

4 System Norms

4.1 Optimal Feedback Control

Q. Why do people use ‘feedback’ control (vs. open-loop control) ?

Consider a tracking problem, with disturbance rejection, measurement noise, and control input signal limitations, as shown in Fig. 1. We would want to design a controller to keep tracking errors and control input signal small for all reasonable reference commands, sensor noise, and external force disturbances. Thus, a reasonable performance objective is the closed-loop “gain” from exogenous influences (reference commands, sensor noise, and external force disturbances) to regulated variables (tracking errors and control input signal). The magnitude of certain closed-loop TM norms are use as performance objectives in popular optimal control methods. Often, there exists a tradeoff between tracking/disturbance error reduction and minimizing sensitivity to measurement noise or uncertainty (we delay formal discussion to later).

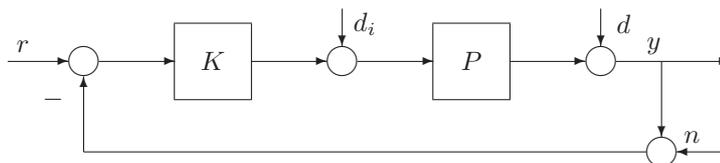


Figure 1: Standard feedback control configuration

The main subject of discussion in this lecture is the standard LTI feedback optimization setup. There are three basic concepts behind the standard feedback optimization setup:

- the notion of a multi-input, multi-output (MIMO) linear time-invariant (LTI) finite order system,
- the notion of an internally stable feedback interconnection of two MIMO LTI systems, and
- the notion of a system norm.

Let T denote the closed-loop mapping from the outside influences to the

regulated variables,

$$\underbrace{\begin{bmatrix} \text{tracking error} \\ \text{control input} \end{bmatrix}}_{\text{regulated variables}} = T \underbrace{\begin{bmatrix} \text{reference} \\ \text{external force} \\ \text{noise} \end{bmatrix}}_{\text{outside influences}} \quad (1)$$

We can associate good performance with the gain of T being small. To quantify the term *gain* mathematically, we need to define some additional things.

First, we review a well-known property of an analytic function. Let $S \in \mathbb{C}$ be an open set, and let $f(s)$ be a cpx-valued ftn defined on S . Then $f(s)$ is said to be analytic at a point $z_0 \in S$ if it is differentiable at z_0 and also at each point in some nbhd of z_0 .

If $f(s)$ is analytic at z_0 then f has conti derivatives of all orders at z_0 , and it has a power series representation at z_0 . $f(s)$ is said to be analytic in S if it is analytic at each point of S . A matrix-valued ftn is analytic in S if every element of the matrix is analytic in S . For example, all real rational stable transfer matrices are analytic in RHP.

Theorem 4.1 (max modulus thm) *If $f(s)$ is defined and conti on a closed-bounded set S and analytic on the interior of S , then*

$$\max_{s \in S} |f(s)| = \max_{s \in \partial S} |f(s)|$$

where ∂S denotes the boundary of S .

4.2 Norms of Signals and Systems

For a scalar signal $e(t)$ in the time domain, we often use the 2-norm (or \mathcal{L}_2 norm), which is defined as

$$\|e\|_2 := \left(\int_{-\infty}^{\infty} e^2(t) dt \right)^{\frac{1}{2}}.$$

If this integral is finite, then we say that the signal e is *square integrable* and $e \in \mathcal{L}_2$ (Lebesgue). Similarly, for vector-valued signals, the 2-norm is defined as

$$\|e\|_2 := \left(\int_{-\infty}^{\infty} \|e(t)\|_2^2 dt \right)^{\frac{1}{2}} = \left(\int_{-\infty}^{\infty} \|e^T(t)e(t)\| dt \right)^{\frac{1}{2}}.$$

For a signal $e(t) \in \mathcal{L}_\infty$, the \mathcal{L}_∞ norm is

$$\|e\|_\infty := \text{ess. sup}_t |e(t)| = \inf\{B : |e| \leq B(a.e.)\}.$$

For $f(t), g(t) \in \mathcal{L}_2$, let

$$F(j\omega) = \mathcal{F}\{f(t)\} \triangleq \int_{-\infty}^{\infty} f(t)e^{-j\omega t} dt,$$

and

$$f(t) = \mathcal{F}^{-1}\{F(j\omega)\} \triangleq \frac{1}{2\pi} \int_{-\infty}^{\infty} F(j\omega) e^{j\omega t} d\omega .$$

