

[Exercises 5] Samples

5.3. $y = u^{1/3} \Rightarrow h(u) = u^{1/3} \Rightarrow y = h(u) = Hu.$

(a) $\sup_{t \geq 0} |h(u(t))| \leq \left(\sup_{t \geq 0} |u(t)| \right)^{1/3}$

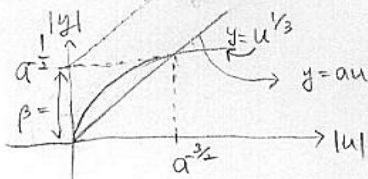
$\Rightarrow \| (Hu)_\tau \|_{L_\infty} = \| y_\tau \|_{L_\infty} \leq \left(\| u_\tau \|_{L_\infty} \right)^{1/3}$

Let $\alpha(r) = r^{1/3}$, class K_∞ function defined on $[0, \infty)$

$\therefore \| (Hu)_\tau \|_{L_\infty} \leq \alpha(\| u_\tau \|_{L_\infty}) + \frac{0}{\text{bias}}$

\therefore Def. 5.1 에 의하여 system 은 L_∞ stable with zero bias.

(b) We want $\| (Hu)_\tau \|_{L_\infty} \leq \gamma \| u_\tau \|_{L_\infty} + \beta$
 $\frac{\beta}{a}$ $\left(\frac{1}{a}\right)^{1/2}$



$u^{1/3} = au \Rightarrow u^{-2/3} = a \Rightarrow u = a^{-3/2}$

(a) 에 의하여 $\| y_\tau \|_{L_\infty} \leq \left(\| u_\tau \|_{L_\infty} \right)^{1/3}$

$\| u_\tau \|_{L_\infty} \leq a^{-3/2}$ 이라면 $\| y_\tau \|_{L_\infty} \leq \left(a^{-3/2} \right)^{1/3} = a^{-1/2} = \left(\frac{1}{a} \right)^{1/2} = \beta.$

$\| u_\tau \|_{L_\infty} \geq a^{-3/2}$ 이라면 $\| y_\tau \|_{L_\infty} \leq a \| u_\tau \|_{L_\infty}$

For positive a , 위 부등호의 우변은 모두 양수.

\therefore 모든 $\| u_\tau \|_{L_\infty}$ 에 대하여.

$\| y_\tau \|_{L_\infty} \leq a \| u_\tau \|_{L_\infty} + \underbrace{\left(\frac{1}{a} \right)^{1/2}}_{= \beta}$

$$\# 5.11 (3) \quad \dot{\alpha}_1 = (\alpha_1 + u)(\|\alpha\|_2^2 - 1)$$

$$\dot{\alpha}_2 = \alpha_2(\|\alpha\|_2^2 - 1)$$

$$y = \alpha_1$$

Sol)

$$V = \frac{1}{2}\alpha_1^2 + \frac{1}{2}\alpha_2^2$$

$u = 0$ 일 때

$$\begin{aligned} \dot{V} &= \alpha_1 \dot{\alpha}_1 + \alpha_2 \dot{\alpha}_2 = \alpha_1(\alpha_1 + \cancel{u})(\|\alpha\|_2^2 - 1) + \alpha_2^2(\|\alpha\|_2^2 - 1) \\ &= \|\alpha\|_2^2(\|\alpha\|_2^2 - 1) \end{aligned}$$

$\|\alpha\|_2^2 > 1$ 이서 증가하는 solution은 발생 \Rightarrow output y is not bounded

\Rightarrow not L_∞ stable

For $\|\alpha\|_2^2 \leq 1 - 2\varepsilon$, $\dot{V} \leq -\varepsilon \|\alpha\|_2^2$, $\varepsilon > 0$ (식 (5.1)에 해당)

\therefore Theorem 5.1의 조건은 만족한다.

$$\begin{cases} c_1 = c_2 = \frac{1}{2} \\ c_3 = \varepsilon \\ c_4 = 1 \\ L = 1 \\ \eta_1 = 1 \\ \eta_2 = 0 \end{cases}$$

\therefore small-signal finite gain L_∞ stable 하다.

