MPC Path Tracking Control Based on GA-PAO

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Abstract. In order to improve the path tracking performance and stability of driverless vehicles. In this paper, a path tracking control strategy based on MPC is proposed to establish a three-degree-of-freedom vehicle dynamical model as a reference model, design the MPC controller, determine the objective function and add constraints. Optimization of important time-domain parameters of model predictive controllers by improved GA-PSO. A Carsim/Simulink co-simulation platform was built to simulate the controller under double-shifted line conditions to verify its effectiveness. Simulation results show that the tracking performance and stability of the optimized MPC controller are much better.

Keywords: Path Tracking; MPC; Dynamical Model; GA-PSO.

1. Introduction

In recent years, with the development of computer, sensor and communication technologies, autonomous driving has become an important research direction in the field of vehicle engineering[1]. Path tracking control is a key link in realizing automated vehicle driving, which needs to achieve the maximum degree of tracking accuracy and stability under the premise of meeting vehicle safety requirements. Several algorithms exist for implementing path tracking control. Compared with other algorithms, the MPC algorithm[2]can effectively handle multi-objective and multi-constraint optimization problems.

The control parameters of the traditional MPC algorithm are generally fixed, and the path tracking performance and stability cannot reach the ideal state, so how to improve the MPC algorithm to improve the tracking accuracy and stability of the path tracking control has become the focus of the current research. Al-Mayyahi[3]et al. used particle swarm optimization algorithm for iterative optimization of PID related parameters to achieve optimal control, which provides better performance and adaptability during path tracking. Liu et al[4]designed an adaptive MPC path tracking controller based on the vehicle coordinate system to improve the tracking accuracy of vehicles passing through roads with large curvature. Zhou et al[5]used a genetic algorithm to improve the time domain parameters based on factors such as vehicle speed and road type, effectively reducing the lateral error. Hu et al[6]used a fuzzy control algorithm to determine the optimal time-domain parameters based on the real-time speed and with reference to the path curvature, with good control accuracy and robustness.

In this paper, a path tracking control strategy based on MPC is designed to optimize the important time-domain parameters in the MPC algorithm in order to improve the tracking accuracy and stability of vehicle path tracking control.

2. MPC Controller Design

2.1 Model Building

A three-degree-of-freedom nonlinear dynamics model is established as a reference model for path tracking control, as shown in Fig. 1. Where xoy is the vehicle coordinate system and XOY is the geodetic coordinate system. Neglecting the vehicle vertical motion and axle load transfer, only the lateral, longitudinal and transverse pendulum motion of the vehicle is considered.

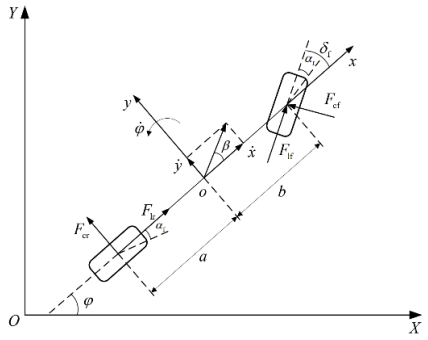


Fig 1. 3-DOF vehicle model

According to Newton's second law the nonlinear model formulation of vehicle dynamics can be obtained as shown in equation (1):

$$\begin{cases} m\ddot{y} = -m\dot{x}\dot{\varphi} + 2\left[C_{\mathrm{cf}}\left(\delta_{\mathrm{f}} - \dfrac{\dot{y}+a\dot{\varphi}}{\dot{x}}\right) + C_{\mathrm{cr}}\dfrac{b\dot{\varphi}-\dot{y}}{\dot{x}}\right] \\ m\ddot{x} = m\dot{y}\dot{\varphi} + 2\left[C_{\mathrm{lf}}s_{\mathrm{f}} + C_{\mathrm{cf}}\left(\delta_{\mathrm{f}} - \dfrac{\dot{y}+a\dot{\varphi}}{\dot{x}}\right)\delta_{\mathrm{f}} + C_{\mathrm{lr}}s_{\mathrm{r}}\right] \\ \dot{\varphi} = \dot{\varphi} \\ I_z\ddot{\varphi} = 2\left[aC_{\mathrm{cf}}\left(\delta_{\mathrm{f}} - \dfrac{\dot{y}+a\dot{\varphi}}{\dot{x}}\right) - bC_{\mathrm{cr}}\dfrac{b\dot{\varphi}-\dot{y}}{\dot{x}}\right] \\ \dot{Y} = \dot{x}\sin\varphi + \dot{y}\cos\varphi \\ \dot{X} = \dot{x}\cos\varphi - \dot{y}\sin\varphi \end{cases} \tag{1}$$

Where, a , b are the vehicle center of mass to the front and rear axle distance; m is the vehicle mass; C_{cf}、C_{cr}、C_{lf}、C_{lr} are the vehicle front and rear tire stiffness; s_f、s_r are the front and rear tire slip rate.

