

Design of Neural Network-based Backstepping Controller for the Folding-Boom Aerial Platform Vehicle

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Abstract—In this paper, the robust trajectory tracking problem is addressed for the work platform of folding-boom aerial platform vehicle in the presence of uncertainties and disturbances. The control objective is to make the work platform move along a desired reference trajectory and make the vibration inhibit at the same time. Since neural network system can approximate any nonlinear function with arbitrary accuracy over a compact set in the light of the universal approximation theorem, a neural network-based backstepping controller, which composed of backstepping control and neural network, is proposed for the trajectory tracking control of the work platform in the case of modeling uncertainties and disturbances. According to Lyapunov stability theorem, the stability and convergence of the overall system can be guaranteed by the derived control law. In addition, simulation results demonstrate that the proposed controller is effective for suppressing the vibration and reducing trajectory tracking error of the work platform.

Keywords—aerial platform vehicle; model uncertainties; trajectory tracking control; backstepping controller; neural network

I. INTRODUCTION

Folding-boom aerial platform vehicle is a kind of device which can lift people to the height for installation or maintenance [1], the scheme of which is shown in Figure.1.

As it requires very high safety, both the stability of movement and the accuracy of positioning of work platform should be guaranteed.

Since the light-long beam is widely used in the arm system, the influence of elastic deformations of beam should be considered. Therefore, in the literature [1], the beams are seen as flexible and the dynamics equations of the arm system of folding-boom aerial platform vehicle are set up based on flexible multi-body dynamics theory and Lagrange's equation. The establishment of the model

lays foundation of the research of steady movement and accurate positioning of work platform.

Due to the robust performance, integrator backstepping control has been applied to many nonlinear systems successfully, such as single link flexible manipulator [2] and multiple link rigid manipulator [3], etc. In addition, in [4], the backstepping control scheme has been used for the control of work platform of folding-boom aerial platform vehicle effectively. However, this method can only be used for the accurate dynamic model of the arm system of folding boom aerial platform vehicle.

In fact, there exist various uncertainties due to external disturbances and approximation of the modeling [5, 6]. As a result, a robust adaptive control scheme is developed for a class of uncertain nonlinear systems by the combination of backstepping control method and fuzzy control method in [7]. Moreover, as neural network can be used to approximate any nonlinear function over a compact set with arbitrary accuracy [8], it has attracted a wide spread attention. In [9, 10], the combination of backstepping design and neural network has been used in the control of uncertain nonlinear systems.

In this paper, a neural network-based backstepping controller, which combines backstepping control with neural network, is proposed for the trajectory tracking control of work platform with modeling uncertainties. As the control law is derived from the Lyapunov stability conditions, the stability and convergence of the overall system can be ensured. Furthermore, simulation results demonstrate the effectiveness of the proposed controller for suppressing the vibration and reducing the tracking error of work platform in the presence of model uncertainties.

The organization of this paper is as follows. Flexible multi-body dynamic model of arm system of folding-boom aerial platform vehicle is presented in Section II. Section III proposes a neural network-based backstepping controller, which is used for trajectory tracking control of work platform. Finally, simulation

results are illustrated in Section IV, and some conclusions are drawn in Section V.

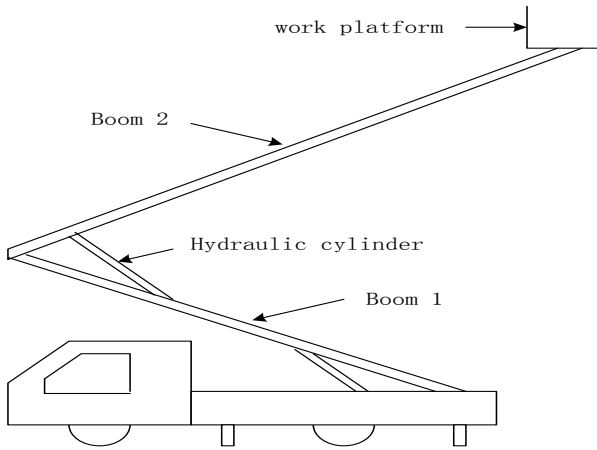


Figure 1. Scheme of folding-boom aerial platform vehicle

II. FLEXIBLE MULTI-BODY DYNAMICS MODEL OF ARM SYSTEM

The flexible multi-body dynamics model of arm system is represented by [1]

