

MPC based Trajectory Following Controller

1、MPC Controller Design

1.1 System Model

Due to low vehicle speed, we utilize the kinematic model as the system model:

$$\begin{cases} \dot{p}_x = v \cos(\phi) \\ \dot{p}_y = v \sin(\phi) \\ \dot{\phi} = \frac{v}{L} \tan(\delta) \\ \dot{v} = a \end{cases}$$

State: $X = [x \ y \ \phi \ v]^T$, Input: $U = [a \ \delta]$

- *Linearization*

For improving the solving efficiency, we linearize the nonlinear system model. There are two different method.

- Linearization along the state trajectory:

We can linearize the system model based on the result of last run.

- **Linearization along the reference trajectory**

we can linearize the system model based on the reference state.

Define the linearization point as follows:

$$\bar{X} = [\bar{p}_x \ \bar{p}_y \ \bar{\phi} \ \bar{v}]^T, \bar{U} = [\bar{a} \ \bar{\delta}]^T$$

The linear model:

$$\begin{bmatrix} \dot{p}_x \\ \dot{p}_y \\ \dot{\phi} \\ \dot{v} \end{bmatrix} = \begin{pmatrix} 0 & 0 & -\bar{v} \sin \bar{\phi} & \cos \bar{\phi} \\ 0 & 0 & \bar{v} \cos \bar{\phi} & \sin \bar{\phi} \\ 0 & 0 & 0 & \frac{\tan \bar{\delta}}{L} \\ 0 & 0 & 0 & 0 \end{pmatrix} \begin{bmatrix} p_x \\ p_y \\ v \\ \phi \end{bmatrix} + \begin{pmatrix} 0 & 0 \\ 0 & 0 \\ 0 & \frac{\bar{v}}{L} \frac{1}{\cos^2 \bar{\delta}} \\ 1 & 0 \end{pmatrix} \begin{bmatrix} a \\ \delta \end{bmatrix} + \begin{pmatrix} \bar{v} \sin \bar{\phi} \\ -\bar{v} \cos \bar{\phi} \\ -\bar{v} \frac{\bar{\delta}}{L \cos^2 \bar{\delta}} \\ 0 \end{pmatrix}$$

- Discretization

For computer calculation, we discretize the continuous system with forward Euler difference:

$$\begin{aligned} A_{\text{discrete}} &= I + \Delta T \times A_{\text{linearized}} \\ B_{\text{discrete}} &= \Delta T \times B_{\text{linearized}} \\ g_{\text{discrete}} &= \Delta T \times g_{\text{linearized}} \end{aligned}$$

1.2 Define Cost Function

The objective is to follow the trajectory accurately, the cost function can be defined as follows:

$$\begin{aligned}
& \min \sum_{k=1}^N (x_k - \bar{x}_k)^T Q (x_k - \bar{x}_k) + u_{k-1}^T R u_{k-1} \\
& \text{s.t. } x_0 = x, \\
& x_{k+1} = f(x_k, u_k), \quad k = 0, \dots, N-1 \\
& \underline{x} \leq x_k \leq \bar{x}, \quad k = 1, \dots, N \\
& \underline{u} \leq u_k \leq \bar{u}, \quad k = 0, \dots, N-1
\end{aligned}$$

1.3 Prediction

$$\eta = AAx_0 + BBu + G$$

$$\eta = [x_1 \ x_2 \ \dots \ x_N]^T, U = [u_0 \ u_1 \ u_2 \ \dots \ u_{N-1}]^T$$

$$\begin{aligned}
AA &= \begin{bmatrix} A_0 \\ A_1 A_0 \\ \vdots \\ \prod_{k=0}^{N-1} A_k \end{bmatrix} \\
BB &= \begin{bmatrix} B_0 & 0 & \dots & 0 & 0 \\ A_1 B_0 & B_1 & \dots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ \prod_{k=1}^{N-1} A_k B_0 & \prod_{k=2}^{N-1} A_k B_1 & \dots & A_{N-1} B_{N-2} & B_{N-1} \end{bmatrix} \\
G &= \begin{bmatrix} g_0 \\ A_1 g_0 + g_1 \\ \vdots \\ \sum_{n=0}^{N-2} \left(\prod_{k=n+1}^{N-1} A_k \right) g_n + g_{N-1} \end{bmatrix}
\end{aligned}$$

Thus we can remove the equality constrain of the optimize problem.

1.4 OSQP Solver

we adopt the QP solver OSQP to solve the QP problem.

OSQP solves convex quadratic programs (QPs) of the form

$$\begin{aligned}
& \text{minimize} \quad \frac{1}{2} x^T P x + q^T x \\
& \text{subject to} \quad l \leq A x \leq u
\end{aligned}$$

where $x \in \mathbf{R}^n$ is the optimization variable. The objective function is defined by a positive semidefinite matrix $P \in \mathbf{S}_+^n$ and vector $q \in \mathbf{R}^n$. The linear constraints are defined by matrix $A \in \mathbf{R}^{m \times n}$ and vectors l and u so that $l_i \in \mathbf{R} \cup \{-\infty\}$ and $u_i \in \mathbf{R} \cup \{+\infty\}$ for all $i \in \{1, \dots, m\}$.

Substituting the prediction model into the cost function, we have

$$U^T (BB^T Q BB) U + 2(x_0 A A^T Q BB + G G^T Q BB - q_x Q BB) U$$

$$q_x = [\bar{x}_1, \dots, \bar{x}_N]$$

2、Result

