Adaptive NNs Fault-Tolerant Control for Nonstrict-Feedback Nonlinear Systems

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Abstract. In this paper, the problem of fault-tolerant control (FTC) is investigated for a class of nonlinear single input and single output (SISO) systems in the non-strict feedback form. The considered system possess unknown nonlinear functions, unmeasured states, unknown time-varying delays, unknown control direction and actuator faults (bias and gain faults). Neural networks (NNs) are adopted to approximate the unknown nonlinear functions. Then, a state observer is constructed to solve the problem of unmeasured states. In the frame of adaptive backstepping design technique, by combining with Nussbaum gain function and Lyapunov-Krasobskii functional theory, an adaptive NNs output feedback FTC method is developed. It is shown that all signals in the closed-loop system are proved to be bounded, and the system output can follow the given reference signal well.

Keywords: Nonstrict-feedback nonlinear systems · Fault-tolerant control · Adaptive NNs control

1 Introduction

In the past decades, fuzzy systems and NNs have been popularly used in fuzzy modeling and controller design for uncertain nonlinear systems [1,2]. However, the results obtained in [1,2] are only suitable for those systems that all the components of the considered systems are in good operating conditions, i.e., the faults did not occur in the considered systems. In practical control systems, there are usually some faults [1]. These faults will make the stability of the system decreased, and even affect the safety and reliability of the control system. Thus, some researches have been done on the problem of FTC for the controlled system, and a deal of effective adaptive neural networks (NNs) or fuzzy FTC design methods have been developed [4–6]. Among, [4] investigated the adaptive NNs FTC problem under the assumption that the states of the systems can be measured directly. Adaptive fuzzy backstepping output-feedback-based fault-tolerant method is developed in [5,6] with unmeasured states. It is worth to be

F. Cong et al. (Eds.): ISNN 2017, Part II, LNCS 10262, pp. 11–19, 2017.
DOI: 10.1007/978-3-319-59081-3_2

noticed that the above-mentioned FTC problems are aiming at the systems in the pure-feedback or strict-feedback forms.

Therefore, the above method cannot be used for non-strict feedback systems [7]. In general, compared with nonlinear strict-feedback systems (or pure-feedback systems), non-strict feedback systems have the unknown nonlinear functions, which contain the whole state vector of each subsystems. And also, the intermediate control functions are the function including whole state vector. If the control method for strict-feedback systems (or pure-feedback systems) were adopted with the aim to solve the control design problem for non-strict feedback systems, the algebraic loop problem may occur. In order to avoid this problem, the study for non-strict feedback systems has gained considerable interest in the past years and some considerable efforts have been developed, for example [8–10]. In addition, the work in [8–10] did not consider the problem of time-varying delay and unknown control direction. Therefore, they cannot be utilized to deal with the control design problem considered in this paper.

In this paper, by using NNs and fuzzy state observer to approximate the unknown nonlinear functions and estimate the unmeasured states, respectively. Combining with Nussbaum gain function methods, and in the frame of adaptive backstepping design technique, an adaptive NNs output feedback FTC method is developed. The proposed method can not only guarantee that all the signals in the closed-loop system are bounded, but also the system output can follow the given reference signal well.

2 Problem Formulations and Preliminaries

2.1 Nonlinear System and Actuator Fault Model

Consider an uncertain SISO nonlinear system with actuator faults.

$$\begin{cases} \dot{\tau}_i = f_i(\bar{\tau}) + \tau_{i+1} + h_i(y(t-\sigma_i(t))), \quad i = 1, \ldots, n-1, \\ \qquad \vdots \\ \dot{\tau}_n = f_n(\bar{\tau}) + gu^q + h_n(y(t-\sigma_n(t))), \\ y = \tau_1 \end{cases} \tag{1}$$

where $\bar{\tau} = [\tau_1, \cdots, \tau_n]^T$ is a state vector, g denotes an unknown constant, while $h_i(y(t-\sigma(t)))$ and $f_i(y)$ are unknown nonlinear functions, u^q denotes the control input of the system.

