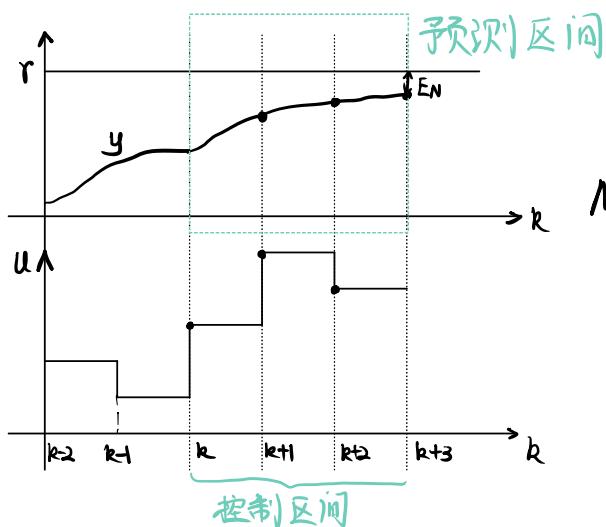


## B 站 Dr. Can 讲解



假设已获得离散模型:

$$\begin{aligned} x_{k+1} &= Ax_k + Bu_k \\ y &= Cx + Du \end{aligned}$$

MPC:

在 k 时刻:

Step 1: 测量/估计系统状态值  $x_k$

Step 2: 基于  $u_k, u_{k+1}, \dots, u_{k+N-1}$  做最优化

Step 3: 只施加  $u_k$

思想: 在 k 时刻, 假设未来一段时间的输入信号为  $u_k, u_{k+1}, \dots, u_{k+N-1}$ , 根据模型预测系统输出, 根据目标函数求解优化问题得  $u_k, \dots, u_{k+N-1}$ . 将  $u_k$  作为 k 时刻的系统控制信号.

Step 2 常用二次规划来作为优化问题, 一般形式:  $\min_{\text{二次型}} \underline{z^T Q z} + \underline{C^T z}$

$$x_{k+1} = Ax_k + Bu_k$$

$$x_k = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}_{n \times 1} \quad A_{n \times n} \quad u_k = \begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ u_p \end{bmatrix}_{p \times 1} \quad B_{n \times p}$$

在第 k 时刻:

$$x_k = \begin{bmatrix} x(k|k) \\ x(k+1|k) \\ \vdots \\ x(k+N|k) \end{bmatrix}_{(N+1)n \times 1} \quad u_k = \begin{bmatrix} u(k|k) \\ u(k+1|k) \\ \vdots \\ u(k+N-1|k) \end{bmatrix}_{Np \times 1}$$

$x(k+i|k)$ : 在 k 时刻预测的  $k+i$  时刻的状态  
 $u(k+i|k)$ : 在 k 时刻假设的  $k+i$  时刻的控制信号

假设  $y=x$ , 参考信号  $R=0$ , 误差  $E=y-R=x$ .

目标函数:

$$\min J = \underbrace{\sum_{i=0}^{N-1} x_{(k+i|k)}^T Q x_{(k+i|k)} + u_{(k+i|k)}^T R u_{(k+i|k)}}_{\text{误差}} + x_{(k+N|k)}^T F x_{(k+N|k)}$$

要使用二次规划(只含一个变量), 需消除 J 中的一个变量(消 x, 因为我们关心 u)

$X(k|k) = X_k$  Step 1 中测量或估计(状态观测量, 卡尔曼滤波等) 得到

$$X(k+1|k) = Ax(k|k) + Bu(k|k) = Ax_k + bu(k|k)$$

$$X(k+2|k) = Ax(k+1|k) + bu(k+1|k) = A^2x_k + ABu(k|k) + bu(k+1|k)$$

$$\vdots \\ X(k+N|k) = A^N x_k + A^{N-1} B u(k|k) + A^{N-2} B u(k+1|k) + \cdots + A B u(k+N-2|k) \\ + B u(k+N-1|k)$$

$$X_k = \begin{bmatrix} X(k|k) \\ X(k+1|k) \\ \vdots \\ X(k+N|k) \end{bmatrix} = \begin{bmatrix} I_{n \times n} \\ A_{n \times n} \\ A^2 \\ \vdots \\ A^N \end{bmatrix}_{(N+1)n \times n} X_k \begin{matrix} n \times 1 \\ \end{matrix} + \begin{bmatrix} 0 & 0 & \cdots & 0 \\ B & 0 & \cdots & 0 \\ AB & B & \ddots & \vdots \\ \vdots & & & B \end{bmatrix}_{(N+1)n \times N_p} \begin{bmatrix} u(k|k) \\ u(k+1|k) \\ u(k+2|k) \\ \vdots \\ u(k+N-1|k) \end{bmatrix}_{N_p \times 1}$$

