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Adaptive Neural Fault Tolerant Control of a 3-DOF Model Helicopter System

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***Abstract*—In this paper, an adaptive neural fault-tolerant control scheme is proposed for the three degrees of freedom model helicopter, subject to system uncertainties, unknown external disturbances, and actuator faults. To tackle the system uncertainty and the nonlinear actuator fault problems, the neural network disturbance observer is developed based on the radial basis function neural network. The unknown external disturbance and the unknown neural network approximation error are treated as a compound disturbance that is estimated by another nonlinear disturbance observer. A disturbance observer based adaptive neural fault-tolerant control scheme is then developed to track the desired system output in the presence of system uncertainty, external disturbance, and actuator faults. The stability of the whole closed-loop system is analyzed using the Lyapunov method, which guarantees the convergence of all closed-loop signals. Finally, the simulation results are presented to illustrate the effectiveness of the new control design techniques.**

***Index Terms*—3-DOF model helicopter, Neural network, Disturbance observer, Adaptive control, Fault tolerant control**

I. Introduction

In recent years, unmanned helicopters have been widely developed because of their unique features such as hovering, and vertical take-off and landing. In order to successfully complete given tasks such as above-ground traffic transport, ground security detection, traffic condition assessment, forest fire monitoring, and crime prevention, an efficient flight control system is needed for the unmanned helicopter [1]. The unmanned helicopter is a multiple-input multiple-output (MIMO) nonlinear system subject to external disturbances and large uncertainties [2]–[8]. Thus, there have been many studies on robust adaptive flight control schemes for unmanned helicopters. They include a fuzzy gain-scheduler for the attitude control of an unmanned helicopter in [9], an active model-based predictive control and experimental investigation for unmanned helicopters in the full flight envelope in [10], a linear tracking control method for small-scale unmanned helicopters in [11], and a nonlinear model predictive control with neural network optimization for the autonomous autorotation of small unmanned helicopters in [12]. While these control schemes are shown to be effective, in the initial design stage of the flight control system for the unmanned helicopter, there exists a high risk of causing physical damage if the actual helicopter system is directly used to test the designed control approaches.

In order to provide a platform for testing flight control schemes for unmanned helicopters, several devices of three degrees of freedom (3-DOF) model helicopters have been developed by Quanser Consulting Inc. and Googol Technology Ltd. for laboratory use [13]. The nonlinearity, system uncertainty, measurement noise, and unknown disturbances have been included in these 3-DOF model helicopters [14], thus providing a realistic test platform for control schemes for studies of the 3-DOF model helicopter. Among the control schemes investigated are a practical stabilization control for a 3-DOF remote controlled helicopter in [15], a robust attitude control scheme based on linear quadratic regulator (LQR) method for a 3-DOF laboratory helicopter for aggressive maneuvers in [16], an adaptive output feedback control on a laboratory model helicopter in [17], a trajectory tracking control for a 3-DOF laboratory helicopter under input and state constraints in [18], and a nonlinear adaptive model following control scheme for a 3-DOF tandem-rotor model helicopter in [19]. Although many efficient flight control schemes have been developed for 3-DOF model helicopters, they do not consider the effect of the actuator faults on the system reliability.

Treating unmanned helicopters as a class of complex nonlinear systems, a key control challenge is to achieve satisfactory flight performance in the presence of nonlinearity and actuator faults [20]–[22]. They can cause system performance degradation and instability, leading to undesirable consequences [23]–[32]. Since operational safety is paramount, it follows that fault tolerant control is an important research topic in flight control [33], [34]. In [35], a decentralized fault-tolerant control system was designed to accommodate failures in higher-order flight control actuators. Adaptive tracking control and identification were in [25], [36]. In [37], an adaptive fault-tolerant tracking control scheme was developed for near-space vehicles using Takagi-Sugeno fuzzy models. Adaptive sliding mode fault tolerant attitude tracking control was proposed for flexible spacecraft under actuator saturation in [38]. In [39], a model predictive control-based nonlinear fault tolerant control was developed for air-breathing hypersonic vehicles. Fault detection and fault-tolerant control were studied for civil aircraft using a siding-mode-based scheme in [40]. With the 3-

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DOF model helicopter being an ideal test platform, it is natural to develop the fault tolerant control scheme for the helicopter, especially when the helicopter is subject to unknown external disturbances that will further affect the control performance. To improve the disturbance rejection ability, the dynamic information of time-varying external disturbances can be used in the flight control design for 3-DOF model helicopters.

Since the disturbance observer can estimate the unknown disturbance well, it can be employed to compensate for the unknown external disturbance. In the past decades, a number of disturbance observers have been designed and the corresponding disturbance observer based control (DOBC) has been developed. Among them, a nonlinear disturbance observer was proposed for robotic manipulators to estimate the unknown disturbance in [41]. The general framework was studied for the DOBC of nonlinear systems with disturbances in [42]. In [43], a nonlinear disturbance observer was proposed for a multivariable minimum-phase system which has arbitrary relative degrees. The disturbance attenuation and rejection problem was studied for a class of MIMO nonlinear systems with unknown disturbance in [44]. In [45], the robust autopilot design was presented for bank-to-turn missiles using the disturbance observer. Robust autopilot design was developed for uncertain bank-to-turn missiles using state-space disturbance observers in [46]. A related development is the universal function approximators (such as fuzzy logical systems and neural networks), which can efficiently tackle the unknown continuous system uncertainty in nonlinear systems [47]–[52]. Thus, various robust control schemes have been developed for the uncertain nonlinear system by using fuzzy logical systems and neural networks [53]–[59]. In [60], the tracking error constrained problem was firstly investigated for multi-input and multi-output (MIMO) uncertain nonlinear systems with unmeasured states, and the stability proofs was given of the closed-loop systems. Observer-based adaptive fuzzy backstepping dynamic surface control was proposed for a class of MIMO nonlinear systems in [61]. Thus, the fuzzy logical systems and neural networks can be combined with the disturbance observer to fully utilize their advantages and enhance the robustness of the closed-loop system [62], [63] for 3-DOF model helicopters.

This work is motivated by the adaptive neural fault-tolerant control scheme of 3-DOF model helicopters with unknown external disturbance, system uncertainty, and actuator faults. The main contributions of this paper are as follows:

(i) A state dependent nonlinear actuator fault model is proposed for the uncertain dynamic of the 3-DOF model helicopter;

(ii) A neural network disturbance observer is developed to handle system uncertainty and nonlinear actuator faults of the 3-DOF model helicopter based on the radial basis function neural network (RBFNN);

(iii) A nonlinear disturbance observer is proposed to estimate the compound disturbance that combines the approximation error of the RBFNN with the unknown external disturbance;

(iv) An adaptive neural fault-tolerant control scheme is developed using outputs of the developed two disturbance observers to improve the control robustness.

Fig. 1. 3-DOF model helicopter system manufactured by Googol Technology Ltd.

