Control of a Parallel Manipulator Driven by Pneumatic Muscle Actuators Based on a Hysteresis Model*

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Abstract

This paper presents an approach to modeling the hysteresis nonlinearity of pneumatic muscle actuators and to coping with undesirable hysteresis effects in controlling a manipulator consisting of pneumatic muscles by using a hysteresis model. The hysteresis model is constructed in the form of the Preisach model originally developed for magnetic materials and is used to describe hysteresis nonlinearity in the relationship between the contraction and internal pressure of pneumatic muscle. This model is also used for control of a parallel manipulator driven by three pneumatic muscles. The control system is based on contraction motion control system of each muscle that is composed of a contraction controller reinforced by an internal pressure controller and a feedforward controller that works to produce inputs in order to compensate for hysteresis behavior of the muscle. In addition, a component for switching the hysteresis compensator using a learning vector quantization neural network is attached to the system in order to overcome performance deterioration caused when the manipulator handles external objects. Experimental results show that incorporating the hysteresis compensator leads to an improvement in the control performance of the pneumatic muscle manipulator.

Key words : Oil and Air Hydraulics, Pneumatic Muscle Actuator, Motion Control, Manipulator, Hysteresis, Modeling, Neural Network

1. Introduction

A pneumatic muscle actuator (PMA) consists of a flexible rubber tube surrounded by a braided shell with fibers. When the actuator is pressurized by supplying the rubber tube with compressed air, it inflates radially and simultaneously performs a contraction motion longitudinally. In general, this type of actuator has the following advantages⁽¹⁾:

- It has a high power/weight ratio and a high tensile force.
- It has no moving mechanical parts and therefore creates much less friction than do standard pneumatic cylinders. As such, the PMA has a long period of durability.
- Its inherent flexibility can avoid damage in the event of a collision with handled objects or humans.
- It is applicable in clean conditions because lubrication is not required.

These features meet many of the requirements for applications that involve direct contact and interactions with humans. Therefore, the applicability of PMAs to not only industrial machinery but also to applications such as a wearable device for assisting people⁽²⁾ and a rehabilitation exercise robot⁽³⁾ has been investigated in recent years. Greater efforts may accelerate the development of safe and useful PMA-driven robots for use by humans.

As the contraction depends on the pressure of air inside a PMA, properly increasing or decreasing the internal pressure allows us to control the contraction motion. Meanwhile, the relationship between the contraction and the internal pressure in the pressurizing process

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Fig. 1 Experimental setup for measuring hysteresis of a pneumatic muscle actuator

differs from that in the depressurizing process due to the elasticity of the fibers, the frictional loss between the rubber tube and fibers, and the elasticity of the rubber, and differences in these relationships cause hysteresis nonlinearity, which often leads to inaccuracy and difficulty in the control of a PMA. Although more precise models aid in the design of controllers with better performance, an effective and decisive way to deal with such hysteresis has not been established yet. In Refs. (4) and (5), approximate models that represent the curve passes through the middle of the hysteresis loop are proposed. In Refs. (6) and (7), a model for the inflation of a PMA and that for the deflation are derived separately.

In the field of magnetics, the Preisach model provides a mathematical description of hysteresis that appears in the magnetization process of magnetic materials⁽⁸⁾. The applications of this model are not limited to the field of magnetic, and the model has been extensively studied and tested for hysteresis behavior related to various physical phenomena^{(9),(10)}. In addition, a control scheme in which hysteresis is canceled out by using the Preisach model has been proposed by Ge and Jouaneh^{(11),(12)}, who applied this scheme to the control of a piezoceramic actuator and obtained good experimental results.

