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HYDRAULIC SERVO CONTROL USING A NEURAL NET

1. Introduction

This study considers a position control system using a servovalve controlled cylinder and a Neural Network in the feedback loop. The object of the research is to examine the capability for robust control by only using the simplified plant model and constant gain controller. Firstly, the transfer function model is identified simply by using a self-excited oscillation method under the condition that the loaded masses have been removed. Based on the linearized transfer function of the nominal plant, a Neural Net feedback controller with a fixed gain can be designed. In addition, a quasi model reference adaptive control scheme [1] is presented so that the Neural Net controller can accommodate considerable changes in disturbance by means of on-line training.

2. System Model of Servovalve Controlled Cylinder

A schematic diagram of the electrohydraulic cylinder drive employed in this study is shown in Fig. 1.

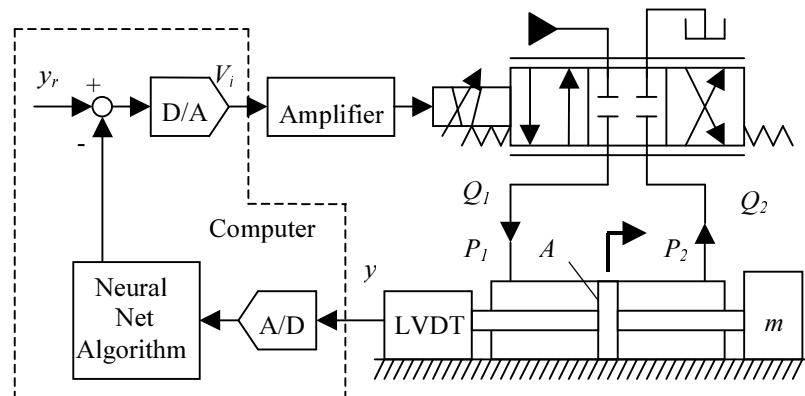


Fig. 1. Test apparatus for hydraulic servo control using a Neural Net

It consists of a symmetrical double-rod cylinder, a load mass, a servo amplifier, a servovalve, a LVDT, and a 32 bit micro-computer with an I/O card. If the hydraulic cylinder is operated around the neutral position, the linearized transfer function for the hydraulic servo system can be simply expressed as follows:

$$\frac{y(s)}{V_i(s)} = \frac{K_o}{s(\tau s+1)} \quad (1)$$

However, an electrohydraulic cylinder drive is an inherently non-linear system because of the fluid compressibility, leakage, and servovalve flow characteristics. In view of the controller design, it is not so easy to obtain the exact coefficients from the component specifications and static experiments, and it is crucial that the dynamic model represents the actual hydraulic system. Therefore, in order to clarify the dynamic parameters of the approximated transfer function, a simple and convenient identification method using self-excited oscillation has been introduced [2]. Although the values are affected by the supply pressure, the equivalent time constant $\tau = 8.6$ msec and open-loop gain $K_o = 32$ mm/V in the transfer function will be representatively determined as the nominal values.

3. Position Control by the On-line Training of the Neural Network

Feedback compensation is the one of the effective strategies to overcome the non-linearity and sensor noise of the control system. The velocity feedback compensation is generally utilised as a common design method for this type of servo system. Considering equation (1), the closed-loop transfer function will become:

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

In order to achieve the demanded damping coefficient ζ_d and undamped natural frequency ω_{nd} for the resulting closed-loop transfer function, the feedforward gain K_p and feedback gain K_f must satisfy the following equations:

$$K_p = \tau \omega_{nd}^2 / (K_o K_d), \quad K_f = (2\tau \zeta_d \omega_{nd} - 1) / (K_o K_d) \quad (3)$$

If the desired dynamic parameters are determined as $\zeta_d = 1.2$, $\omega_{nd} = 60$ rad/s, both gains become $K_p = 9.675$ and $K_f = 0.0745$. In the next stage, only the feedback compensator $K_f s$ is mapped to a Neural Net, which will be performed by the on-line training.

