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Actuator Fault Compensation Control for Nonlinear Systems

S. Joe Qin * and Yingwei Zhang **

**The Mork Family Department of Chemical Engineering and Materials Science, Ming Hsieh Department of Electrical Engineering, Daniel J. Epstein Department of Industrial and Systems Engineering, University of Southern California, 925 Bloom Walk, HED 210, Los Angeles, CA 90089-121190*
(email:sqin @usc.edu)
***Key Laboratory of Integrated Automation of Process Industry, Ministry of Education , Northeastern University, Shenyang, Liaoning 110004, P. R. China*
(zhangyingwei@ise.neu.edu.cn)

Abstract: The partial loss of actuator effectiveness is considered for the control of a class of nonlinear processes in the presence of a fault. Not only unmatched uncertainties, but also matched uncertainties are discussed in Lyapunov stability sense. The partial loss of actuator effectiveness is approximated by high order neural networks. Application of the proposed design indicates that the fault compensation control law is effective for a nonlinear fermentation system.

1. INTRODUCTION

The study of fault diagnosis and fault-tolerant control has attracted much attention (Patton et al. (2000) and Zhang et al. (2004)), due to the industrial demands for safety and efficiency. For certain processes, it is important not only to detect (and identify) but also to accommodate any faults quickly. Fault-tolerant controls have been developed to keep such processes in control, in spite of the occurrence of a fault. For most control systems the faults can be seen in their actuators, sensors, and systems themselves. The purpose of fault detection and diagnosis (FDD) is to use available inputs, outputs, and operating points of the systems to detect faults. Once the faults are detected, fault diagnosis should be performed so as to locate the fault and also give a good estimation of fault sizes. (Zhang et al. (2002)).

In terms of fault-tolerant control, various techniques have been developed which can be roughly classified into passive and active fault-tolerant control schemes. The former is 'similar' to robust control while the latter can be regarded as a reinforced nonlinear control in the sense that control structures and parameters are improved so as to realize a reliable operation of concerned closed-loop systems before a scheduled repair is made. (El-Farra et al. (2005)).

In an active fault-tolerant control, faults are accommodated, typically by a reconfiguration of the feedback control law. Faults are typically associated with sensors and actuators failures; accordingly, respective compensation strategies can be designed. For example, sensor fault compensations for MIMO systems have been discussed by Tortora et al. (2002).

Adaptive approaches have also been used in fault tolerant control. For example, an adaptive compensation method for actuator faults with known plant dynamics has been formulated by Zhang et al. (2004) and Sastry and Isidori (1989); Idan (2001) presents an intelligent fault tolerant flight control system design method that blends aerodynamic and propulsion actuation for safe flight operation in the presence of actuator failures by utilizing redundancy. The actuator and component faults are combined and denoted as a nonlinear function (Zhang and Qin (2007)). The partial loss of actuator effectiveness are considered and represented as $(I-\Gamma)u$ with the fault parameter Γ in this paper. Specially, not only unmatched uncertainties, but also matched uncertainties are discussed.

Based on neural networks which are capable of approximating, with arbitrary accuracy, any real continuous function on a compact set, the partial loss of actuator effectiveness is approximated by the neural networks. Then an adaptive compensation control law is formulated to ensure the system stability.

The remainder of the paper is organized as follows. The problem statement and its assumptions are given in section 2, followed by the formulation of our controller and its relevant proofs in section 3. An illustrative example is given in section 4 to demonstrate the effectiveness of the proposed method. Finally, conclusions are drawn in section 5.

2. PROBLEM STATEMENT

The following actuator fault model is adopted in this paper (Veillette 1995): $i=1,\cdots,m$, $j=1,\cdots,L$

$$u_{ij}^{C}=(1-\Gamma_i^j)u_i(t),\ 0\le\underline{\Gamma}_i^j\le\Gamma_i^j\le\overline{\Gamma}_i^j\le 1 \tag{1}$$

