Trajectory Tracking Control of Unmanned Vehicle Based on Data-driven Optimization

Yu Huang, Chao Wei*
National Defense Key Laboratory of Tank Transmission
Beijing Institute of Technology
Beijing, China
Yuhuang_cqu@163.com, bitchaowei@163.com

Yulong Sun
Inner Mongolia First Machinery (Group) Co., Ltd.
China North Industries Group Corporation Limited
Baotou, China
syl2022123@163.com

2022 IEEE Asia-Pacific Conference on Image Processing, Electronics and Computers (IPEC) | 978-1-6654-0902-5/22/$31.00 ©2022 IEEE | DOI: 10.1109/IPEC54454.2022.9777522

***Abstract*—Since the traditional Model Predictive Control(MPC), which is widely used for trajectory tracking of autonomous vehicle, cannot analyze and determine specific parameters of the controller by mathematical methods. In this paper, a trajectory tracking control method based on model prediction is proposed to solve the problem of unmanned vehicle trajectory tracking, and the controller is optimized in a performance objective driven way. Specifically, the cost function of the model predictive controller is parameterized. And the global optimal performance in a specific scenario as the goal to build the global performance cost function. Then, the global performance cost is expressed as a Gaussian process, and new parameters of the next optimization are inferred by Bayesian optimization. The controller parameters of global performance optimization are found with a small learning cost through multiple iterations to improve tracking performance. To verify the effectiveness of this data-driven optimization algorithm, lane-changing experiments with Carsim and Matlab/Simulink are carried out. According to the test data, it is proved that the performance of trajectory tracking under this data-driven MPC algorithm is optimized.**

Keywords—unmanned vehicle, trajectory tracking, Bayesian optimization, data-driven based MPC

I. INTRODUCTION

In recent years, with the success of machine learning and the improvement of computing power of modern control systems, many scholars are more and more interested in learning and data-driven technologies[1]. Model Predictive Control (MPC), as the primary method of constraint control, provide an important opportunity to utilize rich data in a reliable manner, especially when safety constraints are considered[2], [3]. Scholars are committed to studying the parameters related to the model extracted from the data for learning and improving the prediction model[4]–[6].

To solve the problem of inaccurate prediction model, T.Kim et al. from Seoul National University in South Korea proposed an online reinforcement learning method to update the prediction model to reduce the lateral error of path tracking[7]. J. Kabzan et al from ETH Zurich used autonomous driving car for experiments and proposed a control method of autonomous driving car based on learning. The controller uses online learning and selects gaussian regression model to consider the uncertainty of the model to achieve safe driving behavior[8].In model predictive control, the learning-based and data-driven methods are not only suitable for model improvement, but also difficult to describe the relationship between the specific parameters and the performance of the control system through analysis. And there's not a lot of research on that[9].

Therefore, this paper proposes a data-driven model predictive control algorithm for trajectory tracking control. The model predictive controller is parameterized and the global cost function of a specific scene is designed as the performance evaluation function. Then, a global optimization algorithm is set based on the Bayesian optimization algorithm for the prediction time domain and control time domain, and the next parameter is learned by using the optimization method. Finally, the optimal parameters are learned in the iterative process to improve the accuracy of the trajectory tracking controller.

II. VEHICLE MODEL FOR CONTROLLER

A. Vehicle mathematical model

Vehicle is a nonlinear system with multiple degree of freedom in reality. Researchers have developed a variety of vehicle models to study the dynamics of vehicle and controller design for different kinds of applications. There should be a balance between model accuracy and model order. In this paper, an improved vehicle model considering longitudinal, lateral and yaw motion is employed for designing the trajectory tracking controller, see Fig 1. Where, OXY is the inertia coordinate system and oxy is the local body-fixed system. The vehicle mathematical notations are listed in Table I. According to Newton's second law, the vehicle motion relationship is obtained as follows:

