TELKOMNIKA, Vol.12, No.2, June 2014, pp. 343~348
ISSN: 1693-6930, accredited A by DIKTI, Decree No: 58/DIKTI/Kep/2013
DOI: 10.12928/TELKOMNIKA.v12i2.2112

Self-learning PID Control for X-Y NC Position Table with Uncertainty Base on Neural Network

Hu Xiaoping*, Wang Chao, Zhang Wenhui, Ma Jing
Institute of Technology,Lishui University
China -323000, Telp 0578-2271250, Fax 0578-2271250
*Corresponding author, e-mail: 715703595@qq.com

Abstract

An adaptive radical basis function (RBF) neural network PID control scheme for X-Y position table is proposed by the paper. Firstly, X-Y position table model is established, controller based on neutral network is used to learn adaptive and compensate uncertainty model of X-Y position table, neutral network is used to study model. PID neural network controller base on augmented variable method is designed. PID controller is used as assistant direction error controller, neural network parameters base on stochastic gradient algorithm can be adjust adaptive on line. The simulation results show that the presented controller has important engineering value.

Keywords: *RBF neural network; Self-learning control; X-Y NC position table; PID control*

1. Introduction

Along with the computer and advanced control technology development, the high precision digital motor drive technology has become the mainstream of the development of numerical control (NC) table. X-Y NC table is a plane control system in two dimensional spaces. It can not only complete two dimensional plane processing, also can be used as a large prototype machine for NC table、robots and other equipment. But the NC table has certain nonlinear and coupling characters, so if the higher control accuracy is need, the traditional PID control technology is difficult to meet the higher control accuracy requirements [1]-[2]. To eliminate these nonlinear factors of X-Y NC table, some advanced control strategies are used for the nonlinear system [3]-[5]. For example: adaptive control and robust control [6]-[7], fuzzy control [8]-[13], neural network control, et al [14]-[17].

The nonlinear uncertain problems of system are considered by paper, adaptive control strategy can achieve good control effect, but the control strategy is difficult to copy with the no-linearization parameter of system. “Chattering” problem of variable structure control can not be eliminated. Robust control strategy need the upper bound of uncertain parts .Because neural network has good learning ability, neural network can approach uncertainty model of the nonlinear system. Neural network control strategy is used more and more widely in the nonlinear system.

Wei [18], Ma [19] put forward fuzzy adaptive control scheme, but there are too many rules of fuzzy logic to be designed, the calculation with the number of rules increase the calculation burden. If rules are too little, the fuzzy adaptive control scheme can’t ensure the control accuracy. Wen [20] put forward neutral network control scheme for the X-Y table, but the back-propagation algorithm need large amount of calculation, so it is difficult in engineering application. Wang [21] proposed a robust adaptive control method for X-Y table, but this method requires the upper bound of some uncertain system.

According to the defect of these control methods, the radial basis function (RBF) neural network Self-learning control strategy is put forward for uncertainty X-Y position table system by the paper. Firstly, the X-Y position table shaft system dynamics model is established, and the neural network PID controller base on augmented variable value method is designed, because of good approximation ability of neural network, RBF neural network is used to achieve self-learning control. Adaptive adjustment law of the network weights and hidden layer parameters is designed by the improvement stochastic gradient algorithm; the improvement algorithm can improve the learning speed. PID controller is main controller in the early stage of control.

Received January 13, 2014; Revised April 17, 2014; Accepted May 2, 2014

Gradually, neural network becomes main controller by learning. At last, simulation results show that the proposed scheme is effective and has the higher control accuracy.

2. Dynamic Equation of X-Y Position Platform

X-Y NC positioning table system is shown in figure 1. The system consist of the ball screw, servo driver, servo motors, industrial control equipments, motion control cards and the code disk system, et al.