The organization of this paper is as follows. Section 2 details the problem description. The adaptive fault tolerant control scheme is designed based on disturbance observers and RBFNN in Section 3. The simulation results of the 3-DOF model helicopter are presented in Section 4 to demonstrate the effectiveness of the adaptive neural fault tolerant control scheme, followed by some concluding remarks in Section 5.

II. Problem Description

The 3-DOF model helicopter manufactured by Googol Technology Ltd., shown in Figure 1, has three degrees of freedom, elevation, pitch, and travel [13]. Included in this 3-DOF model helicopter are the basic machine, propeller motor, position sensor, balance block, and collector ring.

Since the 3-DOF model helicopter has two inputs and three independent outputs, the adaptive neural fault-tolerant control scheme intends to deal with tracking the elevation reference signal and the pitch reference signal. To design the adaptive neural fault-tolerant control, the nonlinear model of elevation and pitch motion of the Googol's 3-DOF model helicopter can be described as

$$\begin{cases} \ddot{\theta} = \frac{l_1 k}{J_1}(v_1 + v_2)\cos\phi - \sin(\theta + \alpha_0)\frac{T_g}{J_1} \\ \ddot{\phi} = \frac{l_r k}{J_3}(v_1 - v_2) \end{cases} \tag{1}$$

where θ is the elevation angle; ϕ is the pitch angle; v_1 and v_2 are control voltages of the front and back motors, respectively; J_1 and J_3 are moments of inertia about elevation and pitch axes, respectively; α_0 is the initial angle between the helicopter arm and its base; l_r is the distance between the pitch axis and the helicopter propeller; $T_g = m_k g l_1 - m_b g l_2$ is the effective gravity moment, where g is the acceleration due to gravity; l_1 is the distance between the elevation axis and the helicopter propeller; l_2 is the distance between the elevation axis and the counterweight; m_k is the mass of the helicopter propeller, and m_b is mass of the counterweight.

Define $x = [x_1, x_2]^T$, $x_1 = [\theta, \phi]^T$ and $x_2 = [\dot{\theta}, \dot{\phi}]^T$. Then, considering the system uncertainty and unknown time-varying disturbance, the model of the helicopter can be transformed into the following general MIMO nonlinear system:

$$\begin{aligned}\dot{x}_1 &= x_2 \\ \dot{x}_2 &= F(x) + \Delta F(x) + (G(x) + \Delta G(x))u + d(t) \\ y &= x_1 \end{aligned} \quad (2)$$

where $\Delta F(x)$ and $\Delta G(x)$ are the system uncertainties, and $d(t)$ is the unknown disturbance. $F(x)$ and $G(x)$ are given by

$$F(x) = \begin{bmatrix} -\sin(\theta+\alpha_0)\frac{T_g}{J_1} \\ 0 \end{bmatrix} \quad (3)$$

$$G(x) = \begin{bmatrix} \frac{l_1 k}{J_1}\cos\phi & \frac{l_1 k}{J_1}\cos\phi \\ \frac{l_r k}{J_3} & -\frac{l_r k}{J_3} \end{bmatrix} \quad (4)$$

For a 3-DOF model helicopter described by (2), the actuator may suffer from such faults as actuator gain fault. In this case, the actuator gain fault is expressed as

$$u_i^f(t) = \rho_i u_i(t),\ t \geq t_f,\ i = 1,2 \quad (5)$$

where ρ_i is the nonlinear remaining control rate coefficient and t_f is the failure time instant, which is unknown. The remaining nonlinear control rate coefficient ρ_i is written as

$$\rho_i = \frac{1}{1+\beta_i e^{-\xi_i(x)}},\quad i = 1,2 \quad (6)$$

where $\xi_i(x)$ is an unknown continuous bounded function and $\beta_i \geq 0$ is an unknown constant at the failure time instant t_f.

Invoking (6), the actuator gain fault (5) can be written as

$$\begin{aligned} u_i^f(t) &= u_i(t) - (u_i(t) - \rho_i u_i(t)) \\ &= u_i(t) - H_i(x, u_i) \end{aligned} \quad (7)$$

where $H_i(x,u_i) = u_i(t) - \rho_i u_i(t)$, which is unknown due to the nonlinear remaining control rate coefficient ρ_i with unknown $\xi_i(x)$ and β_i.

Considering (7), the MIMO nonlinear system (2) with actuator faults can be further expressed as

$$\begin{aligned}\dot{x}_1 &= x_2 \\ \dot{x}_2 &= F(x) + \Delta F(x) + d(t) \\ &+ (G(x) + \Delta G(x))(u - H(x,u)) \\ y &= x_1 \end{aligned} \quad (8)$$

where $H(x,u) = [H_1(x,u_1), H_2(x,u_2)]^T$.

Since the matrix inverse of the control gain matrix $G(x)$ may not exist, to develop the adaptive neural fault-tolerant control scheme, we design $u = G^T(x)v$, with v being a desired control input signal which will be proposed. Then, the dynamic of the system state x_2 can be rewritten as

$$\begin{aligned}\dot{x}_2 &= F(x) + \Delta F(x) + G(x)u - G(x)H(x,u) \\ &+ \Delta G(x)(u - H(x,u)) + d(t) \\ &= F(x) + \Delta F(x) + G(x)G^T(x)v - G(x)H(x,u) \\ &+ \Delta G(x)(u - H(x,u)) + d(t) \\ &= F(x) + \Delta F(x) - \lambda I_{n\times n}v \\ &+ (G(x)G^T(x) + \lambda I_{n\times n})v \\ &- G(x)H(x,u) + \Delta G(x)(u - H(x,u)) + d(t) \end{aligned} \quad (9)$$

where $\lambda > 0$ is a design parameter.

Let us define

$$P(x,u) = L\Delta P(x,u) \quad (10)$$

where $L = L^T > 0$ is a design parameter and $\Delta P(x,u) = \Delta F(x) - \lambda I_{n\times n}v - G(x)H(x,u) + \Delta G(x)(u - H(x,u))$.

Considering (9) and (10) yields

$$\begin{aligned}\dot{x}_1 &= x_2 \\ \dot{x}_2 &= F(x) + (G(x)G^T(x) + \lambda I_{n\times n})v \\ &+ L^{-1}P(x,u) + d(t) \\ y &= x_1 \end{aligned} \quad (11)$$

In this paper, the control objective is that the adaptive neural fault tolerant control scheme is developed to follow a given desired output y_d of the 3-DOF model helicopter (1) in the presence of system uncertainties, unknown time-varying external disturbances, and actuator faults. For tracking the desired system output y_d, the required adaptive neural fault tolerant control should be such that all closed-loop system signals converge.

