Adaptive Neural Network Control of Space Flexible Robot Based on Calculated Torque for Non-cooperative Targets

Jinmiao Shen, Wenhui Zhang, Yangfan Ye, Yinfa Zhu, and Xiaoping Ye

***Abstract*—An adaptive neural network control method based on computed torque is proposed to solve the target acquisition problem of non-cooperative space flexible robots. The dynamic model of free-floating space flexible robot is established, and the model is decomposed into two dynamic submodels, rigid and flexible, using singular perturbation theory. Aiming at the quality uncertainty of non-cooperative targets, a weighted recursive least squares method (WRLSM) is designed to realize online real-time estimation of unknown quality. A computational torque controller based on error estimation model is designed to realize partial decoupling of nonlinear dynamics of space flexible robot; To solve the problem of incomplete decoupling caused by uncertain models, an adaptive neural network is designed to compensate the error model and complete the complete decoupling of the nonlinear model. Aiming at the problem of elastic vibration caused by flexible characteristics, a linear quadratic regulator (LQR) controller is designed to suppress the elastic vibration of. Simulation results verify the effectiveness of the controller.**

***Index Terms*—Space flexible manipulator; Load change; Quality estimation; Adaptive control; Neural network; Vibration suppression.**

I. INTRODUCTION

The development of control technology and new materials provides a broad application prospect for space flexible manipulator. Compared with rigid manipulator, flexible scholars at home and abroad. From the earlier Canada-II space manipulator has lighter weight, higher speed and lower energy consumption [1-3], so it has been widely concerned by manipulator of the European Union "International Space Station" to the large space manipulator of the Chinese "Tiangong I" space station. The body of the manipulator is made of carbon fiber composite materials, which makes the space manipulator actually present certain flexible characteristics, which can better absorb the impact energy generated by the accidental collision between the space manipulator and the external environment, and reduce the damage of the space robot. However, the flexible characteristics will lead to the vibration of the space manipulator in the movement process, which will seriously affect the control accuracy of the end effector [4]. Moreover, considering the complex task conditions of the space robot, such as cleaning up space garbage or capturing unknown targets [5-7], the target load quality is unknown. If the difference between the captured target load and the preset load is too large, it is easy to cause load mutation, which will damage the stability of the control system and the actuator [8, 9].

In recent years, few scholars in the world have studied the load acquisition of non-cooperative targets. However, there are still many research results on the control of unloaded robots, and many control strategies have been proposed, such as terminal sliding mode control [10-12], adaptive control [13,14], neural network control [15,16], robust control [17], and have also made some meaningful research results on the control of space flexible manipulators with cooperative target load [18-23]. Lei et al. [24] Proposed a fault-tolerant control method based on neural network for floating space flexible manipulator, and designed a quadratic optimal robust controller to suppress elastic vibration. Chen et al. [25] proposed an active disturbance rejection control (ADRC) method for the single flexible manipulators with disturbance. By designing a time-varying high gain extended state observer to estimate the disturbance, and designing a feedback controller to eliminate the disturbance. Hamzeh et al. [26] proposed a composite control scheme based on fractional order sliding mode for a single flexible manipulator, in which one controller realizes position tracking and the other controller suppresses elastic vibration. Lei et al. [27] proposed an adaptive control method based on $H\infty$ for free floating space flexible manipulator, designed a robust controller based on $H\infty$ to track the desired trajectory, and designed an adaptive controller based on optimal control theory to suppress elastic vibration.

At present, scholars at home and abroad mainly focus on the vibration suppression of flexible manipulators without considering the load change, but the research on variable load target is relatively few. In fact, considering the complex task conditions of the space robot, such as cleaning up space

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garbage or capturing unknown targets, the target load quality is unknown. If the difference between the captured target load and the preset load is too large, it is easy to cause load mutation, which will damage the stability of the control system and the actuator. Therefore, it is of great significance to study the control of space flexible manipulators based on non-cooperative variable load target acquisition.

Based on the above research, a neural network control method based on calculated torque is proposed, which takes into account the uncertainty of non-cooperative target load and external interference. The purpose of the controller is to estimate the unknown load mass in real time, and realize the complete decoupling of the unknown nonlinear model, and suppress the elastic vibration caused by the flexible manipulators. The main technical contributions of the proposed method are summarized below.

1) Different from the traditional control, which controls the robot dynamics model as a whole, this research decomposes the dynamics model into two dynamics subsystem models based on the singular perturbation theory to realize the separate control of the two subsystems;

2) Different from the traditional control object which is a constant mass load, the recursive weighted least squares method is designed to realize the online real-time identification of the variable mass load;

3) Different from the partial decoupling of the nonlinear model in traditional control, a computational-transfer controller and a neural network adaptive controller are designed to realize the hybrid control, thus completing the complete decoupling of the nonlinear model. At the same time, a linear quadratic regulator (LQR) controller is designed to suppress the elastic vibration.

II. DYNAMIC MODELING OF FLOATING SPACE FLEXIBLE MANIPULATOR

As shown in Fig. 1, the free-floating space flexible manipulator is composed of carrier B_0 , flexible rods B_1 and B_2 . The joint coordinate system $B_i(i=0,1,2)$ of each split $O_i x_i y_i$ is established. The load mass p is m , and the specific parameters are defined in references [24,28].

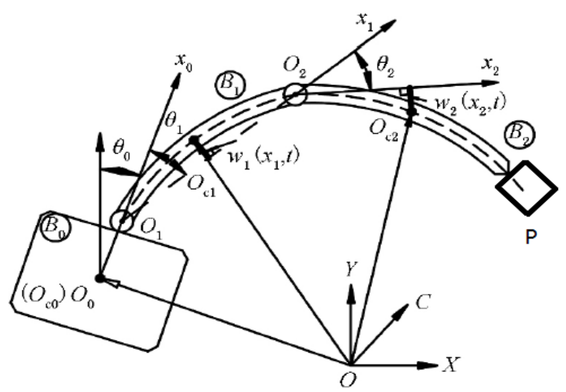

Fig. 1. Two-bar flexible space robot system

Assuming that the flexible arm with two degrees of freedom is a slender homogeneous arm, if rod B_1 is regarded as a simply supported beam and rod B_2 as a cantilever beam, it can be regarded as a Bernoulli Euler beam [25]. Here, bending deformation is mainly considered. Shear deformation is ignored. Vibration is in the plane. If the linear density of the flexible rod $B_i(i=1,2)$ is ρ_i and the bending rigidity of the section is $(EI)_i$, its elastic deformation is recorded as

$$u_i(x_i,t)=\sum_{i=1}^{\infty}\phi_{ij}(x_i)q_{ij}(t) \tag{1}$$

Where $u_i(x_i,t)$ is the transverse elastic deformation of B_i at section $x_i(0\le x_i\le l_i)$. $\phi_{ij}(x_i)$ is the j order modal function of B_i. The specific modal function is referred to [28]. $q_{ij}(t)$ is the modal coordinate corresponding to $\phi_{ij}(x_i)$. n_i is the number of truncation terms. where the first two modes are taken as $i=1,2$.

Based on the Lagrange equation of the second kind and the momentum conservation theorem, the dynamic equation of the floating space double link flexible manipulator can be obtained as follows and the detailed calculation process is shown in [31]:

$$M(\theta_b,q)\begin{bmatrix}\ddot{\theta}\\ \ddot{q}\end{bmatrix}+H(\theta_b,\dot{\theta},q,\dot{q})\begin{bmatrix}\dot{\theta}\\ \dot{q}\end{bmatrix}+\begin{bmatrix}\xi\\ Kq\end{bmatrix}=\begin{bmatrix}\tau\\ 0\end{bmatrix} \tag{2}$$

Where $\theta_b=[\theta_0,\theta]^T$, $\theta=[\theta_1,\theta_2]^T$ and θ_0 are the angular position of the base body, and θ is the rigid generalized coordinate column vectors of the joint angle of the arm. $q=[q_{11}\quad q_{12}\quad q_{21}\quad q_{22}]^T$ is the flexible generalized coordinate column vector of the flexible modal coordinates of the member. $H(\theta_b,\dot{\theta},q,\dot{q})$ is the column vector containing Coriolis force and centrifugal force. $K=\mathrm{diag}(k_{11},k_{12},k_{21},k_{22})$ is the stiffness matrix of the member, $k_{ij}=(EI)_i\int_0^{li}(\phi_{ij}'')^T\phi_{ij}''dx_i$. $\tau=[\tau_1\quad\tau_2]^T$ is the output torque of the rod joint, and ξ is the external interference and joint friction.

