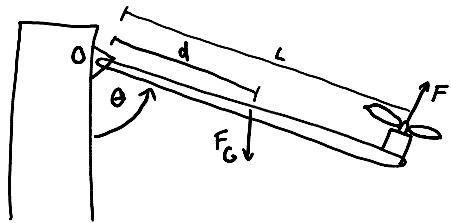


## Cascaded Control

### System Model:



$$v: F \quad x_1: \theta \quad x_2: \dot{\theta} \quad y: \theta$$

$$\sum M_{o,i} = L \cdot F(t) - d \cdot m \cdot g \cdot \sin(\theta(t))$$

$$\rightarrow \ddot{\theta}(t) = \frac{1}{J_0} (L \cdot F(t) - d \cdot m \cdot g \cdot \sin(\theta(t)))$$

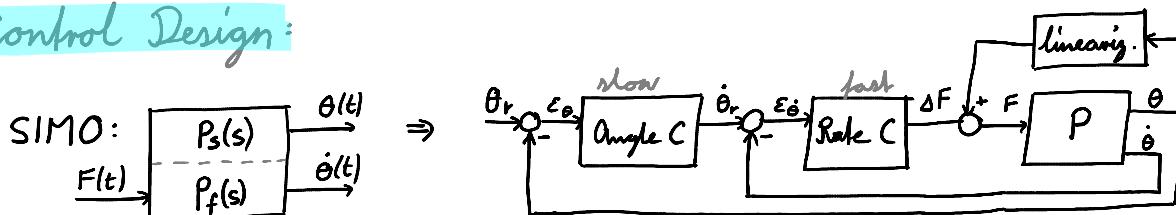
$$\dot{x} = \begin{pmatrix} \dot{x}_1 \\ \dot{x}_2 \end{pmatrix} = \begin{pmatrix} \dot{\theta} \\ \ddot{\theta} \end{pmatrix} = f(x, v) = \begin{pmatrix} \dot{\theta} \\ \frac{L}{J_0} \cdot F(t) - \frac{dmg}{J_0} \cdot \sin(\theta(t)) \end{pmatrix} = \begin{pmatrix} x_2 \\ \frac{L}{J_0} \cdot v - \frac{dmg}{J_0} \cdot \sin(x_1) \end{pmatrix}$$

operating point:  $\theta_{op} = \pi/2, \dot{\theta}_{op} = 0 \rightarrow F_{op} = \frac{dmg}{J_0}$

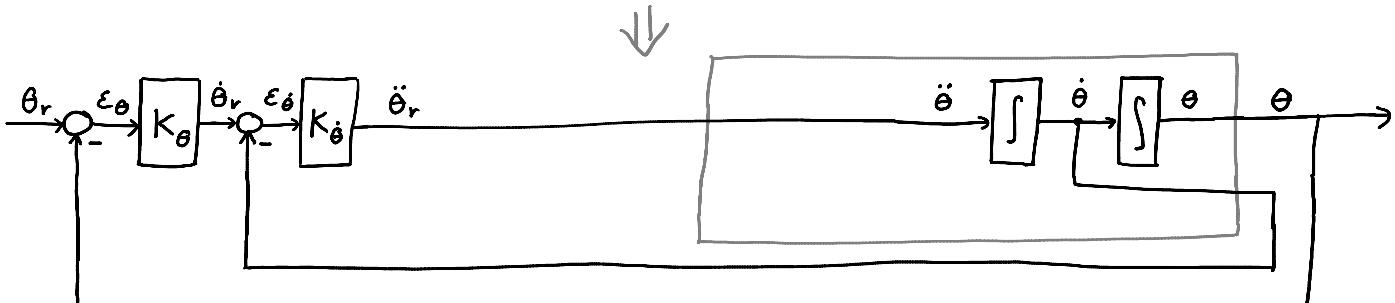
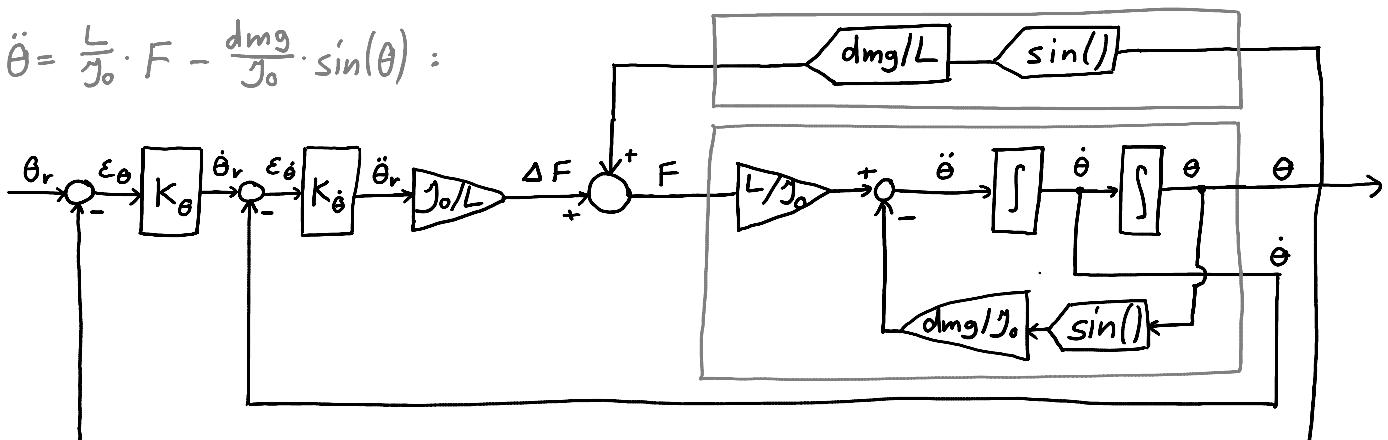
$$A = \left( \begin{array}{cc} \frac{\partial f_1}{\partial x_1} & \frac{\partial f_1}{\partial x_2} \\ \frac{\partial f_2}{\partial x_1} & \frac{\partial f_2}{\partial x_2} \end{array} \right) \Big|_{op} = \left( \begin{array}{cc} 0 & 1 \\ -\frac{dmg}{J_0} \cos(\theta_{op}) & 0 \end{array} \right) \Big|_{op} = \left( \begin{array}{cc} 0 & 1 \\ 0 & 0 \end{array} \right) \quad B = \left( \begin{array}{c} \frac{\partial f_1}{\partial v} \\ \frac{\partial f_2}{\partial v} \end{array} \right) = \left( \begin{array}{c} 0 \\ \frac{L}{J_0} \end{array} \right) \quad C = \begin{pmatrix} 1 & 0 \end{pmatrix} \quad D = 0$$

$$\rightarrow P(s) = (C \cdot (s \cdot I - A)^{-1} \cdot b + d) = \frac{L/J_0}{s^2}$$