To proceed with the design of the adaptive neural fault tolerant control scheme, the following lemmas and assumptions are required:

Lemma 1: [64] As a class of linearly parameterized neural networks, RBFNNs are adopted to approximate the continuous function $f(Z): R^q \to R$, and can be expressed as follows:

$$f(Z) = \hat{W}^T\phi(Z) + \varepsilon \quad (12)$$

where $Z = [z_1, z_2, \ldots, z_q]^T \in R^q$ is the input vector of the RBFNN, $\hat{W} \in R^p$ is a weight vector, $\phi(Z) = [\phi_1(Z), \phi_2(Z), \ldots, \phi_p(Z)]^T \in R^p$ is the basis function, and ε is the approximation error of the RBFNN. The optimal weight value W^* is given by

$$W^* = \arg\min_{\hat{W}\in\Omega_f}[\sup_{z\in S_Z}|\hat{f}(Z|\hat{W}) - f(Z)|] \quad (13)$$

where $\Omega_f = \{\hat{W} : \|\hat{W}\| \leq M\}$ is a valid field of the estimate parameter $\hat{W}$, M is a design parameter and $S_Z \subset R^n$ is an allowable set of the state vector. Using the optimal weight value yields

$$\begin{aligned} f(Z) &= W^{*T}\phi(Z) + \varepsilon^* \\ |\varepsilon^*| &\leq \bar{\varepsilon} \end{aligned} \quad (14)$$

where ε^* is the optimal approximation error and $\bar{\varepsilon} > 0$ is the upper bound of the approximation error.

Lemma 2: [64] For bounded initial conditions, if there exists a C^1 continuous and positive definite Lyapunov function $V(x)$ satisfying $\pi_1(\|x\|) \leq V(x) \leq \pi_2(\|x\|)$, such that $\dot{V}(x) \leq -c_1 V(x) + c_2$, where $\pi_1, \pi_2 : R^n \to R$ are class K functions and c_1, c_2 are positive constants, then the solution $x(t)$ is uniformly bounded.

Assumption 1: [65] For all $t > 0$, there exist known constants Δ_0 and Δ_1 such that $||y_d(t)|| \leq \Delta_0$ and $||\dot{y}_d(t)|| \leq \Delta_1$.

Assumption 2: For the time-varying unknown external disturbance $d(t)$, there exists an unknown positive constant δ_0 such that $||\dot{d}(t)|| \leq \delta_0$.

Remark 1: To avoid the singularity of the control gain matrix $G(x)$, the control input u is designed as $u = G^T(x)v$

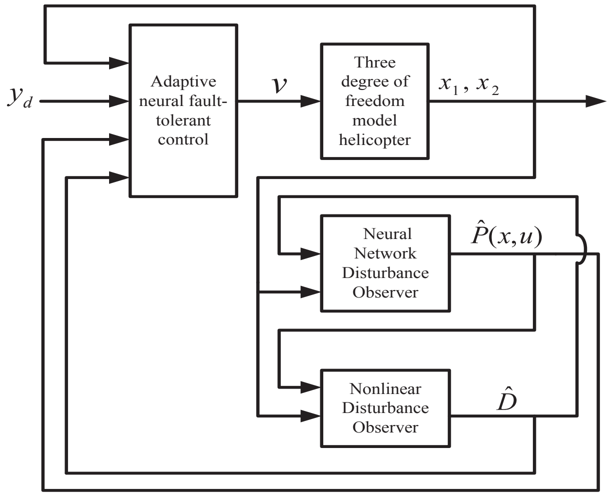

Fig. 2. Adaptive neural fault-tolerant control block diagram

and a positive design parameter λ is introduced to render $(G(x)G^T(x) + \lambda I_{n\times n})$ nonsingular, which leads to an easy design of the fault tolerant control scheme. Meanwhile, Assumption 2 is introduced to account for the limited energy that an external disturbance can exert on the system. More specifically, a time-varying external disturbance can only have band-limited frequency spectrum such that its rate of change is insufficient to cause the 3-DOF model helicopter to become uncontrollable.

Remark 2: In this paper, the actuator fault is considered for the 3-DOF model helicopter. Comparing with the existing actuator fault model, the state dependent nonlinear actuator fault model given in (5) is more intuitive. It shows that the nonlinear remaining control rate coefficient ρ_i satisfies $0 < \rho_i \leq 1$. When $\beta_i = 0$, the remaining control rate coefficient $\rho_i = 1$, which means there does not exist actuator fault. When $\beta_i \to \infty$, it gives $\rho_i = 0$, which means a total actuator failure.

III. Fault Tolerant Control Based on Disturbance Observers and Neural Networks

In this section, two disturbance observers are designed to enable the adaptive neural fault tolerant control scheme to track a given desired output y_d of the 3-DOF model helicopter (1) subject to system uncertainties, unknown time-varying external disturbances, and actuator faults. The block diagram of the adaptive neural fault-tolerant control scheme is shown in Figure 2. Among the control blocks, the neural network disturbance observer is employed to tackle the unknown continuous function $P(x,u)$ and the nonlinear disturbance observer is used to handle the unknown external disturbance $d(t)$ and the neural network approximation error ε^*.

A. Design of Neural Network Disturbance Observer

Since $\Delta F(x)$, $\Delta G(x)$, and $H(x,u)$ are unknown, $P(x,u)$ is also unknown, and they are thus estimated with the neural network disturbance observer. To develop the neural network disturbance observer, the following dynamic system is designed:

$$\begin{aligned} \dot{\eta} &= -\Gamma\eta + \psi(x,u,\hat{W}) \\ \psi(x,u,\hat{W}) &= \Gamma x_2 + F(x) + (G(x)G^T(x) + \lambda I_{n\times n})v \\ &+ L^{-1}\hat{W}^T\Phi(Z) + \hat{D} \end{aligned} \quad (15)$$

where η is the state vector of the dynamic system (15), $\Gamma = \Gamma^T > 0$ is a designed parameter, $\hat{D}$ is the estimate of the unknown compound disturbance $D(t)$ which will be defined, and $\hat{W}$ is the estimated value of the optimal weight value W^* for the RBFNN. From (15), we know that $\hat{W}^T\Phi(Z)$ is the estimate of $P(x,u)$, $\Phi(Z)$ is the radial basis function, and $Z = [x,u]^T$.

The optimal approximation output of RBFNN can be written as

$$P^*(x,u) = W^{*T}\Phi(Z) + \varepsilon^* \quad (16)$$

where ε^* is the smallest approximation error between the optimal output of RBFNN and the unknown continuous function $P(x,u)$. The approximation error ε^* can be arbitrarily small owing to the approximation ability of the RBFNN. According to Lemma 1, we obtain that $\| \varepsilon^* \| \leq \bar{\varepsilon}$.

