

Today: 13.1, 13.2, 13.3

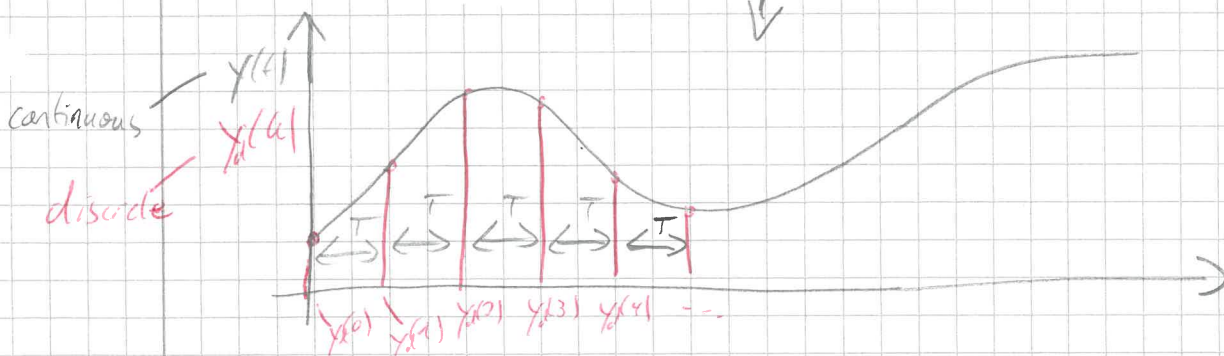
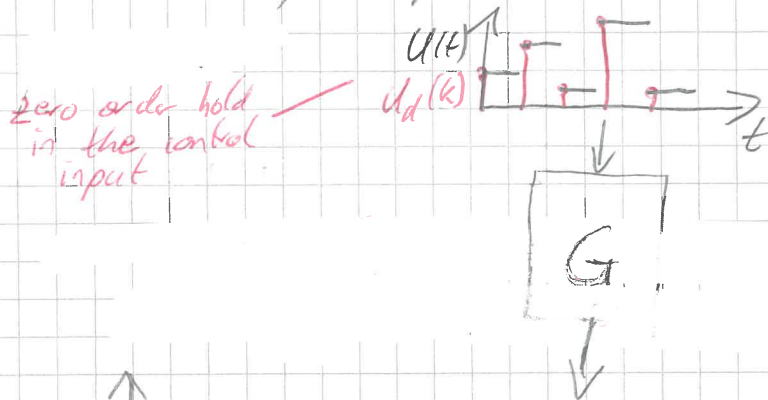
— Discrete time systems

— Model Predictive Control (including hard constraints)

Discrete time systems, we for instance
obtained by sampling a continuous time system.

advantage

as in
Matlab
simulink



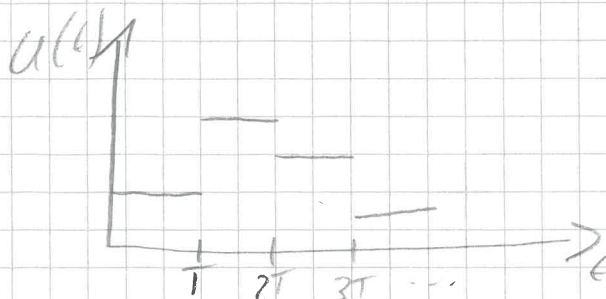
Periodic sampling means $y_d(k) = y(k \cdot T)$, where
 T is the sampling period.

Now given

$$\dot{x}(t) = Ax(t) + Bu(t)$$

$$y(t) = Cx(t)$$

and assuming that $u(t) = \text{constant}$ for all
 $t \in [kT, (k+1)T)$



we get :

$$x_d(k+1) = F x_d(k) + G u_d(k)$$

$$y_d(k) = C x_d(k)$$

with $F = e^{AT}$
 $G = \int_0^T e^{A\tau} B d\tau$

// can be derived by
looking at the solution
 $x(t) = e^{At} x(0) + \int_0^t e^{A(t-s)} B u(s) ds$
at times $t = kT$

Note e^{AT} is the matrix exponential

→ $\text{expm}(AT)$ in Matlab

with $e^{AT} = I + \sum_{i=1}^{\infty} \frac{A^i T^i}{i!}$

or $e^{AT} = \mathcal{L}^{-1} \left\{ (sI - A)^{-1} \right\} \Big|_{t=T}$

Controllability: Controllable iff

$$R = \begin{bmatrix} G & FG & \dots & F^{n-1}G \end{bmatrix} \text{ has full rank}$$

