# **Neural Network Adaptive Control for X-Y Position Platform with Uncertainty**

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## Abstract

An improvement neural network adaptive control strategy is put forward for X-Y position platform with uncertainty by the paper. Firstly, dynamics model of X-Y position platform is established. Then, RBF neural network with good learning ability is used to approach non-linear system. The early period control accuracy of the problem is considered by the paper, because good precision in the early period is difficult to be obtained by neural network controller, so PID controller is designed to compensate control. An improvement dynamic optimization adjustment algorithm of network weights is designed to speed up the learning speed. Simulation results show that the control method is more effective to improve the control precision and real-time and has a good application value.

Keywords: Neural network; X-Y position platform; PID controller; Optimized learning algorithm

## 1. Introduction

With the development of computers and advanced control technology. High-precision digital drive technology has become the mainstream in the development of the numerical control (NC) machine tools. The X-Y NC platform is a flat with two-dimensional space control system. It is not only able to complete the two-dimensional space plane processing, and can be used as the prototype of the NC machine tools (for example, robots and other large equipment). The NC platform has a certain degree of nonlinear and coupling, and therefore obtains higher control accuracy; it is difficult for the traditional PID control technology to meet the control requirements ref.[1]-[4]. To eliminate the influence of these non-linear factors, all sorts of presented control strategies such as adaptive control, fuzzy control and neural network control have been used on X-Y NC platform ref. [5]-[10].

For these nonlinear uncertain systems, the adoption of adaptive control method can achieve better results, but the ascertainment of the linear parameters and the regression matrix require large number of calculations, which affect its application. As the neural network control is not required to know the exact model of control object, at the same time the controller is simple and has learning ability, it is increasingly widely used in the field of space control. Now people have made some research results.

Ref. [11]-[12] present a fuzzy control scheme, but there are too much fuzzy rules, which will lead to the computational geometry multiply, and too little cannot guarantee the accuracy of control. Ref [13] presents X-Y platform control scheme of Elman neural network, but there are disadvantages of large amount of calculation and time-consuming of using back-propagation algorithm, it is difficult to guarantee real-time and need offline training. Ref [14] presents robust adaptive control for X-Y platform, which needs a certain degree of uncertainty on the system boundary, and it is not the best control method.

For the above shortcomings, a radial basis function (RBF) neural network adaptive PID control strategy is put forward for X-Y position platform with uncertainty. Firstly, dynamics model of X-Y position platform is established. Then, RBF neural network with good learning ability is used to adaptive control non-linear system. The good control accuracy is difficult to be obtained in the early period of study, so PID controller is designed as a compensation controller. Dynamic optimization algorithm of network weights is designed to speed up the learning speed and the adjustment velocity.

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#### 2. Dynamic Equation of X-Y Position Platform

The Figure 1 shows the schematic diagram of X-Y position platform system.



Figure.1 X-Y Position platform

The motor dynamics is ignored by the paper, the inertia force friction and other disturbances are considered, the system dynamics model from each axis is obtained by ref. [14].

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

Where,  $\dot{q}$ ,  $\ddot{q}$  represent the velocity and acceleration of the system movement respectively. D is designed as the quality of the positioning platform; q is designed as the displacement of the screw carried by the slider;  $C\dot{q}$  is designed as the viscous friction; C is designed as the viscous friction coefficient, F are designed as the static friction and coulomb friction;  $\tau$  is designed as the output torque of motor.

## 3. Designed of PID Controller Base on Neural Network

If  $H = C\dot{q} + F$ , then the above dynamic model can be written as

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

Augmented variable input method is used for the above dynamic model. Error vector is defined as  $e = q_d - q$ ,  $q_d$  is the desired trajectory, unmolded dynamics isn't considered in the situation of the system (2), the following controller(3) can guarantee the system stability.

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

Where,  $K_p$ ,  $K_d$  is defined as feedback gain matrix. However, the platform model is difficult to get accurately in practice; the ideal nominal model can be created. If the system nominal model is expressed as  $\hat{D}$ ,  $\hat{H}$ .

Then the control law design is designed as :

$$\tau = \hat{D}(\ddot{q} + K_{p}e + K_{d}\dot{e}) + \hat{H}$$
(4)

To put the control law (4) into the control law (5), it can be obtained:

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

Where,  $\Delta D = D - \hat{D}, \Delta H = H - \hat{H}$ .