Considering (11) and (16) yields

$$\begin{aligned} \dot{x}_1 &= x_2 \\ \dot{x}_2 &= F(x) + (G(x)G^T(x) + \lambda I_{n\times n})v \\ &+ L^{-1}W^{*T}\Phi(Z) + L^{-1}\varepsilon^* + d(t) \\ y &= x_1 \end{aligned} \quad (17)$$

To handle the neural network approximation error ε, we define $D(t) = L^{-1}\varepsilon^* + d(t)$. Then, (17) can be written as

$$\begin{aligned} \dot{x}_1 &= x_2 \\ \dot{x}_2 &= F(x) + (G(x)G(x)^T + \lambda I_{n\times n})v \\ &+ L^{-1}W^{*T}\Phi(Z) + D(t) \\ y &= x_1 \end{aligned} \quad (18)$$

The nominal estimate error of the neural network disturbance observer is defined as

$$e_f = x_2 - \eta \quad (19)$$

Considering (15), (18) and (19), we have

$$\dot{e}_f = -\Gamma e_f + L^{-1}(W^{*T}\Phi(Z) - \hat{W}^T\Phi(Z)) + D - \hat{D} \quad (20)$$

Defining $\tilde{D} = D - \hat{D}$ and $\tilde{W} = W^* - \hat{W}$ yields

$$\dot{e}_f = -\Gamma e_f + L^{-1}\tilde{W}^T\Phi(Z) + \tilde{D} \quad (21)$$

Invoking (21), we have

$$\begin{aligned} e_f^T\dot{e}_f &= -e_f^T\Gamma e_f + e_f^T L^{-1}\tilde{W}^T\Phi(Z) + e_f^T\tilde{D} \\ &\leq -e_f^T(\Gamma - 0.5I_{n\times n})e_f + 0.5\|\tilde{D}\|^2 \\ &+ e_f^T L^{-1}\tilde{W}^T\Phi(Z) \end{aligned} \quad (22)$$

If e_f, $\tilde{D}$, and $\tilde{W}$ are convergent, then the output of the designed neural network disturbance observer is $\hat{W}^T\Phi(Z)$, which can approximate $W^{*T}\Phi(Z)$.

B. Design of Nonlinear Disturbance Observer

Since the compound disturbance $D(t)$ is unknown, it cannot be used directly to design the neural network disturbance observer (15) and the adaptive neural fault tolerant control scheme. To handle it efficiently, the nonlinear disturbance observer is proposed to estimate it.

According to the approximation ability of the RBFNN, we know that $\|\dot{\varepsilon}^*\|$ is bounded. Thus, invoking Assumption 2 yields

$$\|\dot{D}(t)\| \leq \delta \tag{23}$$

where δ is unknown positive constant.

The nonlinear disturbance observer is proposed as

$$\begin{aligned} \hat{D} &= L(x_2 - z) \\ \dot{z} &= F(x) + (G(x)G(x)^T + \lambda I_{n\times n})v \\ &+ L^{-1}\hat{W}^T\Phi(Z) + \hat{D} \end{aligned} \tag{24}$$

where $L = L^T > 0$ is a design parameter of the nonlinear disturbance observer.

Considering (18), and (24), we obtain

$$\begin{aligned} \dot{\hat{D}} &= L(\dot{x}_2 - \dot{z}) = L(D(t) - \hat{D}(t)) \\ &+ (W^{*T}\Phi(Z) - \hat{W}^T\Phi(Z)) \end{aligned} \tag{25}$$

Invoking $\tilde{D} = D - \hat{D}$ and $\tilde{W} = W^* - \hat{W}$ and considering (25) yields

$$\begin{aligned} \dot{\tilde{D}} &= \dot{D} - \dot{\hat{D}} = \dot{D} - L(D(t) - \hat{D}(t)) \\ &- (W^{*T}\Phi(Z) - \hat{W}^T\Phi(Z)) \\ &= \dot{D} - L\tilde{D} - \tilde{W}^T\Phi(Z) \end{aligned} \tag{26}$$

Invoking (26), we have

$$\tilde{D}^T\dot{\tilde{D}} = \tilde{D}^T\dot{D} - \tilde{D}^T L\tilde{D} - \tilde{D}^T\tilde{W}^T\Phi(Z) \tag{27}$$

Considering Assumption 2, (23), and the following fact

$$\begin{aligned} -2\tilde{D}^T\tilde{W}^T\Phi(Z) &\leq 2||\tilde{D}||||\tilde{W}||||\Phi(Z)|| \\ &\leq \gamma\tau^2||\tilde{D}||^2 + \frac{1}{\gamma}||\tilde{W}||^2 \end{aligned} \tag{28}$$

yields

$$\begin{aligned} \tilde{D}^T\dot{\tilde{D}} &\leq 0.5||\tilde{D}||^2 + 0.5||\dot{D}||^2 - \tilde{D}^T L\tilde{D} \\ &+ 0.5\gamma\tau^2||\tilde{D}||^2 + \frac{1}{2\gamma}||\tilde{W}||^2 \\ &\leq -\tilde{D}^T(L - (0.5 + 0.5\gamma\tau^2)I_{n\times n})\tilde{D} \\ &+ 0.5\delta^2 + \frac{1}{2\gamma}||\tilde{W}||^2 \end{aligned} \tag{29}$$

where $||\Phi(Z)|| \leq \tau$ and $\gamma > 0$ is a design parameter.

C. Design of Adaptive Neural Fault Tolerant Control

With two disturbance observers developed for the 3-DOF model helicopter, we are ready to design the adaptive neural fault tolerant control scheme based on the outputs of the designed disturbance observers by using the backstepping technique. The design process is as follows.

Step 1: To design the adaptive neural fault tolerant control scheme, we define

$$e_1 = x_1 - y_d \tag{30}$$

$$e_2 = x_2 - \alpha_1 - \dot{y}_d \tag{31}$$

where $\alpha_1 \in R^2$ is a virtual control law which will be designed.

Considering (18) and differentiating e_1 with respect to time yields

$$\dot{e}_1 = \dot{x}_1 - \dot{y}_d = x_2 - \dot{y}_d \tag{32}$$

Considering (31), we obtain

$$\dot{e}_1 = e_2 + \alpha_1 \tag{33}$$

The virtual control law α_1 is designed as

$$\alpha_1 = -K_1 e_1 \tag{34}$$

where $K_1 = K_1^T > 0$.

Substituting (34) into (33), we have

$$\dot{e}_1 = -K_1 e_1 + e_2 \tag{35}$$

Consider the Lyapunov function candidate

$$V_1 = \frac{1}{2}e_1^T e_1 \tag{36}$$

Invoking (35), the time derivative of V_1 is given by

$$\dot{V}_1 = -e_1^T K_1 e_1 + e_1^T e_2 \tag{37}$$

Step 2: Considering (18) and differentiating e_2 with respect to time yields

$$\begin{aligned} \dot{e}_2 &= \dot{x}_2 - \dot{\alpha}_1 - \ddot{y}_d = F(x) + (G(x)G^T(x) + \lambda I_{n\times n})v \\ &+ L^{-1}W^{*T}\Phi(Z) + D(t) - \dot{\alpha}_1 - \ddot{y}_d \end{aligned} \tag{38}$$

where $\dot{\alpha}_1 = -K_1\dot{e}_1$.