### Control Design:



$$\ddot{\theta} = \frac{L}{J_0} \cdot F - \frac{dmg}{J_0} \cdot \sin(\theta) :$$



$$\Rightarrow \frac{\theta(s)}{\theta_r(s)} = T(s) = \frac{K_\theta K_{\dot{\theta}}}{s^2 + K_\theta s + K_\theta K_{\dot{\theta}}} = \frac{K \omega_0^2}{s^2 + 2\zeta\omega_0 s + \omega_0^2}$$

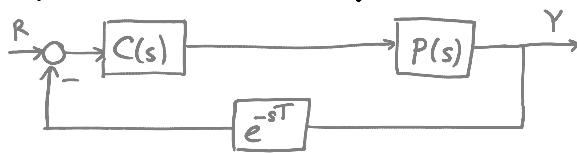
$K=1$  (static gain)     $\omega_0 = \sqrt{K_\theta K_{\dot{\theta}}}$  (nat. freq)     $\frac{1}{2}\sqrt{\frac{K_{\dot{\theta}}}{K_\theta}}$  (damping)

$\omega_0 = 1 \text{ rad/s}$  (aggressiveness)     $\zeta = 1$  (critically damped)

$\hookrightarrow K_\theta = \frac{1}{2} ; K_{\dot{\theta}} = 2$

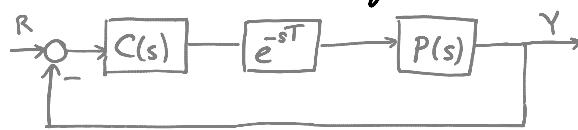
## Smith Predictor (Control design for time-delay)

System output delay:



$$Y(s) = \frac{P(s)C(s)}{1 + P(s)C(s)e^{-sT}} \cdot R(s)$$

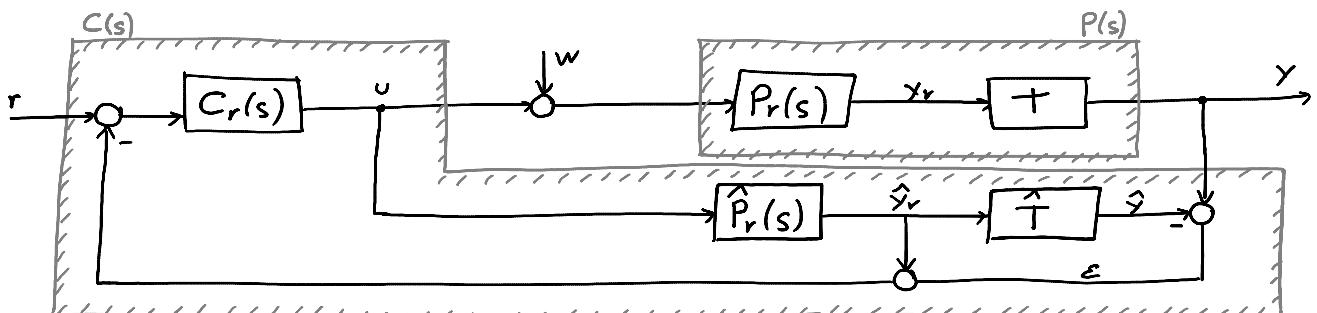
System input delay:



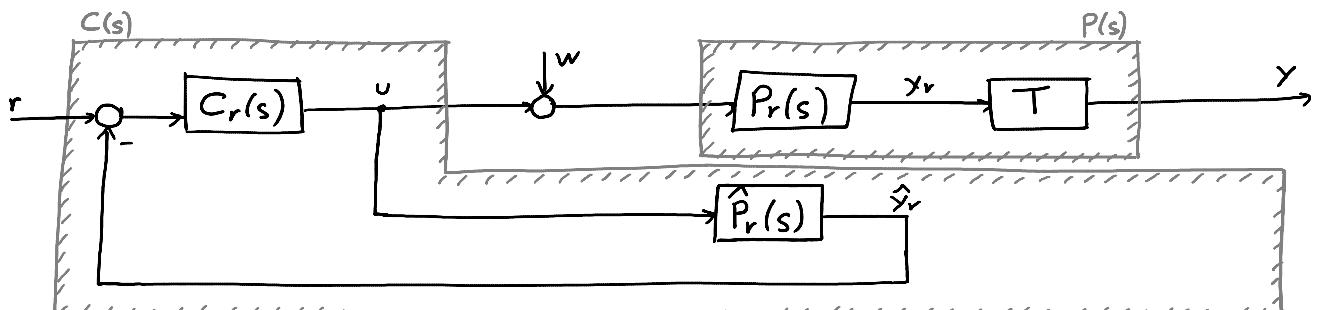
$$Y(s) = \frac{P(s)C(s)e^{sT}}{1 + P(s)C(s)e^{sT}} \cdot R(s)$$

- Requirements:
- $T/(T+\tau) > 0.3$  ( $P(s) \approx \frac{K}{1+\zeta s} \cdot e^{-Ts}$ )
  - $P(s)$  is asymptotically stable.
  - very good model of the plant.

Control Design:

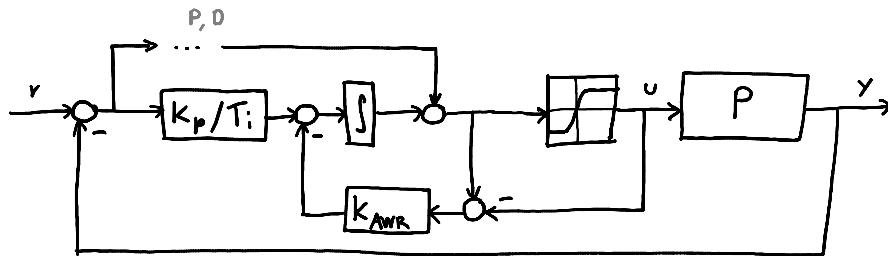


$$w = 0 ; \hat{P}_r(s) = P_r(s) ; \hat{T} = T \quad \Downarrow$$



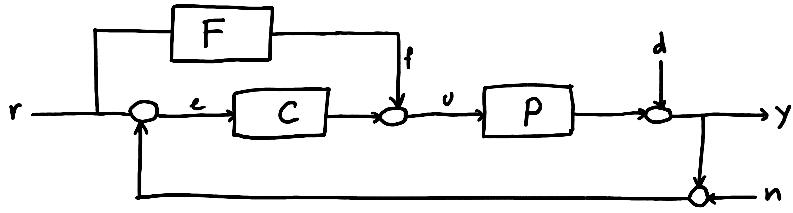
$$\hookrightarrow Y(s) = e^{-sT} \cdot \frac{\hat{P}_r(s)C(s)}{1 + \hat{P}_r(s)C(s)}$$

## Input saturation / Anti reset-windup



Prevent integrators from filling up because of saturation (e.g. 1 in PID)

## Feedforward



### Feedforward:

- No influence on stability
- No effect on disturbances
- Better Tracking performance

$$Y = T \cdot R + P \cdot S \cdot F \cdot R + S \cdot D - T \cdot N \quad \left( T = \frac{PC}{1+PC} \quad S = \frac{1}{1+PC} \right)$$

$$\text{if: } F = P^{-1} \rightarrow Y = (T+S) \cdot R + \dots = R + \dots$$

often impossible b.c.  $P^{-1}$  not causal.