Observability: Observable iff

$$O = \begin{bmatrix} C \\ CF \\ \vdots \\ CF^{n-1} \end{bmatrix} \text{ has full rank}$$

stability: stable iff

$$| \lambda_i | < 1 \quad \checkmark_i$$

13.1)

Consider

rotational matrix

$$\dot{x}(t) = \begin{bmatrix} 0 & \omega \\ -\omega & 0 \end{bmatrix} x(t) + \begin{bmatrix} 1 \\ 0 \end{bmatrix} u(t) = Ax + Bu$$

$$y(t) = \begin{bmatrix} 1 & 0 \end{bmatrix} x(t) = Cx$$

The sampled system is

$$x_d(k+1) = F x_d(k) + G u_d(k)$$

$$y_d(k) = C x_d(k)$$

with

$$\begin{aligned} F = e^{AT} &= \mathcal{L}^{-1} \left\{ (sI - A)^{-1} \right\} \Big|_{t=T} \\ &= \mathcal{L}^{-1} \left\{ \begin{bmatrix} s & -\omega \\ \omega & s \end{bmatrix}^{-1} \right\} \Big|_{t=T} \\ &= \mathcal{L}^{-1} \left\{ \frac{1}{s^2 + \omega^2} \begin{bmatrix} s & \omega \\ -\omega & s \end{bmatrix} \right\} \Big|_{t=T} \\ &= \begin{bmatrix} \cos(\omega T) & \sin(\omega T) \\ -\sin(\omega T) & \cos(\omega T) \end{bmatrix} \end{aligned}$$

$$\begin{aligned} G &= \int_0^T \begin{bmatrix} \cos(\omega \tau) & \sin(\omega \tau) \\ -\sin(\omega \tau) & \cos(\omega \tau) \end{bmatrix} \begin{bmatrix} 1 \\ 0 \end{bmatrix} d\tau \\ &= \int_0^T \begin{bmatrix} \cos(\omega \tau) \\ -\sin(\omega \tau) \end{bmatrix} d\tau = \frac{1}{\omega} \begin{bmatrix} \sin(\omega T) \\ \cos(\omega T) \end{bmatrix}^T_0 \\ &= \frac{1}{\omega} \begin{bmatrix} \sin(\omega T) \\ \cos(\omega T) - 1 \end{bmatrix} \end{aligned}$$

What if $T = \frac{n \cdot 2\pi}{\omega}$ for $n = 0, 1, \dots$?

When is the system observable?

Form $O = \begin{bmatrix} C \\ CF \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ \cos(\omega T) & \sin(\omega T) \end{bmatrix}$

needs to have $\text{rank}(O) = 2$!

we need hence

$$\Rightarrow \sin(\omega T) \neq 0$$

Hence $\omega T \neq n \cdot \pi$

$$\Rightarrow \boxed{T \neq \frac{n \cdot \pi}{\omega}}$$

Model Predictive Control

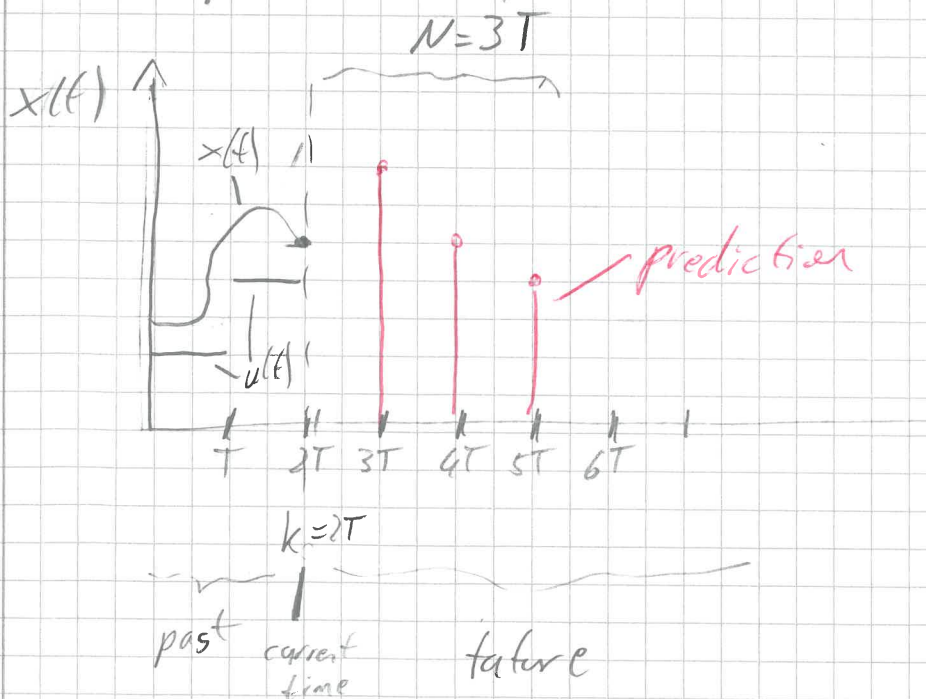
Assume k to be the current time.
We use a finite prediction horizon N