Writing (2) as a block matrix in the form of

$$\begin{bmatrix}M_{rr}&M_{rf}\\ M_{fr}&M_{ff}\end{bmatrix}\begin{bmatrix}\ddot{\theta}\\ \ddot{q}\end{bmatrix}+\begin{bmatrix}H_{rr}&H_{rf}\\ H_{fr}&H_{ff}\end{bmatrix}\begin{bmatrix}\dot{\theta}\\ \dot{q}\end{bmatrix}+\begin{bmatrix}\xi\\ Kq\end{bmatrix}=\begin{bmatrix}\tau\\ 0\end{bmatrix} \tag{3}$$

Where $M_{rr}\in\mathbb{R}^{2\times2}$, $M_{fr}=M_{fr}^T\in\mathbb{R}^{2\times4}$, $M_{ff}\in\mathbb{R}^{4\times4}$, $H_{\mathrm{rr}}\in\mathbb{R}^{2\times2}$, $H_{ff}\in\mathbb{R}^{4\times4}$, $H_{fr}\in\mathbb{R}^{4\times2}$, $H_{rf}\in\mathbb{R}^{2\times4}$.

Since $M(\theta_b,q)$ is a symmetric positive definite matrix, its inverse is

$$N^{-1}=M=\begin{bmatrix}M_{rr}&M_{rf}\\ M_{fr}&M_{ff}\end{bmatrix}^{-1}=\begin{bmatrix}N_{rr}&N_{rf}\\ N_{fr}&N_{ff}\end{bmatrix} \tag{4}$$

If the singular perturbation scale factor is defined as $\mu=(\min(k_{11},k_{12},k_{21},k_{22}))^{-1/2}$, and the state variable is defined as $z=q/\mu^2$, and the new stiffness matrix is defined as $\tilde{K}=\mu^2K$, then (3) can be decomposed into and

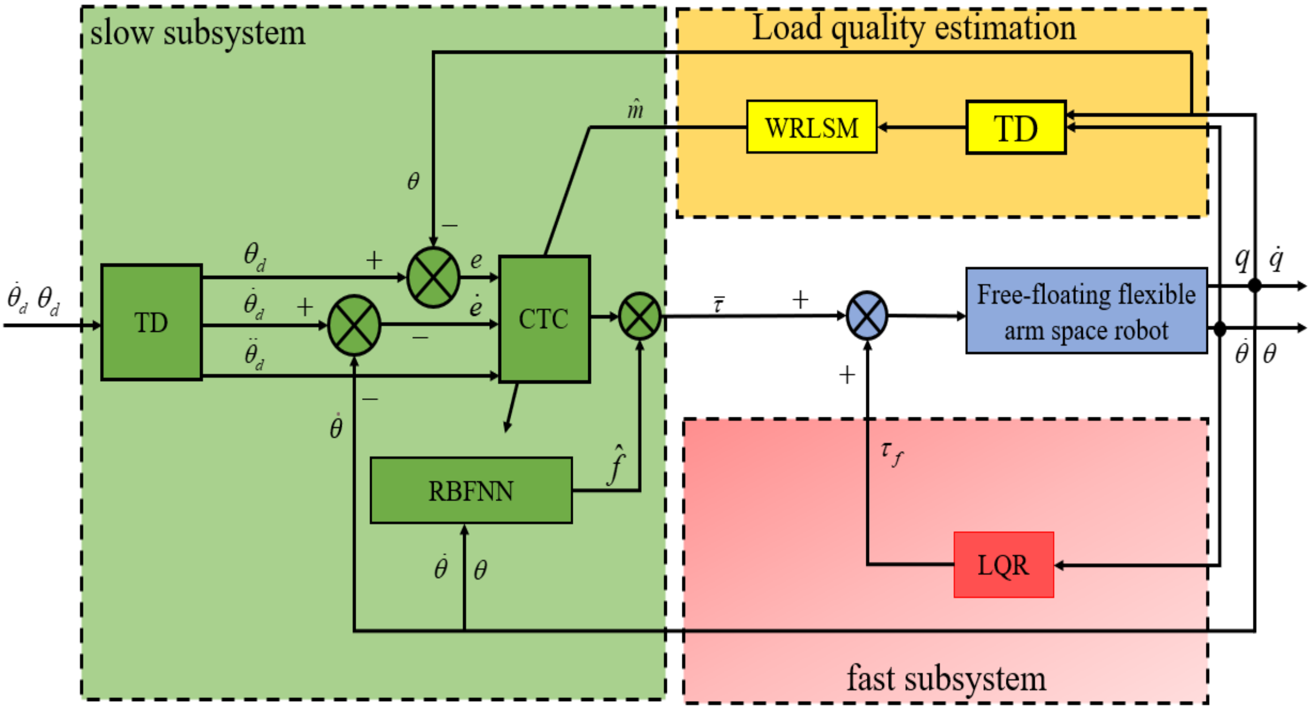

Fig. 2. Main design ideas of control system

characterized as a fast subsystem with flexible characteristics:

$$\ddot{\theta} = -(N_{rr}H_{rr} + N_{rf}H_{fr}) - (N_{rr}H_{rf} + N_{rf}H_{ff})\mu^2\dot{z} - N_{rf}\tilde{K}z + N_{rr}(\tau - \xi) \tag{5}$$

$$\mu^2\ddot{z} = -(N_{fr}H_{rr} + N_{ff}H_{fr})\dot{\theta} - (N_{fr}H_{rf} + N_{ff}H_{fr})\mu^2\dot{z} - N_{ff}\tilde{K}z + N_{fr}(\tau - \xi) \tag{6}$$

The design master controller is

$$\tau = \bar{\tau} + \tau_f \tag{7}$$

Where $\bar{\tau}$ is a slowly varying subsystem controller, which is used to track the desired trajectory. τ_f is a fast-changing subsystem controller, which is used to suppress elastic vibration.

In order to obtain the slowly varying subsystem model representing the rigid characteristics, letting $\mu = 0$ be substituted into equation (6) to sort out the slowly varying manifold expression $\bar{z}$:

$$\bar{z} = \tilde{K}^{-1}\bar{N}_{ff}^{-1}[-(\bar{N}_{fr}\bar{H}_{rr} + \bar{N}_{ff}\bar{H}_{fr})\dot{\theta} + \bar{N}_{fr}(\bar{\tau} - \xi)] \tag{8}$$

Where the superscript "-" represents the physical quantity of the slowly varying subsystem. Then, substituting (8) into (7) and combining with $\bar{M}_{rr}^{-1} = \bar{N}_{rr} - \bar{N}_{rf}\bar{N}_{ff}\bar{N}_{rf}$, the slowly varying subsystem is obtained as follows:

$$\bar{M}_{rr}\ddot{\theta} + \bar{H}_{rr}\dot{\theta} + \xi = \bar{\tau} \tag{9}$$

In order to obtain the model of the fast-varying subsystem that characterizes the flexibility, the time scale of the fast-varying subsystem $p_1 = z - \bar{z}, p_2 = \mu\dot{z}$ is set as $\varpi = t/\mu$ and t as time. Let $\mu = 0$ be carried into (6) to sort out the expression of fast-changing manifold:

$$\frac{dp_1}{d\varpi} = p_2 \tag{10}$$

$$\frac{dp_2}{d\varpi^2} = -\bar{N}_{ff}\tilde{K}p_1 + \bar{N}_{fr}\tau_f \tag{11}$$

III. Design of Robust Compensation Controller Based on Adaptive Neural Network

Fig.2 is the flow chart of the control system designed for the floating space flexible manipulator.