From the above equation, as can be known that the uncertainty of system modeling will lead to the degradation of control performance.

The good learning ability of neural network is considered to solve the nonlinear effects of X-Y NC platform; controller based on neutral network is designed. A partial generalization of RBF network is chosen to accelerate the learning speed and to avoid local minima value problems ref. [16].

According to the nonlinear dynamic model of the X-Y NC platform (2), it can be obtained:

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

The total control input  $\tau$  contains  $\tau_{\rm PD}$  and  $\tau_{\rm NN}$ . The PID feedback controller is designed as:

$$\tau_{PD} = K_d \dot{e} + K_p e \tag{7}$$

The RBF neural network controller is designed as:

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

Where,  $\phi$ : output hidden layer, *b*: node threshold.

$$\tau = \tau_{PD} + \tau_{NN} \tag{9}$$

The structure of control system is shown in Figure 2



Figure 2. Neural network PID control system

Because the neural network cannot fully complete study in the initial stage, the condition results in a bigger error. To solve this problem, PID feedback controller participates in compensation control of neural network, the combination controller ensure stability of system. PID feedback controller mainly plays the leading role in the early stage of control, Along with learning of the neural network, errors are decreased gradually, PID feedback controller function get smaller and smaller gradually.

Where, a variable learning law in Local generalization network of RBF is used to accelerate the learning speed and convenient in applications in real-time.

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For the membership function of the hidden layer of RBF neural inverse mode approaching and neural controller to take the Gaussian function, the hidden node output is:

$$\phi_j(k) = \exp(-\frac{||X - c_j||^2}{b_j^2})$$
(10)

The output of the output layer is:

$$y(k) = \sum_{j=1}^{m} W_{ij}(k)\phi_j(k) \quad (i = 1, 2)$$
(11)

Where,  $W_{ii}(k)$ : connection weights of hidden layer and output layer.

The error signal of online learning is defined as:

$$E = \frac{1}{2} \left[ y(k) - y_d(k) \right]^T \left[ y(k) - y_d(k) \right]$$
(12)

$$J(W) = \frac{1}{2} \sum_{i=1}^{2} E_i^2(W)$$
(13)

According to function extreme value theory from ref [15]: the quadratic approximation of the performance indicators near the minima of J(W) is:

$$S_{k}(W) = G_{k} + (W - W_{k})^{T} H_{k}^{-1}(W - W_{k})$$
(14)

Where,  $G_k$ : The minimum of the quadratic approximation function,  $W_k$ : minima of  $S_k(W)$ ,  $H_k^{-1}$ : positive definite Hessian matrix.

The function  $E_i(W)$  take the first-order Taylor polynomial in the near of  $W_k$ :

$$E_{i}(W) = E_{i}(W_{k}) + (W - W_{k})^{T} \cdot \nabla E_{i}(W_{k}) + o(\cdot)$$
(15)

Where,  $\nabla E_i(W_k)$  is defined as  $E_i(W_k)$  to  $W_k$  on the gradient.

To omit the higher order terms  $o(\cdot)$  of the above equation, putting it into(25), the following the equation can be obtained:

$$J(W) = \sum_{i=1}^{2} \left[ E_i (W_k) + (W - W_k)^T \cdot \nabla E_i (W_k) \right]^2$$
(16)

The second approximation on the above equation is expanded as:

$$J_{k+1}(W) = [E_i(W_k) + (W - W_k)^T \cdot \nabla E_i(W_k)]^2 + \alpha J_k(W)$$
(17)

Where,  $\alpha$  :forgetting factor,  $0 < \alpha < 1$ .

$$J_{k+1}(W) = E_i^2(W_k) + \alpha G_k + 2E_i (W_k)(W - W_k)^T \cdot \nabla E_i (W_k) + (W - W_k)^T [\alpha H_k^{-1} + \nabla E_i (W_k) \cdot \nabla E_i^T (W_k)](W - W_k)^T$$
(18)

According to(14), it can be obtained:

$$S_{k+1}(W) = G_{k+1} + (W - W_k)^T H_{k+1}^{-1}(W - W_{k+1})$$

$$S_{k+1}(W) = G_{k+1} + (W_k - W_{k+1})^T H_{k+1}^{-1}(W_k - W_{k+1}) + 2(W - W_k)^T H_{k+1}^{-1}(W_k - W_{k+1})$$

$$+ (W - W_k)^T H_{k+1}^{-1}(W - W_k)$$
(19)