2.2 MPC Design

2.2.1 Predictive Model

The nonlinear vehicle model acting on the model measurement control will reduce the real-time performance of the controller, so the nonlinear model is linearized [16]. Linear time-varying equations are obtained:

$$\dot{\zeta} = A_{dyn}(t)\zeta_{dyn}(t) + B_{dyn}(t)u_{dyn}(t) \tag{2}$$

Where, $A_{dyn}(t) = \dfrac{\partial f_{dyn}}{\partial u_{dyn}}\Big|_{\zeta_t, u_t}$; $B_{dyn}(t) = \dfrac{\partial f_{dyn}}{\partial u_{dyn}}\Big|_{\zeta_t, u_t}$

Taking the sampling time, Eq. (2) is discretized to obtain the discrete state space expression:

$$\zeta(k+1) = A_k\zeta_{dyn}(k) + B_k u_{dyn}(k) \tag{3}$$

Where, $A_k = E + TA_{dyn}(t)$; $B_K = TB_{dyn}(t)$

Let the state increment is $\Delta\zeta(k) = \zeta(k) - \zeta(k-1)$, The control increment is $\Delta u(k) = u(k) - u(k-1)$ into Eq. (3) yields:

$$\zeta(k+1) = \zeta(k) + A_k\Delta\zeta(k) + B_k\Delta u(k) \tag{4}$$

A new state space tableau can be obtained:

$$\begin{cases} \xi(k+1) = \widetilde{A}_k\xi(k) + \widetilde{B}_k\Delta u(k) \\ y(k) = \widetilde{C}_k\xi(k) \end{cases} \tag{5}$$

Where, $\xi(k) = \begin{bmatrix} \Delta\zeta(k) \\ y(k) \end{bmatrix}^T$; $\widetilde{A}_k = \begin{bmatrix} A_k & 0 \\ C_kA_k & I \end{bmatrix}$; $\widetilde{B}_k = \begin{bmatrix} B_k \\ C_kB_k \end{bmatrix}$; $\widetilde{C}_k = \begin{bmatrix} o_k & 1 \end{bmatrix}$

The output prediction equation can be obtained after iteration. The output quantity expression is shown in Eq. (6):

$$Y(k)=\psi_t\xi(k)+\Theta_t\Delta U(k)+\Phi_t D(k) \tag{6}$$

Where, $Y(k)$ is the state output quantity in the prediction time domain; $D(k)$ is the amount of state deviation in the prediction time domain; ψ_t、Θ_t、Φ_t is the matrix obtained by iteration.

2.2.2 Objective Function and Constraints

Through a rolling optimization strategy, has to compute at each moment the control increment for the next Nc moment so that the predicted output value of the system at the next Np moments approximates the given desired value. The objective function is defined as:

$$J=\sum_{t=1}^{N_p}\|Y(k+i\mid k)\|_Q^2+\sum_{t=1}^{N_c-1}\|\Delta u(k+i\mid k)\|_R^2+\rho\varepsilon^2 \tag{7}$$

Where, Q is the tracking error weight matrix; R is the control increment matrix.

Combining the objective function and constraints [7], the optimization problem expression solved by the path tracking controller is as follows:

$$\begin{cases}\Delta U_{\min}\le\Delta U_{\mathrm{k}}\le\Delta U_{\max}\\ U_{\min}\le A\Delta U_{\mathrm{k}}+U_{\mathrm{k}}\le U_{\max}\\ y_{\mathrm{hc,min}}\le y_{\mathrm{hc}}\le y_{\mathrm{hc,max}}\\ y_{\mathrm{sc,min}}-\varepsilon\le y_{\mathrm{sc}}\le y_{\mathrm{sc,max}}+\varepsilon\\ \varepsilon>0\end{cases} \tag{8}$$

Where, $\Delta U_{\min}$、$\Delta U_{\max}$ are the control increment limit value; $U_{\min}$、$U_{\max}$ are the control volume limit value; y_{hc} is hard bound output; y_{sc} is the soft constraint output; $y_{\mathrm{hc,min}}$, $y_{\mathrm{hc,max}}$ are the hard constraint limit; $y_{\mathrm{sc,min}}$, $y_{\mathrm{sc,max}}$ are the soft constraint limit value.

