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Enhanced Data Driven Model-Free Adaptive Yaw Control of Unmanned-Aerial-Vehicle Helicopter

Hongcheng Zhou [1, 2], Daobo Wang[1] and Dezhi Xu[3]

[1]*College of Automation Engineering, Nanjing University of Aeronautics and Astronautics, Nanjing 210016, China*
[2]*Institute of Information, JinLing Institute of Technology, Nanjing 211169, China*
[3]*Key Laboratory of Advanced Process Control for Light Industry (Ministry of Education), Institute of Automation, Jiangnan University, Wuxi 214122, China*
E-mail:zhouhc8@163.com

Abstract

In this paper, an enhanced data driven model-free adaptive yaw control tracking control scheme is proposed for the yaw channel of an unmanned-aerial-vehicle helicopter that is non-affine in the control input. By dynamic linearization and observer techniques, the proposed control algorithm is only based on the PPD parameter estimation derived online from the I/O data of the controlled system, and Lyapunov-based stability analysis is used to prove all signals of close-loop control system are bounded. Compared with the traditional model free adaptive control, the proposed enhanced model free control algorithm can make the closes-loop control system with stronger robustness and better anti-jamming ability. Finally, the simulation results of the dynamic model of a real helicopter-on-arm are offered to demonstrate the effectiveness of the proposed new control techniques.

***Keywords**: Unmanned-aerial-vehicle helicopter, yaw control, model free adaptive control, internal model*

1. Introduction

Potential use of unmanned-aerial-vehicle (UAV) helicopter can be found in military and civilian applications, although military applications dominate the non-military ones. Military and civilian applications include power lines inspection, surveillance, national defense, agricultural, disaster rescue applications and so on [1]. Dynamics of UAV helicopter are strong nonlinearity, serious multivariate coupling, inherently unstable and a non-minimum phase system with time-varying parameters.

So control the UAV helicopter is not an easy task. Researching on reliability and robustness of the nonlinear control methods to improve the performance of UAV helicopter has been an important focus in the control area [1-2].

As a highly nonlinear and uncertain system, helicopter flight control system design has been dominated by linear control techniques. In the past few decades, Linear control algorithms have been extensively researched [1,3-5]. Many linear control technologies were used to design the UAV helicopter control system [1,6-10]. However, for the tracking control, the controller based on fixed linear models may result in an unacceptable response and even in instability of the closed-loop system. Because linearized models cannot guarantee the global model approximation. Nonlinear control methods have been used in the control system design. Such as [2,11-12]. Furthermore, in a lot of control systems, the nonlinear model of plant dynamics is generally non-affine in input and is commonly simplified around a trim point, that is, an operating point dependent on the current system states [13]. And, because of coupled with the uncertainties associated with

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varying environment and changing flight conditions, developing a controller to adequately compensate for the time varying uncertainties have been more difficult tasks [14].

As one of the data drive control methods, MFAC has been proposed and applied in several areas. Hou [15-17] has designed MFAC algorithm based on compact form dynamic linearization (CFDL), partial form dynamic linearization (PFDL), and full form dynamic linearization (FFDL) for single input single-output (SISO), multi-input single-output (MISO), and multi-input multi-output (MIMO) systems. However, the MFAC is still developing. How to prove the stability and convergence of the tracking problems is one of the open problems in MFAC [20]. We all know, Lyapunov functional is widely used to analysis the stability of close-loop system [15].

In this paper, we focus on how to design data-driven controller based on Lyapunov method. Inspired by the work of dynamic linearization technique of Hou [15], we present an enhanced adaptive observer based control strategies for nonlinear processes systems in which the pseudo-partial derivative (PPD) theory is used to dynamically linearize the nonlinear system. First, a novel adaptive strategy for computing the PPD term is designed by using the Lyapunov method. Then, the internal model approach is used to design the data-driven controller via CFDL. The stability analysis for tracking error of the proposed algorithm is provided. Last, an application of the proposed controller design for a small scale UAV helicopter mounted on an experiment platform is also given to show the control algorithm's effectiveness.