0 指零矩阵  $0_{n \times p}$

$$M_{(N+1)n \times n} \quad C_{(N+1)n \times N_p}$$

$$X_k = M X_k + C U_k$$

$$\begin{aligned} \min J &= \left[ \sum_{i=0}^{N-1} \underbrace{X_{(k+i|k)}^T Q X_{(k+i|k)}}_{\text{误差}} + \underbrace{U_{(k+i|k)}^T R U_{(k+i|k)}}_{\text{控制信号}} \right] + X_{(k+N|k)}^T F X_{(k+N|k)} \\ &= X_{(k|k)}^T Q X_{(k|k)} + X_{(k+1|k)}^T Q X_{(k+1|k)} + \cdots + X_{(k+N-1|k)}^T Q X_{(k+N-1|k)} \\ &\quad + X_{(k+N|k)}^T F X_{(k+N|k)} \end{aligned}$$

$$+ U_{(k|k)}^T R U_{(k|k)} + U_{(k+1|k)}^T R U_{(k+1|k)} \cdots + U_{(k+N-1|k)}^T R U_{(k+N-1|k)}$$

$$= \begin{bmatrix} X(k|k) \\ X(k+1|k) \\ \vdots \\ X(k+N-1|k) \\ X(k+N|k) \end{bmatrix}^T \begin{bmatrix} Q & & & \\ & Q & & \\ & & \ddots & \\ & & & Q \end{bmatrix} \begin{bmatrix} X(k|k) \\ X(k+1|k) \\ \vdots \\ X(k+N-1|k) \\ X(k+N|k) \end{bmatrix}$$

$$+ \begin{bmatrix} U(k|k) \\ U(k+1|k) \\ \vdots \\ U(k+N-1|k) \end{bmatrix}^T \begin{bmatrix} R & & & \\ & R & & \\ & & \ddots & \\ & & & R \end{bmatrix} \begin{bmatrix} U(k|k) \\ U(k+1|k) \\ \vdots \\ U(k+N-1|k) \end{bmatrix} = X_k^T \bar{Q} X_k + U_k^T \bar{R}^T U_k$$

$$\min J = X_k^T \bar{Q} X_k + U_k^T \bar{R} U_k$$

$$\text{代入 } X_k = M X_k + C U_k$$

$$\min J = (X_k^T M^T + U_k^T C^T) \bar{Q} (M X_k + C U_k) + U_k^T \bar{R} U_k$$

$$= X_k^T M^T \bar{Q} M X_k + \underbrace{X_k^T M^T \bar{Q} C U_k + U_k^T C^T \bar{Q} M X_k}_{+ U_k^T \bar{R} U_k} + U_k^T C^T \bar{Q} C U_k$$

J是一个数, 等式右边每一项均为一个数,  
且可证明这两项相等.

$$= \underbrace{X_k^T M^T \bar{Q} M X_k}_G + 2 \underbrace{X_k^T M^T \bar{Q} C U_k}_E + \underbrace{U_k^T (C^T \bar{Q} C + \bar{R}) U_k}_H$$

$$= \underbrace{X_k^T C X_k}_{\text{常数项}} + 2 \underbrace{X_k^T E U_k}_{\text{线性项}} + \underbrace{U_k^T H U_k}_{\text{二次型}}$$

