Article ID: 1000 - 8152(2001)06 - 0932 - 03

The Neura Network Predictive Control of Time-Delay Systems

XU Xiangyuan
(Department of Electrical Engineering, Guangdong University of Technology · Guangzhou, 510090, P.R.China)
MAO Zongyuan
(Department of Automatic Control Engineering, South China University of Technology · Guangzhou, 510640, P.R.China)

Abstract: With regards to the characteristics of time-delay system and the weakness of single predictive control, this paper puts forward a control scheme of multi-step-ahead prediction and compensation, which increases control power effectively, and improves dynamic characteristics of the system. The paper also discusses the relationship between the step number of prediction and compensation and the stability of systems.

Key words: time-delay systems; multi-step prediction and compensation; increased step number p; stability
Document code: A

时滞系统的神经网络预测控制

徐湘元　　毛宗源
(广东工业大学电气工程系·广州,510090)　(华南理工大学自动控制工程系·广州,510640)

摘要: 针对时滞系统的特点和采用神经网络单值预测控制存在的不足,提出了多步超前预测与补偿的控制算法,有效地增加了控制力度,改善了动态性能,并论述了增加的预测与补偿步数与稳定的关系.

关键词: 时滞系统; 多步预测与补偿; 增加的步数 p; 稳定性

1 Introduction

Besides the characteristics of general nonlinearity, the nonlinear plants with time-delay have the phenomenon of output-delay, which increases the degree of difficulty to control further.

The single predictive control based on neural networks is an effective way to solve this problem[1,2]. But $u(k)$ only affects the output at step $k+d$ in future. Control power is weak, and the dynamic response is poor, especially when reference inputs change or disturbances occur. In addition, as the actual output $y(k+i)(i=1,2,\cdots,d)$ can not be got at step k, the drill in the neural networks cannot avoid the difficulty.

2 The algorithm of multi-step prediction and compensation control

To overcome the weakness of the single prediction control, we put forward the following approach: increase d steps prediction to $d+p$ steps prediction, and change one point compensation to multi-point compensation, i.e. from $k+d$ to $k+d+1,\cdots,k+d+p$. Based on step k, we put $p+1$ errors between the reference input and the predictive output into the cost function of neural network controller, and strive the optimal control $u(k)$ that makes

$$J_c=\frac{1}{2}[y_r(k+d)-y_p(k+d)]^2+\frac{1}{2}\sum_{i=1}^{p}[y_r(k+d+i)-y_p(k+d+i)]^2+\frac{1}{2}\alpha[\Delta u(k)]^2 \tag{1}$$

minimal, where p is the increased prediction horizon and compensation, y_r and y_p is reference input and system predictive output respectively.

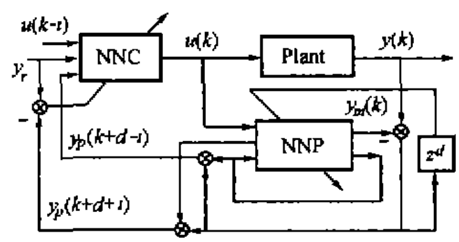

Fig. 1 Control structure

Received date: 2000 - 05 - 17; Revised date: 2001 - 01 - 04.

The control structure of multi-step prediction and compensation based on neural networks is shown in Fig.1, where NNC is the neural network controller, NNP is the neural network predictor.

$$u(k) = \mathrm{NNC}[y_r(k+d), y_p(k+d-1), \cdots, y_p(k+d-n), u(k-1), \cdots, u(k-m)]$$

determined by the neural network controller has to make J_c minimal.

$y_p(k+d+i)(i=0,1,\cdots,p)$ are gained by the neural network predictor after $u(k)$ has been got and remained not changed.

