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运动规划第六章作业分享



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1. Implement MPC of tracking the reference trajectory in C++;
2. Implement MPC with delays in C++;

本章用的是自行车模型求解线性时变 MPC 问题。首先根据给定的运动模型构造矩阵 A_c , B_c , g_c 。

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

然后根据 $k+1$ 时刻的状态方程与 k 时刻的关系，可以得到所需的 A_d , B_d , g_d 。

$$x_{k+1} = (I + T_s A_c) x_k + T_s B_c u_k + T_s g_c$$

也即有以下关系：

$$A_d = I + T_s A_c \quad B_d = T_s B_c \quad g_d = T_s g_c$$

MPC

```
//  $x_{k+1} = A_d * x_k + B_d * u_k + g_d$ 
// TODO: set values to Ad_, Bd_, gd_
Ad_ << 0, 0, -v*sin(phi), cos(phi),
      0, 0, v*cos(phi), sin(phi),
      0, 0, 0, tan(delta)/ll_,
      0, 0, 0, 0;
Ad_ = MatrixA::Identity()+dt_*Ad_;

Bd_ << 0, 0,
      0, 0,
      0, v/(ll_*pow(cos(delta),2)),
      1, 0;
Bd_ = dt_*Bd_;

gd_ << v*phi*sin(phi),
      -v*phi*cos(phi),
      -v*delta/(ll_*pow(cos(delta),2)),
      0;
gd_ = dt_*gd_;

return;
}
```

不等式约束 $a \leq \Delta \leq a$, 主要是对各个矩阵C的构造。

```
// set lower and upper boundaries
for (int i = 0; i < N; ++i) {
    // TODO: set stage constraints of inputs (a, delta, ddelta)
    // -a_max <= a <= a_max for instance:
    Cu_.coeffRef(i * 3 + 0, i * m + 0) = 1;
    lu_.coeffRef(i * 3 + 0, 0) = -a_max_;
    uu_.coeffRef(i * 3 + 0, 0) = a_max_;
    // ...
    Cu_.coeffRef(i * 3 + 1, i * m + 1) = 1;
    lu_.coeffRef(i * 3 + 1, 0) = -delta_max_;
    uu_.coeffRef(i * 3 + 1, 0) = delta_max_;

    if(i>0){Cu_.coeffRef(i * 3 + 2, (i-1) * m + 1) = -1;}
    Cu_.coeffRef(i * 3 + 2, i * m + 1) = 1;
    lu_.coeffRef(i * 3 + 2, 0) = -dt * ddelta_max_;
    uu_.coeffRef(i * 3 + 2, 0) = dt * ddelta_max_;

    // TODO: set stage constraints of states (v)
    // -v_max <= v <= v_max
    Cx_.coeffRef(i, i*n+3)=1;
    // lx_.coeffRef(i,0)=-0.1;
    lx_.coeffRef(i,0)=-v_max_;
    ux_.coeffRef(i,0)=v_max_;
}
```

设置完约束后，我们就可以考虑求解二次规划的问题。之前我们已经得到了状态方程，将其离散化后每个时刻构造一个大的矩阵X，则可以得到新的关于矩阵X的状态方程。如下推导所示：

- Linear prediction model:
$$\begin{cases} \mathbf{x}_{k+1} = \mathbf{A}\mathbf{x}_k + \mathbf{B}\mathbf{u}_k \\ \mathbf{y}_k = \mathbf{C}\mathbf{x}_k \end{cases}$$
- Relation between input and states:
$$\mathbf{x}_k = \mathbf{A}^k \mathbf{x}_0 + \sum_{j=0}^{k-1} \mathbf{A}^j \mathbf{B} \mathbf{u}_{k-1-j}$$
- Forward simulation as matrix equation:

$$\begin{bmatrix} \mathbf{x}_1 \\ \mathbf{x}_2 \\ \vdots \\ \mathbf{x}_{N-1} \\ \mathbf{x}_N \end{bmatrix} = \begin{bmatrix} \mathbf{B} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{AB} & \mathbf{B} & \cdots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{A}^{N-1}\mathbf{B} & \mathbf{A}^{N-2}\mathbf{B} & \cdots & \mathbf{B} \end{bmatrix} \begin{bmatrix} \mathbf{u}_0 \\ \mathbf{u}_1 \\ \vdots \\ \mathbf{u}_{N-1} \end{bmatrix} + \begin{bmatrix} \mathbf{A} \\ \mathbf{A}^2 \\ \vdots \\ \mathbf{A}^N \end{bmatrix} \mathbf{x}_0$$