Then

$$\mathcal{F}\{f(t) * g(t)\} = F(j\omega)G(j\omega) ,$$

where

$$f(t) * g(t) \triangleq \int_{-\infty}^{\infty} f(\tau)g(t - \tau)d\tau : \text{convolution.}$$

Theorem 4.2 (Parseval) For $f(t), g(t) \in \mathcal{L}_2$,

$$\int_{-\infty}^{\infty} f(t)g(t)dt = \frac{1}{2\pi} \int_{-\infty}^{\infty} F(j\omega)G^*(j\omega)d\omega ,$$

in particular,

$$\int_{-\infty}^{\infty} |f(t)|^2 dt = \frac{1}{2\pi} \int_{-\infty}^{\infty} |F(j\omega)|^2 d\omega .$$

A state-space model for a finite order CT LTI system H with input $u(t)$, output $y(t)$, and state $x(t)$ has the form

$$\begin{aligned} \dot{x} &= Ax + Bu \\ y &= Cx + Du \end{aligned}$$

where A, B, C, D are constant matrices with real entries. Given an input $u(t)$ and the initial state vector $x(0)$, the output $y(t)$ is defined according to the formula

$$y(t) = Ce^{At}x(0) + Du(t) + \int_0^{\infty} Ce^{A\tau}Bu(t - \tau)d\tau .$$

The transfer matrix (transfer function in the case when both u and y are scalar) of the system is defined for all complex s such that $sI - A$ is invertible by

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

Two mathematically convenient measures of the TM $G(s)$ in the frequency domain are the matrix \mathcal{H}_2 and \mathcal{H}_∞ norms (Hardy):

- **The \mathcal{H}_∞ norm** $\|G\|_\infty$ of G is defined as the supremum (minimal upper bound) of the largest singular number of its TM over the imaginary axis:

$$\|G\|_\infty \triangleq \sup_{\text{Re}(s)>0} \sigma_{\max}(G(j\omega)) = \sup_{\omega \in \mathbf{R}} \sigma_{\max}(G(j\omega)),$$

where, for an k -by- m complex matrix M , $\sigma_{\max}(M) = \max_{u \in \mathbb{C}^m, |u|=1} |Mu|$ and $|v|$ denotes the standard Hermitian norm (length) of vector v .

- **The \mathcal{H}_2 norm** $\|G\|_2$ of a finite order stable CT LTI system with $D = 0$ is defined by the integral

$$\begin{aligned}\|G\|_2 &= \int_0^\infty \text{tr}(g(t)g(t)') dt \\ &= \frac{1}{2\pi} \int_{-\infty}^\infty \text{tr}(G^*(j\omega)G(j\omega)) d\omega \\ &= \left[\frac{1}{2\pi} \int_{-\infty}^\infty \|G(j\omega)\|_F^2 d\omega \right]^{\frac{1}{2}}\end{aligned}$$

where $g(t) = Ce^{At}B$ is the impulse response matrix of G , and $\|\cdot\|_F$ is the Frobenius norm.

4.3 Interpretations for \mathcal{H}_2 and \mathcal{H}_∞ norms

\mathcal{H}_∞ and \mathcal{H}_2 norms are frequently used as the cost measure in feedback optimization. Both these TM norms have time-domain interpretations. Suppose that the initial condition is $x(0) = 0$, then

- for a unit intensity white noise input u , the steady-state variance of output y is $\|G\|_2$.
- The \mathcal{L}_2 (RMS) gain from u to y is $\|G\|_\infty$:

$$\max_{d \neq 0} \frac{\|y\|_2}{\|u\|_2} = \|G\|_\infty$$

This section describes interpretations of the norms as performance measures.

4.3.1 $\|H\|_\infty$ as \mathcal{L}_2 gain

The \mathcal{L}_2 gain of a continuous time linear system (strictly speaking, \mathcal{L}_2 -to- \mathcal{L}_2 gain of a continuous time system with input u and output y) is defined as the minimal $\gamma \geq 0$ such that

$$\inf_{T \geq 0} \int_0^T \gamma^2 |u(t)|^2 - |y(t)|^2 dt > -\infty$$

for all input/output pairs u and y where input u is square integrable over arbitrary finite intervals.

The informal rationale behind the definition of the \mathcal{L}_2 norm is as follows: for zero initial conditions, we expect the energy of the output to be bounded by the energy of the input times the \mathcal{L}_2 gain squared. Since non-zero initial conditions can produce nonzero output even for zero input, the actual definition says that the difference between the energies must be bounded on one side. \mathcal{L}_2 gain is a key concept in robustness analysis. The importance of the \mathcal{H}_∞ norm is largely due to the fact that, for a stable finite order LTI system, \mathcal{H}_∞ norm equals \mathcal{L}_2 gain.

