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Neural networks-based command filtering control for a table-mount experimental helicopter[☆]

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Abstract

This paper presents neural networks based on command filtering control method for a table-mount experimental helicopter which has three rotational degrees-of-freedom. First, the controller is designed based on backstepping technique, and further command filtering technique is used to solve the derivative of the virtual control, thereby avoiding the effects of signal noise. Secondly, the model uncertainty of the table-mount experimental helicopter's system is estimated by using neural networks. And then, Lyapunov stabilization analysis proves the stability of the table-mount experimental helicopter closed-loop attitude tracking system. Finally, the experiment is carried out to clarify the effectiveness of the proposed method.

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1. Introduction

The control of aircrafts has long been an active topic in the field of unmanned aerial systems (UAS) because of both their wide applications and theoretical difficulties. As a kind of aircrafts, helicopter has always been the focus of attention, and it plays a key role both in military field and in the civil field [1–4]. However, there are still many problems needed to be

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Fig. 1. Photograph of Quanser table-mount experimental helicopter.

addressed in helicopter system, such as high nonlinearity of model, underactuated with strong coupling, system unmodeled dynamics, externally uncertain interference, noise reduction and energy saving. Although the previous work proposed some control methods [5–11] and further addressed some problems, the research on the helicopter is still a huge challenge. Additionally, experimental conditions are also very limited for helicopter research. As shown in Fig. 1, a 3-DOF (three-degrees-of-freedom) table-mount experimental helicopter developed by Quanser Consulting Inc. Researchers did related research and achieved some corresponding results for the 3-DOF helicopter. For example, in [12], the authors proposed a robust linear quadratic regulation (LQR) controller for a 3-DOF helicopter, which contained three parts: a nominal feedforward controller, a nominal LQR controller, and a robust compensator, thereby nonlinear, external interference, and other issues of a 3-DOF helicopter were well resolved. In [13], a robust control method based on sliding-modes technique was proposed for a 3-DOF helicopter. One method of outputting feedback [14,15] was proposed for a 3-DOF helicopter, thereby avoiding the use of angular velocity sensors. A robust integral-adaptive approach combining with backstepping technique [16] was proposed to study a 3-DOF helicopter. Fault-tolerant control of a 3-DOF helicopters was studied in [17,18]. Although some related problems of a 3-DOF helicopter have been solved, there are also some shortcomings. In [14,15], the authors only considered 3-DOF helicopter's pitch axis, however, system coupling was not taken into account. In [16], the final tracking effect was also greatly affected by the inaccurate modeling of the 3-DOF helicopter system. For [17,18], in order to verify the proposed method, the authors only conducted numerical simulation, but there was still a certain deviation between numerical simulation and actual experimental results. Additionally, some control methods have their own disadvantages. For example, the sliding-mode control is developed for many complex control problems and has good applications. However, due to the uninterrupted logic conversion, the tremble phenomenon is inevitable and may cause unstable or unsmooth flying of the helicopter. And some researchers also use disturbance observer to control the corresponding system, but for a helicopter system with high real-time performance requirements, its external disturbance may be real-time uncertain disturbance, so the disturbance observer may take some time to adjust the system, and then the delay will affect the stability of the system.

Therefore, there has been space for improvement in the study of the 3-DOF helicopter.

In the past years, neural network has been developing and it is widely used in many fields. For example, image processing, signal processing, pattern recognition, aircraft control and robot control. For nonlinear uncertain function existing in nonlinear systems [19–22], the approximation of neural networks can be utilized to estimate this nonlinear uncertain function. In order to improve the performance of the neural network and further control one or more nonlinear systems more accurately, the researchers optimized the parameters of the neural network in [19,21]. Additionally, many researchers use neural networks to estimate the uncertain items in the 3-DOF helicopter system model in order to improve the performance of the control algorithm [17,23].

For a nonlinear system, while designing the controller, the backstepping technique is often used due to its structural and systematic advantages. However, it is well known that the use of backstepping technology will bring complex analytic derivation problem, and further will cause signal noise. In response to this phenomenon, researchers proposed the dynamic surface control (DSC)[24], but the use of DSC technology will bring the corresponding filtering error. In [25], the authors first proposed the command filtering backstepping control algorithm, and this paper pointed out the problems in the standard backstepping control algorithm and proposed a practical solution.

