

14/5-18 Föreläsning 12

1) From output - to state - feedback design

2) Eigenvalue assignment (EA)

3) Optimal eigenvalue assignment (Linear quadratic control, (LQR))

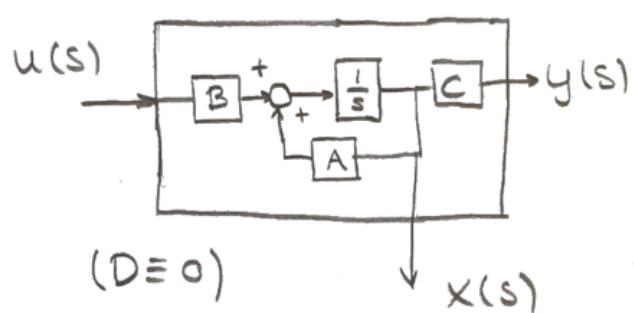
1). From output - to state - feedback design

Idea: Instead of $y(t)$, let's use the state $x(t)$ for $u(t)$.

IO-model



state-space models



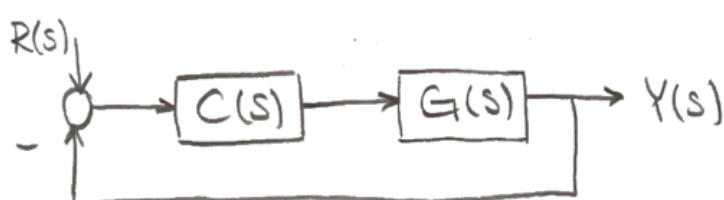
$$G(s) = C(sI - A)^{-1}B$$

Input to output vs. Internal

i) input to $x(s)$

ii) $x(s)$ to $y(s)$

IO-model based controller design
(output-feedback)



We know how to find $C(s)$

$$u(s) = C(s)(R(s) - Y(s))$$

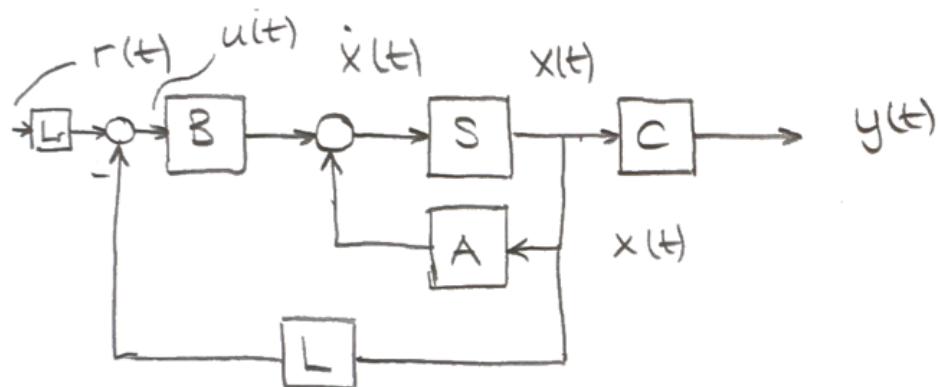
state feedback

$X(s)$ and feed it back (time domain)

$$u(t) = -Lx(t) + L_r r(t)$$

Condition: $x(t)$ measured.

$$D \equiv 0$$



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

$$y(t) = Cx(t) \quad (D \equiv 0)$$

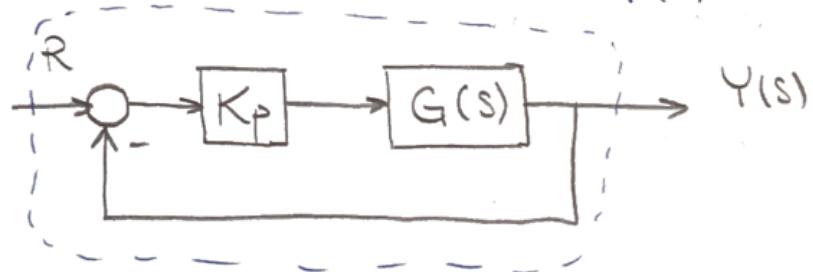
How design L, L_r ?