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where Γ_i^j is an unknown constant. Here, the index j denotes the j th fault mode and L is the total fault modes. Let u_{ij}^C represent the signal from the i th actuator that has failed in the j th fault mode. For every fault mode, $\underline{\Gamma}_i^j$ and $\overline{\Gamma}_i^j$ represent the lower and upper bounds of Γ_i^j, respectively. Note that, when $\underline{\Gamma}_i^j = \overline{\Gamma}_i^j$ =0, there is no fault for the i th actuator u_i in the j th fault mode. When $\underline{\Gamma}_i^j = \overline{\Gamma}_i^j$ =0=1, the i th actuator u_i is outage in the j th fault mode. When $0 \le \underline{\Gamma}_i^j \le \rho_i^j \le \overline{\Gamma}_i^j \le 1$, in the j th fault mode the type of actuator faults is loss of effectiveness. Denote

$$u_{ij}^C = [u_{1j}^C, \quad u_{2j}^C, \quad \cdots, \quad u_{mj}^C] = (I - \Gamma^j)u(t)$$

where $\Gamma^j = diag[\Gamma_1^j, \Gamma_2^j, \cdots, \Gamma_m^j]$, $j = 1, 2, \cdots, L$. Considering the lower and upper bounds $(\underline{\Gamma}_i^j, \overline{\Gamma}_i^j)$, the following set can be defined

$$N_{\rho^j} = \{\Gamma^j \,|\, \Gamma^j = diag[\Gamma_1^j, \Gamma_2^j, \cdots, \Gamma_m^j], \\ \Gamma_i^j = \underline{\Gamma}_i^j \ or\ \Gamma_i^j = \overline{\Gamma}_i^j \}$$

For all fault modes L, the uniform actuator fault model

$$u_F = (I - \Gamma)u, \Gamma \in \{\Gamma^1, \Gamma^2, \cdots, \Gamma^L\}$$

where Γ can be described by

$$\Gamma = diag[\Gamma_1, \Gamma_2, \cdots, \Gamma_m]. \tag{2}$$

Consider a system described as:

$$\dot{x} = \zeta(x) + \Delta\zeta(x) + G(x)[(I - \beta(t-T)\Gamma)u + \Delta g(x)] \tag{3}$$

where $x \in R^n, u \in R^m$ are the state and input of the system, respectively, $\Delta\zeta(x)$ and $\Delta g(x)$ are the model uncertainty in the normal operation. The normal system, in the absence of any faults, is described by

$$\dot{x} = \zeta(x) + \Delta\zeta(x) + G(x)[u + \Delta g(x)] \tag{4}$$

The fault matrix Γ is multiplied by a switching function $\beta(t-T)$,

$$\beta(t-T) = diag \ (\beta_1(t-T), \beta_2(t-T), \cdots, \beta_m(t-T))$$

where

$$\beta_i(t-T) = \begin{cases} 0 & if \quad t < T \\ 1 & if \quad t \ge T \end{cases}, \quad i = 1, \ 2, \cdots, m \ ,$$

where T is the fault occurrence time. The problem considered is as follows:
Fault compensation (FC) problem: Given system (1), design a control u_N for the normal system, and an additional control u_F for fault compensation, so that $u = u_N + u_F$ as the new control after the occurrence of a fault can guarantee the resulted closed-loop nonlinear system to be stable.

The following assumptions are used.
Assumption 1: There exists $u = u^a(x)$ and Lyapunov function $\overline{V}(x)$, such that

$$k_1 |x|^2 \le \overline{V}(x) \le k_2 |x|^2, \\ \frac{\partial \overline{V}(x)}{\partial x}\left(\zeta(x) + G(x)u^a(x)\right) \le -k_3 \left|\frac{\partial \overline{V}(x)}{\partial x}\right|^2 \\ \le -k_4 \overline{V}(x) \tag{5}$$

where k_1, k_2, k_3, k_4 are positive constants.

Assumption 2: For system (1)

$$\|\Delta g(x)\| \le \xi(x) \tag{6}$$

$$\left\| \left(\frac{\partial \overline{V}(x)}{\partial x}\right)^T \Delta\zeta(x) \right\| \le \rho(x)$$

where $\dfrac{\rho(x)}{\left\| G^T(x) \left(\dfrac{\partial \overline{V}(x)}{\partial x}\right) \right\|}$ is continuous, $\xi(\bullet)$ and $\rho(\bullet)$ are known and continuous.