$$\begin{cases} G\ddot{\theta} + U\dot{\theta}^2 + H\dot{q} + R = Q_\theta \\ M\ddot{q} + Nq + H^T\ddot{\theta} + V^T\dot{\theta}^2 = Q_q \end{cases} \quad (1)$$

where, $Q_\theta = [Q_1 \ Q_2]^T$, $Q_q = [Q_3 \ Q_4 \ Q_5 \ Q_6]^T$,
 $\ddot{\theta} = [\ddot{\theta}_1 \ \ddot{\theta}_2]^T$, $\dot{\theta}^2 = [\dot{\theta}_1^2 \ \dot{\theta}_2^2]^T$,
 $q = [q_{11} \ q_{12} \ q_{21} \ q_{22}]^T$,

$\ddot{q} = [\ddot{q}_{11} \ \ddot{q}_{12} \ \ddot{q}_{21} \ \ddot{q}_{22}]^T$, G , M , H are the mass matrix and can be described as follows:

$$G = \begin{bmatrix} (m_1/3 + m_2 + m)l_1^2 & (m_2/2 + m)l_1l_2 \cos(\theta_1 - \theta_2) \\ (m_2/2 + m)l_1l_2 \cos(\theta_1 - \theta_2) & (m_2/3 + m)l_2^2 \end{bmatrix}$$

$$M = \text{diag}[m_1/2 \ m_1/2 \ m_2/2 \ m_2/2]$$

$$H = \begin{bmatrix} m_1l_1/\pi & -m_1l_1/2\pi & 2m_2l_1/\pi \cos(\theta_1 - \theta_2) & 0 \\ 0 & 0 & m_2l_2/\pi & -m_2l_2/2\pi \end{bmatrix}$$

U , V and N are the coefficient matrix and can be expressed as

$$U = \begin{bmatrix} 0 & (m_2/2 + m)l_1l_2 \sin(\theta_1 - \theta_2) \\ -(m_2/2 + m)l_1l_2 \sin(\theta_1 - \theta_2) & 0 \end{bmatrix}$$

$$V = \begin{bmatrix} 0 & 0 & -2m_2l_1 \sin(\theta_1 - \theta_2)/\pi & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

$$N = \text{diag}[EI_1\pi^4/2l_1^3 \ 8EI_1\pi^4/l_1^3 \ EI_2\pi^4/2l_2^3 \ 8EI_2\pi^4/l_2^3]$$

R is column vector and is given by

$$R = [2/\pi m_2l_1 \sin(\theta_1 - \theta_2)(\dot{\theta}_1 + \dot{\theta}_2)\dot{q}_{21} + (m_1/2 + m_2 + m)gl_1 \cos \theta_1 \\ (m_2/2 + m)gl_2 \cos \theta_2]^T$$

III. THE DESIGN OF NEURAL NETWORK-BASED BACKSTEPPING CONTROLLER FOR FOLDING-BOOM AERIAL PLATFORM VEHICLE

Defining $x_1 = [\theta_1 \ \theta_2 \ q_{11} \ q_{12} \ q_{21} \ q_{22}]^T$,
 $x_2 = [\dot{\theta}_1 \ \dot{\theta}_2 \ \dot{q}_{11} \ \dot{q}_{12} \ \dot{q}_{21} \ \dot{q}_{22}]^T$, then the state equations of (1) can be written as

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = \bar{M}^{-1}(Q - \bar{V}x_2^2 - \bar{N}x_1 - \bar{R}) \end{cases} \quad (2)$$

where, $\bar{M} = \begin{bmatrix} G & H \\ H^T & M \end{bmatrix}$, $\bar{M} = \begin{bmatrix} G & H \\ H^T & M \end{bmatrix}$, $\bar{N} = \begin{bmatrix} 0 & 0 \\ 0 & N \end{bmatrix}$,

$$\bar{R} = [R^T \ 0]^T, \ x_2^2 = [\dot{\theta}_1^2 \ \dot{\theta}_2^2 \ \dot{q}_{11}^2 \ \dot{q}_{12}^2 \ \dot{q}_{21}^2 \ \dot{q}_{22}^2]^T$$

Choose the reference trajectory as $r(t) = [r_1(t) \ r_2(t) \ r_3(t) \ r_4(t) \ r_5(t) \ r_6(t)]^T$, then $\dot{r}(t) = [\dot{r}_1(t) \ \dot{r}_2(t) \ \dot{r}_3(t) \ \dot{r}_4(t) \ \dot{r}_5(t) \ \dot{r}_6(t)]^T$,
 $\ddot{r}(t) = [\ddot{r}_1(t) \ \ddot{r}_2(t) \ \ddot{r}_3(t) \ \ddot{r}_4(t) \ \ddot{r}_5(t) \ \ddot{r}_6(t)]^T$.

