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Research Article

A Backstepping Controller with the RBF Neural Network for Folding-Boom Aerial Work Platform

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Aerial work platform is a kind of engineering vehicle which is used for hoisting personnel to the appointed place for maintenance or installation. Based on the dynamics model considering the flexible deformation existing in the arm system of folding-boom aerial platform vehicle, this study presents a NN-based backstepping controller used for trajectory tracking control of work platform. The proposed controller can reduce tracking error of work platform and suppress the vibration simultaneously by using the RBF neural network system to compensate model uncertainties and disturbances. Furthermore, we prove that the whole system is stable and convergent by Lyapunov stability theorem. In addition, we give the simulation results which show that the good control performance of the designed controller for trajectory tracking and vibration inhabiting of work platform in the case of model uncertainties.

1. Introduction

Folding-boom aerial work platform is a kind of engineering apparatus which can hoist personnel to the designated position in the air along with their tools for installation and maintenance, as shown in Figure 1.

With the gradual optimization of arm structure of aerial platform, the composite materials with lighter weight and stronger toughness have been gradually used in the arm system. As the usage of light-long beam in the arm system of aerial platform, the flexible deformation existed in the beam cannot be neglected. However, the elastic deformation will cause vibration and positioning deviation of the work platform. Therefore, the accurate positioning and steady movement of work platform must be obtained to ensure the safety of working personnel.

To realize the tracking control of work platform, a self-tuning fuzzy PID controller is designed in Miao et al. [1], and the adaptive neural network control scheme is proposed in Jia et al. [2]. However, the elastic deformation of beam is ignored in these models established. Considering the elastic deformation, the dynamics model of the arm system is created for folding-boom aerial platform vehicle with flexible beam powered by the hydraulic cylinder based on flexible multibody dynamics theory and Lagrange's equation in Hu et al. [3]. The vibration is found in the established equations. In addition, a similar model is created, and a fuzzy PID controller is designed for work platform's tracking control in Meng [4]. Although simulation results reflect the effectiveness of the control method, the stability of the system has not been proved.

In Hu et al. [5], a backstepping controller is designed for aerial platform vehicle based on the flexible dynamics model with strong nonlinear and coupling. The backstepping method, as one of the controller design methods of nonlinear systems, has received great successes [6–10]. It is a systematic and step-by-step recursive design method [11], the basic idea of which is to decompose the overall system into lower dimension subsystems; then, the pseudocontrol inputs are designed for each subsystem by choosing proper functions recursively. When the design procedure terminates, the ultimate control input can be obtained.

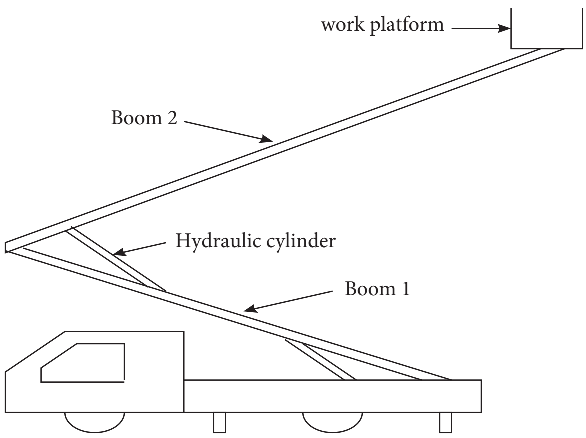


Figure 1: Scheme of folding-boom aerial platform vehicle.

Meanwhile, the stability of the system can be ensured due to the use of Lyapunov functions recursively. However, this method has a key assumption that the dynamics model is exactly known. In fact, there are unknown uncertainties that arise from model approximation and external disturbances [12, 13]. Thus, the stability and performance of the system cannot be guaranteed by using the backstepping control method alone. To solve this problem, a robust adaptive control is proposed for a class of nonlinear systems with uncertainties by combining the fuzzy logic system with a backstepping design procedure [14]. Moreover, the artificial neural network (ANN) is originated from the biological network, which is one kind of dynamic complex networks [15–17] closely related to the graph theory. Due to the universal approximation capability, the ANN is widely used as an approximator of unknown nonlinear function in the controller design [16, 18–23]. As a result, the tracking performances of the uncertain nonlinear system have been improved by using the ANN to compensate the model uncertainties.

In this study, we use the ANN to handle the unknown nonlinear function existed in the dynamics model of aerial work platform. Combining the backstepping design method with the ANN, we propose a controller applied for the trajectory tracking control of work platform. As the controller is acquired by using the Lyapunov functions recursively, the stability of the whole closed loop system can be guaranteed. Furthermore, the simulation results illustrate that the effectiveness of the presented controller for restraining the vibration and attenuating the tracking error when there exist model uncertainties. Although we had acquired the similar results in the previous article [24], we have made some improvements on the control performance in this study.

This study is organized as follows. Flexible multibody dynamics equations of the arm system of folding-boom aerial work platform are given in Section 2. In Section 3, a neural network-based backstepping controller is designed to realize the control objective. The simulation results for trajectory tracking control of work platform are presented in Section 4. Finally, the concluding remarks are provided in Section 5.

