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Research on Convoy Coordination Method Based on Speed Planning and Tracking Control

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Abstract: In order to solve the complexity of speed planning and control in heterogeneous fleets, this paper proposes a fleet speed planning and tracking control method based on a two-layer control structure, which consists of a speed planning layer and a fleet control layer. The speed planning layer generates a reference speed trajectory through the fleet average model, and designs dynamic programming algorithms in combination with time sampling and space sampling to optimize the fuel economy and trajectory smoothness of the fleet; the fleet control layer designs a continuous controller and a discrete controller to achieve accurate tracking of the reference trajectory, and ensures the robustness and safety of the fleet through queue stability analysis. Simulation experiments show that the proposed method is superior to other methods in trajectory smoothness, queue stability and fuel economy.

Keywords: speed planning, tracking control, convoy coordination, queue stability

1. Introduction

In recent years, with the rapid growth of global transportation demand, problems such as traffic congestion, energy consumption, and environmental pollution have become increasingly prominent. The development of an efficient, intelligent, and environmentally friendly transportation system has become a hot topic of social concern [1][2]. In the field of intelligent transportation, convoy control is considered to be one of the important technologies to solve the above problems. It realizes convoy driving through efficient collaboration between multiple vehicles, which helps to reduce traffic energy consumption, improve road capacity, and reduce driver fatigue. The core of convoy cooperative control is to achieve coordinated movement between vehicles, which mainly includes two key tasks: speed planning and tracking control [3]. Among them, speed planning aims to generate a global optimal reference speed trajectory for the convoy, comprehensively consider vehicle dynamics constraints and road environment factors, and ensure that the convoy achieves the optimal balance between energy consumption, time, and safety [4]; tracking control focuses on how each vehicle locally tracks the reference trajectory to maintain the stability of the convoy [5]. The organic combination of the two is the core issue of convoy control research. Although convoy control has been widely studied, there are still many challenges in actual scenarios. First, in heterogeneous convoys, due to the differences in vehicle dynamics and parameters, the traditional planning method based on the lead vehicle model is difficult to meet the needs of all vehicles [6]. Secondly, changes in external environments such as road slope and traffic congestion further increase the complexity of

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the speed planning problem. In addition, vehicle communication delay and nonlinear dynamics put forward higher robustness requirements for the stability of convoy driving [7]. Therefore, studying how to generate more effective speed planning trajectories under heterogeneous convoy conditions and achieve coordinated movement between vehicles through robust control methods has become a hot topic and difficulty in the current convoy control field.

In the field of convoy control, numerous studies utilize optimization algorithms to generate reference speed trajectories for convoys, aiming to minimize energy consumption or maximize traffic efficiency. Centralized methods such as Model Predictive Control (MPC) address speed planning issues through global optimization, but they suffer from high computational complexity and are challenging to apply in real-time for large-scale convoys[8]. The essence of tracking control is to ensure vehicles accurately follow the reference trajectory and maintain a safe distance. Traditional control methods like Proportional-Integral-Differential Control (PID control) and Linear Quadratic Regulator (LQR) are simple to implement but struggle with nonlinear characteristics and external disturbances[9]. Stability in convoy control is crucial, focusing on ensuring that the distance error between vehicles quickly converges[10]. To tackle these issues, this paper introduces a convoy speed planning and tracking control method based on a dual-layer control structure, divided into a speed planning layer and a convoy control layer, enabling precise trajectory tracking.

2. Melt Pool Monitoring Network Based on Multi-branch Residual

In order to solve the complexity of fleet speed planning and tracking control, this paper proposes a two-layer control structure, including speed planning layer and fleet control layer. The following will elaborate on the modeling, algorithm design and theoretical analysis of the two-layer structure.

2.1. Speed planning layer

The core task of the speed planning layer is to generate an optimal fleet speed trajectory so that the fleet can achieve fuel economy and comfort optimization while meeting vehicle dynamic constraints and road conditions.

