

AMS 231: Nonlinear Control Theory: Winter 2018

Homework #4

Name:

Due: February 22, 2018

NOTE: Please show all the steps in your solution. Turn in a hard copy of your HW stapled with this as cover sheet with your name written in the above field. Please submit your HW in class on the due date.

Problem 1

State Space Computation of \mathcal{H}_∞ Norm

(25+20+15+20 = 80 points)

In class (Lecture 12), we derived that the worst-case \mathcal{L}_2 gain of a stable LTI system is

$$\gamma_{\text{LTI}} = \|G(j\omega)\|_\infty := \sup_{\omega \in \mathbb{R}} \sigma_{\max}(G(j\omega)), \quad j := \sqrt{-1}, \quad G(s) = C(sI - A)^{-1}B + D,$$

where $G(j\omega)$ is the associated transfer matrix. However, this frequency domain formula is inconvenient for computing γ_{LTI} , since it requires solving a nonlinear optimization problem in ω . The purpose of this exercise is to demonstrate an alternate method for computing γ_{LTI} using state space formulation, for the case $D = 0$ (no direct feedthrough).

(a) By specializing the \mathcal{L}_2 gain theorem for nonlinear systems (Lecture 12 notes, page 8 and 9) for $f(\underline{x}) = A\underline{x}$, $g(\underline{x}) = B$, $h(\underline{x}) = C\underline{x}$, and $V(\underline{x}) = \frac{1}{2} \underline{x}^\top P \underline{x}$ where $P \succ 0$, prove that **if** the following optimization problem:

$$\begin{aligned} & \underset{\gamma, P}{\text{minimize}} \quad \gamma \\ & \text{subject to} \quad \gamma > 0, \quad P \succ 0, \quad PA + A^\top P + \frac{1}{\gamma^2} PBB^\top P + C^\top C \preceq 0, \end{aligned}$$

has unique solution, **then** the answer of this optimization problem gives the tightest upper bound of \mathcal{L}_2 gain γ_{LTI} . (In fact, when the triple (A, B, C) is minimal, meaning both controllable and observable, then the answer of this optimization problem equals γ_{LTI} , and hence equals $\|G(j\omega)\|_\infty$. But you can ignore this detail).

(b) At first glance, it may seem that the optimization problem in part (a) is nonlinear in both variables: scalar γ and matrix P , due to the last inequality constraint. However, this difficulty can be overcome via the following lemma.

Lemma: Consider real square matrices Q, R, S with Q and R symmetric. The linear matrix inequality $\begin{bmatrix} Q & S \\ S^\top & R \end{bmatrix} \succeq 0$ is equivalent to (if and only if) $R \succ 0$ and $Q - SR^{-1}S^\top \succeq 0$.

Prove this lemma.

(c) Using the lemma in part (b), and introducing $\sigma := \gamma^2$, show that the optimization problem derived in part (a) is equivalent to the following optimization problem:

$$\begin{aligned} & \underset{\sigma, P}{\text{minimize}} && \sigma \\ & \text{subject to} && \sigma > 0, \quad P \succ 0, \quad \begin{bmatrix} A^\top P + PA + C^\top C & PB \\ B^\top P & -\sigma I \end{bmatrix} \preceq 0, \end{aligned}$$

which is linear in both variables σ and P . Here I denotes the identity matrix of appropriate dimension.

(d) The type of optimization problem derived in part (c) is called semi-definite programming (SDP) problem that minimizes linear objective subject to linear matrix inequalities. SDPs are convex optimization problems, and can be solved efficiently via software like `cvx` in `MATLAB`.

Download `cvx` from <http://cvxr.com/cvx/download/> and follow installation instructions in <http://cvxr.com/cvx/doc/install.html>. To understand how to specify an optimization problem in `cvx`, you may want to take a look at: <http://cvxr.com/cvx/examples/>

Then write a `MATLAB` code to compute the \mathcal{H}_∞ norm of the following stable, controllable and observable linear system (see partial code) in two ways: by using `cvx` to solve the optimization in part (c), and by using `MATLAB` command `norm(sys,inf)` to solve the frequency domain optimization problem. Report the \mathcal{H}_∞ norms computed from the two methods, and submit your code.