Therefore, according to [2,8], The bias and gain faults are as the following form:

$$u^q(t) = (1-m)u(t) + \omega(t) \tag{2}$$

where $\omega(t)$ denotes a bounded function, which can be given in the next section. $0 \leq m \leq 1$ denotes the lost control rate, which is an unknown constant.

In this paper, the control objective is to develop an observer-based adaptive NNs backstepping FTC strategy for the system (1) with bias and gain faults (2), which can not only validate the boundeness of the whole signals y_r in the closed-loop system, but also ensure that the system output can follow the given reference signal y well.

To achieve the above objective, several assumptions are given.

Assumption 1: There exist known constants d_i, $(1 \le i \le n)$, such that the time delays $|\sigma_i(t)| \le d_i$

Assumption 2: $h_i(\cdot)$ is a nonlinear function, and it satisfies the following inequality:

$$|h_i(y(t))|^2 \le z_1(t)H_i(z_1(t)) + \bar{h}_i(y_r(t)) + \varpi_i \quad (1 \le i \le n) \tag{3}$$

where $h_i(\cdot)$ is a bounded function and $h_i(\cdot) = 0$, $H_i(\cdot)$ is a known function, ϖ_i are unknown constants.

2.2 Neural Network System

In this paper, the unknown nonlinear functions existed in controlled system are approximated by employing NNs. The general form of neural network system is $f(\tau) = \xi^T \phi(\tau)$, where $\xi \in R^v$, the NN node number $v > 1$ and ξ is the parameter estimation vector. $\phi(\tau)$ are chosen as the form of Gaussian functions, i.e. Then $\xi^T \phi(\tau)$ can approximate any given function $f(\tau)$ in a compact set, i.e.

$$f(\tau) = \xi^T \phi(\tau) + \delta \tag{4}$$

where δ is the approximation error with $|\delta| \le \delta^*$ and δ^* is an unknown positive parameter.

2.3 Nussbaum-Type Function

A Nussbaum gain technique-based design method is adopted in this paper, and Nussbaum-type function $N(\varsigma)$ owns the following characteristics:

$$\begin{array}{c} \lim\limits_{m\to\infty} \sup \frac{1}{m}\int_0^m N(\varsigma)d\varsigma = \infty \\ \lim\limits_{m\to\infty} \sup \frac{1}{m}\int_0^m N(\varsigma)d\varsigma = -\infty \end{array} \tag{5}$$

Nussbaum common features are $\varsigma^2\cos(\varsigma)$, $\varsigma^2\sin(\varsigma)$ and $\exp(\varsigma^2)\cos(\varsigma^2)$. In this paper, the form of $\exp(\varsigma^2)\cos(\varsigma^2)$ is adopted.

Lemma 1: For system (1), define $N(\varsigma) = \exp(\varsigma^2)\cos(\varsigma^2)$,$0 \le \varsigma < t$, there exists a function $V(t) \ge 0$, positive constants C and D, such that the following inequality holds:

$$\dot{V}(t) \le -CV(t) + \sum\nolimits_{i=1}^{n} \ell_j[\beta_i N'(\varsigma_i) + 1]\dot{\varsigma}_i + D \tag{6}$$

3 Design of Fuzzy State Observer

Since the states of the considered systems are partial measurable, a state observer is needed with the aim to estimate the unmeasured states.