Inspired by these results, this paper presents a neural networks based on command filtering combined with a filtering error compensation mechanism method for a 3-DOF helicopter. The main contributions of this paper are as follows:

- (a) Due to the utilization of backstepping technology, the virtual control needs to be derivative. However, in this process, certain signal noise will be brought. Further, we use command filtering technology to reduce the influence of signal noise on the controller.
- (b) The system model nonlinearity, model uncertainty and external interference problems of the 3-DOF helicopter are addressed by using the control method proposed in this paper, and further improve the robustness of the system.
- (c) The experimental results show the 3-DOF helicopter's elevation axis and pitch axis can track a given reference signal with higher precision under the control of this method.

The remainder of this paper is organized as follows: Section 2 introduces the 3-DOF helicopter system and the problem statement. A neural network base on command filtering controller is designed and the stability analysis of the closed-loop system is given in Section 3. Section 4 concludes the paper.

2. Mathematical Model of 3-DOF helicopter and problem formulation

As shown in Fig. 1, One end of the 3-DOF helicopter is a counterweight, which serves to balance the entire fuselage, and the other end is a rectangular frame with two DC motors mounted inside the frame, and each DC motor is equipped with a propeller. As the DC motor drive the propeller to produce force, by controlling the two motor voltage input to control the helicopter suffered by the external force, and then produce elevation, pitch and travel three degrees of freedom of movement [26].

The 3-DOF helicopter's elevation axis, pitch axis and travel axis dynamics equations [26] can be obtained from the simplified model of Fig. 2.

Elevation axis:

$$J_{\theta}\ddot{\theta} = k_f l_a \cos(\varphi)(v_f + v_b) - (m_f + m_b)gl_a \cos(\theta) + m_w gl_w \cos(\theta) \quad (1)$$

Fig. 2. Schematic of the table-mount experimental helicopter.

where θ and φ represent the elevation and pitch angles respectively, J_θ is the moment of inertia of the elevation axis, k_f represents the torque coefficient, l_a denotes the vertical distance from the center of the body of the 3-DOF helicopter to the pitch axis, l_w is the vertical distance from the fulcrum of the 3-DOF helicopter to the counterweight, m_f and m_b represent the mass of the front motor and the back motor, m_w shows the mass of the counterweight, g is the local gravitational acceleration, and v_f and v_b indicate the input voltage values of the front motor and the back motor.

Pitch axis:

$$J_\varphi \ddot{\varphi} = k_f l_h (v_f - v_b) \quad (2)$$

where J_φ is the moment of inertia of the pitch axis, l_h indicates the distance from the center of the propeller to the pitch axis center.

Travel axis:

$$J_\psi \ddot{\psi} = k_f l_a \sin(\varphi)(v_f + v_b) + k_f l_a \sin(\theta)(v_f - v_b) \quad (3)$$

where ψ indicates travel angle, J_ψ is the moment of inertia of the travel axis.

In order to facilitate the design of the controller design, as well as to analyze the model uncertainty and external disturbances of the 3-DOF helicopter system. The dynamics of the 3-DOF helicopter can be written in the form of state space.

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = g_1(x_3)u_s - G(x_1) + f_\theta(\bar{x}) + d_\theta(t) \\ \dot{x}_3 = x_4 \\ \dot{x}_4 = g_2 u_d + f_\varphi(\bar{x}) + d_\varphi(t) \end{cases} \quad (4)$$

where $x_1 = \theta$, $x_2 = \dot{\theta}$, $x_3 = \varphi$, $x_4 = \dot{\varphi}$, $g_1(x_3) = k_f l_a \cos(x_3)/J_\theta$, $g_2 = k_f l_h/J_\varphi$ and $G(x_1) = [(m_f + m_b)g l_a \cos(\theta) - m_w g l_w \cos(\theta)]/J_\theta$. u_s and u_d represent the sum of the front motor and the back motor and the difference between the two motors, respectively. $f_\theta(\bar{x})$ indicates the model uncertainty of the elevation axis, $f_\varphi(\bar{x})$ is the model uncertainty of the pitch axis, and $\bar{x} = (x_1, x_2, x_3, x_4)$. $d_\theta(t)$ and $d_\varphi(t)$ represent the external disturbances on the elevation axis and pitch axis, respectively.

