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## Robust control of high-order nonlinear systems with unknown measurement sensitivity

Cai-Yun LIU<sup>1</sup>, Zong-Yao SUN<sup>1\*</sup>, Qinghua MENG<sup>2</sup> & Wei SUN<sup>3</sup>

<sup>1</sup>Institute of Automation, Qufu Normal University, Qufu 273165, China;

<sup>2</sup>School of Mechanical Engineering, Hangzhou Dianzi University, Hangzhou 310018, China; <sup>3</sup>School of Mathematics Science, Liaocheng University, Liaocheng 252000, China

School of Mathematics Science, Eulocheng Oniversity, Eulocheng 252000, China

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Dear editor,

• LETTER •

Recently, considerable attention has been devoted to output feedback control and practical tracking of nonlinear systems [1,2]. Unfortunately, limitations of sensor techniques can cause sensitivity errors in practical environments. For example, Ref. [3] showed that the displacement sensor of a magnetic bearing suspension system experienced  $\pm 10\%$  sensitivity error in practice. Thus, investigating nonlinear systems with unknown measurement sensitivity is valuable.

In addition, stabilizing high-order nonlinear systems is seen as a highly challenging problem, because it has uncontrollable linearization around the origin. Hence, this study investigates the system described by

$$\begin{cases} \dot{x}_1 = g_1(x_1)x_2^{p_1} + f_1(x_1) + \omega_1(t), \\ \dot{x}_2 = g_2(x_1, x_2)u^{p_2} + f_2(x_1, x_2) + \omega_2(t), \end{cases}$$
(1)

where  $x_1 \in \mathbb{R}$  and  $x_2 \in \mathbb{R}$  are system state variables, and  $u \in \mathbb{R}$  is the control input. For  $i = 1, 2, f_i$  and  $g_i$  are unknown smooth functions,  $p_i \ge 1$  are odd integers, and  $\omega_i(t)$  are bounded disturbances. Here, we should emphasize that the state variables  $x_1, x_2$  are not directly available to the control design owing to being measured by sensors. The measured values are perturbed as follows:

$$\hat{x}_i(t) = \theta_i(t)x_i, \ i = 1, 2,$$
(2)

where the function  $\theta_i$  characterizes the sensor sensitivity, and  $\hat{x}_i$  which is available denotes the sensor measurement. To understand the physical meaning of this problem, let us consider the special case where  $x_1$  is perturbed by (2),  $p_1 = p_2 = 1$ ,  $g_1 = g_2 = 1$ , and  $\omega_1 = \omega_2 = 0$ . Now  $\dot{x}_1 = x_2 + f_1(x_1)$  and  $\dot{x}_2 = u + f_2(x_1, x_2)$ . Additionally, if we define  $y = \theta_1 x_1$ , it yields the model in [3].

The control objective is to design an input u(t) such that  $x_i(t) \in S \triangleq \{z \in \mathbb{R} : |z| \leqslant M\}$  for all  $t \ge$ 

**Assumption 1.** For i = 1, 2, the function  $\theta_i$  satisfies  $\underline{\theta} < \theta_i < \overline{\theta}$  and  $|\dot{\theta}_i| < \theta$ , where  $\underline{\theta}$ ,  $\overline{\theta}$ , and  $\theta$  are known positive constants.

**Assumption 2.** For i = 1, 2, the function  $g_i$  satisfies  $\underline{g} < g_i < \overline{g}$ , where  $\underline{g}$  and  $\overline{g}$  are known positive constants.

Although Assumptions 1 and 2 are standard (being used in [4]), this study makes three innovative contributions. (i) Instead of using a neural network approximation [5], we use two new tangent functions equipped with a nonzero tuning function to dominate completely unknown nonlinearities  $f_1$  and  $f_2$ . This enables us to overcome the restriction that the state variables must lie within some compact set. (ii) We present a new method, different from that given in [3], of obtaining the bound of the sensor sensitivity as large as possible. (iii) The theoretical analysis is more straightforward than that in [4], because we provide a direct proof rather than that by contradiction.

We introduce a technical lemma for later use in the control design.

**Lemma 1** ([3]). For given positive constants c and d and any smooth function  $\gamma(x, y)$ , we have

$$|x|^c|y|^d \leqslant \frac{c}{c+d} \gamma(x,y) |x|^{c+d} + \frac{d}{c+d} \gamma^{-\frac{c}{d}}(x,y) |y|^{c+d}.$$

 $Main\ result.$  Now, we are ready to present the main result of this study.