值得注意的是，由于我们这里的系统是跟随时
间变化的，因此A, B矩阵事实上都是随时间改
变的，所以此处正确的形式应该是如下形式。

这里参考了此帖子：

https://blog.csdn.net/qq_42286607/article/details/124972866

- **Extended System State:**

$$X = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_N \end{bmatrix}$$

- **Extended A_0 :**

$$A_0 = \begin{bmatrix} A_0 \\ A_1 A_0 \\ \vdots \\ \prod_{k=0}^{N-1} A_k \end{bmatrix}$$

- **Extended B**, which contains all the control matrices in discrete system equations, stacked:

$$B = \begin{bmatrix} B_0 & 0 & \dots & 0 & 0 \\ A_1 B_0 & B_1 & \dots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ \prod_{k=1}^{N-1} A_k B_0 & \prod_{k=2}^{N-1} A_k B_1 & \dots & A_{N-1} B_{N-2} & B_{N-1} \end{bmatrix}$$

- **Extended G**, which contains all the constant terms in discrete system equations, stacked:

$$G = \begin{bmatrix} g_0 \\ A_1 g_0 + g_1 \\ \vdots \\ \sum_{n=0}^{N-2} (\prod_{k=n+1}^{N-1} A_k) g_n + g_{N-1} \end{bmatrix}$$

```
for (int i = 0; i < N_; ++i) {
    callLinPoint(s0, phi, v, delta);
    if (phi - last_phi > M_PI) {
        phi -= 2 * M_PI;
    } else if (phi - last_phi < -M_PI) {
        phi += 2 * M_PI;
    }
    last_phi = phi;
    linearization(phi, v, delta);

    if (i == 0) {
        BB.block(0, 0, n, m) = Bd_;
        AA.block(0, 0, n, n) = Ad_;
        gg.block(0, 0, n, 1) = gd_;
    } else {
        // TODO: set BB AA gg
        // ...
        BB.block(n*i, m*i, n, m) = Bd_;
        for(int j = i-1; j >= 0; j--){
            BB.block(n*i, m*j, n, m) = Ad_ * BB.block(n*(i-1), m*j, n, m);
        }
        AA.block(n*i, 0, n, n) = Ad_ * AA.block(n*(i-1), 0, n, n);
        gg.block(n*i, 0, n, 1) = Ad_ * gg.block(n*(i-1), 0, n, 1) + gd_;
    }
}
```


由于最终我们是依靠 osqp 来求解二次凸优化问题，而其接口形式为

$$J = 0.5z^T Q z + q^T z$$

其中 Q 和 q 分别为 X 的二次项和一次项系数矩阵。

因此我们就需要将 cost function J 写成如下形式：

$$J = 0.5X^T Q X + qX + \text{const}$$

我们首先求解 Q ，由于我们的 cost function J 定义为：

$$J = (x - x_r)^2 + (y - y_r)^2 + \rho (\phi - \phi_r)^2$$

则我们可以把 J 的二次项表达为如下式的形式

$$J = (x - x_r)^T Q (x - x_r)$$

对比两式就可以得到 Q ，且 Q 是一个稀疏矩阵。形式如下：

$$Q = \begin{pmatrix} \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & \rho & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} & & & \\ & \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & \rho & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} & & \\ & & \ddots & \\ & & & \begin{bmatrix} \rho_N & 0 & 0 & 0 \\ 0 & \rho_N & 0 & 0 \\ 0 & 0 & \rho * \rho_N & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \end{pmatrix}$$

