A Disturbance Estimation Type Control for Pneumatic Servo System Using Neural Network*

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This paper presents a control scheme of pneumatic servo systems for practical use, in which a two-layer neural network is used to construct the inverse system of the plant, and disturbance to the plant is estimated. The influence of the disturbance is eliminated by subtracting the estimated disturbance from the output of the controller. To improve the learning ability of the NN, $\sigma$ modification method, which is one of the robust parameter adjusting methods of the robust adaptive control, is introduced. To confirm the effectiveness of the proposed control scheme, experiments using an existent pneumatic servo system were conducted. The experimental results showed that the external force was estimated well by the disturbance estimation mechanism, and the influence of the external force to the plant output was eliminated immediately after the external force was applied. In addition, high-speed learning of NN could be realized using the switching $\sigma$ modification method.

Key Words: Air Hydraulics, Servo Mechanism, Neural Network, Disturbance Estimation Type Control, $\sigma$ Modification Method, Practical Use, Positioning Accuracy

1. Introduction

Pneumatic actuators have already been used in various autonomous machines, and have become indispensable to modern industry. This is because the energy source is air, which is economical, safe, and pollution-free. In addition, pneumatic actuators are small, light, and easily maintained. Pneumatic servo systems incorporate various factors which have a negative influence on the system such as compliance characteristics, response delay of the pressure, and non-linearity caused by compressibility of air or friction between pistons and cylinders. When the non-linearity is small, it is effective to apply linear control methods such as optimal control(1) or adaptive control(2), (3) to the pneumatic system.

However, it is difficult to achieve satisfactory control performance using linear control methods when the non-linearity of the plant is not negligible. A neural network (NN) is effective for such non-linear plants because it has excellent learning ability and can identify arbitrary input-output relations. From this point of view, several control methods to overcome non-linearity of the pneumatic servo system were reported. For example, an adaptive control incorporating NN was applied to a pneumatic servo system(4), (5), and a direct neuro controller, in which the sigmoid function is used for the output of the network to compensate for the non-linearity, was applied to a pneumatic servo system(6).

On the other hand, a disturbance observer, in which the non-linearity of the plant is regarded as a disturbance and the amount of disturbance is estimated, is also effective(7), (8). For the disturbance observer, the difference between the output of the inverse system of the nominal model of the plant and the output of the controller corresponds to the estimated disturbance. By subtracting the amount of the estimated disturbance from the control input, the influence of the various factors with regard to the non-linearity on the plant can be reduced, and satisfactory control performance will be expected.

A practical control method in which the disturbance is estimated using a NN is proposed for pneumatic servo systems with non-linearity in this paper. In the proposed method, the NN constructs the inverse system of the plant based on the approximated linear model, which is given as known information, instead of identifying the nominal model of the plant. In this method, disturbance is estimated by subtracting the output of the controller from the

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output of the NN.

Since the learning of a conventional NN takes much time, it is important to improve the learning algorithm of the proposed method for practical use. On the other hand, \( \sigma \) modification method is an effective parameter adjustment method for robust adaptive control\(^9\). We try to apply \( \sigma \) modification method to the learning of a NN to realize high speed learning in this paper. The composition in which \( \sigma \) modification method is introduced to the learning of a NN is applied to an existent horizontal type pneumatic servo system.

2. Construction of the Pneumatic Servo System

Figure 1 shows the schematic diagram of the pneumatic servo system. The air cylinder is of the dual-rod type with a diameter of 55 mm and a stroke of 170 mm. The rod has a diameter of 22 mm. The cylinder is set up horizontally and is constructed so that the mass can be moved in the horizontal directions. It is assumed that the zero point is located at the stroke center of the cylinder. The piston and rod are sealed with labyrinth seal and pneumatic bearings respectively to alleviate the effect of friction. The control valves are three-directional electro-pneumatic proportional pressure ones. Labyrinth seal has already been used as a shaft seal of spinning machines, and pneumatic bearing is available on the market. Therefore, it is possible to construct the same system as this experimental system for the practical use.