Act on the first element as the actual control input increment to the system:

$$u(k)=u(k-1)+\Delta u_k^* \tag{9}$$

At moment k+1, Eq. (9) is solved with the currently derived vehicle state quantities, and so on and so forth to realize the tracking of the reference path.

2.2.3 Optimization of Time-domain Parameters

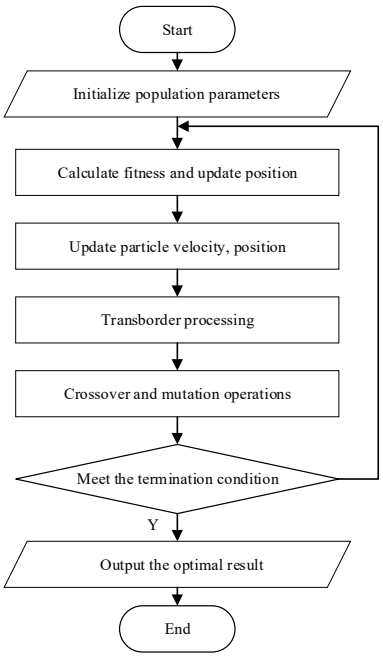


Fig 2. GA-PSO algorithm parameter optimization flowchart

The selection of time-domain parameters of the MPC controller has a great influence on the performance of the MPC path-tracking controller.

In order to solve the parameter selection problem, this paper designs the GA-PSO optimization algorithm [8] to optimize the prediction time domain Np, and control time domain Nc of the MPC controller, which can improve the solution rate and accuracy. Figure 2 shows the flow chart of the algorithm. The absolute error integration criterion is used to express the transverse error, the center of mass lateral deflection error, and the transverse pendulum angular velocity error:

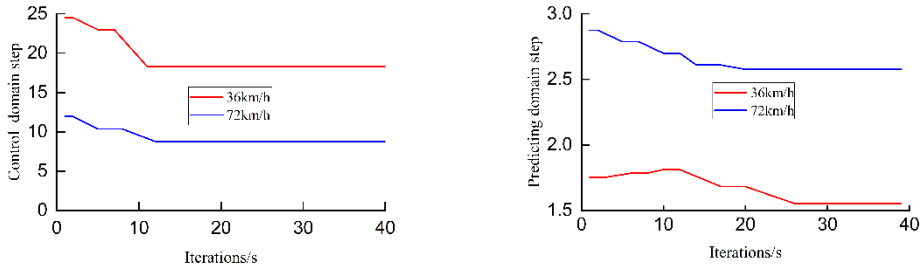
$$J_{IAE}=\int_0^T t(|e_d(t)|+|e_\omega(t)|+|e_\beta(t)|+|e_\delta(t)|)dt \tag{10}$$

Each particle in the swarm consists of its position and velocity as shown in Eq. (11):

$$\begin{cases} V_j(t+1)=\eta V_j(t)+\sigma_1(p_j-P_j(t))+\sigma_2(g_j-P_j(t)) \\ P_j(t+1)=P_j(t)+V_j(t+1) \end{cases} \tag{11}$$

Where, $V_j(t)$, $P_j(t)$ are the velocity and position in the iteration, respectively. p_j is individually optimal solution. g_j is globally optimal solution, η is the inertia factor. σ_1、σ_2 are the learning factor.

The GA-PSO optimization algorithm is used to find the optimal time domain parameters by simulation experiments at 36km/h and 72km/h operating conditions respectively. From Fig. 3(a) and Fig. 3(b), it can be seen that the variation of control time domain parameters and prediction time domain parameters with the number of iterations. The optimized parameter values at 36km/h speed are 17.632 and 8.752, respectively; and the optimized parameter values at 72km/h speed are 9.785 and 7.658, respectively.



(a) (b)

Fig 3. Optimization of time domain parameters

3. Simulation Analysis

Through the Carsim/Simulink simulation platform, simulation tests are carried out on the reference path of double-shifted line items under different working conditions to verify the effectiveness of the controller.