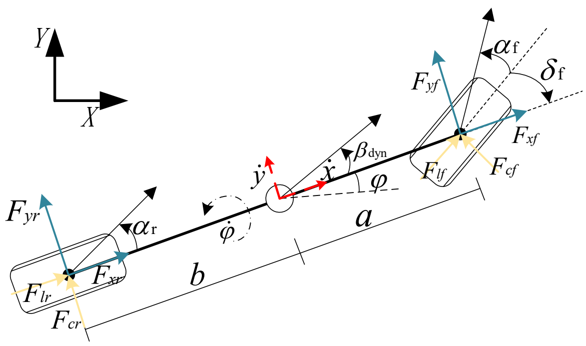

Fig. 1. Vehicle dynamic model.

TABLE I. VEHICLE PARAMETERS

Notation	Description	Unit
a / b	Distance from CG to the front/rear axle	m
F_{lf} / F_{lr}	Longitudinal force of tire in tire coordinates	N
F_{cf} / F_{cr}	Lateral tire force of tire in tire coordinates	N
F_{xf} / F_{xr}	Longitudinal force of the front/rear tire in oxy	N
F_{yf} / F_{yr}	Lateral force of the front/rear tire in oxy	N
α_f / α_r	Sideslip Angle of the front/rear tire	rad
C_{lf} / C_{lr}	Longitudinal stiffness of the front/rear tire	N/rad
C_{cf} / C_{cr}	Cornering stiffness of the front/rear tire	N/rad
S_f / S_r	Slip ration of the front/rear tire	/
m	Vehicle mass	kg
φ	Heading angle of vehicle body in OXY	rad
δ_f	Front wheel steering angle	rad
I_z	Yaw moment of inertia of vehicle	Kg.m2
v_y	Lateral speed of vehicle in oxy	m/s
v_x	Longitudinal speed of vehicle in oxy	m/s
β	Sideslip angle of the center of mass	rad
X	The lateral position of the vehicle in OXY	m
Y	The longitudinal position of the vehicle in OXY	m

$$\begin{cases} \ddot{x} = 2(F_{lf}\cos\delta_f - F_{cf}\sin\delta_f)/m + 2F_{lr}/m + v_y\dot{\varphi} \\ \ddot{y} = 2(F_{lf}\sin\delta_f + F_{cf}\cos\delta_f)/m + 2F_{cr}/m - v_x\dot{\varphi} \\ \ddot{\varphi} = \dfrac{2a}{I_z}(F_{lf}\sin\delta_f + F_{cf}\cos\delta_f) - \dfrac{2b}{I_z}F_{cr} \\ \dot{Y} = v_x\sin\varphi + v_y\cos\varphi \\ \dot{X} = v_x\cos\varphi - v_y\sin\varphi \end{cases} \tag{1}$$

For normal driving maneuvers, small-angle assumption and linear tire model are assumed to simply the mathematical model, given by:

$$\begin{cases} F_{lf} = C_{lf}s_f, \quad F_{lr} = C_{lr}s_r \\ F_{cf} = C_{cf}\left(\delta_{\mathrm{f}} - \dfrac{v_y + a\dot{\varphi}}{v_x}\right), \quad F_{cr} = C_{cr}\dfrac{b\dot{\varphi} - v_y}{v_x} \end{cases} \tag{2}$$

By combining eqs. (1~2), and applying small angle approximation, a nonlinear vehicle dynamics model can be obtained:

$$\xi(t+1) = f(\xi(t), u(t)) \tag{3}$$

where, the state vector is $\xi = [v_y, v_x, \varphi, \dot{\varphi}, Y, X]^T \in \mathbb{R}^6$, the control input is the front wheel steering angle $u = \delta_f \in \mathbb{R}$.