In accordance with Assumption 1, using the output of the designed neural network disturbance observer and the nonlinear disturbance observer, the adaptive neural fault tolerant control law is proposed as

$$v = -(G(x)G^T(x) + \lambda I_{n\times n})^{-1}v_0 \tag{39}$$

where $K_2 = K_2^T > 0$ is a design parameter and $v_0 = K_2 e_2 + F(x) + L^{-1}\hat{W}^T\Phi(Z) + \hat{D}(t) - \ddot{y}_d - \dot{\alpha}_1 + e_1$.

Substituting (39) into (38) yields

$$\begin{aligned} \dot{e}_2 &= -K_2 e_2 + L^{-1}W^{*T}\Phi(Z) - L^{-1}\hat{W}^T\Phi(Z) \\ &+ D - \hat{D} - e_1 \end{aligned} \tag{40}$$

Considering $\tilde{D} = D - \hat{D}$ and $\tilde{W} = W^* - \hat{W}$, (40) can be written as

$$\dot{e}_2 = -K_2 e_2 + L^{-1}\tilde{W}^T\Phi(Z) + \tilde{D} - e_1 \tag{41}$$

Invoking (41), we have

$$\begin{aligned} e_2^T\dot{e}_2 &= -e_2^T K_2 e_2 + e_2^T L^{-1}\tilde{W}^T\Phi(Z) + e_2^T\tilde{D} - e_2^T e_1 \\ &\leq -e_2^T(K_2 - 0.5I_{n\times n})e_2 + e_2^T L^{-1}\tilde{W}^T\Phi(Z) \\ &+ 0.5\|\tilde{D}\|^2 - e_2^T e_1 \end{aligned} \tag{42}$$

We choose the adaptive law for the neural network parameter $\hat{W}$ as

$$\dot{\hat{W}} = \Lambda(\Phi(Z)L^{-1}(e_f + e_2) - \sigma_0 \hat{W}) \tag{43}$$

where $\Lambda = \Lambda^T > 0$ and $\sigma_0 > 0$ are the design parameters.

The above adaptive neural fault tolerant control design procedure for the 3-DOF model helicopter (1) can be summarized in the following theorem.

Theorem 1: Consider the 3-DOF model helicopter (1) subject to system uncertainties, unknown disturbances and actuator faults. The neural network disturbance observer is designed as (15), the nonlinear disturbance observer is designed as (24), and the parameter updated law of the RBFNN is chosen as (43). Then, the adaptive neural fault tolerant control law is proposed as (39). Under the developed adaptive fault tolerant control scheme, all closed-loop system signals are semiglobally uniformly bounded and the tracking error of the 3-DOF model helicopter (1) is convergent.

Proof: Consider the Lyapunov function candidate

$$\begin{aligned} V &= \frac{1}{2}e_1^T e_1 + \frac{1}{2}e_2^T e_2 + \frac{1}{2}e_f^T e_f \\ &+ \frac{1}{2}\tilde{D}^T \tilde{D} + \frac{1}{2}\mathrm{tr}(\tilde{W}^T \Lambda^{-1} \tilde{W}) \end{aligned} \tag{44}$$

Invoking (22), (29), (37) and (42), the time derivative of V is

$$\begin{aligned} \dot{V} &= e_1^T \dot{e}_1 + e_2^T \dot{e}_2 + e_f^T \dot{e}_f + \tilde{D}^T \dot{\tilde{D}} + \mathrm{tr}(\tilde{W}^T \Lambda^{-1} \dot{\tilde{W}}) \\ &\le -e_f^T(\Gamma - 0.5I_{n\times n})e_f + e_f^T L^{-1}\tilde{W}^T\Phi(Z) + \|\tilde{D}\|^2 \\ &- \tilde{D}^T(L - (0.5 + 0.5\gamma\tau^2)I_{n\times n})\tilde{D} + 0.5\delta^2 + \frac{1}{2\gamma}||\tilde{W}||^2 \\ &- e_1^T K_1 e_1 - e_2^T(K_2 - 0.5I_{n\times n})e_2 \\ &+ e_2^T L^{-1}\tilde{W}^T\Phi(Z) + \mathrm{tr}(\tilde{W}^T\Lambda^{-1}\dot{\tilde{W}}) \end{aligned} \tag{45}$$

Since $\tilde{W} = W^* - \hat{W}$, invoking the weight value adaptation law (43), the derivative (45) can be written as

$$\begin{aligned} \dot{V} &\le -e_1 K_1 e_1 - e_2^T(K_2 - 0.5I_{n\times n})e_2 \\ &- e_f^T(\Gamma - 0.5I_{n\times n})e_f \\ &- \tilde{D}^T(L - (1.5 + 0.5\gamma\tau^2)I_{n\times n})\tilde{D} \\ &+ \frac{1}{2\gamma}||\tilde{W}||^2 - \sigma_0\mathrm{tr}(\tilde{W}^T\hat{W}) + 0.5\delta^2 \end{aligned} \tag{46}$$

Considering the following fact

$$2\mathrm{tr}(\tilde{W}^T\hat{W}) = \|\tilde{W}\|^2 + \|\hat{W}\|^2 - \|W^*\|^2 \ge \|\tilde{W}\|^2 - \|W^*\|^2 \tag{47}$$

we obtain

$$\begin{aligned} \dot{V} &\le -e_1 K_1 e_1 - e_2^T(K_2 - 0.5I_{n\times n})e_2 \\ &- e_f^T(\Gamma - 0.5I_{n\times n})e_f \\ &- \tilde{D}^T(L - (1.5 + 0.5\gamma\tau^2)I_{n\times n})\tilde{D} \\ &- (\frac{\sigma_0}{2} - \frac{1}{2\gamma})||\tilde{W}||^2 + \frac{\sigma_0}{2}\|W^*\|^2 + 0.5\delta^2 \\ &\le -\kappa V + C \end{aligned} \tag{48}$$

where

$$\begin{aligned} \kappa: &= \min\begin{pmatrix} \lambda_{\min}(K_1), \lambda_{\min}(K_2 - 0.5I_{n\times n}), \\ \lambda_{\min}(\Gamma - 0.5I_{n\times n}), \\ \lambda_{\min}(L - (1.5 + 0.5\gamma\tau^2)I_{n\times n}), \\ \frac{2(\frac{\sigma_0}{2} - \frac{1}{2\gamma})}{\lambda_{\max}(\Lambda^{-1})} \end{pmatrix} \\ C: &= \frac{\sigma_0}{2}\|W^*\|^2 + 0.5\delta^2 \end{aligned} \tag{49}$$

To ensure closed-loop system stability, the corresponding design matrices K_1, K_2, Γ, Λ, L, γ, and σ_0 should be chosen to make $K_2 - 0.5I_{n\times n} > 0$, $\Gamma - 0.5I_{n\times n}$, $L - (1.5 + 0.5\gamma\tau^2)I_{n\times n} > 0$ and $\frac{\sigma_0}{2} - \frac{1}{\tau} > 0$.

