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RBF Adaptive Control Strategy Based on Sub-Block Approximation Algorithm for Binocular Vision Robot

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Abstract

Intelligent robot not only can realize reservation on conduct and actions, but also can be understand the characteristics of the unknown environment and adapt to changes in the environment through their own "sensory system", robots get outside information mainly by vision, this paper take the joint robot of binocular robot vision system as control plant, pointing on the problem of the uncertainties that existed in the dynamic model of binocular vision robot may cause instability. This paper has proposed a sliding model control scheme with RBF neural network adaptive control strategy based on sub-block approximation algorithm, in this control method, sliding model control was used to control trajectory of the joints of robot, and utilize the RBF neural network to approximate the each uncertain in the dynamic model of robot. The simulation results show that compared with the RBF neural network adaptive control strategy based on integral approximation for uncertainness, the proposed control method has features with good position tracking.

Keywords*: Binocular vision robot, Sliding model control, Model approximation, RBF neural network, Sub-block approximation*

1. Introduction

With the development of science and technology, intelligent robot is the robot's developing direction, Intelligent robot not only can realize reservation on conduct and actions, but also can understand the characteristics of the unknown environment and adapt to changes in the environment through their own "sensory system" [1-2], Human access to the outside world, more than 80% of the information is from the visual system, also robots get outside information mainly by visual [3], in the field of industrial robot, vision system is mainly used for welding, painting, and handling in the production of measuring and positioning of workpiece. It's mainly consists of robot and visual systems. Multi-joint robot is a kind of wide application of robots, the vast majority of industrial robot and intelligent mobile robot is a multi-joint robot, which have multiple joint robotic arm [4], as the control plant, Robot system is a very complicated nonlinear system with the features of multiple input multiple output with time-varying, strong coupling and nonlinear dynamics [5], and there always existed modeling error and external disturbance in the robot and so forth, also its dynamic model has strong uncertainty, thus control the stability of the mechanical arm system is required highly [6], the control problem of robot has become the hotspot in the field of control [7].

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Sliding mode variable structure control is very suitable for nonlinear system, for discrete model of the system and uncertain system [8], which was proposed by the former Soviet union scholar Emelyanov, Utkin and Itkin in the early 1960s [9-11], the Sliding mode variable structure control scheme was widely used in motor, the control of complex systems, such as robots and spacecraft [12]. Also, Control method based on model is under the condition of known the precise mathematical model of the robot system to control it, but in practical engineering, because there are many uncertainty factors, this control method makes difficult to keep the trajectory tracking error convergence [13].

Due to the artificial intelligence neural network can approximate arbitrary precision nonlinear model, and the control performance can improve through the self-learning and compensation for modeling error, the development of which open up new ways to solve the problem of the robot control. So intelligent control based on neural network has been widely used in the manipulator adaptive control [14-22], Literature [14] has used the RBF neural network to identify the dynamics model coefficient matrix of the manipulator that has realized the manipulator trajectory tracking, but they does not take the influence of external disturbance into account. Reference [15] has adopted the RBF neural network to identify the whole system control input that has realized adaptive control, but there existed weakness in the proposed method that the friction model must be accurately known.

Considering the nonlinearity and uncertainty in the system ,this paper has proposed a RBF neural network adaptive control strategy based on sub-block approximation algorithm for binocular vision robot, in this strategy, sliding model control was used to control trajectory of the joints of robot, so that the stability and robustness can be improved, considering there existed uncertainties in the dynamic model of binocular vision robot that may cause instability, we utilize the RBF neural network to approximate the each uncertain in the dynamic model of robot. In order to verify the validity of the control algorithm, we realized the RBF neural network adaptive control strategy based on sub-block approximation algorithm in MATLAB.

This paper has been organized as follows, in the section two was the design of the binocular vision, section three has illustrated the principle of the RBF, the equation for manipulator with six joints was shown the section four, in the five section we has designed the Controller based on RBF with overall approach, RBF neural network adaptive control strategy based on sub-block approximation algorithm was designed in the six section, the seven section is numerical simulation.