What are the benefits of SF?

By using only $y(t)$ for controller design, some internal ($x(t)$) related info is hidden / not used.

Eg. $G(s) = \frac{1}{s^2 - s - 2}$, Find $C(s) = K_p$ that stabilizes $T(s)$

stabilizes $T(s)$.



$$T(s) = Y(s) / R(s)$$

comp. sens. fcn.

$$T(s) = \frac{L(s)}{1 + L(s)} ; \quad L(s) = G(s) K_p$$

$$T(s) = \frac{\frac{K_p}{s^2 - s - 2}}{1 + \frac{K_p}{s^2 - s - 2}} = \frac{K_p}{s^2 - s - 2 + K_p} , \text{ stable?}$$

Need for checking the poles of $T(s)$

$$s^2 - s - 2 + K_p = 0$$

$$P_{1,2} = \frac{-(-1) \pm \sqrt{1 - 4(K_p - 2)}}{2} , \forall K_p \text{ we will have}$$

1 pole $\operatorname{Re}(p) > 0$
 \Rightarrow unstable.

The controller structure is not enough.
(endast en parameter influeras utav K_p ,
inte $(-s)$)

\Rightarrow We need a PD-controller!

$$C(s) = K_p(1 + T_d \cdot s)$$

$$T_d \rightarrow s^2 + (K_p T_d - 1)s + K_p - 2 = 0$$

We now influence both coefficients in the characteristic polynomial and hence we can stabilize. What if we have

$$G(s) = b_0 \frac{\prod_{j=1}^m (s - z_j)}{\prod_{i=1}^n (s - p_i)}$$

\Rightarrow That claims n th order PD-term
for stabilization.

In time domain:

$$\sum_{i=0}^n a_i \frac{d^{(n-i)} y(t)}{dt^{(n-i)}} = \sum_{j=0}^m b_j \frac{d^{(m-j)} u}{dt^{(m-j)}}$$

$a_0 = 1$ (monic polynomial)

Introduce

$$x(t) = \left[\begin{array}{c} \frac{dy^{(n-1)}}{dt^{(n-1)}} \\ \vdots \\ y(t) \end{array} \right] \quad \left\{ \text{n elements} \right.$$

$$x(t) \in \mathbb{R}^n$$

$m=0 \downarrow$

$$\dot{x}(t) = \begin{bmatrix} -a_1 & -a_2 & \dots & -a_n \\ 1 & 0 & & 0 \\ 0 & 1 & & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 0 \end{bmatrix} x(t) + \begin{bmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix} u(t)$$

$$y(t) = [0 \dots 0 1] x(t)$$

What if $x(t)$ is measured?

Let's use it

2) Eigenvalue assignment

E.g. $\ddot{y}(t) - \dot{y}(t) - 2y(t) = u \quad L^{-1}\{Y(s) = G(s)U(s)\}$

$$x(t) = \begin{bmatrix} \dot{y}(t) \\ y(t) \end{bmatrix}$$

$$\dot{x}(t) = Ax(t) + Bu(t), \quad y(t) = cx(t), \quad D \in \mathbb{O}$$

$$A = \begin{bmatrix} \alpha_1 & -\alpha_2 \\ 1 & 0 \end{bmatrix}, \quad B = \begin{bmatrix} 1 \\ 0 \end{bmatrix}, \quad C = [0 \ 1]$$

Let's use state-space for stabilization

When can we say a state-space form is stable

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

$$A \in \mathbb{R}^{n \times n}$$

stability

$$\det(\lambda I - A)^{-1} = 0 \quad \text{eigenvalues of } A$$

$\operatorname{Re}(\lambda_i) < 0 \quad \forall i$ then a state-space model is asymptotically stable.