In this study, we apply the Preisach model to a PMA. In the first stage of this study, we measure the contraction-pressure relationship of a PMA, describe the hysteresis existing in the measured relationship in the form of the Preisach model, and verify the availability and effectiveness of this model for a PMA experimentally. The objective of the second stage is to design a control system for a parallel manipulator driven by three PMAs (PMPMA) that possesses the features of softness, a high power/volume ratio, and compact structure with a high degree of freedom of motion in parallel mechanisms. The control system includes a compensator based on the Preisach hysteresis model for attenuating undesirable effects of the hysteresis on its tracking performance. In the third stage of this study, the hysteresis model-based compensator is extended so that it can be switched according to the mass of an object handled by the manipulator, because additional loads affect the characteristics of a PMA. A learning vector quantization neural network supervises the motions of the manipulator and selects the compensator suitable for it online. We conduct experiments to test the performance of the PMPMA control system combined with the mechanism of switching the hysteresis compensator.

2. Hysteresis modeling

2.1. Hysteresis of a pneumatic muscle actuator

Figure 1 illustrates the experimental setup used for determining the actual relationship between the contraction and the internal pressure of a PMA. The investigated PMA has a diameter of 20 mm and a nominal length of 200 mm. As shown in Fig. 1, this muscle is mounted vertically, and a weight is suspended on its bottom flange. The internal pressure, p , is detected by a pressure transducer, and its signal is sent to a PC through an A/D interface. A PI control algorithm for regulating the internal pressure is implemented on the PC, which

Fig. 2 Measured contraction-pressure characteristics in a pneumatic muscle actuator

Fig. 3 Hysteresis operator

produces the operating voltage of a proportional control valve to adjust the air flow rate into the actuator. Applying the voltage through a D/A interface to the valve allows the internal pressure to be set to a reference pressure. The contraction of the muscle, Δl , is measured by a linear potentiometer. The outputs of all the sensing devices are recorded on the PC.

The contraction-pressure characteristics of a PMA obtained using the above experimental setup are shown in Fig. 2. Sinusoidal signals with a time period of 60 s and of various amplitudes were inputted to the pressure controller as reference values in the experiments. The amplitudes were increased from 25 kPa to 250 kPa at a constant interval of 25 kPa. The experimental data were recorded under a supply pressure of 560 kPa at a sampling frequency of 200 Hz. The mass of the weight lifted by the actuator was 2 kg. As seen in Fig. 2, hysteresis nonlinearity appears for all the amplitudes on the actual contraction-pressure curves of the PMA.

2.2. Hysteresis modeling with the Preisach model

Although, in preceding researches on PMAs⁽⁴⁾⁻⁽⁷⁾, several approaches were proposed to cope with the hysteresis nonlinearity of PMAs (e.g., Fig. 2), an effective and decisive way has not yet been established. In this paper, we suggest applying the Preisach model⁽⁸⁾, which was originally developed to model hysteresis in the relationship between the magnetic flux density and the magnetic field of magnetic materials, to describe the hysteresis in PMAs.

The mathematical form of the Preisach model is generally defined as follows:

$$f(t) = \iint_{\alpha \geq \beta} \mu(\alpha, \beta) \gamma_{\alpha\beta}[u(t)] d\alpha d\beta \quad (1)$$

where $f(t)$ is the output, $u(t)$ is the input, $\gamma_{\alpha\beta}$ denotes a hysteresis operator that outputs 1 when $u(t) \geq \alpha$ and -1 when $u(t) \leq \beta$, and $\mu(\alpha, \beta)$ is a weight function that expresses the distribution of $\gamma_{\alpha\beta}$, which is referred to as the Preisach function. This model represents the hysteresis behavior of a magnetic material as an integration of the hysteresis operators multiplied by the Preisach function.

