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Research Article

The Model Relief Food Free Control Technology Based on the Cascade Observer

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Abstract: In this study, the methods are applied to the control of the relief food helicopter and achieve good control performance and effect. The design of the fuzzy controller does not depend on the model of the controlled object. But it depends very closely on the experiences and knowledge of control experts or operators. But it is difficult to design a high-level fuzzy controller. Moreover the fuzzy controller is not easy to control learning and adjustment of the parameters, which makes the structure of the self-adaptive fuzzy controller difficult. Self-adaptive learning technology can effectively compensate for the decline of control performance caused by the imperfection of the rule base. The self-adaptive fuzzy control has two kinds of forms.

Keywords: Cascade observer, fuzzy controller, relief food helicopter

INTRODUCTION

At present, many scholars have studied the design of the course channel controller for relief food helicopters under the condition of the model having been established. In fact, the dynamical models of course channels of air vehicles with different types and different parameters are different. And the establishment of the course channel model is cumbersome and complex, so it is necessary and urgent to research the model free control method independent of mathematical models. As one of the most important methods in the model free control field, the intelligent control method has garnered widespread attention from scholars (Raptis and Valavanis, 2011). But on account of being in the stage of theoretical research without many practical applications, the intelligent control method is tried in the design of course channel controller for relief food helicopters in this study.

Problem description: In this study, we study the system aiming at the following class of nonlinear systems (Cai *et al*., 2008):

$$
\begin{aligned}
x_1 &= x_2 \\
x_1 &= x_{i+1} \\
&\mathrm{L} \\
x_n &= f(x) + bu(t) + d(t) \\
y &= x_1
\end{aligned}
\qquad (1)
$$

where, $f(x)$ and $d(t)$ denote the unknown nonlinear function and the complex time-varying interference; $u(t)$ is the control input; $x = [x_1, x_2, L, x_n]^T = [y, y, L, y^{(n-1)}]^T$. Expand the SISO method to the following multi-input and multi-output model later:

$$y_i^{n_i} = f_i(X, t) + b_i\, u_i\,(t) + \mathrm{d}_i(t),\ i = 1, L, p \qquad (2)$$

where, $\mathrm{X} = [X_1^T, X_2^T, \mathrm{L}\ X_p^T]^{\mathrm{T}}$ is the output differential vector; $X_i = [y_i, y_i^{(1)}, \mathrm{L}\ y_i^{(n_i-1)}]^{\mathrm{T}}$ is the ith output differential vector,; y_i and u_i respectively express the ith output and the ith input; $d_i(t)$ denotes the unknown complex time-varying interference. It assumes that $f_i(.)$ is the unknown time-varying bounded smooth nonlinear function and satisfies an increasing condition, namely Lipchitz.

MATERIALS AND METHODS

Cascade observer: In the actual system, through sensors we can only obtain the position signals, but not the high order differential signals, so it is necessary to obtain it through mathematic methods. Tracking-differentiator is a useful tool to obtain high-order differential signals. Studies on this field are much more and there is mainly high-gain observer method, etc. A cascaded observer design method proposed in this section is used to estimate high order differential signals (Xu *et al*., 2013). The purpose of the design is to ensure the convergence of the observer cascade method, i.e.:

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$\hat{x}_1 = \hat{x}_1 \rightarrow \hat{x}_2 = \hat{x}_1 \rightarrow \hat{x}_2 = \hat{x}_1 = \hat{x}_1 \rightarrow \hat{x}_3 = \hat{x}_2 \rightarrow \hat{x}_3 = \hat{x}_2 = \hat{x}_1$, L, $\hat{x}_{n+1} = \hat{x}_n \rightarrow \hat{x}_{n+1} = \hat{x}_n = x_1^{(n)}$