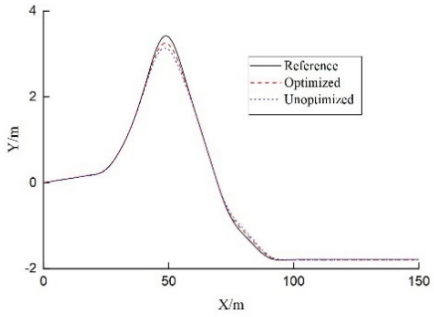
(1). Simulation of path-tracking control with an attachment factor of 0.8 and a vehicle speed of 36 km/h

From the analysis of Fig. 4(a)-Fig. 4(b) and Table 1, it can be seen that under the road surface adhesion coefficient of 0.8 and vehicle speed of 36km/h, the optimized MPC controller improves the maximum value of lateral displacement error by 38.58% and the maximum value of transverse pendulum angular error by 21.67%, compared with that of the unoptimized MPC controller. The optimized center of mass lateral deflection angle and transverse pendulum angular velocity perform better.

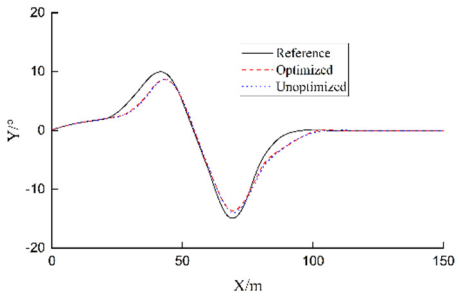
(2). Simulation of path-tracking control with an attachment factor of 0.8 and a vehicle speed of 72 km/h

From the analysis of Fig. 5(a)-Fig. 5(b) and Table 2, it can be obtained that the maximum value of the lateral displacement error of the optimized MPC controller is improved by 26.81% and the maximum value of the lateral sway angle error is improved by 27.64% compared to the unoptimized MPC controller under the condition of the road surface adhesion coefficient of 0.8 and the vehicle

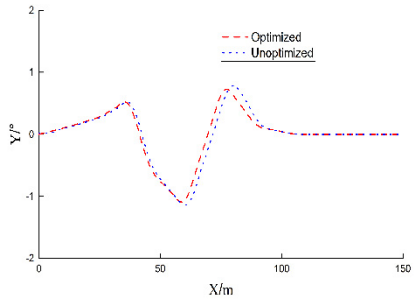
speed of 72km/h. Fig. 5(c) shows that the unoptimized MPC controller shows overshooting near 90m of longitudinal displacement, while the optimized MPC controller shows more stable performance, which reduces the maximum value of the center of mass lateral deflection error by 25.02%. It shows that the optimized MPC controller based on GA-PSO algorithm can effectively improve the tracking accuracy and stability of path tracking.



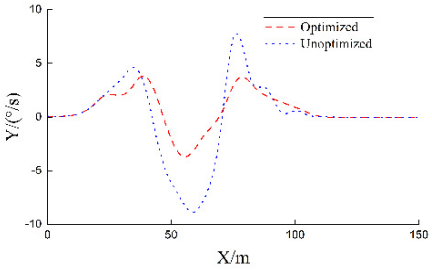
(a) transverse displacement



(b) Transverse pendulum angle



(c) Lateral deflection of the center of mass



(d) Angular velocity of the pendulum

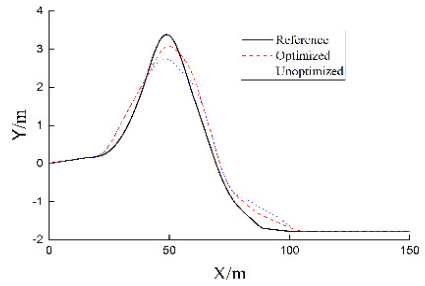
Fig 4. Simulation effect of path tracking for 36km/h condition

Table 1. Vehicle speed 36km/h working condition path tracking simulation effect

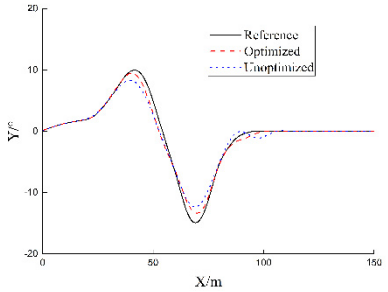
sports event	Performance indicators	MPC	optimized MPC	degree of improvement
Transverse error/m	max	0.174	0.104	38.58%
	rms	0.059	0.036	36.48%
Pendulum angle error/(°)	max	3.468	2.706	21.67%
	rms	1.325	0.963	27.02%
Center of mass lateral deflection/(°)	max	1.119	1.107	1.07%
	rms	0.419	0.408	2.63%