Let $\eta = g(1-m)$, $x_i = \bar{\tau}/\eta = [\tau_1/\eta, \tau_2/\eta, \cdots \tau_n/\eta]^T$, thus the system (1) becomes

$$\begin{cases} \dot{x}_i = x_{i+1} + \frac{f_i(\bar{\tau})}{\eta} + \frac{1}{\eta} h_i(y(t-\sigma_i(t))), i = 1, 2, \cdots n-1 \\ \quad \vdots \\ \dot{x}_n = u(t) + \frac{f_i(\bar{\tau})}{\eta} + \frac{1}{\eta} h_n(y(t-\sigma_n(t))) \\ \dot{y} = f_1(\bar{\tau}) + \eta x_2 + h_1(y(t-\sigma_1(t))) \end{cases} \tag{7}$$

According to the transformation from (1) to (7), the coefficient of $u(t)$ becomes 1, while the coefficient of x_2, which is in the last equation of (7), is η, rather than 1. Hence, the Nussbaum technique should be adopted in this paper with the aim to erase the effect of η.

Constructing a state observer for system (7) as

$$\begin{cases} \dot{\hat{x}}_i = -k_i \hat{x}_1 + \hat{x}_{i+1} + k_i y, \ i = 1, 2, \cdots, n-1 \\ \dot{\hat{x}}_n = -k_n \hat{x}_1 + u(t) + k_i y \end{cases} \tag{8}$$

Let $e_i = x_i - \hat{x}_i$ be the observer errors, where $\hat{x}_i = [\hat{x}_1, \cdots \hat{x}_n]^T$. Based on (7) and (8), we have

$$\dot{e}_i = \dot{x}_i - \dot{\hat{x}}_i = Ae_i + B\frac{\omega(t)}{\eta} + \frac{F}{\eta} + \frac{h}{\eta} \tag{9}$$

where $F = [f_1(\bar{\tau}), \cdots, f_n(\bar{\tau})]^T$, $h = [h_1(y(t-\sigma_1(t))), \cdots h_n(y(t-\sigma_n(t)))]$, $B = [\underbrace{0, \cdots, 0}_{n-1} \ 1]^T$ and $A = \begin{bmatrix} -k_1 & & \\ \vdots & I_{(n-1)\times(n-1)} & \\ -k_n & 0 \quad \cdots & 0 \end{bmatrix}$

According to selecting the appropriate vector $[k_1, \cdots, k_n]^T$, thus the matrix A can be guaranteed a Hurwitz form. And also, for any given $Q = Q^T > 0$, there exists $P = P^T > 0$ such that

$$A^T P + PA = -Q \tag{10}$$

Consider a Lyapunov function candidate:

$$V_0 = e^T Pe/2 + W_0 \tag{11}$$

where

$$W_0 = \frac{1}{2b(1-\sigma^*)} \|P\|^2 e^{-rt} \sum\nolimits_{i=1}^{n} \int_{t-\sigma(t)}^{t} e^{rm} z_1(m)(H_i(z_1(m)))dm \tag{12}$$

where b is a known constant. The time derivative of V_0 is

$$\dot{V}_0 = -\frac{1}{2} e^T Qe + e^T P(B\frac{\omega(t)}{\eta} + \frac{F}{\eta} + \frac{h}{\eta}) + \dot{W}_0 \tag{13}$$

Thus, from mean value theorem, the function $f_i(\bar{\tau})$ can be represented as the following formula

$$f_i\left(\bar{\tau}\right) = y\bar{f}_i\left(\bar{\tau}\right) \tag{14}$$

According to (4), the nonlinear function $\|P\|^2 \sum_{i=1}^{n} y\bar{f}_i^2(\bar{\tau})/\eta^2$ can be approximated by NNs, one has

$$\|P\|^2 \sum_{i=1}^{n} \frac{y\bar{f}_i^2(\bar{\tau})}{\eta^2} = \Psi^{*T}\phi(\bar{\tau}) + \varepsilon \tag{15}$$

where $b' = be^{r\sigma}$ and $|\omega(t)/\eta| \leq \kappa$ where κ is an unknown constant and $|\varepsilon| \leq \varepsilon^*$, then we can obtain

$$\begin{aligned} \dot{V}_0 \leq & -(\lambda_{\min}(Q) - \tfrac{1}{2} - \tfrac{1}{2b'} - \tfrac{b'}{2\underline{\eta}})\|e\|^2 + y(\Psi^{*T}\phi(\tau) + \varepsilon) \\ & + \tfrac{b'}{2}\|P\|^2 \sum_{i=1}^{n} \kappa^2 + \tfrac{1}{2b(1-\sigma^*)}\|P\|^2 \sum_{i=1}^{n} z_1 H_1(z_1) - rW_0 + d_0^* \end{aligned} \tag{16}$$

where d_0^* is a constant and $d_0^* \geq \|\|^2(\bar{h}_i(y_r(t)) + \varpi_i)\Big/ 2b'$