5.18

$$\dot{x} = f(x) + G(x)u + K(x)\omega$$

$$y = h(x)$$

$$f(x_0) = 0, h(x_0) = 0$$

$$u = -G^T(x) \left(\frac{\partial V}{\partial x} \right)^T$$

$$\frac{\partial V}{\partial x} f(x) + \frac{1}{2} \frac{\partial V}{\partial x} \left[\frac{1}{\gamma^2} K(x)K^T(x) - G(x)G^T(x) \right] \left(\frac{\partial V}{\partial x} \right)^T + \frac{1}{2} h^T(x)h(x) = 0$$

sol)

$$\dot{x} = f(x) - G(x)G^T(x) \left(\frac{\partial V}{\partial x} \right)^T + K(x)\omega$$

$$\omega \rightarrow \begin{bmatrix} y \\ u \end{bmatrix} \quad \dot{x} = f'(x) + K(x)\omega$$

Theorem 5.5 γ gain $\leq \gamma$ $y' = \begin{bmatrix} y \\ u \end{bmatrix} = \begin{bmatrix} h(x) \\ -G^T(x) \left(\frac{\partial V}{\partial x} \right)^T \end{bmatrix} = h'(x)$

$$\frac{\partial V}{\partial x} f'(x) + \frac{\partial V}{\partial x} K(x)\omega = -\frac{1}{2} \gamma^2 \|\omega\|_2^2 - \frac{1}{\gamma^2} K^T(x) \left(\frac{\partial V}{\partial x} \right)^T \left\| \frac{\partial V}{\partial x} f'(x) + \frac{1}{2\gamma^2} \frac{\partial V}{\partial x} K(x)K^T(x) \left(\frac{\partial V}{\partial x} \right)^T + \frac{1}{2} \gamma^2 \|\omega\|_2^2 \right\|_2^2$$

$$f'(x) = f(x) - G(x)G^T(x) \left(\frac{\partial V}{\partial x} \right)^T \text{ 이므로 위 부등식은 이음}$$

$$\frac{\partial V}{\partial x} f'(x) + \frac{\partial V}{\partial x} K(x)\omega \leq \frac{1}{2} \gamma^2 \|\omega\|_2^2 - \frac{1}{2} \|y'\|_2^2 - \frac{1}{2} \gamma^2 \|\omega\|_2^2 - \frac{1}{\gamma^2} K^T(x) \left(\frac{\partial V}{\partial x} \right)^T \left\| \frac{\partial V}{\partial x} f'(x) + \frac{1}{2\gamma^2} \frac{\partial V}{\partial x} K(x)K^T(x) \left(\frac{\partial V}{\partial x} \right)^T + \frac{1}{2} \gamma^2 \|\omega\|_2^2 \right\|_2^2$$

$$\leq \frac{1}{2} \gamma^2 \|\omega\|_2^2 - \frac{1}{2} \|y'\|_2^2$$

$$V(x(\tau)) - V(x_0) \leq \frac{1}{2} \gamma^2 \int_0^\tau \|\omega(t)\|_2^2 dt - \frac{1}{2} \int_0^\tau \|y'(t)\|_2^2 dt$$

Using $V(x) \geq 0$

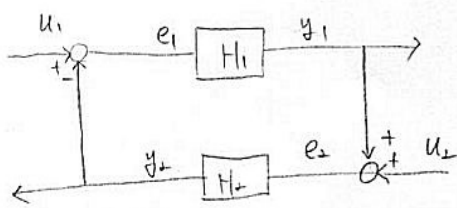
$$\int_0^\tau \|y'(t)\|_2^2 dt \leq \gamma^2 \int_0^\tau \|\omega(t)\|_2^2 dt + 2V(x_0)$$

$\sqrt{a^2 + b^2} \leq a + b$ for nonnegative number, square root

$$\|y'\|_{L_2} \leq \gamma \|u\|_{L_2} + \sqrt{2V(x_0)}$$

\therefore finite gain L_2 stable with L_2 gain less than or equal to γ .