4. Conclusion

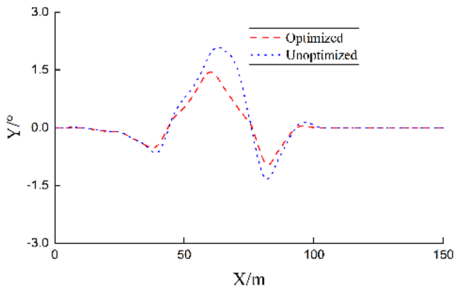
This paper addresses the lack of accuracy and poor stability in the path tracking control of unmanned vehicles. A path tracking control strategy based on MPC is designed, a three-degree-of-freedom vehicle dynamics model is established as a reference model, the objective function and constraints are added, and the GA-PSO algorithm is used to optimize the time-domain parameters of the MPC controller, and its effectiveness is verified through simulation. The results show that the control method improves the tracking accuracy and stability of path tracking control.



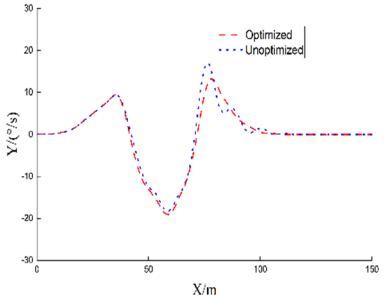
(a) transverse displacement



(b) Transverse pendulum angle



(c) Lateral deflection of the center of mass



(d) Angular velocity of the pendulum

Fig 5. Simulation effect of path tracking for 72km/h condition

Table 2. Vehicle speed 72km/h working condition path tracking simulation effect

sports event	Performance indicators	MPC	optimized MPC	degree of improvement
Transverse error/m	max	0.602	0.438	26.81%
	rms	0.246	0.189	23.17%
Pendulum angle error/(°)	max	3.380	2.409	27.64%
	rms	1.160	0.827	28.71%
Center of mass lateral deflection/(°)	max	2.180	1.635	25.02%
	rms	0.739	0.523	29.23%

References

[1] Zhang Yujin. Research and Prospect of unmanned driving technology under the background of Artificial Intelligence [J]. Digital Communications World,2018(2):1-2.

[2] Chen Huiyan, Chen Shuping, Gong Jianwei. Research review on lateral control methods of intelligent vehicles [J]. Journal of Military Engineering, 2017, 38(6) : 1203 - 1214.

[3] Al-Mayyahi A, Wang W, Birch P. Path tracking of autonomous ground vehicle based on fractional order PID controller optimized by PSO[C]//2015 IEEE 13th International Symposium on Applied Machine Intelligence and Informatics (SAMI). IEEE, 2015: 109-114.

[4] LIU J, YANG C. Adaptive Path Tracking Controller forIntelligent Driving Vehicles for Large Curvature Paths[J].SAE International Journal of Connected and AutomatedVehicles, 2022, 6(2): 199-219.

[5] ZHOU B, SU X, YU H, et al. Research on path tracking of articulated steering tractor based on modified model predictive control[J]. Agriculture, 2023, 13(4): 871.

[6] Hu Minmin, Wei Xinhua, Wang Aichen, et al. Path tracking control method of tractor based on adaptive MPC[J]. Research on Agricultural Mechanization, 2024, 46(6):227-233.

[7] Dong Na, Chen Zengqiang, Sun Qinglin, et al. Constrained model predictive controller based on particle swarm optimization. Control Theory and Applications, 2009, 26(09): 965-969.

[8] Feng, Wang Hui, Yu Lei, et al. Matlab intelligent algorithm 30 case analysis [M]. Beijing: Beijing University of Aeronautics and Astronautics, 2011.

[9] Falcone P. Nonlinear model predictive control for autonomous vehicles. Benevento: University of Sannio, 2007.

[10] Gong Jianwei, Jiang Yan, Xu Wei. Autonomous vehicle model predictive control [M]. Beijing: Beijing Institute of Technology, 2014.