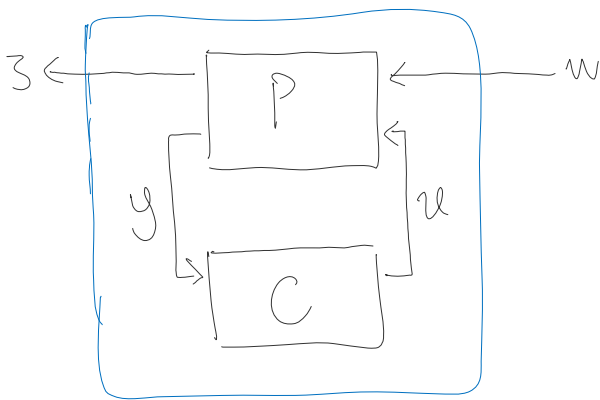


goal: concepts & definitions we'll use to quantify robustness

refs: Zha, Doyle, Glover - Robust & Optimal Control, 1996

Dullerud & Paganini - A course in robust control theory, 2013

• consider the following feedback block diagram between process P and controller C :



- w contains disturbances (i.e. both input & output disturbances)
- z contains "errors" to be minimized (i.e. tracking error, control effort)

$$T_{zw} = P_{zw} + P_{zu}(I - C P_{yu})^{-1} C P_{yw} \rightarrow \text{verify this formula}$$

* our goal as control engineers is to minimize $\|T_{zw}\|$
 \rightarrow remainder of this lecture will develop math to define

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norms

• a norm $\|\cdot\| : V \rightarrow [0, \infty)$ on vector space V satisfies:

1°. $\|v\| = 0 \Leftrightarrow v = 0$

– definiteness

2°. $\|\alpha \cdot v\| = |\alpha| \cdot \|v\|, \alpha \in \mathbb{C}$

– positive-homogeneity

3°. $\|v_1 + v_2\| \leq \|v_1\| + \|v_2\|$

– triangle inequality

ex: $\mathbb{C}^n, \mathbb{R}^n$ $\|v\|_p = (|v_1|^p + \dots + |v_n|^p)^{1/p}$, eg $\|v\|_2 = \sqrt{\sum_{i=1}^n |v_i|^2}$

$$\|v\|_\infty = \max_{1 \leq i \leq n} |v_i|$$

ex: $\mathbb{C}^{m \times n}, \mathbb{R}^{m \times n}$ $|M|_F = (\text{tr } M^* M)^{1/2} = \sqrt{\sum_{i,j} |M_{ij}|^2}$ – Frobenius

$$\sigma_{\max}(M) = (\lambda_{\max}(M^* M))^{1/2} \text{ – max singular value}$$

ex: $L_p(-\infty, \infty) = \{u : (-\infty, \infty) \rightarrow \mathbb{C}^n \mid \|u\|_p < \infty\}$

$$\|u\|_p = \left(\int_{-\infty}^{\infty} \|u(t)\|_p^p dt \right)^{1/p} \quad \|u\|_\infty = \text{ess sup}_{t \in \mathbb{R}} \|u(t)\|_\infty = \max_{t \in \mathbb{R}} \|u(t)\|_\infty$$

inner products

• an inner product $\langle \cdot, \cdot \rangle : V \times V \rightarrow \mathbb{C}$ on vector space V :

$$\left. \begin{array}{l} 1^\circ. \langle v, v \rangle \geq 0 \\ 2^\circ. \langle v, v \rangle = 0 \Leftrightarrow v = 0 \end{array} \right\} \text{ definiteness}$$

3°. $w \mapsto \langle v, w \rangle$ is linear for all v

$\rightarrow \|v\| = \sqrt{\langle v, v \rangle}$ is a norm; v, w orthogonal if $\langle v, w \rangle = 0$

ex: \mathbb{C}^n $\langle x, y \rangle = x^* y$ \mathbb{R}^n $\langle x, y \rangle = x^T y = "x \cdot y"$

ex: $\mathbb{C}^{m \times n}, \mathbb{R}^{m \times n}$ $\langle A, B \rangle = \text{tr } A^* B$, $\text{tr } M = \sum_{i=1}^n M_{i,i}$

ex: L_2 $\langle u_1, u_2 \rangle = \int_{-\infty}^{\infty} u_1^*(t) u_2(t) dt = \int_{-\infty}^{\infty} \langle u_1(t), u_2(t) \rangle dt$

\hookrightarrow induces L_2 norm above

linear functions (linear transformations)

• a linear function $L: V \rightarrow W$ between normed vector spaces
has an induced norm $\|L\|_{V \rightarrow W} = \max_{v \neq 0} \frac{\|Lv\|_W}{\|v\|_V}$

ex: $x \mapsto Mx$, $M \in \mathbb{C}^{m \times n}$ $\|M\|_{\mathbb{C}^m \rightarrow \mathbb{C}^n} = \sigma_{\max}(M)$

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$$\|M\|_{\mathbb{C}^m \rightarrow \mathbb{C}^n} = \sigma_{\max}(M)$$

↳ assuming 2-norms on $\mathbb{C}^m, \mathbb{C}^n$

Fourier transform — relate time- and frequency-domain

• let $\hat{L}_2(j\mathbb{R})$ be inner product space of signals $\hat{u}: j\mathbb{R} \rightarrow \mathbb{C}^n$
with $\langle \hat{u}, \hat{v} \rangle = \frac{1}{2\pi} \int_{-\infty}^{\infty} \langle \hat{u}(j\omega), \hat{v}(j\omega) \rangle d\omega$, $\|\hat{u}\|_2 = \sqrt{\langle \hat{u}, \hat{u} \rangle} < \infty$

• the Fourier transform of $u: \mathbb{R} \rightarrow \mathbb{C}^n$ is

$$\hat{u}(j\omega) = (\Gamma u)(j\omega) = \int_{-\infty}^{\infty} u(t) e^{-j\omega t} dt$$

facts (Plancherel): this defines linear $\Gamma: L_2 \rightarrow \hat{L}_2$

with inverse $\Gamma^{-1}: \hat{L}_2 \rightarrow L_2$, $u(t) = (\Gamma^{-1} \hat{u})(t) = \frac{1}{2\pi} \int_{-\infty}^{\infty} \hat{u}(j\omega) e^{j\omega t} d\omega$

and, moreover, Γ is an isometry, i.e. preserves lengths ($\|\cdot\|$)
and angles ($\langle \cdot, \cdot \rangle$)

→ so $\|u\|_{L_2} = \|\hat{u}\|_{\hat{L}_2}$, $\hat{u} = \Gamma u \iff u = \Gamma^{-1} \hat{u}$

$$\langle u, v \rangle_{L_2} = \langle \hat{u}, \hat{v} \rangle_{\hat{L}_2}$$

so we'll drop subscripts L_2, \hat{L}_2
when clear from context