Make

$$J_{k+1}(W) = S_{k+1}(W)$$

Then

$$E_i^2(W_k) + \lambda G_k = G_{k+1} + (W_k - W_{k+1})^T H_{k+1}^{-1}(W_k - W_{k+1})$$
(20)

$$H_{k+1}^{-1} = \alpha H_k^{-1} + \nabla E_i (W_k) \cdot \nabla E_i^T (W_k)$$
(21)

$$E_i(W_k) \cdot \nabla E_i(W_k) = H_{k+1}^{-1}(W_k - W_{k+1})$$
(22)

Using the matrix inverse theorem and according to (22), as can be obtained:

$$H_{k+1} = \alpha^{-1} (H_k - H_k \nabla E_i (W_k) \cdot \nabla E_i^T (W_k) H_k / \gamma_k)$$
<sup>(23)</sup>

$$\gamma_k = \alpha + \nabla E_i^T (W_k) H_k \cdot \nabla E_i (W_k)$$
<sup>(24)</sup>

In (22), the same multiplied by  $H_k$  on both sides,  $H_{k+1}^{-1} = \gamma_k H_k^{-1}$ , and put it into (23), after collated, the final learning algorithm of neural network weights can be obtained:

$$W_{k+1} = W_k - H_k E_i(W_k) \cdot \nabla E_i(W_k) / \gamma_k$$
<sup>(25)</sup>

So, the algorithm of the RBF neural network weights is designed as

$$\nabla E_{i}(W_{k}) = \partial E_{i} / \partial W$$

$$= -\tau_{PD} \partial O^{(2)} / \partial W$$

$$= -\tau_{PD} \cdot O_{j}^{(1)}(k)$$
(26)

#### 4. Simulation and Analysis

In order to illustrate the effectiveness of the control algorithm, the paper designs the dynamic model parameters as:

D = 6, C = 3,  $F = 0.1 \sin t$ 

The desired trajectory of the X-Y platform is:

$$X: x_{d1} = \cos 0.1\pi t$$
;

 $Y: x_{d2} = \sin 0.2\pi t \, .$ 

PD controller gain:

$$K_{p} = diag(20, 20); K_{d} = diag(30, 30).$$

Learning factor:  $\alpha = 0.6$ . The initial value of the X-Y platform movement:

 $X: x_1 = -2$ ,  $\dot{x}_1 = -2$ ;

 $Y: x_2 = 4$ ,  $\dot{x}_2 = 0$ .

The simulation results are shown in the follow figures. Where Figure 3 and Figure 4 is the trajectory tracking curve and the speed tracking error curve in this paper program Figure5 is control input of X-Y platform.



Figure 3. Position tracking of X-Y platform

According to the Figure3, as can be learned that the design of RBF neural network PID controller is able to fast-track the expected angle of trajectory in a relatively short period of time, but also to achieve better tracking of angular velocity. It turns out that in the initial phase of the control process, the RBF neural network is still in the learning period, now neural network cannot approach system model, in this time, neural network controller together with the conventional PD feedback controller meet the tracking error of the joint angle. With the study of neural network, better control effect can be obtained. According to the figure 4, the good velocity tracking can be achieved in 5s. From figure 5, control torques is small, and relatively smooth. Simulation shows the proposed control method is effective, and has better engineering value.



(a) Velocity tracking of X

(b) Velocity tracking of Y

Figure 4. Velocity tracking of X-Y platform



Figure 5. Control input of X-Y platform

## 5. Conclusion

Trajectory tracking control problems X - Y NC platform system with uncertainty are studied by the paper, an improvement neural network PID control strategy is proposed.

- An integrated controller is designed. The controller integrates neural network controller with PID controller, the good control precision can be achieved in the initial learning phase of neural network, because of compensation affection of PID controller;
- 2) Improvement optimization learning algorithm is designed, the algorithm can ensure the online real-time adjustment of the weights of network;
- 3) The control mechanism is analyzed in detail, the simulation proves the validity of the scheme.

The improvement neural network control strategy can achieve good control effect, and has high engineering application value for X-Y NC control platform system with uncertainty.

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