4 Neural Networks Control Design

In this section, according to the backstepping technique, an adaptive fuzzy output feedback fault tolerate controller design method will be presented, and the Lyapunov function stability theory is adopted to verify the stability of the considered system. The coordinate transformation of n-step backstepping control design is chosen as

$$z_1 = y - y_r,\; z_i = \hat{x}_i - \alpha_{i-1}\,, (i = 2, \cdots n) \tag{17}$$

where z_1 is the system's tracking error. α_{i-1} denotes the virtual control input.

Step 1: From (7) and (17), we have

$$\dot{z}_1 = f_1(\bar{\tau}) + \eta x_2 + h_1(y(t - \sigma_i(t))) - \dot{y}_r \tag{18}$$

Consider a Lyapunov function candidate:

$$V_1 = \frac{1}{2}z_1^2 + \frac{1}{2\gamma_1}\tilde{\theta}_1^2 + \frac{1}{2\gamma_2}\tilde{\theta}_2^2 + W_1 + V_0 \tag{19}$$

where $\gamma_1 > 0$ and $\gamma_2 > 0$ are design constants, and

$$W_1 = \frac{1}{2b(1-\sigma^*)}e^{-rt}\int_{t-\sigma_1(t)}^{t} e^{rm} z_1(m)(H_1(z_1(m)))dm \tag{20}$$

According to (4), we use NN to approximate the unknown nonlinear function $f_1(\bar{\tau})$ as:

$$f_1(\bar{\tau}) = \Phi^{*T}\xi(\bar{\tau}) + \mu_1(\bar{\tau}) \tag{21}$$

Where $|\mu_1(x)| \leq \mu^*$. Define $\theta_1^* = \Psi_1^{*T}\Psi_1^*$, $\theta_2^* = \Phi_1^{*T}\Phi_1^*$, $\hat{\theta}_1$ and $\hat{\theta}_2$are used to estimate θ_1^* and θ_2^*, respectively. The estimation error is $\tilde{\theta}_i = \theta_i^* - \hat{\theta}_i$ $(i = 1, 2)$. The time derivative of V_1 is

$$\begin{aligned} \dot{V}_1 \leq & -(\lambda_{\min}(Q) - \tfrac{1}{2b'} - \tfrac{b'}{2\underline{\eta}} - 1 - \tfrac{\bar{\eta}^2}{b'})\|e\|^2 + \tfrac{1}{\gamma_2}\tilde{\theta}_2^T(\tfrac{\gamma_{21}^2 z_1^2}{4\lambda} - \dot{\theta}_2) \\ & + z_1(\tfrac{z_1}{2} + \tfrac{b'\bar{\eta}z_1}{4} + \tfrac{b' z_1}{2} + \tfrac{\hat{\theta}_1 z_1}{4\lambda} + \tfrac{\hat{\theta}_2 z_1}{4\lambda} + \tfrac{1}{2b(1-\sigma^*)} z_1 H_1(z_1)) \\ & + z_1 \tfrac{1}{2b(1-\sigma^*)}\|P\|^2 \sum_{i=1}^{n} z_1 H_i(z_1) + \tfrac{1}{\gamma_1}\tilde{\theta}_1^T(\tfrac{\gamma_1^2 z_1^2}{4\lambda} - \dot{\theta}_1) \\ & + \eta z_1 z_2 + \eta z_1 \alpha_1 - z_1 \dot{y}_r + d_0^* + \bar{d}_1 + D_1 - rW_0 - rW_1 \end{aligned} \tag{22}$$

where $D_1 = b'\|P\|^2 \sum_{i=1}^{n} \kappa^2 \Big/ 2 + y^2/2 + \theta_1^* + 2\varepsilon^2 + \mu_1^2(\bar{\tau}) + 2\lambda$ and $\bar{d}_1 = d_0^* \Big/ \|P\|^2$.