5.21



$$e_{1t} = u_{1t} - (H_2 e_2)_t$$

$$e_{2t} = u_{2t} + (H_1 e_1)_t$$

By theorem 5.6의 proof

$$\|e_1\|_L \leq \frac{1}{1 - \gamma_1 \gamma_2} (\|u_1\|_L + \gamma_2 \|u_2\|_L + \beta_2 + \gamma_2 \beta_1) \quad (5.40)$$

$$\|e_2\|_L \leq \frac{1}{1 - \gamma_1 \gamma_2} (\|u_2\|_L + \gamma_1 \|u_1\|_L + \beta_1 + \gamma_1 \beta_2) \quad (5.41)$$

only if \Rightarrow

$$\|y_1\|_L \leq \gamma_1 \|e_1\|_L + \beta_1$$

$$\leq \gamma_1 \left[\frac{1}{1 - \gamma_1 \gamma_2} (\|u_1\|_L + \gamma_2 \|u_2\|_L + \beta_2 + \gamma_2 \beta_1) \right] + \beta_1$$

$$= \frac{\gamma_1}{1 - \gamma_1 \gamma_2} \|u_1\|_L + \frac{\gamma_1 \gamma_2}{1 - \gamma_1 \gamma_2} \|u_2\|_L + \frac{\gamma_1 (\beta_2 + \gamma_2 \beta_1)}{1 - \gamma_1 \gamma_2} + \beta_1$$

$$\|y_2\|_L \leq \frac{\gamma_2}{1 - \gamma_1 \gamma_2} \|u_2\|_L + \frac{\gamma_2 \gamma_1}{1 - \gamma_1 \gamma_2} \|u_1\|_L + \frac{\gamma_2 (\beta_1 + \gamma_1 \beta_2)}{1 - \gamma_1 \gamma_2} + \beta_2$$

only if \Leftarrow

$$(u_1, u_2) \rightarrow (y_1, y_2) \Leftrightarrow (u_1, u_2) \rightarrow (e_1, e_2)$$

* if (\Leftarrow) 조건과 only if (\Rightarrow) 조건을 증명하기 위해서 먼저 한 조건을 가정한 다음에 그 가정을 이용해서 결론을 이끌어 내야 함.

To show that $A \Rightarrow B$, assume A holds.

By using A , we conclude that B holds.

mapping from (u_1, u_2) to (e_1, e_2) is finite gain L stable

증명 \Leftarrow from (u_1, u_2) to (y_1, y_2) is also finite gain L stable //

증명 \Leftarrow 마찬가지로 하면

$$e_{1t} = u_{1t} - y_{2t}$$

$$\|e_1\|_L \leq \|u_1\|_L + \|y_2\|_L$$

$$\leq \|u_1\|_L + \frac{\gamma_2}{1 - \gamma_1 \gamma_2} \|u_2\|_L + \frac{\gamma_2 \gamma_1}{1 - \gamma_1 \gamma_2} \|u_1\|_L + \frac{\gamma_2 (\beta_1 + \gamma_1 \beta_2)}{1 - \gamma_1 \gamma_2} + \beta_2$$

$$= \frac{1}{1 - \gamma_1 \gamma_2} (\|u_1\|_L + \gamma_2 \|u_2\|_L + \beta_2 + \gamma_2 (\beta_1 + \gamma_1 \beta_2) + \beta_2 - \beta_2 \gamma_1 \gamma_2)$$

$$= \frac{1}{1 - \gamma_1 \gamma_2} (\|u_1\|_L + \gamma_2 \|u_2\|_L + \beta_2 + \beta_2 + \gamma_2 \beta_1)$$

$$\|e_2\|_L \leq \|u_2\|_L + \|y_1\|_L \leq \frac{1}{1 - \gamma_1 \gamma_2} (\|u_2\|_L + \gamma_1 \|u_1\|_L + \beta_1 + \gamma_1 \beta_2) //$$