Based on this concept, the designed cascade observer is shown as follows:

$$\begin{aligned} &\hat{x}_1 = \hat{x}_2 + l_1(y-\hat{x}_1) + \hat{\rho}_1 \mathrm{sgn}\,(y - \hat{x}_1) \\ &\hat{x}_i = \hat{x}_{i+1} + I_i\,(\hat{x}_{i-1} - \hat{x}_i) + \hat{\rho}_i\, \mathrm{sgn}\,(\hat{x}_{1-1} - \hat{x}_i),\ i = 2, L,n \\ &\hat{x}_{n+1} = l_{n+1}\,(\hat{x}_n - \hat{x}_1) + \hat{\rho}_{n+1}\, \mathrm{sgn}\,(\hat{x}_n - \hat{x}_{n+1}) \\ &\hat{y} = \hat{x}_1 \end{aligned} \tag{3}$$

Utilizing the following conditions, $|\hat{x}_{i+1} - \hat{x}_{i-1}| \le \rho_i$, $i = 1$, L, $n + 1$

$$\text{and } \mathrm{sgn}(a) = \begin{pmatrix} 1 & ,if \quad a > 0 \\ 0 & ,if \quad a = 0 \\ -1 & ,if \quad a < 0 \end{pmatrix}$$

Note: ρ_i, i = 1, 2, 3, ρ_{n+1} is the upper limit value and a constant. This will be proved in theorem 1. Theorem 1 shows that ρ_i has a boundary. $\hat{\rho}_i$ denotes the estimated value of ρ_i. l_i is a positive value. When select l_i s, l_i is even larger than l_{i+1}. The reason is that the contribution of estimating the previous step exceeds the cascade structure of estimating the latter (Kim *et al*., 2012). Such gain selection needs a smaller gain value to increase with the state order, which is different from the high-gain observer requiring a higher gain value to increase with the state order:

$$\hat{\rho}_i = \begin{cases} \gamma_i\, |\hat{x}_{i-1} - \hat{x}_i| & if\ \hat{\rho}_i \le \bar{\rho}_i \\ \gamma_i \left(1 + \frac{\bar{\rho}_i - \hat{\rho}_i}{\delta_i}\right) |\hat{x}_{i-1} - \hat{x}_i|, & other \end{cases} \quad i = 1, L, n+1 \tag{4}$$

where, δ_i is a positive constant, that plays a big role for reducing the self-adaptive gain $\hat{\rho}_i > \bar{\rho}_i$ and preventing the divergence of $\hat{\rho}_i$. $\bar{\rho}_i$ can be set to any positive and the choice should be rational, because they affect the transient response of the cascade observer. The Eq. (4) guarantees $\hat{\rho}_i$ bounded.

Theorem 1: The designed cascade observers (3) and (4) can guarantee the asymptotic stability of the estimation error of the differential, i.e., $\lim_{t \to \infty} \sum_{i=1}^{n+1} (\hat{x}_{i-1}(t) - \hat{x}_i(t)) = 0$.

Prove: In order to test the stability analysis of the proposed observer, we have considered the Lyapunov function:

$$V = \frac{1}{2} \sum_{i=1}^{n+1} (\hat{x}_{i-1} - \hat{x}_i)^2 + \frac{1}{2} \sum_{i=1}^{n+1} \frac{1}{\gamma_i} \rho\%_i^2 \tag{5}$$

where, $\rho\%_i^2 = \rho_i - \hat{\rho}_i$ Following the trajectory of the system, i.e., the differential of V, we can get:

$$V = \sum_{i=1}^{n+1} (\hat{x}_{i-1} - \hat{x}_i)\,(\hat{x}_{i-1} - \hat{x}_i) + \sum_{i=1}^{n+1} \frac{1}{\gamma_i} \rho\%_i \rho\%_i \tag{6}$$

Put Eq. (5) into (6) and we can get:

$$\begin{aligned} V &= -\sum_{i=1}^{n+1} (\hat{x}_{i-1} - \hat{x}_i)\,[\hat{x}_{i+1} + l_i\,(\hat{x}_{i-1} - \hat{x}_{i-1}) + \hat{\rho}_{i-1} \mathrm{sgn}\,(\hat{x}_{i-1} - \hat{x}_i)] + \sum_{i=1}^{n+1} \hat{x}_{i-1}(\hat{x}_{i-1} - \hat{x}_i) + \sum_{i=1}^{n+1} \frac{1}{\gamma_i} \rho\%_i\, \rho\%_i \\ &= -\sum_{i=1}^{n+1} (\hat{x}_{i-1} - \hat{x}_i) \times [\hat{x}_{i+1} + \hat{x}_{i-1} + \hat{\rho}_i\, \mathrm{sgn}(\hat{x}_{i-1} - \hat{x}_i)] \\ &\quad -i \sum_{i=1}^{n+1} l_i (\hat{x}_{i-1} - \hat{x}_i)^2 + -\sum_{i=1}^{n+1} \frac{1}{\gamma_i} \rho\%_i\, \rho\%_i \\ &\le -\sum_{i=1}^{n+1} l_i (\hat{x}_{i-1} - \hat{x}_i)^2 + \sum_{i=1}^{n+1} |\hat{x}_{i-1} - \hat{x}_i|\, |\hat{x}_{i+1} - \hat{x}_{i-1}| \\ &\quad - \sum_{i=1}^{n+1} \hat{\rho}_i \mathrm{sgn}(\hat{x}_{i-1} - \hat{x}_i)\,(\hat{x}_{i-1} - \hat{x}_i) + \sum_{i=1}^{n+1} \frac{1}{\gamma_i} \rho\%_i\, \rho\%_i \\ &\le -\sum_{i=1}^{n+1} l_i (\hat{x}_{i-1} - \hat{x}_i)^2 + \sum_{i=1}^{n+1} \rho_i |\hat{x}_{i-1} - \hat{x}_i| - \sum_{i=1}^{n+1} \hat{\rho}_i |\hat{x}_{i-1} - \hat{x}_i| + \sum_{i=1}^{n+1} \frac{1}{\gamma_i} \rho\%_i\, \rho\%_i \\ &= -\sum_{i=1}^{n+1} l_i (\hat{x}_{i-1} - \hat{x}_i) + \sum_{i=1}^{n+1} \rho\%_i |\hat{x}_{i-1} - \hat{x}_i| - \sum_{i=1}^{n+1} \frac{1}{\gamma_i} \rho\%_i\, \rho\%_i \end{aligned} \tag{7}$$

Substituting the Eq. (4) into the (7), we can get:

$$V \le -\sum_{i=1}^{n+1} l_i (\hat{x}_{i-1} - \hat{x}_i)^2 \tag{8}$$

From Eq. (8), we can confirm that $(\hat{x}_{i-1} - \hat{x}_i)$ and $\rho\%_i$ are bounded. Similarly, $\hat{\rho}_i$ is bounded from Eq. (4). Integrate the Eq. (8) and we can get:

$$\begin{aligned} &\int_0^t \sum_{i=1}^{n+1} l_i\,(\hat{x}_{i-1}(\tau) - \hat{x}_i(\tau))^2\, d\tau \le -V(t) + V(0) \le V(0) \\ &= \frac{1}{2} \sum_{i=1}^{n+1} (\hat{x}_{i-1}(0) - \hat{x}_i(0))^2 + \sum_{i=1}^{n+1} \frac{1}{2\gamma_i} \rho\%_i^2(0) \end{aligned} \tag{9}$$

Then, as $V(0)$ and l_i are constants, $\sum_{i=1}^{n+1} (\hat{x}_{i-1} - xi) \in L_2$. As ρi, $(xi-1-xi)$, and $|xi+1-xi-1|$ have been proved bounded, we can get $\sum_{i=1}^{n+1} \frac{d}{dt} (\hat{x}_{i-1} - \hat{x}_i) \in L_\infty$. Through using Barbalat's lemma, $\lim_{t \to \infty} \sum_{i=1}^{n+1} (\hat{x}_{i-1}(t) - \hat{x}_i(t)) = 0$.

Theorem 2: (non-adaptive stability) for the system (1), the cascade differential tracker of $\gamma_i = 0$ is given to guarantee that the differential estimation error is globally uniformly bounded.