↓  
二次规划

$$M = \begin{bmatrix} I_{n \times n} \\ A_{n \times n} \\ A^2 \\ \vdots \\ A^N \end{bmatrix}_{(N+1)n \times n} \quad C = \begin{bmatrix} 0 & 0 & \cdots & 0 \\ B & 0 & \cdots & 0 \\ AB & B & \ddots & \vdots \\ \vdots & & & B \end{bmatrix}_{(N+1)n \times Np}$$

$$Q_{n \times n}$$

$$R_{p \times p}$$

$$F_{n \times n}$$

$$\bar{Q} = \left[ \begin{array}{cccc} Q & & & \\ & Q & & \\ & & \ddots & \\ & & & Q \end{array} \right]_{(N+1)n \times (N+1)n}^{N \text{ 项}} \quad \bar{R} = \left[ \begin{array}{cccc} R & & & \\ & R & & \\ & & \ddots & \\ & & & R \end{array} \right]_{Np \times Np}^{N \text{ 项}}$$

$$G = M^T \bar{Q} M \quad [n \times n]$$

$$E = M^T \bar{Q} C \quad [n \times N_p]$$

$$H = C^T \bar{Q} C + \bar{R} \quad [N_p \times N_p]$$

-般情况,  $y = Cx$ , 参考信号  $r \neq 0$ , 误差  $E = y - r$

目标函数

$$\min J = \left[ \sum_{k=0}^{N-1} E(k)^\top Q E(k) + U(k)^\top R U(k) \right] + E(N)^\top F E(N)$$

$$\begin{aligned} E^\top Q E &= (y - r)^\top Q (y - r) \\ &= (y^\top - r^\top) Q (y - r) \\ &= (x^\top C^\top - r^\top) Q (Cx - r) \\ &= x^\top C^\top Q C x - x^\top C^\top Q r - r^\top Q C x + r^\top Q r \\ &= x^\top C^\top Q C x - 2x^\top C^\top Q r + r^\top Q r \end{aligned}$$

与优化无关

$$\begin{aligned} \left[ \sum_{k=0}^{N-1} E(k)^\top Q E(k) \right] + E(N)^\top F E(N) &= [x_{(k)}^\top C^\top Q C x_{(k)} - 2x_{(k)}^\top C^\top Q r] + \\ &\quad [x_{(k+1)}^\top C^\top Q C x_{(k+1)} - 2x_{(k+1)}^\top C^\top Q r] + \\ &\quad \vdots \\ &\quad [x_{(k+N-1)}^\top C^\top Q C x_{(k+N-1)} - 2x_{(k+N-1)}^\top C^\top Q r] + \\ &\quad [x_{(k+N)}^\top C^\top F C x_{(k+N)} - 2x_{(k+N)}^\top C^\top F r] \end{aligned}$$

$$= \begin{bmatrix} x_{(k)} \\ x_{(k+1)} \\ x_{(k+2)} \\ \vdots \\ x_{(k+N)} \end{bmatrix}^\top \begin{bmatrix} C^\top Q C & & & & \\ & C^\top Q C & & & \\ & & C^\top Q C & & \\ & & & \ddots & \\ & & & & C^\top F C \end{bmatrix} \begin{bmatrix} x_{(k)} \\ x_{(k+1)} \\ x_{(k+2)} \\ \vdots \\ x_{(k+N)} \end{bmatrix} -$$

$\bar{Q}_1$

$$2 \begin{bmatrix} x_{(k)} \\ x_{(k+1)} \\ x_{(k+2)} \\ \vdots \\ x_{(k+N)} \end{bmatrix}^\top \begin{bmatrix} C^\top Q r \\ C^\top Q r \\ C^\top Q r \\ \vdots \\ C^\top F r \end{bmatrix} = X_k^\top \bar{Q}_1 X_k - 2 X_k^\top \bar{Q}_2$$

$\bar{Q}_2$

$$\begin{aligned} \min J &= X_k^\top \bar{Q}_1 X_k - 2 X_k^\top \bar{Q}_2 + U_k^\top \bar{R} U_k \quad \text{代入 } X_k = M X_k + D U_k \\ &= (X_k^\top M^\top + U_k^\top D^\top) \bar{Q}_1 (M X_k + D U_k) - 2(X_k^\top M^\top + U_k^\top D^\top) \bar{Q}_2 + U_k^\top \bar{R} U_k \\ &= X_k^\top M^\top \bar{Q}_1 M X_k + X_k^\top M^\top \bar{Q}_1 D U_k + U_k^\top D^\top \bar{Q}_1 M X_k + U_k^\top D^\top \bar{Q}_1 D U_k \\ &\quad - 2 X_k^\top M^\top \bar{Q}_2 - 2 U_k^\top D^\top \bar{Q}_2 + U_k^\top \bar{R} U_k \end{aligned}$$

$$= \underbrace{2 U_k^\top (\bar{Q}_1 M X_k - \bar{Q}_2 D)}_{\substack{\text{线性项} \\ E \\ N_p \times 1}} + \underbrace{U_k^\top (\bar{D}^\top \bar{Q}_1 D + \bar{R}) U_k}_{\substack{\text{二次项} \\ H}}$$