The virtual control α_1 and the parameters adaptive functions θ_i $(i = 1, 2)$ as:

$$\begin{aligned} \alpha_1 = & \dot{N}(\varsigma)[c_1 z_1 - \dot{y}_r + \tfrac{z_1}{2} + \tfrac{b'\bar{\eta}z_1}{4} + \tfrac{b' z_1}{2} + \tfrac{\hat{\theta}_1 z_1}{4\lambda} + \tfrac{\hat{\theta}_2 z_1}{4\lambda} \\ & + \tfrac{n}{2b(1-\sigma^*)} H_1(z_1) + \tfrac{1}{2b(1-\sigma^*)}\|P\|^2 \sum_{i=1}^{n} z_1 H_i(z_1)] \end{aligned} \tag{23}$$

$$\begin{aligned} \dot{\vartheta} = & \tfrac{z_1}{\ell}[c_1 z_1 - \dot{y}_r + \tfrac{z_1}{2} + \tfrac{b'\bar{\eta}z_1}{4} + \tfrac{b' z_1}{2} + \tfrac{\hat{\theta}_1 z_1}{4\lambda} + \tfrac{\hat{\theta}_2 z_1}{4\lambda} \\ & + \tfrac{n}{2b(1-\sigma^*)} H_1(z_1) + \tfrac{1}{2b(1-\sigma^*)}\|P\|^2 \sum_{i=1}^{n} z_1 H_i(z_1)] \end{aligned} \tag{24}$$

$$\dot{\theta}_1 = \frac{\gamma_1^2 z_1^2}{4\lambda} - \rho_1\theta_1, \dot{\theta}_2 = \frac{\gamma_2^2 z_1^2}{4\lambda} - \rho_2\theta_2 \tag{25}$$

Substituting (23)–(25) into (22) results in

$$\begin{aligned} \dot{V}_1 \leq & -(\lambda_{\min}(Q) - \tfrac{1}{2b'} - \tfrac{b'}{2\underline{\eta}} - 1 - \tfrac{\bar{\eta}^2}{b'})\|e\|^2 + \eta z_1 z_2 - c_1 z_1^2 \\ & + \ell_1(\eta N'(\varsigma) + 1)\dot{\varsigma} - \tfrac{n-1}{2b(1-\sigma^*)} z_1 H_1(z_1) + \sum_{i=1}^{2} \tfrac{\rho_i}{\gamma_i}\tilde{\theta}_i^T\hat{\theta}_i \\ & + d_0^* + \bar{d}_1 + D_1 - rW_0 - rW_1 \end{aligned} \tag{26}$$

Step i: From (8), (9) and (18), we have

$$\begin{aligned} \dot{z}_i = & z_{i+1} + \alpha_i - k_i\hat{x}_1 - \tfrac{\partial\alpha_1}{\partial y}(\Phi_1^T\xi(\tau) + \mu_1(\tau) + \eta\hat{x}_i + \eta e_i \\ & + h_1(y(t - \sigma_1(t)))) - \sum_{j=1}^{i} \tfrac{\partial\alpha_{i-1}}{\partial y_r^{(j-1)}} y_r^{(j)} - \sum_{i=1}^{2} \tfrac{\partial\alpha_{i-1}}{\partial\theta_i}\dot{\theta}_i \end{aligned} \tag{27}$$

where $i = 2, 3, \cdots n-1$, then construct a Lyapunov function V_i as

$$V_i = V_{i-1} + \frac{1}{2}z_i^2 + W_1 \tag{28}$$

Similar to α_1, the virtual control input α_i as:

$$\begin{aligned} \alpha_i = & -c_i z_i + k_i\hat{x}_1 - z_{i-1} - \tfrac{z_i}{2}(\tfrac{\partial\alpha_{i-1}}{\partial y})^2 - \tfrac{z_i}{4\lambda}(\tfrac{\partial\alpha_{i-1}}{\partial y})^2 + \sum_{j=1}^{2} \tfrac{\partial\alpha_{i-1}}{\partial\theta_j}\dot{\theta}_j \\ & - \tfrac{z_i}{4\lambda}(\tfrac{\partial\alpha_{i-1}}{\partial y})^2\hat{x}_2^2 - \tfrac{b'}{2}(\tfrac{\partial\alpha_{i-1}}{\partial y})^2 z_i + \sum_{j=1}^{i} \tfrac{\partial\alpha_{i-1}}{\partial y_r^{(j-1)}} y_r^{(j)} \end{aligned} \tag{29}$$

The time derivative of V_i is

$$\begin{aligned}\dot{V}_i \leq & -(\lambda_{\min}(Q) - \tfrac{1}{2b'} - \tfrac{b'}{2\underline{\beta}} - 1 - \tfrac{\bar{\eta}^2}{b'} - (i-1)\lambda\bar{\eta}^2)\|e\|^2 + z_i z_{i-1} \\ & - \tfrac{n-i}{2b(1-\sigma^*)} z_1 H_1(z_1) - \sum_{j=1}^{i} c_j z_j^2 + \sum_{i=1}^{2} \tfrac{\rho_i}{\gamma_i} \tilde{\theta}_i^T \hat{\theta}_i - rW_0 \\ & - irW_1 + \ell_1(\eta N'(\varsigma) + 1)\dot{\vartheta} + \eta z_1 z_2 + d_0^* + i\bar{d}_1 + D_i\end{aligned} \tag{30}$$

where $D_i = D_{i-1} + \lambda\bar{\eta}^2 + \theta_2^* + \mu_i^{*2}$.

Step *n*: In this step, the actual control input $u(t)$ appears. From (7), (8) and (17), we have

$$\begin{aligned}\dot{z}_n = & u(t) - k_n \hat{x}_1 - \sum_{i=1}^{n} \tfrac{\partial \alpha_{n-1}}{y_r^{(i-1)}} y_r^{(i)} - \sum_{i=1}^{2} \tfrac{\partial \alpha_{n-1}}{\partial \theta_1} \dot{\theta}_i - \tfrac{\partial \alpha_1}{\partial y}(\Phi_1^T \xi(\tau) \\ & + \mu_1(\tau) + \eta \hat{x}_2 + \eta e_2 + h_1(y(t - \sigma_1(t))))\end{aligned} \tag{31}$$

Construct a Lyapunov function V_n as:

$$V_n = V_{n-1} + \frac{1}{2} z_n^2 + W_1 \tag{32}$$

Design the actual controller $u(t)$ as:

$$\begin{aligned}u(t) = & k_n \hat{x}_1 + \sum_{i=1}^{n} \tfrac{\partial \alpha_{n-1}}{y_r^{(i-1)}} y_r^{(i)} + \sum_{i=1}^{2} \tfrac{\partial \alpha_{n-1}}{\partial \theta_1} \dot{\theta}_i - \tfrac{b'}{2} (\tfrac{\partial \alpha_{n-1}}{\partial y})^2 \\ & - \tfrac{z_n^2}{4\lambda} (\tfrac{\partial \alpha_{n-1}}{\partial y})^2 \hat{x}_2^2 - \tfrac{z_n^2}{2} (\tfrac{\partial \alpha_{n-1}}{\partial y})^2 - \tfrac{z_n^2}{4\lambda} (\tfrac{\partial \alpha_{n-1}}{\partial y})^2 - c_n z_n - z_{n-1}\end{aligned} \tag{33}$$