Static feedforward: (Flying arm example)

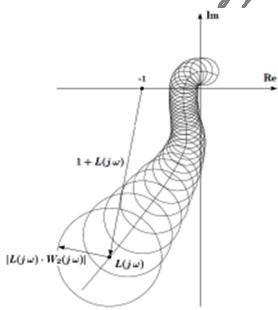
$$f = F_0 \rightarrow F = \frac{dmg}{L} \cdot \sin(\theta_0) \quad (\text{algebraic term})$$

Dynamic feedforward:

Design  $C \rightarrow T_{fb}, S_{fb} \rightarrow$  pick  $r$ -to- $y$ :  $T_{ref} = \frac{1}{(0.2s+1)^2} \rightarrow F = \frac{T_{ref} - T_{fb}}{P \cdot S_{fb}} \rightarrow$  add roll-off:  $F_{roll} = F \cdot \frac{1}{(1+0.01s)^2}$

## Robustness and performance criteria

### Robust Nyquist Theorem:

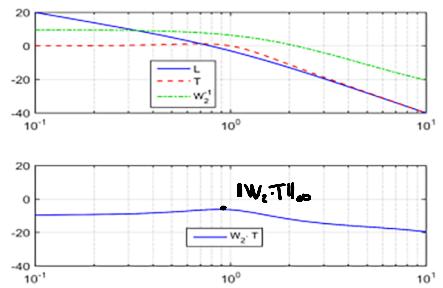


$W_2(i\omega)$ : Model error at freq  $\omega$ .

$$|1+L(i\omega)| > |L(i\omega) \cdot W_2(i\omega)|$$

↓

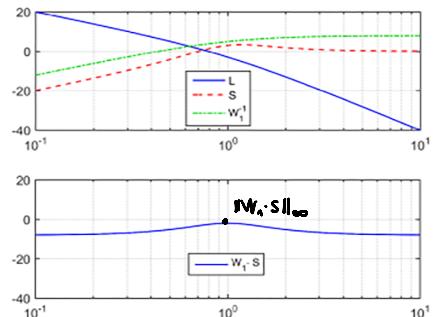
$$\begin{aligned} &= |T(i\omega)| \cdot |W_2(i\omega)| < 1 \quad \forall \omega \in [0, \infty) \\ &\quad \|T(i\omega) \cdot W_2(i\omega)\|_\infty < 1 \end{aligned}$$



### Nominal performance:

$W_1(i\omega)$ : Upper bound for  $S \rightarrow$  good perf.

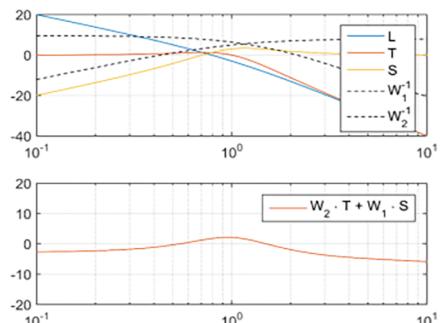
$$\begin{aligned} &= |S(i\omega)| \cdot |W_1(i\omega)| < 1 \quad \forall \omega \in [0, \infty) \\ &\quad \|S(i\omega) \cdot W_1(i\omega)\|_\infty < 1 \end{aligned}$$



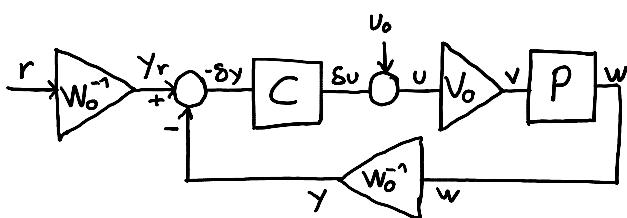
### Robust performance:

Robust Nyq. + Nominal perf.

$$\begin{aligned} &= |S(i\omega)| \cdot |W_1(i\omega)| + |T(i\omega)| \cdot |W_2(i\omega)| < 1 \quad \forall \omega \in [0, \infty) \\ &\quad \|S(i\omega) \cdot W_1(i\omega) + T(i\omega) \cdot W_2(i\omega)\|_\infty < 1 \end{aligned}$$



## Controller implementation



Physics / Experiment

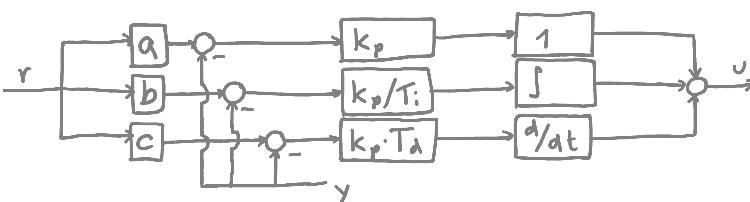
- Mod.  $\frac{d}{dt} z(t) = f(z(t), v(t))$
- Norm.  $w(t) = g(z(t), v(t))$
- Lin.  $\frac{d}{dt} \delta x(t) = f_0(x(t), u(t))$
- $y(t) = g_0(x(t), u(t))$
- $\frac{d}{dt} \delta x(t) = A \cdot \delta x(t) + b \cdot \delta u(t)$
- $\delta y(t) = c \cdot \delta x(t) + d \cdot \delta u(t)$

Plant Model based on Physics or Experiment

Normalize all to 0-1  
 $x_i = \frac{x_i - x_{i,c}}{x_{i,c}}$ ;  $u = \frac{v}{V_0}$ ;  $y = \frac{w}{W_0}$

Linearize around eq.  
 $\delta x_i = x_i - x_{i,c}$ ;  $\delta u = u - u_c$ ;  $\delta y = y - y_c$

### Setpoint weighting for PID



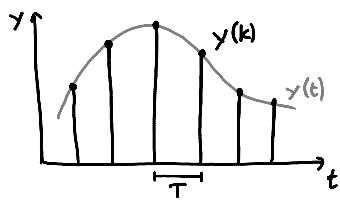
$$0 < a < 1$$

$$b = 1$$

$$c = 0$$

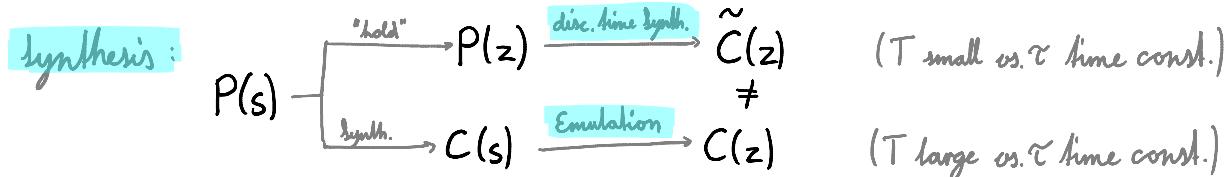
(other options: low-pass before r; roll-off after u.)