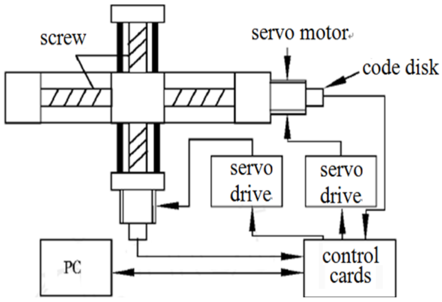


Figure 1. X-Y Position platform

Dynamic model of motor is ignored, inertial force and friction force and other disturbance are considered by the paper in the operation process of the table, system dynamics model can be written as [21]:

$$D\ddot{x}+C\dot{x}+F=\tau \tag{1}$$

Where, $\dot{x}$, $\ddot{x}$ are defined as the system movement speed and acceleration separately. D is defined as positioning table quality. x is defined as screw with sliding block displacement; $C\dot{x}$ is defined as viscous friction; C is defined as viscous friction coefficient, F is defined as static friction force and coulomb friction force and the friction Stribeck effect; τ is defined as motor output torque.

3. Designed of PID Controller base on Neural Network

Set $H=C\dot{x}+F$, then the dynamic model can be written as

$$D\ddot{x}+H=\tau \tag{2}$$

System (2) does not exist unmodeled dynamics and friction force; the following designed controller (3) can guarantee the stability of the system.

$$\tau=D(\ddot{x}+K_pe+K_d\dot{e})+H \tag{3}$$

Where, $e=x_d-x$ is defined as position error vector, x_d is defined as the desired position, K_p and K_d are defined as the feedback gain matrix.

The stability of the system based on the Lyapunov theory can be guaranteed by the controller (3). However, accurate model of X-Y NC table system is difficult to get in practice engineering; the ideal model can only be built. If the system estimated model are defined as $\hat{D}$ and $\hat{H}$.

The controller of the estimated model is designed as follows:

$$\tau=\hat{D}(\ddot{x}+K_pe+K_d\dot{e})+\hat{H} \tag{4}$$

The control law (4) and control law (5), that is

$$\ddot{e}+K_d\dot{e}+K_pe=\hat{D}^{-1}[\Delta D\ddot{x}+\Delta H] \quad (5)$$

Where $\Delta D = D-\hat{D}$, $\Delta H = H-\hat{H}$ .Uncertainty modeling of system will decline control performance.

To solve nonlinear effect of the X-Y table, good nonlinear approximation ability of the neural network is considered by the paper. Further, because RBF neural network is local generalization network, so controller base on RBF neural network can greatly speed up the learning speed and avoid local minimum problem.

The X-Y NC table of the nonlinear dynamic model (2) can be written as:

$$\tau = D\ddot{x}+H = f(\ddot{x},\dot{x},x) \quad (6)$$

Where, the total control τ consist of PID feedback controller τ_{PD} and RBF neural network controller τ_{NN} .

PID feedback controller is designed

$$\tau_{PD} = K_d\dot{e}+K_pe \quad (7)$$

RBF neural network controller is designed

$$\tau_{NN} = M(\ddot{x},\dot{x}_d,x_d,o) \quad (8)$$

The total controller is designed

$$\tau = \tau_{PD}+\tau_{NN} \quad (9)$$

The control system structure is designed as follow:

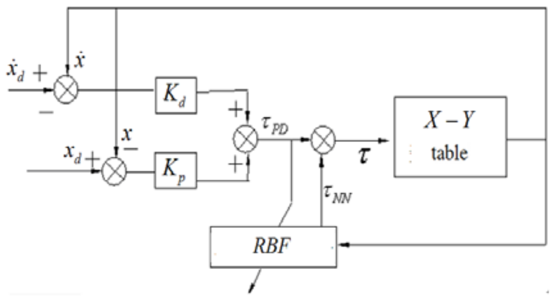


Figure 2. Neural network Self-learning control system

Where, PID feedback controller plays main control function in begin stage, neural network belongs to learn stage. at this time, neural network controller can not complete learning, error should be bigger. But PID feedback controller participate in compensation control, the combination controller ensure that the system is stable. So, as τ_{NN} learning, control function of τ_{PD} become more and more small.