Prove: as $\gamma_i = 0$ and the parameter estimated value $\hat{\rho}_i$ is a constant. For the non-adaptive Lyapunov function, we hold that:

$$V_{cl} = -\frac{1}{2} \sum_{i=1}^{n+1} (\hat{x}_{i-1} - \hat{x}_i)^2 \tag{10}$$

From the Eq. (7), we can obtain:

$$V_{cl} = -\sum_{i=1}^{n+1} l_i (\hat{x}_{i-1} - \hat{x}_i)^2 + \sum_{i=1}^{n+1} \rho\%_i |\hat{x}_{i-1} - \hat{x}_i| \tag{11}$$

where, set $\chi = 2V_{cl} = \sum_{i=1}^{n+1} (\hat{x}_{i-1} - \hat{x}_i)^2$, ; $l_0 = (n+1)\min_{1 \le i \le n+1} l_i$ and $\rho\%_0 = (n+1)\max_{1 \le i \le n+1} \rho\%_i$. Then use

$\sum_{i=1}^{n+1} |\hat{x}_{i-1} - \hat{x}_i| \leq \sqrt{n+1}\left\{\sum_{i=1}^{n+1}(\hat{x}_{i-1} - \hat{x}_i)^2\right\}^{\frac{1}{2}} = \sqrt{n+1}\,\chi^{\frac{1}{2}}$.

By Schwarz inequality, we can get:

$$\frac{d\chi}{dt} \leq 2\sqrt{n+1}\,\rho\text{‰}_0\,\chi^{\frac{1}{2}} - 2l_0\chi \quad (12)$$

By replacing, solve this type of equation. In fact, set $\eta = \chi^{\frac{1}{2}}$ and we can get:

$$\frac{d\eta}{dt} = \frac{1}{2}\chi^{-\frac{1}{2}}\frac{d\chi}{dt} \quad (13)$$

Rewrite (12) and we can get:

$$\chi^{-\frac{1}{2}}\frac{d\chi}{dt} = 2\sqrt{n+1}\,\rho\text{‰}_0 - 2l_0\chi|^{-\frac{1}{2}} = 2\sqrt{n+1}\,\rho\text{‰}_0\ 2l_0\ \eta \quad (14)$$

Plugging the Eq. (14) into the (13), we can get:

$$\eta + l_0\,\eta = \sqrt{n+1}\,\rho\text{‰}_0 \quad (15)$$

Solve the linear Eq. (16) to get the solution of η and it is available that:

$$\eta(t) = \sqrt{n+1}\,\frac{\rho\text{‰}_0}{l_0}(1 - e^{-l_0 t}) + \eta(0)\ {-e^{-l_0 t}} = \sqrt{n+1}\frac{\rho\text{‰}_0}{l_0}\left(\eta(0) - \sqrt{n+1}\frac{\rho\text{‰}_0}{l_0}\right) \quad (16)$$

Return χ by the replacement $\chi = \eta^2$, then we can get:

$$\chi(t) = \left\{\sqrt{n+1}\frac{\rho\text{‰}_0}{l_0} + e^{-l_0 t}\left(\chi(0)^{\frac{1}{2}} - \sqrt{n+1}\frac{\rho\text{‰}_0}{l_0}\right)\right\}^2 \leq \left\{2\sqrt{n+1}\frac{\rho\text{‰}_0}{l_0}\left(\chi(0)^{\frac{1}{2}} - \sqrt{n+1}\frac{\rho\text{‰}_0}{l_0}\right) + \chi(0)12{-}n{+}1\rho\%0l0e{-}l0t + (n+1)\,\rho\%0l02 \right. \quad (17)$$

This proves that the solution of χ is globally uniformly non-adaptive bounded, i.e., when $t \to \infty$ $\chi(t) \to (n+1)\left(\frac{\rho\text{‰}_0}{l_0}\right)^2$.