## Discrete-time system



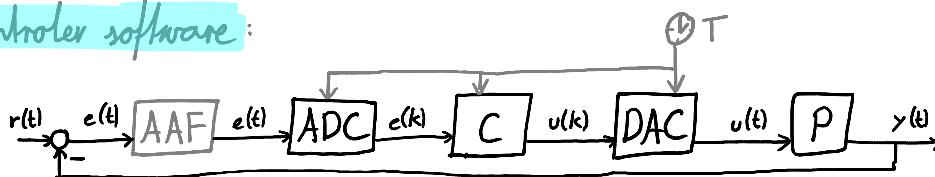
$$\begin{aligned} \dot{x}(t) &= f(x(t), u(t)) \\ y(t) &= g(x(t), u(t)) \end{aligned} \Rightarrow \begin{aligned} x(k+1) &= f_k(x(k), u(k)) \\ y(k) &= g_{k\cdot}(x(k), u(k)) \end{aligned}$$

Discrete final value theorem:  $\lim_{k \rightarrow \infty} w(kT) = \lim_{z \rightarrow 1} (z-1) W(z) = \lim_{z \rightarrow 1} (1-z^{-1}) W(z^{-1})$

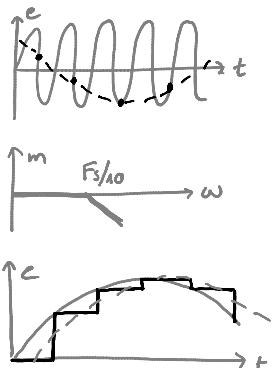


Emulation       $(P(s) \rightarrow C(s) \rightarrow C(z))$

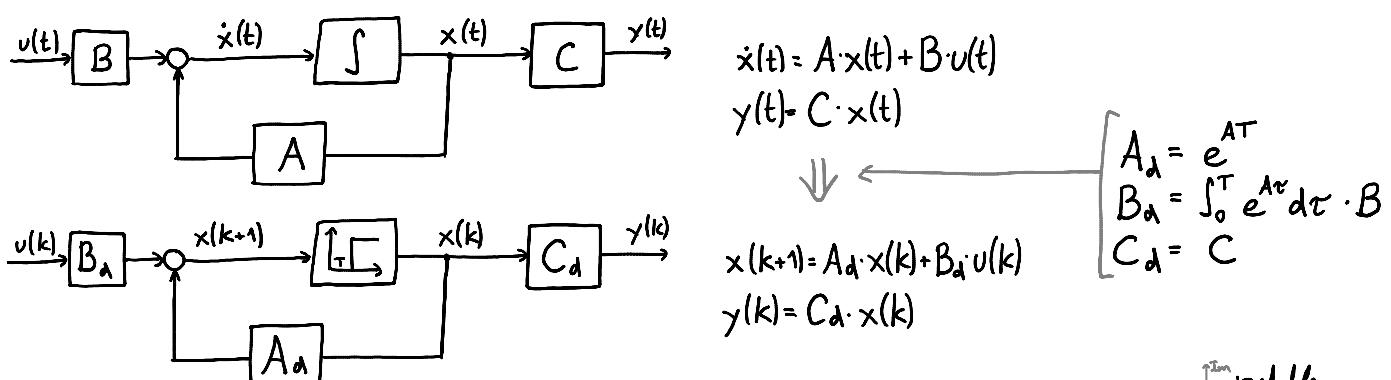
Controller software:



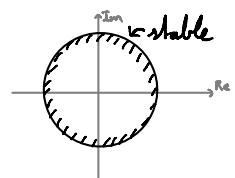
- Anti-aliasing filter AAF: Sampling Rate  $F_s = \frac{1}{T} \geq 10 \cdot \frac{\omega_c}{2\pi}$   
or Lowpass-filter for  $F_s/10$  before C
- Digital-Analog conv. DAC: introduces  $T/2$  time delay!



Controller discretization: (in state-space)



Stability:  $\operatorname{Re}(\lambda_{c,i}) < 0 \quad \forall i; \lambda_{c,i} = \operatorname{EW}(A) \Rightarrow |\lambda_{d,i}| < 1 \quad \forall i; \lambda_{d,i} = \operatorname{EW}(A_d)$



## Controller discretization: (frequency domain)

$$C(s) \rightarrow C(z) \quad \text{mit} \quad z^n \cdot u(k) = u(k+n)$$

$$(z \cdot u(k) = u(k+1))$$

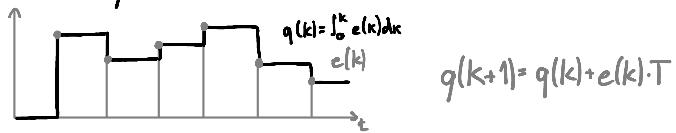
• Direct:

$$C(z) = C(s) \Big|_{s=\ln(z)/T_s}$$

$C(z)$  identical to  $C(s)$ !

• Euler forward:

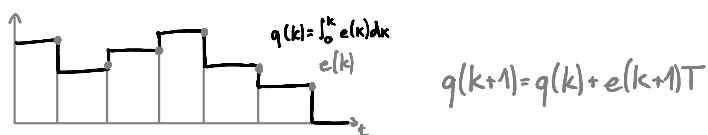
$$C(z) = C(s) \Big|_{s=\frac{z-1}{T}}$$



$C(z)$  can become unstable!  
(bad)

• Euler backward:

$$C(z) = C(s) \Big|_{s=\frac{z-1}{zT}}$$



$C(z)$  stable if  $C(s)$  stable!  
(good)

• Tustin (trapez.):

$$C(z) = C(s) \Big|_{s=\frac{2}{T} \cdot \frac{z-1}{z+1}}$$

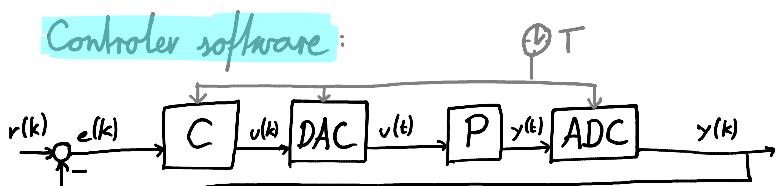


$C(z)$  stable if  $C(s)$  stable!  
(best)

