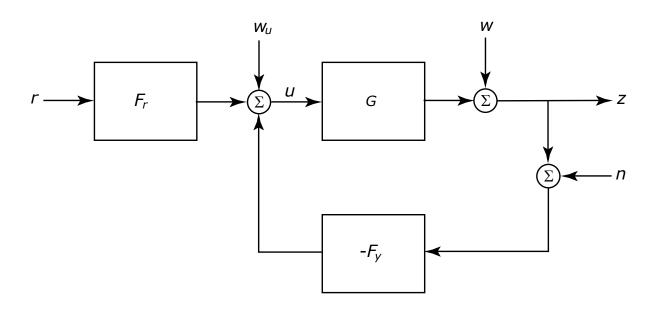


# **EL2520 Control Theory and Practice**

#### Lecture 5: Multivariable systems

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#### So far...



#### SISO control revisited:

- Signal norms, system gains and the small gain theorem
- Shaping the loop by weighted sensitivity functions
- The closed-loop system and the design problem
  - characterized by six transfer functions: need to look at all!
  - fundamental limitations, conflicts and waterbed effect.

#### From now and on: MIMO

Linear systems with multiple inputs and multiple outputs

- Basic properties of multivariable systems
- Decentralized control and decoupling
- State-space theory, state feedback and observers
- $H_2$  and  $H_{\infty}$ -optimal control
- Robust loop shaping

The final part of the course considers systems with constraints

## Today's lecture

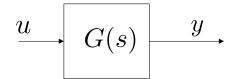
Basic properties of multivariable systems

- Transfer matrices
- Poles and zeros
- Directionality
- Interactions and the RGA (whiteboard)
- Decoupling

Chapters 2-3 and 8.3 in the textbook, Lecture notes 5

# Multivariable Systems

Consider a MIMO system with m inputs and p outputs



All signals are vectors

$$u = \begin{pmatrix} u_1 \\ u_2 \\ \vdots \\ u_m \end{pmatrix} \; ; \quad y = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_p \end{pmatrix}$$

The transfer-matrix G(s) has elements

$$G_{ij}(s) = \frac{y_i(s)}{u_j(s)}$$

#### Transfer-Matrix from LTI model

Given a linear time-invariant system

$$\dot{x} = Ax(t) + Bu(t) ; \quad x \in \mathbb{R}^n, \ u \in \mathbb{R}^m$$

$$y(t) = Cx(t) + Du(t) ; \quad y \in \mathbb{R}^p$$

Laplace transform (assuming u(t)=0 for t<0 and x(0)=0)

$$Y(s) = \{C(sI - A)^{-1}B + D\}U(s) = G(s)U(s)$$

If system has multiple inputs and outputs, U and Y are vector-valued and G(s) is a  $p \times m$  transfer-matrix

# Example

LTI system

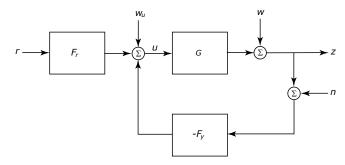
$$\dot{x} = \begin{pmatrix} -1 & -2 \\ 0 & -2 \end{pmatrix} x(t) + \begin{pmatrix} 2 & 2 \\ 0 & 1 \end{pmatrix} u(t)$$

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

Laplace transform yields

$$G(s) = \begin{pmatrix} \frac{2}{s+1} & \frac{1}{s+2} \\ \frac{s+3}{s+1} & \frac{2}{s+2} \end{pmatrix}$$

## Closed-Loop Transfer-Matrices



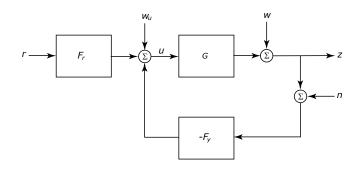
To derive transfer-function from an input to an output; use algebra or employ simple rule:

- 1. Start from output and move against signal flow towards input
- 2. Write down blocks, from left to right, as you meet them
- 3. When you exit a loop, add the term  $(I + L)^{-1}$ , where L is the loop transfer-function evaluated from the exit against the signal flow
- 4. Parallell paths should be added together

Also useful is the "push through" rule (for matrices of appropriate dimensions)

$$A(I + BA)^{-1} = (I + AB)^{-1}A$$

#### Closed-Loop Transfer-Matrices



#### Examples:

$$z = (I + GF_y)^{-1}w = Sw$$

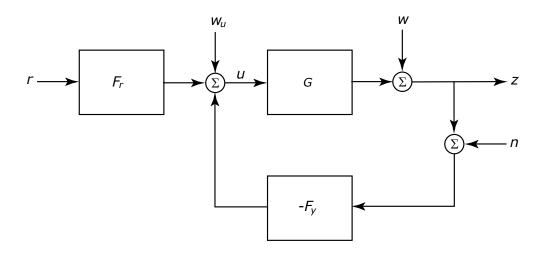
$$z = GF_y(I + GF_y)^{-1}n = Tn$$

$$z = G(I + F_yG)^{-1}w_u = (I + GF_y)^{-1}Gw_u = SGw_u$$

$$u = (I + F_yG)^{-1}w_u = S_uw_u$$

$$(I + GF_y)^{-1} \neq (I + F_yG)^{-1}$$

#### Quiz



- What is transfer-function from r to z?
- What is transfer-function from n to u?