Figure 2 indicates a block diagram which incorporates a quasi model reference adaptive control scheme with the position control system by means of the Neural Net feedback compensator. Considering the sampling period of 2 msec, the discrete transfer function of the reference model can be obtained. The reference model output y_m is compared with the position signal y , and the Neural Net structure is adjusted by changing the weights and biases between each neuron, so as to maintain the demanded dynamic characteristics. Hence, the heuristic technique is an adaptive robust control approach that can accommodate load disturbances and driving conditions, such as load inertia, friction resistance, supply pressure, and fluid temperature.

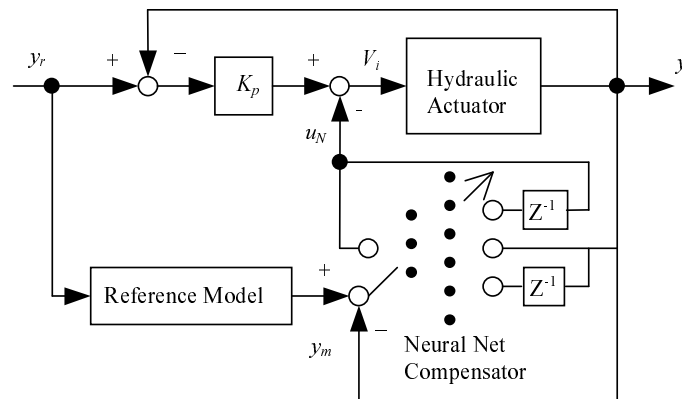


Fig. 2. Quasi model reference adaptive control by Neural Net on-line training

4. Experimental Results

Based upon the simulation results which have been fully discussed, the real time implementation was carried out using a sampling time of 2 msec. The control circuit of the servovalve controlled cylinder has already been given in Fig.1. The position signal from the LVDT is sent to the Neural Net feedback controller via the 12 bit A/D converter which was assembled within the microcomputer. A mass m is loaded into a cart which is rigidly connected to the cylinder rod, but in fact the friction against the floor cannot be neglected. Figure 3 shows a typical experimental result when the supply pressure P_s equals 9 MPa, and the range of the input signal is set to $y_r = \pm 4$ mm. As shown in the time history, the steady state error and overshooting are observed until $t = 6$ sec.

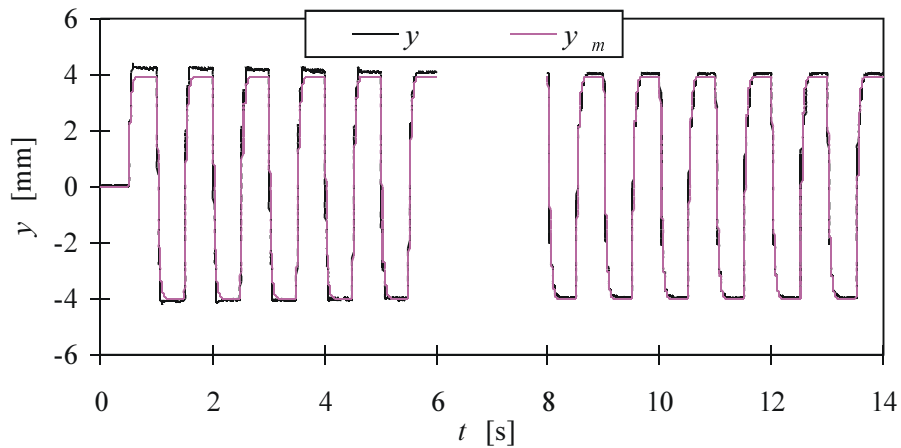


Fig. 3. Typical experimental result ($P_s = 9$ MPa, $m = 4.6$ kg)

However, the position sensor signal y matches well to the model reference signal y_m as time goes by, although the accuracy of the position tracking error is still not improved. This means that the adaptation capability of the Neural Network compensator in the real-time system is good enough for the system parameter changes, when on-line training is attained.

References

1. T.Nishiumi, J.Watton: Model reference adaptive control of an electrohydraulic motor drive using an artificial Neural Network compensator, Inst. Mech. Engrs. Vol. 211, Part I, 111/122 (1997)
2. T.Nishiumi, S.Konami, H.Uchino: An application of the identification method using self-excited oscillation to a hydraulic motor/load system, 10th Bath International Fluid Power Workshop, 381/395 (1997)