A. Unknown load quality estimation

Considering the unknown and uncertainty of the end load mass, the model items containing the load mass is decomposed into:

$$\bar{M}_{rr}(\theta_b) = M_0(\theta_b) + C_m(\theta_b)\hat{m} \tag{12}$$

$$\bar{H}_{rr}(\theta_b, \dot{\theta}) = H_0(\theta_b, \dot{\theta}) + C_H(\theta_b, \dot{\theta})\hat{m} \tag{13}$$

Where $M_0(\theta_b)$ and $H_0(\theta_b, \dot{\theta})$ are known deterministic models. $C_m(\theta_b)m$, $C_H(\theta_b, \dot{\theta})m$ are unknown uncertain models.

Substituting (12) and (13) into (2) to obtain

$$\phi^T\hat{m} = \eta \tag{14}$$

Where

$\phi^T = C_m(\theta_b)\ddot{\theta} + C_H(\theta_b, \dot{\theta})\dot{\theta}$;

$\eta = \bar{\tau} - d - M_0(\theta_b)\ddot{\theta} - H_0(\theta_b, \dot{\theta})\dot{\theta}$.

Assuming that the actual quality of the load is m and the estimated quality is $\hat{m}$, the quality estimator is designed based on the improved weighted recursive least square method (WRLSM):

$$\hat{m}_k = \hat{m}_{k-1} + K_k(\eta_k - \phi_k^T\hat{m}_{k-1}) \tag{15}$$

$$N_k = N_{k-1} - N_{k-1}\phi_k (L_k + \phi_k^T N_{k-1}\phi_k)^{-1}\phi_k^T N_{k-1} \quad (16)$$

$$K_k = N_{k-1} - \phi_k (L_k + \phi_k^T N_{k-1}\phi_k)^{-1} \quad (17)$$

Where $\eta_k - \phi_k^T \hat{m}_{k-1}$ is the prediction error. K_k is the gain matrix. L_k is the weighting matrix.

According to (14), the designed quality estimator needs to know the angular acceleration signal. The higher-order differential of the angular position signal. Then the tracking differentiator (TD) is designed as:

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = h(x_1 - \overline{\tau}, x_2, r, h_0) \end{cases} \quad (18)$$

Where $x_1 = \theta$ and h_0 are filter factors. r are velocity factors. $\overline{\tau}$ are torque output.

Design the function of $h(x_1 - \overline{\tau}, x_2, r, h_0)$ as

$$\begin{cases} h = -r\,\mathrm{sgn}(a) & |a| > d_0 \\ h = -ra/d & |a| \le d_0 \end{cases} \quad (19)$$

Where

$$a = \begin{cases} x_2 + 0.5(a_0 - d)\mathrm{sgn}(y) & |y| > d_0 \\ x_2 + y/h_0 & |y| \le d_0 \end{cases}, \quad d_0 = h_0 d,$$

$a_0 = \sqrt{d^2 + 8r|y|}$, $d = rh_0$, $y = x_1 + h_0 x_2$.

B. Robust controller design based on adaptive neural network

e is joint angle estimation error and $\dot{e}$ is joint angular velocity estimation error

$$\begin{cases} e = \theta - \theta_d \\ \dot{e} = \dot{\theta} - \dot{\theta}_d \end{cases} \quad (20)$$

Where θ_d is the desired trajectory.

If the model is considered to be accurate and $\xi = 0$, the design control law is:

$$\overline{\tau}^1 = \overline{M}_{rr}(\ddot{\theta}_d - k_v\dot{e} - k_p e) + \overline{H}_{rr}\dot{\theta} \quad (21)$$

Where k_p, k_v is a positive definite symmetric matrix.

Substituting the control law (21) into (9), the stable closed-loop system is obtained as

$$\ddot{e} + k_v\dot{e} + k_p e = 0 \quad (22)$$

Then, the control system is stable.

However, in the actual project, joint friction and external interference $\xi \ne 0$, and the designed load quality estimator must have some identification errors. Especially in the initial stage, there are few sample data at this moment, resulting in large identification errors. With the iteration of online data samples, the identification accuracy is getting higher and higher. Assuming that the identification result of the load mass estimator is $\hat{m}$ and the actual mass is m, the mass identification error is $\Delta m = \hat{m} - m$, so that $\hat{\overline{M}}_{rr}$ and $\hat{\overline{H}}_{rr}$ are the dynamic models based on the load estimated mass, $\Delta\overline{M}_{rr}$, and $\Delta\overline{H}_{rr}$ are the error models caused by the mass estimation error. From (12) - (13), the model error is

$$\Delta\overline{M}_{rr} = \hat{\overline{M}}_{rr} - \overline{M}_{rr} = C_m \Delta m \quad (23)$$

$$\Delta\overline{H}_{rr} = \hat{\overline{H}}_{rr} - \overline{H}_{rr} = C_H \Delta m \quad (24)$$

Then the controller (17) is modified as:

$$\overline{\tau}^2 = \hat{\overline{M}}_{rr}(\ddot{\theta}_d - k_v\dot{e} - k_p e) + \hat{\overline{H}}_{rr}\dot{\theta} \quad (25)$$

Substituting (25) into (9) to obtain

$$\ddot{e} + k_v\dot{e} + k_p e = \hat{\overline{M}}_{rr}^{-1}(\Delta\overline{M}_{rr}\ddot{\theta} + \Delta\overline{H}_{rr}\dot{\theta} + \xi) \quad (26)$$

It can be seen from the above formula that the inaccuracy of the model error will lead to the decline of the control performance. Therefore, it is necessary to compensate the modelling uncertainty:

$$f = \hat{\overline{M}}_{rr}^{-1}(\Delta\overline{M}_{rr}\ddot{\theta} + \Delta\overline{H}_{rr}\dot{\theta} + \xi) \quad (27)$$

Assuming that the uncertain model f is known, the modified control law is:

$$\overline{\tau}^3 = \hat{\overline{M}}_{rr}(\ddot{\theta}_d - k_v\dot{e} - k_p e - f) + \hat{\overline{H}}_{rr}\dot{\theta} \quad (28)$$

Substituting (28) into (9) can obtain a stable closed-loop system (22).

Because the uncertainty f is a completely unknown and uncertain nonlinear function. Considering that the neural network has excellent nonlinear approximation ability, and the radial basis function neural network (RBFNN) belongs to the local generalization network, which has fast learning speed and can avoid the local minimum problem, it is widely used in the field of motion control [29, 30].

RBF neural network is used to approximate the unknown nonlinear model f, and its optimal output is

$$f(x) = W^{*T}\varphi(x) + \varepsilon \quad (29)$$

Where $x = (\theta_0, \theta_1, \theta_2)$ is the input of the neural network, W^* is the optimal network weight matrix. ε is the approximation error of the neural network, and $\varphi(x)$ is a Gaussian function.

Assumption 1: The optimal weight parameter W^* of neural network is bounded, that is, there is a normal number W_M, which satisfies $\|W^*\| \le W_M$.

Assumption 2: For the optimal weight vector W^*, there is any small positive number ε_M, so that the neural network approximation error ε can meet $|\varepsilon| < \varepsilon_M$.

In fact, the output of RBF neural network does not necessarily output the optimal value. If its actual output is $\hat{f}$, then

$$\hat{f} = \hat{W}^T\varphi \quad (30)$$

Where $\hat{W}$ is the actual weight of neural network.

To ensure that the weight is bounded, the adaptation law is:

$$\dot{\hat{W}} = \gamma\varphi s^T PB + k_1\gamma\|s\|\hat{W} \quad (31)$$

Where $k_1 > 0$, $\tilde{W} = \hat{W} - W^*$. Matrix P is a symmetric positive definite matrix.