Fig. 4 Geometric interpretation of the Preisach model

For the purpose of adapting this model to piezoceramic actuators, Ge and Jouaneh⁽¹¹⁾ proposed a modification of the hysteresis operator $\gamma_{\alpha\beta}$ in Eq. (1); i.e., they assumed that the output of the operator has two values, 0 and 1, as shown in Fig. 3. As a result of this modification, the output of the Preisach model, $f(t)$, depends only on subdivision S_1 corresponding to $\alpha \geq \beta$ and $\gamma_{\alpha\beta} = 1$ on the $\alpha - \beta$ plane (see Fig. 4), since there is a one-to-one correspondence between $\gamma_{\alpha\beta}$ and points (α, β) on the $\alpha - \beta$ plane. In the practical applications of this modified model, the Preisach function, $\mu(\alpha, \beta)$, has to be identified from a set of pairs of measured values, $u(t)$ and $f(t)$. This identification of $\mu(\alpha, \beta)$ requires to differentiate experimentally obtained data twice, which would amplify errors in the data. In addition, the computation of the output requires the numerical evaluation of double integrals. For these reasons, the explicit numerical forms on the basis of the geometrical mapping of a variation on the input-output curve (see Fig. 4 (a)) to a variation in subdivision S_1 on the $\alpha - \beta$ plane (see Fig. 4 (b)) are usually employed for experimentally measured data; that is, by introducing a new function, $F(\alpha', \beta') = f_{\alpha'} - f_{\alpha'\beta'}$, the output, $f(t)$, for monotonically increasing inputs, $u(t)$, is expressed as follows:

$$f(t) = \sum_{j=1}^n [F(\alpha'_j, \beta'_{j-1}) - F(\alpha'_j, \beta'_j)] + F(u(t), \beta'_j) \quad (2)$$

and also for monotonically decreasing inputs, $u(t)$, the output, $f(t)$, is given by

$$f(t) = \sum_{j=1}^{n-1} [F(\alpha'_j, \beta'_{j-1}) - F(\alpha'_j, \beta'_j)] + [F(\alpha'_n, \beta'_{n-1}) - F(\alpha'_n, u(t))] \quad (3)$$

where $f_{\alpha'}$ is the output on an ascending curve when $u(t) = \alpha'$, $f_{\alpha'\beta'}$ is the output on a descending curve from α' when $u(t) = \beta'$, and j denotes the number of descending curves. $F(\alpha', \beta')$ is equivalent to a double integral of $\mu(\alpha, \beta)$ over a variation, S_2 , of subdivision S_1 on the $\alpha - \beta$ plane.

We construct a PMA model by applying the Preisach model of Eqs. (2) and (3) to the actual contraction-pressure hysteresis given in Fig. 2. In the modeling process, α' is the maximum pressure in the i th hysteresis loop in Fig. 2, β' is the pressure at an arbitrary point on the descending curve of the i th hysteresis loop, and our discretized data set consists of α' , β' , and the corresponding contraction to β' . The data sets are collected through the descending curve of the i th hysteresis loop while changing the β' value at a constant interval. By repeating this

Fig. 5 Modeling result using the Preisach model and measured hysteresis

for all the hysteresis loops, we acquire the data sets required for the modeling. The model output to a given input can be calculated by first finding the corresponding contraction to the input among the data sets (we use an interpolation to compute the output at a point where the measured data does not exist), and then by substituting the contraction to the function $F(\alpha', \beta')$. Accordingly, the model's accuracy depends on the number of data sets. The use of more experimental data for creating the data sets results in higher model accuracy but requires larger memory capacity. To understand the dependence of model accuracy on the number of data sets, we carried out the preliminary modeling tests for 660, 335, 270, 140, and 75 sets, which differed in the discretization interval with respect to β . Since reducing the number of data sets to 140 led to considerably decreased model accuracy, we chose 270 sets (a discretization interval of 12.5 kPa in the β axis direction) for the modeling by taking account of both desired accuracy and memory savings.

A simulated contraction-pressure curve using the Preisach hysteresis model of a PMA is shown in Fig. 5. In modeling the muscle, the output, $f(t)$, and the input, $u(t)$, in Eqs. (2) and (3) are defined as the contraction and the internal pressure of the PMA, respectively. Also, we collected the data sets for the modeling from the experimentally measured data shown in Fig. 2 at an interval of 50 kPa in the α axis direction and at an interval of 12.5 kPa in the β axis direction on the α - β plane. In Fig. 5, the solid line indicates a response simulated using the hysteresis model for a sinusoidal input with an amplitude of 150 kPa and a bias pressure of 200 kPa, and the dotted line indicates a response measured under the same condition as the simulation. The difference between the two responses is fairly small in Fig. 5, and this supports that the Preisach model is valid for representing the hysteresis behavior of a PMA.

