LS-SVM Based Modeling and Model Predictive Control for a Water-Hydraulic Artificial Muscle Actuator

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Abstract: Artificial muscle actuators (AMAs) driven by the pressure of tap water are flexible and lightweight and are therefore safe for humans and suitable for wearable power-assist devices. This paper proposes a modeling approach for a water-hydraulic AMA based on least squares support vector machines (LS-SVMs). Modeling tests are carried out on this LS-SVM approach with experimentally acquired data and show that the proposed model can capture the hysteresis characteristics of the water-hydraulic AMA. In addition, we constructed a state-space model of the water-hydraulic AMA into which the proposed LS-SVM-based model was incorporated and propose a model predictive control system based on the state-space model. An experimental comparison of the proposed control system and a control system with an inverse model of the water-hydraulic AMA, used in our previous study, demonstrated that the proposed one exceeds the previous one in control performance.

Key Words: artificial muscle actuator, water-hydraulic system, least squares support vector machine, hysteresis, model predictive control.

1. Introduction

Wearable power-assist devices are capable of aiding various human daily activities such as load carrying and walking. As the super-aging of the world population advances, such devices will increasingly be needed in a wide range of applications. Since wearable power-assist devices involve direct contact and interactions with human users, they require a very high degree of safety. Artificial muscle actuators (AMAs), which principally comprise a soft rubber tube and chemical fiber mesh, are flexible and lightweight and therefore very safe [1]–[3]. In our previous paper [4], we proposed a power-assist device with an AMA driven by the pressure of tap water. Water-hydraulic AMAs do not emit heat and cannot cause electrification. In addition, as this type of water-hydraulic AMA uses the pressure of tap water directly, it does not entail pumps. The assistive performance of the power-assist device greatly depends on the control accuracy of the water-hydraulic AMA.

The contraction and extension motion of typical AMAs is regulated by the internal pressure. For example, the relation between the contraction and internal pressure in the pressurizing process is different from that in the depressurizing process, due to the elasticity of the rubber and the friction between the rubber tube and fibers. This results in hysteresis nonlinearity [1]. In addition, depending on the contracting and extending rates and the magnitude of the load exerted on AMAs, the hysteresis curves become distorted. Such complicated nonlinear behavior can lead to inaccuracy and difficulty in controlling AMAs. More precise models for AMAs could aid in the design of controllers with better performance.

With regard to pneumatically driven AMAs, several mathematical models and control strategies have been presented to date [5]–[11]. In addition, two studies described the Preisach hysteresis modeling of a pneumatic AMA [12],[13]. Despite efforts, universal modeling methodologies have not yet been established. There have been fewer studies on modeling and control of water-hydraulic AMAs than on pneumatic AMAs. An approximate mathematical model of a water-hydraulic AMA has been described [14]; however, it does not take hysteresis into account. A previous study [15] applied the Bouc-Wen hysteresis model to the modeling of a water-hydraulic AMA. Also, a control scheme with adaptive parameter estimation has been proposed for a water-hydraulic AMA [16].

Machine learning techniques are useful for modeling and control of hysteretic systems. For example, neural networks (NNs) are a representative tool for dealing with such problems [17],[18]. The application of least squares support vector machines (LS-SVMs) [19] to the modeling of the rate-dependent hysteretic behavior of piezoelectric actuators has been demonstrated [20],[21], and the created model has been used for the control of those actuators [22],[23].

In our preceding study [24], we applied the LS-SVM-based modeling technique [22] to a water-hydraulic AMA, assessed the modeling accuracy experimentally, and showed that the LS-SVM-based modeling outperformed SVM-based modeling. We further constructed and tested a control system of the AMA, which includes a compensator with an inverse model created by the LS-SVM-based modeling. The tracking performance of the control system was verified through experiments. However, this previous approach has the following issues:

- It created a nonlinear regression model by means of LS-SVMs. In this method, the current output was estimated by the model from current and previous inputs and previous outputs. The internal pressure of the water-hydraulic AMA was defined as input and its contraction as output.
The model was capable of capturing the rate-dependent hysteretic behavior. However, our previous work [24] handled hysteresis in the contraction-pressure relation only and did not consider the force of the water-hydraulic AMA. In addition to the contraction-pressure relation, hysteresis exists in the force-pressure relation and in the force-contraction relation in AMAs [1],[5].