**Recap:** Design  $C(s) \rightarrow$  Pick  $F_s \rightarrow$  AAF  $\rightarrow$  Evaluate  $C(z) \rightarrow$  Analyse stability  $\rightarrow$  Implement

## Discrete time synthesis

$$(P(s) \rightarrow P(z) \rightarrow C(z))$$



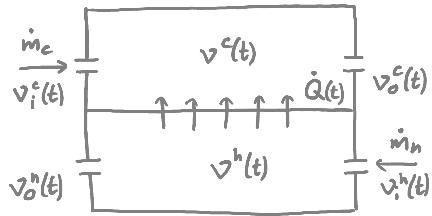
## Plant discretization:

$$P(z) = (1-z^{-1}) \cdot \sum \left\{ \lambda^{-1} \left( \frac{P(s)}{s} \right) (kT) \right\}$$

$$(W(z) = \sum \{w(k)\} = \sum_{k=0}^{\infty} w(k) \cdot z^k)$$

# MIMO Time-domain

## Modeling:



- $x_1(t) = v^h(t)$ : Temp. hot fluid
- $x_2(t) = v^c(t)$ : Temp. cold fluid
- $U_1(t) = v_i^h(t)$ : Temp. entering hot fluid
- $U_2(t) = v_i^c(t)$ : Temp. entering cold fluid
- $y_1(t) = v_o^h(t)$ : Temp. exiting hot fluid
- $y_2(t) = v_o^c(t)$ : Temp. exiting cold fluid

$$\begin{aligned}\frac{d}{dt} U^h &= \dot{H}_i^h - \dot{H}_o^h - \dot{Q} \\ \frac{d}{dt} U^c &= \dot{H}_i^c - \dot{H}_o^c + \dot{Q} \\ \dot{Q} &= k \cdot F(v^h - v^c)\end{aligned}$$

$$\begin{aligned}U^{h,c} &= g \cdot V \cdot c \cdot v^{h,c} \\ \dot{H}_{i,o}^{h,c} &= \dot{m} \cdot c \cdot v_{i,o}^{h,c}\end{aligned}$$

$$\begin{aligned}g V c \frac{dx_1}{dt} &= \dot{m} c (U_1 - x_1) - k F (x_1 - x_2) \\ g V c \frac{dx_2}{dt} &= \dot{m} c (U_2 - x_2) - k F (x_1 - x_2)\end{aligned}$$

$$\begin{aligned}\tau \dot{x}_1 &= -x_1 + \alpha x_2 + \beta U_1 \\ \tau \dot{x}_2 &= -x_2 + \alpha x_1 + \beta U_2\end{aligned}\quad \begin{aligned}\tau &= \frac{g V c}{\dot{m} c + k F} \\ \alpha &= \frac{k F}{\dot{m} c + k F} \\ \beta &= \frac{\dot{m} c}{\dot{m} c + k F}\end{aligned}$$

$$\begin{aligned}\begin{pmatrix} \dot{x}_1 \\ \dot{x}_2 \end{pmatrix} &= \begin{pmatrix} -1/\tau & \alpha/\tau \\ \alpha/\tau & -1/\tau \end{pmatrix} \cdot \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} + \begin{pmatrix} \beta/\tau & 0 \\ 0 & \beta/\tau \end{pmatrix} \begin{pmatrix} U_1 \\ U_2 \end{pmatrix} \\ \begin{pmatrix} y_1 \\ y_2 \end{pmatrix} &= \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \cdot \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} + \begin{pmatrix} 0 & 0 \\ 0 & 0 \end{pmatrix} \begin{pmatrix} U_1 \\ U_2 \end{pmatrix}\end{aligned}$$

State-space:  $\frac{d}{dt} \underline{x} = \underline{\underline{A}} \underline{x} + \underline{\underline{B}} \underline{u}$

$$n \begin{pmatrix} 1 \\ \vdots \\ 1 \end{pmatrix} = n \begin{pmatrix} n \\ \vdots \\ n \end{pmatrix} \cdot n \begin{pmatrix} 1 \\ \vdots \\ 1 \end{pmatrix} + n \begin{pmatrix} m \\ \vdots \\ m \end{pmatrix} \cdot m \begin{pmatrix} 1 \\ \vdots \\ 1 \end{pmatrix}$$

$$x \in \mathbb{R}^n$$

$$u \in \mathbb{R}^m$$

$$y \in \mathbb{R}^p$$

$$\underline{x} = \underline{\underline{C}} \underline{x} + \underline{\underline{D}} \underline{u}$$

$$p \begin{pmatrix} 1 \\ \vdots \\ 1 \end{pmatrix} = p \begin{pmatrix} n \\ \vdots \\ n \end{pmatrix} \cdot n \begin{pmatrix} 1 \\ \vdots \\ 1 \end{pmatrix} + p \begin{pmatrix} m \\ \vdots \\ m \end{pmatrix} \cdot m \begin{pmatrix} 1 \\ \vdots \\ 1 \end{pmatrix}$$

Equilibria:  $0 = \underline{\underline{A}} \cdot \underline{x}_e + \underline{\underline{B}} \cdot \underline{u}_e \rightarrow \underline{x}_e = -\underline{\underline{A}}^{-1} \underline{\underline{B}} \cdot \underline{u}_e$

Stability:  $\det(\lambda \cdot I - \underline{\underline{A}}) = 0 \rightarrow \operatorname{Re}(\lambda_n) < 0 \rightarrow \text{asympt. stable}$

Controllability:  $R_n = [B, AB, \dots, A^{n-1}B] \in \mathbb{R}^{n \times (n \cdot m)}$  has indep. rows

Observability:  $O_n = [C^T, AC^T, \dots, (A^{n-1})^T C^T]^T \in \mathbb{R}^{(n \cdot p) \times n}$  has indep. columns

## MIMO Frequency-domain

Transfer func.:  $\underline{P}(s) = \underline{C} \cdot (s \cdot \underline{I} - \underline{A})^{-1} \cdot \underline{B} + \underline{D}$  (or exp. holding  $U$ 's...)

$$\underline{Y}(s) = \underline{P}(s) \cdot \underline{U}(s) \Leftrightarrow \begin{pmatrix} Y_1(s) \\ Y_2(s) \\ \vdots \\ Y_p(s) \end{pmatrix} = \begin{pmatrix} P_{11}(s) & P_{12}(s) & \cdots & P_{1m}(s) \\ P_{21}(s) & P_{22}(s) & \cdots & P_{2m}(s) \\ \vdots & \ddots & \ddots & \vdots \\ P_{p1}(s) & P_{p2}(s) & \cdots & P_{pm}(s) \end{pmatrix} \cdot \begin{pmatrix} U_1(s) \\ U_2(s) \\ \vdots \\ U_m(s) \end{pmatrix}$$

Poles: Roots of the least common denominator of all minors of  $P(s)$

Zeros: Roots of the greatest common divisor of the numerators of the maximum minors of  $P(s)$

Pole/Zero Example:

$$P(s) = \begin{pmatrix} \frac{2}{s+1} & \frac{3}{s+2} \\ \frac{1}{s+1} & \frac{1}{s+1} \end{pmatrix} \quad \text{Minors: } \frac{2}{s+1}, \frac{1}{s+1}, \frac{1}{s+1}, \frac{3}{s+2}, \frac{(-s+1)}{(s+1)^2(s+2)}$$

least comm. den.:  $(s+1)^2(s+2) \rightarrow \text{IT}_{1,2} = -1, \text{IT}_3 = -2$   
great. comm. div of max minor:  $(-s+1) \rightarrow \xi_1 = 1$

Zeros/Pole cancellation: (... ? ...)