3. Hysteresis compensation control

3.1. Parallel manipulator

We use the hysteresis model obtained in §2.2 for the control of a PMPMA. Figure 6 is a schematic diagram of the PMPMA. The coordinate systems $O_b - x_b y_b z_b$ and $O_e - x_e y_e z_e$ shown in Fig. 6 are referred to hereafter as the base coordinate system and the end coordinate system, respectively. As in the figure, three PMAs connect the movable end part with the fixed base part in parallel through spherical bearings, and a parallel mechanism is formed. Link 1 is attached to the center of the base part, and only its length is freely adjustable. Link 2 is fixed at the center of the end part. Our original universal joint is employed for the connection between link 1 and link 2. In this study, the rotation around the x_b -axis (θ) and the rotation around the y_b -axis (ϕ) at the origin O_e to the base coordinate system are controlled, and the position in the z_b -direction is always constant.

All the PMAs have the same specifications as those of the PMA used in the previous section. The radius of the base part and that of the end part are 0.06 m, the total length of the

Fig. 6 Schematic diagram of a pneumatic muscle parallel manipulator

Fig. 7 Control system structure with hysteresis compensation

actuator with the joints mounted at both ends is 0.52 m when unpressurized, and the length of link 2 is 0.3 m. A proportional control valve is connected to a port of each PMA, and a pressure transducer is attached to another port to detect the internal pressure. The rotation angles of link 2 (θ and ϕ), which can be regarded as the elbow joint angles of the manipulator, are measured by two potentiometers mounted on the end part. The operating voltages of the three valves are computed on a PC, based on the detected angles and pressures, by implementing a control algorithm, and individually controlling the three PMAs by feeding them to the valves realizes bending motions of the elbow joint of the manipulator.

The kinematics of this PMPMA can be expressed as follows⁽¹³⁾:

$$\mathbf{r}_c + \mathbf{R}\mathbf{r}_{ei} - \mathbf{r}_{bi} = l_i \mathbf{a}_i \quad (4)$$

where $\mathbf{r}_c$ is the position vector from O_b to O_e , $\mathbf{R}$ is the rotation matrix of the end coordinate system to the base coordinate system, $\mathbf{r}_{ei}$ is the position vector from O_e to the i th joint on the end part, $\mathbf{r}_{bi}$ is the position vector from O_b to the i th joint on the base part, l_i is the length of the i th actuator, and $\mathbf{a}_i$ is the directional vector of the i th actuator ($i = 1 \sim 3$).

3.2. Control system design

We design a system to enable the elbow joint angles of the PMPMA, θ and ϕ , to be followed as references by controlling the contraction of each actuator, Δl_i . Figure 7 shows the overall structure of the control system. In this system, the reference length of each actuator, l_{di} , is computed from the prescribed reference joint angles, θ_r and ϕ_r , by means of an inverse kinematics equation derived from Eq. (4) and is then provided for the controller of each PMA. Each PMA controller is composed of a basic feedback part and a hysteresis model-based feedforward part. The feedback part comprises an inner PID pressure control loop and an outer PID contraction control loop. The inner loop is introduced to reduce the time delay in an internal pressure change to a control command signal, because the contraction motion

Fig. 8 Experimental responses for tracking control of the pneumatic muscle manipulator

of a PMA depends greatly on the responsiveness of the internal pressure⁽¹⁴⁾. The role of the feedforward part is to restrain the performance deterioration arising from the hysteresis by canceling it out⁽¹²⁾. The control law is represented as follows:

$$\begin{cases} p_{di}(t) = p_{fi}(t) + g_4 e_i(t) - g_5 \dot{\Delta} l_i(t) + g_6 \int_0^t e_i(\tau) d\tau \\ v_i(t) = g_1 e_{pi}(t) - g_2 \dot{p}_i(t) + g_3 \int_0^t e_{pi}(\tau) d\tau \end{cases} \quad (5)$$

where $e_i(t) = \Delta l_{di}(t) - \Delta l_i(t)$, $e_{pi}(t) = p_{di}(t) - p_i(t)$, p_{di} is the reference internal pressure, v_i is the operating voltage of the valve, and $g_1 \sim g_6$ are the gains ($i = 1 \sim 3$). Here, p_{fi} is the hysteresis compensation input, which is determined by the following algorithm⁽¹²⁾:

- 1) Calculate the predicted pressure, p_{ri} , from the reference contraction, Δl_{di} , by using a linearized model of the actual contraction-pressure relationship.
- 2) Obtain the predicted contraction, Δl_{ri} , by inputting p_{ri} into the hysteresis model.
- 3) Compare the predicted contraction, Δl_{ri} , with the reference contraction, Δl_{di} , and
 - a) if $\Delta l_{ri} = \Delta l_{di}$, proceed to step 4.
 - b) if $\Delta l_{ri} \neq \Delta l_{di}$, adjust p_{ri} slightly and go back to step 2.
- 4) Determine p_{ri} as the compensation input, p_{fi} .

Prior to executing the control, $p_{fi}(t)$ for the reference joint angles, $\theta_r(t)$ and $\phi_r(t)$, is calculated throughout the entire path by following the above procedure. While executing the control, $p_{fi}(t)$ is substituted into Eq. (5). Using this algorithm proposed by Ge and Jouaneh allows us to avoid making an inverse model of the Preisach model, and to produce the inputs to compensate for the hysteresis nonlinearity in the same manner as the case with the inverse model.

3.3. Experimental results

To examine the performance of the tracking control of the PMPMA system, we performed experiments. For simplicity, the case with the hysteresis compensator described in §3.2 is hereafter referred to as "compensation A," and an extension version of the compensation A is referred to as "compensation B." In compensation B, the hysteresis compensation input, p_{fi} , in the control law of Eq. (5) is replaced by $g_7 p_{fi} + g_8 \dot{p}_{fi}$ (g_7 and g_8 are the gains). The purpose of this replacement is to facilitate the tuning of the controller to attain quicker responses. In addition, the controller without the hysteresis compensation, i.e., $p_{fi} = p_0$ in Eq. (5), was tested for comparison (this is referred to as the "non-compensation").

In all the experiments, the three PMAs were pressurized initially up to the bias pressure, p_0 ($= 280$ kPa). When the actuators were pressurized to p_0 , the joint angles were set as 0 deg. A sinusoidal input with an amplitude of 20 deg and a period of 8 s for θ_r and that with an amplitude of 10 deg and the same period for ϕ_r were used as the reference continuous

Fig. 9 Comparison of experimental frequency responses using the three schemes

paths of the joint angles. Control results for these references are shown in Fig. 8. In this figure, the dotted lines indicate the references, and the dashed lines indicate responses for the non-compensation case, which are equivalent to those with conventional PID control. The dashed-dotted lines and the solid lines correspond to responses with compensation A and B, respectively. The values of the gains in the controller were determined independently by a trial-and-error approach in every case under the consideration of sensitivity to noise, but with regard to $g_1 \sim g_6$ in compensation A and B the same values were set. As shown in Fig. 8, introducing compensation A or B results in more reduction in the tracking errors than in the non-compensation case, and compensation B achieves the smallest tracking errors among them.

Frequency responses for the three cases are plotted in Fig. 9, which were obtained from the time responses when a constant value for ϕ_r and various sinusoidal signals with a period between 2 s and 30 s for θ_r were inputted. The symbols $\times$, $\square$, and $\circ$ in this figure denote the experimental data for the non-compensation, compensation A, and compensation B cases, respectively. Among the three cases shown in Fig. 9, compensation B exhibits the best gain and phase performance, and the performance deterioration at a high-frequency range is the smallest with compensation B, supporting the effectiveness of compensation B. As for the slight resonance phenomenon observed in the gain plots of the compensation A and B cases, its cause is that the controller gains in these two cases are lower than those in the non-compensation case, and moreover the hysteresis compensation inputs are not adaptively adjustable during operation. Although compensation B requires the construction of the Preisach model and the determination of the hysteresis compensation inputs for entire reference paths based on the model, our tests confirm that it can enhance the tracking performance.