我们之前已经得到了 X 的形式

$$X = BB * U + AA * x_0 + gg$$

将其代入 J 计算，并将输入 U 写成 Z 就又可得到如下关于 J 的式子

$$J = 0.5Z^T BB^T Q BB Z + (AAx_0 + gg - x_r)^T Q BB Z + \text{const}$$

则不难得到 q ：

$$q^T = (AAx_0 + gg - x_r)^T Q BB$$

则有

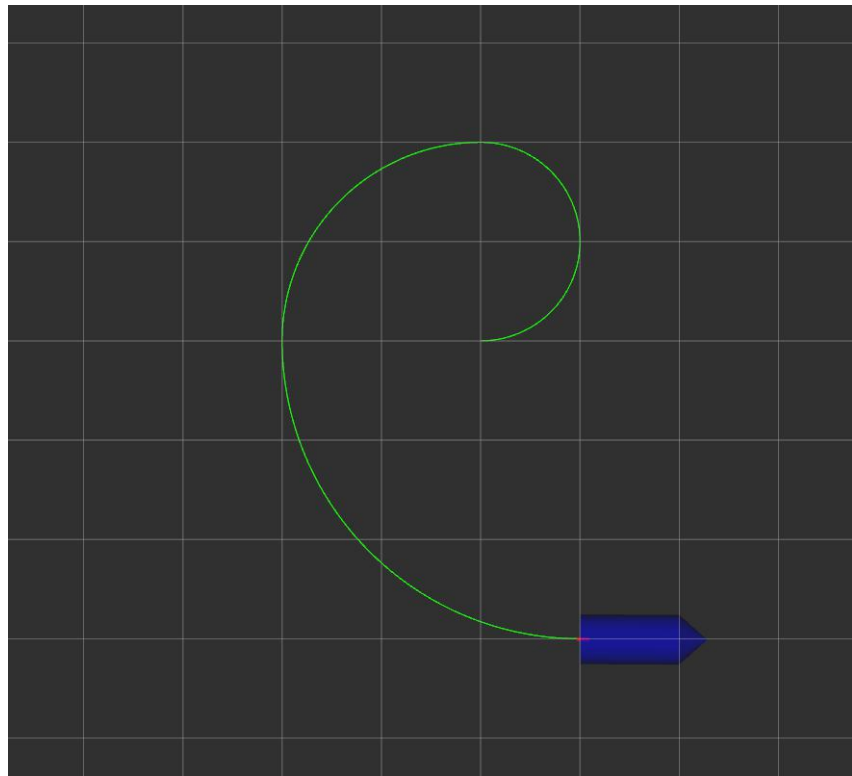
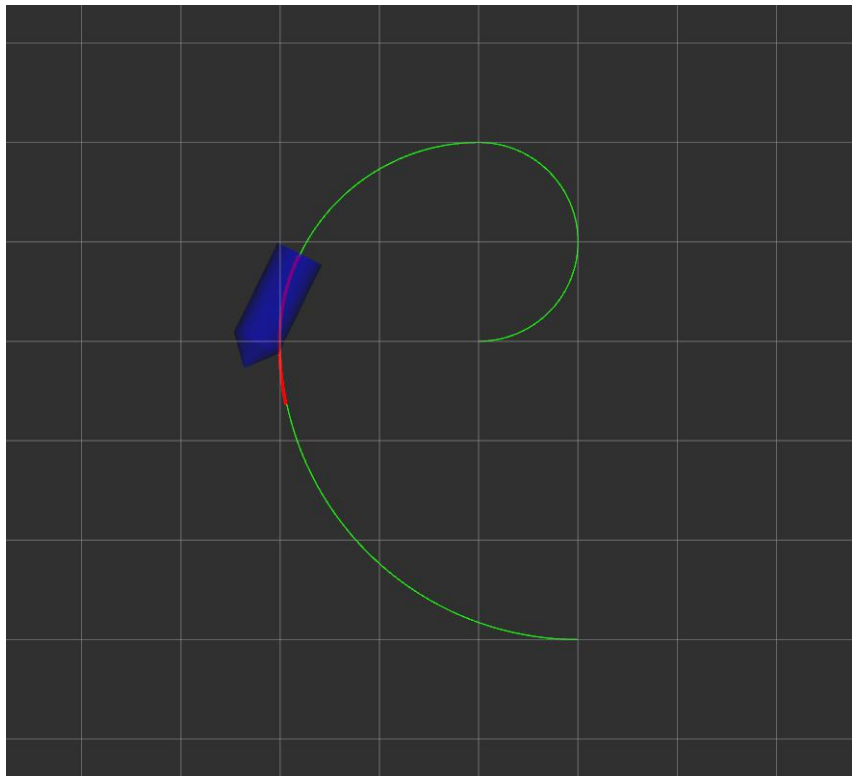
$$q = BB^T Q (AAx_0 + gg - x_r)$$

```
// TODO: set qx
Eigen::Vector2d xy = s_(s0); // reference (x_r, y_r)

// cost function should be represented as follows:
/* *
 *      /  x1  \T      /  x1  \      /  x1  \
 *      |  x2  |      |  x2  |      |  x2  |
 *  J = 0.5 |  x3  |  Qx_ |  x3  | + qx^T |  x3  | + const.
 *      |  ...  |      |  ...  |      |  ...  |
 *      \  xN  /      \  xN  /      \  xN  /
 * */

// qx.coeffRef(...)
// ...
qx.coeffRef(n*i+0, 0) = -Qx_.coeffRef(n*i+0, n*i+0)*xy(0);
qx.coeffRef(n*i+1, 0) = -Qx_.coeffRef(n*i+1, n*i+1)*xy(1);
qx.coeffRef(n*i+2, 0) = -Qx_.coeffRef(n*i+2, n*i+2)*phi;
// qx.coeffRef(n*i+3, 0) = -Qx_.coeffRef(n*i+3, n*i+3)*v;
qx.coeffRef(n*i+3, 0) = 0;
```