#### Poles

**Definition.** The *poles* of a linear system are the eigenvalues of the system matrix A in a minimal state-space realization.

**Definition.** The *pole polynomial* is the characteristic polynomial of the A matrix,  $\lambda(s) = \det(sI-A)$ .

Alternatively, the poles of a linear system are the zeros of the pole polynomial, i.e., the values  $p_i$  such that  $\lambda(p_i) = 0$ 

# Poles from G(s)

Since the transfer matrix is given by

$$G(s) = C(sI - A)^{-1}B + D = \frac{1}{\det(sI - A)}r(s)$$

where r(s) is a polynomial matrix in s (see book for precise expression), the pole polynomial must be "at least" the least common denominator of the elements of the transfer matrix.

**Example:** The system

$$G(s) = \begin{bmatrix} \frac{2}{s+1} & \frac{3}{s+2} \\ \frac{1}{s+1} & \frac{1}{s+1} \end{bmatrix} = \frac{1}{(s+1)(s+2)} \begin{bmatrix} 2(s+2) & 3(s+1) \\ (s+2) & (s+2) \end{bmatrix}$$

must (at least) have poles in s=-1 and s=-2.

# Poles from G(s)

**Theorem.** The pole polynomial of a system with transfer matrix G(s) is the least common denominator of all minors of G(s)

**Recall:** a minor of a matrix M is the determinant of a (smaller) square matrix obtained by deleting some rows and columns of M

**Example:** The minors of

$$G(s) = \begin{bmatrix} \frac{2}{s+1} & \frac{3}{s+2} \\ \frac{1}{s+1} & \frac{1}{s+1} \end{bmatrix}$$

are 
$$\frac{2}{s+1}$$
,  $\frac{3}{s+2}$ ,  $\frac{1}{s+1}$  and  $\det G(s) = \frac{1-s}{(s+1)^2(s+2)}$ 

Thus, the system has poles two poles in s=-1 and one pole in s=-2

#### Zeros

**Zeros** are essentially the values of s where G(s) looses rank

**Theorem.** The zero polynomial of G(s) is the greatest common divisor of the maximal minors of G(s), normed so that they have the pole polynomial of G(s) as denominator. The zeros of G(s) are the roots of its zero polynomial.

**Example:** The maximal minor of

$$G(s) = \begin{bmatrix} \frac{2}{s+1} & \frac{3}{s+2} \\ \frac{1}{s+1} & \frac{1}{s+1} \end{bmatrix}$$

is 
$$\det G(s) = \frac{1-s}{(s+1)^2(s+2)}$$
 (already normed!).

Thus, G(s) has a zero at s=1 (and G(1) is rank 1)

#### Quiz: multivariable poles and zeros

What are the poles and zeros of the multivariable system

$$G(s) = \frac{1}{(s+1)} \begin{pmatrix} 1 & s+1 \\ s-1 & 1 \end{pmatrix}$$

#### Pole and Zero Directions

For scalar system G(s) with poles p<sub>i</sub> and zeros z<sub>i</sub>,

$$G(z_i) = 0, \quad G(p_i) = \infty$$

But, for a multivariable system directions matter!

For a system with pole p, there exist vectors  $u_p$ ,  $v_p$ :

$$u_p^*G(p) = \infty$$
  $G(p)v_p = \infty$ 

Similarly, a zero at z<sub>i</sub> implies the existence of vectors u<sub>z</sub>, v<sub>z</sub>:

$$u_z^*G(z) = 0 \qquad G(z)v_z = 0$$

**Note:** a transfer-matrix may have a pole and a zero at the same location without cancelling, provided they have different directions

## **Amplification and Frequency**

 Recall: for a linear SISO system the amplification from input to output depends on frequency

$$\frac{|Y(i\omega)|_2}{|U(i\omega)|_2} = |G(i\omega)|$$

The maximum amplification is the system gain

$$\sup_{u} \frac{\|y\|_{2}}{\|u\|_{2}} = \sup_{\omega} |G(i\omega)| = \|G\|_{\infty}$$

# **Amplification and Direction**

Linear mapping y = Ax

Since

$$|y|^2 = |Ax|^2 = (Ax)^*Ax = x^*A^*Ax$$

we get

$$|x|^2 \lambda_{min}(A^*A) \le |y|^2 \le |x|^2 \lambda_{max}(A^*A)$$

and so

$$\underbrace{\sqrt{\lambda_{min}(A^*A)}}_{\underline{\sigma}(A)} \le \frac{|y|}{|x|} \le \underbrace{\sqrt{\lambda_{max}(A^*A)}}_{\bar{\sigma}(A)}$$

where  $\underline{\sigma}(A)$ ,  $\bar{\sigma}(A)$  are the minimum and maximum singular values of A, respectively