2. Design of the Binocular Vision

We utilize the whole manipulators of binocular vision system on a FPGA chip, the FPGA is a kind of embedded processors that can realize parallel computing, the FPGA can be divided into different regions which can be controlled by different peripheral module, At the beginning of the FPGA, because of fewer resources, the FPGA can only be shown for glue logic and state machine control. with the development of the technology of FPGA, FPGA scale is bigger and bigger and power consumption is more and more low, now a single FPGA chip can own millions internal resources, we use the FPGA to constitute a complete system is not a problem. Because FPGA has the rich interface and interface type is adjustable, so FPGA can connect a number of different types of peripherals together, from the simple LED driver to the direct drive LCD liquid crystal display, from the SRAM, SDRAM to today's higher frequency DDR SDRAM control, From simple I2C communication, RS232 communication to the TCP/IP protocol, With the rapid development of FPGA, FPGA can now replace the MCU, DSP and ARM to be the core control unit of the embedded system.

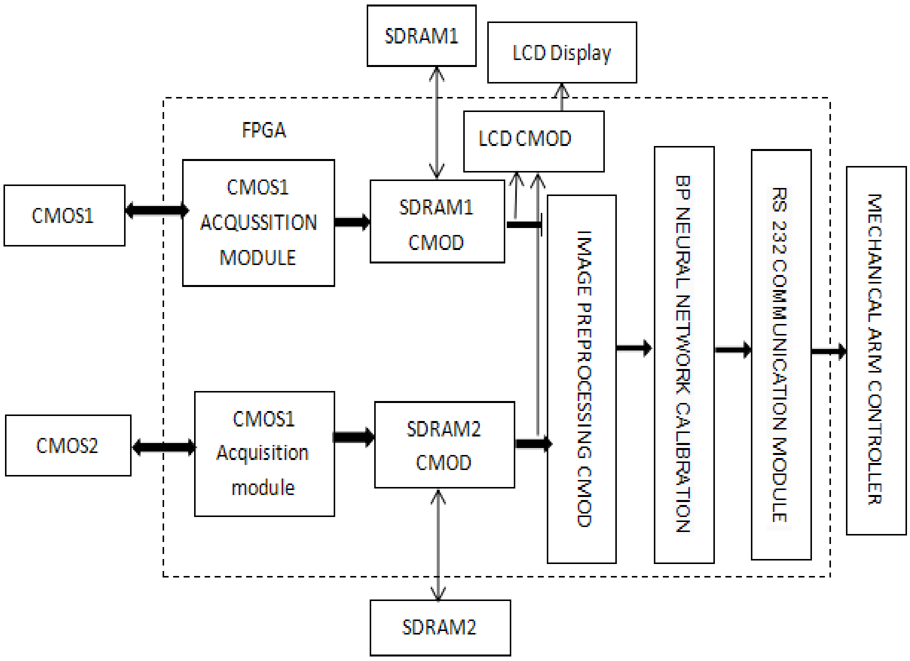

Figure 1. The Binocular Vision Positioning System

The binocular vision positioning system was shown in Figure 1, the binocular vision positioning system was consisted of Altera EP2C70F896C PGA, two OV7670 CMOS camera, two SDRAM, ADM320 RS-232, DV7123 LCD controller, LCD and so forth. System need to collect the image of the two cameras, and temporary store each frame image of collection data, then make preprocessing for each frame of the image, finally, the realize the positioning of the target object after the camera calibration methods. Processed or unprocessed images can be displayed on the LCD monitor real-time image, and at the same time display system monitoring function can be done. Location information after positioning can be transported to the mechanical arm controller through RS - 232 serial port communication and.