Considering (48), the signals e_1, e_2, e_f, $\tilde{D}$, and $\tilde{W}$ are semiglobally uniformly bounded by using Lemma 2. According to (48), we have

$$0 \le V \le \frac{C}{\kappa} + \left[\ V(0) - \frac{C}{\kappa}\ \right] e^{-\kappa t} \tag{50}$$

From (50), we can know that V is convergent, that is, $\lim_{t\longrightarrow\infty} V = \frac{C}{\kappa}$. Hence, the tracking error e_1 and the approximation errors $\tilde{e}_f$, $\tilde{D}$, and $\tilde{W}$ of the closed-loop system are bounded. Thus, the control objective is achieved. This concludes the proof. $\diamondsuit$

Remark 3: In our developed adaptive fault control scheme, two disturbance observers were designed. The neural network disturbance observer is employed to tackle the unknown continuous term $P(x, u)$ which represents uncertainties caused by system operations and actuator faults. At the same time, we can see that only variables e_f and e_2 are employed to update the neural network parameter $\hat{W}$. Furthermore, to handle the external time-varying disturbance and the neural network approximation error efficiently, a compound disturbance D is defined and a nonlinear disturbance observer is proposed to estimate the given compound disturbance.

Remark 4: For the developed adaptive neural fault-tolerant control scheme based on the disturbance observer, it is worth pointing out that the convergence performance of the tracking error e_1, the disturbance estimate errors $\tilde{D}$ and the parameter estimate errors $\tilde{W}$ depend on the choice of design parameters K_1, K_2, Γ, L, Γ, σ_0, and γ. To guarantee closed-loop system stability, these design parameters should be positive-definite or positive, which should be chosen to make $K_2 - 0.5I_{n\times n} > 0$, $\Gamma - 0.5I_{n\times n}$, $L - (1.5 + 0.5\gamma\tau^2)I_{n\times n} > 0$, and $\frac{\sigma_0}{2} - \frac{1}{\tau} > 0$. Furthermore, to obtain a good tracking performance and reduce disturbance estimate error, the design parameters K_1 and L can be larger.

IV. Simulation Study

In this section, the simulation results of the 3-DOF model helicopter manufactured by Googol Technology Ltd. are presented to illustrate the effectiveness of the proposed adaptive neural fault-tolerant control scheme using the disturbance observers. In the experiment, the neural network disturbance observer is designed as (15), the nonlinear disturbance observer is designed as (24), and the adaptive neural fault tolerant control law is designed as (39). The simulation setup is shown in Figure 3.

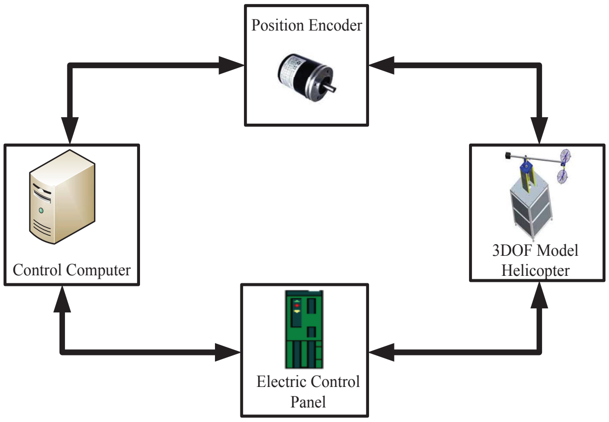

Fig. 3. Control schematic of 3-DOF helicopter manufactured by Googol Technology Ltd.

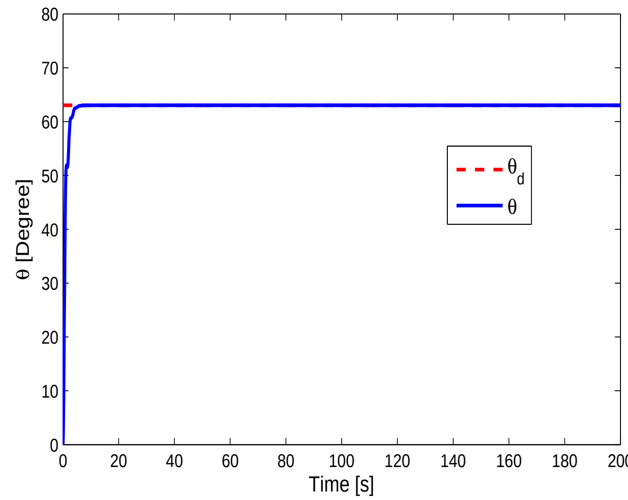

Fig. 4. Elevation angle θ tracking control result of Case 1

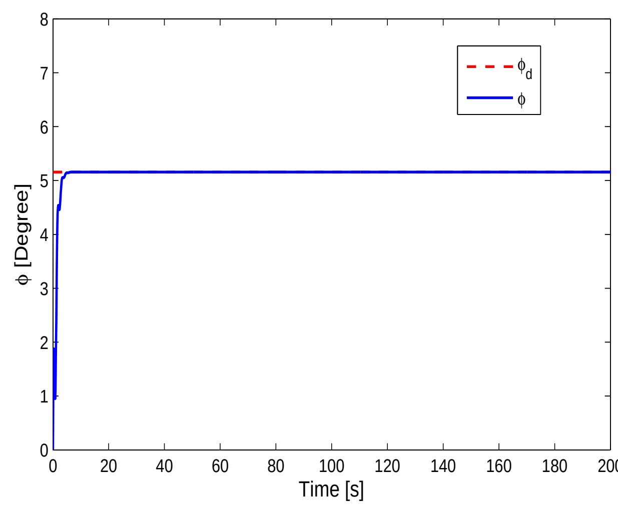

Fig. 5. Pitch angle ϕ tracking control result of Case 1

From Figure 3, the elevation and pitch angles are measured by position encoders and the measurements are sent to the computer. According to the received elevation and pitch angles and the output signal of the reference model, the control command can be generated using the developed adaptive neural fault-tolerant control scheme (39). Then, the control command is executed via the electric control panel to achieve the desired tracking control.

The system parameters for the 3-DOF helicopter manufactured by Googol Technology Ltd. are given in Table 1.

Table 1: Parameters of the two-link robotic manipulator

Parameter	Value
l_1	1 m
l_2	0.8m
J_1	5kg.m
J_3	5kg.m
m_k	0.5kg
m_b	1.5kg

In the adaptive neural fault-tolerant control design, we assumed that all parameters have 20% uncertainties.

The initial state conditions are chosen as $x_1 = [-0.2, -0.002]^T$, $x_2 = [0.02, 0.0002]^T$. All design parameters of the disturbance-observer-based adaptive neural fault-tolerant control scheme are chosen as $K_1 = \text{diag}\{5\}_{2\times2}$, $K_2 = \text{diag}\{15\}_{2\times2}$, $L = \text{diag}\{150\}_{2\times2}$, $\Gamma = \text{diag}\{10\}_{2\times2}$, $\Lambda = \text{diag}\{5\}$, $\gamma = 10$ and $\sigma_1 = 0.2$. Furthermore, the time-varying disturbances are taken as $d_1(t) = -0.2\sin(t)$ and $d_1(t) = -0.1[\sin(0.5t) + \sin(0.2t)]$.