The rest of this paper is organized as follows. Section 2, the yaw dynamic of helicopter and the simplified model are given. In Section 3, main results of internal model approach based data-driven control via CFDL are proposed. Simulation results are presented to show the effectiveness of the proposed technique in Section 4. Finally, some conclusions are made at end of this paper.

2.Problem Formulation

It is clearly known that yaw channel control is one of the most challenging jobs in controlling small scale UAV helicopters [4,10]. Due to the small size of small-scale UAV helicopter, the torque combined with the yaw dynamic is highly sensitive. To improve the performance of the yaw control, a more precise model characterizing of the channel is necessary. A framework of the simulation model for the helicopter (see Figure1) is set up using rigid body equations of motion of the helicopter fuselage.
In this way the influence of the aerodynamic forces and moments working on the helicopter are expressed. The total aerodynamic forces and moments acting on a helicopter can be computed by summing up the contributions of all parts on the helicopter (including main rotor, fuselage, tail rotor, vertical fin and horizontal stabilizer). So, the yaw channel dynamic equations are given by:

$$\begin{aligned} \dot{\varphi} &= r \\ I_{zz}\dot{r} &= N_{mr} + N_{tr} + N_{fus} + N_{hs} + N_{vf} \end{aligned} \tag{1}$$

Where φ and r are the yaw angle and angular rate of the helicopter; I_{zz} is the inertia around z-axis; N_{mr}, N_{tr}, N_{hs}, N_{fus} and N_{vf} present the torque of main rotor, tail rotor, horizontal, fuselage and vertical fin worked on the helicopter respectively.

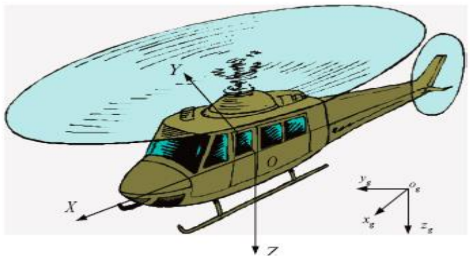

Figure 1. The Frame of Helicopter

In hovering and low-velocity flight, the dominant torque is caused by main rotor and tail rotor [18]. By simplifying the fuselage and vertical fin damping, the yaw channel dynamics can be rewritten as:

$$\dot{\varphi} = r$$
$$I_{zz}\dot{r} = -Q_{mr} + T_{tr}l_{tr} + b_1 r + b_2\varphi \tag{2}$$

Where Q_{mr} is the torque of main rotor, T_r is the thrust of tail rotor, l_{tr} is the distance between the tail rotor and z-axis, b_1 and b_2 are damping constants.

$$\begin{aligned}
Q_{mr} &= \frac{1}{8}C_{d2}\rho c\Omega^2(R^4 - R_0^4)\theta_{mr}^2 \\
&+\Big[8C_{d2}\Omega\sqrt{\rho\pi R^2(2C_1\theta_{mr} + C_2^2 - C_2\sqrt{C_2^2 + 4C_2\theta_{mr}})}(R_0^3 - R^3) \\
&+ 4a\Omega\sqrt{\rho\pi R^2(2C_1\theta_{mr} + C_2^2 - C_2\sqrt{C_2^2 + 4C_1\theta_{mr}})}(R^3 - R_0^3) + +6C_{d2}C_1(R^2 - R_0^2) \\
&+6aC_1(R_0^2 - R^2) + 6C_{d1}\rho\pi\Omega^2R^2(R^4 - R_0^4)\Big]\frac{c\theta_{mr}}{48\pi R^2} + \Big[3C_{d2}C_2\sqrt{C_2^2 + 4C_1\theta_{mr}}(R_0^2 - R^2) \\
&+3aC_2\sqrt{C_2^2 + 4C_1\theta}(R^2 - R_0^2) + 6C_{d0}\rho\pi\Omega^2R^2(R^4 - R_0^4) + 3C_{d2}C_2^2(R^2 - R_0^2) \\
&+4C_{d1}\Omega\sqrt{\rho\pi R^2(2C_1\theta_{mr} + C_2^2 - C_2\sqrt{C_2^2 + 4C_1\theta_{mr}})}(R_0^3 - R^3) + 3aC_2^2(R_0^2 - R^2)\Big]\frac{c}{48\pi R^2}
\end{aligned} \tag{3}$$