Notation $(\cdot)^T$ denotes the transposition of a matrix or a vector, $\mathrm{diag}(\cdot)$ denotes the diagonal matrix, $(\cdot)^{-1}$ denotes the inverse of a matrix, $\|\cdot\|_F$ denotes the Frobenius norm, and $\|\cdot\|$ denotes the 2-norm.

2. Problem Formulation and Preliminaries

In [1], we create the flexible multibody dynamics model of the arm system as follows:

$$\begin{cases} M\ddot{\theta} + U\dot{\theta}^2 + V\ddot{q} + N = Q_\theta, \\ H\ddot{q} + Cq + V^T\ddot{\theta} + K^T\dot{\theta}^2 = Q_q, \end{cases} \tag{1}$$

in which $Q_\theta = [Q_1, Q_2]^T$, $Q_q = [Q_3, Q_4, Q_5, Q_6]^T$, $\ddot{\theta} = [\ddot{\theta}_1, \ddot{\theta}_2]^T$, and $\dot{\theta}^2 = [\dot{\theta}_1^2, \dot{\theta}_2^2]^T$.

$q = [\delta_{11}, \delta_{12}, \delta_{21}, \delta_{22}]^T$, $\ddot{q} = [\ddot{\delta}_{11}, \ddot{\delta}_{12}, \ddot{\delta}_{21}, \ddot{\delta}_{22}]^T$, and M, H, V are the mass matrix which are given by

$$\begin{aligned} M &= \begin{bmatrix} \left(\dfrac{m_1}{3} + m_2 + m\right)d_1^2 & \left(\dfrac{m_2}{2} + m\right)d_1 d_2 \cos(\theta_1 - \theta_2) \\ \left(\dfrac{m_2}{2} + m\right)d_1 d_2 \cos(\theta_1 - \theta_2) & \left(\dfrac{m_2}{3} + m\right)d_2^2 \end{bmatrix}, \\ H &= \mathrm{diag}\left[\dfrac{\mathrm{m}_1}{2}\ \dfrac{\mathrm{m}_1}{2}\ \ \dfrac{\mathrm{m}_2}{2}\ \dfrac{\mathrm{m}_2}{2}\right], \\ V &= \begin{bmatrix} \dfrac{m_1 d_1}{\pi} & \dfrac{m_1 d_1}{2\pi} & \dfrac{2m_2 d_1 \cos(\theta_1 - \theta_2)}{\pi} & 0 \\ 0 & 0 & \dfrac{m_2 d_2}{\pi} & \dfrac{m_2 d_2}{2\pi} \end{bmatrix}, \end{aligned} \tag{2}$$

where m_1, m_2, and m represent masses of beams 1, 2, and load, respectively; θ_1 and θ_2 are the included angles of beams 1 and 2 with horizontal direction; d_1, d_2 are the lengths of beams 1 and 2; the generalized coordinates q reflect the deformation of the beams.

In addition, the coefficient matrices U, K, and C are given by

$$U = \begin{bmatrix} 0 & \left(\frac{m_2}{2}+m\right)d_1 d_2 \sin(\theta_1-\theta_2) \\ -\left(\frac{m_2}{2}+m\right)d_1 d_2 \sin(\theta_1-\theta_2) & 0 \end{bmatrix},$$
$$K = \begin{bmatrix} 0 & 0 & \frac{-2m_2 d_1 \sin(\theta_1-\theta_2)}{\pi} & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}, \quad (3)$$
$$C = \operatorname{diag}\left[\frac{EI_1\pi^4}{2d_1^3} \; \frac{8EI_1\pi^4}{d_1^3} \; \frac{EI_2\pi^4}{2d_2^3} \; \frac{8EI_2\pi^4}{d_2^3}\right],$$

in which I_1 and I_2 are the moment of inertia about cross-section of beams 1 and 2; E denotes the elastic modulus of beam material.

The column vector N can be expressed as

$$N = \left[\frac{2}{\pi m_2 d_1 \sin(\theta_1-\theta_2)(\dot\theta_1+\dot\theta_2)\dot\delta_{21}} + \left(\frac{m_1}{2}+m_2+m\right)g d_1 \cos\theta_1, \; \left(\frac{m_2}{2}+m\right)g d_2 \cos\theta_2\right]^T. \quad (4)$$

Assume that $x_1 = [\theta_1, \theta_2, \delta_{11}, \delta_{12}, \delta_{21}, \delta_{22}]^T$ and $x_2 = [\dot\theta_1, \dot\theta_2, \dot\delta_{11}, \dot\delta_{12}, \dot\delta_{21}, \dot\delta_{22}]^T$; then, we can express the state equations of (1) as

$$\begin{cases} \dot x_1 = x_2, \\ \dot x_2 = \overline{H}^{-1}\left(Q - \overline{K}x_2^2 - \overline{C}x_1 - \overline{N}\right), \end{cases} \quad (5)$$

where $\overline{H} = \begin{bmatrix} M & H \\ V^T & V \end{bmatrix}$, $\overline{K} = \begin{bmatrix} U & 0 \\ K^T & 0 \end{bmatrix}$, $\overline{C} = \begin{bmatrix} 0 & 0 \\ 0 & C \end{bmatrix}$, $\overline{N} = [N^T, 0]^T$, $x_2^2 = [\dot\theta_1^2, \dot\theta_2^2, \dot\delta_{11}^2, \dot\delta_{12}^2, \dot\delta_{21}^2, \dot\delta_{22}^2,]^T$.

