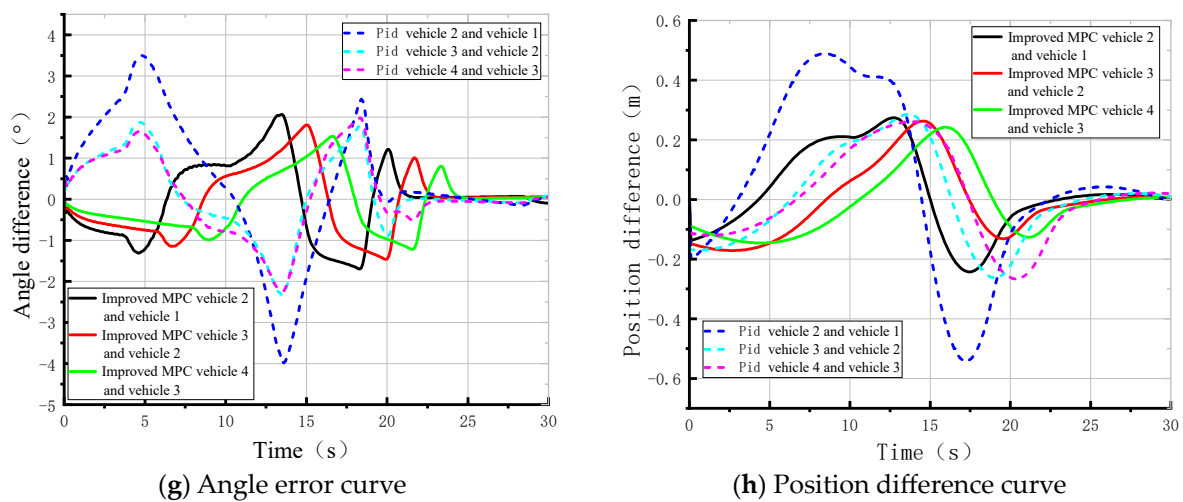


**Figure 7.** Improved MPC and PID performance comparison diagram for horizontal and vertical control of intelligent vehicle platoon.

Figure 7a–c show the horizontal and longitudinal control performance curve of the intelligent platoon controlled by the MPC improved by Kalman filtering. Figure 7a illustrates the intelligent platoon's driving trajectory. It can be seen from the figure that three following vehicles have better driving control following the lead vehicle on the curved road. Figure 7b displays the longitudinal velocity diagram of the intelligent vehicle platoon, revealing three stages of expected velocity changes: deceleration, acceleration, and uniform velocity. Figure 7c shows the longitudinal displacement curve of the intelligent vehicle platoon. It can be seen from the figure that there is no cross-collision in the intelligent vehicle platoon during the driving process. Figure 7d–h, respectively, exhibit the improved model prediction controller and PID controller's horizontal and vertical control effects on the intelligent platoon.

The changes in longitudinal velocity difference and inter-vehicle distance of the intelligent platoon are illustrated in Figure 7d–f. To enhance vehicle driving safety, this study employs a constant time distance strategy to calculate the expected inter-vehicle distance longitudinally. As can be seen from the figure, when utilizing the improved model for controller prediction, the maximum velocity difference of the intelligent platoon during the driving process is about 2.12 m/s, and the maximum vehicle spacing difference is about 1.95 m, both of which occur between the following vehicle 1 and the lead vehicle, without the situation of backward expansion. At the end of the simulation time, the overall velocity of the intelligent platoon converges to 0, and the workshop distance converges to the expected workshop distance of 16 m. When employing a PID controller, the maximum velocity difference is about 2.95 m/s, the maximum vehicle spacing difference is about 3.1 m, both approaching 0 at simulation completion time. By comparison with PID control algorithm results, it can be observed that this paper's proposed algorithm can reduce the maximum velocity difference by approximately 28% and the maximum vehicle spacing difference by roughly 37%. Furthermore, by comparing the time of maximum velocity difference and workshop distance difference to steady state, it can be seen that the convergence time of the proposed algorithm is shorter.