Assumption 1. The reference signal and its derivatives are continuously differentiable, it is required to satisfy the first order differential as shown below:

$$\frac{d^i x_d(t)}{dt^i} \in \ell_\infty \quad \text{for } i = 0, 1 \quad (5)$$

Assumption 2. External disturbances on the elevation axis and pitch axis of the 3-DOF helicopter are bounded, as follows:

$$|d_\theta(t)| < d_\theta \quad \text{and} \quad |d_\varphi(t)| < d_\varphi \quad (6)$$

Remark 1. Since this paper mainly considers the model uncertainty and external disturbance of the 3-DOF helicopter, the problem of underactuated is not considered, and then the elevation axis and pitch axis are controlled with high precision, and the travel axis is free to move.

Remark 2. For the 3-DOF helicopters, the pitch angle is limited to within $(-\pi/2, \pi/2)$ mechanically, and angle sensors and angular velocity sensors are equipped for the implementation of later state controllers.

Neural Networks:

In order to design the controller of the 3-DOF helicopter, radial basis function (RBF) neural networks will be used to estimate the model uncertainty of system. For arbitrary $\bar{\sigma} > 0$, there exists a neural network $W^T S(X)$ [27] such that

$$f(X) = W^T S(X) + \sigma(X) \quad |\sigma(X)| \leq \bar{\sigma} \quad (7)$$

where $f(X)$ and X are defined on a compact set Ω . $S(X) = [s_1(X), s_2(X), \dots, s_N(X)]^T$ represents a basis function vector, $W = [w_1, w_2, \dots, w_N]^T$ represents a weight vector, and $N > 0$ indicates the number of nodes in the RBF neural network. A set of Gaussian functions will be chosen as the basis function vector in the RBF neural network, i.e., for $i = 1, 2, \dots, N$.

$$s_i(X) = \exp\left[-\frac{(X - \mu_i)^T (X - \mu_i)}{\delta_i^2}\right] \quad (8)$$

where δ_i and μ_i are the width and center values of the Gaussian function, respectively.

Remark 3. The ideal weight vector W in the neural networks is unknown, so we use the estimated value $\hat{W}$ of the weight vector and then we define the weight error as $\tilde{W} = W - \hat{W}$.

3. Control law design

In this section, in order to achieve the 3-DOF helicopter high precision tracking performance. An adaptive control method based on the RBF neural networks with command filtering is proposed. The block diagram of the entire control system is shown in Fig. 3.

In order to construct the following controller of the 3-DOF helicopter, define the errors as follows:

$$e_1 = x_1 - x_{\theta d} \quad (9)$$

$$e_2 = x_2 - x_{1,c} \quad (10)$$

$$e_3 = x_3 - x_{\varphi d} \quad (11)$$

Fig. 3. Control scheme of the 3-DOF helicopter.

$$e_4 = x_4 - x_{2,c} \quad (12)$$

In the design process of the attitude tracking controller of the 3-DOF helicopter, due to the use of backstepping technology, the virtual controller needs to be constructed. In order to avoid the signal noise caused by the derivative of the virtual controller, a command filtering is used, where virtual controllers α_i as control signals of command filtering, $x_{i,c}$ as output of command filtering. Specific command filtering [28] is as follows:

$$\begin{cases} \dot{\eta}_1 = \omega_n \eta_2 \\ \dot{\eta}_2 = -2\zeta \omega_n \eta_2 - \omega_n (\eta_1 - \alpha_i) \end{cases} \quad (13)$$

where $\eta_1(0) = \alpha_i(0)$, $\eta_2(0) = 0$, $\omega_n > 0$, $\zeta \in (0, 1]$ and $i = 1, 2$.

Remark 4. In the use of the command filtering, there will be a smaller filtering error. For the 3-DOF helicopter system, in order to achieve high precision flight effect, this part will introduce an error compensation mechanism (ESC).

Define a auxiliary system [29] as follows:

$$\begin{cases} \dot{\zeta}_1 = -k_1 \zeta_1 + \zeta_2 + (x_{1,c} - \alpha_1) \\ \dot{\zeta}_2 = -k_2 \zeta_2 - \zeta_1 \\ \dot{\zeta}_3 = -k_3 \zeta_3 + \zeta_4 + (x_{2,c} - \alpha_2) \\ \dot{\zeta}_4 = -k_4 \zeta_4 - \zeta_3 \end{cases} \quad (14)$$

where k_1, k_2, k_3 and k_4 are positive controller parameters, ζ_i is the filtering error compensation signal, $||\zeta_i||$ is bounded and the specific proof process can refer to reference [29].