3. Radial Basis Function Neural Network

The radial basis function neural network is a neural network model, which is proposed by J. Moody and C. J. Darken in the late 1980 [23]. RBF network is a single hidden layer with three layer forward network, mapping from input to output is nonlinear, and mapping from the hidden layer of space to the output space mapping is linear, unit transformation function of hidden layer is the gaussian basis function, which is radial symmetric nonnegative nonlinear function for the center of attenuation.

Gaussian basis function value is a non-zero value in the input space limited range, RBF network is local approximation

RBF network structure was shown in Figure 2,from the RBF network structure we know that there have n input nodes and hidden nodes m and one output node in RBF network structure, structure by using RBF neural network approximation one object is shown in Figure 3 [24-25].

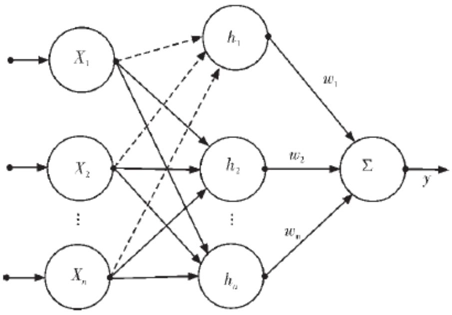

Figure 2. RBF Neural Network Structure

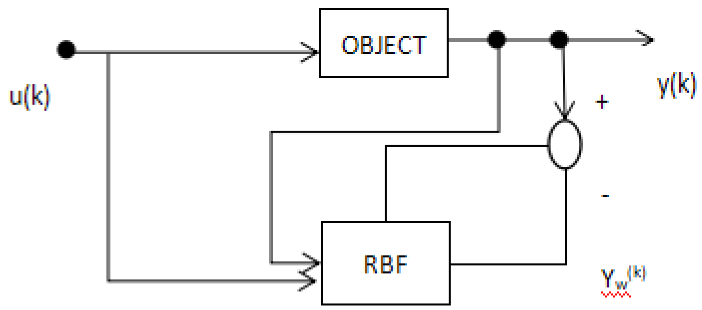

Figure 3. RBF Neural Network Approximation

Take gaussian function as the RBF network of radial basis function:

$$\varphi_i = g(\frac{\|x-c_i\|^2}{\sigma_i^2}), i = 1,2,3,\cdots,n \tag{1}$$

The ideal neural network output is:

$$f(x) = W\varphi(x) + \varepsilon = Wg(\frac{\|x-c_i\|^2}{\sigma_i^2}) + \varepsilon, i = 1,2,3,\cdots,n \tag{2}$$

4. Problem Statement

Supposed that the equation for manipulator with n joints is:

$$M(q)\ddot{q} + C\left(q,\dot{q}\right)\dot{q} + G(q) + F\left(\dot{q}\right) + \tau_d = \tau \tag{3}$$

Where, $M(q)$ is positive definite inertia matrix with $n\times n$, $C\left(q,\dot{q}\right)$ is inertia matrix with $n\times n$, $G(q)$ is inertia vector with $n\times 1$, $F\left(\dot{q}\right)$ is the friction force, τ_d is unknown External disturbance, τ is input of control.

Define the position tracking error as:

$$e(t) = q_d(t) - q(t) \tag{4}$$

Define error function as:

$$r = \dot{e} + \Lambda e \tag{5}$$

Where $\Lambda = \Lambda^{\mathrm{T}} > 0,$ then

$$\dot{q} = -r + \dot{q}_d + \Lambda e$$

$$M\dot{r} = M\left(\ddot{q}_d - \ddot{q} + \Lambda e\right) = M\left(\ddot{q}_d + \Lambda e\right) - M\ddot{q}$$
$$= M\left(\ddot{q}_d + \Lambda e\right) + C\dot{q} + G + F + \tau_d - \tau$$
$$= M\left(\ddot{q}_d + \Lambda \dot{e}\right) - Cr + C\left(\dot{q}_d + \Lambda \dot{e}\right) + G + F + \tau_d - \tau$$
$$= -Cr - \tau + f + \tau_d \tag{6}$$