3. Backstepping Control Design

3.1. Design of Backstepping Controller. We choose x_d as the reference trajectory, and it can be expressed as

$$x_d = [r_1(t), r_2(t), r_3(t), r_4(t), r_5(t), r_6(t)]^T. \quad (6)$$

Then, $\dot x_d = [\dot r_1(t), \dot r_2(t), \dot r_3(t), \dot r_4(t), \dot r_5(t), \dot r_6(t)]^T$,

$$\ddot x_d = [\ddot r_1(t), \ddot r_2(t), \ddot r_3(t), \ddot r_4(t), \ddot r_5(t), \ddot r_6(t)]^T. \quad (7)$$

Define the position tracking error as

$$e_1 = x_1 - x_d. \quad (8)$$

Then, we choose the virtual control as

$$\alpha_1 = -c_1 e_1, \quad (9)$$

in which $c_1 > 0$.

Furthermore, define

$$e_2 = x_2 - \alpha_1 - \dot x_d. \quad (10)$$

Then, we design the control law Q as follows:

$$Q = \overline{H}[-e_1 - c_2 e_2 - c_1(x_2 - \dot x_d) + \ddot x_d] + \overline{K}x_2^2 + \overline{C}x_1 + \overline{N}, \quad (11)$$

where $c_2 > 0$.

In addition, we define nonlinear function as

$$g(x) = -\overline{H}^{-1}\left(\overline{K}x_2^2 + \overline{C}x_1 + \overline{N}\right), \quad (12)$$

where $g(x)$ is a 6×1 vector and can be expressed as $g(x) = [g_1(x), g_2(x), \ldots, g_6(x)]^T$. Then, the state equation (5) can be rewritten as follows:

$$\begin{cases} \dot x_1 = x_2, \\ \dot x_2 = \overline{H}^{-1}Q + g(x). \end{cases} \quad (13)$$

As a result, the control law Q can be expressed as

$$Q = \overline{H}[-e_1 - c_2 e_2 - c_1(x_2 - \dot x_d) + \ddot x_d - g(x)]. \quad (14)$$

From study [4], it is concluded that for the dynamics model (2), the control law is designed as (6); then, the trajectory tracking error of work platform will converge to zero by choosing suitable design constants c_1 and c_2.

3.2. Design of Backstepping Controller with RBF. In order to realize the control law (14), we should achieve the accurate values of modeling information $g(x)$. However, it is very difficult to get the accurate dynamics model in practical engineering. To resolve this problem, we can use the RBF neural network to approximate $g(x)$. The block diagram of the closed loop NN-based adaptive backstepping control scheme of the arm system of folding-boom aerial platform vehicle is shown in Figure 2.

In this study, we choose the RBF neural network with three layers, and the structure of it is shown in Figure 3.

In the RBF neural network, $x = [x_1^T, x_2^T]^T$ is the input vector. Assume there are m^{th} neural nets, and radial basis function vector in the hidden layer of RBF is $\zeta = [\zeta_j]^T = [\zeta_1, \zeta_2, \ldots, \zeta_m]^T$, ζ_j is Gaussian function value for neural net j in the hidden layer, $j = 1, 2, \ldots, m$, and $\zeta_j = \exp(-(x - b_j{}^2/2\sigma_j^2))$, where $b_j = [b_{ji}]^T = [b_{j1}, b_{j2}, \ldots, b_{jl}]^T$ represents the value of center vector of Gaussian function of neural net j for the i^{th} input, $i = 1, 2, \ldots, l$, $l = 12$. The width vector of Gaussian function is $\sigma = [\sigma_j]^T = [\sigma_1, \sigma_2, \ldots, \sigma_m]^T$, where $\sigma_j > 0$ represents the width value of Gaussian function of neural net j. Therefore, the unknown function $g(x)$ can be expressed as follows:

$$g(x) = W^{*T}\zeta + \varepsilon_1, \tag{15}$$

where W^* is the optimization weight values matrix of the neural network and ε_1 is called the smallest approximation error.