Relative Gain Array (RGA):

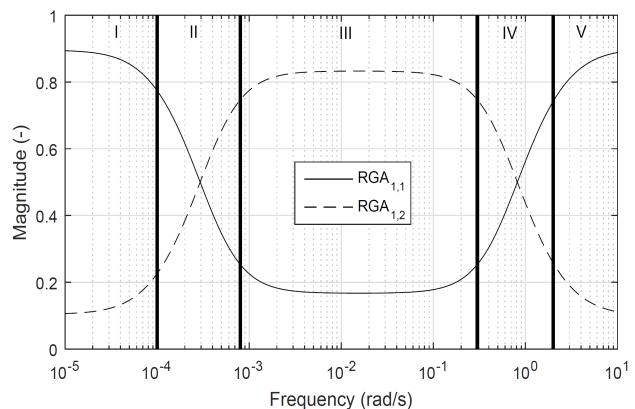
$$\text{RGA}(s) = P(s) \odot (P(s)^{-1})^T$$

↑ elementwise multip.

(if  $P$  not square use pseudo-inverse)

$$\begin{cases} \text{RGA}_{1,1} = \text{RGA}_{2,2} \approx 1 \Rightarrow \text{SISO } U_1 \rightarrow Y_1, U_2 \rightarrow Y_2 \\ \text{RGA}_{1,1} = \text{RGA}_{2,2} \approx 0 \Rightarrow \text{SISO } U_1 \rightarrow Y_2, U_2 \rightarrow Y_1 \end{cases}$$

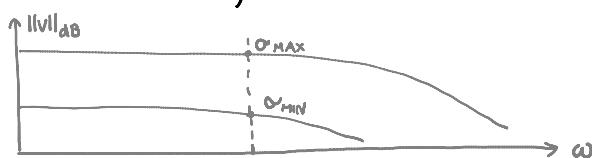
else  $\Rightarrow$  MIMO



Frequency response:

$$U(t) = \begin{pmatrix} \mu_1 \cdot \cos(\omega t + \psi_1) \cdot h(t) \\ \mu_2 \cdot \cos(\omega t + \psi_2) \cdot h(t) \\ \vdots \\ \mu_m \cdot \cos(\omega t + \psi_m) \cdot h(t) \end{pmatrix} \Rightarrow Y_\infty(t) = \begin{pmatrix} v_1 \cdot \cos(\omega t + \varphi_1) \cdot h(t) \\ v_2 \cdot \cos(\omega t + \varphi_2) \cdot h(t) \\ \vdots \\ v_m \cdot \cos(\omega t + \varphi_m) \cdot h(t) \end{pmatrix}$$

$$\min \sigma_i(P(j\omega)) \leq \frac{\|v\|}{\|\mu\|} \leq \max \sigma_i(P(j\omega))$$



$$\left( \sigma_i(P(j\omega)) : \text{singular values} \right) = \sqrt{\text{EW}(P^T(j\omega) \cdot P(j\omega))}$$

## MIMO Feedback system



$$Y(s) = \underbrace{P(s) \cdot C(s)}_{L_e(s)} \cdot R(s) - \underbrace{P(s) C(s)}_{L_y(s)} \cdot Y(s)$$

$$E(s) = R(s) - \underbrace{P(s) \cdot C(s)}_{L_e(s)} \cdot E(s)$$

$$U(s) = C(s) \cdot R(s) - \underbrace{C(s) \cdot P(s)}_{L_u(s)} \cdot U(s)$$

loop gain:  $L_e(s) = P(s) \cdot C(s)$

$$L_u(s) = P(s) \cdot C(s)$$

Return difference:  $D_e(s) = I + L_e(s)$

$$D_u(s) = I + L_u(s)$$

sensitivity:  $S_e(s) = (I + L_e(s))^{-1}$

$$S_u(s) = (I + L_u(s))^{-1}$$

Comp. sensitivity:  $T_e(s) = (I + L_e(s))^{-1} \cdot L_e(s)$

$$T_u(s) = (I + L_u(s))^{-1} \cdot L_u(s)$$

$$T_e(s) + S_e(s) = I$$

$$T_u(s) + S_u(s) = I$$

## Closed-loop Stability:

- Nyquist theorem:

$$n_c = n_0/2 + n_+ \Rightarrow \text{stable}$$

$n_0$ : # of poles of  $L_e$  with  $\text{Re}(\lambda)=0$

$n_+$ : # of poles of  $L_e$  with  $\text{Re}(\lambda)>0$

$n_c$ : # of CCW encirclements of -1 by  $N(\omega)$

$$N(\omega) = \det(I + L_e(\omega i)) \quad \omega \in [-\infty, \infty]$$

- State-space analysis:

Plant:  $\frac{d}{dt} \underline{x}(t) = \underline{A} \underline{x}(t) + \underline{B} \underline{u}(t)$

$$\underline{x}(t) = \underline{C} \underline{x}(t)$$

Controller:  $\frac{d}{dt} \underline{z}(t) = \underline{F} \underline{z}(t) + \underline{G} \underline{e}(t)$

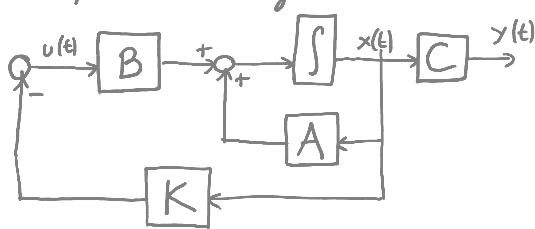
$$\underline{u}(t) = \underline{H} \underline{z}(t)$$

$$\left\{ \begin{array}{l} \frac{d}{dt} \begin{pmatrix} \underline{x} \\ \underline{z} \end{pmatrix} = \begin{pmatrix} \underline{A} & \underline{B} \cdot \underline{H} \\ -\underline{G} \cdot \underline{C} & \underline{F} \end{pmatrix} \cdot \begin{pmatrix} \underline{x} \\ \underline{z} \end{pmatrix} + (\dots) \\ \frac{d}{dt} \underline{\tilde{x}} = \underline{\tilde{A}} \cdot \underline{\tilde{x}} + (\dots) \end{array} \right.$$

all  $\text{Re}(\text{EW})$  of  $\underline{\tilde{A}} < 0 \Rightarrow \text{stable}$

