FORCE CONTROL OF PNEUMATIC SERVO SYSTEM USING NEURAL NETWORK

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ABSTRACT

A pneumatic servo system has been expected to be applied to contact tasks because of the ability of collision force absorption, delicate force control and so on due to air compressibility. However, the high nonlinearity and friction in the pneumatic system make a satisfactory servo-type force control not easy. The purpose of this study is to develop a pneumatic servo-type force control system which can be applied to the system with unknown and variable parameters and environments by using a neural network controller with the capability of learning and adaptability. The controller is installed in parallel with an usual linear controller. Some experiments confirm that the neural network controller is one of effective approaches to realize the advanced force control of a pneumatic servo system.

KEY WORDS

Pneumatic servo, Force control, Neural network control, Learning, Adaptability

INTRODUCTION

A pneumatic actuation has been used mainly for simple tasks. Recently, however, it is desired to develop the pneumatic servo system with more elaborate control performance to be applied to robotics and mechatronics. A contact task is one of the effective applications of a pneumatic servo system because of the flexibility from air compressibility which produces the important ability of collision force absorption, delicate force control and so on. The fine control performance can be obtained by some control strategies of an optimal control and an

adaptive control and so on [1]. However, the design of such a linear controller requires mathematical modelling and identification of a controlled plant, which are not necessarily easy in the pneumatic system. Also the property of the contacted object is not always exactly known and constant. A neural network controller is useful for such a kind of plant.

In this study, a neural network is applied to the force control of a servo system comprising a pneumatic cylinder and electro-pneumatic proportional control valves. The neural network with input/output layers

and one hidden layer is installed in parallel with the usual linear PI controller. The network learns the dynamics of the controlled pneumatic plant including the object based on the back propagation algorithm referring to the reference input signal, the output signal and their derivatives. The control error is used as a teaching signal, which is made minimum through the learning. First, the proposed control system using a fundamental neural network is described. Next, its ability of both learning and adaptability for the change of the object stiffness are discussed experimentally. Finally, an improved learning algorithm considering the plant dynamics is proposed. This study assures the effectiveness of the neural network control to realize an advanced pneumatic servo-type force control system.

CONTROL SYSTEM

Structure of control system

Figure 1 shows the proposed control system. A control input u is the sum of outputs u_r and u_N , from feedback (Cf) and neural network (NN) controllers, respectively. Cf contributes to ensuring the stability of the system at the beginning of learning. NN adds the adaptability for variations of operational conditions. With the progress of learning, the output from linear controller decreases and the neural network controller becomes to dominate the overall control system. The control error $e (=f_r - f)$ is used as a teaching signal to be minimized.

Figure 1. Proposed neural network control system

Neural network

Figure 2 shows the neural network built up in the personal computer with C program language. The input layer has seven neurons including a neuron with the output of -1 to set the bias value of each neuron in the hidden layer. There are fourteen neurons including a neuron with -1 in the hidden layer. All layers are connected in only the forward direction. The input to each neuron is given as the weighted sum of outputs

from the previous layer. The output of each neuron is generated by the linear function in the input layer, in the hidden and output layers the following sigmoid function is used.

$$f_{sig}(x) = \frac{1}{1 + \exp(-x)} \quad (1)$$

Figure 2. Structure of neural network

Learning algorithm

In Figure 2, the following symbols are defined:

- i_j^I : input to the j th neuron in the input layer
- o_j^I : output from the j th neuron in the input layer
- i_k^H : input to the k th neuron in the hidden layer
- o_k^H : output from the k th neuron in the hidden layer
- i^O : input to the output layer
- o^O : output from the output layer
- w_{jk}^{IH} : weight from the j th neuron in the input layer to the k th neuron in the hidden layer
- w_k^{HO} : weight from the k th neuron in the hidden layer to the output layer

The control input u_N is given by

$$u_N = k_N (o^O - 0.5) \quad (2)$$

The operation of each neuron is described as:

$$o_j^I = i_j^I \quad (3)$$

$$o_k^H = f_{sig}(i_k^H), \quad i_k^H = \sum_j w_{jk}^{IH} o_j^I \quad (4)$$

$$o^O = f_{sig}(i^O), \quad i^O = \sum_k w_k^{HO} o_k^H \quad (5)$$

The learning process is based on the back propagation algorithm, which minimizes E given by

$$E = \frac{1}{2} e^2 \quad (6)$$

The weights are updated by the following increments to minimize E :

$$\Delta w_{jk}^{II} = -\eta^* \frac{\partial E}{\partial w_{jk}^{II}} \quad (7)$$

$$\Delta w_k^{HO} = -\eta^* \frac{\partial E}{\partial w_k^{HO}} \quad (8)$$

where $\eta^* > 0$ is a learning rate to determine the speed of learning.