The brief presentation of the forces and torques computing can be obtained by using the blade element method [18]. The torque which is generated by main rotor can be described by:

$$Q_{mr} = \int_{R_0}^{R}\left(\frac{\rho\Omega^2r^2C_lc\phi}{2} + \frac{\rho\Omega^2r^2C_dc}{2}\right)rdr \tag{4}$$

With $\phi = \upsilon_1/(\Omega r)$, $C_l = a\alpha$, $C_d \approx C_{d0} + C_{d1}\alpha + C_{d2}\alpha^2$, where ρ, a, r, α, c, υ_1, ϕ and Ω are density of air, slope of the lift curve, speed radial distance, the angle of attack of the blade element, chord of the blade, induced speed, inflow angle and rotor speed of the main rotor respectively. After complete employment with the help of Maple, we obtain (4) with $C_1 = \frac{1}{6}\rho abc\Omega^2(R^3 - R_0^3)$, $C_2 = \frac{1}{8}\rho abc\Omega\sqrt{2/\rho\pi R^2}(R^2 - R_0^2)$.

Where θ_{mr}, R and b are pitch angle of main rotor, radial and number of the rotor. Likewise, the force which is created by the tail rotor can be expressed by the following form

$$T_{tr} = \frac{1}{2}\rho a_{tr}b_{tr}c_{tr}\Omega_{tr}^2\int_{R_{tr0}}^{R_{tr}}\left(\theta_{tr}r_{tr}^2 - \frac{\upsilon_{tr1}}{\Omega_{tr}}r\right)dr_{tr} \tag{5}$$

$$\upsilon_{tr1} = \sqrt{\frac{T_{tr}}{2\rho A_{tr}}} \tag{6}$$

Combing (5) with (6), we have

$$T_{tr} = \frac{1}{2}\rho a_{tr} b_{tr} c_{tr} \Omega_{tr}^2 \int_{R_{tr0}}^{R_{tr}} \left(\theta_{tr} r_{tr}^2 - \sqrt{\frac{T_{tr}}{2\rho A_{tr}}} \frac{r}{\Omega_{tr}} \right) dr_{tr}$$
$$= C_3\theta_{tr} + \frac{1}{2} C_4 \left(C_4 + \sqrt{C_4^2 + 4C_3\theta_{tr}} \right) \tag{7}$$

With $C_3 = \frac{1}{6}\rho a_{tr} b_{tr} c_{tr} \Omega_{tr}^2 (R_{tr}^3 - R_{tr0}^3)$, $C_4 = \frac{1}{8}\rho a_{tr} b_{tr} c_{tr} \Omega_{tr} \sqrt{2/\rho\pi R_{tr}^2}(R_{tr}^2 - R_{tr0}^2)$. where a_{tr}, c_{tr}, b_{tr}, Ω_{tr}, θ_{tr}, r_{tr}, υ_{tr} and A_{tr} are slope of the lift curve, chord of the blade, number of the rotor, speed of the tail rotor, pitch angle, radial distance, induced speed of the tail rotor and area of the tail rotor disc, respectively.

Similarly, the force of the main rotor is

$$T_{mr} = C_1\theta_{mr} + \frac{1}{2} C_2 \left(C_2 + \sqrt{C_2^2 + 4C_1\theta_{mr}} \right) \tag{8}$$

The yaw angle φ is controlled through the θ_{tr}. The θ_{tr} is chosen as the control input u. The φ is chosen as the control objective y. From above modeling of UAV yaw-channel, we can see that it is difficult to find a model-based feedback controller to stabilization system (2). Moreover, the input output relation of this process can be written in the following second-order Nonlinear Auto Regressive with eXogenous input (NARX) model:

$$y(k+1) = f(y(k),\cdots,y(k-n_d),u(k),\cdots,u(k-n_n)) + d(t) \tag{9}$$

Where $d(t)$ denotes the external disturbance and assumes its slowly time-varying. Currently, in order to control the yaw-channel of UAV, various control methods are proposed by [6-9], for example, nonlinear adaptive control, back-stepping control, neural network control and so on. For the nonlinear system (9), there must exist a parameter $\vartheta(k)$, called pseudo-partial derivative (PPD), system (9) can be transformed into the following compact form dynamic linearization (CFDL) description when $|\Delta u(k)| \neq 0$:

$$\Delta y(k+1) = \Delta u(k)\vartheta(k) + \Delta d(k) = \Phi^T(k)\theta(k) \tag{10}$$

Where $\Delta d(k) = d(k) - d(k-1)$, $\theta(k) = [\vartheta(k), \Delta d(k)]^T$, $\Phi(k) = [\Delta u(k), 1]^T$.