**Theorem 1.** For system (1), under Assumptions 1 and 2 and subject to (2), there exists a continuously differentiable controller that ensures that the state variables remain within a predetermined bounded domain.

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<sup>0</sup> and i = 1, 2, where M is a predetermined known constant. We also make Assumptions 1 and 2.

 $<sup>\ ^*</sup> Corresponding \ author \ (email: \ sunzongyao@sohu.com)$ 

*Proof.* Using (2), we can rewrite system (1) as

$$\dot{x}_1 = F_1(x_1, \theta_1, \dot{\theta}_1) + D_1(t) + G_1(\theta_1, \theta_2, x_1) \dot{x}_2^{p_1}, \\ \dot{x}_2 = F_2(x_1, x_2, \theta_2, \dot{\theta}_2) + D_2(t) + G_2(\theta_2, x_1, x_2) u^{p_2},$$
(3)

where  $F_1 = \dot{\theta}_1 x_1 + \theta_1 f_1$ ,  $F_2 = \dot{\theta}_2 x_2 + \theta_2 f_2$ ,  $D_1 = \theta_1 \omega_1$ ,  $D_2 = \theta_2 \omega_2$ ,  $G_1 = \theta_1 g_1 / \theta_2^{p_1}$ , and  $G_2 = \theta_2 g_2$ . Now, define

$$\xi_1(t) = \hat{x}_1(t)\beta(t), \tag{4}$$

$$\xi_2(t) = \hat{x}_2(t)\beta(t) - \alpha_1(t),$$
 (5)

where the tuning function  $\beta$  is defined by

$$\beta(t) = \begin{cases} \sin\left(\frac{\pi t}{2\tau}\right) + \varepsilon, & t < \tau, \\ 1 + \varepsilon, & t \ge \tau, \end{cases}$$
(6)

and the function  $\alpha_1$  is defined by

$$\alpha_1 = -b_1 \varphi_1(\xi_1, \sigma_1), \quad \varphi_1(\xi_1, \sigma_1) = \tan\left(\frac{\pi \xi_1}{2\sigma_1}\right).$$
 (7)

Herein, we introduce the positive constants  $b_1$  and  $\varepsilon$  to avoid having to deal with division by zero in the subsequent analysis, and use the positive constant  $\sigma_1$  to characterize the ultimate bound of  $\xi_1$ . In addition,  $\tau > 0$  is a constant (to be chosen later), and we use  $\beta(t)$  to adjust the deviation between  $\hat{x}_i(t)$  and  $\xi_i(t)$  in terms of the appropriate choices of  $\alpha_1$  and  $\tau$ . Differentiating (4) yields

$$\dot{\xi}_1 = \beta^{1-p_1} G_1 \sum_{j=0}^{p_1} \xi_2^j (-1)^{p_1-j} b_1^{p_1-j} \varphi_1^{p_1-j} C_{p_1}^j + \Delta_1(x_1, \theta_1, \dot{\theta}_1, \beta, \dot{\beta}),$$
(8)

where  $\Delta_1 = \hat{x}_1 \dot{\beta} + \beta (F_1 + D_1)$ . If we choose the controller

$$u = -b_2\varphi_2(\xi_2, \sigma_2), \quad \varphi_2(\xi_2, \sigma_2) = \tan\left(\frac{\pi\xi_2}{2\sigma_2}\right), \qquad (9)$$

where  $b_2$  is a positive constant and  $\sigma_2$  represents the ultimate bound of  $\xi_2$ . The derivative of (5) along the solution to (3) is  $\dot{\xi}_2 = \Delta_2(x_1, x_2, \theta_2, \dot{\theta}_2, \beta, \dot{\beta}) - G_2 b_2^{p_2} \varphi_2^{p_2} \beta$ , where  $\Delta_2 = (F_2 + D_2)\beta + \dot{\beta} \dot{x}_2 - \dot{\alpha}_1$ .

In the following, we use reductio ad absurdum to prove that

$$|\xi_i(t)| < \sigma_i, \ i = 1, 2, \ \forall t \ge 0.$$

$$(10)$$

Suppose that the inequality (10) is first violated at finite time  $t_1$  and  $t_2$ . Then, for i = 1, 2, we must have  $|\xi_i(t_i)| = \sigma_i$  and  $|\xi_i(t)| < \sigma_i$ ,  $t \in [0, t_i)$ .

To facilitate the proof process, we divide this into two separate cases.