## Regulators (stabilization, dist. rejection, no ref. track)

- State-feedback Regulator:



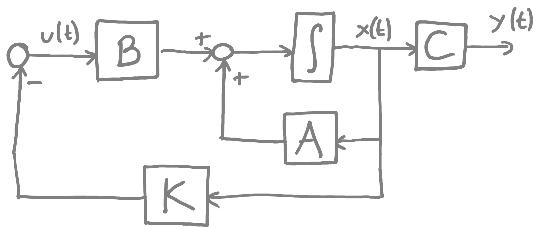
$$u(t) = -K \cdot x(t)$$

$$A_{cl} = A - B \cdot K \quad (\dot{x} = A_{cl} \cdot x)$$

$n \times n - n \times m = n \times n$

↳ pick  $K$  to move poles of  $A_{cl}$

- Linear Quadratic Regulator (LQR):



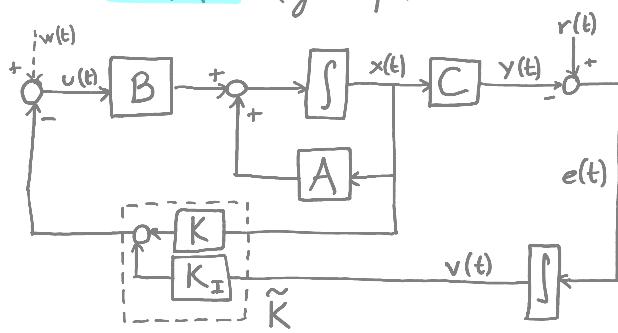
$$\text{minimize } \int_0^\infty \underbrace{\dot{x} \cdot Q \cdot \dot{x}^T}_{Q^T = Q \geq 0} + \underbrace{u \cdot R \cdot u^T}_{R^T = R > 0} dt$$

$$K = R^{-1} \cdot B^T \cdot \Phi \quad (\Phi \cdot B \cdot R^{-1} \cdot B^T \cdot \Phi - \Phi \cdot A - A^T \cdot \Phi - Q = 0)$$

$$\text{good choice: } Q = C^T \cdot C \quad R = r \cdot I_{m \times m}$$

( $Q \gg R \rightarrow$  cheap ctrl.E    $Q \ll R \rightarrow$  expensive ctrl.E)

- LQRI (yes ref. track!):



$$\tilde{K} = \begin{pmatrix} K & -K_I \end{pmatrix} \mathbb{I}_m \quad \tilde{x} = \begin{pmatrix} x \\ v \end{pmatrix} \mathbb{I}_n$$

$$\hookrightarrow \tilde{Q} = \begin{pmatrix} Q & 0 \\ 0 & \gamma \cdot I_{p \times p} \end{pmatrix}; \quad \tilde{R} = R$$

→ solve for  $\tilde{K}$  like LQR then extract  $K, K_I$

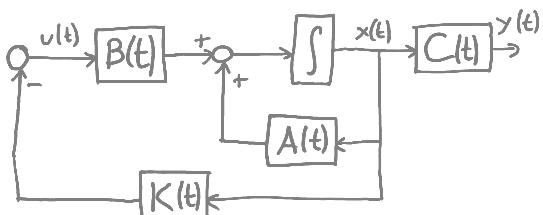
$$\left( \frac{d}{dt} \tilde{x} \cdot \tilde{x}(t) = \tilde{A} \cdot \tilde{x}(t) + \tilde{B}_u \cdot u(t) + \tilde{B}_r \cdot r(t) + \tilde{B}_w \cdot w(t) \right)$$

$$\begin{pmatrix} \frac{d}{dt} \tilde{x} \\ \tilde{x} \end{pmatrix} = \begin{pmatrix} A & 0 \\ C & 0 \end{pmatrix} \begin{pmatrix} \tilde{x} \\ v \end{pmatrix} + \begin{pmatrix} B_u & 0 \\ B_r & 0 \\ B_w & 0 \end{pmatrix} \begin{pmatrix} u \\ r \\ w \end{pmatrix}$$

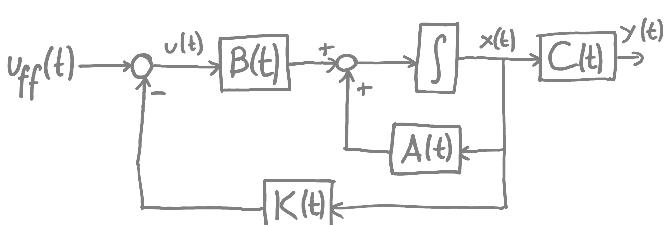
$$\text{minimize } \int_0^T \dot{x} \cdot Q \cdot \dot{x}^T + u \cdot R \cdot u^T dt + x(T)^T P x(T)$$

solve for  $K(t) \rightarrow$  store in memory

- Finite horizon LQR:



- Feedforward LQR (+finite horizon):



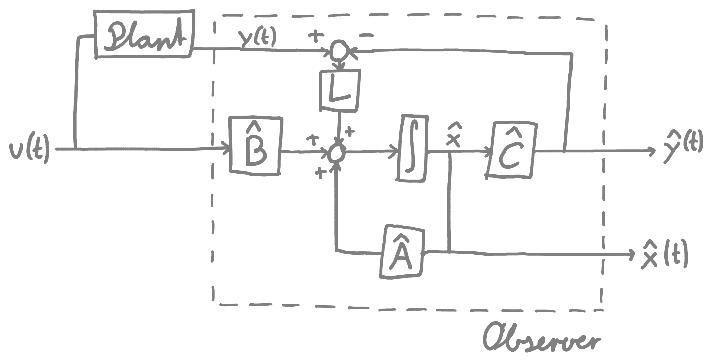
$$\min_{u(t)} \int_0^T \underbrace{L(x(t), u(t)) dt}_{\text{Stage cost}} + \underbrace{m(x(T))}_{\text{Terminal cost}}$$