Define the following compensation tracking errors.

$$v_1 = e_1 - \zeta_1 \quad (15)$$

$$v_2 = e_2 - \zeta_2 \quad (16)$$

$$v_3 = e_3 - \zeta_3 \quad (17)$$

$$v_4 = e_4 - \zeta_4 \quad (18)$$

For the 3-DOF helicopter system, the actual controllers, the virtual controllers and adaptive laws are designed as follows:

$$u_s = \frac{1}{g_1(x_3)} [-k_2 e_2 - v_2 - e_1 + \dot{x}_{1,c} + G(x_1) - \hat{W}_1^T S_1(X)] \quad (19)$$

$$u_d = \frac{1}{g_2} [-k_4 e_4 - v_4 - e_3 + \dot{x}_{2,c} - \hat{W}_2^T S_2(X)] \quad (20)$$

$$\alpha_1 = -k_1 e_1 + \dot{x}_{\theta d} \quad (21)$$

$$\alpha_2 = -k_3 e_3 + \dot{x}_{\varphi d} \quad (22)$$

$$\dot{\hat{W}}_1 = \Gamma_1 [S_1(X) v_2 - \tau_1 \hat{W}_1] \quad (23)$$

$$\dot{\hat{W}}_2 = \Gamma_2 [S_2(X) v_4 - \tau_2 \hat{W}_2] \quad (24)$$

where Γ_1 and Γ_2 represent positive definite symmetry matrices, τ_1 and τ_2 represent positive constants.

Theorem 1. *For the 3-DOF helicopter closed-loop system (4), controllers u_s , u_d and adaptive laws $\hat{W}_1$, $\hat{W}_2$ are used, further neural networks are used to estimate the model uncertainty of the 3-DOF helicopter system. In addition, initial conditions are given. And then we can get the tracking error of the 3-DOF helicopter system and all the signals are bounded.*

Proof.

Step 1: Consider a Lyapunov function as follows:

$$V_1 = \frac{1}{2} v_1^2 \quad (25)$$

Derivation of V_1 can be obtained:

$$\dot{V}_1 = v_1 \dot{v}_1 \quad (26)$$

By using Eqs. (4) (9) (10) (14) (15) (16) and (21), $\dot{V}_1$ can be written as follows:

$$\dot{V}_1 = -k_1 v_1^2 + v_1 v_2 \quad (27)$$

Step 2: Choose a Lyapunov candidate function as:

$$V_2 = V_1 + \frac{1}{2} v_2^2 + \frac{1}{2} \tilde{W}_1^T \Gamma_1^{-1} \tilde{W}_1 \quad (28)$$

The derivative of V_2 is given by:

$$\dot{V}_2 = \dot{V}_1 + v_2 \dot{v}_2 - \tilde{W}_1^T \Gamma_1^{-1} \dot{\tilde{W}}_1 \quad (29)$$

Applying Eqs. (4) (10) and (16) results in:

$$\dot{V}_2 = \dot{V}_1 + v_2[-k_2 v_2 - v_2 - v_1 - \hat{W}_1^T S_1(X) + f_\theta(\bar{x}) + d_\theta(t)] - \tilde{W}_1^T \Gamma_1^{-1} \dot{\tilde{W}}_1 \quad (30)$$

Further using RBF neural networks, then the following equation holds:

$$\dot{V}_2 = -k_1 v_1^2 - k_2 v_2^2 + v_2[-v_2 - \hat{W}_1^T S_1(X) + W_1^T S_1(X) + \sigma_1(x) + d_\theta(t)] - \tilde{W}_1^T \Gamma_1^{-1} \dot{\tilde{W}}_1 \quad (31)$$

By using Young inequality and assumptions 2, from Eq. (31) results in:

$$v_2 \sigma_1(X) \leq \frac{v_2^2}{2} + \frac{\bar{\sigma}_1^2}{2} \quad (32)$$

$$v_2 d_\theta(t) \leq \frac{v_2^2}{2} + \frac{d_\theta^2}{2} \quad (33)$$

Then, substituting Eqs. (19) (23) (32) and (33) into Eq. (31) leads to:

$$\dot{V}_2 \leq -k_1 v_1^2 - k_2 v_2^2 + \frac{\bar{\sigma}_1^2 + d_\theta^2}{2} + \tau_1 \tilde{W}_1^T \hat{W}_1 \quad (34)$$