$$\begin{cases} y_m(k+d) = \mathrm{NNP}[y_m(k+d-1) \cdots y_m(k+d-n)\ u(k)\ u(k-1) \cdots u(k-m)], \\ y_p(k+d) = y_m(k+d) + y(k) - y_m(k). \end{cases} \tag{2}$$

$$\begin{cases} y_m(k+d+i) = \mathrm{NNP}[y_m(k+d+i-1) \cdots y_m(k+d+i-n)\ u(k)\ u(k) \cdots u(k-m+i)], \\ y_p(k+d+i) = y_m(k+d+i) + y(k) - y_m(k), \\ \quad (i=1,2,\cdots,p). \end{cases} \tag{3}$$

where $y_m(k+d+i)$ is the model predictive output. $y_p(k+d+i)$ is the system predictive output, which forms a closed-loop corrective system and can decrease the model errors. Adopt

$$J_p = \frac{1}{2}[y(k+d) - y_m(k+d)]^2$$

as the cost function of the neural network predictor. When the linking weighting coefficients of the neural network predictor are adjusted and since actual output $y(k+d)$ can not be got at step k, this paper proposes:

$$y(k+d) \approx y(k) + y_m(k+d) - y_m(k).$$

This is because the changing magnitude of the model predictive output from step k to step $k+d$ is similar to the actual outputs. As the networks converge, the error caused by the approximation will be very small. The steps of this control algorithm are

1) Bring $y_r(k+d), y_p(k+d-1), \cdots, y_p(k+d-n), u(k-1), \cdots, u(k-m)$ to bear on NNC, get $u(k)$, and then send $u(k)$ to the plant and NNP.

2) Put $y_m(k+d-1), \cdots, y_m(k+d-n), u(k), u(k-1), \cdots, u(k-m)$ to NNP, and get $y_p(k+d)$ by formula (2).

3) Do not change the linking weighting coefficients of NNP, using formula (3) to get $y_p(k+d+1), y_p(k+d+2), \cdots, y_p(k+d+p)$.

4) Adjust the linking weighing coeffiicents of NNC and NNP respectively

$$W_c(k+1) = W_c(k) - B_c \frac{\partial J_c}{\partial W_c(k)},$$

$$W_p(k+1) = W_p(k) - \beta_p \frac{\partial J_p}{\partial W_p},$$

where W_c and W_p are the linking weighting coefficients of NNC and NNP respectively, β_c and β_p are the studying step-sizes of NNC and NNP respectively.

5) $k = k+1$, return to step 1).

3 The relationship between the increased step number of prediction and compensation and system stability

Theorem If the increased step number p of prediction and compensation satisfies the following inequality, then, the control system's stability is not affected.

$$0 < \beta_c < 2\left\{\left(\frac{\partial e(k+d)}{\partial W_e}\right)^2 + \frac{\partial e(k+d)}{\partial W_c} \cdot \sum_{i=1}^{p}\left[\frac{e(k+d+i)}{e(k+d)} \frac{\partial e(k+d+i)}{\partial W_c}\right] + \frac{a\Delta u(k)}{e(k+d)} \frac{\partial u(k)}{\partial W_c} \frac{\partial e(k+d)}{\partial W_e}\right\}^{-1}, \tag{4}$$

where $e(k+d) = y_r(k+d) - y_p(k+d)$, β_c is the studying step-size of NNP.

Proof Select Lyapunov function

$$V(k) = e^2(k+d) = [y_r(k+d) - y_p(k+d)]^2,$$

thus

$$\Delta V = V(k+1) - V(k) = e^2(k+d+1) - e^2(k+d) = [e(k+d+1) - e(k+d)][e(k+d+1) + e(k+d)] = \Delta e(k+d)[\Delta e(k+d) + 2e(k+d)], \tag{5}$$

where

$$\Delta e(k+d) = e(k+d+1) - e(k+d) \approx \frac{\partial e(k+d)}{\partial W_c} \Delta W_c. \tag{6}$$

To the cost function of NNC, there is

$$\Delta W_c = -\beta_c \frac{\partial J_c}{\partial W_c} = -\beta_c\left[e(k+d)\frac{\partial e(k+d)}{\partial W_c} + \sum_{i=1}^{p} e(k+d+i) \cdot \frac{\partial e(k+d+i)}{\partial W_c} + a\Delta u(k)\frac{\partial u(k)}{\partial W_c}\right]. \tag{7}$$

Put (6) and (7) into (5), there is

$$\Delta V = \{\beta_c \frac{\partial e(k+d)}{\partial W_c}[e(k+d)\frac{\partial e(k+d)}{\partial W_c} + \sum_{i=1}^{p} e(k+d+i)\frac{\partial e(k+d+i)}{\partial W_c} + a\Delta u(k)\frac{\partial u(k)}{\partial W_c}]\} \cdot \{\beta_c \frac{\partial e(k+d)}{\partial W_c}[e(k+d)\frac{\partial e(k+d)}{\partial W_c} + \sum_{i=1}^{p} e(k+d+i)\frac{\partial e(k+d+i)}{\partial W_c} + a\Delta u(k)\frac{\partial u(k)}{\partial W_c}] - 2e(k+d)\}.$$

Let $\Delta V < 0$, and given $\beta_c > 0$, there is formula (4). As Lyapunov stability theorem, the neural network controller's study would be convergent, and the system's stability is not affected.