Where:

$$f(x) = M\left(\ddot{q}_d + \Lambda \dot{e}\right) - Cr + C\left(\dot{q}_d + \Lambda \dot{e}\right) + G + F.$$

In practice, the model uncertainties f is unknown, so we need to approximate the Uncertainties

In this paper we adopt the RBF to approximate the uncertainties, according to equation of

$f(x)$, the input of RBF network is:

$$x = \left[e^T \quad \dot{e}^T \quad q_d^T \quad \dot{q}_d^T \quad \ddot{q}_d^T\right] \tag{7}$$

Define the control law as:

$$\tau = \hat{f} + K_v r \tag{8}$$

Where, $\hat{f}(x)$ is estimation value for $f(x)$.

The control law type (8) generation type (6), put the (8) into equation (6), we can get that:

$$M\dot{r} = -Cr - \hat{f} - K_v r + f + \tau_d = -\left(K_v + C\right)r + \tilde{f} + \tau_d = -\left(K_v + C\right)r + \zeta_0 \tag{9}$$

Where $\tilde{f} = f - \hat{f}, \zeta_0 = \tilde{f} + \tau_d$

5. Controller Based on RBF with Overall Approach

5.1. The Design of the Controller

Adopt the RBF neural network to approach the f, then the output of the RBF neural network is:

$$\hat{f}(x) = \hat{W}^T \varphi(x) \tag{10}$$

Taken

$$\tilde{W} = W - \hat{W}, \ \|W\|_F \le W_{\max} \tag{11}$$

Define the control law as:

$$\tau = \hat{f}(x) + K_v r - v = \hat{W}^T \varphi(x) + K_v r - v \tag{12}$$

Where v is the robust item that is used to overcome the approximation error by using RBF neural network.

Put the control law (11) into equation (6), then:

$$M\dot{r} = -\left(K_v + C\right)r + \tilde{w}^T \varphi\left(x\right) + \left(\varepsilon + \tau_d\right) + v = -\left(K_v + C\right)r + \zeta_1 \tag{13}$$

Where $\zeta_1 = \tilde{w}^T \varphi\left(x\right) + \left(\varepsilon + \tau_d\right) + v$.

5.2. Stability and Convergence Analysis

If there have $v(t)$, ε and τ_d will cause different convergence.

(1) Take $v(t) = 0$, there have ε and τ_d

Define Lyapunov function as:

$$L = \frac{1}{2} r^T M r + \frac{1}{2} tr\left(\tilde{W}^T F^{-1} \tilde{W}\right) \tag{14}$$

Then

$$\dot{L} = r^T M \dot{r} + \frac{1}{2} r^T \dot{M} r + tr\left(\tilde{W}^T F^{-1} \dot{\tilde{W}}\right) \tag{15}$$

Considering the robot features, we take:

$$\dot{\tilde{W}} = -F\varphi r^T \tag{16}$$

Then, the neural network adaptive law is:

$$\dot{\hat{W}} = F\varphi r^T \tag{17}$$

$$\dot{L} = -r^T K_v r + r^T\left(\varepsilon + \tau_d\right) \le -\mathrm{K}_{v\min}\left\|r\right\|^2 + \left(\varepsilon_N + b_d\right)\left\|r\right\| \tag{18}$$

where $\left\|\varepsilon\right\| \le \varepsilon_N, \left\|\tau_d\right\| \le b_d$.