Remark 1: From Assumption 2, we have $\rho(x) = 0$, if

$$G^T(x)\left(\frac{\partial \overline{V}(x)}{\partial x}\right) = 0 .$$

3. FAULT COMPENSATION

The partial loss of actuator effectiveness can be approximated by the neural networks. Then system (3) can be rewritten as:

$$\dot{x} = \zeta(x) + \Delta\zeta(x) + G(x)[u + W^* S(x) + \varepsilon(x) + \Delta g(x)] \tag{7}$$

where, $\varepsilon(x) = \left| f(x) - W^* S(x) \right| \le \varepsilon$ is the estimation error. If we denote W as the estimate of the uncertain weight matrix W^*, then

$$\dot{x} = \zeta(x) + \Delta\zeta(x) + G(x)[u - \tilde{W}S(x) + WS(x) + \varepsilon(x) + \Delta g(x)] \quad (8)$$

where $\tilde{W} = W - W^*$ and it has the appropriate dimension. $S(x)$ is a vector with $S_i(x)$, $i = 1, 2, \cdots, L$. Here, $S_i(x) = \prod_{j \in J_i} [s(x_j)]^{l_j(i)}$ with J_i, $i = 1, 2, \cdots, L$ and $l_j(i)$ is nonnegative integers. Because W^* is bounded, we assume $\|W^*\| < M_W$.

Theorem 1: Under Assumptions 1 and 2, we can design a controller in the form of the following:

$$u = u_N + u_F \quad (9)$$

$$u_N = u^a + u^b + u^c$$

where u_N is the control law of "healthy" systems (4) and u_F is the fault compensation. And u^a is given by Assumption 1, and let

$$E = \left\{ x \mid G(x)^T \frac{\partial \bar{V}(x)}{\partial x} = 0 \right\},$$

$$u^b = \begin{cases} -\dfrac{G^T(x)\dfrac{\partial \bar{V}(x)}{\partial x}}{\left\| G^T(x)\dfrac{\partial \bar{V}(x)}{\partial x} \right\|} \xi(x), & x \notin E \\ 0, & x \in E \end{cases}, \quad (10)$$

$$u^c = \begin{cases} -\dfrac{G^T(x)\dfrac{\partial \bar{V}(x)}{\partial x}}{\left\| G^T(x)\dfrac{\partial \bar{V}(x)}{\partial x} \right\|^2} \rho(x), & x \notin E \\ 0, & x \in E \end{cases}, \quad (11)$$

$$u_F = \frac{WS(x)u_N}{\lambda[1 + \|G(x)\|^2]} + \frac{\Theta\ u_N}{\lambda_1[1 + \|G(x)\|^2]} \quad (12).$$

Where $\Theta \in R^{n \times L}$ and $\Theta = [\theta, 0, \cdots, 0]^T$. Then, the state x is ultimately consistently bounded by the set:

$$D = \left\{ x \in R^n : v_0(x) \le \frac{\mu}{k_0 \alpha}, \frac{\bar{k}_2}{\bar{k}_1} \le k_0 \le 1 \right\}, \quad (13)$$

with the following adaptive weight update law

$$\dot{W} = \begin{cases} 2k_0 \dfrac{\partial v_0}{\partial x} S^T(x) & if\ \|W\| < M_W \\ -\beta W + 2k_0 \dfrac{\partial v_0}{\partial x} S^T(x) & if\ \|W\| \ge M_W \end{cases} \quad (14)$$

$$\dot{\theta} = -\gamma_1 \theta + k_0 \left| \frac{\partial v_0}{\partial x} \right| \quad (15)$$

The parameters of λ, λ_1, $\bar{k}_1$, $\bar{k}_2$, α, μ can be determined as in the proof. The novelty of this paper is that fault compensation controller is clearly given after faults occur. The main contributions of this paper are the design of the corrective control law of nonlinear system with unmatched and matched uncertainties, and the stability analysis of the closed-loop system in the presence of the fault modeling errors is proposed.