RESULTS AND DISCUSSION

The design of model free controller: Set y_{ri} (i = 1,L,p) as the ith given input. $X_{ri} = [y_{ri}, y_{ri}^{(1)}, L, y_{ri}^{(n_i-1)}]^T$ is the ith given input differential vector. $\bar{X}_{ri} = [X_{ri}^T, y_{ri}^{(n_i)}]^T$ and $\bar{X}_i = [X_i^T, y_i^{(n_i)}]^T$ denote respectively the ith given input expanding differential vector and output expanding differential vector:

$$E_i = [E_{i1}, E_{i2}, L, E_{in_i}]^T = X_{ri} - X_i$$
$$= [\varepsilon_i, \varepsilon_i^{(1)}, L, \varepsilon_i^{(n_i-1)}]^T$$
$$\bar{E}_i = \bar{X}_{ri} - \bar{X}_i = [E_i^T, \varepsilon_i^{(n_i)}]^T \quad (18)$$

E_i and $\bar{E}_i$ in Eq. (18) denote respectively the ith error differential vector, the ith error expanding differential vector. Therein, $\varepsilon_i = y_{ri} - y_i$. It assumes that y_{ri} can achieve the n_i-order bounded differential (Wang *et al*., 2009).

Theorem 3: For system (2), the model free controller can be expressed as follows:

$$u_i = \frac{1}{b_i}\bar{K}_i\bar{E}_i + \hat{u}_i \quad i = 1, L, \quad (19)$$

where, $\bar{K}_i\,[k_{in_i}, L, k_{i1}, 1]$ makes $s^{n_i} + k_{i1}s^{n_i-1} + L + k_{in_i}$ become a Hurwitz polynomial, $\hat{u}_i$ is the estimated value of u_i. Then the received model free control algorithm has the following properties:

- It can realize the linear decoupling control.
- It makes the closed-loop system asymptotically stable and meets the following convergence:

$$\lim_{t\to\infty}\lim_{\lambda\to\infty} X_i = X_{ri} \quad (20)$$

- All system variables are bounded.

Prove: putting Eq. (19) into (2), it is available that:

$$y_i^{(n_i)} = f_i(X, t) + b_i(\bar{K}_i\bar{E}_i + \hat{u}_i) + d_i(t),\ i = 1, L, p \quad (21)$$

Then, we can get:

$$(y_i^{(n_i)} + k_{i1}y_i^{(n_i-1)} + L + k_{in_i}y_i) = (y_{ri}^{(n_i)} + k_{i1}y_{ri}^{(n_i-1)} + L + k_{in_i}y_{ri})\ i = 1, L, p \quad (22)$$

where $\delta_i = \hat{u}_i - u_i$. Based on Eq. (22), p linear decoupling differential equations are obtained. From the definition of scalar ε_i in formula (22) and the definition of scalar E_{ik}, we can get:

$$\varepsilon_i^{(n_i)} = -\ k_{i1}\varepsilon_i^{(n_i-1)} - L - k_{in_i}\varepsilon_i + b_i\,\delta_i \quad (23)$$

i.e.,

$$E_{in_i} = -\ k_{i1}\,E_{in_i} - L - k_{in_i}\,E_{i1} + c_i b_i \delta_i \quad (24)$$

It is easy to get the following important equation from Eq. (24) and the definition of vector E_i in Eq. (25):

$$E = A_{mi}\,E_i + c_i\,b_i\,\delta_i \quad (25)$$

where, $A_{mi} \in R^{n_i\times n_i}$ is a controllable matrix and the matrix parameters are k_{n_i}, L, k_{i1} and $c_i = [0, L, 0,1]^T \in R^{n_i\times 1}$. Similar to the proof of the Theorem 1, $\delta_i \to 0$. Moreover, from Eq. (25), it can be seen that $s^{n_i} + k_{i1}s^{n_i-1} + L + k_{in_i}$ is a Hurwitz polynomial and we can get:

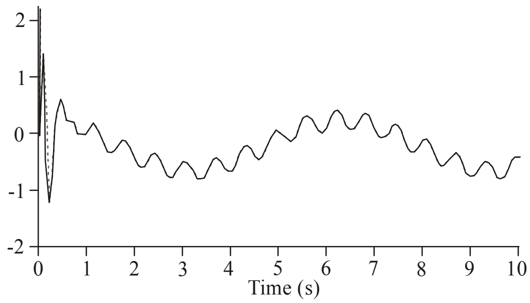


Fig. 1: First-order differential signal estimations of course angles

$$\lim_{t \to \infty} E_i = 0 \quad (26)$$

Hence, based on the higher-order differentiator in the above section, we can obtain the model free controller of the MIMO system below.