$\partial E / \partial w_k^{HO}$ in Eq.(8) can be calculated by

$$\frac{\partial E}{\partial w_k^{HO}} = \frac{\partial E}{\partial i^O} \frac{\partial i^O}{\partial w_k^{HO}} \quad (9)$$

$$\frac{\partial i^O}{\partial w_k^{HO}} = \frac{\partial}{\partial w_k^{HO}} \left(\sum_i w_k^{HO} o_k^H \right) = o_k^H \quad (10)$$

$$\frac{\partial E}{\partial i^O} = -\delta^{O*} \quad (11)$$

$$\frac{\partial E}{\partial w_k^{HO}} = -\delta^{O*} o_k^H \quad (12)$$

where δ^{O*} is called a generalized error calculated by

$$\delta^{O*} = -\frac{\partial E}{\partial f} \frac{\partial f}{\partial o^O} \frac{\partial o^O}{\partial i^O} \quad (13)$$

$$\frac{\partial E}{\partial f} = \frac{\partial}{\partial f} \left\{ \frac{1}{2} (f_r - f)^2 \right\} = -e \quad (14)$$

$$\frac{\partial o^O}{\partial i^O} = \frac{\partial f_{sig}(i^O)}{\partial i^O} = f'_{sig}(i^O) \quad (15)$$

The dynamics of the controlled plant is not considered to calculate $\partial f / \partial o^O$ assumed to be constant.

$$\frac{\partial f}{\partial o^O} = a_o \quad (16)$$

The increment of weight can be written as:

$$\Delta w_k^{HO} = \eta^* \delta^{O*} o_k^H \quad (17)$$

Defining the modified generalized error $\delta^O = \delta^{O*} / a_o$ and the learning rate $\eta = \eta^* a_o$, the number of parameters to be set can be decreased. Consequently, the weight is updated by

$$w_k^{HO} = w_k^{HO} + \eta \delta^O o_k^H \quad (18)$$

The update equation Eq.(19) of the weight w_{jk}^{II} can be

derived in the same manner.

$$w_{jk}^{II} = w_{jk}^{II} + \eta \delta_k^H o_j^I \quad (19)$$

EXPERIMENTAL PNEUMATIC SERVO SYSTEM

Figure 3 shows the pneumatic servo system. A single rod pneumatic cylinder with inner diameter of 50mm, rod diameter of 20mm and full stroke of 200mm is horizontally installed, which is connected with a load mass of 26.5kg sliding on a guide rail. The supply pressure P_s is 490kPa. The mass contacts with the object through a force sensor. Four proportional flow control valves operate as a single input four way control valve, of which the change of the opening areas from the equilibrium state ($f=0$) are adjusted as a control input u . The contact force f is detected with the resolution of 0.51N, of which derivatives are computed by the differential approximation. The control program is written with C language.

Figure 3. Experimental pneumatic servo system

EXPERIMENTAL RESULTS AND DISCUSSION

A steel piece and a spring with stiffness of 3900N/m are used as an object. For two objects, the control performances from an usual PI controller with constant gains and the proposed neural network controller are discussed. The discrete-time control input from the PI controller is given by

$$u(k) = k_P e(k) + k_I \sum_i e(k) T_s \quad (20)$$

$$e(k) = f_r(k) - f(k) \quad (21)$$

T_s is the sampling period of 1ms. It is 2.6ms in the

neural network control system. The initial values of weights of the network are given by random numbers from -0.1 to 0.1. In Eq.(2), $k_N = 1.0 \times 10^{-6}$.

Adaptability to object stiffness

Figure 4 shows the response of the PI control system with control gains optimally adjusted in an experiment for the rigid object, i.e., $k_p = 1.0 \times 10^{-8} \text{ m}^2/\text{N}$, $k_i = 1.0 \times 10^{-8} \text{ m}^2/\text{N}\cdot\text{s}$. (a) is the response for the rigid object. It follows nearly the reference, but not a little the phase lag remains, which cannot be perfectly compensated by the PI controller. The same PI controller gives the response in (b) for the elastic object. The change of the object stiffness varies the property of the controlled plant, so that the response becomes worse. The control gains are readjusted for the elastic object as $k_p = 1.5 \times 10^{-8} \text{ m}^2/\text{N}$, $k_i = 2.0 \times 10^{-8} \text{ m}^2/\text{N}\cdot\text{s}$. Although the response can be improved to some extent, the phase lag still remains, also a stick-slip phenomena appears due to the static friction as shown in Figure 5. The usual PI controller with constant gains cannot sufficiently deal with the variation of the plant parameters including the stiffness of the object.

(a) Rigid object

(b) Elastic object

Figure 4. Usual PI control

Figure 5. Readjusted usual PI control for elastic object

(a) Beginning of learning

(b) End of learning

(c) Transition of performance index

Figure 6. Neural network control for elastic object

Figure 6 shows the result of the neural network control system shown in Figure 1 for the elastic object. The learning rate η is 2.5×10^{-5} . The PI controller in Figure 4(a) and (b) is used as a feedback controller C_f . (a) and (b) are the response at the beginning and after the end (at the 30th trial) of learning, respectively. Where one trial corresponds to one period (10 seconds) of the reference input. (c) shows the transition of the performance index defined by

$$\bar{E} = \frac{2J}{N_s} \quad (22)$$

$$J = \sum_i \frac{1}{2} e^2 \quad (23)$$

where J is the sum of sampled values in one trial, N_s means the sampling times over one trial.