# The Singular Value Decomposition

A mxr matrix (with r<m, rank(A)=r), can be represented by its singular value decomposition (SVD)

$$A = U\Sigma V^* = \begin{bmatrix} u_1 & \cdots & u_r \end{bmatrix} \operatorname{diag}(\sigma_i) \begin{bmatrix} v_1 & \cdots & v_r \end{bmatrix}^* = \sum_{i=1}^r \sigma_i u_i v_i^*$$

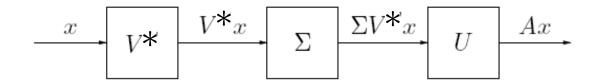
#### where

- the positive scalars  $\sigma_i$  are the *singular values* of A
- v<sub>i</sub> are the input singular vectors of A, V\*V=I
- u<sub>i</sub> are the output singular vectors of A, U\*U=I

Matlab: [u,s,v]=svd(A)

# **SVD** interpretation

$$A = U\Sigma V^* = \sum_{i=1}^r \sigma_i u_i v_i^*$$



Interpretation: linear mapping y=Ax can be decomposed as

- compute coefficients of x along input directions v<sub>i</sub>
- scale coefficients by  $\sigma_i$
- reconstitute along output directions u<sub>i</sub>

If  $\sigma_1 \leq \cdots \leq \sigma_r$  then an input in the  $v_r$  direction is amplified the most. It generates an output in the direction of  $u_r$  (typically different from  $v_r$ ).

# The MIMO frequency response

For a linear multivariable system Y(s)=G(s)U(s), we have

$$Y(i\omega) = G(i\omega)U(i\omega)$$

Since this is a linear mapping, at any given frequency

$$\underline{\sigma}(G(i\omega)) \le \frac{|Y(i\omega)|}{|U(i\omega)|} \le \overline{\sigma}(G(i\omega))$$

The maximum amplification, at a given frequency is then

$$\frac{|Y(i\omega)|}{|U(i\omega)|} = \overline{\sigma}(G(i\omega))$$

# The system gain

As for scalar systems, we have

$$||y||_2 \le ||G||_\infty ||u||_2$$

where  $\|G\|_{\infty}=\sup_{\omega}|G(i\omega)|=\sup_{\omega}\overline{\sigma}(G(i\omega))$   $picks\ worst\ direction$   $picks\ worst\ frequency$ 

**Note:** the infinity norm computes the maximum amplification across both frequencies and input directions

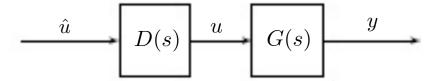
**Next time:** extensions of SISO results on robustness and performance limitations to the MIMO case using singular values and the infinity norm as defined above

#### Decentralized Control and the RGA

Whiteboard only

## Decoupling

 If there are strong interactions (large RGA elements), then one option is to design a decoupler



- Design D(s) so that G(s)D(s) is diagonal  $\forall s$  or for some frequency, e.g.,  $\omega = 0$  (static decoupling)
- There may be problems with
  - non-realizable D, due to improperness and non-causality
  - internal stability, due RHP pole zero cancellations
  - model uncertainty

## Decoupling and Model Uncertainty

Ex.1, no model uncertainty

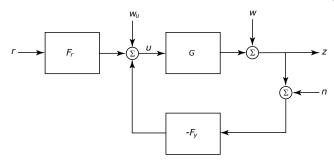
$$G = \begin{pmatrix} 1 & -1 \\ 1.1 & -1 \end{pmatrix} \; ; \quad D = \begin{pmatrix} 1 & -1 \\ 1.1 & -1 \end{pmatrix}^{-1} \quad \Rightarrow \quad GD = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$$

Ex.2, 10% uncertainty in elements of G

$$G = \begin{pmatrix} 1 & -1 \\ 1.1 & -1 \end{pmatrix} \; ; \quad D = \begin{pmatrix} 1.1 & -0.9 \\ 1.2 & -0.9 \end{pmatrix}^{-1} \quad \Rightarrow \quad GD = \begin{pmatrix} 3.3 & -2.2 \\ 2.3 & -1.2 \end{pmatrix}$$

- small uncertainty results in poor decoupling
- better is to design multivariable controller taking model uncertainty into account; later

#### **Internal Stability**



• Consider one input and one output at either side of the two blocks in the loop , e.g.,  $w,w_u$  and z,u

$$z = \underbrace{(I + GF_y)^{-1}}_{S} w + \underbrace{G(I + F_yG)^{-1}}_{GS_u = SG} w_u$$

$$u = \underbrace{-F_y(I + GF_y)^{-1}}_{F_yS = S_uF_y} w + \underbrace{(I + F_yG)^{-1}}_{S_u} w_u$$

• Thus, require stability of  $S, SG, S_u, S_uF_y$  and  $F_r$ 

#### Next time

 Extending SISO results on design specifications and fundamental limitations to MIMO case