In this section, use the dynamical model of a miniature relief food helicopter in vertical flight to verify MIMO model free control. The relief food helicopter flight height changes with the change of the pitch angle. Shown in Fig. 1. Neglecting the influence of ground factors, the relief food helicopter dynamic equations are described as follows:

$$\dot{x} = f(x) + g_1(x)u_1 + g_2(x)u_2 + \Delta$$
$$y = [y_1, y_2]^T = [x_1, x_4]^T \quad (27)$$

where, $x = [x_1, x_2, x_3, x_4, x_5]^T = [h, h, \omega, \theta, \theta]^T$. h is height. ω is the rotate speed of rotor blade, θ is the collective pitch pitching angle of rotor blade. u_1 is the throttle control input. u_2 is the collective pitch control input. $g_1(x) = [0, 0, 1, 0, 0]^T$ and $g_2(x) = [0, 0, 1, 0, 0]^T$. Δ is the modeling uncertainty:

$$f(x) = [f_1, f_2, f_3, f_4, f_5]^T = \begin{bmatrix} x_2 \\ a_0 + a_1 x_2 + a_0 x_2^2 + (a_3 + a_4 x_4 - \sqrt{a_5 + a_4 x_4})x_3^2 \\ a_7 + a_8 x_3 + [a_9 \sin x_4 + a_{10}]x_3^2 \\ x_5 \\ a_{11} + a_{12} x_4 + a_{15} x_3^2 + \sin x_4 + a_{14} x_5 \end{bmatrix} \quad (28)$$

Formula (28) is written as the following form:

$$\begin{cases} x_1 = x_2 \\ x_2 = f_2 = a_0 + a_1 a_2 + a_2 x_2^2 + \left(a_3 + a_4 x_4 - \sqrt{a_5 + a_4 x_4}\right)x_3^2 \\ x_3 = f_3 + u_1 = a_7 + a_8 x_3 + [a_9 \sin x_4 + a_{10}]x_3^2 + u_1 \\ x_4 = x_5 \\ x_5 = f_5 + u_2 = a_{11} + a_{12} x_4 + a_{15} x_3^2 \sin a_4 + a_{14} x_5 + u_2 \end{cases} \quad (29)$$

It can be seen from the relief food helicopter vertical dynamical model (29) that throttle control u_1 acts on ω directly and collective pitch control input u_2 acts on $\ddot{\theta}$ directly. Shown in Fig. 2. The outputs of the controlled objects of relief food helicopters are height h and collective pitch pitching angle θ. u_1 has control relations with the rotary speed of propeller blade and collective pitch pitching angles. u_2 also has control relations with collective pitch pitching angles and rotary speed of propeller blade. Height h is associated with the rotary speed of propeller blade and collective pitch pitching angles as well. Therefore, there are strong coupling characteristics in relief food helicopter vertical dynamics.

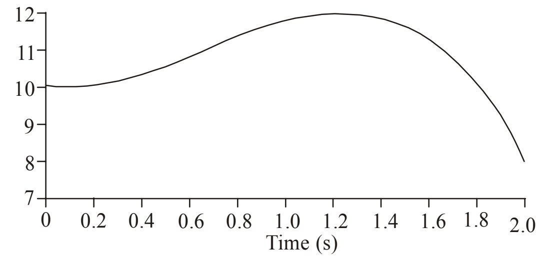
One of the two designed tracking differentiators is third-order and another is second-order. The model parameters in simulations are as follows:

$a_0 = -17.67$, $a_0 = -17.67$, $a_3 = 5.31 \times 10^{-4}$,
$a_5 = -2.82 \times 10^{-7}$, $a_3 = 5.31 \times 10^{-4}$, $a_6 = 1.632 \times 10^{-5}$,
$a_7 = -13.92$, $a_8 = -0.7$, $a_9 = a_{10} = -0.0028$,
$a_{11} = -434.88$, $a_{12} = -800$, $a_{13} = -0.1$, $a_{14} = -65$.