3. Main Results

a. Model parameter estimation algorithm

The proposed parameter identification observer has the following structure

$$\hat{y}(k+1) = \hat{y}(k) + \Phi^T(k)\hat{\theta}(k) + Ke_o(k) \tag{11}$$

Where $e_o(k) = y(k) - \hat{y}(k)$ is the output estimation error, $\hat{\theta}(k) = [\hat{\vartheta}(k), \Delta\hat{d}(k)]^T$, and the gain K is chosen such that $F = 1 - K$ in the unit circle.

Hence, in view of (10) and (11), the output estimation error dynamics is given by

$$e_o(k+1) = \Phi^T(k)\tilde{\theta}(k) + Fe_o(k) \tag{12}$$

Where $\tilde{\theta}(k) = \theta(k) - \hat{\theta}(k)$ represents the parameter estimation error. The adaptive update law for the estimated parameters $\theta(k)$ can be chosen as

$$\hat{\theta}(k+1) = \hat{\theta}(k) + \Phi(k)\Gamma(k)(e_o(k+1) - Fe_o(k)) \tag{13}$$

The gain $\Gamma(k)$ is chosen as follows

$$\Gamma(k) = 2\left(\|\Phi(k)\|^2 + \mu\right)^{-1} \tag{14}$$

Where μ is a positive constant, hence, $\Gamma(k)$ is positive definite for all k. Notice that, by virtue of assumption $\|\Phi(k)\| \le \Omega$, $\Gamma(k)$ can be lower bounded as

$$\| \Gamma(k) \| \geq \frac{2}{\Omega^2 + \mu} = \gamma > 0$$

By taking into account (12) and (13), the estimation error dynamics can be written as

$$\begin{aligned} e_o(k+1) &= \Phi^T(k)\tilde{\theta}(k) + Fe_o(k) \\ \tilde{\theta}(k+1) &= H\tilde{\theta}(k) \end{aligned} \tag{15}$$

Where H_c is given by $H = I_2 - \Phi(k)\Gamma(k)\Phi^T(k)$ and I_2 denotes the (2×2) identity matrix.

Theorem 1: The equilibrium $[e_o, \tilde{\theta}^T]^T = [0, \mathbf{0}_{2\times1}^T]^T$ of the system (15) is globally uniformly stable. Furthermore, the estimation error $e_o(k)$ converges asymptotically to 0.

Proof: Consider the Lyapunov function

$$V_1(k) = Pe_o^2(k) + \lambda\tilde{\theta}^T(k)\tilde{\theta}(k)$$

Where λ, P are positive constants and P is the solution by $P + F^2P = Q$ with Q is positive constant.

By taking into (15), we have

$$\begin{aligned} &\Delta V_1(k) = V_1(k+1) - V_1(k) \\ &= P\Phi^T(k)\tilde{\theta}(k)\tilde{\theta}^T(k)\Phi(k) + 2PF\Phi^T(k)\tilde{\theta}(k)e_o(k) + Pe_o^2(k) + PF^2e_o^2(k) \\ &+\tilde{\theta}^T(k)\left(\lambda H^T H - \lambda\right)\tilde{\theta}(k) = -Qe_o^2(k) - \Theta^T(k)\left[\lambda\mu\Gamma^T(k)\Gamma(k) - P\right]\Theta(k) + 2PFe_o(k)\Theta(k) \\ &\leq -Q|e_o(k)|^2 - \left[\lambda\mu\Gamma^T(k)\Gamma(k) - P\right]\| \Theta(k)\|^2 + 2PF|e_o(k)|\| \Theta(k)\| \\ &\leq -c_1|e_o(k)|^2 - c_2\| \Theta(k)\|^2 \end{aligned}$$

