

# **Longitudinal MPC**

This repository implement speed planning via MPC.

## **Basic MPC**

$$J = \min_{x_k, u_k} \sum_{k=0}^{N-1} \left[ \left( x_k - x_{k,r} 
ight)^T Q \left( x_k - x_{k,r} 
ight) + u_k^T R u_k 
ight] + \ \left( x_N - x_{N,r} 
ight)^T Q_N \left( x_N - x_{N,r} 
ight) \ s.t. \ x_{k+1} = A x_k + B u_k \ \left[ egin{align*} x_{min,k} \ u_{min,k} \ \end{array} 
ight] \leq A_{ineq} \left[ egin{align*} x_k \ u_k \ \end{array} 
ight] \leq \left[ egin{align*} x_{max,k} \ u_{max,k} \ \end{array} 
ight]$$

where

- $x_k$  is state variable;
- $x_{k,r}$  is state reference;
- $u_k$  is control variable;
- $Q_N$  is usually solved by an algebraic discrete Riccati equation.

# **Longitudinal MPC**

In this section, we will modify J to fit for a speed planning problem.

$$J = \min_{x_k, u_k} \sum_{k=0}^{N-1} \left[ \left( x_k - x_{k,r} 
ight)^T Q \left( x_k - x_{k,r} 
ight) + u_k^T R u_k + \dot{u}_k^T \dot{R} \dot{u}_k 
ight] + \left( x_N - x_{N,r} 
ight)^T Q_N \left( x_N - x_{N,r} 
ight) + \sigma_k^T W \sigma_k$$

where, specifically, in this equation,

•  $x_k$  represents  $[s_k, \dot{s}_k]^T$ ;

- $x_{k,r}$  represents  $[s_{k,r}, \dot{s}_{k,r}]^T$ ;
- $u_k$  represents  $\ddot{s}_k$ ;
- $\sigma_k$  represents slack variables.

## To a Quadratic Problem

We have a standard QP formulation as below.

$$J = \min_{z} rac{1}{2} z^T P z + q^T z \ s.t. \ z_{min} \leq Az \leq z_{max}$$

### Cost

First of all,  $\dot{u}_k$  could be written as

$$\dot{u}_k = rac{u_k - u_{k-1}}{\Delta t}$$

where k = 1, ..., N - 1.

Perticular.

$$\dot{u}_0=rac{u_0-u_{-1}}{\Delta t_{-1}}$$

where -1 index means the previous control command. For simplicity, we choose  $\Delta t_{-1}$  equals  $\Delta t$ .

Thus, the control part is

$$egin{aligned} u_k^T R u_k + \dot{u}_k^T \dot{R} \dot{u}_k &= u_k^T R u_k + rac{(u_k - u_{k-1})^T}{\Delta t} \dot{R} rac{u_k - u_{k-1}}{\Delta t} \ &= u_k^T (R + rac{\dot{R}}{\Delta t^2}) u_k + u_{k-1}^T rac{\dot{R}}{\Delta t^2} u_{k-1} \ &- u_k^T rac{\dot{R}}{\Delta t^2} u_{k-1} - u_{k-1}^T rac{\dot{R}}{\Delta t^2} u_k \end{aligned}$$

Then, we have

### **Constraints**

#### **Equality Constraints**

We consider an error differential equation

$$\dot{x}(t) = A_c x(t) + B_c u(t)$$

where x(t) is state variable; u(t) is control variable.

Here, we have

$$x_k = \left[s_k, \dot{s}_k
ight]^T$$

$$u_k = [\ddot{s}_k]$$

Then,

$$egin{aligned} A_c &= egin{bmatrix} 0 & 1 \ 0 & 0 \end{bmatrix} \ B_c &= egin{bmatrix} 0 \ 1 \end{bmatrix} \end{aligned}$$

Thus, the equality constraints

$$x_{k+1} = (I + A_c \Delta t) x_k + B_c \Delta t u_k$$

could be written in the following format

$$b_{eq} \leq A_{eq}z \leq b_{eq}$$

where

$$A_{eq} = egin{bmatrix} -I & & 0 & & & & \ I+A_c\Delta t & -I & & B_c\Delta t & & & \ & \ddots & \ddots & & & & \ & I+A_c\Delta t & -I & & B_c\Delta t & 0 \end{bmatrix} \ b_{eq} = egin{bmatrix} -x_0 \ 0 \ dots \ 0 \end{bmatrix}$$

#### **Inequality Constraints**

Generally, maximum ranges of acceleration and jerk of the ego vehicle constrain a speed planning problem. Slack variables are often applied to relax station and velocity constraints. In this section, we only support to relax  $s_k$  and  $\dot{s}_k$  with slack variables, denoting as  $\sigma_{x,k}$  for upper bounds and  $\mu_{x,k}$  for lower bounds.

$$A_{ineq} = egin{bmatrix} 1_{x,k} & -1_{\sigma_{x,k}} \ 1_{x,k} & 1_{u,k} \ a_{u,k} & 1_{\sigma_{x,k}} \end{bmatrix} \ b_{ineq,lower} = egin{bmatrix} -\infty \ x_{min,k} \ u_{min,k} \ b_{u,k,min} \ 0_{\sigma_{x,k}} \end{bmatrix} \ b_{ineq,upper} = egin{bmatrix} x_{max,k} \ +\infty \ u_{max,k} \ b_{u,k,max} \ \sigma_{max,x,k} \end{bmatrix}$$

where

$$a_{u,k} = egin{bmatrix} 1 & & & & & \ -1 & 1 & & & \ & \ddots & \ddots & & \ & -1 & 1 \end{bmatrix} \ b_{u,k,max} = egin{bmatrix} u_{-1} + j_{max} \Delta t \ j_{max} \Delta t \ dots \ j_{max} \Delta t \end{bmatrix} \ b_{u,k,min} = egin{bmatrix} u_{-1} + j_{min} \Delta t \ j_{min} \Delta t \ dots \ j_{min} \Delta t \ dots \ j_{min} \Delta t \end{bmatrix}$$

Please Note that we do **NOT** support to constrain lower slack variables  $\mu_{x,k}$  of  $x_k$ .