In addition, assume that the weight values estimation matrix of W^* is

$$\widehat{W} = \left[\widehat{w}_{ij}\right]^T = \begin{bmatrix} \widehat{w}_{11} & \widehat{w}_{21} & \cdots & \widehat{w}_{m1} \\ \widehat{w}_{12} & \widehat{w}_{22} & \cdots & \widehat{w}_{m2} \\ \vdots & \vdots & \vdots & \vdots \\ \widehat{w}_{1n} & \widehat{w}_{2n} & \cdots & \widehat{w}_{mn} \end{bmatrix}^T. \tag{16}$$

Then, $g(x)$ can be approximated by the RBF neural network as

$$\widehat{g}(x) = \widehat{W}^T\zeta. \tag{17}$$

Therefore, considering (14), the control law can be chosen as

$$Q = \overline{H}[-e_1 - c_2e_2 - c_1(x_2 - \dot{x}_d) + \ddot{x}_d - \widehat{g}(x)]. \tag{18}$$

Theorem 1. *For the dynamics model (equation (2)) with tracking errors (equations (3)–(5)), the backstepping controller is designed as equation (11) and the approximation of equation (9) is obtained by equation (10); then, the desired trajectory can be converged by the actual trajectory.*

Proof. Define $\widehat{S} = \text{diag}[0, \widehat{W}]$, $S = \text{diag}[0, W^*]$ with $S_F \le S_M$, where $\|\cdot\|_F$ represents the Frobenius norm. Let $\widetilde{S} = S - \widehat{S}$ and $\eta = [e_1^T, e_2^T]^T$; then, Lyapunov candidate function can be designed as follows:

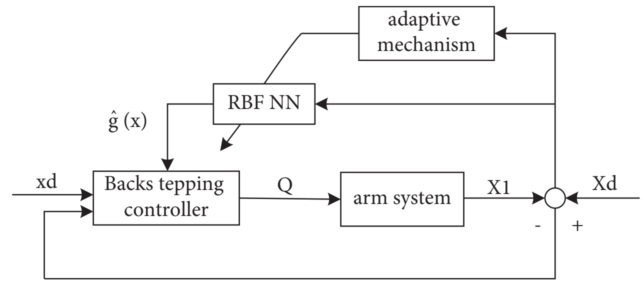


Figure 2: NN-based adaptive backstepping control scheme of the arm system.

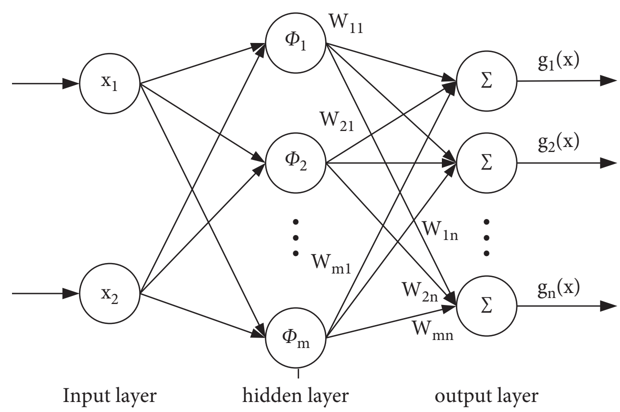


Figure 3: The structure of the RBF neural network.

$$L = \frac{1}{2}\eta^T\eta + \frac{1}{2}tr\left(\widetilde{S}^T\overline{\Sigma}^{-1}\widetilde{S}\right), \tag{19}$$

where $\overline{\Sigma}$ is given by $\overline{\Sigma} = \text{diag}[0, \Sigma]$, in which Σ is a 6×6 positive-definite matrix.

Let adaptive law of neural network weights as

$$\dot{\widehat{S}} = \overline{\Sigma}\overline{\zeta}\eta^T - \gamma\overline{\Sigma}\eta\widehat{S}, \tag{20}$$

where $\overline{\zeta} = [0, \zeta^T]^T$ and γ is a positive real number, and $\|\cdot\|$ denotes the 2-norm.

The derivative of (19) is

$$\dot{L} = \eta^T\dot{\eta} + tr\left(\widetilde{S}^T\overline{\Sigma}^{-1}\dot{\widetilde{S}}\right). \tag{21}$$

Substituting (15), (10), and (18) into (21), we have

$$\dot{L} = -c_1e_1^Te_1 - c_2e_2^Te_2 + e_2^T\left[\left(W^{*T} - \widehat{W}^T\right)\zeta + \varepsilon_1\right] + tr\left(\widetilde{S}^T\overline{\Sigma}^{-1}\dot{\widetilde{S}}\right). \tag{22}$$

Let $\widetilde{W}^T = W^{*T} - \widehat{W}^T$; then, $\dot{L} = -c_1e_1^Te_1 - c_2e_2^Te_2 + e_2^T[\widetilde{W}^T\zeta + \varepsilon_1] + tr(\widetilde{S}^T\overline{\Sigma}^{-1}\dot{\widetilde{S}})$.

Define $\Lambda = \begin{bmatrix} c_1I & 0 \\ 0 & c_2I \end{bmatrix}$, $\varepsilon = [0, \varepsilon_1^T]^T$, and assume that $\varepsilon < \varepsilon_N$; then, derivative of Lyapunov function becomes

Table 1: Design parameters and initial values.