When meet the convergence condition of the following $\dot{L} \le 0$:

$$\left\|r\right\| > \left(\varepsilon_N + b_d\right) / \mathrm{K}_{v\min} \tag{19}$$

(2) Take $v(t) = 0, \varepsilon = 0, \tau_d = 0$

Define Lyapunov function as:

$$L = \frac{1}{2} r^T M r + \frac{1}{2} tr\left(\tilde{W}^T F^{-1} \tilde{W}\right) \tag{20}$$

Then the neural network adaptive and control law are:

$$\tau = \tilde{W}^T \varphi\left(x\right) + K_v r \tag{21}$$

$$\dot{\hat{W}} = F\varphi r^T \tag{22}$$

Then

$$\dot{\mathrm{L}} = r^T M \dot{\mathrm{r}} + \frac{1}{2}\dot{M} r = -r^T K_v r \tag{23}$$

Due to the $\ddot{\mathrm{L}} = -r^T K_v \dot{r}$, then $\ddot{\mathrm{L}}$ is bounded, according to the barbalat lemma $\dot{\mathrm{L}} \to 0$, so, $\mathrm{r} \to 0$.

(3) Take $v(t)=0,$ and there have ε and τ_d, also the adaptive law is
Define Lyapunov function and control law same as (20) and (21), the adaptive law is:

$$\dot{\hat{W}} = F\varphi r^T - kF\|r\|\hat{W} \tag{24}$$

Then

$$\begin{aligned}\dot{L} &= -r^T K_v r + tr\tilde{W}^T\left(-\varphi r^T + k\|r\|\overline{w} + \varphi r^T\right) + r^T\left(\varepsilon + \tau_d\right) \\ &= -r^T K_v r + k\|r\| tr\tilde{W}^T\left(w - \overline{w}\right) + r^T\left(\varepsilon + \tau_d\right)\end{aligned} \tag{25}$$

Due to

$$tr\tilde{W}^T\left(W - \overline{W}\right) = \left(\tilde{W}, W\right)_F - \left\|\tilde{W}\right\|_F^2 \le \left\|\tilde{w}\right\|_F \|W\|_F - \left\|\tilde{W}\right\|_F^2 \tag{26}$$

So

$$\begin{aligned}\dot{L} &\le -K_{v\min}\|r\|^2 + k\|r\|\left\|\tilde{w}\right\|_F\left(W_{\max} - \left\|\tilde{W}\right\|_F\right) + \left(\varepsilon + \tau_d\right)\|r\| \\ &= -\|r\|\left(K_{v\min}\|r\| + k\left\|\tilde{w}\right\|_F\left(\left\|\tilde{W}\right\|_F - W_{\max}\right) - \left(\varepsilon + \tau_d\right)\right)\end{aligned} \tag{27}$$

In order to make $\dot{L} < 0$, we need that:

$$\|r\| > \frac{kW_{\max}^2 + \left(\varepsilon + \tau_d\right)}{K_{v\min}} \tag{28}$$

Or

$$\left\|\tilde{W}\right\|_F > W_{\max}/2 + \sqrt{kW_{\max}^2/4 + \left(\varepsilon + \tau_d\right)/k} \tag{29}$$

(4)There have ε and τ_d, and also consider the robust item $v(t)$
We design the robust item $v(t)$ as:

$$v = -\left(\varepsilon + \tau_d\right)\operatorname{sgn}(r) \tag{30}$$

Take the (12) as control law, and adaptive law for RBF is (18).
Define Lyapunov function as:

$$L = \frac{1}{2}r^T M r + \frac{1}{2}tr\left(\tilde{W}^T F^{-1}\tilde{W}\right) \tag{31}$$

Then

$$\dot{L} = r^T M\dot{r} + \frac{1}{2}r^T\dot{M}r + tr\left(\tilde{W}^T F^{-1}\dot{\tilde{W}}\right) \tag{32}$$

Because

$$r^T\left(\varepsilon + \tau_d + v\right) = r^T\left(\varepsilon + \tau_d\right) + r^T v = r^T\left(\varepsilon + \tau_d\right) - \|r\|\left(\varepsilon + \tau_d\right) \le 0 \tag{33}$$

Then

$$\dot{L} \le 0 \tag{34}$$

6. RBF Neural Network Adaptive Control Strategy Based on Sub-Block Approximation Algorithm

6.1 Control Law

Take the control law as:

$$\tau = \hat{W}^T \varphi(x) + K_v r - v \tag{35}$$

Take equation (30) as robust item v.