- It consisted of a feedforward controller with the LS-SVM-based inverse model and a PID feedback controller. Since the model is nonlinear, it is not suitable for model-based control system design.

Meanwhile, the use of LS-SVMs for modeling the water-hydraulic AMA was valid because of the high generalization ability of LS-SVMs.

The objective of this paper is to propose an improved LS-SVM model for a water-hydraulic AMA and a model predictive control (MPC) system [25] based on a state-space model containing the proposed LS-SVM model. In the first stage of this study, we create a model of the water-hydraulic AMA with the LS-SVM by using experimentally acquired data and show that the proposed model can capture the hysteretic characteristics of the water-hydraulic AMA. In the second stage, we construct a state-space model of the water-hydraulic AMA system into which the proposed LS-SVM model is incorporated and design the MPC system based on it. The control performance is compared with our previous control system [24]. The contributions of this study are as follows:

- Because LS-SVMs use the kernel trick, the proposed LS-SVM model is represented as a linear form with a kernel function and training data in order to facilitate the application to the control of the water-hydraulic AMA. Unlike in NNs, a globally optimal solution can be obtained in LS-SVMs.

- Unlike the input and output in our preceding work [24], input in the proposed LS-SVM model is comprised of the contraction rate, contraction velocity, and internal pressure of the water-hydraulic AMA, and output is its force. Due to the high generalization ability of LS-SVMs, the proposed model has both the representation capability of hysteretic characteristics and adaptability to rate and load variations.

- The proposed model can be incorporated directly into a state equation of the water-hydraulic AMA system without losing the above abilities, and model-based control system design is feasible by using it.

The remainder of this paper is organized as follows: Section 2 describes the LS-SVM-based modeling approach for the water-hydraulic AMA and the experimental setup with the water-hydraulic AMA. It also provides experimental modeling test results. Section 3 presents the design of our proposed control system with the proposed LS-SVM model and the results of verification experiments. Section 4 contains our conclusions.

2. LS-SVM Based Modeling

2.1 Least Squares Support Vector Machines

In this study, we employ LS-SVMs [19],[26] to model the water-hydraulic AMA. The LS-SVM determines the following scalar function by using data pairs for training \((\mathbf{x}_i, f_i)\) \((i = 1, \ldots, N)\):

\[
   f(x) = w^T \phi(x) + b, \tag{1}
\]

where \(x_i\) denotes the \(i\)th input vector, \(f_i\) is the scalar output for the input vector, \(x\) is the new input vector, \(f\) is the scalar output for \(x\) (their size is the same as that of the training data \((x_i, f_i)\)), \(w\) is the coefficient vector, \(b\) is the bias term, and \(\phi(x)\) is the mapping function between the input vector \(x\) and the feature space.

The problem in determining the above equation with the LS-SVM is defined as the following optimization problem [19]:

\[
   \min \ J(w, e) = \frac{1}{2} w^T w + \frac{\gamma}{2} \sum_{i=1}^{N} e_i^2 \tag{2}
\]

such that \(f_i = w^T \phi(x_i) + b + e_i \ (i = 1, \ldots, N), \tag{3}\)

where \(e_i\) is the slack variable for \(x_i\), \(e = [e_1, \ldots, e_N]^T\), and \(\gamma\) is the margin parameter.

By introducing the Lagrange multiplier \(\alpha_i\) into Eqs. (2) and (3), the Lagrangian is given by

\[
   L(w, e, b, \alpha) = J(w, e) - \sum_{i=1}^{N} \alpha_i \left[ w^T \phi(x_i) + b + e_i - f_i \right], \tag{4}
\]

where \(\alpha = [\alpha_1, \ldots, \alpha_N]^T\). Unlike in the case of ordinary SVMs, in the LS-SVM the optimality conditions derived from Eq. (4) become equality constraints, and therefore the optimization problem is eventually reduced to the problem of solving a set of simultaneous linear equations.

Training of the LS-SVM model is performed to determine \(\alpha\) and \(b\) by solving the above optimization problem. After calculating \(\alpha\) and \(b\), we can obtain the function (1) by introducing the kernel function \(K(x, x_i)\) as the following form:

\[
   f(x) = \sum_{i=1}^{N} \alpha_i K(x, x_i) + b, \tag{5}
\]

where \(x_i\) is the training data and \(x\) is the new input data.