5.3) (a) $y = u^{\frac{1}{3}}$ 이므로

$$|y| \leq |u|^{\frac{1}{3}}$$

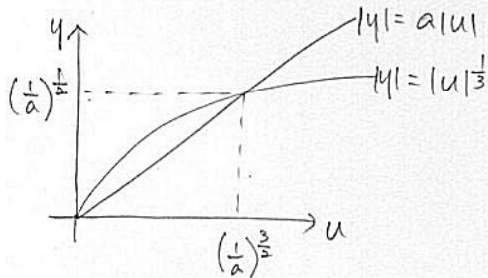
$$\therefore \|y\|_{L_{\infty}} \leq (\|u\|_{L_{\infty}})^{\frac{1}{3}}$$

$\alpha(r) = r^{\frac{1}{3}}$ 이라 하자. $\alpha(\cdot)$ 는 class K_{∞} function이다.

$$\therefore \|y\|_{L_{\infty}} \leq \alpha(\|u\|_{L_{\infty}})$$

\therefore 이 시스템은 L_{∞} stable 이고 $\beta = 0$ 이므로 zero bias.

(b) $|y| = |u|^{\frac{1}{3}}$ 과 $|y| = a|u|$ 의 교차점은 $(\left(\frac{1}{a}\right)^{\frac{3}{2}}, \left(\frac{1}{a}\right)^{\frac{1}{2}})$ 이다.



따라서 $\left\{ \begin{array}{l} |u| \leq \left(\frac{1}{a}\right)^{\frac{3}{2}} \text{ 인 영역에서 } |y| \leq \left(\frac{1}{a}\right)^{\frac{1}{2}} \\ |u| > \left(\frac{1}{a}\right)^{\frac{3}{2}} \text{ 인 영역에서 } |y| \leq a|u| \end{array} \right.$

\therefore 모든 $|u| \geq 0$ 영역에서

$$|y| \leq \left(\frac{1}{a}\right)^{\frac{1}{2}} + a|u|$$

$\therefore r = a, \beta = \left(\frac{1}{a}\right)^{\frac{1}{2}}$ 로 잡으면

$$\|y\|_{L_{\infty}} \leq r\|u\|_{L_{\infty}} + \beta$$

같이 되어 이 시스템이 finite-gain L_{∞} stable임을 알 수 있다.

(c) ???

$$5. (1)(3) \begin{cases} \dot{x}_1 = (x_1 + u)(\|x\|_2^2 - 1) \\ \dot{x}_2 = x_2(\|x\|_2^2 - 1) \\ y = x_1 \end{cases}$$

$$V(x) = \frac{1}{2}(x_1^2 + x_2^2) \text{ 이라 하면,}$$

$$\dot{V}(x) = x_1 \dot{x}_1 + x_2 \dot{x}_2 = x_1(x_1 + u)(\|x\|_2^2 - 1) + x_2^2(\|x\|_2^2 - 1)$$

$$= (\|x\|_2^2 - 1)(x_1^2 + x_2^2 + x_1 u)$$

$$\leq (\|x\|_2^2 - 1)(\|x\|_2^2 + \|x\|_2 |u|)$$

$$\leq -\|x\|_2^2 + \|x\|_2^4 + \|x\|_2^3 |u|$$

$$= -(1-\theta)\|x\|_2^2 - \theta\|x\|_2^2 + \|x\|_2^4 + \|x\|_2^3 |u|, \quad 0 < \theta < 1$$

if $u=0$,

$$\dot{V} \leq -\|x\|_2^2(1 - \|x\|_2^2)$$

$\forall x$ s.t. $\|x\|_2 > 1$, $\dot{V} > 0$.