二次规划

$$M^T = \begin{bmatrix} I_{mn} \\ A \\ A^2 \\ \vdots \\ A^n \end{bmatrix}_{(N+1)n \times n}$$

$$D = \begin{bmatrix} 0 & 0 & \cdots & 0 \\ B & 0 & \cdots & 0 \\ AB & B & \ddots & \\ \vdots & & & \\ A^{N_1}B & A^{N_2}B & & B \end{bmatrix}_{(N+1)n \times N_p}$$

$A_{n \times n}$   
 $B_{n \times p}$

$$\bar{Q} = \begin{bmatrix} C^T Q C & C^T Q C & C^T Q C & \dots \\ & C^T F C & & \\ & & C^T F C & \\ & & & C^T F C \end{bmatrix}_{(N+1)n \times (N+1)n}$$

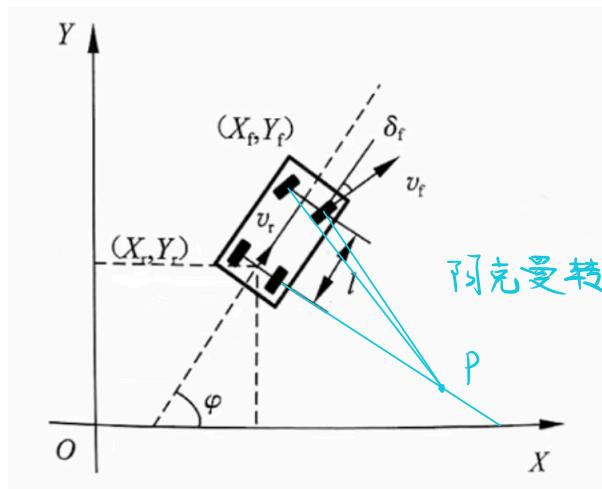
$$\bar{Q}_2 = \begin{bmatrix} C^T Q R \\ C^T Q R \\ C^T Q R \\ \vdots \\ C^T F R \end{bmatrix}_{(N+1)n \times 1}$$

$y_{m \times 1} = C_{mn} \rightarrow_{n \times 1}$   
 $Q_{m \times m} \quad Y_{m \times 1}$   
 $R_{p \times p}$   
 $F_{m \times m}$

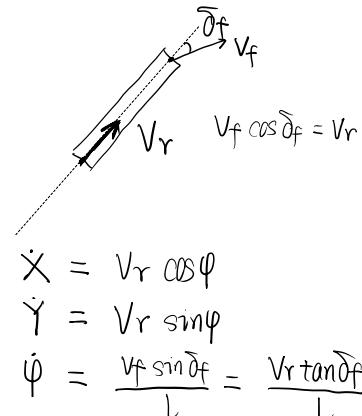
$$\bar{R} = \begin{bmatrix} R & & \\ & R & \\ & & \ddots & \\ & & & R \end{bmatrix}_{N_p \times N_p}$$

# B 站 模型预测控制 MPC

## 车辆运动学建模



抽象为两轮模型



$$\begin{aligned}\dot{X} &= V_r \cos \varphi \\ \dot{Y} &= V_r \sin \varphi \\ \dot{\varphi} &= \frac{v_f \sin \delta_f}{l} = \frac{V_r \tan \delta_f}{l}\end{aligned}$$

$$\text{状态量 } \xi = \begin{bmatrix} X \\ Y \\ \varphi \end{bmatrix}$$

$$\text{控制量 } u = \begin{bmatrix} V \\ \delta \end{bmatrix}$$

$X, Y$  为车辆后轴中心坐标  
 $V$  后轴速度  $\delta$  前轮偏角

$$\begin{bmatrix} \dot{X} \\ \dot{Y} \\ \dot{\varphi} \end{bmatrix} = \begin{bmatrix} \cos \varphi \\ \sin \varphi \\ \frac{\tan \delta}{l} \end{bmatrix} V$$