Then the controller based on neural network is designed as:

$$\bar{\tau}^4 = \hat{\bar{M}}_{rr}(\ddot{\theta}_d - k_v\dot{e} - k_p e - \hat{f}) + \hat{\bar{H}}_{rr}\dot{\theta} \tag{32}$$

Substituting (32) into (9) yields:

$$\ddot{e} + k_v\dot{e} + k_p e + \hat{f} = f \tag{33}$$

Taking $s = [e \quad \dot{e}]$, then the above formula can be written as:

$$\dot{s} = As + B\{f - \hat{f}\} \tag{34}$$

Where $A = \begin{bmatrix} 0 & I \\ -k_p & -k_v \end{bmatrix}, B = \begin{bmatrix} 0 \\ I \end{bmatrix}$.

Because

$$\begin{aligned} f - \hat{f} &= W^{*T}\varphi(x) + \varepsilon - \hat{W}^T\varphi \\ &= \varepsilon - \tilde{W}^T\varphi \end{aligned}$$

Then

$$\dot{s} = As + B(\varepsilon - \tilde{W}^T\varphi(x)) \tag{35}$$

Theorem: For the dynamic model (9) of a free-floating space flexible manipulator, under the condition that assumptions 1 to 2 are satisfied, the controller (32), neural network controller (30) and neural network adaptive law (31) are adopted to ensure uniform ultimate boundedness (UUB) of the error signal.

Proof: define Lyapunov function

$$V = \frac{1}{2}s^T Ps + \frac{1}{2\gamma}\left\|\tilde{W}\right\|^2 \tag{36}$$

Where $\gamma > 0$.

Matrix P is a symmetric positive definite matrix and satisfies the following Lyapunov equation

$$PA + A^T P = -\Xi \tag{37}$$

Define

$$\left\|R\right\|^2 = \sum_{i,j}\left|r_{ij}\right|^2 = tr(RR^T) = tr(R^T R)$$

Where $tr(\bullet)$ is the trace of the matrix, $\left\|\tilde{W}\right\|^2 = tr(\tilde{W}^T\tilde{W})$.

Then

$$\begin{aligned} \dot{V} &= \frac{1}{2}[s^T P\dot{s} + \dot{s}^T Ps] + \frac{1}{\gamma}tr(\dot{\tilde{W}}^T\tilde{W}) \\ &= \frac{1}{2}[s^T P(As + B(\mu - \tilde{W}^T\varphi)) + (s^T A^T + \\ &\quad (\varepsilon - \tilde{W}^T\varphi^T B^T)Ps] + \frac{1}{\gamma}tr(\dot{\tilde{W}}^T\tilde{W}) \\ &= \frac{1}{2}[s^T(PA + A^T P)s + (-s^T PB\tilde{W}^T\varphi \\ &\quad + s^T PB\varepsilon - \varphi^T\tilde{W}B^T Ps + \varepsilon^T B^T Ps] \\ &\quad + \frac{1}{\gamma}tr(\dot{\tilde{W}}^T\tilde{W}) \\ &= -\frac{1}{2}s^T\Xi s - \varphi^T\tilde{W}B^T Ps + \varepsilon^T B^T Ps \\ &\quad + \frac{1}{\gamma}tr(\dot{\tilde{W}}^T\tilde{W}) \end{aligned} \tag{38}$$

Where

$s^T PB\tilde{W}^T\varphi = \varphi^T\tilde{W}B^T Ps$;

$s^T PB\varepsilon = \varepsilon^T B^T Ps$.

Because

$$\varphi^T\tilde{W}B^T Ps = tr[B^T Ps\phi^T\tilde{W}]$$

Then

$$\dot{V} = -\frac{1}{2}s^T\Xi s + \frac{1}{\gamma}(-\gamma B^T Ps\varphi^T\tilde{W} + \dot{\tilde{W}}^T W) + \varepsilon^T B^T Ps \tag{39}$$

Substituting (31) into (39) to obtain

$$\begin{aligned} \dot{V} &= -\frac{1}{2}s^T\Xi s + \frac{1}{\gamma}tr(k_1\gamma\left\|s\right\|\hat{W}^T\tilde{W}) + \varepsilon^T B^T Ps \\ &= -\frac{1}{2}s^T\Xi s + k_1\left\|s\right\|tr(\hat{W}^T\tilde{W}) + \varepsilon^T B^T Ps \end{aligned} \tag{40}$$

According to the properties of F norm

$$\begin{aligned} tr[\hat{W}^T\tilde{W}] &= tr[\tilde{W}^T\hat{W}]tr[\tilde{W}^T(W^* + \tilde{W})] \\ &\le \left\|\tilde{W}\right\|_F\left\|W^*\right\|_F - \left\|\tilde{W}\right\|_F^2 \end{aligned}$$

Because

$$k_1\left\|\tilde{W}\right\|_F^2 - k_1\left\|\tilde{W}\right\|_F W_{\max} = k_1(\left\|\tilde{W}\right\|_F - \frac{W_{\max}}{2})^2 - \frac{k_1}{4}W_{\max}^2$$

Then

$$\begin{aligned} \dot{V} &\le -\frac{1}{2}s^T\Xi s + k_1\left\|s\right\|(\left\|\tilde{W}\right\|_F\left\|W^*\right\|_F - \left\|\tilde{W}\right\|_F^2) + \varepsilon^T B^T Ps \\ &\le -\frac{1}{2}\lambda_{\min}(\Xi)\left\|s\right\|^2 + k_1\left\|s\right\|\left\|\tilde{W}\right\|_F\left\|W^*\right\|_F \\ &\quad - k_1\left\|s\right\|\left\|\tilde{W}\right\|_F^2 + \left\|\varepsilon_M\right\|\lambda_{\max}(P)\left\|s\right\| \\ &\le -\left\|s\right\|(\frac{1}{2}\lambda_{\min}(\Xi)\left\|s\right\| - k_1\left\|\tilde{W}\right\|_F W_{\max} + k_1\left\|\tilde{W}\right\|_F^2 \\ &\quad - \left\|\varepsilon_M\right\|\lambda_{\max}(P)) \\ &= -\left\|s\right\|(\frac{1}{2}\lambda_{\min}(\Xi)\left\|s\right\| + k_1(\left\|\tilde{W}\right\|_F - \frac{W_{\max}}{2})^2 - \frac{k_1}{4}W_{\max}^2 \\ &\quad - \left\|\varepsilon_M\right\|\lambda_{\max}(P)) \end{aligned} \tag{41}$$

To make $\dot{V} \le 0$, you need to meet the following conditions:

$$\frac{1}{2}\lambda_{\min}(\Xi)\left\|s\right\| \ge \frac{k_1}{4}W_{\max}^2 + \left\|\varepsilon_M\right\|\lambda_{\max}(P)$$

The convergence condition is:

$$\left\|s\right\| \ge \frac{2}{\lambda_{\min}(\Xi)}(\frac{k_1}{4}W_{\max}^2 + \left\|\varepsilon_M\right\|\lambda_{\max}(P))$$

Or

$$\left\|\tilde{W}\right\|_F \ge \frac{W_{\max}}{2} + \sqrt{\frac{1}{4}W_{\max}^2 + \frac{1}{k_1}\left\|\varepsilon_M\right\|\lambda_{\max}(P)}$$

Therefore, the adaptive law (31) can guarantee the boundedness of the weights. It solves the convergence problem of the weights of the neural network. From the convergence of $\|s\|$, the larger the eigenvalue of Ξ, the smaller the eigenvalue of P, the smaller the approximation error ε_M, and $W_{\max}$ also is the smaller. The smaller the convergence radius of s error signal, the better the tracking effect.

C. Quick change subsystem LQR controller

LQR controller is used to actively suppress the vibration of double flexible links. Writing (10) ~ (11) in the form of state space, and making $L=\begin{bmatrix} p_1 \\ p_2 \end{bmatrix}$ state variable, which express as:

$$\dot{L}=A_f L+B_f\tau_f \tag{42}$$

Where $A_f=\begin{bmatrix} 0 & I \\ -\bar{N}_{ff}\tilde{K} & 0 \end{bmatrix}$. $B_f=\begin{bmatrix} 0 \\ \bar{N}_{fr} \end{bmatrix}$.