4. Switching control with LVQNN

4.1. Switching control system design

The characteristics of a PMA vary due to the load of an object lifted by the muscle⁽⁴⁾, which can augment the tracking errors when the PMPMA handles an object. To overcome this problem, Ahn and Nguyen⁽¹⁵⁾ proposed an algorithm to switch PID controller gains on-line according to an estimate of an external load obtained with a neural network. However, conventional PID controllers are insufficient in performance for the control of the PMPMA, as demonstrated in the previous section. In our approach, since the compensator is based on the predetermined hysteresis model, the difference between the modeled hysteresis and the actual hysteresis causes degradation of the control accuracy. We propose a control system that enables the hysteresis compensation input in Eq. (5) to switch according to an estimate of an external load. The structure of this control system is shown in Fig. 10. The manipulator carries 5-kg or 10-kg weights, or no object, in operation, and it is assumed that there is no information available about an external load before the execution of the control. During the execution of the control, a neural network online selects one of the above three load condi-

Fig. 10 Control system structure with switching mechanism

Fig. 11 Neural network architecture

tions, and then the hysteresis compensation input, p_{fi} , to the resulting load condition is used. We utilize a learning vector quantization neural network (LVQNN) for this task. A LVQNN offers a classification method in which each output unit represents a particular class.

The architecture of the LVQNN is illustrated in Fig. 11. The LVQNN consists of a hidden competitive layer and a linear output layer. The input vector and the output vector are defined as $\mathbf{x} = [x_1, x_2, \dots, x_N]^T$ and $\mathbf{y} = [y_1, y_2, \dots, y_M]^T$, respectively, where N is the number of inputs and M is the number of units in the output layer. The weight vector for each unit in the competitive layer and that for each output unit are denoted by $\mathbf{w} = [w_{ij}]$ ($i = 1, 2, \dots, S; j = 1, 2, \dots, N$) and $\mathbf{W} = [W_{ij}]$ ($i = 1, 2, \dots, M; j = 1, 2, \dots, S$), respectively, where S is the number of units in the competitive layer. In the competitive layer, the weights for a unit are moved according to the distance from the input vector through supervised learning. During this learning process, if $\mathbf{x}$ is classified correctly, the weights are adjusted by

$$\mathbf{w}_c(k+1) = \mathbf{w}_c(k) + \eta\{\mathbf{x}(k) - \mathbf{w}_c(k)\} \quad (6)$$

and if $\mathbf{x}$ is classified incorrectly, the weights are adjusted by

$$\mathbf{w}_c(k+1) = \mathbf{w}_c(k) - \eta\{\mathbf{x}(k) - \mathbf{w}_c(k)\} \quad (7)$$

where c means the closest unit to the input vector and η is the learning rate⁽¹⁶⁾. In the output layer, a class obtained in the competitive layer is converted into a target class. A step function is used as a transfer function in all the units in this layer.

4.2. Experimental results

In the following experimental verification of our control system, the input to the LVQNN comprises the normalized values of the contraction, Δl_i , and the internal pressure, p_i , of the three PMAs. The output is one of three discrete classes referred to as class 1, 2, or 3. Class 1 corresponds to the case when the PMPMA has no object, and classes 2 and 3 correspond to the cases when it conveys 5-kg and 10-kg weights, respectively. Each unit in the linear layer outputs a 0 or 1, and, for example, $[y_1, y_2, y_3] = [0, 1, 0]$ means class 2. We use compensation B, because it outperforms the other types.