From (33), one has

$$\begin{aligned}\dot{V}_n \leq & -(\lambda_{\min}(Q) - \tfrac{1}{2b'} - \tfrac{b'}{2\underline{\eta}} - 1 - \tfrac{\bar{\eta}^2}{b'} - (n-1)\lambda\bar{\eta}^2)\|e\|^2 \\ & -(c_n - \tfrac{1}{2}\bar{\eta}^2) z_1^2 - (c_n - \tfrac{1}{2}\bar{\eta}^2) z_2^2 - \sum_{i=1}^{2} \tfrac{\rho_i}{\gamma_i} \tilde{\theta}_i^2 - \sum_{j=3}^{n-1} c_j z_j^2 \\ & + \sum_{i=1}^{2} \tfrac{\rho_i}{2\gamma_i} \theta_i^{*2} + d_0^* + n\bar{d}_1 + D_n - rW_0 - nrW_1 + \ell_1(\eta N'(\varsigma) + 1)\dot{\varsigma}\end{aligned} \tag{34}$$

The inequality (34) can be rewritten as

$$\dot{V}_n \leq -CV_n + D \tag{35}$$

where

$$\begin{aligned}C = \min\{ & -(\lambda_{\min}(Q) - 1/2b' - b'/2\underline{\eta} - 1 - \bar{\eta}^2/b' - (n-1)\lambda\bar{\eta}^2), \\ & 2(c_1 - \bar{\eta}^2/2), 2(c_2 - \bar{\eta}^2/2), 2c_3, 2c_4 \cdots 2c_{n-1}, \rho_1/2\gamma_1, \rho_2/2\gamma_2\}\end{aligned} \tag{36}$$

There exists a constant $\tilde{D}$ such that $\tilde{D} \geq \varsigma_1(\eta N'(\varsigma) + 1)\dot{\vartheta}$, and

$$D = d_0^* + n\bar{d}_1 + D_n - rW_0 - nrW_1 + \tilde{D} + \sum_{i=1}^{2} \frac{\rho_i}{2\gamma_i} \theta_i^{*2} \tag{37}$$

Integrate the differential inequality (35), we have

$$V = V_n \leq e^{-ct}(V(0) - D/C) + D/C \tag{38}$$

From (38) and Lemma 1, the boundeness of the whole signals in the closed-loop system can be obtained.

The above design and analysis are summarized in the Theorem 1.

Theorem 1: For system (1) with fault, under Assumptions 1, 2 and Lemma 1, the controller functions (33), state observer (8), the intermediate control functions (23) and (29), and the parameter adaptation functions (25) obtained based on the above derivations, the following properties can hold: (1) The boundeness of the whole signals in the closed-loop system can be validated; (2) The system output can follow the given reference signal well.

5 Conclusions

This paper has presented an observer-based adaptive NNs FTC method. Firstly, NNs have been utilized for approximating the unknown nonlinear functions, and the states observers have been constructed for estimating the unmeasured states. Then, by using the properties of Nussbaum gain function and Lyapunov-Krasobskii functional theory, and combining with adaptive backstepping design technique, the problem of FTC with unknown time-varying delays, unmeasured states, and unknown control direction has been solved. It is shown that not only all signals in the closed-loop system are proved to be bounded, but the system output can follow the given reference signal well.

Acknowledgments. This work was supported by the National Natural Science Foundation of China (Nos. 61573175, 61572244) and Liaoning BaiQianWan Talents Program.

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http://www.springer.com/978-3-319-59080-6

Advances in Neural Networks - ISNN 2017
14th International Symposium, ISNN 2017, Sapporo, Hakodate, and Muroran, Hokkaido, Japan, June 21–26, 2017, Proceedings, Part II
Cong, F.; Leung, A.C.-S.; Wei, Q. (Eds.)
2017, XXII, 595 p. 251 illus., Softcover
ISBN: 978-3-319-59080-6