The optimal control technology is adopted for vibration suppression. The objective function is selected as

$$J=\frac{1}{2}\int_0^{\infty}(L^T QL+\tau_f^T R\tau_f)dt \tag{43}$$

Where Q and R are positive definite weight coefficient matrices. If the standard LQR design is adopted, the control output is

$$\tau_f=-KL \tag{44}$$

Where $K=-R^{-1}B^T P(t)$.

P by satisfying Riccati equation:

$$\dot{P}(t)=-P(t)A_f-A_f^T P(t)+P(t)BR^{-1}B^T P(t)-Q \tag{45}$$

IV. Experimental Simulation

Taking the dynamic model given in Fig. 1 as an example, combined with the load estimation (16) - (18), the simulation is carried out by using the slow subsystem controller (23) and the fast subsystem controller (44). The parameters of the floating space flexible manipulator are as follows:

$l_0=l_1=2m$, $l_2=2m$, $m_0=40kg$, $m_1=5kg$, $m_2=3kg$, $J_0=35kg\cdot m^2$, $\rho_1=4kg/m$, $\rho_2=1.2kg/m$, $EI_1=50N\cdot m^2$, $EI_2=50N\cdot m^2$.

The trajectory of the manipulator is:

$q_d=[2-\cos 0.25\pi t \quad 1+\sin 0.25\pi t]^T$

Joint friction and external interference are:

$\xi=[q_1\dot{q}_1 0.3\sin t \quad q_2\dot{q}_2 0.3\sin t]$

The controller parameters are:

$k_p=diag[100,100]$, $k_v=diag[30,30]$,

$\Xi=diag[50,50,50,50]$, $\gamma=20$, $k_1=0.01$.

TD parameters are:

$r_{11}=r_{12}=3200$, $h_{110}=h_{120}=0.04$, $r_{21}=1500$, $r_{22}=2000$, $h_{210}=0.03$, $h_{220}=0.04$.

The weight coefficient matrix of LQR is selected as:

$Q=diag[100,10,10,10,10,10,10,10]$,

$R=\mathrm{diag}[100,10]$.

The initial values of joints and rotor of space manipulators with flexible joints are: $\theta_0(0)=0$ $q_1(0)=\theta_1(0)=0$, $q_2(0)=\theta_2(0)=0$.

The number of hidden layer elements in radial basis function network is $n=25$, and the initial weights of the network, the width of each basis function and the center of the basis function are randomly selected within (0 ~ 0.01).

A. Mass identification of end load

The initial parameters of the WRLSM quality estimator is $N_0=1000$ and $\hat{m}$ is the estimated load mass. The given initial mass is $3kg$ and the real mass is set to $9kg$. At this time, $\Delta M=2m_2=6kg$ is twice the mass of arm 2. The end load identification is shown in Fig. 3.

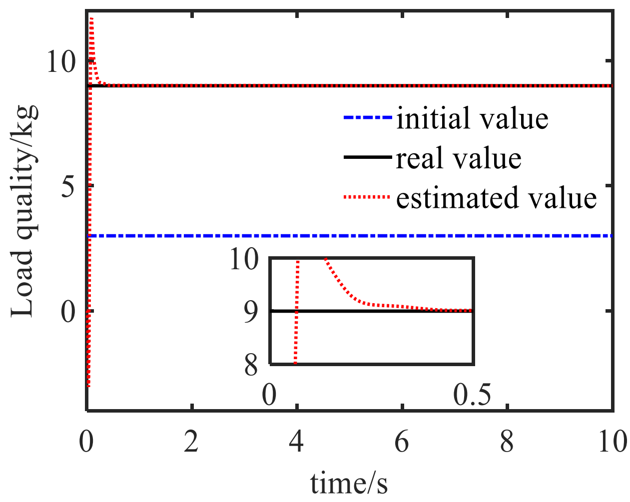

Fig.3. Estimation error value of neural network

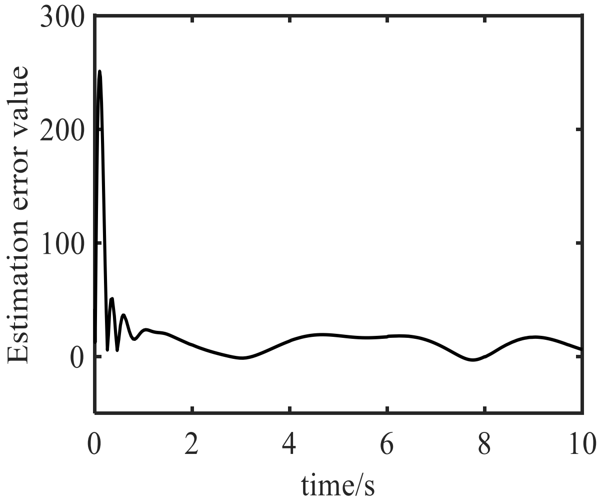

Fig.4. Load quality identification

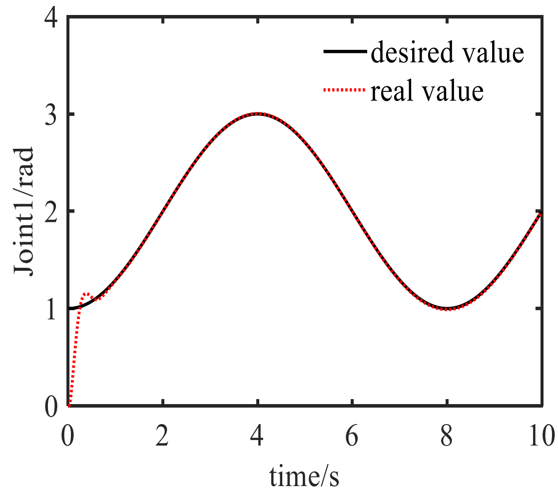

Fig.5. Joint angle position tracking (W-ANNCT)

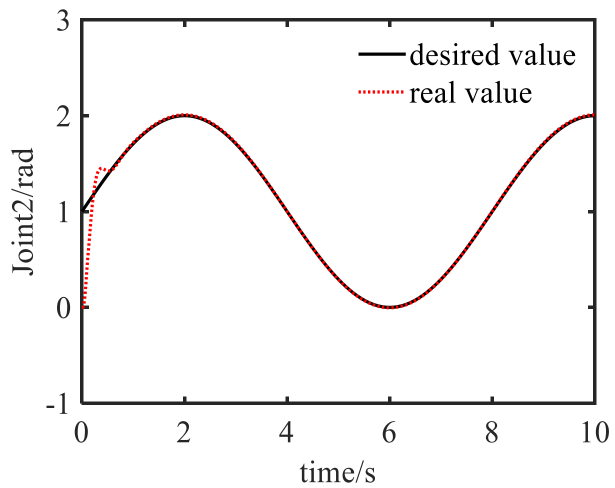

Fig.7. Joint angle position tracking (W-ANNCT)

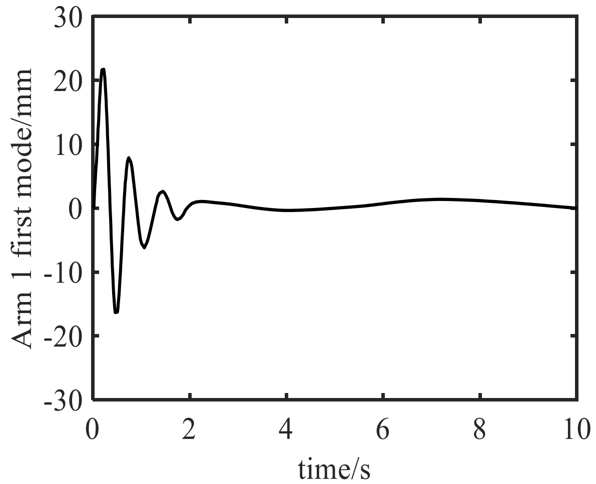

Fig.6. First order mode of flexible manipulators (W-ANNCT)