To determine several parameters included in the LVQNN, we carried out preliminary trials to train the LVQNN. To create the inputs to the LVQNN for the training trials, we

Fig. 12 Experimental responses for tracking control of the pneumatic muscle manipulator using the LVQNN switching mechanism with an object of 10 kg

acquired typical responses of the PMPMA for the three classes, 1 ~ 3, experimentally by using the hysteresis compensation input, p_{fi} , of the no load case (class 1) and the same reference joint angles as those shown in Fig. 8. Extracting data from each experimental response from the start step to step T at an interval of ΔT produced the inputs. Some parameters, such as the number of units in a LVQNN, in general, affect the classification accuracy and the time taken to calculate the outputs. As a result of a series of offline training trials, we selected the following values for parameters: $\Delta T = 10$, the number of units in the competitive layer $S = 27$, the fixed learning rate = 0.001 in both the competitive layer and the output layer, and the number of iterations = 5000. To cope with frequent and unnecessary fluctuations in the output of the LVQNN, we used a rounded value of $C(k)$ obtained by $C(k) = \lambda C(k) + (1 - \lambda)C(k - 1)$ as the final classification result at the step $k^{(15)}$, where $\lambda = 0.4$.

After training a LVQNN with the above parameters, we investigated the switching control system with the LVQNN for the PMPMA experimentally. Figure 12 demonstrates results obtained in the experiments for the same reference joint angles as shown in Fig. 8. The reference joint angles are plotted as dotted lines, and the responses with and without the LVQNN-based switching mechanism are plotted as solid and dashed-dotted lines, respectively. A weight of 10 kg was mounted on link 2 of the manipulator, and the hysteresis compensator that corresponds to the no load case (class 1) was used in the initial condition. The hysteresis models and the hysteresis compensation inputs required for the case with 5-kg and 10-kg weights on the PMPMA were predetermined by following the procedure described above. The hysteresis compensator was switched correctly from the compensator for class 1 to that for class 3 at the time 0.10 s in the switching control result given in Fig. 12. The average time found by repeating the same experiment ten times for the 5-kg case was 0.43 s, and that for the 10-kg case was 0.10 s. Additional experiments were conducted to evaluate the switching performance for amplitude changes in the reference joint angles without tuning any of the control system parameters. In the 5-kg case, the average time for the reference joint angles, θ_r and ϕ_r , with an amplitude of 5 deg was 0.70 s, and that for the references with an amplitude of 10 deg was 0.35 s. In the 10-kg case, 0.20 s for a 5-deg amplitude and 0.15 s for a 10-deg amplitude were obtained. For period changes in the references, the LVQNN-based switching mechanism did not work accurately. Consequently, for variations in the magnitude of the inputs to the LVQNN, the LVQNN is robust to some extent, although a delay in the switched time occurs. As can be seen in Fig. 12, less oscillation appears in the responses with the switching mechanism than in those without the switching mechanism. In addition, the tracking error decreases at about 35% in terms of the integral of the squared errors between the reference values and the actual values if the switching mechanism is active. Further improvement is required even in the switching control system, because the tracking performance is lower in comparison with

the results shown in Fig. 8.

5. Conclusion

The purpose of the present study is to model the hysteresis existing in the inflation and deflation cycle of a PMA and to enhance the control performance of a PMPMA by introducing the hysteresis model-based compensator. The results obtained in this study can be summarized as follows:

(1) There is a difference between the pressurizing process and the depressurizing process in the PMA's contraction-pressure characteristics, and this difference causes hysteresis nonlinearity. To model it, we used the Preisach model. Experimental comparisons showed that the modeled hysteresis agreed well with the measured one and that the Preisach model was applicable for a PMA.

(2) A control system into which a feedforward compensation component based on the hysteresis model was incorporated was constructed for a PMPMA. Using this compensator resulted in an improvement of the tracking performance in experiments.

(3) To cope with variations in the characteristics of a PMA due to external loads, a mechanism of switching the hysteresis compensator with a LVQNN was added to the system. Adequately switching the compensator reduced the performance deterioration caused when the manipulator carried weights.

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