Defining $z_1 = x_1 - r(t)$ as the position tracking error, then the virtual control is given by $\alpha_1 = -k_1 z_1$, in which, k_1 is positive constant. Furthermore, defining $z_2 = x_2 - \alpha_1 - \dot{r}(t)$, then the control law Q is designed as follows:

$$Q = \bar{M}[-z_1 - k_2 z_2 - k_1(x_2 - \dot{r}(t)) + \ddot{r}(t)] + \bar{V}x_2^2 + \bar{N}x_1 + \bar{R}. \quad (3)$$

where $k_2 > 0$.

From paper [4], it is concluded that for the dynamics model (2), the control law is designed as (3), then the trajectory tracking error of work platform will converge to zero by choosing suitable design constant k_1 and k_2 .

In practice, there exist various uncertainties in the model. Considering the model uncertainties, the state equation (2) can be rewritten as follows

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = \bar{M}^{-1}Q + f(x) \end{cases} \quad (4)$$

where $f(x) = -\bar{M}^{-1}(\bar{V}x_2^2 + \bar{N}x_1 + \bar{R})$ is the model uncertainties. The output of neural network $\hat{f}(x)$ is used to approximate it. Therefore, considering (3), the control law can be chosen as

$$Q = \bar{M}[-z_1 - k_2 z_2 - k_1(x_2 - \dot{r}(t)) + \ddot{r}(t) - \hat{f}(x)]. \quad (5)$$

where $\hat{f}(x)$ can be expressed as follows:

$$\hat{f}(x) = \hat{W}^T \phi. \quad (6)$$

In which, \hat{W} is the neural network weights matrix, $\phi = [\phi_1 \ \phi_2 \ \dots \ \phi_6]^T$ are base functions of neural

network. In addition, the uncertainties $f(x)$ can be expressed as

$$f(x) = W^{*T} \phi + \varepsilon_1. \quad (7)$$

where, W^* is optimization weights matrix, ε_1 is the smallest approximation error of neural network.

Defining $\hat{\Lambda} = \text{diag}[0 \ \hat{W}]$, $\Lambda = \text{diag}[0 \ W^*]$ with $\|\Lambda\|_F \leq \Lambda_M$, in which, $\|\cdot\|_F$ denote the Frobenius norm. Let $\tilde{\Lambda} = \Lambda - \hat{\Lambda}$ and $z = [z_1^T \ z_2^T]^T$, then consider the following Lyapunov candidate function:

$$V = \frac{1}{2} z^T z + \frac{1}{2} \text{tr}(\tilde{\Lambda}^T \Sigma^{-1} \tilde{\Lambda}). \quad (8)$$

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

Choose the following adaptive law of neural network weights:

$$\dot{\hat{\Lambda}} = \Sigma \Phi z^T - n \Sigma \|z\| \hat{\Lambda}. \quad (9)$$

where, n is positive real number and $\Phi = [0 \ \phi^T]^T$, $\|\cdot\|$ denote the 2-norm.

The derivative of (8) is

$$\dot{V} = z^T \dot{z} + \text{tr}(\tilde{\Lambda}^T \Sigma^{-1} \dot{\tilde{\Lambda}}). \quad (10)$$

Substituting (5)、(6) and (7) into (10) yields

$$\dot{V} = -k_1 z_1^T z_1 - k_2 z_2^T z_2 + z_2^T [(W^{*T} - \hat{W}^T) \phi + \varepsilon_1] + \text{tr}(\tilde{\Lambda}^T \Sigma^{-1} \dot{\tilde{\Lambda}})$$

Let $\tilde{W}^T = W^{*T} - \hat{W}^T$, then

$$\dot{V} = -k_1 z_1^T z_1 - k_2 z_2^T z_2 + z_2^T (\tilde{W}^T \phi + \varepsilon_1) + \text{tr}(\tilde{\Lambda}^T \Sigma^{-1} \dot{\tilde{\Lambda}}).$$