Where $\Theta(k) = \Phi^T(k)\tilde{\theta}(k)$, $c_1 = Q - \frac{1}{\varsigma}$, $c_2 = \mu\lambda\gamma^2 - P - \varsigma P^2F^2$. Hence, $\Delta V_1(k) \leq 0$ provided that ς, Q and λ satisfy the following inequalities

$$Q > \frac{1}{\varsigma},\ \mu\lambda\gamma^2 - P - \varsigma P^2F^2 > 0$$

Notice that $\Delta V_1(k)$ is negative definite in the variables $e_o(k)$, $\Theta(k)$. Since $V(k)$ in a decreasing and non-negative function, it converges to a constant value $V_1^\infty \geq 0$, as $k \to \infty$, hence, $\Delta V_1(k) \to 0$. This implies that both $e_o(k)$ and $\tilde{\theta}(k)$ remain bounded for all k, and $\lim_{k\to\infty} e_o(k) = 0$.

b. Controller design

Based on the observer (11), the data-driven inverse control law can be described as

$$u(k) = u(k-1) + \frac{\hat{\vartheta}(k)\left(y^*(k+1) - \hat{y}(k) - Ke_o(k) - \Delta\hat{d}(k)\right)}{\hat{\vartheta}^2(k) + \alpha},\ \ for\ |\Delta u(k)| \leq \delta \tag{16}$$

$$u(k) = u(k-1) + \delta\text{sign}(\Delta u(k)),\ \text{for}\ |\Delta u(k)| > \delta$$

Where $y^*(k)$ is reference trajectory. α and δ as given finite positive numbers. Notice that, in many practical systems, because their actuators cannot change too fast, the number δ can be jammy obtained.

Define observer tracking error $e(k) = y^*(k) - \hat{y}(k)$, thus

$$e(k+1) = y^*(k+1) - \hat{y}(k+1) = y^*(k+1) - \hat{y}(k) - \Phi^T(k)\hat{\theta}(k) - Ke_o(k) \tag{17}$$

The robustness of the stability and the performance for data-driven control law (16) are given in Theorem 2.

Theorem 2: For given $|y^*(k)-y^*(k-1)|\le \Delta y^*$, using the data-driven control law (16), the solution of close-loop observer error system (17) is uniformly ultimately bounded (UUB) [19] for all k with ultimate bound $\lim_{k\to\infty}|e_o(k)|\le \frac{a_2}{1-a_1}$.

Where Δy^* is a given positive constant, $0<s_0(k)\le 1$,

$$a_1 = 1-s_0(k)+\frac{s_0(k)\alpha}{\hat{\vartheta}^2(k)+\alpha},$$

$$a_2=\left(1-s_0(k)+\frac{s_0(k)\alpha}{\hat{\vartheta}^2(k)+\alpha}\right)\left|\Delta y^*-Ke_o(k)-\Delta\hat{d}(k)\right|.$$

Proof: Define a variable $s_0(k)$ where $0<s_0(k)\le 1$ for all k. The control law (16) is equivalently expressed as

$$\Delta u(k)=\frac{\hat{\vartheta}(k)\left(y^*(k+1)-\hat{y}(k)-Ke_o(k)-\Delta\hat{d}(k)\right)}{\hat{\vartheta}^2(k)+\alpha}s_0(k) \tag{18}$$

Where

$$\begin{aligned} s_0(k)&=1, && \text{for } |\Delta u(k)|\le\delta \\ 0<s_0(k)&<1, && \text{for } |\Delta u(k)|>\delta \end{aligned}$$

Using (18), (17) becomes

$$\begin{aligned} |e(k+1)| &= \left(1-s_0(k)+\frac{s_0(k)\alpha}{\hat{\vartheta}^2(k)+\alpha}\right)\times\left|\left(y^*(k+1)-\hat{y}(k)-Ke_o(k)-\Delta\hat{d}(k)\right)\right| \\ &= \left(1-s_0(k)+\frac{s_0(k)\alpha}{\hat{\vartheta}^2(k)+\alpha}\right)\times\left|\left(y^*(k+1)-y^*(k)+e(k)-Ke_o(k)-\Delta\hat{d}(k)\right)\right| \\ &\le \left(1-s_0(k)+\frac{s_0(k)\alpha}{\hat{\vartheta}^2(k)+\alpha}\right)\left|e(k)\right|+\left(1-s_0(k)+\frac{s_0(k)\alpha}{\hat{\vartheta}^2(k)+\alpha}\right)\Delta y^*-Ke_o(k)-\Delta\hat{d}(k) \\ &= a_1|e_o(k)|+a_2 \end{aligned} \tag{19}$$