By equation (6), $f(x)$ can be written as:

$$f(x) = M(q)\zeta_1(t) + C\left(q, \dot{q}\right)\zeta_2(t) + G(q) + F\left(\dot{q}\right) \tag{36}$$

Where $\zeta_1(t) = \ddot{q}_d + \Lambda \dot{e},\ \zeta_2(t) = \dot{q}_d + \Lambda \mathrm{e}$.

Adopt the RBF neural network to approach the uncertainties based on sub-block approximation algorithm, we can approximate the each factors based on sub-block approximation algorithm:

$$\hat{M}(q) = \hat{M}_M^T \varphi_M(q),\quad \hat{C}\left(q, \dot{q}\right) = \hat{M}_V^T \varphi_V\left(q, \dot{q}\right),$$
$$\hat{G}(q) = \hat{M}_G^T \varphi_G(q),\quad \hat{F}\left(\dot{q}\right) = \hat{M}_F^T \varphi_F\left(\dot{q}\right). \tag{37}$$

Then

$$\hat{f}(x) = \begin{bmatrix} \hat{W}_M^T \zeta_1(t) & \hat{W}_V^T \zeta_2(t) & \hat{W}_G^T & \hat{W}_F^T \end{bmatrix} \begin{bmatrix} \varphi_M \\ \varphi_V \\ \varphi_G \\ \varphi_F \end{bmatrix} \tag{38}$$

Where $\varphi(x) = \begin{bmatrix} \varphi_M \\ \varphi_V \\ \varphi_G \\ \varphi_F \end{bmatrix}, \hat{W}^T = \begin{bmatrix} \hat{W}_M^T & \hat{W}_V^T & \hat{W}_G^T & \hat{W}_F^T \end{bmatrix}$.

Define the adaptive law as:

$$\dot{\hat{W}}_M = F_M \varphi_M r^T - k_M F_M \|r\| \hat{W}_M \tag{39}$$

$$\dot{\hat{W}}_V = F_V \varphi_V r^T - k_V F_V \|r\| \hat{W}_V \tag{40}$$

$$\dot{\hat{W}}_G = F_G \varphi_G r^T - k_G F_G \|r\| \hat{W}_G \tag{41}$$

$$\dot{\hat{W}}_F = F_F \varphi_F r^T - k_F F_F \|r\| \hat{W}_F \tag{42}$$

Where $k_M > 0, k_V > 0, k_G > 0, k_F > 0$.

6.2. Numerical Simulation

In order to verify the effectiveness of the proposed algorithm in this paper, take the robot arm system with two joints as the research object, we realized the RBF neural network adaptive control strategy based on sub-block approximation algorithm in MATLAB, the dynamics model for the robot arm system with two joints was:

$$M(q)\ddot{q}+V\left(q,\dot{q}\right)\dot{q}+G(q)+F\left(\dot{q}\right)+\tau_d=\tau \tag{43}$$

Where

$$M(q)=\begin{bmatrix} p_1+p_2+2p_3\cos q_2 & p_2+p_3\cos q_2 \\ p_2+p_3\cos q_2 & p_2 \end{bmatrix},$$

$$V\left(q,\dot{q}\right)=\begin{bmatrix} -p_3\dot{q}_2\sin q_2 & -p_3\left(\dot{q}_1+\dot{q}_2\right)\sin q_2 \\ p_3\dot{q}_1\sin q_2 & 0 \end{bmatrix}$$

$$G(q)=\begin{bmatrix} p_4 g\cos q_1+p_5\cos\left(q_1+q_2\right) \\ p_5 g\cos\left(q_1+q_2\right) \end{bmatrix},$$

$$F\left(\dot{q}\right)=0.02\,\mathrm{sgn}\left(\dot{q}\right),\quad \tau_d=\left[0.2\sin(t)\quad 0.2\sin(t)\right]^T.$$

Control algorithm is realized by using Simulink and S function. Adopt the RBF neural network adaptive control strategy based on integral approximation for uncertainness, in this algorithm take (12) as the control law,(17) as adaptive law, in the RBF neural network adaptive control strategy based on sub-block approximation algorithm, take (35) as the control law,(39-42) as adaptive laws .The simulation results were shown in fgiure1 to Figure 6.