$$\dot{\xi} = f(\xi, u)$$

非线性模型, 无法写为  $\dot{x} = Ax + Bu$  的形式

线性化:

$$\dot{\xi}_r = f(\xi_r, u_r), r \text{ 指参考量}$$

将  $\dot{\xi} = f(\xi, u)$  在参考轨迹点处泰勒展开且忽略高阶项

$$\dot{\xi} = f(\xi_r, u_r) + \left. \frac{\partial f(\xi, u)}{\partial \xi} \right|_{\substack{\xi=\xi_r \\ u=u_r}} (\xi - \xi_r) + \left. \frac{\partial f(\xi, u)}{\partial u} \right|_{\substack{\xi=\xi_r \\ u=u_r}} (u - u_r)$$

令  $\tilde{\xi} = \xi - \xi_r$ , 即误差

$$\dot{\tilde{\xi}} = \left. \frac{\partial f}{\partial \xi} \right|_{\substack{\xi=\xi_r \\ u=u_r}} (\xi - \xi_r) + \left. \frac{\partial f}{\partial u} \right|_{\substack{\xi=\xi_r \\ u=u_r}} (u - u_r)$$

$$= A \tilde{\xi} + B u$$

$\frac{\partial f}{\partial \xi}, \frac{\partial f}{\partial u}$  均为雅可比矩阵

$$\frac{\partial f}{\partial \xi} = \begin{bmatrix} 0 & 0 & -V \sin \varphi_r \\ 0 & 0 & V \cos \varphi_r \\ 0 & 0 & 0 \end{bmatrix}$$

$$\frac{\partial f}{\partial u} = \begin{bmatrix} \cos \varphi_r & 0 \\ \sin \varphi_r & 0 \\ \frac{\tan \delta}{l} & \frac{V}{l \cos \delta} \end{bmatrix}$$

$$\tilde{\xi} = \begin{bmatrix} x - x_r \\ y - y_r \\ \varphi - \varphi_r \end{bmatrix} \quad \tilde{U} = U - U_r = \begin{bmatrix} v \\ \delta \end{bmatrix}$$

离散化(前向欧拉法):

$$\dot{\tilde{\xi}} = \frac{\tilde{\xi}(k+1) - \tilde{\xi}(k)}{T} = A \tilde{\xi}(k) + B \tilde{U}(k)$$

$$\tilde{\xi}(k+1) = (I + TA) \tilde{\xi}(k) + TB \tilde{U}(k)$$

$$= \tilde{A} \tilde{\xi}(k) + \tilde{B} \tilde{U}(k) = \tilde{A} \tilde{\xi}(k) + \tilde{B} U(k)$$

$$\tilde{A} = \begin{bmatrix} 1 & 0 & -TV \sin \varphi_r \\ 0 & 1 & TV \cos \varphi_r \\ 0 & 0 & 1 \end{bmatrix} \quad \tilde{B} = \begin{bmatrix} T \cos \varphi_r & 0 \\ T \sin \varphi_r & 0 \\ \frac{T \tan \delta}{L} & \frac{TV}{L \cos \delta} \end{bmatrix}$$

线性时变

预测

$$\tilde{\xi}(k+1) = \tilde{A} \tilde{\xi}(k) + \tilde{B} U(k)$$

$$\tilde{\xi}(k+2) = \tilde{A}^2 \tilde{\xi}(k) + \tilde{A} \tilde{B} U(k) + B U(k+1)$$

$$\tilde{\xi}(k+3) = \tilde{A}^3 \tilde{\xi}(k) + \tilde{A}^2 \tilde{B} U(k) + \tilde{A} \tilde{B} U(k+1) + \tilde{B} U(k+2)$$

$$\tilde{\xi}(k+N) = \tilde{A}^N \tilde{\xi}(k) + \tilde{A}^{N-1} \tilde{B} U(k) + \tilde{A}^{N-2} \tilde{B} U(k+1) + \cdots + \tilde{A} \tilde{B} U(k+N-2) + \tilde{B} U(k+N-1)$$