Choosing a Lyapunov function as $V(k)=|e_o(k)|$, from (19), one has $\Delta V(k+1)=|e_o(k+1)|-|e_o(k)|=(1-a_1)V(k)+a_2$. Since $0\le a_1<1$ and a_2 is bounded, according to the lemma in [19], using the control law (16), the results of close-loop observer system (17) are UUB for all k with ultimate bound $\lim_{k\to\infty}|e_o(k)|\le\frac{a_2}{1-a_1}$.

Corollary 1: Under the controller (16), together with the observer (11), adaptive laws (13), we can guarantee that the system (9) tracking error $e_c(k)=y^*(k)-y(k)$ is UUB with ultimate bound $\lim_{k\to\infty}|e(k)|\le\frac{a_2}{1-a_1}$.

Proof: Since

$$e_c(k)=e(k)-e_o(k) \tag{20}$$

Taking the absolute value and limiting on both sides of (20), we obtain

$$\lim_{k\to\infty}|e(k)|\le \lim_{k\to\infty}|e_o(k)|+\lim_{k\to\infty}|e_c(k)|\le\frac{a_2}{1-a_1} \tag{21}$$

So the tracking error $e(k)$ is UUB for all k with ultimate bound $\lim_{k\to\infty}|e(k)|\le\frac{a_2}{1-a_1}$.

c. Enhanced controller design

In this paper, the internal model structure is adopted to improve the robustness of close-loop system. Where observer (11) is seem as internal model. Although adaptive internal model can ensure the close-loop is stable. The modeling errors is still existing, and it will reduce the robustness and stability. The traditional method is to introduce a feedback low-pass filter. In order to further improve the robustness, the low-pass filter can be designed in the proposed controller. The block diagram of the enhanced model free adaptive control method is shown in Figure 2, where the low-pass filter is described as

$$F(z) = \frac{1-\varsigma}{1-\varsigma z^{-1}} \tag{22}$$

Under the control architecture as shown in Figure 2, the equivalent control law can be expressed as follows:

$$u(k) = u(k-1) + \frac{\hat{\vartheta}(k)\left(y^*(k+1) - \hat{y}(k) - Ke_o(k) - \Delta\hat{d}(k) - F(z)e_o(k)\right)}{\hat{\vartheta}^2(k)+\alpha}, \quad for \ |\Delta u(k)| \le \delta$$

$$u(k) = u(k-1) + \delta \operatorname{sign}(\Delta u(k)), \ \text{for} \, |\Delta u(k)| > \delta \tag{23}$$

Corollary 2: For given $|y^*(k) - y^*(k-1)| \le \Delta y^*$, using the enhanced model free control law (23), the solution of tracking error $e_c(k)$ is UUB where Δy^* is a given positive constant.

Proof: The proof is similar as Theorem 2 with Corollary 1.

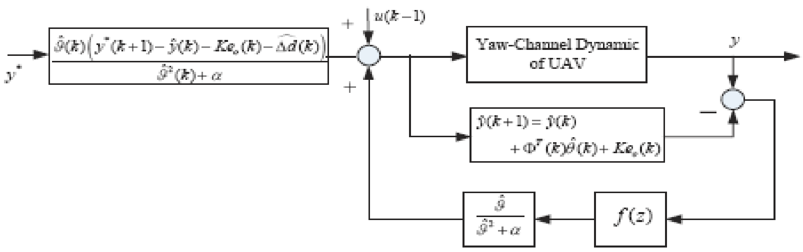

Figure 2: Block Diagram of Enhanced Model Free Adaptive Control Method

4. Simulation Results

In this section, the control algorithm is validated by the simulation model which is obtained from the helicopter-on-arm platform [10]. A small-scale electrical helicopter is mounted at the end of a 3-DOF arm, while the weight of the helicopter is balanced at the other side of the arm. First, the parameters of the nonlinear yaw dynamic model are identified as follows

$$\begin{aligned} \dot{\varphi} &= r \\ \dot{r} &= k_1 r + k_2\varphi + k_3\theta_{tr} + k_4\theta_{tr}^2 + k_5\Omega\theta_{tr} + d(t) \end{aligned} \tag{24}$$