2.1.1. Fleet nonlinear dynamics modeling

In the process of speed planning, it is necessary to fully consider the nonlinear characteristics of vehicle dynamics and the impact of the external environment on fleet operation. The longitudinal dynamics model of a single vehicle can be described as:

$$\dot{v}_i = \frac{1}{m_i}\left(F_{\text{drive},i} - F_{\text{drag},i} - F_{\text{gravity},i} - F_{\text{brake},i}\right) \tag{1}$$

Where: v_i is the speed of the i vehicle; m_i is the vehicle mass; $F_{\text{drive},i}$ is the driving force, provided by the engine and power system; $F_{\text{drag},i} = c_d v_i^2$ is the air resistance, where c_d is the drag coefficient; $F_{\text{gravity},i} = m_i \text{gsin}(\theta)$ is the gravity component caused by the slope, where g is the acceleration of gravity, θ is the road slope angle; $F_{\text{drive},i}$ is the braking force. In addition, the driving force and braking force of the vehicle are limited by vehicle dynamics and control constraints, namely:

$F_{\text{drive},i} \le F_{\text{max}}$, $F_{\text{brake},i} \le F_{\text{brake,max}}$. Where F_{max} and $F_{\text{brake,max}}$ are the upper limits of the vehicle's driving and braking capabilities. In order to simplify the planning calculation, we introduce the average model of the fleet. The average fleet model assumes that the motion state of all vehicles can be represented by the average speed of the fleet v_{avg}:

$$v_{\text{avg}} = \frac{1}{N}\sum_{i=1}^{N} v_i \tag{2}$$

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where N is the total number of vehicles in the fleet. Based on the average fleet model, speed planning can avoid the complexity of single-vehicle dynamics and is more suitable for heterogeneous fleet scenarios.

2.1.2. Mathematical modeling of speed planning problem

The speed planning problem of a fleet can be transformed into an optimization problem, whose goal is to minimize the following combined cost function:

$$J = \int_0^T \left[\alpha E\big(v(t)\big) + \beta T\big(a(t)\big) + \gamma S\big(v(t), a(t)\big)\right] dt \tag{3}$$

Where, $E\big(v(t)\big)$ represents the energy consumption model of the vehicle; $T\big(a(t)\big)$ represents the comfort cost of vehicle acceleration; $S\big(v(t), a(t)\big)$ represents the smoothness constraint of the speed trajectory; α, β, γ are weight factors of different cost items; T is the planning time range. The energy consumption model $E\big(v(t)\big)$ can be defined by the vehicle fuel consumption rate function $f(v, a)$:

$$E\big(v(t)\big) = f\big(v(t), a(t)\big) \tag{4}$$

Where $a(t)$ is the acceleration, the specific function form can be experimentally calibrated based on the vehicle dynamics characteristics. The comfort cost $T\big(a(t)\big)$ is defined as the square form of acceleration:

$$T\big(a(t)\big) = a(t)^2 \tag{5}$$

This form shows that smoother acceleration changes can significantly improve the riding experience. The speed smoothness constraint $S\big(v(t), a(t)\big)$ constrains the second-order derivatives of velocity and acceleration:

$$S\big(v(t), a(t)\big) = \left(\frac{d^2 v(t)}{dt^2}\right)^2 + \left(\frac{da(t)}{dt}\right)^2 \tag{6}$$

Thereby ensuring the continuity and executableness of the speed trajectory.

2.1.3. Planning method based on time sampling

In speed planning based on time sampling, the planning problem is discretized into a multi-stage decision problem with multiple time steps t_k. The cost function in discrete form is:

$$J_t = \sum_{k=1}^{K} \left[\alpha E(v_k) + \beta T(a_k) + \gamma S(v_k, a_k)\right] \tag{7}$$

Where K is the total number of time steps. Based on the method of dynamic programming (DP), the planning problem can be divided into multiple sub-problems, so as to gradually solve the optimal speed trajectory. At each time step t_k, the cumulative cost is calculated iteratively:

$$J_t(t_k) = min_{a_k}\left[J_t(t_{k-1}) + \alpha E(v_k) + \beta T(a_k) + \gamma S(v_k, a_k)\right] \tag{8}$$

And the global optimal solution is obtained by recursive method.