B. Discrete Linear Vehicle Model

To facilitate controller design and implementation, vehicle model is usually linearized by using first-order approximation of Taylor expansion and discretized by zero-order holder (ZOH). Therefore, a discrete time-varying linear vehicle state-space model can be obtained based on equations (1) and (3):

$$\begin{cases} \xi(k+1\,|\,t) = A_\xi(k\,|\,t)\xi(k\,|\,t) + B_\xi(k\,|\,t)u(k\,|\,t) + w_\xi(k\,|\,t) \\ k = t, t+1, \ldots, t+N_p-1 \end{cases} \tag{4}$$

where N_p is prediction horizon, $k|t$ represents the step sequence at the current time. And system coefficient matrices $A_\xi(k\,|\,t) \in \mathbb{R}^{6\times 6}$ and $B_\xi(k\,|\,t) \in \mathbb{R}^6$ are the discretized Jacobian matrix. Meanwhile, $w_\xi(k\,|\,t) \in \mathbb{R}^6$ deals with measurement disturbance and model uncertainty. In the process of tracking, the heading Angle and longitudinal tracking error as well as the yaw stability constraint is considered. Hence, the output of control system is chosen as $\eta = [v_y, \varphi, \dot{\varphi}, Y]^T$.

III. LOCAL MPC TRACKING CONTROLLER DESIGN

Trajectory tracking control is an optimal control problem with multi-constraints to ensure the accuracy of the tracking and dynamics constraints. MPC has the characteristics of strong robustness and multi-constraints processing in receding horizons. Furthermore, vehicle dynamics can be considered in MPC to transfer into an optimal control problem. Hence, the model predictive control algorithm is adopted for designing of local trajectory tracking controller in this section.

A. Augmented System for Control

In order to achieve safe and smooth control, the trajectory tracking issue is transformed to an augmented linear quadratic problem in the following. We take the control increment into consideration by incorporating the control quantity into the system state vector. The augmented state-space model is designed as:

$$\begin{cases} \boldsymbol{\mathcal{X}}(k+1\,|\,t) = \tilde{\boldsymbol{A}}(k\,|\,t)\boldsymbol{\mathcal{X}}(k\,|\,t) + \tilde{\boldsymbol{B}}(k\,|\,t)\Delta u(k\,|\,t) + \tilde{\boldsymbol{\omega}}(k\,|\,t) \\ \boldsymbol{\mathcal{Y}}(k\,|\,t) = \tilde{\boldsymbol{C}}(k\,|\,t)\boldsymbol{\mathcal{X}}(k\,|\,t) \end{cases} \tag{5}$$

where $\tilde{\boldsymbol{A}}(k\,|\,t) \in \mathbb{R}^{7\times 7}$, $\tilde{\boldsymbol{B}}(k\,|\,t) \in \mathbb{R}^7$, $\tilde{\boldsymbol{C}}(k\,|\,t) \in \mathbb{R}^{4\times 7}$ and $\tilde{\boldsymbol{\omega}}(k\,|\,t) \in \mathbb{R}^7$ are the augmented dynamics matrices, which are defined as:

$$\boldsymbol{\mathcal{X}}(k\,|\,t) = \left[\zeta(k\,|\,t) \quad u(k-1\,|\,t)\right]^T$$

$$\tilde{\boldsymbol{A}}(k\,|\,t) = \begin{bmatrix} A(k\,|\,t) & B(k\,|\,t) \\ 0_{1*6} & 1 \end{bmatrix}, \quad \tilde{\boldsymbol{B}}(k\,|\,t) = \begin{bmatrix} B(k\,|\,t) \\ 1 \end{bmatrix} \tag{6}$$

The prediction horizon of MPC as the length of the optimization window and control horizon as the length of control input sequence. The state variable $\boldsymbol{\mathcal{X}}(t+1\,|\,t), \ldots, \boldsymbol{\mathcal{X}}(t+N_p\,|\,t)$ can be predicted for N_p steps ahead with the given current plant information , which is obtained by state observing. Applying the sequence of future input increments computed at current time t as the input variable, the output augmented system for MPC is derived as:

$$\mathcal{Q}(t)=\mathcal{C}_t\mathcal{X}(t\mid t)+\mathcal{D}_t\Delta\mathcal{U}(t)+\mathcal{H}_t\mathcal{W}(t) \tag{7}$$