\therefore not Lyapunov stable..

$$p(s) = -\theta y^2 + y^4 + y^3 s = 0, \quad s \geq 0 \text{ 의 가장 큰 실근이라고 하면,}$$

$$\dot{V} < -(1-\theta)\|x\|_2^2, \quad \forall \|x\|_2 \geq \frac{p(|u|)}{2}$$

\therefore 이 시스템은 input-to-state stable. $\rightarrow \|x\|_2 \leq \frac{-|u| + \sqrt{|u|^2 + 4\theta}}{2}$

$\forall x$ s.t. $\|x\|_2 < 1$

$$\dot{x} = \frac{\partial f}{\partial x} \Big|_{x=0} x; \text{ exp. stable}$$

\therefore small-signal finite-gain

Lyapunov stable..

$$y = h(x) = x_1 \text{ 이므로}$$

$$\|h(t, x, u)\| \leq \alpha_1(\|x\|) + \alpha_2(\|u\|) + \eta$$

$$\alpha_1(r) = r, \quad \alpha_2(\cdot) = 0, \quad \eta = 0 \text{ 일 때 위식 만족.}$$

\therefore 이 시스템은 L_∞ stable. (x)

5.18)

$$\begin{cases} \dot{x} = f(x) + G(x)u + K(x)w & \dots \textcircled{1} \\ y = h(x) & \dots \textcircled{2} \\ u = -G^T(x) \left(\frac{\partial V}{\partial x} \right)^T & \dots \textcircled{3} \end{cases}$$

closed-loop map from w to $\begin{bmatrix} y \\ u \end{bmatrix}$ 는

$$\begin{cases} \dot{x} = f_c(x) + G_c(x)w \\ y_c = h_c(x) \end{cases}, \quad \begin{cases} f_c(x) = f(x) - G(x)G^T(x) \left(\frac{\partial V}{\partial x} \right)^T \\ G_c(x) = K(x) \\ y_c = \begin{bmatrix} y \\ u \end{bmatrix}, \quad h_c(x) = \begin{bmatrix} h(x) \\ -G^T(x) \left(\frac{\partial V}{\partial x} \right)^T \end{bmatrix} \end{cases}$$

문제에서 주어진 조건들이 theorem 5.5의 조건에 부합하므로

Hamilton-Jacobi inequality가 성립하면 finite-gain L_2 stable이고 L_2 gain이 γ 이하임을 알 수 있다.

$$\begin{aligned} \mathcal{H}(V, f_c, G_c, h_c, r) &= \frac{\partial V}{\partial x} f_c(x) + \frac{1}{2\gamma^2} \frac{\partial V}{\partial x} G_c(x) G_c^T(x) \left(\frac{\partial V}{\partial x} \right)^T + \frac{1}{2} h_c^T(x) h_c(x) \\ &= \frac{\partial V}{\partial x} \left(f(x) - G(x)G^T(x) \left(\frac{\partial V}{\partial x} \right)^T \right) + \frac{1}{2\gamma^2} \frac{\partial V}{\partial x} K(x) K^T(x) \left(\frac{\partial V}{\partial x} \right)^T \\ &\quad + \frac{1}{2} h^T(x) h(x) + \frac{1}{2} \left(\frac{\partial V}{\partial x} \right) G(x) G^T(x) \left(\frac{\partial V}{\partial x} \right)^T \\ &\leq \frac{\partial V}{\partial x} f(x) + \frac{1}{2} \frac{\partial V}{\partial x} \left[\frac{1}{\gamma^2} K(x) K^T(x) - G(x) G^T(x) \right] \left(\frac{\partial V}{\partial x} \right)^T + \frac{1}{2} h^T(x) h(x) \dots \textcircled{5} \end{aligned}$$

⑤ 식은 문제에서 주어진 조건에 따라 ⑤ ≤ 0

$\therefore \mathcal{H}(V, f, G, h, r) \leq 0$ 이므로 closed-loop map from w to $\begin{bmatrix} y \\ u \end{bmatrix}$ 는 finite-gain L_2 stable 이고 L_2 gain은 γ 이하이다.