2.1.4. Planning method based on spatial sampling

In the scenario where the road slope changes significantly, the time sampling method may not be able to fully capture the spatial information. Therefore, the method based on spatial sampling is adopted to plan on a fixed spatial interval x_k. The discrete form of the planning problem is:

$$J_x = \sum_{k=1}^{K} \left[\alpha E(v_k) + \beta T(a_k) + \gamma S(v_k, a_k)\right] \tag{9}$$

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Where x_k is a discrete point in space. By extending the dynamic programming framework to the spatial domain, the cumulative cost is calculated using the spatial step size:

$$J_x(x_k) = min_{a_k}[J_x(x_{k-1}) + \alpha E(v_k) + \beta T(a_k) + \gamma S(v_k, a_k)] \quad (10)$$

2.2. Fleet Control Layer

The main task of the fleet control layer is to design a control algorithm that enables the vehicle to accurately follow the reference trajectory generated by the speed planning layer while ensuring the stability of the queue. For the continuous controller, the following control law is designed based on the nonlinear feedback linearization method:

$$u_i = K_p(v_{\text{ref},i} - v_i) + K_d(a_{\text{ref},i} - a_i) \quad (11)$$

where $v_{\text{ref},i}$ and $a_{\text{ref},i}$ are the reference velocity and reference acceleration, respectively, and K_p and K_d are the proportional and differential gains. For the discrete controller, the vehicle state is defined as $x_k = [v_k, d_k]$, where d_k represents the vehicle spacing, and the control input is u_k. The state equation is described as:

$$x_{k+1} = Ax_k + Bu_k \quad (12)$$

where A and B are the discretized system matrices. The control objective is to minimize the tracking error of the platoon, and the error is defined as $e_k = x_k - x_{ref.k}$. Using the quadratic cost function:

$$J_c = \sum_{k=1}^{K} [e_k^T Q e_k + u_k^T R u_k] \quad (13)$$

whereQ and R are weight matrices. The optimal control law is $u_k = -Kx_k$, where K is the gain matrix, obtained by solving the discrete algebraic Riccati equation (DARE). The stability criterion of the platoon is defined as:

$$\Delta d_i \neq |d_{i,\text{ref}} - d_i| \quad (14)$$

and the error propagation characteristics between vehicles are analyzed. When the maximum error converges, the platoon is considered stable. In view of communication delay and disturbance, the following improved criteria are proposed:

$$\Delta d_i(t) = \Delta d_{i-1}(t - \tau) + \eta \cdot \Delta d_i(t) \quad (15)$$

Where τ is the communication delay, η is the robustness parameter.

3. Experiment analysis

We design a series of simulation experiments to evaluate the performance of the algorithm from the aspects of fuel economy, trajectory smoothness, platoon stability, computational efficiency, etc. The experiments were simulated using MATLAB/Simulink and Python platforms, setting up a complex environment including flat roads, sloped roads, and random disturbances, and comparing the performance with other comparison algorithms.

3.1. Simulation experiment settings

The simulation experiment implements speed planning and controller design based on MATLAB/Simulink, and uses Python to complete the dynamic planning optimization process. The main parameters of the experiment are as follows. Number of vehicles: 5 heterogeneous vehicles form a fleet with different dynamic parameters. Vehicle dynamic parameters: Mass m_i ranges from 1200kg to 1500kg; air resistance coefficient $c_d = 0.3$. Road slope: Set the slope angle range to $[-5°, 5°]$. Communication delay: $\tau = 0.1s$. Sampling time: $T_s = 0.05s$. Power constraints: driving force $F_{\text{max}} = 4000N$, braking force $F_{\text{brake,max}} = 5000N$ The experiment includes the following three typical scenarios. (1) Flat road scenario. (2) Slope road scenario. (3) Disturbance scenario. In order

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to evaluate the performance of this method, it is compared with the following mainstream methods: Centralized MPC method: centralized speed planning and control using model predictive control. Method based on the lead vehicle model: using the speed trajectory of the lead vehicle as a reference. Traditional PID controller: as a benchmark method for tracking control.