to predict $x(k+1), x(k+2), \dots, x(k+N)$
by using $x(k+1) = Fx(k) + Gu(k)$ recursively
and solve

$$\min_{\bar{u}} \sum_{i=k+1}^{k+N} x^T(i) Q_1 x(i) + u^T(i-1) Q_2 u(i-1)$$

with $\bar{u} = \begin{bmatrix} u(k) \\ u(k+1) \\ \vdots \\ u(k+N-1) \end{bmatrix}$

at every sampling step. We then apply $\bar{u}(1) = u(k)$ to the system and repeat the procedure by setting $k = k+1$.



13.2) Consider

$$x(k+1) = \begin{bmatrix} 1.2 & 1 \\ -0.7 & 0 \end{bmatrix} x(k) + \begin{bmatrix} 0.9 \\ -0.6 \end{bmatrix} u(k) = Fx(k) + Gu(k)$$

$$y(k) = \begin{bmatrix} 1 & 0 \end{bmatrix} x(k) = Cx(k)$$

and determine

$$u(k) = -F_y y(k) + F_r v(k)$$

by minimizing

$$J = \sum_{i=1}^3 \underbrace{(v(k+i) - y(k+i))^2}_{\text{reference tracking}} + 0.1 \underbrace{u(k+i-1)^2}_{\text{input minimization}}$$

with respect to \bar{u} .

$$\textcircled{1} \quad \bar{r} = \begin{bmatrix} r(k+1) \\ r(k+2) \\ r(k+3) \end{bmatrix}$$

← We assume to know this in advance

$$\bar{y} = \begin{bmatrix} y(k+1) \\ y(k+2) \\ y(k+3) \end{bmatrix}$$

← estimated by the discrete state-space model

$$\bar{u} = \begin{bmatrix} u(k) \\ u(k+1) \\ u(k+2) \end{bmatrix}$$

← to be determined

$$\text{Then } J = (\bar{r} - \bar{y})^T (\bar{r} - \bar{y}) + 0.1 \bar{u}^T \bar{u}$$

② Find analytical expression for \bar{y}

$$x(k) = x(k)$$

$$x(k+1) = Fx(k) + Gu(k)$$

$$x(k+2) = F^2 x(k) + FG u(k) + G u(k+1)$$

$$x(k+3) = F^3 x(k) + F^2 G u(k) + FG u(k+1) + G u(k+2)$$

$$y(k) = Cx(k)$$

$$y(k+1) = Cx(k+1)$$

⋮

Hence we get

$$\begin{aligned} \bar{Y} = \begin{bmatrix} y(k+1) \\ y(k+2) \\ y(k+3) \end{bmatrix} &= \begin{bmatrix} CF \\ CF^2 \\ CF^3 \end{bmatrix} x(k) + \begin{bmatrix} CG & 0 & 0 \\ CFG & CG & 0 \\ CF^2G & CFG & CG \end{bmatrix} \bar{u} \\ &= P x(k) + Q \bar{u} \end{aligned}$$

$P \in \mathbb{R}^{N \times n}$
 $Q \in \mathbb{R}^{N \times N \cdot m}$

$$\begin{aligned} \text{Hence } J &= (\bar{r} - P x(k) - Q \bar{u})^T (\bar{r} - P x(k) - Q \bar{u}) + 0.1 \bar{u}^T \bar{u} \\ &= \bar{r}^T \bar{r} - 2 \bar{r}^T P x(k) - 2 \bar{r}^T Q \bar{u} + x^T(k) P^T P x(k) \\ &\quad + 2 x^T(k) P^T Q \bar{u} + \bar{u}^T Q^T Q \bar{u} + 0.1 \bar{u}^T \bar{u} \end{aligned}$$