预测时, 将  $\tilde{A}$  视为不变, 即使  $A$  是时变的

控制区间(可以比预测区间短, 但绝不能比预测区间长)

$$\begin{bmatrix} \tilde{\xi}(k+1) \\ \tilde{\xi}(k+2) \\ \tilde{\xi}(k+3) \\ \vdots \\ \tilde{\xi}(k+N) \end{bmatrix} = \begin{bmatrix} \tilde{A} \\ \tilde{A}^2 \\ \tilde{A}^3 \\ \vdots \\ \tilde{A}^N \end{bmatrix} \tilde{\xi}(k) + \begin{bmatrix} \tilde{B} & 0 & & & \\ \tilde{A}\tilde{B} & \tilde{B} & 0 & & \\ \tilde{A}^2\tilde{B} & \tilde{A}\tilde{B} & \tilde{B} & & \\ \vdots & \vdots & \vdots & \ddots & \\ \tilde{A}^{N-1}\tilde{B} & \tilde{A}^{N-2}\tilde{B} & \tilde{A}^{N-3}\tilde{B} & \cdots & \tilde{B} \end{bmatrix} \begin{bmatrix} U(k) \\ U(k+1) \\ U(k+2) \\ \vdots \\ U(k+N-1) \end{bmatrix}$$

$$Y_k = \underline{\xi}_k + \theta U_k$$

$$\underline{\xi}_k = \begin{bmatrix} \underline{x}_k \\ \underline{y}_k \\ \underline{\varphi}_k \end{bmatrix}$$

当预测区间长度  $N_p$  等于控制区间长度  $N_c + 1$  时,  $\theta$  才为下三角矩阵.

## 优化一二次规划 (QP)

二次规划

$$\min_{\Delta U, \epsilon} \frac{1}{2} x^T H x + f^T x$$

s.t.

$$Ax \leq b$$

$$A_{eq}x = B_{eq}$$

$$lb \leq x \leq ub$$

$\epsilon$  为松弛因子, 为了更  
快得结果

优化目标

$$\min Y_k^T Q Y_k + U_k^T R U_k$$

并不符合二次规划的形

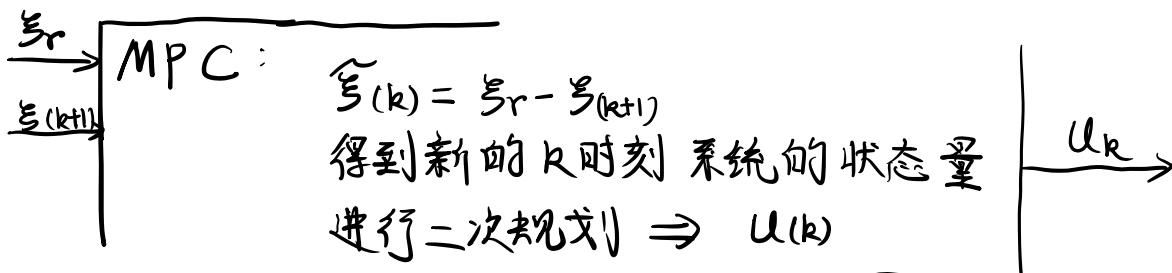
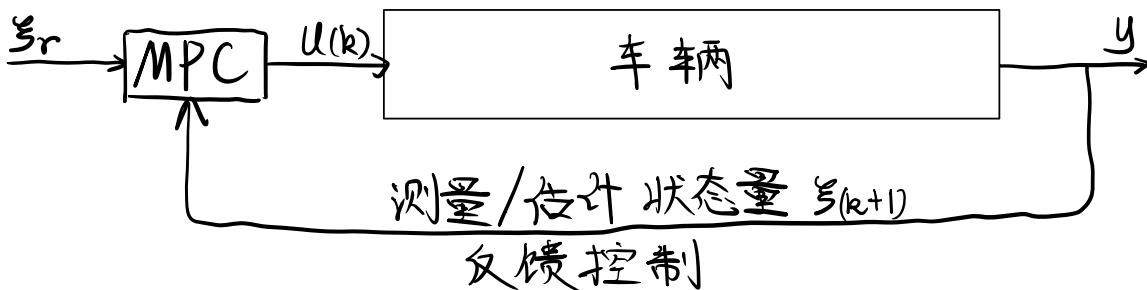
$$\downarrow \text{代入 } Y_k = E \tilde{x}_k + \theta U_k$$

$$\min 2E^T Q \theta U_k + U_k^T (\theta^T Q \theta + R) U_k \quad \text{二次规划}$$

$$\text{s.t. } lb \leq U_k \leq ub \quad \text{参考 Matlab 中 quadprog 函数.}$$

控制:

二次优化得到  $U_k$ , 只取  $u(k)$  作控制量.