Proof: step 1
Substituting the controller Eqs. (9-12) into system (1), we have:

$$\dot{x} = \zeta(x) + \Delta\zeta(x) + G(x)[u^a + u^b + u^c + \Delta g(x)]$$

Define a positive function $v_0(x) = \bar{V}(x)$, then we have:

$$\dot{v}_0(x) = \left(\frac{\partial \bar{V}(x)}{\partial x}\right)^T (\zeta(x) + G(x)u^a) + \left(\frac{\partial \bar{V}(x)}{\partial x}\right)^T G(x)(u^b + \Delta g(x)) + \left(\frac{\partial \bar{V}(x)}{\partial x}\right)^T (\Delta\zeta(x) + G(x)u^c)$$

From Assumption 1, we have

$$\left(\frac{\partial \bar{V}(x)}{\partial x}\right)^T (\zeta(x) + G(x)u^a) \le -k_3 \left| \frac{\partial \bar{V}(x)}{\partial x} \right|^2 \quad (16)$$

From Assumption 2 and the structure of $u^b(x)$, we have

$$\left(\frac{\partial \bar{V}(x)}{\partial x}\right)^T G(x)(u^b + \Delta g(x)) = \left(G^T(x)\frac{\partial \bar{V}(x)}{\partial x_i}\right)^T (u^b + \Delta g(x)) = 0$$

when $x \in E$, and

$$(\frac{\partial \bar{V}(x)}{\partial x})^T G(x)(u^b + \Delta g(x))$$
$$= (\frac{\partial \bar{V}(x)}{\partial x})^T G(x)(-\frac{G^T(x)\frac{\partial \bar{V}(x)}{\partial x}}{\left\| G^T(x)\frac{\partial \bar{V}(x)}{\partial x} \right\|}\xi(x) + \Delta g(x))$$
$$= -\left\| G^T(x)(\frac{\partial \bar{V}(x)}{\partial x})^T \right\| \xi(x) + (\frac{\partial \bar{V}(x)}{\partial x})^T G(x)\Delta g(x)$$
$$\le -\left\| G^T(x)(\frac{\partial \bar{V}(x)}{\partial x})^T \right\| \xi(x) + \left\| (\frac{\partial \bar{V}(x)}{\partial x})^T G(x) \right\| \left\| \Delta g(x) \right\|$$
$$\le 0 \ ,$$

when $x \notin E$. Hence

$$(\frac{\partial \bar{V}(x)}{\partial x})^T G(x)(u^b + \Delta g(x)) \le 0 \tag{17}$$

From Assumption 2 and structure of $u^c(x)$, we have

$$(\frac{\partial \bar{V}(x)}{\partial x})^T (\Delta\zeta(x) + G(x)u^c)$$
$$= (\frac{\partial \bar{V}(x)}{\partial x})^T \Delta\zeta(x) + (G^T(x)\frac{\partial \bar{V}(x\ )}{\partial x_i})^T u^c$$
$$\le \left\| (\frac{\partial \bar{V}(x)}{\partial x})^T \Delta\zeta(x) \right\| \le \rho(x) = 0 \ ,$$

when $x \in E$, and

$$(\frac{\partial \bar{V}(x)}{\partial x})^T (\Delta\zeta(x) + G(x)u^c)$$
$$= (\frac{\partial \bar{V}(x)}{\partial x})^T \Delta\zeta(x)$$
$$u_F = \frac{WS(x)}{\lambda[1 + \|G(x)\|^2]} + \frac{\Theta}{\lambda_1[1 + \|G(x)\|^2]}$$

where $\Theta \in R^n$ and $\Theta = [\theta, 0, \cdots, 0]^T$. When $x \notin E$. Hence

$$(\frac{\partial \bar{V}(x)}{\partial x})^T (\Delta\zeta(x) + G(x)u^c) \le 0 \tag{18}$$

Thus, we obtain

$$\dot{v}_0(x) \le -k_3 \left| \frac{\partial \bar{V}(x)}{\partial x} \right|^2 \tag{19}$$

From (19), the stability of the normal system is proven.