Defining $K_Z = \text{diag}[k_1 I \ k_2 I]$, $\varepsilon = [0 \ \varepsilon_1^T]^T$ and assuming that $\|\varepsilon\| < \varepsilon_N$, there yields

$\dot{V} = -z^T K_Z z + z^T \varepsilon + \text{tr}(\tilde{\Lambda}^T \Sigma^{-1} \dot{\tilde{\Lambda}} + \tilde{\Lambda}^T \Phi z^T)$. As $\dot{\tilde{\Lambda}} = -\dot{\hat{\Lambda}}$, considering (9), the derivative of V becomes

$$\dot{V} = -z^T K_Z z + z^T \varepsilon + n \|z\| \text{tr}(\tilde{\Lambda}^T (\Lambda - \tilde{\Lambda})). \quad (11)$$

According to Schwarz inequality

$$\text{tr}(\tilde{\Lambda}^T (\Lambda - \tilde{\Lambda})) \leq \|\tilde{\Lambda}\|_F \|\Lambda\|_F - \|\tilde{\Lambda}\|_F^2, \quad \text{since}$$

$z^T K_Z z \geq k_{\min} \|z\|^2$, where $k_{\min} > 0$ is the minimum eigenvalue of K_Z , then (11) becomes

$$\dot{V} \leq -k_{\min} \|z\|^2 + \varepsilon_N \|z\| + n \|z\| (\|\tilde{\Lambda}\|_F \|\Lambda\|_F - \|\tilde{\Lambda}\|_F^2) \leq -\|z\| [k_{\min} \|z\| - \varepsilon_N + n (\|\tilde{\Lambda}\|_F^2 - \|\tilde{\Lambda}\|_F \Lambda_M)]$$

In order to ensure $\dot{V} < 0$, the inequality $k_{\min} \|z\| - \varepsilon_N + n (\|\tilde{\Lambda}\|_F^2 - \|\tilde{\Lambda}\|_F \Lambda_M) > 0$ should be guaranteed. Therefore, the inequality

$$(\varepsilon_N + \frac{n}{4} \Lambda_M^2) / k_{\min} < \|z\|$$

can be derived. As a result, $\dot{V} < 0$ can be ensured by choosing the suitable values of n and k_{\min} . Therefore, the derived control law (5) can make z_1 and z_2 converge to zero exponentially asymptotically according to Lyapunov stability theorem. That is to say, the trajectory of work platform can follow the desired trajectory without vibration.

IV、SIMULATION RESULTS

The simulation results in Figure. 1~Figure. 6 are based on the following choice of design parameters and initial conditions:

$l_1 = 7.5m$, $l_2 = 8.5m$, $m_1 = 650kg$, $m_2 = 550kg$, $m = 150kg$, $d = 0.05$, $c = 0.03$, $m_{y1} = 20kg$, $m_{y2} = 20kg$, $EI_1 = 6 \times 10^8 N \cdot m^2$, $EI_2 = 5 \times 10^8 N \cdot m^2$, $a_{10} = 0.9m$, $a_{11} = 0.9m$, $a_{12} = 1.8m$, $a_{21} = 1.8m$, $a_{22} = 0.9m$, the initial angular of two beams are $\theta_1 = 2.09rad$ and $\theta_2 = 0.52rad$, initial angular velocity $\dot{\theta}_1$ and $\dot{\theta}_2$ are zero.

Reference trajectory is designed as $r(t) = [2\pi/3 \ \pi t/180 \ 0 \ 0 \ 0 \ 0]^T$, then

$$\dot{r}(t) = [0 \ \pi/180 \ 0 \ 0 \ 0 \ 0]^T,$$

$$\ddot{r}(t) = [0 \ 0 \ 0 \ 0 \ 0 \ 0]^T.$$

In the control law (5), the design parameters are selected as $k_1 = k_2 = 0.5$. In (6), the base functions of

neural network are chosen as $\phi_i = \exp\left(-\frac{\|x\|^2}{2 \times 100^2}\right)$,

$i = 1, 2, \dots, 10$, in which, $x = [x_1^T \ x_2^T]^T$, the center of Gaussian function is set at 0, the width is set at 100. And the parameters in(9) can be set as: $n = 0.01$, $\Gamma = 100 \text{diag}[1 \ 1 \ 1 \ 1 \ 1 \ 1]$. In addition, initial weights are set to zero.