Component	Length (m)	Mass (kg)	EI ($N\cdot m^2$)	Initial angular (rad)	Initial angular velocity (rad/s)
Beam 1	7.5	650	6×10^8	$2\pi/3$	0
Beam 2	8.5	550	5×10^8	0	1
Load	—	—	—	—	—

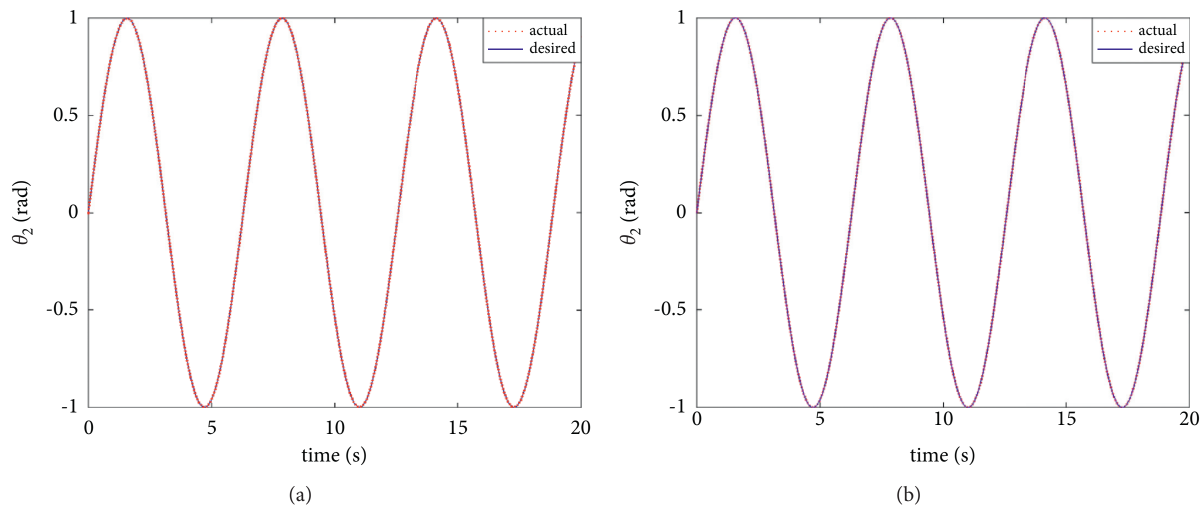


Figure 4: The tracking of θ_2 under the action of (a) backstepping control and (b) NN-based backstepping control.

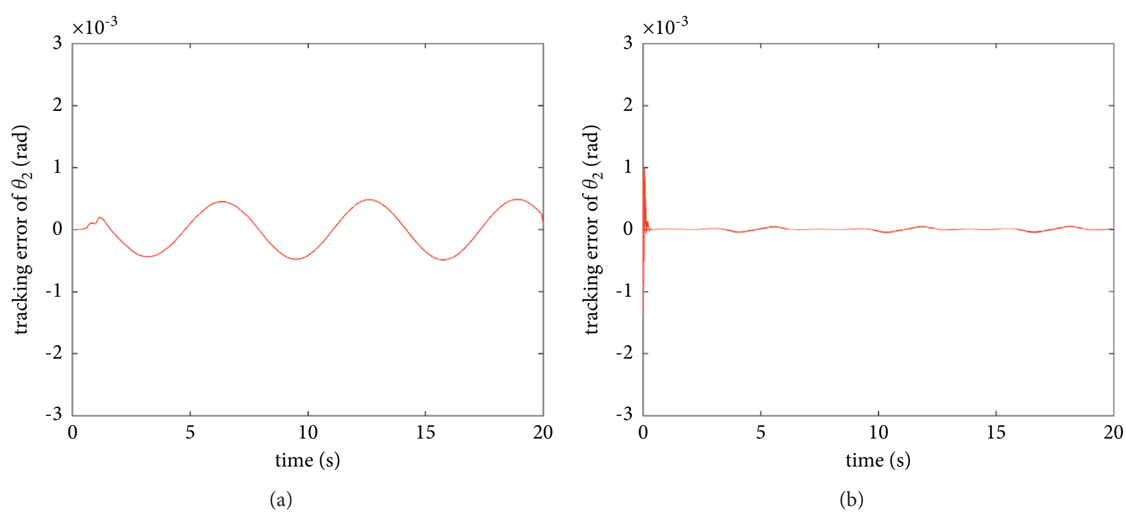


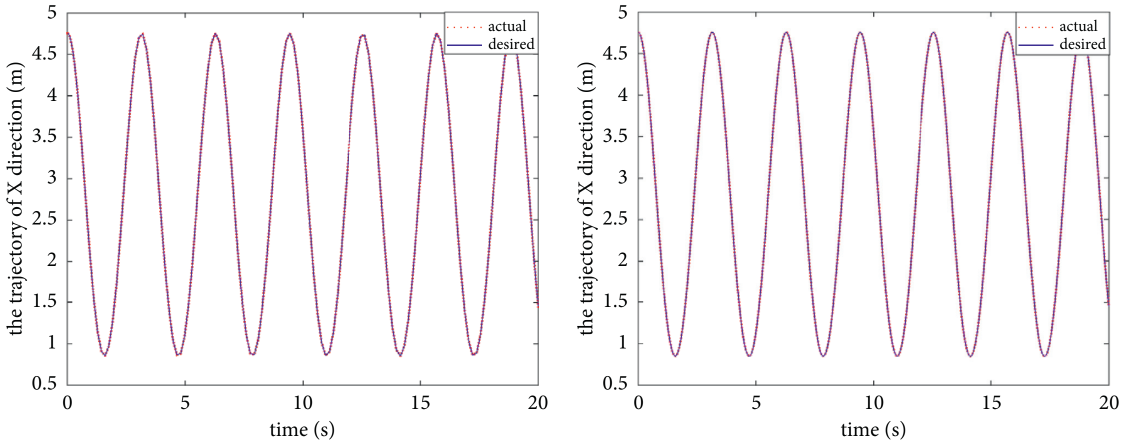
Figure 5: The tracking error of θ_2 under the action of (a) backstepping control and (b) NN-based backstepping control.