Proof: step 2:

Define a Lyapunov function for system (1) of the following form:

$$V\left(x, \tilde{W}, \tilde{\theta}\right) = k_0 v_0\left(x\right) + \frac{1}{2} tr\left\{\tilde{W}^T \tilde{W}\right\} + \frac{1}{2}\tilde{\theta}^2 \tag{20}$$

with $\tilde{\theta} = \theta - \varepsilon$, then the derivatives of V is

$$\dot{V} = k_0 \frac{\partial v_0}{\partial x}\{f(x) + \Delta f(x) + G(x)[u^a + u^b + u^c +$$
$$\Delta g(x)]\} + k_0 \frac{\partial v_0}{\partial x} G(x)u^F - k_0 \frac{\partial v_0}{\partial x} G(x)\tilde{W}S\left(x\right) +$$
$$k \frac{\partial v_0}{\partial x} G(x)WS\left(x\right) + k_0 \frac{\partial v_0}{\partial x} G(x)\varepsilon\left(x\right) +$$
$$tr\left\{\dot{W}^T \tilde{W}\right\} + \tilde{\theta}\dot{\theta} \tag{21}$$

Using (14), we obtain

$$\dot{V} = k_0 \dot{v}_0 + k_0 \frac{\partial v_0}{\partial x} G(x)u^F + k_0 \frac{\partial v_0}{\partial x} G(x)WS\left(x\right)$$
$$+ k_0 \frac{\partial v_0}{\partial x} G(x)\varepsilon\left(x\right) - \beta I_W tr\left\{W^T \tilde{W}\right\} + \tilde{\theta}\dot{\theta}$$

where I_W is the indicator function of W, and it satisfies

$$I_W = \begin{cases} 1 & if \quad \|W\| \ge M_W \\ 0 & if \quad \|W\| < M_W \end{cases} \tag{22}$$

Choosing

$$\lambda \ge \frac{k_0 s}{\sqrt{2\bar{k}_2 \beta - s k_0}}, \tag{23}$$

$$\lambda_1 \ge \frac{k_0}{\sqrt{2k_0 \bar{k}_2 \gamma_1 - k_0}} \ , \tag{24}$$

$$\beta > \frac{s^2 k_0^2}{2\bar{k}_2}, \tag{25}$$

$$\gamma_1 > \frac{k_0}{2\bar{k}_2} \tag{26}$$

By using Eq. (5) from Zhang and Qin (2007) we have

$$\dot{V} \le -\frac{k_0 \bar{k}_3 k_4}{k_3} v_0(x) - \frac{\beta}{2}\|\tilde{W}\|^2 \xi^2 - \frac{\gamma_1}{2}\tilde{\theta}^2 \xi^2 + 2\beta M_W^2 + \frac{\gamma_1}{2}\varepsilon^2 \xi^2 \quad (27)$$

therefore $\dot{V} \le -\alpha V + \mu$, with $\alpha = \min\left\{\frac{\bar{k}_3 k_4}{k_3}, \beta, \gamma_1\right\}$,

$$\mu = 2\beta M_W^2 + \frac{\gamma_1}{2}\varepsilon^2 \quad (28)$$

Integrating both sides of (36) yields

$$V(t) \le \frac{\mu}{\alpha} + \left[V(0) - \frac{\mu}{\alpha}\right] e^{-\alpha t}, \ \forall t \ge 0 \quad (29)$$

Due to (27), it can be deduced that x, $W(x)$,$\theta(x)$ are bounded consistently. From (20), we have

$$k_0 v_0(x) \le V \quad (30)$$

Therefore,

$$v_0(x) \le \frac{\mu}{k_0 \alpha} + \frac{1}{k_0}\left[V(0) - \frac{\mu}{\alpha}\right] e^{-\alpha t}, \ \forall t \ge 0. \quad (31)$$

The above completes the proof that x is ultimately consistently bounded by the set D .

4. ILLUSTRATION EXAMPLE

The fermentation process is assumed to operate at a constant volume V , with the dynamics of biomass X , substrate S , and toxin concentration C_t , described by the follows (Zhang and Qin (2007)):

Defining the state as $x = [X \quad S \quad C_t]^T$, and the input $u = F/V$, the state equations become:

$$\begin{bmatrix} \frac{dX}{dt} \\ \frac{dS}{dt} \\ \frac{dC_t}{dt} \end{bmatrix} = \begin{bmatrix} \mu X \\ -(M + \mu / y)X \\ qX^{1/3} \end{bmatrix} + \begin{bmatrix} -X \\ -S \\ -C_t \end{bmatrix} u \quad (32)$$

Using the data in Table 1, we can find:

$$\zeta(x) = \begin{bmatrix} 0.5x_1 \\ -1.4x_1 \\ 0.6x_1^{1/3} \end{bmatrix}, \ G(x) = \begin{bmatrix} -x_1 \\ -x_2 \\ -x_3 \end{bmatrix} \quad (33)$$

. The parameters of y, q, M and V are given in Table 1 for the process.