Fig. 1~ Fig. 6 show the simulation results of applying the proposed neural network-based backstepping controller for the trajectory tracking control of work platform.

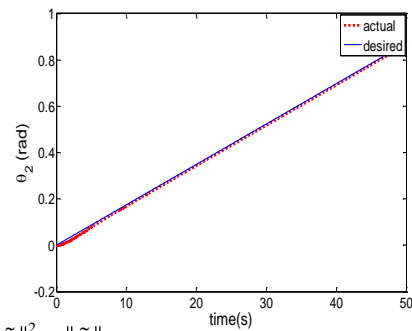


Figure 2. The tracking of θ_2

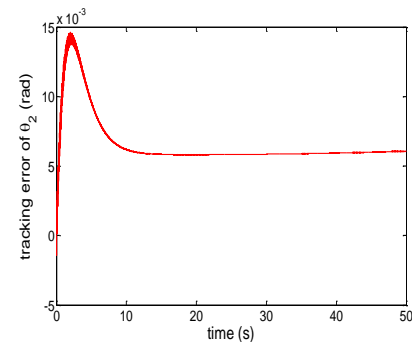


Figure 3. The tracking error of θ_2

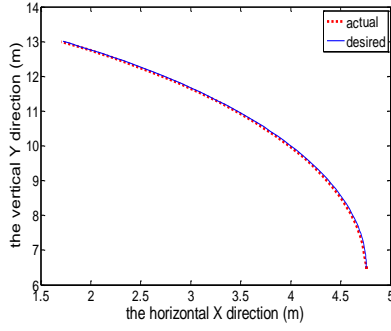


Figure 4. The trajectory tracking of work platform

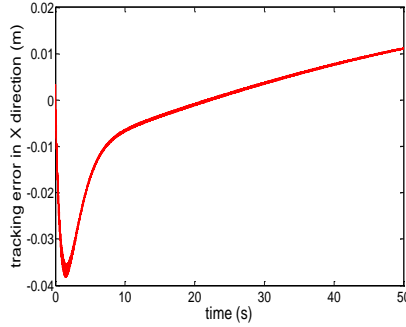


Figure 5. The trajectory tracking error

of work platform in the horizontal x-direction

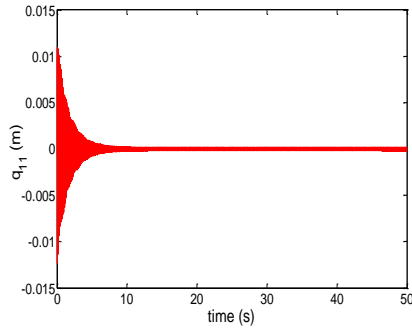


Figure 6. The deformation variable q_{11} changing with time

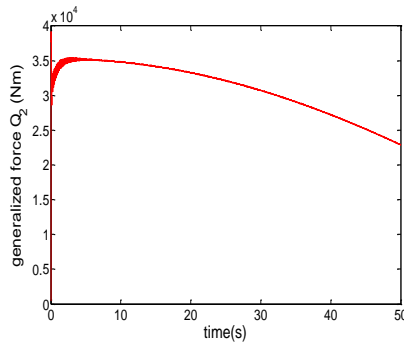


Figure 7. The regulation of generalized force Q_2

It can be seen from Fig .2 and Fig .4 that both the actual trajectory of θ_2 and work platform can follow the desired trajectory closely by using the proposed neural network-based backstepping controller. Simultaneously, Fig .3 and Fig .5 demonstrate that the tracking errors are

small, which reflect that the good tracking performance of the proposed controller. Fig . 6 is the deformation variable q_{11} changing with time, It can be shown from Fig .6 that q_{11} converges to small values with a transient, which means that the vibration is declined. As a result, the work platform can keep the steady movement along the desired trajectory. The regulation of generalized force Q_2 , which is used for realizing the trajectory tracking control of work platform, is shown in Fig .7.

V、CONCLUSION

As neural network can approximate any nonlinear function with arbitrary accuracy, a neural network-based backstepping controller, which is the combination of backstepping control and neural network, is presented for trajectory tracking control of work platform when there exist model uncertainties. Furthermore, simulation results have shown that the proposed controller is an effective control scheme for suppressing vibration and attenuating tracking error of work platform in the case of model uncertainties. As a result, the trajectory of work platform can track the desired trajectory steadily.

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