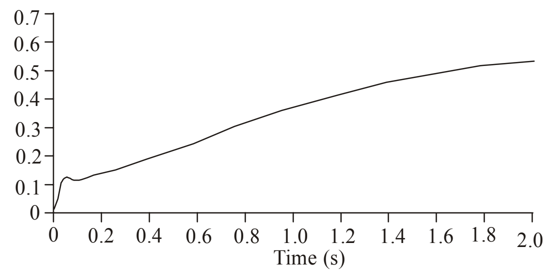
(coupled analysis: control coupling) In the case (M = 2), take the throttle input value of 0 and take the collective pitch control input value of 15. The relief food helicopter height and the time domain response curve of pitch angles are shown in Fig. 3. It can be seen from the open-loop characteristics in Fig. 4a and 4b that whatever the simple collective pitch control input or the simple throttle control input, the height and the pitch angle all have definite influence. Hence, the control coupling of the relief food helicopter model is equally serious.

CONCLUSION

Aiming at the small UAV course system with disturbances, the study has considered its flight control problem and designed the indirect fuzzy self-adaptive supervision course controller. First, take the model transformation for

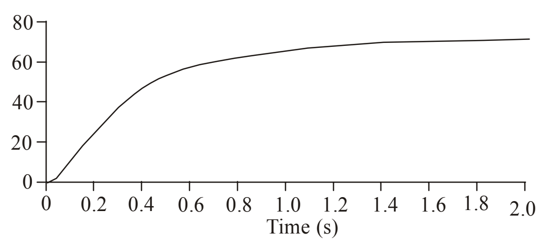


(a)

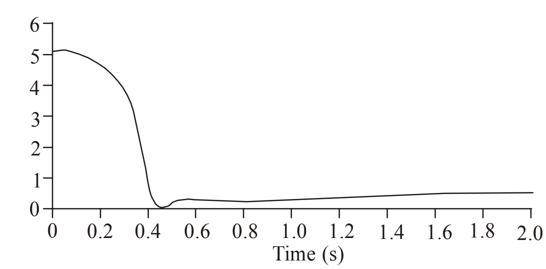


(b)

Fig. 2: Dynamic coupling analysis (M = 1); (a): Height of the relief food helicopter; (b): Pitching angle



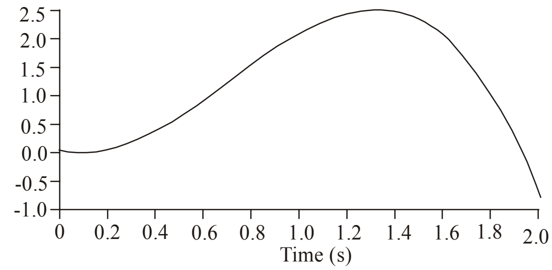
(a)



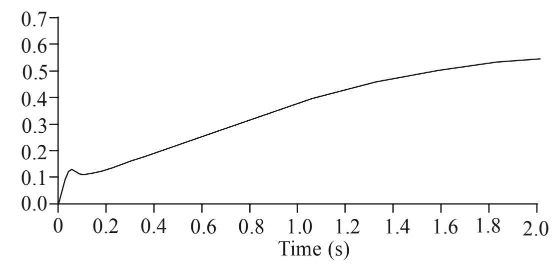
(b)

Fig. 3: Dynamic coupling analysis (M = 2); (a): Height of the relief food helicopter; (b): Pitching angle

the relief food helicopter course system, i.e., the system is transformed into a second-order nonlinear time-varying system. Next, design an indirect fuzzy self-adaptive course controller for the system. Since the designed fuzzy self-adaptive course controller depends on the selection of the fuzzy rule base, in order to reduce this dependence, continue to design a supervision controller in the second layer, so that the stability of the closed-loop system is guaranteed. The combination of the two methods can make the



(a)



(b)

Fig. 4: Control coupling analysis (M = 2); (a): Height of the relief food helicopter; (b): Pitching angle

controller design possess great freedom and flexibility, which can greatly reduce the dependency of control on whether the selection of the rule base is correct or not. Finally, all designed methods are applied to the control of the relief food helicopter course system to realize the tracking control of the relief food helicopter course channel and achieve good control performance and effect.

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