Considering the applied voltage for the power amplifier as the input and the piston position as the output, respectively, the transfer function of this plant is described as

\[
G(s) = \frac{A \alpha e^{-Ls}}{s(D+Ms)(1+\tau s)}
\]  

Here,
- \( A \): pressure area of the piston [cm\(^2\)],
- \( \alpha \): transformation friction gain,
- \( \tau \): time constant [s],
- \( L = 0.04 \): time-delay [s].

The discrete time model of the plant which results from discretization of the continuous-time plant preceded by a zero-order hold and followed by a sampler with the conditions that the sampling time 40 ms, becomes as

\[
y(k) = G_0 \frac{z^{-2}B(z^{-1})}{A(z^{-1})} u(k)
\]  

Here,
\[
\begin{align*}
A(z^{-1}) &= 1 + \sum_{i=1}^{3} a_i z^{-i} \\
B(z^{-1}) &= 1 + \sum_{i=1}^{2} b_i z^{-i}
\end{align*}
\]  

\( y(k) \) and \( u(k) \) in the Eq. (2) are the output and input of the plant respectively, \( G_0 \) is the unknown gain of the plant, \( a_i \) and \( b_i \) are unknown parameters of the plant. \( z^{-1} \) is the time delay element which means \( z^{-1} y(k) = y(k-1) \).

3. Construction of the Control Scheme

3.1 Disturbance estimation mechanism

Figure 2 shows the block diagram of the system. First, Eq. (2) is rewritten as follows to ease the construction of the inverse system.

\[
y(k+2) = -3 \sum_{i=1}^{3} a_i y(k+i+1) + G_0 \left\{ u(k) + 3 \sum_{i=1}^{3} b_i u(k-i) \right\}
\]  

Here,
By arranging with respect to $u(k)$ in Eq. (4), the inverse system can be constructed. However, it is impossible to obtain the output $y(k+2)$. So, we try to construct the inverse system of the plant by replacing $y(k+2)$ with the desired value $y_d(k+2)$ under the assumption that the plant output will follow the desired value perfectly. That is, the inverse system becomes as follows.

$$u(k) = \theta^T I(k).$$  \hspace{1cm} (6)

Here, $\theta$: unknown parameter vector

$$\theta^T = \frac{1}{G_0}[a_1, a_2, a_3, -G_0b_1, -G_0b_2, -G_0b_3]$$  \hspace{1cm} (7)

$I(k)$: output and input vectors

$$I(k)^T = [y_d(k+2), y(k), y(k-1), y(k-2), u(k-1), u(k-2), u(k-3)]$$  \hspace{1cm} (8)

$y_d(d)$: desired value of the plant output

Considering desirable dynamics of the plant such as response speed, the shape of response, etc., the desired value of the plant output is given by the following reference model.

$$y_d(k) = 0.021 \left[ \frac{z^2(1+0.728z^{-1})}{1-1.345z^{-1}+0.383z^{-2}} \right] r(k)$$  \hspace{1cm} (9)

Here, $r(k)$ is the reference input.

Next, unknown parameters of Eq. (7) are identified using a NN. The NN used here has two layers, in which the input layer has seven units and the output layer has one unit. Figure 3 shows the structure of the NN. The input to the NN is given by Eq. (8). The weights between the input layer and the output layer are $W_i(k)$ ($i = 1 – 7$).

It was suggested in Yamada and Yabuta that linear NN controller has similar characteristics to adaptive controller, which is not effective for non-linear plant, and that NN with non-linear input-output relation is effective for non-linear plant. From this viewpoint, the relationship between each unit and output in the NN is given by the following sigmoid function to compensate for the non-linearity of the plant.

$$f(x) = \frac{X_g[1-\exp(-4x/X_g)]}{2\{1+\exp(-4x/X_g)\}}$$  \hspace{1cm} (10)

By giving the appropriate value to $X_g$ for the non-linearity of the plant, desirable control performance is expected. In this research, the appropriate value of $X_g$ is determined by trial and error.

The output of the NN is given by the following equation.

$$u_N(k) = f(W(k)^T I(k))$$  \hspace{1cm} (11)

Here, $W(k)$: weight vector with the elements of $W_i(k)$.