\Rightarrow If eigenvalues are unstable, let's move them to stable domain. (assign stable eigenvalues)

Assume $x(t)$ is measurable

$$u(t) = -L \cdot x(t) + L_r \cdot r(t) \quad ; \quad L \in \mathbb{R}^{1 \times n}; \quad L_r \in \mathbb{R}$$

\uparrow \uparrow
 state reference

How to find L, L_r ?

$$\dim(x) = n$$

Two degree of freedom: L, L_r

DOF 1) L has to stabilize the state-space closed-loop

$$\dot{x}(t) = Ax(t) + B(-Lx(t) + L_r r(t))$$

$$\dot{x}(t) = \underbrace{(A - BL)}_{\text{closed-loop state-space matrix}} x(t) + BL_r r(t) *$$

closed-loop state-space matrix

$$y(t) = Cx(t) + Du(t) = (C - DL)x(t) + DL_r r(t)$$

↑ direct feedthrough active

L has to be chosen such that

$$\det(I - \lambda(A - BL)) \quad \forall i \operatorname{Re}(\lambda) < 0$$

DOF 2) $L_r = ?$

L_r is a shaper, changes $r(t)$

⇒ use to shape $r_\infty = y_\infty$

Match asymptotical tracking of y_∞ over r_∞ .

Steady state tracking

$$0 = (A - BL)x_\infty + BL_r \cdot r_\infty$$

$$y_\infty = (C - DL)x_\infty + DL_r \cdot r_\infty$$

Given L stabilizing $(A - BL)$

$$x_\infty = -(A - BL)^{-1} \cdot BL_r \cdot r_\infty$$

$$y_\infty = ((C - DL)(BL - A)^{-1} B + D)L_r \cdot r_\infty$$

$$y_\infty = r_\infty$$

$$\frac{1}{L_r} = (C - DL)(BL - A)B + D$$

\Rightarrow first L, then L_r

Algorithm (eigenvalue assignment)

Given (A, B, C, D)

Step 1) Check controllability, i.e. (A, B) is controllable. Full state controllability is a must (Kalman rank condition).

Step 2) If controllable $(A, B, C, D) \xrightleftharpoons[T]{T^{-1}} (A_c, B_c, C_c, D_c)$ i.e. transform it into 'canonical' form.

Step 3) for OL:

$$\det(\lambda I - A) = (\lambda - p_1)(\lambda - p_2) \dots (\lambda - p_n) = \\ = \lambda^n + a_1 \lambda^{n-1} + \dots + a_n$$

We know the closed-loop locations

$$\det(\lambda I - A + BL) = (\lambda - \tilde{p}_1)(\lambda - \tilde{p}_2) \dots (\lambda - \tilde{p}_n) \quad \leftarrow CL$$

again $\{p_1 \dots p_n\}$

$$\underbrace{\{\tilde{p}_1 \dots \tilde{p}_n\}}$$

are known

$$L = [l_1, l_2 \dots l_n] \quad \forall i = 1 \dots n$$

$$l_i = \tilde{a}_i - a_i \quad \begin{array}{l} \text{open loop coeffs.} \\ \text{closed loop coeffs.} \end{array} \quad \begin{array}{l} \text{(reason why we} \\ \text{need it in} \\ \text{canonical form)} \end{array}$$

So, given a controller canonical form

$$u(t) = Lx(t) = -[l_1 \dots l_n]x(t)$$

Closed-loop

$$\dot{x}(t) = \begin{bmatrix} -a_1 & -a_2 & \dots & -a_n \\ 1 & \ddots & & 0 \\ 0 & & \ddots & 0 \\ & & & 1 \end{bmatrix} x(t) - \begin{bmatrix} 1 \\ \vdots \\ 0 \end{bmatrix} \underbrace{[l_1 \ l_2 \ \dots \ l_n]}_{-u(t)} x(t)$$