Set

$$Z(p) = \frac{\partial e(k+d)}{\partial W_c}\sum_{i=1}^{p}\frac{e(k+d+i)}{e(k+d)}\frac{\partial e(k+d+i)}{\partial W_c}.$$

As p increases, $Z(p)$ terms increase. Although the positive or negative signs of some terms in $Z(p)$ may change, it is evident that the value of $Z(p)$ becomes greater. As soon as β_c is fixed, formula (4) can not be satified, and then the neural network controller will become unstable. So it is very possible that the system becomes unstable as step number p increases.

4 Simulation experiment

Considering the plant

$$y(k) = \frac{0.2y(k-2)u(k-11)}{1+y^2(k-1)} + u^3(k-10) + \omega(k),\ k < 400,$$

$$y(k) = \frac{0.2u(k-11) - 0.5y(k-1)}{1+y^2(k-1)} + u^2(k-10) + \omega(k),\ k < 400,$$

where $\omega(k)$ is a stochastic disturbance, whose amplitude is 0.06. Structure the predictor and controller with the radial basis function neural networks. Their 3-layer constructions are, respectivey, 4 - 8 - 1, and 4 - 10 - 1. Give reference inputs, then under the same initial conditions and study step-size, we adjust the linking weighting coefficients, central vectors, and shape parameters of the networks[3]. With the single predictive control algorithm, the output is shown in Fig.2. With the above algorithm, the outputs are shown in Fig.3 and Fig.4. Comparing the figures, we can see that as p increases, the response becomes rapid, but the output turbulence increases too.

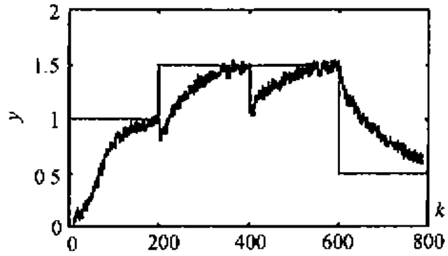

Fig. 2 Output of single predictive control

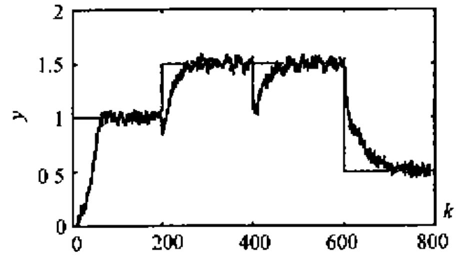

Fig. 3 Output when p=1

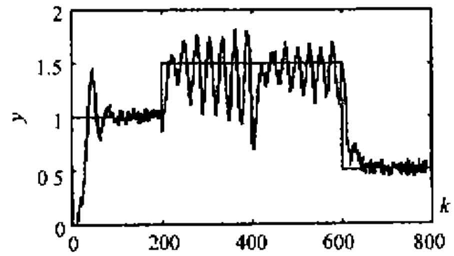

Fig. 4 Output when p=3

5 Conclusion

Through the analysis and simulation experiments, the algorithm with multi-step prediction and compensation proposed in this paper has better control effect. It strengthens the control power, accelerates response speed, and has stronger anti-interference ability. But as p becomes large, the system stability will not remain in good condition.

References

[1] Tan Yonghong and Achiel Van Cauwenberghe. Nonlinear one-step-ahead control using neural networks: control strategy and stability design [J]. Automatica, 1996, 32(12): 1701 - 1706

[2] Liu Baokun, Hang Hui, Cao Ming, et al. Direct optimizing predictive control based on neural networks [J]. Information and Control, 1998, 27(5): 386 - 390

[3] Xu Xiangyuan and Mao Zongyuan. Internal model control based on radial basis neural networks [J]. Journal of Circuits and Systems, 1999, 4(2): 86 - 91

本文作者简介

徐湘元 1956年生.博士.广东工业大学副教授.研究方向为预测控制.

毛宗源 见本刊2001年第2期第165页.