Not difficult to get:

$$\tilde{W}_1^T \hat{W}_1 \leq -\frac{1}{2} \|\tilde{W}_1\|^2 + \frac{1}{2} \|W_1\|^2 \quad (35)$$

Applying Eqs. (34) and (35) result in:

$$\dot{V}_2 \leq -k_1 v_1^2 - k_2 v_2^2 - \frac{\tau}{2} \|\tilde{W}_1\|^2 + \frac{\bar{\sigma}_1^2 + d_\theta^2}{2} + \frac{\tau_1}{2} \|W_1\|^2 \quad (36)$$

Step 3: Define a Lyapunov candidate function:

$$V_3 = V_2 + \frac{1}{2} v_3^2 \quad (37)$$

The derivative of V_3 can be obtained as follows:

$$\dot{V}_3 = \dot{V}_2 + v_3 \dot{v}_3 \quad (38)$$

From Eqs. (4) (11) (12) (14) (17) (18) (22) and (36), one can obtain:

$$\begin{aligned} \dot{V}_3 \leq & -k_1 v_1^2 - k_2 v_2^2 - k_3 v_3^2 + v_3 v_4 - \frac{\tau}{2} \|\tilde{W}_1\|^2 \\ & + \frac{\bar{\sigma}_1^2 + d_\theta^2}{2} + \frac{\tau_1}{2} \|W_1\|^2 \end{aligned} \quad (39)$$

Step 4: Continue to choose a Lyapunov candidate function:

$$V_4 = V_3 + \frac{1}{2} v_4^2 + \frac{1}{2} \tilde{W}_2^T \Gamma_2 \tilde{W}_2 \quad (40)$$

The derivative of the Lyapunov function above can be written as follows:

$$\dot{V}_4 = \dot{V}_3 + v_4 \dot{v}_4 - \tilde{W}_2^T \Gamma_2 \dot{\tilde{W}}_2 \quad (41)$$

Inserting Eqs. (4) (12) (18) as well as (20) result in:

$$\begin{aligned} \dot{V}_4 = & \dot{V}_3 + v_4[-k_4 v_4 - v_4 - v_3 - \hat{W}_2^T S_2(X) + f_\varphi(\bar{x}) \\ & + d_\varphi(t)] - \tilde{W}_2^T \Gamma_2^{-1} \dot{\tilde{W}}_2 \end{aligned} \quad (42)$$

Table 1

Parameters of the table-mount experimental helicopter.

Parameter	Value	Parameter	Value
k_f	0.1188N/V	m_b	0.713 kg
l_a	0.660 m	m_w	1.870 kg
l_h	0.178 m	J_θ	1.034 kg · m ²
l_w	0.470 m	J_φ	0.045 kg · m ²
m_f	0.713 kg	g	9.81 m/s ²

Fig. 4. Specific experimental equipment.

Then, the RBF neural networks are used to estimate the uncertain item that exists in the above equation:

$$\dot{V}_4 = \dot{V}_3 + v_4[-k_4 v_4 - v_4 - v_3 - \hat{W}_2^T S_2(X) + W_2^T S_2(X) + \sigma_2(x) + d_\varphi(t)] - \tilde{W}_2^T \Gamma_2^{-1} \dot{\hat{W}}_2 \quad (43)$$

Similar to the step 2, further use Young inequality, one have:

$$v_4 \sigma_2(X) \leq \frac{v_4^2}{2} + \frac{\bar{\sigma}_2^2}{2} \quad (44)$$

$$v_4 d_\varphi(t) \leq \frac{v_4^2}{2} + \frac{d_\varphi^2}{2} \quad (45)$$

Apply Eqs. (39) (44) and (45), (43) can be written as follows:

$$\begin{aligned} \dot{V}_4 \leq & -k_1 v_1^2 - k_2 v_2^2 - k_3 v_3^2 - k_3 v_3^2 - \frac{\tau_1}{2} \|\tilde{W}_1\|^2 - \frac{\tau_2}{2} \|\tilde{W}_2\|^2 \\ & + \frac{\bar{\sigma}_1^2 + d_\theta^2}{2} + \frac{\bar{\sigma}_2^2 + d_\varphi^2}{2} + \frac{\tau_1}{2} \|W_1\|^2 + \frac{\tau_2}{2} \|W_2\|^2 \end{aligned} \quad (46)$$