The error between the desired value and the plant output becomes,

$$e(k) = y_d(k) - y(k)$$  \hspace{1cm} (12)

From Eqs. (4), (6) and (12),

$$e(k+2) = y_d(k+2) - y(k+2) = G_0z_0(\dot{\zeta} - I(k))$$  \hspace{1cm} (13)

Here, $\zeta(k)$: identification error vector of the parameters

$$\zeta(k) = \theta - W(k)$$  \hspace{1cm} (14)

It is apparent from Eq. (13) that the identification error approaches zero when the learning of the coefficients is accomplished so that the error becomes zero, which means that the plant parameters can be identified.

From these constructions, estimation value of the disturbance $\hat{d}(k)$ is obtained by the next equation.

$$\hat{d}(k) = u_N(k) - u(k)$$  \hspace{1cm} (15)

A limit cycle is apt to occur in a digital control system. To depress the limit cycle and maintain stability, the following low pass filter is applied to the disturbance estimation value.

$$G(s) = \frac{f}{s+f}$$  \hspace{1cm} (16)

The output of the low pass filter which results from discretization of Eq. (16) becomes as follows.

$$d_1(k) = e^{-TT}[d_1(k-1) - \hat{d}(k-1)] + \hat{d}(k-1)$$  \hspace{1cm} (17)

$T$: sampling time

The value of $f$ is determined as 3.0 experimentally in this research.

Fig. 3 Two layers neural network

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3.2 Learning of the neural network

For the learning of the NN, the steepest descent method is generally used. The learning of the NN is constructed to minimize the mean squared error $E(k)$ with regard to the plant output $y(k)$ of the plant and the desired value $y_d(k)$.

$$E(k) = \frac{1}{2}(y(k) - y_d(k))^2 \quad (18)$$

The weight vector is modified at each time step $k$ in the following equation using the steepest descent method.

$$W^T(k+1) = W^T(k-2) + \eta \sigma(k) I(k-2) \quad (19)$$

However, since calculation of the NN takes much time using the steepest descent method, high-speed identification of the reverse system of the plant cannot be expected. On the other hand, $\sigma$ modification method is an effective parameter adjustment method for robust adaptive control. We propose to apply the $\sigma$ modification method to the update rule of weight vectors to realize high-speed learning. Some methods were proposed in the $\sigma$ modification method. We examine the $e_1$ – modification method and the switching $\sigma$ modification method in this paper.

3.2.1 Learning with $e_1$ – modification method

The weight vector is modified at each time step $k$ as in the following equation using $\sigma$ modification method.

$$W^T(k+1) = (1 - \sigma(k))W^T(k-2) + \eta \sigma(k) I(k-2) \quad (20)$$

$$\sigma(k) = \frac{\gamma |e(k)|}{\lambda + \gamma |e(k)|} \quad \lambda > 0 \quad (21)$$

Here, $\eta$: arbitrary constant which determines the convergence speed, $\sigma(k) (0 < \sigma < 1)$ in Eq. (21) is an influence factor. $\lambda$ and $\gamma$ are constants which determine the change rate of $\sigma$.

The relationship between the value of $\sigma(k)$ and the value of $e(k)$ is as follows.

$$\sigma(k) = \begin{cases} 0; & e(k) = 0 \\ 1; & e(k) = \infty \end{cases} \quad (22)$$

When $e(k)$ equals to 0, $\sigma(k)$ becomes 0, which means that weight $W(k-2)$ is almost the same as the true value. The information is given to $W(k+1)$ without any modifications. On the contrary, when $e(k)$ equals infinity, $\sigma(k)$ becomes 1. So, the information of $W(k-2)$ is not given to $W(k+1)$, which means that $W(k+1)$ is modified by the terms without the term of $W(k-2)$. In this manner, effective learning is conducted, and the improvement of the learning speed will be expected.

3.2.2 Learning with the switching $\sigma$ modification method

$\sigma(k)$ in Eq. (20) is defined as Eq. (23).

$$\sigma(k) = \begin{cases} 0; & |W(k-1)| < M_0 \\ \sigma_0 \left( \frac{|W(k-1)|}{M_0} - 1 \right); & M_0 \leq |W(k-1)| < 2M_0 \\ \sigma_0; & |W(k-1)| \geq M_0 \end{cases} \quad (23)$$

under the condition $|W(k)| \leq 2M_0$, $0 < \sigma_0 < 1$.