B. MPC Controller Design for Trajectory Tracking

The optimal control quantity is obtained by solve an appropriate objective function of MPC controller. While the trajectory tracking control is to ensure that the vehi-cle can track the desired trajectory quickly and smooth-ly. As a result, the trajectory tracking issue is formulated as an optimal control problem (OCP) to minimize the error of the vehicle lateral position and the desired tra-jectory. Considering vehicle model and vehicle dynam-ics described above, the optimization can be formulated as:

$$\min_{\Delta u_{(t)}} J\left(\mathcal{X}(t),\Delta\mathcal{U}(t)\right)=\sum_{i=1}^{N_P}\left\|\eta(t+i\mid t)-\eta_{ref}(t+i\mid t)\right\|_{\boldsymbol{Q}}^2+\sum_{i=0}^{N_c-1}\left\|\Delta u(t+i,t)\right\|_{\boldsymbol{R}}^2+\rho\varepsilon^2 \tag{8.a}$$

subject to:

$$\begin{cases}\mathcal{Q}(t)=\mathcal{C}_t\mathcal{X}(t\mid t)+\mathcal{D}_t\Delta\mathcal{U}(t)+\mathcal{H}_t\mathcal{W}(t)\\ \Delta\mathcal{U}_{\min}\le\Delta\mathcal{U}\le\Delta\mathcal{U}_{\max}\\ \mathcal{U}_{\min}\le A\Delta\mathcal{U}+\mathcal{U}\le\mathcal{U}_{\max}\\ \mathcal{Y}_{\min}\le\mathcal{Y}\le\mathcal{Y}_{\max}\\ \varphi_{\min}\le\varphi\le\varphi_{\max}\\ -I_{sc}(k)\le V_{sc}(k)x(k)\le I_{sc}(k)\end{cases} \tag{8.b}$$

where, $\mathcal{Y}_{ref}$ is the reference trajectory given by the upper planning controller; ε is the slack factor; $\boldsymbol{Q}\in\mathbb{R}^4$, $\boldsymbol{R}\in\mathbb{R}$ and $\rho\in\mathbb{R}$ are positive definite weight matrixes of the cost function. The first term corresponds to the goal of path tracking to ensure the accuracy, and the other terms penalize the change of steering angle to ensure control smoothness in the tracking process and set a soft constraint to make OCP always has a feasible solution. Then the control law is implicitly defined as:

$$\boldsymbol{\pi}^{MPC}(\mathcal{X}(t))=u\left(t-1\right)+\Delta\mathcal{U}_t^*[0] \tag{9}$$

where $\Delta\mathcal{U}_t^*[0]$ is the first element of optimal control sequence.

IV. Learning-based Model Predictive Control Scheme

The classical model predictive control is a local optimization method to realize optimal control, which is hard to realize the optimization of control parameters through mathematical analysis in local range. In addition, autonomous vehicle generally performs repetitive tasks during trajectory tracking process, which can be used to improve controller design by learning methods. In this section, a performance driven learning-based MPC (LMPC) scheme is designed to improve the tracking performance by successively adjusting the parameterization in an episodic setting with less cost.