The horizontal control performance curve of the intelligent platoon is depicted in Figure 7g–h. It can be observed from the diagram that when employing the improved model predictive controller, the maximum front wheel angle difference and the maximum lateral position difference of the intelligent platoon during the driving process are about  $2.08^\circ$  and about 0.27 m, respectively, both occurring between following vehicle 1 and the lead vehicle, without the situation of backward expansion. The difference approaches 0 at the end of the simulation time. When PID controller is adopted, the maximum front wheel angle difference is about  $4^\circ$  and the maximum lateral position difference is about 0.56 m

during the driving of the intelligent team, both of which appear between the following vehicle 1 and the lead vehicle, without backward expansion, and approach to 0 at the end of the simulation time. By comparison, compared with PID control algorithm, the proposed algorithm can reduce the maximum angle difference by about 48% and the maximum vehicle spacing difference by roughly 51%.

In summary, compared with the traditional PID control algorithm, the improved MPC algorithm based on KF proposed in this paper has reduced peak values in terms of velocity difference, workshop distance difference, front wheel angle difference, and lateral position difference, and no backward diffusion has occurred, which has effectively enhanced the following and stability of intelligent vehicle platoon.

## 5. Conclusions

The paper has proposed an improved MPC based on KF for the horizontal and longitudinal formation control of intelligent vehicle platoon. A discrete version of the established vehicle dynamics model was obtained to derive the system prediction formula. Considering the influence of external disturbance, noise was added to the system prediction formula and measurement formula, and the noise was reduced by KF to improve the accuracy of the following vehicle in obtaining its own state parameters. Leveraging the KF algorithm, a prediction controller for the horizontal and vertical distributed model of intelligent vehicle platoon was designed, and a quadratic objective function  $J(k)$  was constructed. Simulation experiments were conducted on Carsim and MATLAB/Simulink platforms to compare the proposed method with traditional control algorithms for evaluating their respective control performances. The control performance of the proposed method and the traditional control algorithm has been compared. The simulation results have shown that the improved MPC algorithm based on KF was able to achieve a good following effect at time-varying vehicle velocity by de-disturbing the state variables with interference, and the following error did not spread backward. Compared with the traditional algorithm without noise reduction, the longitudinal and lateral following errors were reduced by 37% and 51%, effectively improving the stability of intelligent vehicle platoon following. The reduction in the longitudinal following distance of the intelligent vehicle platoon greatly improved the utilization rate of road space and could effectively alleviate traffic congestion. The reduction in the lateral following error could reduce the air resistance of the vehicle when it is following, reduce fuel consumption, and reduce environmental pollution. In summary, the reduction of the horizontal and longitudinal following error of the intelligent vehicle platoon has important economic and social value.