Here, $M_0$ is an arbitrary parameter to give the upper limit of the weight vector $W(k-1)$. In the switching $\sigma$ modification method, $\sigma(k)$ is determined by the weight of one sampling time before the current weight, which will influence the speed of learning.

These two methods exhibit excellent convergence ability in the robust parameter adjustment rule of the adaptive control method. By applying these methods to the learning of the NN in the proposed control method, the improvement of learning-speed will be expected for practical use in pneumatic servo systems, and will be confirmed experimentally in this paper.

3.3 Construction of the controller

A proportional controller is adopted in this control system as follows.

$$u'(k) = K_p e(k) \quad (24)$$

$$u'(k): \text{output of the controller}$$

$K_p$: proportional gain

The value of $K_p$ is determined experimentally. Other controllers, such as PID controllers, etc., did not show any better control performance than the proportional controller used in the experiment.

Actual control input to the plant is obtained by subtracting the output of the filter from the output of the controller.

$$u(k) = u'(k) - d_1(k) \quad (25)$$

4. Experiments and Results

The experiments are carried out using an existent pneumatic servo system to confirm the effectiveness of the proposed control scheme from several view points. The reference input is a rectangular wave with an amplitude of ±75 mm from the cylinder center, and a cycle of 30 sec.

4.1 Compensation for the nonlinearity of the pneumatic system

The type of pneumatic cylinder used in the experiment is designed so that the center of the cylinder stroke becomes equilibrium. So, the larger the distance between the piston position and the cylinder center becomes, the more the system parameter evaluated at the center of the cylinder change. This phenomenon originates in the non-linearity of the system. Since the cylinder stroke is 170 mm, the condition that the amplitude is ±75 mm implies that the piston position approaches the end of the cylinder, which means the non-linearity is not negligible. The sigmoid function is introduced to the relationship between each unit and output in the NN to improve the ability to compensate such a non-linearity as this in this paper.

The effectiveness of introducing the sigmoid function to the NN to compensate for the non-linearity is confirmed experimentally. The switching modification method is
used for the learning of the weights in the NN. The experimental conditions are as follows.

\[
\begin{align*}
\text{Mass} & = 2.85 \text{ kg}, \ W_i = 0.01 \ (i = 1 \sim 7), \ \eta = 0.1, \\
K_p & = 1.5, \ M_0 = 0.0065, \\
\sigma_0 & = 0.12, \ f = 3.0, \ X_g = \infty (f(x) = x) \text{ and } X_g = 4.0
\end{align*}
\]

Here, \(X_g\) is the parameter to define the shape of sigmoid function. When \(X_g = \infty\), the input-output relation of the NN becomes \(f(x) = x\), which is linear.

Figure 4 (a) shows the result when \(f(x) = x\), and Fig. 4 (b) shows the result when \(X_g = 4.0\). As shown in Fig. 4 (a), an oscillation appears due to the non-linearity of the system. On the other hand, satisfactory control performance is observed as shown in Fig. 4 (b), which shows the effectiveness of the sigmoid function. Additional experiments are conducted under various values for \(X_g\). It is clarified that the control performance depends on the value of \(X_g\), with the value of 4.0 as the best in this system. The value should be determined according to the characteristics of the non-linearity of the system. From these results, by introducing a sigmoid function with the appropriate value of \(X_g\), the influence of the non-linearity on the control performance can be reduced.

4.2 Effect of the disturbance estimation mechanism

The response to the disturbance input is examined experimentally here. In the experiments, an external force of 50 N is added when the output is in the steady state (the tenth cycle after the control started). The experimental conditions are as follows.

\[
\begin{align*}
\text{Mass} & = 2.85 \text{ kg}, \ W_i = 0.01 \ (i = 1 \sim 7), \ \eta = 0.1, \\
K_p & = 1.5, \ M_0 = 0.0065, \\
\sigma_0 & = 0.12, \ f = 3.0, \ X_g = 4.0
\end{align*}
\]

Figure 5 (a) shows the result when the disturbance estimation mechanism is omitted, and Fig. 5 (b) shows the result of the proposed method. As shown in Fig. 5 (a), a sustained oscillation occurs after the disturbance is added. On the contrary, in the proposed method, the influence of the external force is eliminated immediately after the external force is added, and satisfactory control performance is obtained as shown in Fig. 5 (b). From these results, it is confirmed that the disturbance estimation mechanism functions well in the proposed control scheme.