With $k_1 = -1.38$, $k_2 = -3.33$, $k_3 = 63.09$, $k_4 = 11.65$, $k_5 = -0.14$ and $\Omega = 1200$. It is obviously that $k_3\theta_{tr} + k_4\theta_{tr}^2 + k_5\Omega\theta_{tr}$ is a nonlinear function with respect to the control input θ_{tr}.

For the proposed control law, we choose the sampling time $T_s = 1$. The parameters of proposed control law in Section III are $k_c = 0.9$, $\mu = 0.1$, $\alpha = 0.01$, $\delta = 0.2$, ò $= 10^{-10}$ and $\hat{\phi}(1) = 10$. The parameter of filter (22) is $\varsigma = 0.75$.

In the following simulations, the initial conditions are $\varphi(0)=5$, $r(0)=0$. The tracking command of φ_c is

$$\varphi_c = \begin{cases} 10, & t \le 20 \\ 15, & 20 < t \le 40 \\ 25, & t>40 \end{cases}$$

Pass φ_c through a filter, such as $F_c = \frac{\varphi_d}{\varphi_c} = \frac{0.8}{s+0.8}$. So desired trajectory $\varphi_d = y_d = \frac{0.8}{s+0.8}\varphi_c$. To verify the robustness of our method for the model parameter and disturbance, in the simulation, the disturbance is designed to change according to the time-varying changing, *i.e.*

$$d(t) = \begin{cases} 0 & \text{deg}/s^2 \quad 10 \ge \text{t} \\ 5\sin(\pi t)+4\cos(2\pi t)+3\cos(3\pi t)\sin(2\pi t) & \text{deg}/s^2 \quad 10<\text{t} \end{cases} \tag{25}$$

We compare two control methods, they are proposed in [17] and in this paper. System responses are shown by the control method of [17] in Figure 3, which are included output signals and input signals. From Figure 3-5, because of the fast time-varying disturbance (25), the close-loop control system cannot achieve asymptotic tracking under the [17]. However, it can be seen from Figure 6-8, the tracking error significantly decreases using the proposed control method in this paper. The proposed model free controller can achieve a better performance in the presence of same fast time-varying disturbance (25).