A. Gaussian Process

In episodic learning task, the collected parameters $\mathbf{\Omega}=[\Theta_1,\cdots,\Theta_n]$ and resulting closed-loop cost function $\mathcal{J}_G(\mathbf{\Omega})=[\mathcal{J}_G^1(\Theta_1),\cdots,\mathcal{J}_G^n(\Theta_n)]$ are used as prior data points of Gaussian Process. These data points obey the multivariate Gaussian distribution, expressed as:

$$\mathcal{J}_G(\mathbf{\Omega})\sim\mathcal{N}\left(\boldsymbol{\mu}(\mathbf{\Omega}),\boldsymbol{K}\left(\mathbf{\Omega},\mathbf{\Omega}\right)\right) \tag{10}$$

where $\boldsymbol{\mu}(\mathbf{\Omega}):\mathbb{R}^n\to\mathbb{R}^n$ is the mean vector and $\boldsymbol{K}(\mathbf{\Omega},\mathbf{\Omega})$: $\mathbb{R}^n\times\mathbb{R}^n\to\mathbb{R}^{n\times n}$ is the covariance of the Gaussian distribution. To sample functions from the Gaussian Process, we choose Radial Basis Function (RBF) as the kernel to model the covariance in order to set prior information on this distribution:

$$\kappa\left(\Theta_i,\Theta_j\right)=\sigma^2\exp\left(-\frac{\|\Theta_i-\Theta_j\|_2^2}{2l^2}\right) \tag{11}$$

where σ and l are hyper-parameters of the kernel function. For the arbitrary new point Θ_{n+1} :

$$\begin{bmatrix}\hat{\mathcal{J}}_G(\Theta_{n+1})\\ \mathcal{J}_G(\Theta_{1:n})\end{bmatrix}\sim\mathcal{N}\left(\begin{bmatrix}\boldsymbol{\mu}(\Theta_{n+1})\\ \boldsymbol{\mu}(\Theta_{1:n})\end{bmatrix},\begin{bmatrix}\boldsymbol{K}(\Theta_{n+1},\Theta_{n+1}) & \boldsymbol{K}(\Theta_{n+1},\Theta_{1:n})\\ \boldsymbol{K}(\Theta_{n+1},\Theta_{1:n})^T & \boldsymbol{K}(\Omega_{1:n},\Theta_{1:n})\end{bmatrix}\right) \tag{12}$$

Then we can get the conditional distribution:

$$P\left(\hat{\mathcal{J}}_G(\Theta_{n+1})\mid\Theta_{n+1},\Theta_{1:n},\mathcal{J}_G(\Theta_{1:n})\right)=\mathcal{N}\left(\bar{\boldsymbol{\mu}},\bar{\boldsymbol{K}}\right) \tag{13}$$

where $\bar{\boldsymbol{\mu}}$ is the posterior mean and $\bar{\boldsymbol{K}}$ is the variance of the Gaussian distribution.

B. Bayesian Optimization

Based on current available observations to find the next sampling point may easily miss the global minimum of cost. Here, Bayesian Optimization is employed to trade-off between exploiting of surrogate and exploration of the feasible space. For functions with prior data, Bayesian optimization seeks new sampling points to update a posteriori and approximates the function according to a posteriori. And Gaussian process (GP) is used to approximate a objective function, which is expensive to evaluate. In this paper, considering the overall performance of vehicle trajectory tracking, the global performance objective function is established as following:

$$\mathcal{J}_G=\sum_{k=0}^{T}\left\|x(k)-x_{ref}(k)\right\|^2 \tag{14}$$

where k goes from zero to T, representing the whole process from the starting point of a path to the end point. The equation represents the tracking deviation of the whole tracking process.

Then posteriori suggested sampling points in the search space are obtained by the acquisition function, defined by:

$$\mathrm{EI}_n(X) = \left[\Delta_n(X)\right]^+ + \sigma_n(X)\varphi\left(\frac{\Delta_n(X)}{\sigma_n(X)}\right) - \left|\Delta_n(X)\right|\Phi\left(\frac{\Delta_n(X)}{\sigma_n(X)}\right) \quad (15)$$

where $\sigma_n^2(X)$ is the variance of the posterior distribution of the sampling points. φ and Φ are the probability density function and cumulative distribution function of the standard normal distribution respectively. $\Delta_n(X)$ represents the difference between the mean of current collection points and the maximum function value.