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## Nomenclature

| Name                      | Abbreviation                                                                                                     |
|---------------------------|------------------------------------------------------------------------------------------------------------------|
| Model Predictive Control  | MPC                                                                                                              |
| Kalman Filtering          | KF                                                                                                               |
| Sliding Mode Control      | SMC                                                                                                              |
| Neural Network Control    | NNC                                                                                                              |
| 3-Degree-of-Freedom Model | 3-DOF                                                                                                            |
| Name                      | Implication                                                                                                      |
| $m$                       | mass                                                                                                             |
| $I_z$                     | Moment of inertia of yaw motion                                                                                  |
| $\dot{\varphi}$           | Yaw angular velocity                                                                                             |
| $\delta_w$                | angle                                                                                                            |
| $v_y$                     | Lateral velocity at the center of mass                                                                           |
| $v_x$                     | Longitudinal velocity at the center of mass                                                                      |
| $\ddot{x}, \dot{x}$       | Longitudinal acceleration and velocity                                                                           |
| $\ddot{y}, \dot{y}$       | Lateral acceleration and velocity                                                                                |
| $F_{yf}, F_{yr}$          | Front and rear lateral forces                                                                                    |
| $F_{xf}, F_{xr}$          | Front and rear longitudinal forces                                                                               |
| $l_f, l_r$                | The distance from the center of mass to the front axle and the distance from the center of mass to the rear axle |
| $\alpha_f, \alpha_r$      | The side Angle of the front wheel and the side Angle of the rear wheel                                           |
| $C_{xf}, C_{xr}$          | Longitudinal stiffness of front and rear tires                                                                   |
| $C_{yf}, C_{yr}$          | Lateral stiffness of front and rear tires                                                                        |
| $s_f, s_r$                | Slip rate of front and rear tires                                                                                |
| $\zeta$                   | System state variable                                                                                            |
| $u$                       | System input variable                                                                                            |
| $a_x, \delta_w$           | Control variable acceleration and steering Angle                                                                 |
| $\eta$                    | Output variable                                                                                                  |
| $B_t$                     | Constant matrix of vehicle parameter correlation                                                                 |
| $E_t$                     | Nonlinear input to the equation of state                                                                         |
| $G_t$                     | Output variable constant matrix                                                                                  |
| $u_t$                     | Input parameter                                                                                                  |
| $H(k)$                    | Observation matrix                                                                                               |
| $\omega(k), v(k)$         | Process noise and measurement noise                                                                              |
| $x(0)$                    | The initial status of the system                                                                                 |
| $\rho_0$                  | Initial covariance matrix                                                                                        |
| $q$                       | Error between the observed and predicted values of the system                                                    |
| $\hat{P}$                 | Predicted value of system covariance                                                                             |
| $K$                       | Kalman gain                                                                                                      |
| $N_p, N_c$                | Prediction domain and control domain                                                                             |
| $D_{des}$                 | Expected workshop spacing                                                                                        |
| $C$                       | Safe distance                                                                                                    |
| $h$                       | Head time                                                                                                        |

## References

1. Xue, Y.; Zhang, X.; Cui, Z.; Yu, B.; Gao, K. A platoon-based cooperative optimal control for connected autonomous vehicles at highway on-ramps under heavy traffic. *Transp. Res. Part C Emerg. Technol.* **2023**, *150*, 104083. [\[CrossRef\]](#)
2. Liu, Y.; Yao, D.; Li, H.; Lu, R. Distributed cooperative compound tracking control for a platoon of vehicles with adaptive NN. *IEEE Trans. Cybern.* **2021**, *52*, 7039–7048. [\[CrossRef\]](#) [\[PubMed\]](#)
3. Liu, Z.; Wang, H.; Wang, Y.; Wang, H. Cooperative Platoon Control of Automated Industrial Vehicles: A Synchronization Approach and Real-World Experiments. *IEEE/ASME Trans. Mechatron.* **2022**, *28*, 245–256. [\[CrossRef\]](#)
4. Deng, Z.; Fan, J.; Shi, Y.; Shen, W. A coevolutionary algorithm for cooperative platoon formation of connected and automated vehicles. *IEEE Trans. Veh. Technol.* **2022**, *71*, 12461–12474. [\[CrossRef\]](#)
5. Ding, S.; Mei, K.; Yu, X. Adaptive second-order sliding mode control: A Lyapunov approach. *IEEE Trans. Autom. Control* **2021**, *67*, 5392–5399. [\[CrossRef\]](#)