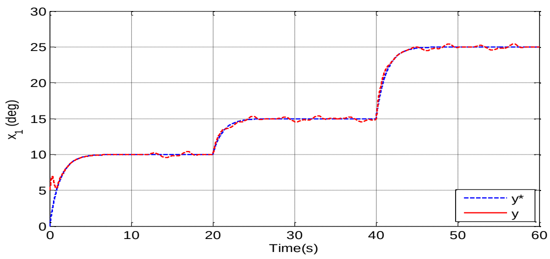

Figure 3. x_1 of System Responses Using the Control Approach

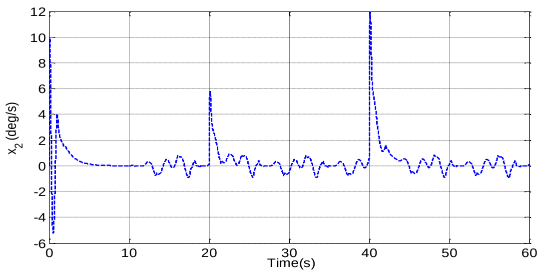

Figure 4. x_2 of System Responses Using the Control Approach

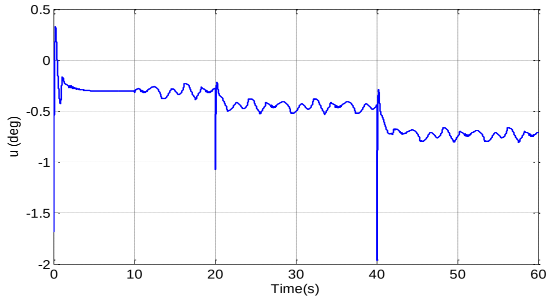

Figure 5. u **of System Responses Using the Control Approach**

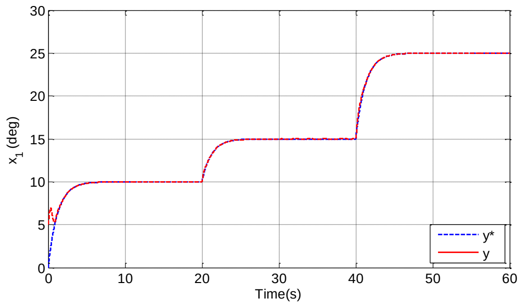

Figure 6. x_1 **of System Responses Using the Proposed Control Approach**

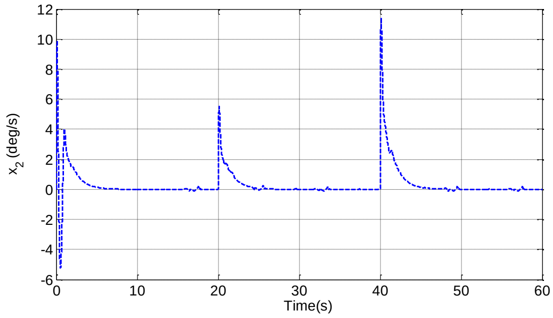

Figure 7. x_2 **of System Responses Using the Proposed Control Approach**

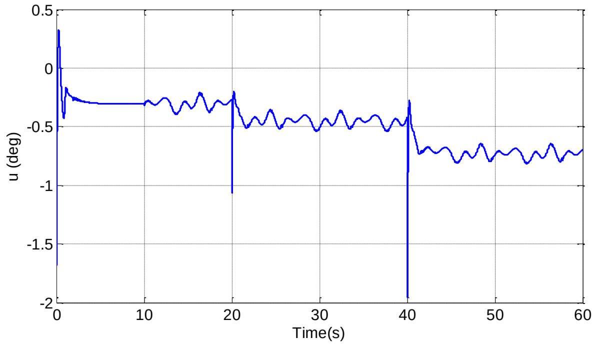

Figure 8. u **of System Responses Using the Proposed Control Approach**

5. Results and Discussions

We have carried out a systematic study on the yaw channel of a UAV helicopter in this paper. The yaw channel of an unmanned-aerial-vehicle helicopter is non-affine in the control input. In order to improve operational performance, we have developed a new model free adaptive control algorithm via CFDL. The proposed model free tracking control scheme can guarantee the asymptotic output tracking of the closed-loop control systems in spite of unknown uncertainties/disturbances. Finally, simulation results are provided on yaw dynamics of a small-scale UAV helicopter to show the effective and advantages of the new control strategy.

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Authors

Hongcheng Zhou, Born in 1978, Yudao Street, Nanjing City, P. R. China. Current position, grades: a Lecturer with the JinLing Institute of Technology, University studies: received the B.S. degree and the M.S. degree from the Shenyang University, and the Ph.D. degree from the Nanjing University of Aeronautics and Astronautics. Scientific interest: fault diagnosis and fault-tolerant control, data-driven control, and system identification. Publications: more than 10 papers published in various journals. Experience: teaching experience of 8 years, 10 scientific research projects.

Daobo Wang, Born in 1957, Yudao Street, Nanjing City, P. R. China. Current position, grades: a Professor with Nanjing University of Aeronautics and Astronautics University studies: received the B.S. degree and the M.S. degree from Nanjing University of Aeronautics and Astronautics Scientific interest: advanced flight control Publications: more than 100 papers published in various journals. Experience: teaching experience of more than 30 years, more than 70 scientific research projects.

Dezhi Xu, Born in 1985, P. R. China. Dezhi Xu received the B.S. degree from the North University of China, Taiyuan, China, the M.S. degree from the Lanzhou University of Technology, Lanzhou, China, and the Ph.D. degree from the Nanjing University of Aeronautics and Astronautics, Nanjing, China.

He is currently a Lecturer with the Jiangnan University, Wuxi, China. His current research interests include fault diagnosis and fault-tolerant control, data-driven control, and system identification.