Let $a = \min\{2k_1, 2k_2, 2k_3, 2k_4, \tau_1, \tau_2\}$ and $b = \frac{\bar{\sigma}_1^2 + d_\theta^2}{2} + \frac{\bar{\sigma}_2^2 + d_\varphi^2}{2} + \frac{\tau_1}{2} \|W_1\|^2 + \frac{\tau_2}{2} \|W_2\|^2$ then one have:

$$\dot{V}_4 \leq -aV_4 + b \quad (47)$$

Table 2
Controller parameters.

Parameter	Value	Parameter	Value
k_1	3	k_3	3
k_2	4	k_4	4
τ_1	0.02	τ_2	0.02
Γ_1	$10I_{5 \times 5}$	Γ_2	$10I_{5 \times 5}$
ω_n	150	ς	0.7

By using the comparison principle, we can obtain:

$$V_4(t) \leq \left(V_4(0) - \frac{b}{a} \right) e^{-at} + \frac{b}{a}, \quad t \geq 0 \tag{48}$$

Remark 5. All the variables of closed-loop system of the 3-DOF helicopter can converge to a small enough neighborhood around the origin by appropriate design parameters. Additionally, the closed-loop signals of the 3-DOF helicopter are semiglobally uniformly ultimately bounded (SGUUB)[30].

The proof is completed here.

4. Experiment Results

This section gives two sets of experiments with comparative experiments to verify the proposed control method. The neural networks based command filtering controller is built in QuaRC environment within MATLAB Simulink. As shown in Fig. 4, the specific experimental equipment includes helicopter plant, data acquisition, PC and power amplifier. Table 1 gives all the parameters associated with Quanser table mount helicopter. During two sets of experiments and comparative experiments, the sampling time is set to 0.001 s. Initial value of elevation angle and pitch angle of the 3-DOF helicopter are -27.5 degrees and 0 degree, respectively. The initial conditions are: $\|\hat{W}_1(0)\| = \|\hat{W}_2(0)\| = 0$. In the RBF neural networks, the basis function vectors $S_1(X)$ and $S_2(X)$ use 5 nodes, and the center values μ_{1j} and μ_{2j} are evenly distributed between $[-1, 1]$, and the width values $\delta_{1j} = 0.5$ and $\delta_{2j} = 0.5$, and where $j = 1, 2, \dots, 5$. The gain and parameters of the controller are chosen as shown in Table 2.

Remark 6. Before the experimental verification of the control method proposed in this paper, we need to use MATLAB to carry out the corresponding simulation experiment, but the simulation experiment and the real experiment are quite different, so we can not fully adopt the controller parameters used in the simulation. In addition, sensor noise is not involved in the simulation experiment, but the sensor noise exists in the real experiment, and the noise will also have a certain impact on the experimental results.

Remark 7. In the specific experiment, the choice of controller parameters is selected according to the requirements of the controller design. In addition, the uncertainty of the 3-DOF helicopter system model and the external interference have a certain impact on the choice of controller parameters. So we need to adjust the controller parameters in real time according to the actual situation of the experiment.

Fig. 5. Tracking response of elevation angle.

Fig. 6. Tracking response of pitch angle.

Experiment: Set-Point Tracking experiment

In the first set of experiments, elevation axis and pitch axis of the 3-DOF helicopter track a set value of -0.1 radian and a set value of 0 radian by using the control method proposed in this paper. The specific experimental results are shown below:

where Fig. 5 shows that the tracking reference signal of the elevation axis and the response of elevation axis under the proposed controller, Fig. 6 describes that the tracking reference signal of the pitch axis and the response of pitch axis under the proposed controller, Further the tracking errors of the 3-DOF helicopter's elevation axis and pitch axis are shown in Fig. 7. Additionally, Fig. 8 shows the input of the 3-DOF helicopter's front motor and back motor in this experiment.