Figure 6 shows the estimated disturbance in the proposed control scheme. As shown in this figure, the estimated disturbance increases by a nearly constant value.
after the external force is added. The increased value is equivalent to the added external force, which means that the disturbance estimation by the NN is excellently accomplished.

4.3 Comparison of the results of different learning methods

Experiments are conducted under the conditions that the steepest descent method, $e_1$ modification method, and switching $\sigma$ modification method are used for the learning of the NN respectively. Figure 7 shows the results when the steepest descent method is used for the learning of the NN. In the figure, (a) shows the output and (b) shows the histogram of the positioning accuracy measured over 30 periods. The measurements of the positioning accuracy are conducted 14 seconds after the sign of the amplitude of reference input changes. Figure 8 shows the results when the $e_1$ modification method is used for the learning of the NN. Figure 5 (b) shows the output when the switching $\sigma$ modification method is used for the learning of the NN as previously shown. Figure 9 shows the histogram of the positioning accuracy when the switching $\sigma$ modification method is used for the learning of the NN. As shown in Fig. 7 (a), Fig. 8 (a), and Fig. 5 (b), satisfactory responses are observed in all the learning methods. However, the error reaches $-0.08 \sim 0.08$ mm in the steepest descent method as shown in Fig. 7 (b). On the contrary, the error is settled within $-0.03 \sim 0.03$ for both the $e_1$ modification method and the switching $\sigma$ modification method as shown in Figs. 8 (b) and 9 (b). The error in the $\sigma$ modification method is smaller than that in the steepest descent method. This is because the learning speed is improved in the $\sigma$ modification method and influence of the enlarged non-linearity caused by the external force is compensated well, whereas, the enlarged non-linearity is not compensated well in the steepest descent method due to the insufficient learning speed. It is experimentally clarified from these results that the methods in which the learning of a neural network conducted by $\sigma$ modification method can realize excellent positioning accuracy after the
external force is added.

Next, Fig. 10 shows the change of error in the steady state (that is, positioning error) before and after the external force is added in each method. In the figure, (a) shows the change of error in the steady state when the steepest descent method is used, (b) shows the change of error in the steady state when the \(e_1\) – modification method is used, and (c) shows the change of error in the steady state when the switching \(\sigma\) modification method is used. As shown in (a), a large oscillation of error in the steady state continues when the steepest descent method is used. On the contrary, oscillation is depressed well for the other methods as shown in (b) and (c). In particular, error in the steady state converges immediately after the external force is added when the switching \(\sigma\) modification method is used as shown in (c). From these results, it is experimentally confirmed that high-speed learning of the NN can be realized using the switching \(\sigma\) modification method.

### 5. Conclusions

A practical control method in which the disturbance is estimated using a NN is proposed for pneumatic servo systems with non-linearity in this paper. In the proposed method, the NN constructs the inverse system of the plant based on the approximated linear model, which is given as known information, instead of identifying the nominal model of the plant. In the method, the sigmoid function is introduced as an input-output relationship to the NN to compensate for the non-linearity of the pneumatic system. In addition, disturbance is estimated by subtracting the output of the controller from the output of the NN. To realize high-speed learning, \(\sigma\) modification method (\(e_1\) – modification method and the switching \(\sigma\) modification method) is introduced to the learning of the NN. The effectiveness of the proposed method is experimentally ex-
ained using an existent pneumatic servo system. The obtained results are as follows.

- By introducing the sigmoid function with the appropriate value of $X_g$, the influence of non-linearity to the control performance can be depressed.
- The disturbance estimation mechanism can estimate the external force added to the system accurately and eliminate its effect well.
- It is experimentally clarified that the methods in which the learning of a neural network conducted by $\sigma$ modification method can realize excellent positioning accuracy after the external force is added.
- It is experimentally confirmed that high-speed learning of the NN can be realized using $\sigma$ modification method.

References