Application of a Neural Network for Identification and Control of a Servovalve Controlled Hydraulic Cylinder System.

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Abstract

This paper examines an application of Neural Network for identification and control of a servovalve controlled hydraulic cylinder system. The linearized transfer function of a nonlinear plant is determined by applying a self-excited oscillation. Neural Network is utilized on-line in mapping the inherent nonlinearities as well as in adaptive identification of system parameters. Neural Network controllers having variable proportional gain together with velocity feedback gain characteristics have been employed. The effectiveness of the Neural Network is confirmed through computer simulations and experiments.

Key Words

Neural Network, Self-Excited Oscillation, Identification, Compensator, Control

Nomenclature

e	: error signal	V_a	: amplitude of self-excited oscillation wave
K_d	: LVDT gain	V_i	: input voltage
K_f	: velocity feedback gain	y	: position signal of cylinder stroke
K_o	: open-loop gain	y_m	: reference model output
K_p	: proportional gain	y_r	: reference input
P_s	: supply pressure	α	: learning rate
t_0	: iteration start time	τ	: time constant of servovalve/cylinder
T	: sampling interval	ω_n	: undamped natural frequency
u_{n1}, u_{n2}	: Neural Network output	ω_s	: frequency of self-excited oscillation wave
		ζ	: damping coefficient

1. Introduction

The application of Neural Network (NN) to hydraulic actuator has received much attention recently in view of modeling, identification, control and so on.

For example, the performance enhancement for position or velocity control of hydraulic motor/cylinder system has been attempted by utilizing NN. NN controller having velocity feedback compensator characteristics has been designed and its effectiveness has been confirmed. [1]~[3]

This paper deals with the feedback compensator design by using NN having characteristics of variable proportional gain together with velocity feedback gain. A self-excited oscillation is utilized in order to find a linearized plant model with appropriate damping coefficient and undamped natural frequency. [4] Identification of plant parameters as well as improvement of position control performance is also attempted by using NN. Through simulation and experiment the performance of NN controller is compared with those of constant gains and different gains according to a range of supply pressure and mass load.

2. System Modeling

Electro hydraulic system circuit diagram used in this research is shown in Figure 1. This station consists of a hydraulic pressure source, an electro-hydraulic servo valve, servo amplifier, hydraulic cylinder, a couple of load mass (1.5, 15kg), LVDT, 12-bit Data Acquisition I/O card and AMD 1.4GHz PC. Specifications of hydraulic components are shown in Table 1.

In Figure 1 and 2, an open loop transfer function of hydraulic servo cylinder may be given as Eq.(1) under the idealized condition such that the servovalve ports are critically-lapped, nonlinear frictions are negligible, etc.

$$\frac{y(s)}{V_i(s)} = \frac{K_o}{s(s^2 + 2\zeta\omega_n s + \omega_n^2)} \quad (1)$$

In Eq.(1), K_o is an open-loop gain, ω_n is an undamped natural frequency, ζ is an open-loop damping ratio.

However the electrohydraulic cylinder drive is inherently a nonlinear system because of fluid

compressibility, leakage, friction, and servo valve flow characteristic. In the view of controller design, it is not easy to obtain the exact coefficients of a dynamic model coinciding with actual hydraulic system. Therefore, in this paper, as a simple and convenient identification method, a self-excited oscillation is utilized to get these dynamic model parameters. [4] From the block diagram in Figure 2, the amplitude V_a and the angular frequency ω_s is determined by analyzing the output oscillation wave. Then a couple of design parameters are obtained using Eq. (2) and (3). [1], [4]

$$\omega_n = \frac{\omega_s}{\xi} \quad (2)$$

$$\zeta = \frac{RK_o K_d e_a}{2V_a \omega_n} \quad (3)$$

Correction factors ξ and R are obtained by simulation analysis, selected as $\xi=0.95$, $R=1.4$. [1], [4] If the damping ratio of hydraulic servo system is higher than $\zeta=0.8$, the transfer function may be simplified to second order as Eq. (4) by defining equivalent time constant τ . [1], [4]

$$\frac{y(s)}{V_i(s)} = \frac{K_o}{s(\tau s + 1)}, \quad \tau = \frac{2\zeta}{\omega_n} \quad (4)$$

Figure 3 shows the identified parameters by self-excited oscillation method, which is to be used for modelling and design of feedback control system for a range of supply pressure.

Table 1 Specification of hydraulic system

Servovalve	Flow rate (30 bar)	5 L/min
Cylinder	Head side area	$A_{p1}=8.043 \times 10^{-4} \text{m}^2$
	Rod side area	$A_{p2}=6.029 \times 10^{-4} \text{m}^2$
	Effective stroke	200mm
LVDT	Accuracy	0.01mm
	Gain K_d	0.1V/mm

3. Design of Neural Network

The utilized NN in this research is shown in Figure 4 where back propagation is used for learning algorithm. Eight neurons in the first hidden layer and four neurons in the second hidden layer with sigmoidal nonlinearity were selected. It was reasonably good in view of accuracy, convergence, and implementation time.

NN is applied to the design of feedback compensator as shown in Figure 5 to overcome nonlinearity of system. Referring to the Eq. (1), the close loop transfer function of plant is described by Eq. (5).