In order to highlight the effectiveness of the proposed control method and the compensation effect of the neural network on the uncertainty of the helicopter system model, a set of comparative experiments is carried out. In the case where the experimental environment and the reference signal are the same, the controller proposed in this paper continues to be used

Fig. 7. Tracking error of both channels.

Fig. 8. Control voltages of proposed controller.

but the neural network is turned off. The corresponding experimental results are shown in the Figs. 9–12.

In the case where the neural network is turned off, the tracking of the 3-DOF helicopter's elevation axis and pitch axis is shown in Figs. 9 and 10, and further tracking errors of these two axis are shown in Fig. 11. Fig. 12 indicates the input of the two motors of the 3-DOF helicopter at this time.

Experiment: Sine-Signal Tracking

In order to further verify the superiority of the control algorithm proposed in this paper, the time-varying reference signal is used. The time-varying reference signals to be tracked by elevation axis and pitch axis are $x_{\theta d} = 0.2 \sin(0.8t) - 0.1$ and $x_{\phi d} = 0.2 \sin(0.5t)$, respectively, where the unit of reference signal is radian.

where Figs. 13 and 14 represent elevation axis and pitch axis of the 3-DOF helicopter tracking response, and Fig. 15 further shows the tracking errors of elevation axis and pitch axis, Fig. 16 indicate the values of the front motor and the back motor when the 3-DOF helicopter elevation axis and the pitch axis track the sinusoidal reference signal, respectively.

Similar to the first set of comparative experiments, the controller that shuts down the neural network is used to control the elevation axis and the pitch axis of the 3-DOF helicopter.

Fig. 9. Tracking response of elevation angle of comparative experiment.

Fig. 10. Tracking response of pitch angle of comparative experiment.

where Figs. 17 and 18 respectively show the results of tracking the sinusoidal signal when the neural network is turned off, and Fig. 19 represents the tracking error of the two axis. Finally, Fig. 20 is the control input at this time.

By analyzing and comparing the above two sets of experiments and comparative experiments, whether the 3-DOF helicopter tracks a fixed value or tracks a time-varying sinusoidal reference signal, the elevation axis and the pitch axis have a high-precision tracking effect under the control method proposed in this paper. Simultaneously, from Figs 7, 11, 15 and 19, it can be compared that the tracking error of the helicopter's the elevation axis and the pitch axis is relatively small when using the control algorithm proposed in this article, so it also demonstrates that the tracking performance of the elevation axis and the pitch axis is perfect. However, when the neural network of the controller in the article is turned off, it can be seen from Figs 9, 10, 17 and 18 that the tracking effect of the helicopter's the elevation and the pitch axis is not ideal, and the tracking error shown in Figs 11 and 19 further illustrates that the tracking performance of the elevation axis and the pitch axis is poor. Therefore, we can conclude that the neural network in controller has a certain compensation for the model uncertainty of the helicopter system, so that the helicopter's the elevation and the pitch axis has high-precision tracking performance.

Fig. 11. Tracking error of both channels of comparative experiment.

Fig. 12. Control voltages of comparative experiment.

Fig. 13. Tracking response of elevation angle.

Fig. 14. Tracking response of pitch angle.

Fig. 15. Tracking error of both channels.

Fig. 16. Control voltages of proposed controller.

Fig. 17. Tracking response of elevation angle of comparative experiment.

Fig. 18. Tracking response of pitch angle of comparative experiment.

Fig. 19. Tracking error of both channels of comparative experiment.

Fig. 20. Control voltages of comparative experiment.

5. Conclusions

In this article, the tracking control problem of a 3-DOF helicopter system was investigated. A novel control method with neural networks based on command filtering was constructed to address the model uncertainty, system nonlinearity, and external interference. Under the control method proposed in this paper, the elevation axis and pitch axis of the 3-DOF helicopter can achieve high precision attitude tracking performance. The experimental results further verify the validity and robustness to unmodeled dynamics and external uncertainties of the 3-DOF helicopter. In the future work, we will further consider the strong coupling and underactuated problem of 3-DOF helicopter, and further study the sensor noise problem in the system.

We declare that we have no financial and personal relationships with other people or organizations that can inappropriately influence our work, there is no professional or other personal interest of any nature or kind in any product, service and/or company that could be construed as influencing the position presented in, or the review of, the manuscript entitled.

Declaration of Competing Interest

None.

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