$\dot{L} = -\eta^T \Lambda \eta + \eta^T \varepsilon + tr(\tilde{S}^T \overline{\Sigma}^{-1} \dot{\tilde{S}} + \tilde{S}^T \overline{\zeta} \eta^T)$. As $\dot{\tilde{S}} = -\dot{\hat{S}}$, considering (20), we can get

$$\dot{L} = -\eta^T \Lambda \eta + \eta^T \varepsilon + \gamma \eta tr\left(\tilde{S}^T (S - \tilde{S})\right). \tag{23}$$

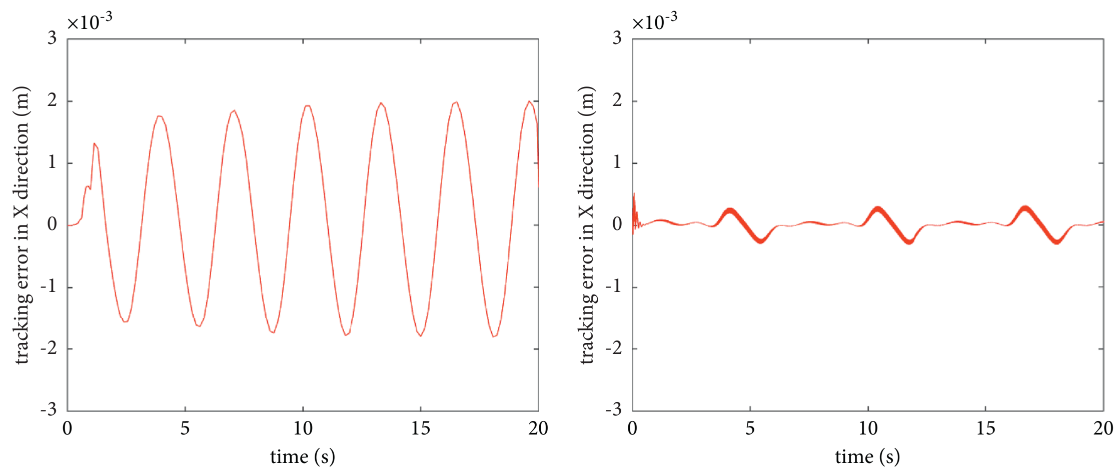
Since $\eta^T \Lambda \eta \geq c_{\min} \eta^2$, where $c_{\min} > 0$ is the minimum eigenvalue of Λ, and according to Schwarz inequality $tr(\tilde{S}^T (S - \tilde{S})) \leq \tilde{S}_F S_F - \tilde{S}_F^2$, we get

$$\dot{L} \leq -c_{\min} \eta^2 + \varepsilon_N \eta + \gamma \eta \left(\tilde{S}_F S_F - \tilde{S}_F^2\right) \leq -\eta \left[c_{\min} \eta - \varepsilon_N + \gamma \left(\tilde{S}_F^2 - \tilde{S}_F S_M\right)\right]. \tag{24}$$



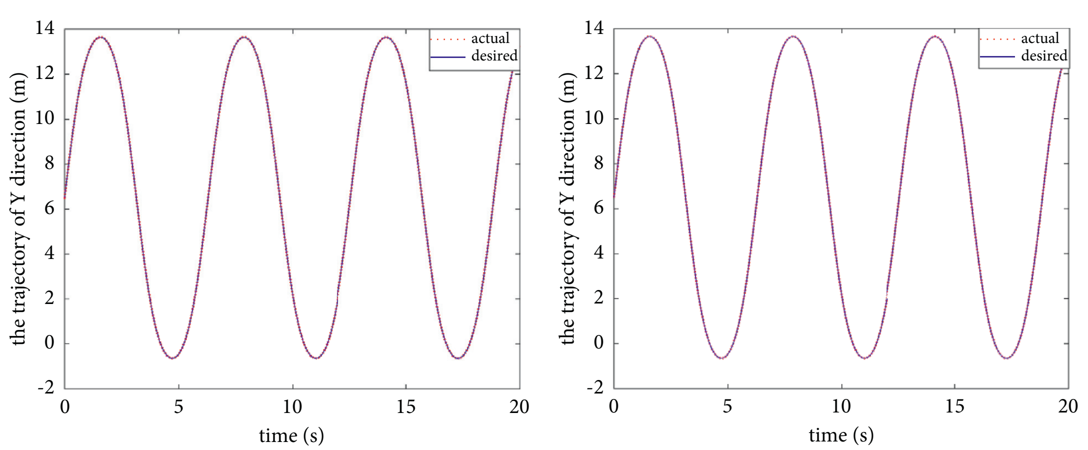
(a) (b)

Figure 6: The trajectory tracking of work platform in the horizontal x direction under the action of (a) backstepping control and (b) NN-based backstepping control.