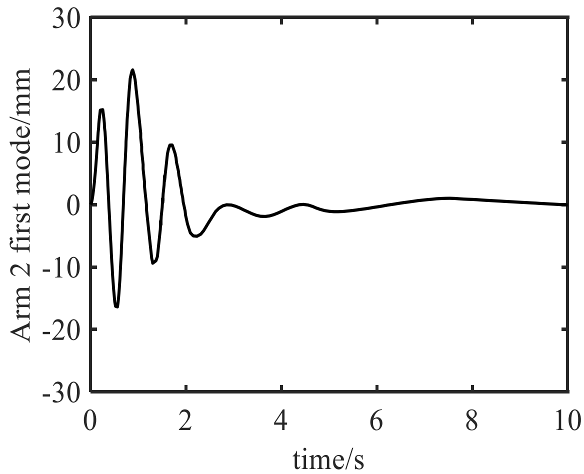

Fig.8. First order mode of flexible manipulators (W-ANNCT)

As can be seen from Fig. 4, when the error of the initial value of load mass is relatively large, the quality estimator quickly converges to the true value in about 0.2s, and the overshoot is small. This shows that the designed WRLSM quality estimator is effective and can accurately estimate the unknown quality when the initial quality error is large. It can be seen from Fig. 4 that the error of the neural network is very large at the beginning. After 1 s, the neural network can better compensate the nonlinear term.

B. Neural network adaptive control of variable load

In order to verify the effectiveness of the proposed adaptive neural network control algorithm based on calculated torque (ANNCT), and verify the influence of WRLSM quality estimator on the control effect. W-ANNCT algorithm using WRLSM quality estimator is represented; ANNCT is used to represent the control algorithm without WRLSM quality estimator. In order to reflect the advantages of the controller, a MLADRC [32] (modified linear active disturbance rejection controller) is used for comparison.

a) Unknown load small range uncertainty $\Delta M = 0.6kg$

When the uncertainty of the end load is small, such as $\Delta M = 0.2m_2 = 0.6kg$, the effectiveness of the proposed control algorithm is verified. Fig. 5,7 is the joint angle trajectory tracking diagram using W-ANNCT algorithm. Fig.6,8 is the first-order modal diagram of the arm using W-ANNCT algorithm. Fig. 9,12 is the joint angle trajectory tracking diagram using ANNCT algorithm. Fig. 10,13 is the first-order modal diagram of the arm using ANNCT algorithm. Fig. 11,14 is the joint angle trajectory tracking diagram using MLADRC algorithm.

As can be seen from Fig. 5,7 and Fig. 9,12, when the load uncertainty is $\Delta M = 0.2m_2 = 0.6kg$, whether the quality estimator is used or not, the proposed W-ANNCT algorithm or ANNCT algorithm can accurately track the actual trajectory within about 1s. Due to the small uncertainty of load, the control effect achieved by using W-ANNCT algorithm or ANNCT algorithm is similar, which shows that the designed ANNCT controller has good robustness and can realize better compensation control for model mutation caused by small load change. In the case of small load uncertainty, it can be seen from Fig. 6,8 and Fig. 10,13 that the first-order modal shape of the flexible arm is not violent and relatively similar. As can be seen from Fig. 11,14, when MLADRC algorithm is used, it is found that the effect is the worst, but it can still track the desired trajectory quickly.

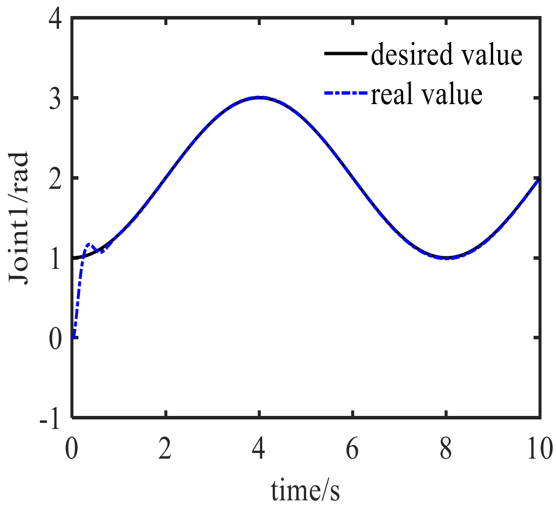

Fig.9. Joint angle position tracking (ANNCT)

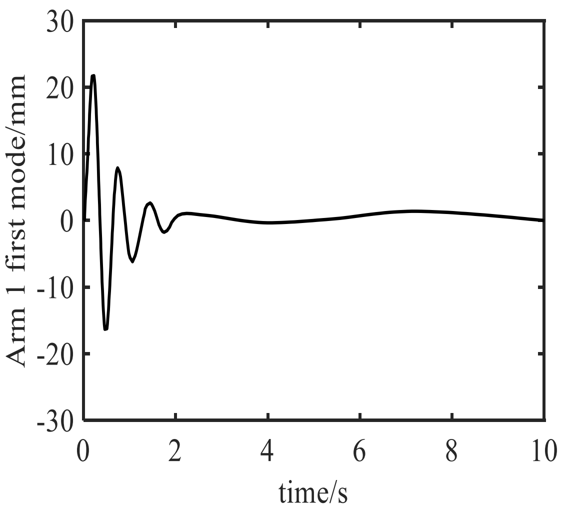

Fig.10. First order mode of flexible arm (ANNCT)

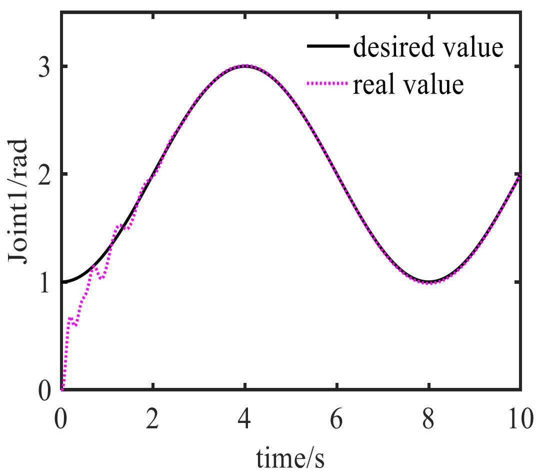

Fig.11. Joint angle position tracking (MLADRC)

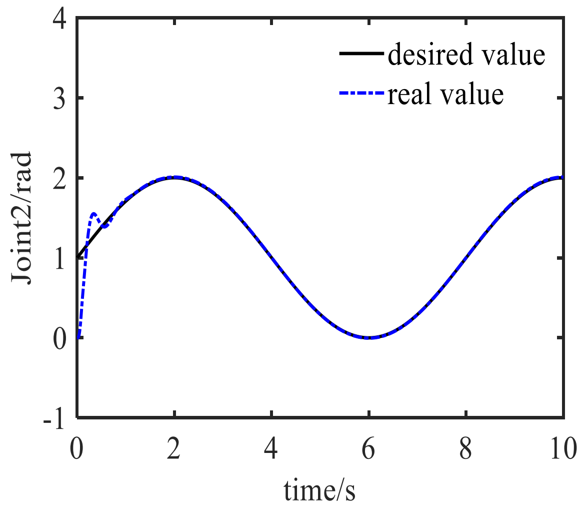

Fig.12. Joint angle position tracking (ANNCT)

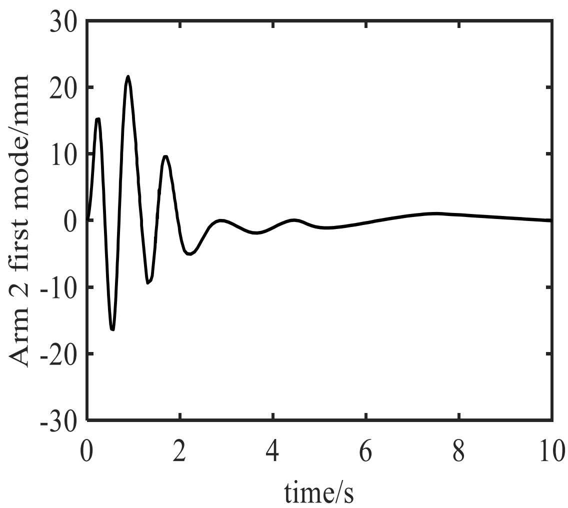

Fig.13. First order mode of flexible arm (ANNCT)