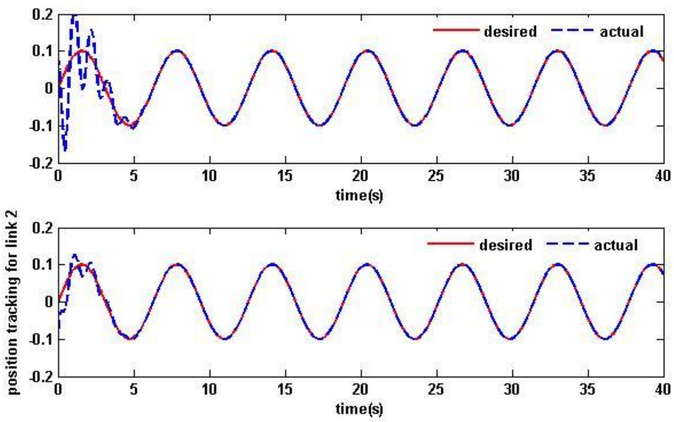

Figure 1. Position Tracking by Using the RBF Neural Network Adaptive Control Strategy Based on Integral Approximation for Uncertainness

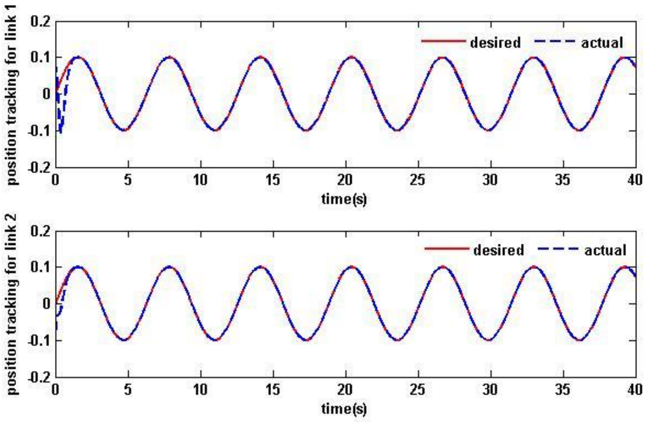

Figure 2. Position Tracking by Using the RBF Neural Network Adaptive Control Strategy Based on Sub-Block Approximation Algorithm

From the Figure 1 and Figure 2 we can find that, compared with the RBF neural network adaptive control strategy based on integral approximation for uncertainness, the proposed control method has features with better convergence at 0-5S, there have chattering phenomenon in the RBF neural network adaptive control strategy based on integral approximation for uncertainness.

From the simulation results the following conclusion can be obtained: the proposed control method has features with good position tracking and smooth movement.

7. Conclusions

Aiming at the uncertainties that existed in the dynamic model of robot may cause instability. This paper has proposed a RBF neural network adaptive control strategy based on sub-block approximation algorithm, in this strategy, sliding model control was used to control trajectory of the joints of robot, so that the stability and robustness can be improved, considering there existed uncertainties in the dynamic model of binocular vision robot that may cause instability, we utilize the RBF neural network to approximate the each uncertain in the dynamic model of robot. In order to verify the validity of the control algorithm, we realized the RBF neural network adaptive control strategy based on sub-block approximation algorithm in MATLAB. From the simulation results the following conclusion can be obtained: Compared with the RBF neural network adaptive control strategy based on integral approximation for uncertainness, the proposed control method has features with good position tracking and smooth movement.

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