To illustrate the effectiveness of the proposed adaptive neural fault-tolerant control scheme using the disturbance observer, the tracking control simulation results of two cases are given for the 3-DOF model helicopter. The first case sets the desired tracking signal y_d as a constant signal. The other case is that the desired tracking signal y_d is time-varying.

A. Simulation Results of Case 1

The desired tracking signal $y_d(t)$ has $\theta_d = 1.1 \times 180/\pi$ degree and $\phi_d = 0.09\times180/\pi$ degree. In the study, we suppose that the actuator fault appears at $t \geq 40$s. The functions $\xi_i(x)$ are assumed to be $\xi_i(x) = 2 + 0.01\sqrt{\cos(x_1x_2)}$ and $\xi_2(x) = 2 - 0.01\sqrt{\sin(x_1x_2)}$ for the nonlinear remaining control rate coefficient $\rho_i, i = 1,2$ and $\beta_i = 1$. Under the proposed adaptive neural fault-tolerant control scheme using the disturbance observer, the attitude tracking control results of the 3-DOF model helicopter are shown in Figures 4 and 5. Although the system uncertainty, time-varying disturbance, and actuator fault exist, we see that the elevation angle θ and the pitch angle ϕ can track the corresponding desired signals θ_d and ϕ_d under the designed adaptive neural fault-tolerant control scheme. Figures 6 and 7 are the responses of attitude angular velocity for the 3-DOF model helicopter and the responses are convergent and bounded. The control input signals presented in Figure 8 are also convergent. From the results shown in Figures 4 - 8, we can conclude that the developed disturbance-observer-based robust adaptive neural fault-tolerant control scheme is valid for the constant desired trajectories of the 3-DOF model helicopter.

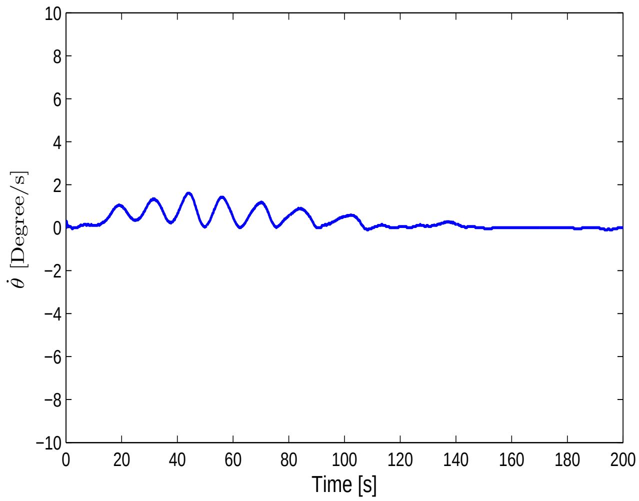

Fig. 6. Elevation angular velocity of Case 1

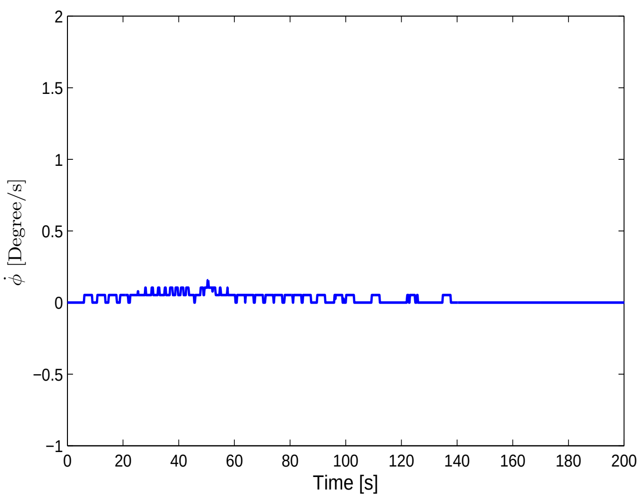

Fig. 7. Pitch angular velocity of Case 1

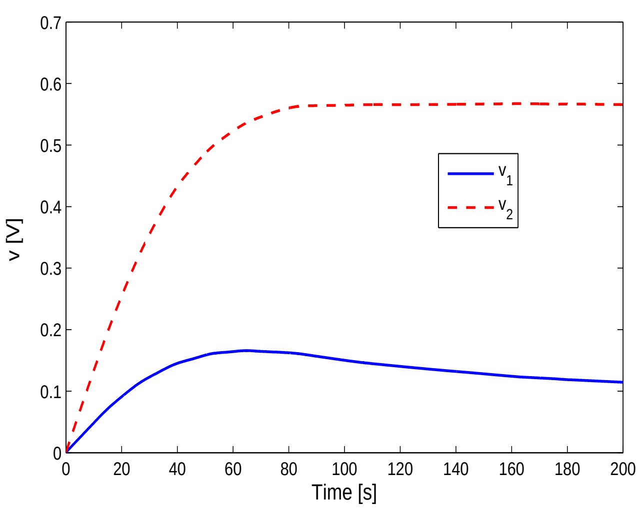

Fig. 8. Control input v of Case 1

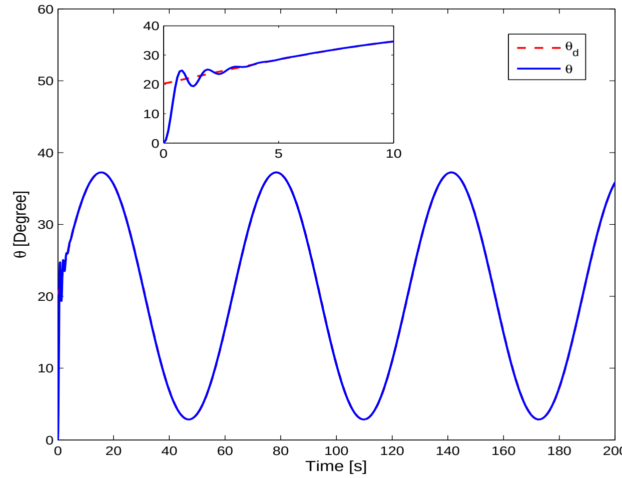

Fig. 9. Elevation angle θ tracking control result of Case 2

B. Simulation Results of Case 2

In this case, the desired tracking signal $y_d(t)$ is $\theta_d = (0.3\sin(0.1t) + 0.35) \times 180/\pi$ degree and $\phi_d = (0.02\sin(0.1t) + 0.03) \times 180/\pi$ degree. In the study, the actuator fault occurs at $t \geq 40$s. The functions $\xi_i(x)$ are taken as $\xi_i(x) = 2 + 0.1e^{-(x_1^2+x_2^2)}$ and $\xi_2(x) = 2 + 0.1\sqrt{\cos(x_1^2 x_2)}$ for the nonlinear remaining control rate coefficient $\rho_i, i = 1, 2$ and $\beta_i = 1$. The tracking control results of the elevation and pitch angles for the 3-DOF model helicopter system are shown in Figures 9 and 10 under the proposed disturbance-observer-based adaptive neural fault-tolerant control scheme. From Figures 9 and 10, for the time-varying desired reference trajectories, we can see that the elevation angle θ and the pitch angle ϕ can track the corresponding desired time-varying tracking signals θ_d and ϕ_d under the our proposed adaptive neural fault-tolerant control scheme when the system uncertainty, time-varying disturbance, and actuator fault are considered. In accordance with the tracking control results, we note that the tracking errors are bounded for the desired time-varying tracking signals, and thus the tracking performance is satisfactory. Figures 11 and 12 show that the attitude angular velocity responses are convergent and bounded. At the same time, the control input signals of the 3-DOF model helicopter are given in Figure 13. According to the results presented in Figures 9- 13, the developed disturbance-observer-based adaptive neural fault-tolerant control scheme is also effective for the time-varying desired trajectories of the 3-DOF model helicopter.