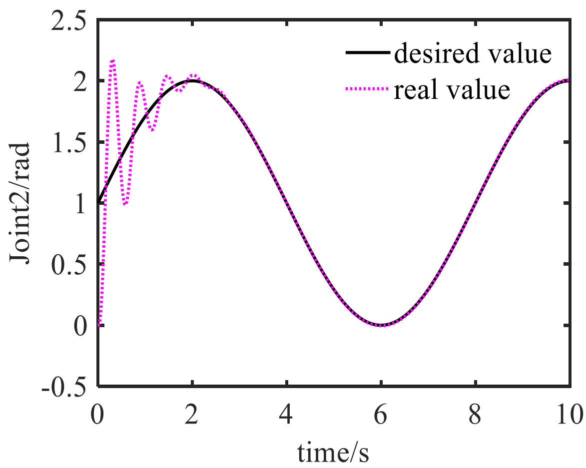

Fig.14. Joint angle position tracking (MLADRC)

C. Unknown load large range uncertainty $\Delta M = 6kg$

When the uncertainty of the end load is large, the change of the end load is twice the mass of the boom, the effectiveness of the proposed control algorithm is verified. Fig. 15,18 is the joint angle trajectory tracking diagram using W-ANNCT algorithm. Fig. 16,19 is the first-order modal diagram of the arm using W-ANNCT algorithm. Fig. 17,20 is the joint angle trajectory tracking diagram using ANNCT algorithm, and Fig. 21,24 is the first-order modal diagram of the arm using ANNCT algorithm. Fig. 22,25 is the joint angle trajectory tracking diagram using MLADRC algorithm.

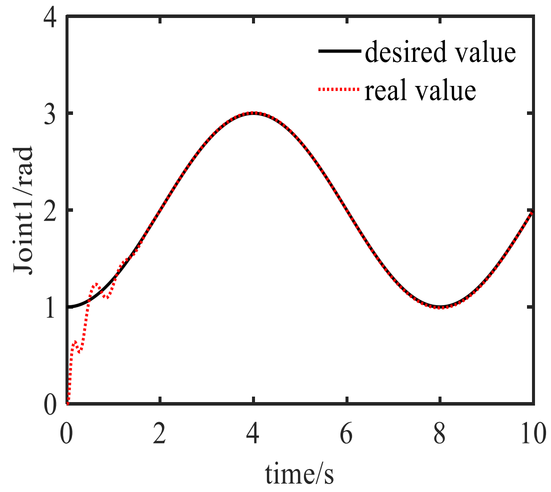

Fig.15. Joint angle position tracking (W-ANNCT)

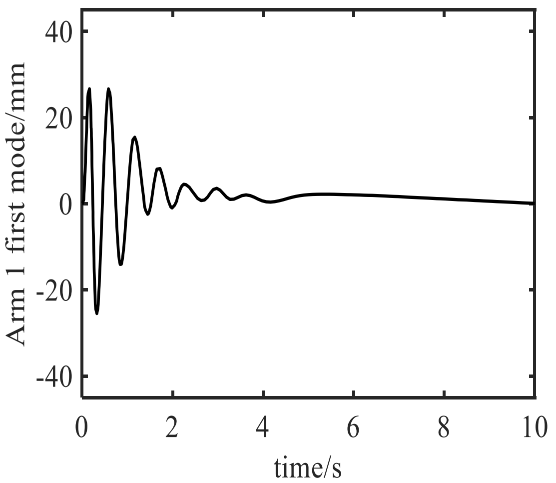

Fig.16. First order mode of flexible arm (W-ANNCT)

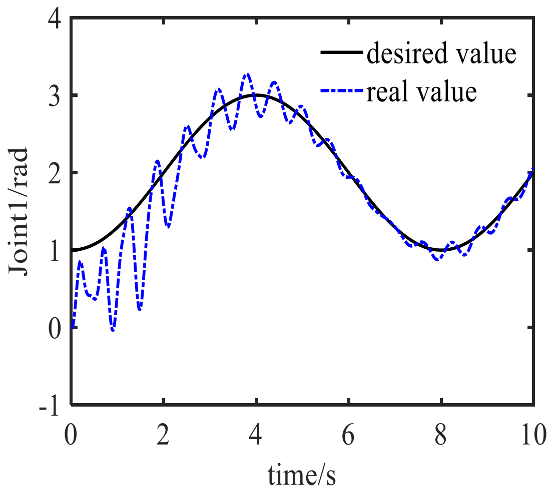

Fig.17. Joint angle position tracking (ANNCT)

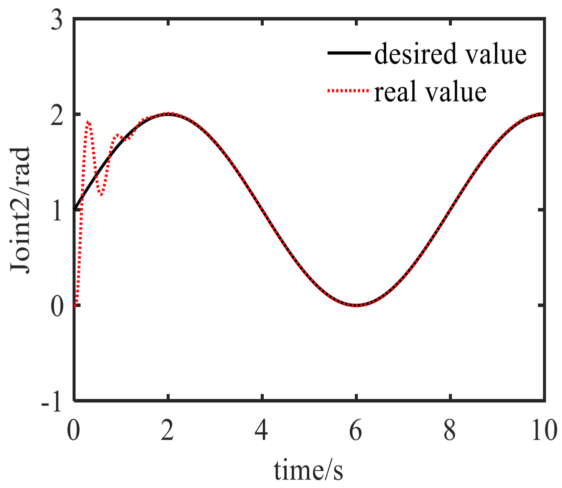

Fig.18. Joint angle position tracking (W-ANNCT)

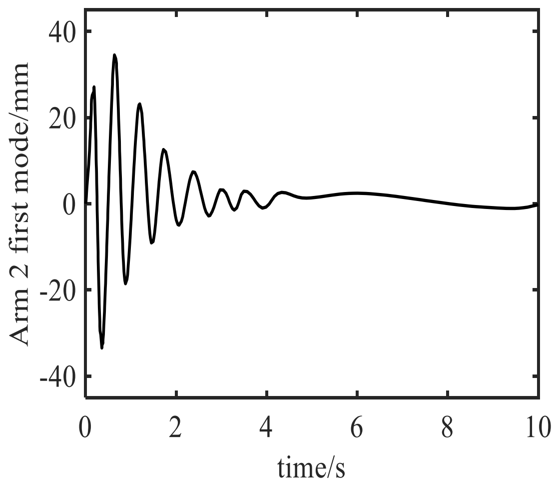

Fig.19. First order mode of flexible arm (W-ANNCT)

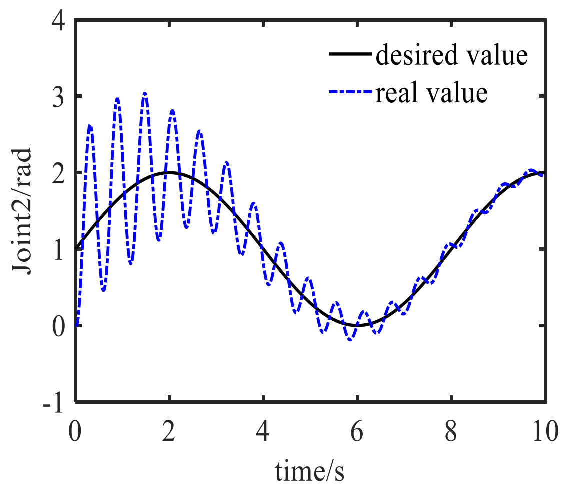

Fig.20. Joint angle position tracking (ANNCT)

It can be seen from Fig. 15,18 and Fig. 17,20 that the proposed two algorithms can gradually converge to the actual trajectory when the load uncertainty is $\Delta M = 2m_2 = 6kg$, which shows that the ANNCT algorithm is effective and still has good robustness when the load changes greatly. The proposed W-ANNCT algorithm can accurately track the actual trajectory in about 2s (Fig. 15,18). Although the ANNCT algorithm still does not track the desired trajectory accurately within 10s, it can achieve the gradual tracking and convergence of the desired trajectory. This shows that if the load uncertainty is large, the control performance obtained by using W-ANNCT algorithm is significantly better than that of ANNCT algorithm. Using quality estimator to estimate the unknown quality can effectively improve the control effect. It can be seen from the comparison between Fig. 16,19, and Fig. 21,24 that when the load is uncertain, the first-order modal vibration morphology of the flexible manipulators is obviously aggravated, and the modal vibration mode generated by W-ANNCT algorithm is better than ANNCT algorithm. As can be seen from Fig. 22,25, when the quality error of load estimation is large, MDADC algorithm cannot track the desired trajectory.