3.2. Experimental results and analysis

On a flat road, the target speed of the fleet is $v_{\text{target}} = 25\text{m}/s$, the simulation time is 30 seconds, and the fuel economy and speed trajectory smoothness are evaluated. Figure 1 shows the comparison of velocity trajectories under different methods.

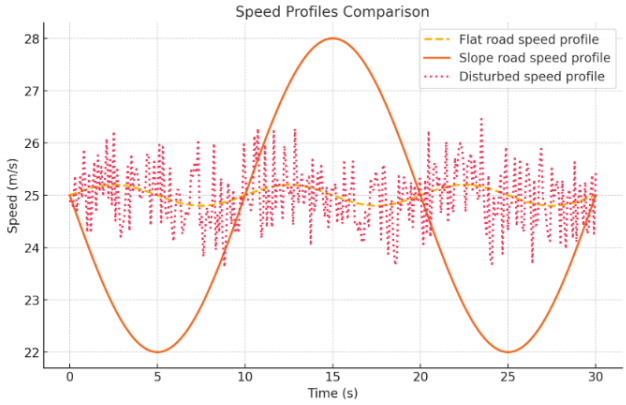

Figure 1: Comparison of speed curves in different road environments

Among them, the reference trajectory generated by the proposed method is smoother and more stable, with a speed fluctuation range of [24.8, 25.2] m/s and a speed error less than 0.5%. The method based on the lead car model has a large speed fluctuation, ranging from [24.0, 25.5] m/s. The trajectory of the centralized MPC method is close to the optimal, but the calculation time increases significantly. Table 1 shows the average fuel consumption of different methods.

Table 1: Average fuel consumption of different methods.

Method	Average fuel consumption(L/100km)	Improvement rate
Ours	5.8	-
lead car model	6.5	10.8%
centralized MPC	5.7	1.7%

Under the slope condition, the slope inclination angle is $[-5°, 5°]$, and the trajectory generated by the dynamic programming algorithm based on spatial sampling in this paper is smooth and adapts to the slope change. The speed fluctuation range is [22.0, 25.5] m/s. Based on the leading vehicle method, obvious overshoot occurs at the top and bottom of the slope, with the maximum speed deviation reaching 3.5m/s. The centralized MPC method has a stable trajectory, but the computation time is three times that of the method in this paper. Table 2 shows a comparison of the acceleration smoothness indicator J_a:

Table 2: Comparison of the acceleration smoothness indicator

Method	$J_a(m^2/s^4)$	Improvement rate
Ours	18.5	-

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Table 2: (continued)

lead car model	27.2	31.9%
centralized MPC	17.8	3.8%

In the case of a communication delay $\tau = 0.1s$ and a random disturbance $F_{distarb}$~N(0,200), the discrete controller design proposed in this paper has the lowest queue error under communication delay and disturbance conditions, which is only 0.15m. The maximum queuing error based on the leading car method is 0.45m, and the maximum error of the centralized MPC method is 0.12m.

4. Conclusion

This paper proposes a convoy speed planning and tracking control method based on a two-layer control structure. Combined with the convoy average model, dynamic programming algorithms based on time sampling and space sampling are designed for speed planning, and continuous and discrete controllers are used to implement Accurate tracking of the reference trajectory. Experimental results show that the proposed method is significantly better than the method based on the lead vehicle model in terms of fuel economy, trajectory smoothness and platoon stability. In the future, the algorithm performance will be further optimized and its practicality will be verified.

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