Initial Conditions  
Constraints

$$u_{ff}(t)$$

## linear Quadratic Gaussian (LQG)

State observer:



$$(\hat{A} = A, \hat{B} = B, \hat{C} = C \text{ from Plant})$$

$$\bar{x}(t) = x(t) - \hat{x}(t) \quad (\text{observation error})$$

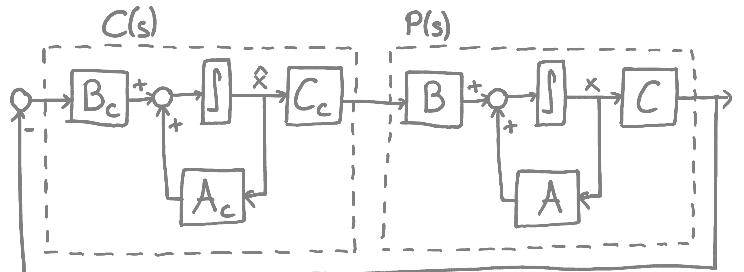
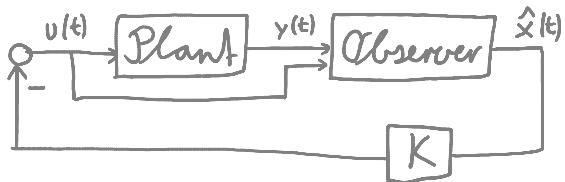
$$\frac{d}{dt} \bar{x}(t) = (A - L \cdot C) \cdot \bar{x}(t)$$

asym. stab. EW  $\rightarrow \bar{x}(t \rightarrow \infty) = 0$

$$L^T = \frac{1}{q} \cdot C \cdot \Psi^{\text{co}} \quad \left( \frac{1}{q} \Psi \cdot C^T \cdot \Psi - \Psi \cdot A^T - A \Psi - B \cdot B^T = 0 \right)$$

$q$  large: fast convergence of  $\hat{x}$  to  $x$   
 $q$  small: noise amplification  
 $B \cdot B^T$ : pick somehow...

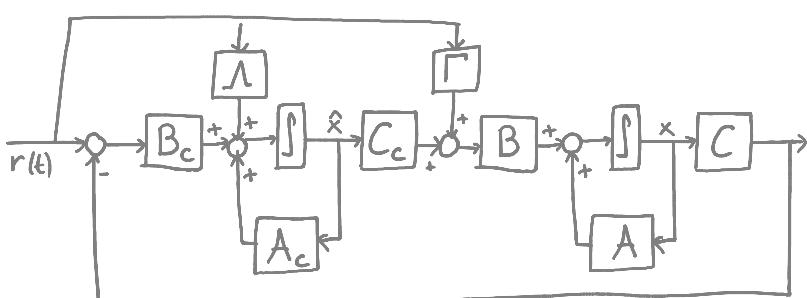
LQG Controller:



$$A_c = A - BK - LC ; B_c = -L ; C_c = -K$$

$$\tilde{x} = \begin{pmatrix} x \\ \hat{x} \end{pmatrix} \rightarrow \tilde{A}_{cl} = \begin{pmatrix} A & -BK \\ LC & A - BK - LC \end{pmatrix}, \tilde{B}_r = \begin{pmatrix} B \\ B \end{pmatrix}, \tilde{C} = (C \mid 0)$$

LQG reference tracking:



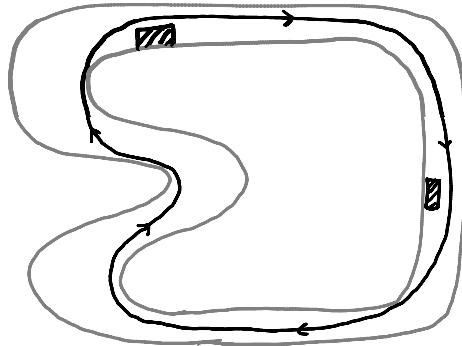
$$\Gamma = -(\tilde{C} \cdot \tilde{A}_{cl}^{-1} \cdot \tilde{B}_r)^{-1}$$

$$\Lambda = L + B \cdot \Gamma$$

$\Gamma, \Lambda$  counteract observation  
 error in  $\hat{x} \rightarrow$  no static error

## Model Predictive Control (MPC)

- 1. Measure/Estimate current state
- 2. Find optimal input trajec. for planning window T
- 3. Implement first st part of trajectory



## Matrix Minors

$$M = \begin{pmatrix} a & b & c \\ d & e & f \\ g & h & i \end{pmatrix} \Rightarrow \text{Submatrices: } \begin{pmatrix} a & b & c \\ d & e & f \\ g & h & i \end{pmatrix}, \begin{pmatrix} a & b \\ d & e \end{pmatrix}, \begin{pmatrix} a & c \\ d & f \end{pmatrix}, \dots, (g), (h), (i)$$

Minors:  $\det([\text{submatrix}])$

Max. Minors:  $\det([\text{biggest submatrix}])$

## Singular value decomposition (SVD)

$$M = U \cdot \Sigma \cdot V^T$$

↑ diag. Mat!

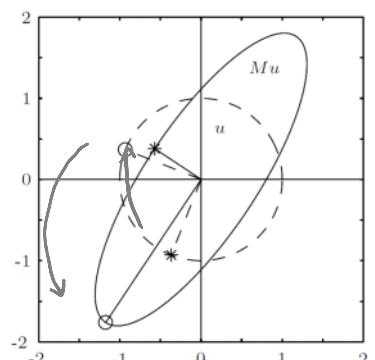
$$p \begin{array}{|c|} \hline M \\ \hline \end{array} = p \begin{array}{|c|} \hline U \\ \hline \end{array} \cdot p \begin{array}{|c|} \hline \Sigma \\ \hline \end{array} \cdot p \begin{array}{|c|} \hline V^T \\ \hline \end{array}$$

$$\begin{pmatrix} \det(U) = \det(V) = 1 \\ U \cdot U^T = I ; V \cdot V^T = I \end{pmatrix}$$

e.g.  $M = \begin{pmatrix} 1.3 & 0.1 \\ 1.5 & -1 \end{pmatrix} = \begin{pmatrix} -0.55 & -0.83 \\ -0.83 & 0.55 \end{pmatrix} \cdot \begin{pmatrix} 2.12 & 0 \\ 0 & 0.68 \end{pmatrix} \cdot \begin{pmatrix} -0.93 & 0.36 \\ -0.36 & -0.93 \end{pmatrix}$

$$\sigma_1 = 2.12 \quad M \cdot \begin{pmatrix} -0.93 \\ 0.36 \end{pmatrix} = 2.12 \cdot \begin{pmatrix} -0.55 \\ -0.83 \end{pmatrix}$$

$$\sigma_2 = 0.68 \quad M \cdot \begin{pmatrix} -0.36 \\ -0.93 \end{pmatrix} = 0.68 \cdot \begin{pmatrix} -0.83 \\ 0.55 \end{pmatrix}$$



Singular Values:  $\sigma_i = \sqrt{\text{EW}_i(\underbrace{M^T \cdot M}_{\text{conj. if complex}})}$

Induced Norm:  $\|M\| = \max_i(\sigma_i)$  (maximum amplification)