Case I. If  $t_1 \leq t_2$ , then for i = 1, 2 we have

$$|\xi_i(t)| < \sigma_i, \ t \in [0, t_1).$$
 (11)

Given the continuity of  $\xi_1$ , we have  $\lim_{t \to t_1^-} |\xi_1(t)| = \sigma_1$ . This, together with the definition of  $\varphi_1$ , implies that

$$\lim_{t \to t_1^-} |\varphi_1(\xi_1(t), \sigma_1)| = \left| \tan\left(\pm \frac{\pi}{2}\right) \right| = +\infty.$$
(12)

The remainder of the proof can be divided into two steps.

Step 1. Prove that  $\xi_1(t)$  is bounded on  $[0, \infty)$ . First, we construct the continuously differentiable function

$$V_1(\xi_1) = \frac{\sigma_1}{\pi} \varphi_1^{p_1 + 1}.$$
 (13)

According to Lemma 1, the time derivative of (13) along the solution to system (8) satisfies

$$\dot{V}_{1} \leqslant \frac{|\varphi_{1}|^{p_{1}}}{\varrho_{1}} (|\Delta_{1}| + \beta^{1-p_{1}} G_{1}|\xi_{2}|^{p_{1}} m_{11}) - \frac{|\varphi_{1}|^{p_{1}}}{2\varrho_{1}} \beta^{1-p_{1}} G_{1} b_{1}^{p_{1}} |\varphi_{1}|^{p_{1}},$$
(14)

where  $\rho_1 = \frac{2\cos^2(\frac{\pi\xi_1}{2\sigma_1})}{p_1+1}$  and  $m_{11} > 0$  is a constant. By virtue of the way  $\beta(t)$  is defined in (6),  $\beta$  and  $\dot{\beta}$  are bounded. It also becomes clear that  $\hat{x}_1, x_1$  and  $\xi_2$  are bounded on  $[0, t_1)$  if we use (2), (4), (5), (11), and  $\beta \neq 0$ . Meanwhile, the continuity of  $f_1$  and  $g_1$ , together with Assumptions 1 and 2, guarantees that  $F_1$  and  $G_1$  are bounded over  $[0, t_1)$ . In addition, the boundedness of  $\omega_1(t)$  implies that  $D_1$  is bounded. Based on the foregoing discussion, we have

$$\begin{aligned} |\Delta_1| \leqslant m_{12}, \quad \beta^{1-p_1} G_1|\xi_2|^{p_1} m_{11} \leqslant m_{13} \\ G_1 &= \frac{g_1 \theta_1}{\theta_2^{p_1}} \geqslant \frac{\underline{g}\underline{\theta}}{\overline{\theta}^{p_1}}, \quad t \in [0, t_1), \end{aligned}$$

where  $m_{12}$  and  $m_{13}$  are positive constants. If we let  $m_1 = m_{12} + m_{13}$ , then we can rewrite (14) as

$$\dot{V}_{1} \leqslant \frac{|\varphi_{1}|^{p_{1}}}{\varrho_{1}} \left( m_{1} - \frac{\underline{g}\underline{\theta}}{2\overline{\theta}^{p_{1}}} \beta^{1-p_{1}} b_{1}^{p_{1}} |\varphi_{1}|^{p_{1}} \right), \ t \in [0, t_{1}).$$

Given (12), there must exist a small constant  $\delta > 0$  such that  $|\varphi_1(t)|^{p_1} \ge \frac{2\hat{\theta}^{p_1}m_1\beta^{p_1-1}}{g\underline{\theta}^{p_1}}$ ,  $t \in [t_1^- -\delta, t_1^-)$ . Consequently,  $\dot{V}_1 \le 0$  on  $[t_1^- -\delta, t_1^-)$ , i.e.,  $V_1(\xi_1(t)) \le V_1(\xi_1(t_1^- -\delta))$ ,  $t \in [t_1^- -\delta, t_1^-)$ . The boundedness of  $V_1(\xi_1(t_1^- -\delta))$  implies that  $V_1(\xi_1(t))$  is bounded on  $[t_1^- -\delta, t_1^-)$ . In addition, the continuity of  $V_1$  guarantees  $V_1(\xi_1(t))$  is bounded on  $[0, t_1^- -\delta]$ . This indicates that  $V_1(\xi_1(t))$  is bounded on  $[0, t_1^-)$ , which in turn implies that  $|\varphi_1(t)|$  is bounded for all  $t \in [0, t_1^-)$ , contradicting  $\lim_{t \to t_1^-} |\varphi_1(t)| = +\infty$  because the function is continuous. Hence,  $|\xi_1(t)| < \sigma_1$  for all  $t \ge 0$ .