③ minimize *only consider terms containing \bar{u}*

$$\frac{\partial J}{\partial \bar{u}} = \frac{\partial}{\partial \bar{u}} (-2 \bar{r}^T Q \bar{u} + 2 x^T(k) P^T Q \bar{u} + \bar{u}^T Q^T Q \bar{u} + 0.1 \bar{u}^T \bar{u})$$

$$(*) = -2 \bar{r}^T Q + 2 x^T(k) P^T Q + 2 \bar{u}^T \underbrace{Q^T Q}_{\text{symmetric}} + 0.2 \bar{u}^T$$

make sure that the dimensions are correct

Setting $(*) = 0$ gives

$$2 \bar{r}^T Q - 2 x^T(k) P^T Q = \bar{u}^T (2 Q^T Q + 0.2 I)$$

$$\Rightarrow (2 \bar{r}^T Q - 2 x^T(k) P^T Q) (2 Q^T Q + 0.2 I)^{-1} = \bar{u}^T \quad \text{recall } (AB)^T = B^T A^T$$

$$\Rightarrow (2 Q^T Q + 0.2 I)^{-1} (2 Q^T \bar{r} - 2 Q^T P x(k)) = \bar{u}$$

$$\Rightarrow (Q^T Q + 0.1 I)^{-1} Q^T (\bar{r} - P x(k)) = \bar{u}$$

Inserting values, we get

$$(**) \quad u(k) = -[1.7 \quad 1.1]x(k) + [0.9 \quad 0.1 \quad 0.01] \bar{v}$$

\Rightarrow Note that $\bar{u} = \begin{bmatrix} u(k) \\ u(k+1) \\ u(k+2) \end{bmatrix}$

Hence we only calculated the first element of \bar{u} which is applied to the system until the procedure is repeated at the next sampling step.

Now: express (**) as $u(k) = F_y y_{\text{past}} + F_v \bar{v}$

We know that (from the system model)

$$x_1(k) = y(k)$$

$$\begin{aligned} \text{and } x_2(k) &= -0.7 x_1(k-1) - 0.6 u(k-1) \\ &= -0.7 y(k-1) - 0.6 u(k-1) \end{aligned}$$

Hence (**) becomes

$$\begin{aligned} u(k) &= -1.7 y(k) + 0.77 y(k-1) + 0.66 u(k-1) \\ &\quad + 0.9 v(k+1) + 0.1 v(k+2) + 0.01 v(k+3) \end{aligned}$$

13.3)

Consider
$$y(k+1) = -y(k) + 2u(k) \\ = Fy(k) + Gu(k)$$

OBS:
// scalar
system!

$$\boxed{\begin{matrix} F = -1 \\ G = 2 \end{matrix}}$$

The MPC formulation is given as

$$(*) \quad \min_u \sum_{i=k}^{k+N_p} y(i)^2 + \sum_{i=k}^{k+N_p-1} u(i)^2$$

$$(**) \quad \text{s.t.} \quad -1 \leq u(k) \leq 1$$

If $N_p = 1$, translate this into

$$\min_u u^T H u + h^T u \\ \text{s.t.} \quad Lu \leq b$$

① Rewrite (*) as:

$$\min_{u(k)} y(k)^2 + y(k+1)^2 + u(k)^2$$

$$\Leftrightarrow \min_{u(k)} y(k)^2 + (Fy(k) + Gu(k))^2 + u(k)^2$$

$$\Leftrightarrow \min_{u(k)} y(k)^2 + F^2 y(k)^2 + 2Fy(k)Gu(k) + G^2 u(k)^2 + u(k)^2$$

$$\Leftrightarrow \min_{u(k)} 2y(k)^2 + 4y(k)u(k) + 5u(k)^2$$

$$\Leftrightarrow \min_{u(k)} -4y(k)u(k) + 5u(k)^2$$

Hence we have $H = 5$ and $h^T = -4y(k)$

⑤ From ~~$A \neq I$~~ we get

$$u(k) \leq 1$$

$$\text{and } -u(k) \leq 1$$

$$\text{and hence } L = \begin{bmatrix} 1 \\ -1 \end{bmatrix} \text{ and } b = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$