Solution

(a) We specialize the \mathcal{L}_2 gain theorem for nonlinear systems (Lecture 12 notes, page 8 and 9) for $f(\underline{x}) = A\underline{x}$, $g(\underline{x}) = B$, $h(\underline{x}) = C\underline{x}$, and $V(\underline{x}) = \frac{1}{2} \underline{x}^\top P \underline{x}$ where $P \succ 0$. Clearly, $V(\underline{0}) = 0$, $V(\underline{x} \neq \underline{0}) > 0$, and the Hamilton-Jacobi PDI reduces to

$$\frac{1}{2} \underline{x}^\top \left[PA + A^\top P + \frac{1}{\gamma^2} PBB^\top P + C^\top C \right] \underline{x} \leq 0,$$

which will hold for all $\underline{x} \in \mathbb{R}^n$ iff

$$PA + A^\top P + \frac{1}{\gamma^2} PBB^\top P + C^\top C \preceq 0.$$

Thus for any $\gamma > 0$ to be an upper bound of the \mathcal{L}_2 gain of the LTI system, it must satisfy the feasibility conditions

$$\gamma > 0, \quad P \succ 0, \quad PA + A^\top P + \frac{1}{\gamma^2} PBB^\top P + C^\top C \preceq 0.$$

The tightest upper bound is obtained by minimizing γ subject to the above constraints. Hence the statement. (**Additional info regarding the qualifier “tightest”**: The fact that this bound cannot be improved by a different choice of Lyapunov function follows from a converse Lyapunov theorem for LTI system – something we will not cover in this course.)

(b) We are going to use three basic facts from linear algebra:

Fact 1: For a *symmetric matrix* X , the congruence transformation $X \mapsto MXM^\top$ via any invertible matrix M , preserves the matrix inertia, i.e., the numbers of positive, negative and zero eigenvalues of X , equal to the same for MXM^\top . (Sometimes this fact is referred to as “Sylvester’s law of inertia”.)

Fact 2: A block triangular matrix is non-singular iff its diagonal blocks are non-singular.

Fact 3: A block diagonal matrix is positive semi-definite iff its diagonal blocks are positive semi-definite.

Now let us give the proof.

(\Rightarrow)

Suppose that $X := \begin{bmatrix} Q & S \\ S^\top & R \end{bmatrix} \succeq 0$, where Q, R are symmetric, and R is invertible (which is implicit in the inequality involving R^{-1}). Notice that **Fact 1** specialized to symmetric sign-definite matrices says that “sign-definiteness is preserved under congruence transformation via any non-singular matrix”. Now let $M := \begin{bmatrix} I & -SR^{-1} \\ 0 & I \end{bmatrix}$, which by **Fact 2** is non-singular. Then by **Fact 1**, we have

$$X := \begin{bmatrix} Q & S \\ S^\top & R \end{bmatrix} \succeq 0 \Leftrightarrow MXM^\top = \begin{bmatrix} I & -SR^{-1} \\ 0 & I \end{bmatrix} \begin{bmatrix} Q & S \\ S^\top & R \end{bmatrix} \begin{bmatrix} I & 0 \\ -R^{-1}S^\top & I \end{bmatrix} = \begin{bmatrix} Q - SR^{-1}S^\top & 0 \\ 0 & R \end{bmatrix} \succeq 0,$$

which by **Fact 3** further implies $Q - SR^{-1}S^\top \succeq 0$ and $R \succeq 0$. Now, $R \succeq 0$ together with the requirement that it is also invertible yields $R \succ 0$. Therefore, $\begin{bmatrix} Q & S \\ S^\top & R \end{bmatrix} \succeq 0 \Rightarrow R \succ 0$ and $Q - SR^{-1}S^\top \succeq 0$. ■

(\Leftarrow)