6. Negash, N.M.; Yang, J. Anticipation-based autonomous platoon control strategy with minimum parameter learning adaptive radial basis function neural network sliding mode control. *SAE Int. J. Veh. Dyn. Stab. NVH* **2022**, *6*, 247–265. [CrossRef]
7. Gao, Z.; Zhang, Y.; Guo, G. Fixed-time prescribed performance adaptive fixed-time sliding mode control for vehicular platoon with actuator saturation. *IEEE Trans. Intell. Transp. Syst.* **2022**, *23*, 24176–24189. [CrossRef]
8. Boo, J.; Chwa, D. Integral Sliding Mode Control-Based Robust Bidirectional Platoon Control of Vehicles With the Unknown Acceleration and Mismatched Disturbance. *IEEE Trans. Intell. Transp. Syst.* **2023**, *24*, 10881–10894. [CrossRef]
9. Zhang, K.; Shi, Y.; Sheng, H. Robust nonlinear model predictive control based visual servoing of quadrotor UAVs. *IEEE/ASME Trans. Mechatron.* **2021**, *26*, 700–708. [CrossRef]
10. Luo, Q.; Nguyen, A.T.; Fleming, J.; Zhang, H. Unknown input observer based approach for distributed tube-based model predictive control of heterogeneous vehicle platoon. *IEEE Trans. Veh. Technol.* **2021**, *70*, 2930–2944. [CrossRef]
11. Hu, X.; Xie, L.; Xie, L.; Lu, S.; Xu, W.; Su, H. Distributed model predictive control for vehicle platoon with mixed disturbances and model uncertainties. *IEEE Trans. Intell. Transp. Syst.* **2022**, *23*, 17354–17365. [CrossRef]
12. Ju, Z.; Zhang, H.; Tan, Y. Distributed stochastic model predictive control for heterogeneous vehicle platoon subject to modeling uncertainties. *IEEE Intell. Transp. Syst. Mag.* **2021**, *14*, 25–40. [CrossRef]
13. Gawlikowski, J.; Tassi, C.R.N.; Ali, M.; Lee, J.; Humt, M.; Feng, J.; Kruspe, A.; Triebel, R.; Jung, P.; Roscher, R.; et al. A survey of uncertainty in deep neural networks. *Artif. Intell. Rev.* **2023**, *56* (Suppl. S1), 1513–1589. [CrossRef]
14. Huang, J.; Chen, J.; Yang, H.; Li, D. Vehicle Platoon Tracking Control Based on Adaptive Neural Network Algorithm. *Int. J. Control Autom. Syst.* **2023**, *21*, 3405–3418. [CrossRef]
15. Wu, Z.; Sun, J.; Hong, S. Rbfnn-based adaptive event-triggered control for heterogeneous vehicle platoon consensus. *IEEE Trans. Intell. Transp. Syst.* **2022**, *23*, 18761–18773. [CrossRef]
16. An, J.; Liu, Y.; Sun, J.; Wang, L.; Xue, H. Distributed fixed-time NN tracking control of vehicular platoon systems with singularity-free. *Neural Comput. Appl.* **2023**, *35*, 2527–2540. [CrossRef]
17. Wen, X.; Nie, Y.; Du, Z.; Huang, L. Operational safety assessment of straddle-type monorail vehicle system based on cloud model and improved CRITIC method. *Eng. Fail. Anal.* **2022**, *139*, 106463. [CrossRef]
18. Wen, X.; Huang, L.; Du, Z.; Chen, L.; Yang, Z. Research on parameter optimization based on multi-body dynamics model of monorail vehicle aiming at reducing running wheel wear. *Proc. Inst. Mech. Eng. Part K J. Multi-Body Dyn.* **2022**, *236*, 588–601. [CrossRef]
19. Harun, M.H.; Hudha, K.; Samin, P.M.; Bakar, S.A.A.; Kadir, Z.A. A new approach in modelling of hitch joint of a tractor semi-trailer using virtual Pacejka tyre model. *Int. J. Heavy Veh. Syst.* **2021**, *28*, 262–290. [CrossRef]
20. Ammari, O.; El Majdoub, K.; Giri, F.; Baz, R. Longitudinal Control of Electric Vehicle Driven by an In-Wheel BLDC Motor Including the Pacejka Tire Model. In Proceedings of the 2023 3rd International Conference on Innovative Research in Applied Science, Engineering and Technology (IRASET), Mohammedia, Morocco, 18–19 May 2023; pp. 1–5.
21. Ministry of Industry and Information Technology Home Page. Available online: <https://www.gov.cn/zhengce/zhengceku/202307/P020230727459713380334.pdf> (accessed on 18 July 2023).

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