MPC运行结果

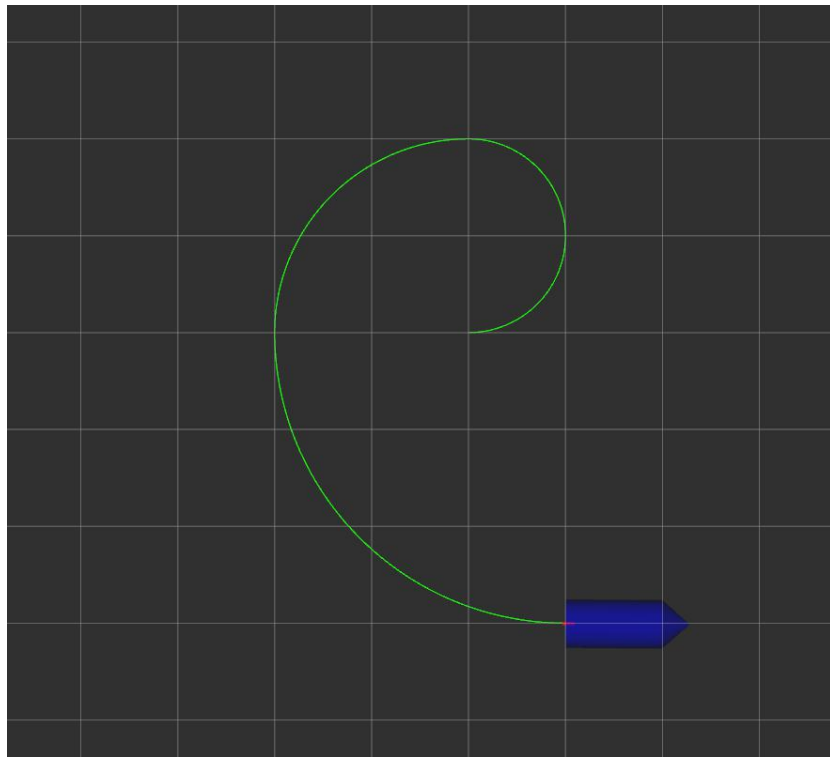
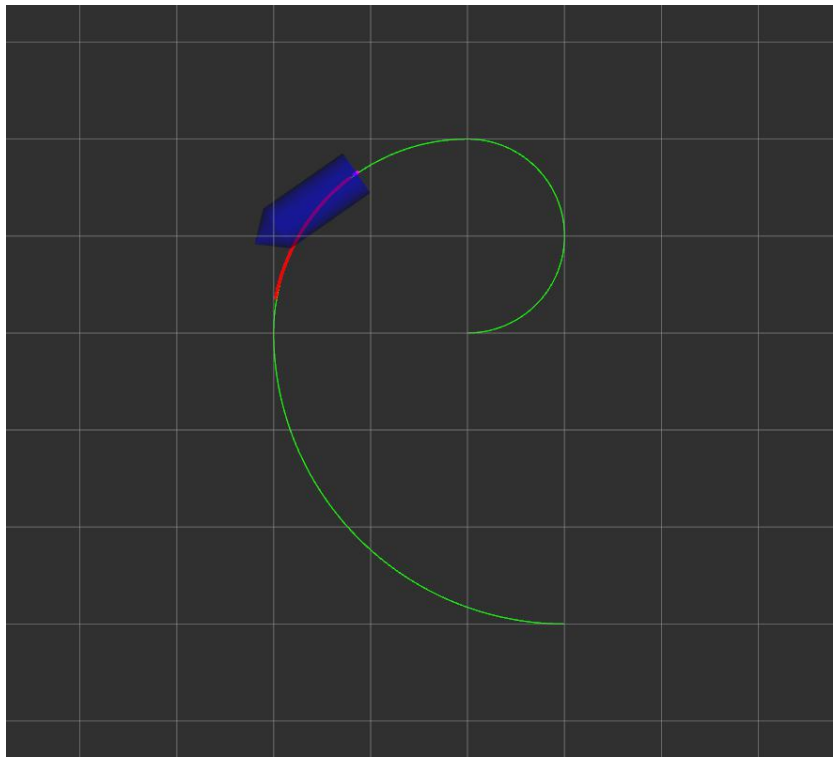