Suppose that $R \succ 0$ and $Q - SR^{-1}S^\top \succeq 0$. Then by **Fact 3**, $Y := \begin{bmatrix} Q - SR^{-1}S^\top & 0 \\ 0 & R \end{bmatrix} \succeq 0$. On the other hand, by **Fact 2**, the matrix $N := \begin{bmatrix} I & SR^{-1} \\ 0 & I \end{bmatrix}$ is non-singular. Therefore, by **Fact 1**, we have

$$NYN^\top = \begin{bmatrix} I & SR^{-1} \\ 0 & I \end{bmatrix} \begin{bmatrix} Q - SR^{-1}S^\top & 0 \\ 0 & R \end{bmatrix} \begin{bmatrix} I & 0 \\ R^{-1}S^\top & I \end{bmatrix} = \begin{bmatrix} Q & S \\ S^\top & R \end{bmatrix} \succeq 0.$$

■

(c) Taking $\sigma := \gamma^2$, this follows immediately from the lemma in part (b) with $R := \sigma I \succ 0$, $Q := -(A^\top P + PA + C^\top C)$, and $S := -PB$. Notice that such choices make Q and R symmetric matrices, as needed to apply the lemma. Furthermore, by the same lemma, the pair of matrix inequalities

$$R := \sigma I \succ 0, \quad \text{and} \quad (-Q) - (-S)R^{-1}(-S^\top) \succeq 0,$$

is equivalent to the single block matrix inequality

$$\begin{bmatrix} -(A^\top P + PA + C^\top C) & -PB \\ -B^\top P & \sigma I \end{bmatrix} \succeq 0 \quad \Leftrightarrow \quad \begin{bmatrix} A^\top P + PA + C^\top C & PB \\ B^\top P & -\sigma I \end{bmatrix} \preceq 0,$$

as claimed.

(d) Both **MATLAB** `norm(sys,inf)` and **cvx** SDP solutions produce the same answer: $\|G(j\omega)\|_\infty = 12.1843$.

MATLAB Code:

```

1 clear; clc;
2
3 A = [-2 1 0 0;
4      -6 -6 0 3;
5      0 0 -1 1;
6      0 0 0 -2];
7 B = [0;1;1;2];
8 C = [0 6 2 -8; 2 -3 4 5];
9 D = 0;
10
11 sys = ss(A,B,C,D);
```

```

12
13 eig(A) % is stable?
14 rank(ctrb(sys))==length(A) % is controllable?
15 rank(observ(sys))==length(A) % is observable?
16
17 dim=size(B); n_x = dim(1); n_u = dim(2);
18
19 cvx_begin sdp
20     % declare variables
21     variable P(n_x,n_x) symmetric;
22     variable sig;
23     % objective
24     minimize sig;
25     subject to
26         % constraints
27         sig >= 0;
28         P >= 0;
29         [A'*P+P*A+C'*C    P*B;
30          B'*P          -sig*eye(n_u)] <= 0;
31 cvx_end
32
33 Hinf_cvx = sqrt(sig);
34
35 Hinf_matlab = norm(sys,inf);

```

Problem 2

Input-to-State Stability (ISS)

(4×5 = 20 points)

Consider the scalar nonlinear systems

$$(a) \dot{x} = -(1+u)x^3, \quad (b) \dot{x} = -(1+u)x^3 - x^5, \quad (c) \dot{x} = -x + x^2u, \quad (d) \dot{x} = x - x^3 + u.$$

Which systems are input-to-state stable (ISS) and which are not? Give reasons.

Solution

(a) Not ISS since $u(t) \equiv \text{constant} > 1$ with $x_0 > 0$ leads to $\lim_{t \rightarrow \infty} x(t) = \infty$.

(b) Let $V(x) = \frac{1}{2}x^2$. Then

$$\dot{V} = -x^4 + ux^4 - x^6 \leq -x^4, \quad \forall |x| > \sqrt{u}.$$

Invoking the ISS Lyapunov theorem (see Lecture 11, pg. 6) with $\alpha_1(|x|) = \alpha_2(|x|) = V(x)$, $W_3(|x|) = x^4$, and $\rho(|u|) = \sqrt{u}$, we conclude that the system is ISS with $\gamma(r) = \rho(r) = \sqrt{r}$.

(c) Not ISS since $u(t) \equiv 1$ with $x_0 > 0$ leads to $\lim_{t \rightarrow \infty} x(t) = \infty$.

(d) Not ISS since the origin of the unforced system ($u(t) \equiv 0$) is unstable.