Where, RBF network local generalization based on stochastic gradient method is used. Gaussian function is used as the membership function of neural network hidden layer, then the output of hidden nodes is [22]

$$o_j^{(1)}(k)=\exp(-\frac{\| X-c_j \|^2}{\sigma_j^2}) \quad (10)$$

Where, c is the center of the basis function, σ is the width of the basis function.

The output of the output layer is

$$o_i^{(2)}(k)=\sum_{j=1}^{m} w_{ij}(k)o_j^{(1)}(k) \quad (i=1,2) \tag{11}$$

Where, $w_{ij}(k)$ is weights of connection hidden layer and output layer.
The output of the output layer is

$$y(k)=\sum_{j=1}^{m} W_{ij}(k)\phi_j(k) \quad (i=1,2) \tag{12}$$

RBF neural network learning error is defined

$$E=\frac{1}{2}\left[y(k)-y_d(k)\right]^T\left[y(k)-y_d(k)\right] \tag{13}$$

The error signal for online learning is defined

$$J(k)=\frac{1}{2}\sum_{i=1}^{2} E_i^2(k) \tag{14}$$

Network parameters updating equations are designed as follows:

$$w(k+1)=w(k)-\mu_w\frac{\partial}{\partial w}J(k) \tag{15}$$

$$c(k+1)=c(k)-\mu_c\frac{\partial}{\partial c}J(k) \tag{16}$$

$$\sigma(k+1)=\sigma(k)-\mu_\sigma\frac{\partial}{\partial \sigma}J(k) \tag{17}$$

Where , μ_w, μ_c and μ_σ is parameters of learning law. Network convergence can be ensured by the above parameters update algorithm.

4. Simulation and Analysis

The effectiveness of the control algorithm is illustrated by this paper, parameters of dynamic model are $D=15$, $C=8$.

The desired trajectory of X and Y axes for X-Y NC table system are:

$$x_{dX}=2+\cos 1.5t\ ; \qquad x_{dY}=2+\sin 2t$$

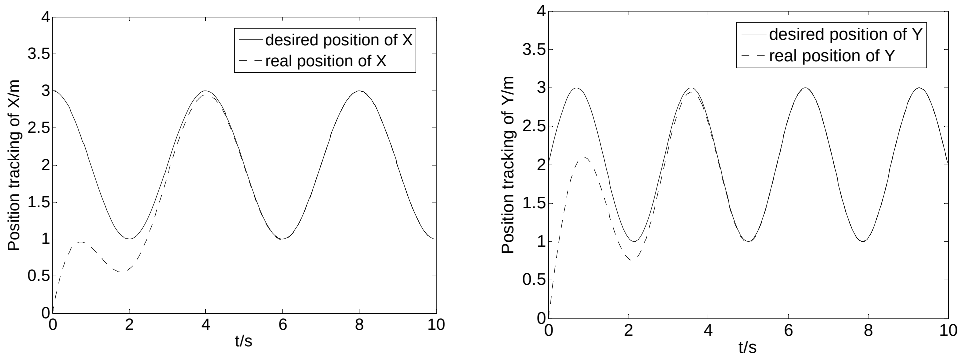
PD controller gains are: $K_p=\mathrm{diag}\{20,20\}$; $K_d=\mathrm{diag}\{30,30\}$

Parameters of controller are: $\mu_w=0.6$, $\mu_c=0.5$, $\mu_\sigma=0.5$.

X-Y NC table system movement initial values are zero. The simulation results as follow. The Figure 3 - Figure 6 are trajectory tracking graph and tracking error curve graph in this scheme, Figure 7 - Figure 8 are control moment graph.