MPC从输入 参考信号以及测量/估计的系统状态量到输出 控制信号，中间的优化过程用到了被控系统的物理模型，所以更复杂，控制效果也更好，对于不同被控系统，都需要重新设计MPC。而PID属于通用控制器，使用过程中只需要考虑如何调整控制器参数，不需要考虑被控系统的物理模型(但还是需要结合模型考虑加入控制器后的系统稳定性)

MPC适用于MIMO系统，而PID更适用于SISO系统；PID只考虑了输出的准度，而MPC不但可以考虑输出的准度，还考虑了输入。

修正：

$$\text{离散化得到的模型: } \tilde{x}_{(k+1)} = \tilde{A}(k) \tilde{x}(k) + \tilde{B}(k) u(k)$$

有些情况下我们更希望控制量的变化量，即  $\Delta U(k)$

$$\text{令 } \tilde{x}(k) = \begin{bmatrix} \tilde{x}(k) \\ u(k-1) \end{bmatrix} \quad \tilde{A} = \begin{bmatrix} \tilde{A}(k) & \tilde{B}(k) \\ 0 & I_p \end{bmatrix} \quad \tilde{B} = \begin{bmatrix} \tilde{B}(k) \\ I_p \end{bmatrix} \quad \tilde{C} = [C \ 0]$$

$$\begin{cases} \tilde{x}(k+1) = \tilde{A} \tilde{x}(k) + \tilde{B} \Delta U(k) \\ \eta(k) = \tilde{C} \tilde{x}(k) \end{cases}$$

预测：

$$Y(k) = \Psi \tilde{x}(k) + \theta \Delta U(k)$$

优化：

$$J = Y(k)^T Q Y(k) + \Delta U(k)^T R \Delta U(k) + \rho \varepsilon^2 \quad \text{松弛项}$$

$\downarrow$   
代入  $Y(k) = \Psi \tilde{x}(k) + \theta \Delta U(k)$   
且令  $E = \Psi \tilde{x}(k)$

$$J = \Delta U(k)^T (\theta^T Q \theta + R) \Delta U(k) + \rho \varepsilon^2 + 2E^T Q \theta \Delta U(k)$$

$$= [\Delta U(k) \ \varepsilon] \begin{bmatrix} \theta^T Q \theta + R & 0 \\ 0 & \rho \end{bmatrix} \begin{bmatrix} \Delta U(k) \\ \varepsilon \end{bmatrix} + [2E^T Q \theta \ 0] \begin{bmatrix} \Delta U(k) \\ \varepsilon \end{bmatrix}$$

$$= X^T H X + 2f^T X$$

约束条件处理：

$$\text{通常我们会约束: } \Delta U_{\min} \leq \Delta U(k) \leq \Delta U_{\max}$$

$$U_{\min} \leq U(k) \leq U_{\max}$$

如何转换为二次规划的标准约束形式?

$$\text{s.t. } Ax \leq b$$

$$A_{eq}x = B_{eq}$$

$$lb \leq x \leq ub$$

$$\Delta U_{\min} \leq \Delta U(k) \leq \Delta U_{\max} \rightarrow lb \leq x \leq ub$$

$$\text{令 } A = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \ddots & 0 \\ 0 & 0 & \cdots & 1 \end{bmatrix}_{Nc \times Nc} \otimes I_p \quad \otimes \text{表示克罗内克积}$$

$$\begin{bmatrix} A & 0 \\ -A & 0 \end{bmatrix} \begin{bmatrix} \Delta U(k) \\ \varepsilon \end{bmatrix} \leq \begin{bmatrix} U_{\max} - U(k) \\ -U_{\min} + U(k) \end{bmatrix} \rightarrow Ax \leq b$$

$$A \Delta U(k) \leq U_{\max} - U(k)$$

$$A \Delta U(k) \geq U_{\min} - U(k)$$

$$U_{\min} \leq U(k) + A\Delta U(k) \leq U_{\max}$$

控制:

$$U(k+1) = U(k) + \Delta U(k)$$