Theorem 4.3 \mathcal{L}_2 gain of a stable finite order LTI system equals its \mathcal{H}_∞ norm.

Proof.

Consider the CT case (the DT case is similar). Let $G(s)$ be the transfer function of the system. To show that \mathcal{L}_2 gain cannot be larger than \mathcal{H}_∞ norm, use the Parseval theorem. Consider the case of zero initial conditions first. For an arbitrary input signal u and for $T > 0$ let u_T denote the signal defined by

$$u_T(t) = \begin{cases} u(t) & t < T \\ 0 & t \geq T \end{cases}$$

Let y and y_T denote the response of the system to u and u_T respectively, both assuming zero initial conditions. Then u_T, y_T are square integrable over $t \in (0, \infty)$ (for y_T this is true since A is a Hurwitz matrix), and hence both have Fourier transforms u_T and y_T respectively. In addition, by causality, $y(t) = y_T(t)$ for $t < T$. Hence

$$\begin{aligned} \int_0^T |y(t)|^2 dt &\leq \int_0^\infty |y(t)|^2 dt \\ &= \frac{1}{2\pi} \int_{-\infty}^\infty |y_T(j\omega)|^2 d\omega \\ &= \frac{1}{2\pi} \int_{-\infty}^\infty |G(j\omega)u_T(j\omega)|^2 d\omega \\ &\leq \frac{1}{2\pi} \int_{-\infty}^\infty \|G\|_\infty^2 |u_T(j\omega)|^2 d\omega \\ &= \frac{1}{2\pi} \|G\|_\infty^2 \int_0^\infty |u_T(j\omega)|^2 dt \\ &= \|G\|_\infty^2 \int_0^T |u(t)|^2 dt \end{aligned}$$

To show that \mathcal{H}_∞ norm cannot be larger than \mathcal{L}_2 gain, consider zero initial conditions and sinusoidal inputs with unit 2-norm, whose frequency ω_0 is a freq where

$$\sigma_{\max}(G(j\omega_0)) = \|G\|_\infty$$

See the text pg. 51 for details.

4.3.2 \mathcal{H}_2 norm and \mathcal{L}_2 -to- \mathcal{L}_∞ gain

\mathcal{L}_2 -to- \mathcal{L}_∞ gain of a stable state space model is defined as the supremum of the amplitude of its time domain response to an input signal of unit energy.

Theorem 4.4 \mathcal{L}_2 -to- \mathcal{L}_∞ gain of a stable LTI system with a scalar output equals its \mathcal{H}_2 norm.

Proof. Consider the continuous-time case (the DT case is similar). To show that \mathcal{H}_2 norm is not smaller than the \mathcal{L}_2 -to- \mathcal{L}_∞ gain, use the standard Cauchy-Schwartz inequality:

$$|y(T)|^2 = \left| \int_0^T h(t)u(T-t)dt \right|^2 \leq \int_0^T |h(t)|^2 dt \int_0^T |u(t)|^2 dt .$$

Since the inequality becomes equality for $u(t) = h(T-t)$, the \mathcal{L}_2 -to- \mathcal{L}_∞ gain actually equals the \mathcal{H}_2 norm.

4.3.3 \mathcal{H}_2 norm and variance of white noise response

\mathcal{H}_2 norm of a system is also an measure of system sensitivity to white noise input. The continuous time white noise (with zero mean, unit variance) is a slightly complicated concept: it is a generalized random process $f = f(t)$ (something akin to the Dirac delta in the world of deterministic functions), which can be characterized by its effect in integration: if

$$\xi = \int_{t_1}^{t_2} h(t)f(t)dt ,$$

where $h(t)$ is a row vector of appropriate length, then

$$E \xi = 0, \quad |\xi|^2 = \int_{t_1}^{t_2} |h(t)|^2 dt .$$

Combining this with the definition of \mathcal{H}_2 norm, we conclude that, for a stable LTI system, the asymptotic (as $t \rightarrow \infty$) variance of white noise response equals square of \mathcal{H}_2 norm.