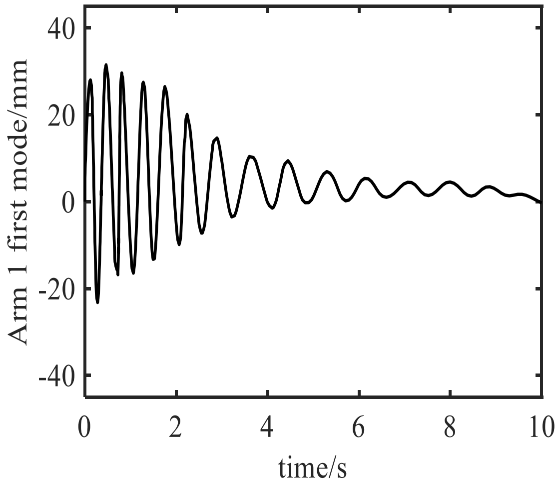

Fig.21. First order mode of flexible manipulators (ANNCT)

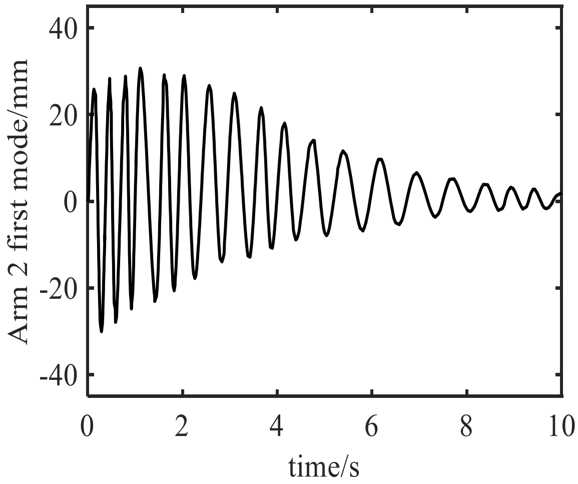

Fig.24. First order mode of flexible manipulators (ANNCT)

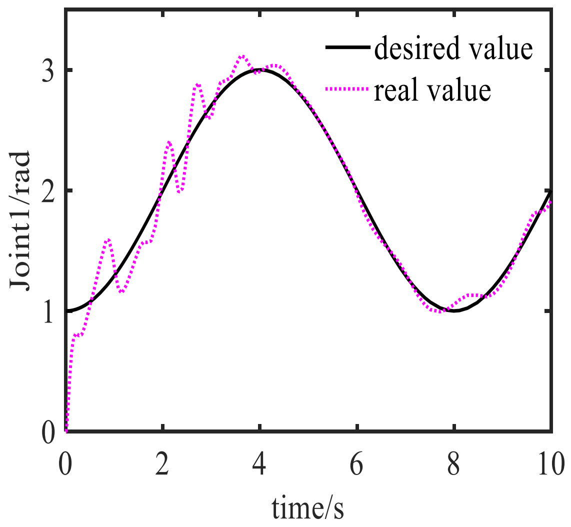

Fig.22. Joint angle position tracking (MLADRC)

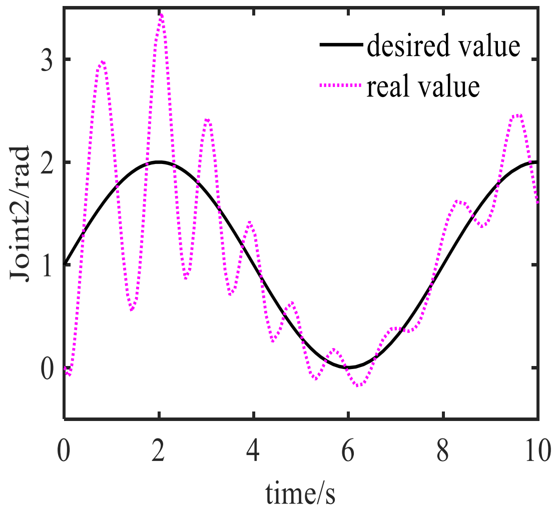

Fig.25. Joint angle position tracking (MLADRC)

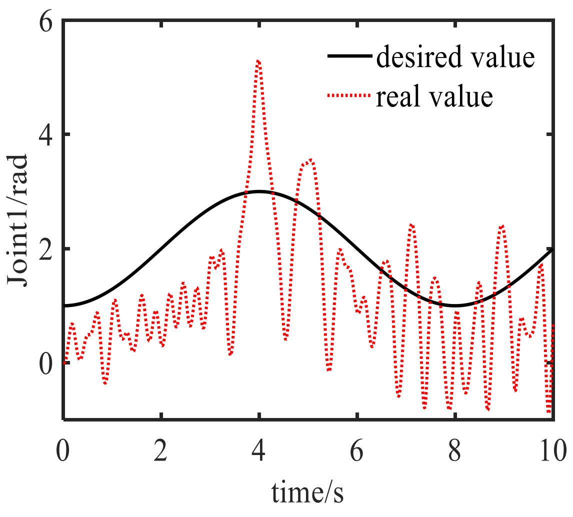

Fig.23. Joint angle position tracking ($\Delta M = 0.6kg$)

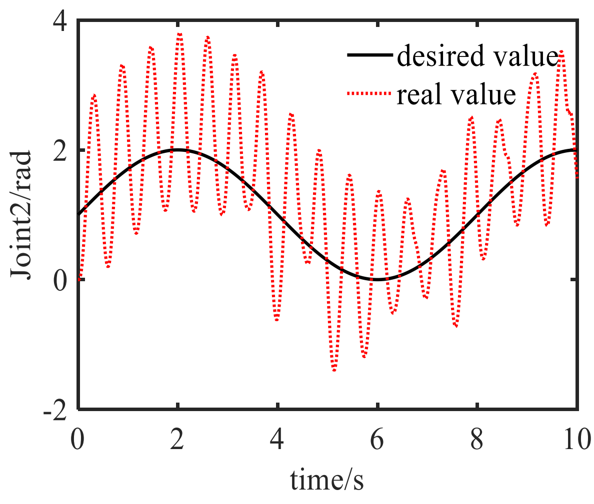

Fig.26. Joint angle position tracking ($\Delta M = 0.6kg$)

D. System simulation analysis when LQR control is closed

It can be seen from Fig.23,26 that if the fast variable LQR controller is turned off, the trajectory will oscillate severely and it is completely impossible to track the upper trajectory. This also proves the effectiveness of the designed LQR fast variable controller from the side.

V. CONCLUSION

An adaptive control method based on mass identification is proposed for the control of space flexible robots with non-cooperative target acquisition. The dynamic model of free-floating space flexible robot is established, and the model is decomposed into two dynamic submodels representing rigid and flexible characteristics by using singular perturbation theory. WRLSM algorithm is designed to realize online identification and real-time estimation of quality. A hybrid controller based on neural network and calculated torque is designed to realize complete decoupling of the nonlinear model. A linear quadratic regulator (LQR) controller is designed to suppress the elastic vibration of the flexible robot. The simulation results show that the designed controller can effectively deal with the quality change, and the control effect is effective.

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