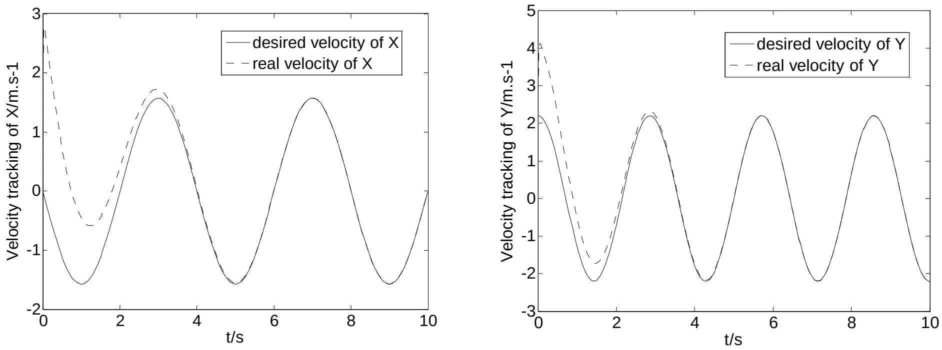
As are shown from Figure 3, even in the initial position errors are larger, RBF neural network feedforward PID controller can still track fastly expected position trajectory in a relatively short time (t=5s); As can be seen from the figure 4 in the initial velocity error larger cases. Neural network PID controller still can guarantee the precise tracking speed at about t = 4s. Control moment is not big , as can be shown from the Figure 5.

RBF neural network is still in a learning period in initial stage in the control process, at this time, neural network controller with conventional PID feedback controller work together to meet tracking error precises of the joint angle, with learning, neural network controller can achieve better control effect.



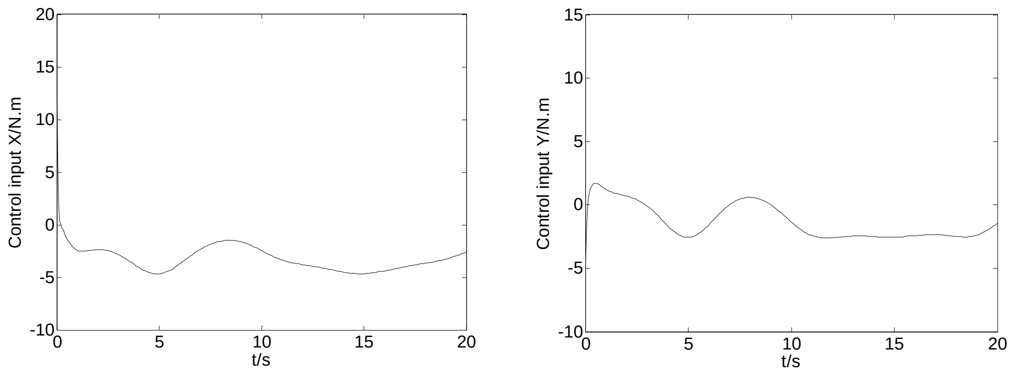
(a) X position trajectory tracking (b) Y position trajectory tracking

Figure 3. Position trajectory tracking curves of X-Y table



(a) X speed trajectory tracking (b) Y speed trajectory tracking

Figure 4. Velocity trajectory tracking curves of X-Y table



(a) Control input curves of X (b) Control input curves of Y

Figure 5. Control input curves of X-Y table

5. Conclusion

The trajectory tracking control problems of uncertain X-Y NC table system with uncertainty are considered. Self-learning control strategy based on radial basis function neural network is proposed by this paper.

1) Neural network PID hybrid controller based on the augmented variable method is designed. the control precision of the system is ensured, this method can speed up errors convergence in early phase.
2) Improved stochastic gradient algorithm is designed to ensure online real-time adjustment of

the network parameters, the improved algorithm can speed up the learning speed.
3) The control mechanism is analysised and simulated by the paper, simulation results show that the control method is effective.

This control scheme can achieve good control effect, and it has higher application value.

Acknowledgments

Project supported by Zhejiang Provincial Natural Science Foundation (No. LY14F030005), Zhejiang Provincial Education Department Science Research Project (No.Y201330000). Zhejiang Provincial Science and Technology Project (No. 2013C3110)

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