4.4 \mathcal{H}_2 and \mathcal{H}_∞ Spaces

- \mathcal{H}_2 Space

consists of matrix functions $F(s)$ that are analytic and bounded in the open right-half plane, with the norm is defined as

$$\|F\|_2 := \sup_{\sigma > 0} \left\{ \frac{1}{2\pi} \int_{-\infty}^{\infty} \text{tr}[F^*(\sigma + j\omega)F(\sigma + j\omega)]d\omega \right\}$$

It can be shown that

$$\|F\|_2 = \frac{1}{2\pi} \int_{-\infty}^{\infty} \text{tr}[F^*(j\omega)F(j\omega)]d\omega .$$

- \mathcal{H}_∞ Space

consists of matrix functions that are analytic and bounded in the open right-half plane, with the norm is defined as

$$\|F\|_\infty := \sup_{\text{Re}(s) > 0} \bar{\sigma}[F(s)]$$

It can be shown that (by generalization of maximum modulus theorem for matrix functions)

$$\|F\|_\infty = \sup_{\omega \in \mathbb{R}} \bar{\sigma}[F(j\omega)].$$

The rational subspace of \mathcal{H}_∞ , denoted by \mathcal{RH}_∞ , consists of all proper and real rational stable transfer matrices.

4.5 Computing \mathcal{H}_2 norms

Lemma 4.5 Consider a TM

$$G(s) = \left[\begin{array}{c|c} A & B \\ \hline C & 0 \end{array} \right]$$

with A stable. Then we have

$$\|G\|_2^2 = \text{tr}(B^*W_oB) = \text{tr}(CW_cC^*) \quad (2)$$

where W_c, W_o are controllability and observability Gramians that can be obtained from Lyapunov Equations:

$$AW_c + W_cA^* + BB^* = 0 \quad A^*W_o + W_oA + C^*C = 0. \quad (3)$$

Proof. Since G is stable, we have

$$g(t) = \begin{cases} Ce^{At}B & t \geq 0 \\ 0 & t < 0 \end{cases}$$

and

$$\begin{aligned} \|G\|_2^2 &= \int_0^\infty \text{tr}\{g^*(t)g(t)\}dt = \int_0^\infty \text{tr}\{g(t)g^*(t)\}dt \\ &= \int_0^\infty \text{tr}\{B^*e^{A^*t}C^*Ce^{At}B\}dt = \int_0^\infty \text{tr}\{Ce^{At}BB^*e^{A^*t}C^*\}dt \\ &= \text{tr}(B^*W_oB) = \text{tr}(CW_cC^*). \end{aligned}$$

And Eqn. (3) follow from the result shown in the controllability/observability chapter.

4.6 Computing \mathcal{H}_∞ norms

The infinity norm of a scalar transfer function G can be interpreted as the distance in the complex plane from the origin to the farthest point on the Nyquist plot of G , or as the peak value on the Bode magnitude plot of $|G(j\omega)|$.

Lemma 4.6 Let $\gamma > 0$ and G is a proper real rational TM with no poles in $j\omega$ axis.

$$G(s) = \left[\begin{array}{c|c} A & B \\ \hline C & D \end{array} \right]$$

Then $\|G\|_\infty < \gamma$ iff $\bar{\sigma}(D) < \gamma$ and the Hamiltonian matrix H has no eigenvalues on the $j\omega$ axis where

$$H := \begin{bmatrix} A + BR^{-1}D^*C & BR^{-1}B^* \\ -C^*(I + DR^{-1}D^*)C & -(A + BR^{-1}D^*C)^* \end{bmatrix} \quad (4)$$

and $R := \gamma^2 I - D^*D$.

Lemma 4.6 lets us use the following iterative algorithm to compute $\|\cdot\|_\infty$.

Bisection Algorithm

1. Set γ_u and γ_l such that $\gamma_l \leq \|G\|_\infty \leq \gamma_u$;
2. If $(\gamma_u - \gamma_l)/\gamma_l \leq \varepsilon$, stop; $\|G\|_\infty \approx (\gamma_u + \gamma_l)/2$. Otherwise go to the next step.
3. Set $\gamma = (\gamma_u + \gamma_l)/2$;
4. Test if $\|G\|_\infty < \gamma$ by calculating the eigenvalues of H for the given γ ;
5. If H has eigenvalues on $j\omega$ axis, set $\gamma_l = \gamma$; otherwise set $\gamma_u = \gamma$; go back to step 2.

Remark. Since $\|G\|_\infty < \gamma$ iff $\|\gamma^{-1}G\|_\infty < 1$, we will assume that $\gamma = 1$ without loss of generality.

Example. `hinfnorm(sys); h2norm(sys);`