Step 2. Prove that  $\xi_2(t)$  is bounded on  $[0, \infty)$ . With the boundedness of  $\xi_1$  and the suppose of  $\xi_2$  in mind, we obtain

$$|\xi_i(t)| < \sigma_i, \quad i = 1, 2, \quad t \in [0, t_2).$$
 (15)

Now, we can prove that  $x_1$ ,  $x_2$ , and  $\hat{x}_2$  are bounded on  $[0, t_2)$  using (6), (7), (15), and Assumption 1, so  $f_2$  and  $F_2$  are bounded as well. In addition, Eq. (7) implies that  $\dot{\alpha}_1$  is also bounded on  $[0, t_2)$ . The time derive of the continuously differentiable function  $V_2(\xi_2) = \frac{\sigma_2}{\pi} \varphi_2^{p_2+1}$  is

$$\dot{V}_2 \leqslant \frac{|\varphi_2|^{p_2}}{\varrho_2} (|\Delta_2| - b_2^{p_2} G_2 \beta |\varphi_2|^{p_2}),$$

where  $\varrho_2 = \frac{2\cos^2(\frac{\pi \xi_2}{2g_2})}{p_2+1}$ . The boundedness of  $\omega_2$  implies that  $|\Delta_2| \leq m_{21}, t < t_2$ , where  $m_{21}$  is a positive constant. Given that  $G_2 = \theta_2 g_2 \geq g\underline{\theta}$ , it is straightforward to show that

$$\dot{V}_2 \leqslant \frac{|\varphi_2|^{p_2}}{\varrho_2} (m_{21} - b_2^{p_2} \underline{g} \underline{\theta} \beta |\varphi_2|^{p_2}), \ t \in [0, t_2)$$

We can now conclude that  $|\varphi_2(t)|$  is bounded on  $[0, t_2)$ by a proof similar to that in Step 1, which contradicts  $\lim_{t \to t_2^-} |\varphi_2(t)| = +\infty$ . Hence,  $|\xi_2(t)| < \sigma_2$  for all  $t \ge 0$ .

Case II. If  $t_1 > t_2$ , then for i = 1, 2 we have

$$|\xi_i(t)| < \sigma_i, \quad t \in [0, t_2).$$
 (16)

By taking a similar reductio ad absurdum approach to that used for Case I, we can first prove the boundedness of  $\xi_2(t)$  on  $[0, \infty)$ , and then go on to show that  $\xi_1(t)$  is also bounded on  $[0, \infty)$ .

Combining Cases I and II completes the proof of (10). All that remains is to proof the convergent adjustment on state variables. With (2) and (4) in mind, we have

$$|x_1(t)| = \frac{|\beta \hat{x}_1(t)|}{|\beta|\theta_1} = \frac{|\xi_1(t)|}{|\beta|\theta_1} \leqslant \frac{\sigma_1}{\varepsilon \underline{\theta}} \stackrel{\Delta}{=} \bar{\sigma}_1, \ t \in [0,\infty).$$

If we let  $\bar{\sigma}_1 \leq M$ , we have  $|x_1(t)| \leq M$ . Given (10), there must exist a constant  $0 < \lambda < \sigma_1$  such that  $|\xi_1(t)| \leq \sigma_1 - \lambda$  for  $t \geq 0$ . Then, it follows from (2), (5)–(7), (10), and Assumption 1 that

$$|x_2(t)| \leqslant \frac{\sigma_2}{\underline{\theta}\varepsilon} + \frac{b_1}{\underline{\theta}\varepsilon} \tan\left(\frac{\pi(1-\lambda/\sigma_1)}{2}\right) \stackrel{\Delta}{=} \bar{\sigma}_2, \ t \in [0,\infty).$$

Because  $\sigma_1, \sigma_2, \lambda, \varepsilon$ , and  $b_1$  are adjustable, we can ensure that  $\frac{\sigma_2}{\theta\varepsilon} \leq \frac{M}{2}$  and  $\frac{b_1}{\theta\varepsilon} \tan(\frac{\pi(1-\lambda/\sigma_1)}{2}) \leq \frac{M}{2}$ . Thus, we have  $|x_2(t)| \leq M$ , completing the proof.

*Conclusion.* We have solved the problem of global robust control for a class of nonlinear systems with unknown

measurement sensitivity. The problem of achieving similar control when  $\theta(t)$  is only required to be continuous remains unsolved.

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