Table 1: Fermentation model parameters

Volume	V	200[l]
Constant	y	0.417
Constant	M	0.0196
Toxin production constant	q	$0.0296[\text{l/h(g/l)}^{2/3}$

The possible fault modes considered are once one of the actuator is outage, the maximum loss of effectiveness of the actuator is 80%. The fault case here is that at the beginning, the first actuator becomes loss of effectiveness of 70%.

The main contribution of the paper is theoretical in nature. In the fermentation example, let $\Delta g(x) = \begin{bmatrix} \theta_1 x_1 x_2 e^{x_2} \\ 2x_2^2 e^{x_2} \sin\theta_2 \\ \theta_3 x_1 e^{x_1} \end{bmatrix}$, $\Delta\zeta(x) = \begin{bmatrix} \theta_2 x_1^2 \cos\theta_1 \\ x_1^2 \sin\theta_2 \\ \theta_3 x_1^2 \end{bmatrix}$, $\theta_1 \in (-2, 2)$ and $\theta_2, \theta_3 \in (-1, 1)$ are the uncertainty parameters. In this example, a radial basis function (RBF) network is chosen to represent the dynamic changes after the fault occurrence, with 10 hidden nodes and 10 centers that are distributed uniformly in region [-1,1].

Choose $\xi(x) = 2|x|^2 e^{|x|}$, $\rho(x) = 2x_1^2$, $v_0 = x^T x = \|x\|^2$. Then the control input is:

$$u^a = -0.4x_1^{2/3} + 0.9x_2$$

$$u^b = \begin{cases} -2|x|^2 e^{|x|} & x_1 \ne 0 \ and \ x_2 \ne 0 \ and \ x_3 \ne 0 \\ 0 & otherwise \end{cases}$$

$$u^c = \begin{cases} -\frac{2x_1^2}{(x_1^2 + x_2^2 + x_3^2)^{1/2}} & x_1 \ne 0 \ and \ x_2 \ne 0 \ and \ x_3 \ne 0 \\ 0 & otherwise \end{cases}$$

$$u^F = \frac{WS(x)}{0.005} + \frac{\begin{bmatrix} \theta \\ 0 \end{bmatrix}}{0.005},$$

In the simulation, taking the weight adaptive law:

$$\dot{W} = 2k_0 \frac{\partial v_0}{\partial x} S^T(x),$$

$$\dot{\theta} = -0.0025\theta + k_0 \left|\frac{\partial v_0}{\partial x}\right|,$$

and the set $D = \left\{ x \in R^n : v_0(x) \le \frac{1.6}{k_0}, 0.5 \le k_0 \le 1 \right\}$

We choose $k_0 = 0.7$, the control result is shown in Fig 1. From Fig. 1, the three states of systems converge to zero, which indicates that the fault compensation control law is effective.

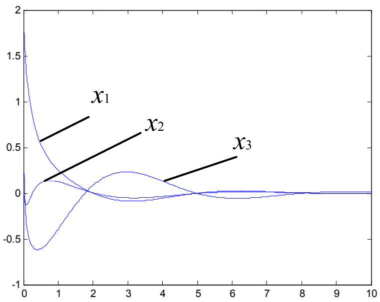

Fig. 1 State responses of systems

5. CONCLUSION

This paper presents a fault compensation scheme for a class of uncertain nonlinear systems with actuator faults. The proposed scheme combines an adaptive estimator with an adaptive feedback control law that provides corrective action following faults. An active fault-compensation control law has been developed to ensure the closed-loop stability for a class of nonlinear systems. The partial loss of actuator effectiveness are considered and represented as $(I-\Gamma)u$ with the fault parameter. Lyapunov techniques are used to analyze closed-loop stability, and the results are applied to a bioreactor example.

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