The acquisition function is used to balance exploitation and exploration. The aim of exploitation is to continue sampling in the area where the alternative function has a good performance, while the exploration is to sampling in the area where the prediction uncertainty is high. The goal of both is to find the best global function value and determine the next sampling point by maximizing Equation(15). The next sampling point is expressed by:

$$\theta_i = \arg\max \mathrm{EI}(\Theta \mid \{\Theta, \hat{\mathcal{J}}_G\}) \quad (16)$$

Then, according to the new sampling point, the tracking task is iteratively performed to obtain the corresponding global performance cost. Iteration for several times, the controller can achieve the optimal global performance optimization with a small learning cost.

V. SIMULATION AND ANALYSIS

To verify the effectiveness of the proposed learning-based tracking optimization algorithm, the lane-changing scenario is tested by Carsim and Matlab/Simulink platform. The testing scenario includes longitudinal and lateral motion of vehicle, shown in Fig. 2. When satisfying the lane-changing conditions, the vehicle completes a lane-changing at 30km/h speed under the trajectory tracking controller with a lateral displacement of about 3.5m. In the course of trajectory tracking, the controller must balance the lateral control and the heading control to achieve the optimal global performance.

The trajectory of autonomous lane change is given by upper path planning. At present, common lane change trajectories include constant-velocity-offset trajectory, circular-lane-change trajectory, hyperbolic-tangent trajectory, polynomial trajectory and so on. This paper reasonably assumes that the longitudinal velocity is constant during the lane change stage, and the hyperbolic positive lane change trajectory expression is as follows:

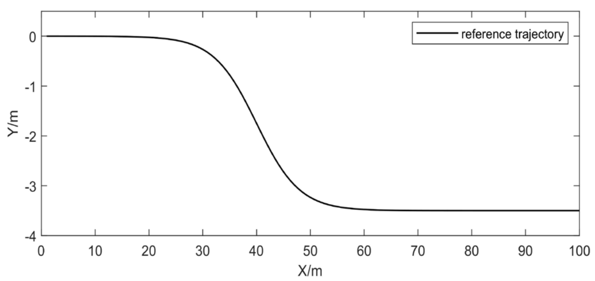

Fig. 2. Schematic of an lane-changing manoeuvre.

TABLE II. CONTROLLER PARAMETER SELECTION

Parameter	Description	Value or Range
N_p	Prediction horizon	[5,40]
N_c	Control horizon	[1,20]
Q	Weight matrices	diag(0,4,0,10)
R	The weight matrices	10
Δu	The control increment(/rad)	[-0.02,0.02]
u	The control input(/rad)	[-0.2,0.2]
T	Sampling time of MPC(/s)	0.05s

$$\begin{aligned} Y_{ref}(\mathrm{X}) &= -\frac{d}{2}\left(1+\tanh\left(\frac{10(\mathrm{X}-\mathrm{L}/2)}{L}\right)\right) \\ \varphi_{ref}(\mathrm{X}) &= \arctan\frac{5d}{L}\left(\tanh^2\left(\frac{10(\mathrm{X}-\mathrm{L}/2)}{L}\right)-1\right) \end{aligned} \quad (17)$$

where d=3.5m, which is the lane width. And L=80m,which is the longitudinal displacement of lane change.

In the experiment, model predictive control algorithm in Section 3 is used as the local controller to track the given reference lateral position and reference heading angle. And learning-based algorithm is taken as the global controller to optimize prediction horizon and control horizon of MPC, thus achieving an optimal global tracking cost. The initial Settings and ranges of controller parameters are shown in Table II. Therefore the initialization of learning-based algorithm has five evaluation points, namely the initial value of horizons and four boundary values, as well as their corresponding global performance costs. These initial sets can provide effective Gaussian prior knowledge to speed up the optimization process.

For each iteration, new parameters are calculated by the global optimization algorithm. And a set of parameters and corresponding global performance costs can be obtained. When the iteration termination condition is satisfied, the optimization test of trajectory tracking control is completed, and the Gaussian process posteriori obtained, shown in Fig. 3.