MPC with delays

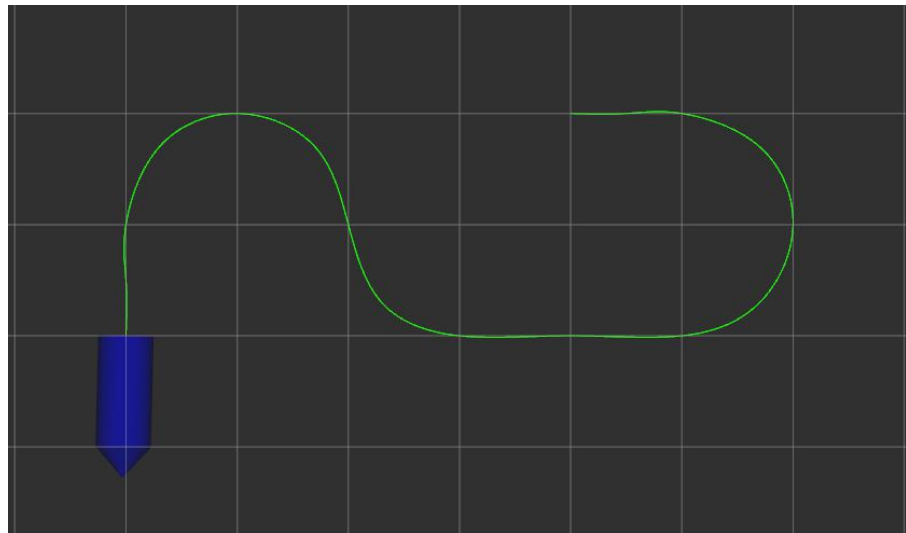
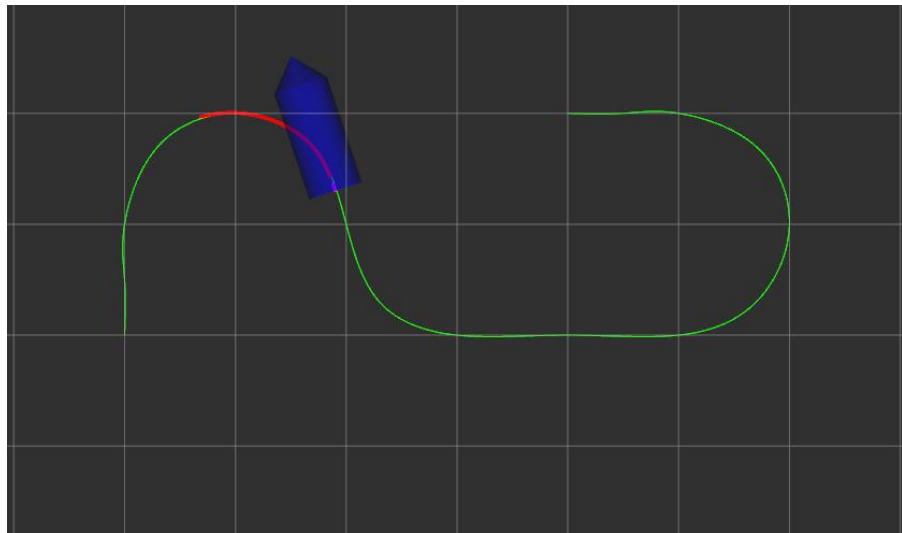
```
inline void step(VectorX& state, const VectorU& input, const double dt) const {  
    // Runge-Kutta  
    VectorX k1 = diff(state, input);  
    VectorX k2 = diff(state + k1 * dt / 2, input);  
    VectorX k3 = diff(state + k2 * dt / 2, input);  
    VectorX k4 = diff(state + k3 * dt, input);  
    state = state + (k1 + k2 * 2 + k3 * 2 + k4) * dt / 6;  
}
```

```
VectorX compensateDelay(const VectorX& x0) {  
    VectorX x0_delay = x0;  
    // TODO: compensate delay  
    // ...  
    double dt = 1e-3;  
    for (double t = delay; t > 0; t -= dt) {  
        int i = std::ceil(t / dt);  
        VectorU input = historyInput_[history_length - i];  
        step(x0_delay, input, dt);  
    }  
  
    return x0_delay;  
}
```