(a) (b)

Figure 7: The trajectory tracking error of work platform in x direction under the action of (a) backstepping control and (b) NN-based backstepping control.



(a) (b)

Figure 8: The trajectory tracking of work platform in the vertical y direction under the action of (a) backstepping control and (b) NN-based backstepping control.

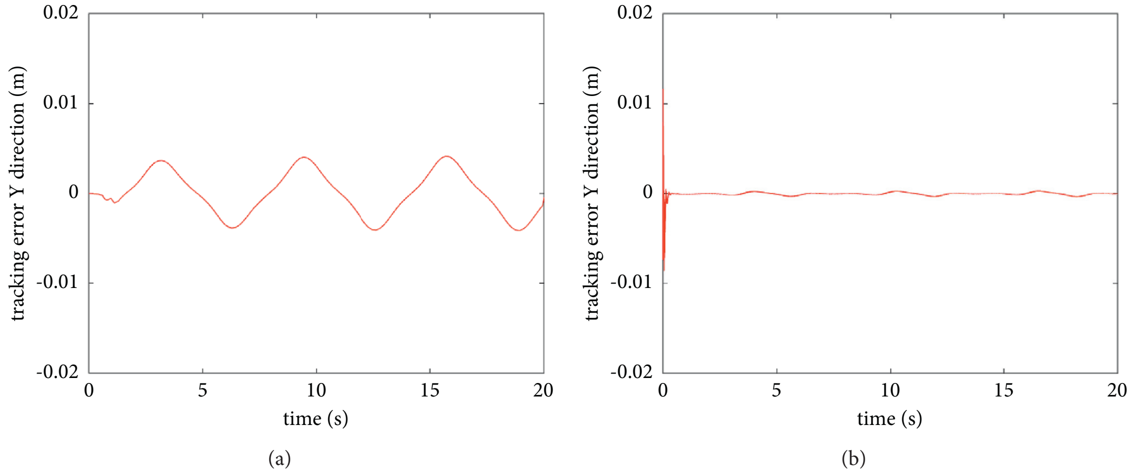


Figure 9: The trajectory tracking error of work platform in y direction under the action of (a) backstepping control and (b) NN-based backstepping control.

To realize $\dot{L}<0$, the inequality $c_{\min}\eta-\varepsilon_N+\gamma\ (\tilde{S}_F^2-\tilde{S}_F S_M)>0$ should be guaranteed. Therefore, we can derive

$$\left(\frac{\left(\varepsilon_N+(\gamma/4)S_M^2\right)}{c_{\min}}\right)<\eta, \tag{25}$$

which means that $\dot{L}<0$ can be obtained by selecting suitable values of γ and $c_{\min}$. As a result, the tracking error e_1 and e_2 will be converged to zero exponentially asymptotically by using the derived control law (18) according to Lyapunov's stability theorem. In other words, the tracking trajectory of work platform will follow the designed trajectory smoothly.

The proof is finished.

4. Simulation Results

In this section, the simulation experiments are carried out to illustrate the effectiveness of the presented NN-based backstepping control scheme. To obtain the trajectory tracking control of work platform, we apply the following proposed NN-based backstepping controller and the simulation parameters.

The design parameters and initial values used for the simulation are given in Table 1.

The desired trajectory is chosen as $x_d=[2\pi/3, \sin(t), 0, 0, 0, 0]^T$; then, $\dot{x}_d=[0, \cos(t), 0, 0, 0, 0]^T$, and $\ddot{x}_d=[0, -\sin(t), 0, 0, 0, 0]^T$.

In the simulation, we adopt the control law (18) with adaptive law (20), and select $c_1=c_2=20$. In (10), to obtain the approximation of $g(x)$, we choose the structure of RBF NN as 12-10-6. The Gaussian base functions are selected as $\phi_j=\exp(-x^2/2\times 50^2)$, $j=1,2,\ldots,10$, in which $x=[x_1^T, x_2^T]^T$ is the input vector of the neural network, the center b_{ji} is set as 0, and the width σ_j as 50. In adaptive law (20), the parameters can be chosen as $\gamma=0.005$ and $\Sigma=250\mathrm{diag}[1,1,1,1,1,1]$. In addition, the initial weight values are set to zero.

The simulations are realized in MATLAB/SIMULINK environment, where the solver is ode45.

Figures 4(b)–9(b) present the simulation results under the control law (18) used for work platform's tracking control when reference trajectory depicts a sine function. To make some necessary comparisons, Figures 4(a)–9(a) represent the simulation results of the backstepping controller described in Section 3 when the exact model is available. Furthermore, for comparative purpose, the parameter values of c_1 and c_2 in the backstepping controller are set to the same as those in the NN-based backstepping controller proposed in this study.