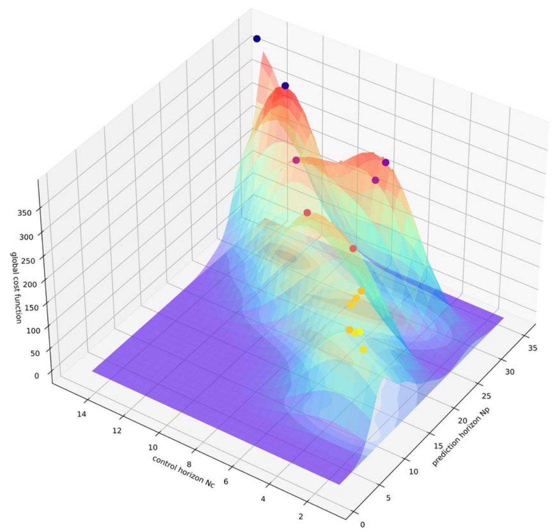

Fig. 3. Gaussian process posteriori of the global optimization test.

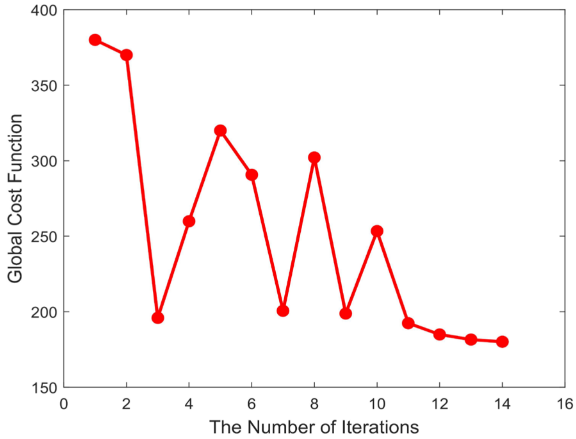

Fig. 4. Global cost value with iterations.

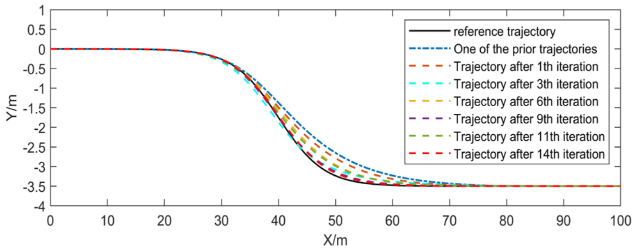

Fig. 5. Trajectory of vehicle motion with iterations.

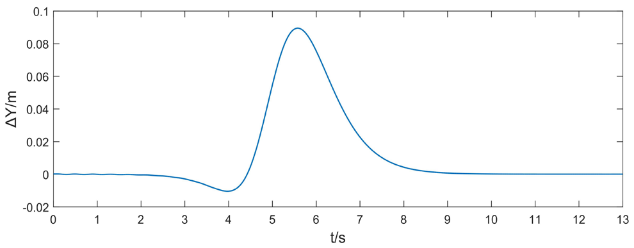

Fig. 6. Lateral bias of trajectory tracking under the optimal horizons.

As we can see, there are 14 posterior points in the figure,. That is to say, the learning algorithm based on Gaussian process and Bayesian optimization achieve the optimal trajectory tracking by improving parameter setting of MPC controller after 14 iterations. As can be seen from the figure, the optimal prediction time domain is Np=9, that is, the prediction time domain corresponding to the minimum performance cost function in the test.