In accordance with above results, satisfactory attitude tracking control performance is obtained under the developed adaptive neural fault-tolerant control scheme of the 3-DOF model helicopter with system uncertainty, unknown external disturbance and actuator fault in this paper.

V. Conclusion

In this paper, the adaptive neural fault-tolerant control approach has been developed for the 3-DOF model helicopter

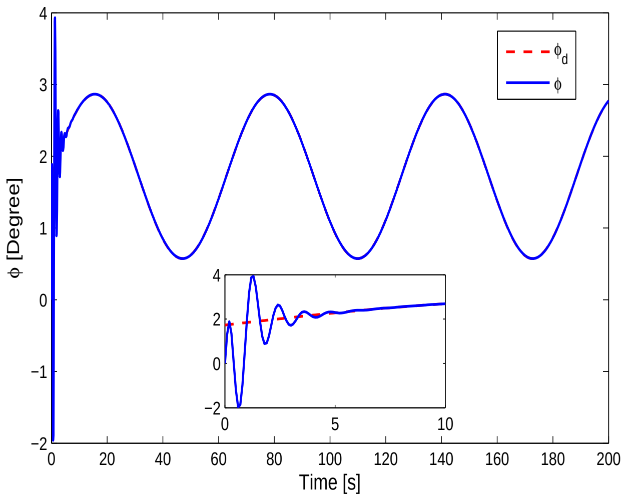

Fig. 10. Pitch angle ϕ tracking control result of Case 2

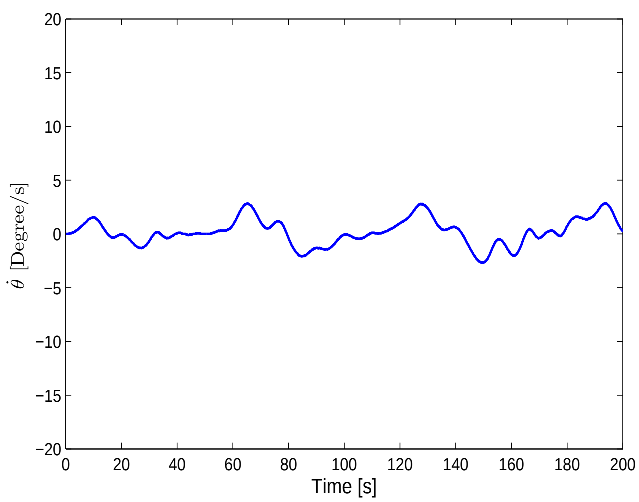

Fig. 11. Elevation angular velocity of Case 2

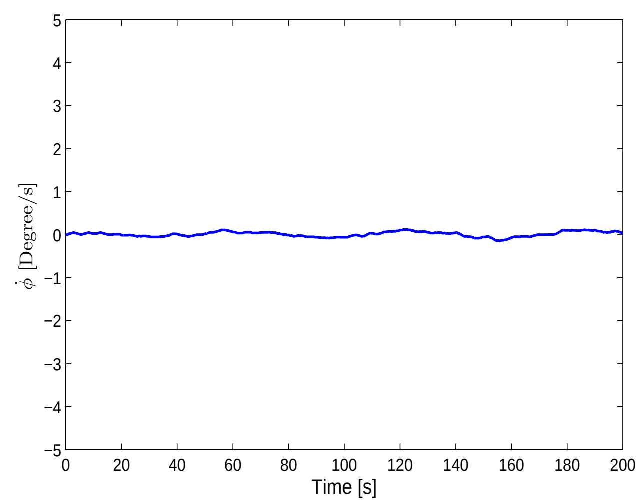

Fig. 12. Pitch angular velocity of Case 2

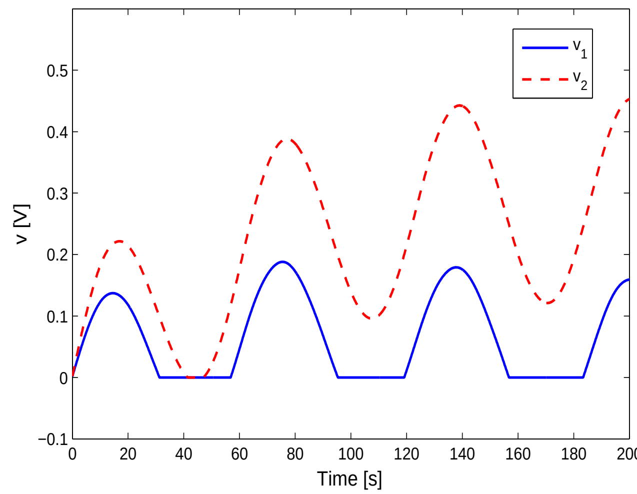

Fig. 13. Control input v of Case 2

in the presence of system uncertainties, unknown external disturbances and actuator faults. To tackle system uncertainty and nonlinear actuator faults, the disturbance observer based on the RBFNN has been designed to approximate these unknowns. The unknown external disturbance and the unknown neural network approximation error are treated as a compound disturbance and is estimated with a nonlinear disturbance observer. Then, the adaptive neural fault-tolerant control scheme was developed for the uncertain 3-DOF model helicopter system using the outputs of two disturbance observers. Lyapunov analysis indicated that the uniformly asymptotical convergence of all closed-loop signals can be guaranteed. Finally, the simulation results are presented to illustrate the effectiveness of the proposed adaptive neural fault-tolerant control scheme. It should be mentioned that the developed adaptive neural fault-tolerant control scheme can be also used in the control of other uncertain MIMO nonlinear systems, which is the subject of our future study.

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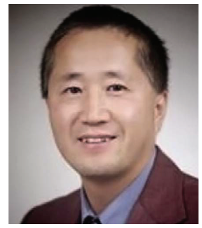

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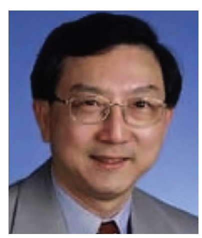

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