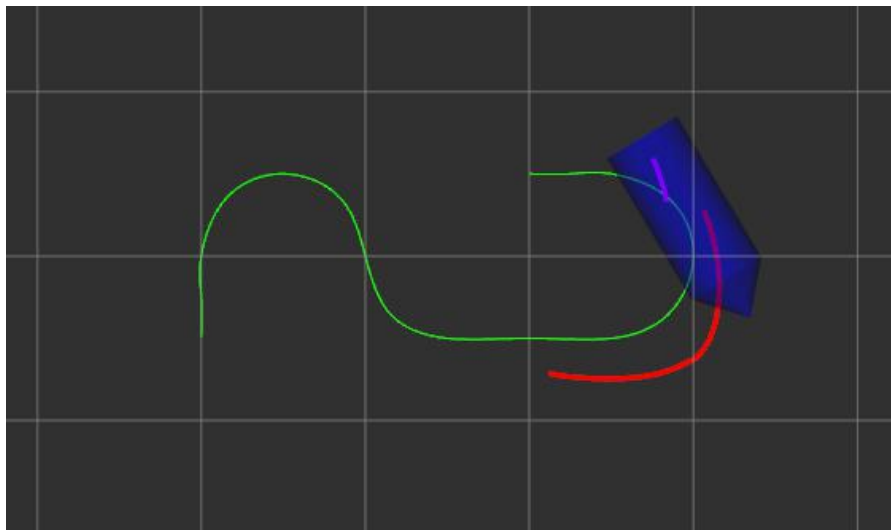
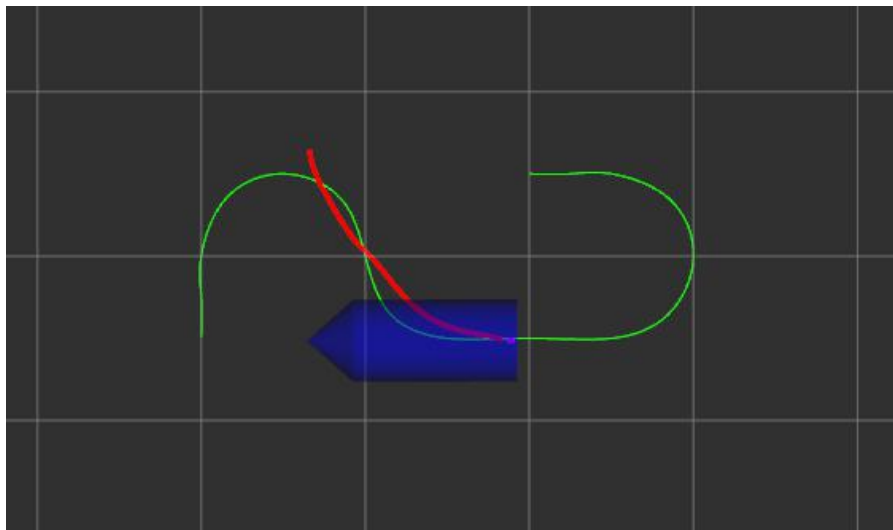
MPC with delays 运行结果