$$\dot{x}(t) = \begin{bmatrix} -a_1 - l_1 & -a_2 - l_2 & \dots & -a_n - l_n \\ 1 & \ddots & & 0 \\ \vdots & & \ddots & \vdots \\ 0 & & & 1 \end{bmatrix} x(t)$$

$$r \equiv 0$$

$$\det(\lambda I - A + BL) = \lambda^n + \underbrace{(a_1 + l_1)}_{\tilde{a}_1} \lambda^{n-1} + \dots + a_n + l_n$$

$$\tilde{a}_1 = a_1 + \tilde{a}_1 - a_1$$

Remark: eigenvalue allocation/poleplacement/Akerman

E.g.

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

Find L , such that $\tilde{p}_1 = \tilde{p}_2 = -1$

$$L = [l_1 \ l_2]$$

$$u(t) = -Lx(t) = -l_1 x_1(t) - l_2 x_2(t)$$

$$l_1 = \tilde{a}_1 - a_1$$

$$l_2 = \tilde{\alpha}_2 - \alpha_2$$

$\{a_1, a_2\}$? coeff. of the open-loop model's characteristics polynomial.

$$\det(\lambda I - A) = \det \begin{bmatrix} \lambda & 1 \\ -1 & \lambda \end{bmatrix} = \underbrace{\lambda^2 + 1}_{\downarrow \quad \downarrow}$$

Closed loop

$$\det(\lambda I - A + BL) = (\lambda - \tilde{p}_1)(\lambda - \tilde{p}_2) = (\lambda + 1)^2 = \underbrace{\lambda^2 + 2\lambda + 1}_{L = [l_1 \ l_2] = [2 \ 0]} \\ \tilde{a}_1 = 2 \quad \tilde{a}_2 = 1$$

$$\Rightarrow u(t) = -2x_1(t)$$

Theorem (EA)

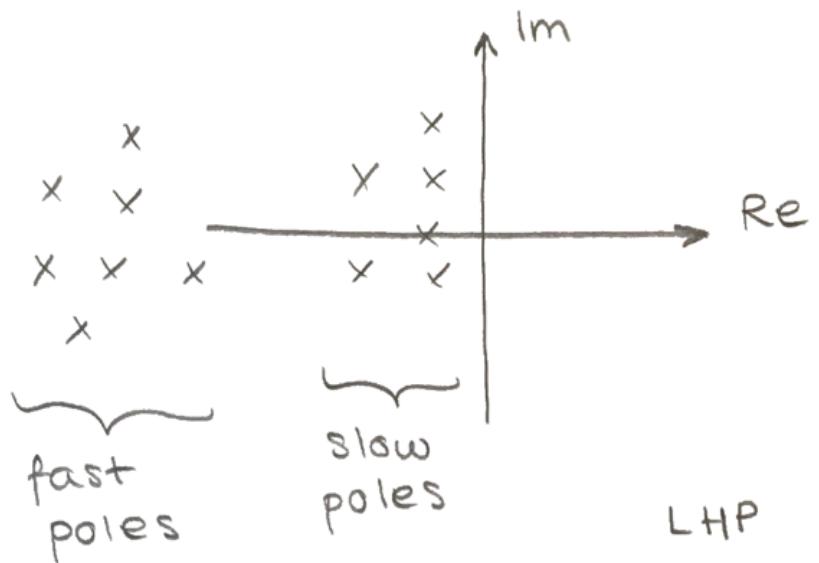
Given a (full state) controllable LTI state-space model with open/closed-loop poles

$\{p_1 \dots p_n\} / \{\tilde{p}_1 \dots \tilde{p}_n\}$, then

$L = L_i T = [l_1 \dots l_n]T$ will assign the closed-loop eigenvalues to $\{\tilde{p}_1, \dots, \tilde{p}_n\}$. T is the similarity state transformation matrix $T \in \mathbb{R}^{n \times n}$

3) Optimal EA

only a region of eigenvalue



How to find the optimal pole location?