From Figures 5, 7, and 9, we can see that the NN-based backstepping controller drives tracking error to a smaller value than the backstepping scheme even if large modeling uncertainty exists, that is to say, the NN-based backstepping controller developed in this study has strong adaptability and obtains better control performance through the neural network learning phase for tracking control of the work platform of folding-boom aerial platform. As shown in Figure 10, the deformation variable δ_{21} converges to a small value after a short fluctuation, which means that the vibration in flexible beam is effectively suppressed simultaneously. As a result, the control objective is achieved by the regulation of control input, as shown in Figure 11. Figure 12 shows the process of approaching system uncertainties $g_2(x)$ by using the output of the neural network. However, the output of the neural network will not converge to the truth value of $g_2(x)$ because the fact that the tracking error performance could be attained by some possible values of $g_2(x)$.

4.1. Remark. It is easily seen from (11) and (13) that a better tracking performance will be attained with the increase of the control gain c_1, c_2, and adaptation gain matrix Σ. However, increasing c_1, c_2 will result in a high gain control. In (13), γ is a small positive constant. And to meet the derived inequality (16), γ should be chosen as small as possible. However, a very small γ may not be sufficient to prevent the weight estimates of the neural network from

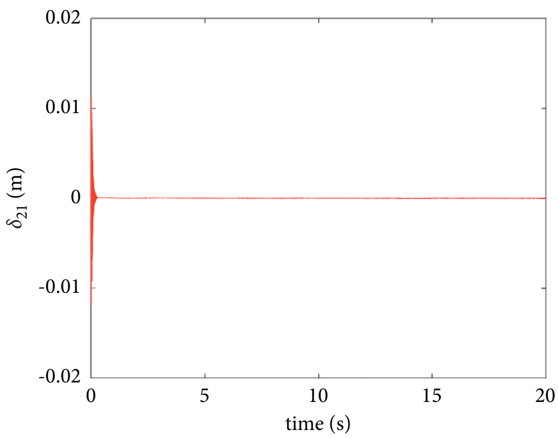


Figure 10: The deformation variable δ_{21} changing with time.

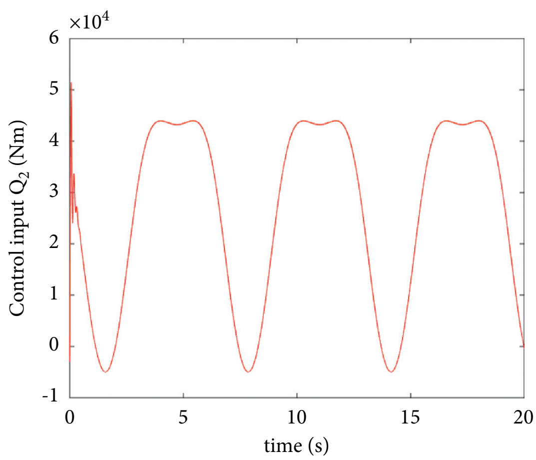


Figure 11: The regulation of generalized force Q_2.

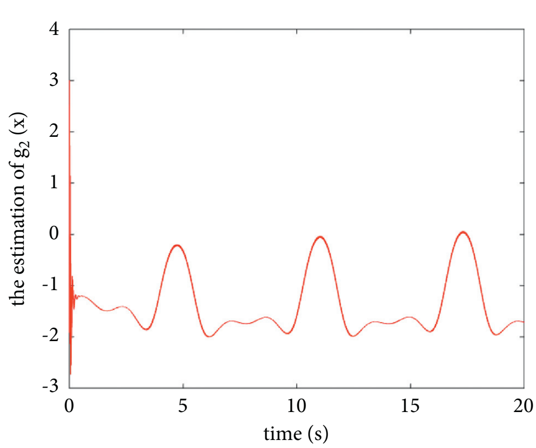


Figure 12: The approximate process of $g_2(x)$.

reaching very large values which might lead to a high gain control. Therefore, in practical applications, we should adjust the design parameters carefully to acquire a good control performance.

5. Conclusions

In this research, we propose a kind of the NN-based backstepping controller based on a new flexible dynamic model created for aerial platform vehicle with flexible beam driven by hydraulic cylinder. Due to the fact that it is difficult to obtain the accurate model of the aerial platform vehicle's arm system in practical engineering, robust control scheme should be used to attain control objectives considering system uncertainties. As any nonlinear function can be approximated with arbitrary accuracy by the neural network, we present a controller by combining backstepping control with the neural network for the tracking control of work platform when there exist model uncertainties in this study. In the process of designing the NN-based backstepping controller, model uncertainties are compensated by neural network output. The controller is proved effective for vibration suppressing and trajectory tracking from the theory and simulation experiment. As the neural network's weight update law is obtained by the Lyapunov method, the convergence and stability can be ensured in the whole system. Furthermore, the simulation is carried out, and the results show that the proposed controller is effective for inhibiting vibration and reducing trajectory tracking error in the presence of model uncertainties. As a result, the work platform can follow the desired trajectory steadily. However, there exist some difficulties in constructing experimental platform to show the effectiveness of the proposed controller at present. We will improve these limitations in the future work.

Data Availability

The data used to support the findings of this study are available from the corresponding author by request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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