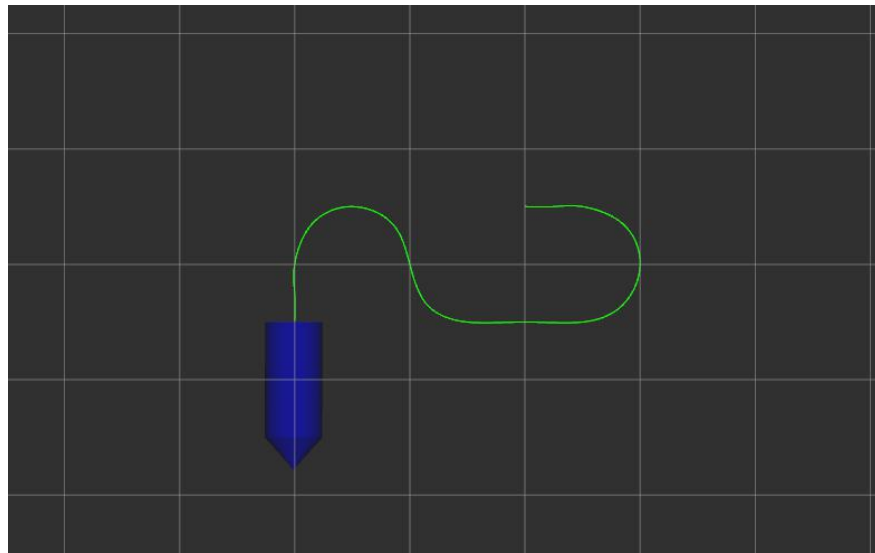
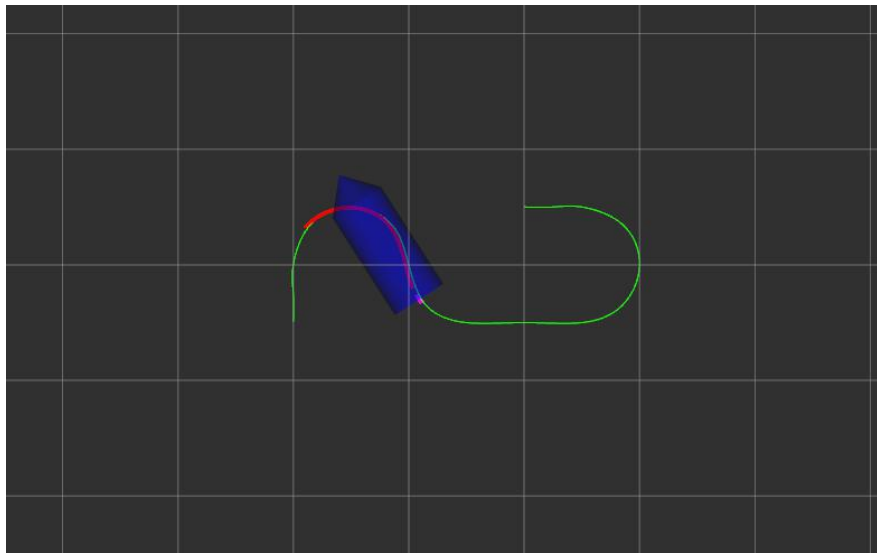
轨迹1



轨迹2 弯道半径过小



轨迹2 修改参数后





感谢各位聆听 !
Thanks for Listening