In Figure 4, the NN receives six inputs, i.e., $y_r(k)$, $y_r(k-1)$, $y(k)$, $y(k-1)$, $u_{n1}(k-1)$, $u_{n2}(k-1)$ and produces two outputs, i.e., u_{n1} and u_{n2} corresponding to outputs of feedback compensators with gains K_p and K_f . Using these output signals, system parameters are identified on line and system is controlled at the same time. Between hydraulic actuator and reference model there may exist position error and velocity error, i.e., e_1 and e_2 . These error signals are utilized for NN. The parameters K_p , K_f , and τ are computed using Eqs. (6), (7), and (8).

$$\frac{y(s)}{y_r(s)} = \frac{\omega_{nd}^2}{s^2 + 2\zeta_d \omega_{nd} s + \omega_{nd}^2} \quad (5)$$

$$K_{pn} = u_{n1} / (y_r - y) \quad (6)$$

$$K_{fn} = u_{n2} / sy \quad (7)$$

$$\tau = \frac{K_{fn} K_o K_d + 1}{2\zeta_d \omega_{nd}} \quad (8)$$

4. Training of Neural Network

Figure 6 shows an overall structure of position control system including NN feed back compensator. For the off-line training model, a second order system with parameters $\zeta_d = 5$, $\omega_{nd} = 10$ rad/s was chosen. The sampling time was chosen to be $T = 10$ msec. Eq. (9) describes a transfer function of reference model. Input signal is selected from -40 mm to $+40$ mm in order to prevent the saturation of hydraulic cylinder. For the off-line training, the learning rate was fixed as $\alpha = 0.001$.

Figure 1 Schematic diagram of hydraulic cylinder system under NN control

Figure 2 Self-excited oscillation system of hydraulic servocylinder system [1]

Figure 3 Identified parameters by self-excited oscillation method

Figure 4 Neural Network controller

Figure 5 Feedback control system of hydraulic cylinder

Figure 6 Overall structure of Neural Network control system

$$\frac{y_m(s)}{y_r(s)} = \frac{100}{s^2 + 100s + 100} \quad (9)$$

For an error criterion, IES (Integral of Error-Squared) was considered using the error signal between the reference model output y_m and the piston position y .

[1]

$$IES = \int_{t_0}^{t_0+1/f} [y_m(t) - y(t)]^2 dt \quad (10)$$

Output signals converge after 10,000 epochs. Figure 7 shows the results just after 10,000 epochs of off-line training. It shows that y_m and y are successfully converging. Also the parameters K_p , K_f , and time constant τ are approximately converging to 1.85, 0.49, and 0.0136. It demonstrates that NN can identify and control system as desired.

5. Simulation

Reference model for simulation was set to have a second-order close loop dynamics with $\zeta_d=5$, $\omega_{nd}=10$ rad/s, and sampling time of $T=10$ msec. The square wave with amplitude of 25mm was used for simulation. The ranges of supply pressure and mass load are 20~60bar and 0~15kg respectively. Figure 8 shows the responses under the conditions that the supply pressure and mass load of hydraulic actuator are changed to 60 bar and 1.5kg respectively ($K_0=9.0475$ $\tau=0.0135$). After the first epoch, the plant output follows the model output and the design parameters K_p , K_f , and time constant τ are approximately converging after 12 epochs. When the operating condition of plant changes to another state, similar results have been observed.

6. Experiments

In on-line training algorithm, the current IES value is compared with the previous value. If the former is larger than the latter, the neuron's weighting and bias is restored to previous one. Reference model for experiments was the same as that for simulation such that $\zeta_d=5$, $\omega_{nd}=10$ rad/s and sampling time $T=10$ msec. In experiment, square wave input signal with amplitude of 25mm was utilized under different operating conditions to examine the adaptability and controllability of NN. Experimental results under a range of supply pressures and mass load conditions are shown in Figure 9. In Figure 9a, the constant feedback gains which were derived from the self-excited oscillation for a supply pressure of 40 bar and mass load of 0 kg were utilized. In Figure 9b, the different feedback gains which were derived from the self-excited oscillation according to a range of supply pressure and mass load were utilized. In

Figure 7 Neural Network off-line training

Figure 8 Simulation result (60bar 1.5 kg)

Figure 9c, the variable feedback gains which were

derived from the NN according to a range of supply pressure and mass load were utilized. In view of the magnitude of IES values, the performance of NN controller is remarkably superior to those of feedback compensators with constant feedback gains or with different gains. Figure 10a shows the comparison of outputs between model and plant when NN is utilized. It seems that they are nearly coinciding. Parameter identification results obtained from NN are compared with those obtained from self-excited oscillation in Figure 10b. There is a small difference between them and also these effects are reflected on the Figures 9b, 9c. The mass load conditions for 1.5kg and 15kg are different. The mass load of 1.5kg moves horizontally, whereas the mass load of 15kg moves vertically. So the gravity force significantly affects the motion of mass 15kg, which induces IES larger.

7. Conclusions

This paper deals with the application of on-line learning NN to feedback compensator design of servovalve controlled hydraulic cylinder system. Through self-excitation method, a second order transfer function of hydraulic actuator having equivalent time constant has been derived, which in turn has been utilized to the design of NN feedback controller. The off-line NN training has been performed prior to simulation and experiment to determine the design parameters. Experimental results in view of IES values show that the performance of NN controller is apparently superior to those of feedback compensators with constant feedback gains or with different gains. The effectiveness of NN controller has been conformed through the simulations and experiments.

(a) Feedback compensation using constant gains

(b) Feedback compensation using different gains

(c) Neural network control

Figure 9 Comparison of IES using experimental results

(a) Outputs of model and plant

(b) Parameters under NN and self-excited oscillation

Figure 10 Comparison of outputs and parameters during experiment (60bar, 1.5 kg)

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