In order to more intuitively show and predict the improvement of lane change performance in the time domain optimization process, some tracks in the test process were compared in Fig. 5. We can see that prior trajectory can track the trajectory planned above, but the lateral deviation is large. With the optimization of prediction time domain and control time domain, the performance of the controller is improved. This performance improvement can be quantitatively analyzed in Fig. 4, that is, with the increase of iterations, the global performance cost shows a downward trend and gradually converges. The lateral position error corresponding to the optimized sampling point in the tracking process is shown in Fig. 6. The figure shows that the maximum lateral error fluctuates between -0.02 and 0.1m. It reveals trajectory tracking based on Bayesian optimization and model predictive control algorithm can achieve better tracking performance than traditional MPC controller.

VI. Conclusion

In this paper, bayesian optimization algorithm is introduced to optimize the parameters of trajectory tracking controller, and simulation tests are carried out on Carsim and Matlab/Simulink. In the test, EI acquisition function can make the best use of the existing data and work out the next optimized parameter faster to improve the controller. After several iterations, the lane-changing performance of unmanned vehicles is gradually optimized from the comparison of actual trajectory and target trajectory as well as the global performance cost. In this process, the parameter adjustment does not need grid search and manual adjustment, which saves a lot of time for the debugging of unmanned vehicle trajectory tracking control. At present, only prediction horizon and control horizon are tuned in the lane-changing experiment to verify the feasibility of the algorithm, which lays a certain foundation for the multidimensional parameter tuning involved in more complex scenes in the future.

References

[1] U. Rosolia, X. Zhang, and F. Borrelli, “Data-Driven Predictive Control for Autonomous Systems,” Annu. Rev. Control Robot. Auton. Syst., vol. 1, no. 1, pp. 259–286, May 2018, doi: 10.1146/annurev-control-060117-105215.

[2] S. Xu and H. Peng, “Design, Analysis, and Experiments of Preview Path Tracking Control for Autonomous Vehicles,” Ieee Trans. Intell. Transp. Syst., vol. 21, no. 1, pp. 48–58, Jan. 2020, doi: 10.1109/TITS.2019.2892926.

[3] X. Weng, J. Zhang, and Y. Ma, “Path Following Control of Automated Guided Vehicle Based on Model Predictive Control with State Classification Model and Smooth Transition Strategy,” Int. J. Automot. Technol., vol. 22, no. 3, pp. 677–686, Jun. 2021, doi: 10.1007/s12239-021-0063-x.

[4] D. Masti, F. Smarra, A. D’Innocenzo, and A. Bemporad, “Learning Affine Predictors for MPC of Nonlinear Systems Via Artificial Neural Networks,” p. 6.

[5] D. Masti and A. Bemporad, “Learning Nonlinear State-Space Models Using Deep Autoencoders,” in 2018 IEEE Conference on Decision and Control, Miami Beach, FL, USA, Dec. 2018, pp. 3862–3867. doi: 10.1109/CDC.2018.8619475.

[6] S. Kuutti, R. Bowden, Y. Jin, P. Barber, and S. Fallah, “A Survey of Deep Learning Applications to Autonomous Vehicle Control,” IEEE Trans. Intell. Transp. Syst., vol. 22, no. 2, pp. 712–733, Feb. 2021, doi: 10.1109/TITS.2019.2962338.

[7] T. Kim and H. J. Kim, “Path tracking control and identification of tire parameters using on-line model-based reinforcement learning,” in 2016 16th International Conference on Control, Automation and Systems (ICCAS), Oct. 2016, pp. 215–219. doi: 10.1109/ICCAS.2016.7832324.

[8] L. Hewing, J. Kabzan, and M. N. Zeilinger, “Cautious Model Predictive Control Using Gaussian Process Regression,” Ieee Trans. Control Syst. Technol., vol. 28, no. 6, pp. 2736–2743, Nov. 2020, doi: 10.1109/TCST.2019.2949757.

[9] L. Hewing, K. P. Wabersich, M. Menner, and M. N. Zeilinger, “Learning-Based Model Predictive Control: Toward Safe Learning in Control,” Annu. Rev. Control Robot. Auton. Syst., vol. 3, no. 1, pp. 269–296, 2020, doi: 10.1146/annurev-control-090419-075625.