5.21) (u_1, u_2) 에서 (y_1, y_2) 로의 mapping이 finite & stable. 증명.
 $\Leftrightarrow (u_1, u_2)$ 에서 (e_1, e_2) 로의 mapping이 finite & stable

1) (u_1, u_2) 에서 (y_1, y_2) 로의 mapping이 finite & stable

$\Rightarrow (u_1, u_2)$ 에서 (e_1, e_2) 로의 mapping이 finite & stable

2) (u_1, u_2) 에서 (y_1, y_2) 로의 mapping이 finite & stable이면,

$$\begin{cases} \|y_{1T}\|_L \leq r_1 \|u_{1T}\|_L + \beta_1 & \dots \textcircled{1} \\ \|y_{2T}\|_L \leq r_2 \|u_{2T}\|_L + \beta_2 & \dots \textcircled{2} \end{cases}$$

figure 5.1에서 $\begin{cases} e_1 = u_1 - y_2 & \dots \textcircled{3} \\ e_2 = u_2 + y_1 & \dots \textcircled{4} \end{cases}$

①식에 ④를 대입하면

$$\|y_{1T}\|_L = \|e_{2T} - u_{2T}\|_L \geq \|e_{2T}\|_L - \|u_{2T}\|_L$$

$$\|e_{2T}\|_L - \|u_{2T}\|_L \leq \|y_{1T}\|_L \leq r_1 \|u_{1T}\|_L + \beta_1$$

$$\therefore \|e_{2T}\|_L \leq r_1 \|u_{1T}\|_L + \|u_{2T}\|_L + \beta_1 \dots \textcircled{5}$$

②식에 ③을 대입하면,

$$\|y_{2T}\|_L = \|u_{1T} - e_{1T}\|_L = \|e_{1T} - u_{1T}\|_L \geq \|e_{1T}\|_L - \|u_{1T}\|_L$$

$$\|e_{1T}\|_L - \|u_{1T}\|_L \leq \|y_{2T}\|_L \leq r_2 \|u_{2T}\|_L + \beta_2$$

$$\therefore \|e_{1T}\|_L \leq \|u_{1T}\|_L + r_2 \|u_{2T}\|_L + \beta_2 \dots \textcircled{6}$$

\therefore 식 ⑤, ⑥에 의해서 (u_1, u_2) 에서 (e_1, e_2) 로의 mapping이 finite gain & stable 임을 알 수 있다.

(ii) (u_1, u_2) 에서 (e_1, e_2) 로의 mapping이 finite L stable

$\Rightarrow (u_1, u_2)$ 에서 (y_1, y_2) 로의 mapping이 finite L stable

(u_1, u_2) 에서 (e_1, e_2) 로의 mapping이 finite L stable 이면,

$$\left\{ \begin{array}{l} \|e_{1r}\|_L \leq \sigma_1 \|u_{1r}\|_L + \beta_1 \quad \dots \textcircled{7} \\ \|e_{2r}\|_L \leq \sigma_2 \|u_{2r}\|_L + \beta_2 \quad \dots \textcircled{8} \end{array} \right.$$

③ 식에 의해서

$$\|e_{1r}\|_L = \|u_{1r} - y_{2r}\|_L = \|y_{2r} - u_{1r}\|_L \geq \|y_{2r}\|_L - \|u_{1r}\|_L$$

⑦ 식에서

$$\|y_{2r}\|_L - \|u_{1r}\|_L \leq \|e_{1r}\|_L \leq \sigma_1 \|u_{1r}\|_L + \beta_1$$

$$\therefore \|y_{2r}\|_L \leq (\sigma_1 + 1) \|u_{1r}\|_L + \beta_1 \quad \dots \textcircled{9}$$

④ 식에 의해서

$$\|e_{2r}\|_L = \|y_{1r} + u_{2r}\|_L \geq \|y_{1r}\|_L - \|u_{2r}\|_L$$

⑧ 식에서

$$\|y_{1r}\|_L - \|u_{2r}\|_L \leq \|e_{2r}\|_L \leq \sigma_2 \|u_{2r}\|_L + \beta_2$$

$$\therefore \|y_{1r}\|_L \leq (\sigma_2 + 1) \|u_{2r}\|_L + \beta_2 \quad \dots \textcircled{10}$$

\therefore 식 ⑨, ⑩에 의해서 (u_1, u_2) 에서 (y_1, y_2) 로의 mapping은 finite gain L stable 이다.

\Rightarrow i), ii) 에 의해서 필요충분조건 증명.