To examine the adaptability for the change of stiffness of the object, the initial weights of the network are set to the values enough learned for the rigid object. As shown in Figure 6(a), the control error is caused by the variation of the plant dynamics due to the change of stiffness at the first trial. The error can be decreased by the learning to obtain the response in Figure 6(b), which is nearly the same as the response for the rigid object being left out on account of limited space. The comparison of Figure 6 (b) with Figure 4(b) and 5 can clarify the effectiveness of the neural network control. Especially, the ability of the neural network controller to compensate the influence of the nonlinear friction is interested. Also the learning process can converge enough fast for the practical application.

Effect of linear feedback controller

Figure 7 shows the effect of the linear feedback controller (C_f) on the learning performance examined experimentally for the elastic object with the same reference input as before. The neural network control system with the PI controller same as in Figure 6 or P controller with $k_p = 1.0 \times 10^{-8} \text{ m}^2/\text{N}$ can converge very fast, where $\eta = 1.0 \times 10^{-3}$. When only the neural network controller is used, the learning process becomes unstable for $\eta = 1.0 \times 10^{-3}$. For $\eta = 5.0 \times 10^{-4}$, it can converge but requires many trials until the satisfactory control accuracy is realized. C_f can stabilize the learning process not only at the beginning but also during the learning, so that the higher learning rate can be set to make the convergence fast. Since the important role of C_f is only to improve the stability of the learning process, the exactly gain tuning is not required. The control accuracy can be mainly ensured

by the neural network controller.

Figure 7. Effect of linear feedback control on learning

LEARNING CONSIDERING PLANT DYNAMICS

Influence of reference input frequency

Figure 8 shows the responses at the 80th learning trial of the control system with the same PI controller as the above when the sinusoidal reference input with 0.3Hz and 1Hz is commanded for the elastic object. The response can well follow the reference with 0.3Hz, but not well for 1Hz where the large control error remains. It seems the reason for the deterioration of the control performance at 1Hz to disregard the plant dynamics to calculate Eq.(16) in deriving the learning algorithm.

Improved learning algorithm

The plant dynamics is described by the following discrete-time equation.

$$f = \sum_m a_m (u_N)_{n-m} \quad (24)$$

where the subscript $(n-m)$ means the value before m samplings from n th sampling. $a_m (m=1, \dots, M)$ denote plant parameters. Also, Eqs.(7), (8) are written as:

$$\Delta w_{jk}^{IH} = -\eta \sum_m^M \frac{\partial E}{\partial (w_{jk}^{IH})_{n-m}} \quad (25)$$

$$\Delta w_k^{HO} = -\eta \sum_m^M \frac{\partial E}{\partial (w_k^{HO})_{n-m}} \quad (26)$$

Considering the above plant dynamics, the following expression can be derived in the same manner as Eqs.(18), (19).

$$w_{jk}^{IH} = w_{jk}^{IH} + \eta \sum_m^M (\delta_k^H)_{n-m} (o_j^I)_{n-m} \quad (27)$$

$$w_k^{HO} = w_k^{HO} + \eta \sum_m^M (\delta^O)_{n-m} (o_k^H)_{n-m} \quad (28)$$

where,

$$(\delta_k^H)_{n-m} = (\delta^O)_{n-m} (w_k^{HO})_{n-m} f'_{sig}((i_k^H)_{n-m}) \quad (29)$$

$$(\delta^O)_{n-m} = e a_m k_N f'_{sig}((i^O)_{n-m}) \quad (30)$$

Figure 9 shows the response of the improved control system using Eqs.(27), (28) instead of Eqs.(18), (19) in the control system used in Figure 8. Where, $\eta = 2.5$, $M = 40$ and $T_s = 32.81\text{ms}$. Comparing Figure 9 with Figure 8, the effect of the improved algorithm is remarkable. Also the convergence of the learning can be made faster by considering the plant dynamics in the learning algorithm.

a_m in Eq.(24) must be known beforehand. Naturally, it is sufficient to calculate them using the nominal plant parameters. However, that cannot help injuring the important advantage of the neural network control what no mathematical plant model is required to design the controller. Some studies have discussed this problem [2,3]. Then, the proposed improved learning algorithm is available when the nominal plant model can be obtained relatively easily.

CONCLUSIONS

The neural network controller with an usual linear PI controller in parallel was proposed for the force control of a pneumatic servo system. The learning algorithm disregarding the plant dynamics is enough sufficient for reference input with relatively low frequency, which can accommodate to the unknown plant and object. If the nominal plant model can be obtained without much difficulties, the improved learning algorithm considering the plant dynamics is effective for the high frequency. The results can contribute to construct the advanced pneumatic servo-type force control system being of much practical use.

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(a) Sinusoidal reference input with 0.3Hz

(b) Sinusoidal reference input with 1Hz

Figure 8. Learning property for fast reference input

(a) Sinusoidal reference input with 0.3Hz

(b) Sinusoidal reference input with 1Hz

Figure 9. Learning property of improved algorithm