2.2 LS-SVM Model

In our previous study [24], we focused on the contraction-pressure relation of the water-hydraulic AMA and created a regression model with LS-SVMs. The internal pressure of the water-hydraulic AMA was defined as input and its contraction as output. In this study, in order to construct an LS-SVM model that can capture hysteretic behavior in the force-pressure and force-contraction relations in the water-hydraulic AMA, we define that an input vector is comprised of the contraction rate, contraction velocity, and internal pressure of the water-hydraulic AMA, and the output is defined as its force.

We utilize a linear kernel as the kernel function in Eq. (5) in this paper. The linear kernel is generally expressed as \(K(x, x_i) = x_i^T x\), where \(x\) is the new input vector and \(x_i\) is the \(i\)th vector in training datasets. By substituting this equation into Eq. (5), the LS-SVM model becomes the following linear equation with the kernel function and the training data:

\[
   f(x) = \sum_{i=1}^{N} \alpha_i x_i^T x + b. \tag{6}
\]
where $x_{ij}$ is detected by a sensor, and the internal pressure $P$ at a certain time. Here we define $x = [x_1, x_2, x_3]^T = [\epsilon, v, P]^T$ and rewrite Eq. (6) by substituting $x$ into it. Then, we have

$$f(x) = (\alpha_1 x_1 + \alpha_2 x_{i2} + \cdots + \alpha_N x_{iN})x_1 + (\alpha_1 x_2 + \alpha_2 x_{i2} + \cdots + \alpha_N x_{iN})x_2 + (\alpha_1 x_3 + \alpha_2 x_{i2} + \cdots + \alpha_N x_{iN})x_3 + b,$$

where $x_{ij}$ denotes the $i$th variable of the $j$th training data vector, $\epsilon (= \frac{L - l}{L})$, $v (= \frac{dv}{dt})$, $l$ is the length of the water-hydraulic AMA, which is detected by a sensor, and $L$ is the initial length of the water-hydraulic AMA with a weight suspended. Unlike ordinary NNs, this model is trained by the optimization problem mentioned in Section 2.1, and therefore it is globally optimal.

2.3 Experimental Setup

A typical AMA consists of a flexible rubber tube covered with braided chemical fibers. When tap water is supplied to the rubber tube, the AMA is pressurized and inflates radially, simultaneously performing a contraction motion longitudinally. AMAs of this type have the following advantages [1],[12]:

- They have a high power-to-weight ratio and generate high contraction force.
- Due to their flexibility and elasticity, typical AMAs will not cause damage in the event of a collision with objects or humans.
- They have no moving mechanical parts, and therefore create very low friction. Also, they do not get rusty.
- They are applicable under clean conditions because lubrication is not required.

Figure 1 illustrates the experimental setup used for acquiring the actual length, internal pressure, and force of a water-hydraulic AMA for modeling. The AMA used in this study had a diameter of 25 mm and a nominal length of 300 mm. As shown in Fig. 1, the AMA was mounted horizontally, and a weight was suspended with a wire rope through a pulley. The internal pressure $P$ was detected by a pressure transducer, and the length of the AMA $l$ was measured by a linear encoder. The force of the AMA $f$ was detected by a load cell. Signals were sent to a PC through an A/D interface. The outputs of all the sensing devices were recorded on the PC. Two proportional control valves were used in this system. One was used to control the water supply flowrate, and the other to control the water exhaust flowrate [4]. A PI (proportional-integral) control algorithm for regulating the internal pressure was implemented on the PC, which produced the operating voltages of the proportional control valves to adjust the water flowrate. By applying the voltages through a D/A interface to the valves, the internal pressure could be set to a reference pressure.

2.4 Modeling Results

2.4.1 Modeling

Hysteresis appears in typical AMAs. In addition, the hysteresis depends on the frequency of the inputs and the magnitude of loads [1],[5]. Figure 2 shows examples of measured hysteresis. Figure 2 (a) demonstrates the effect of load variation ($m$ is the mass), while Fig. 2 (b) curves demonstrate speed variation ($T$ is the cycle). The hysteresis curves are distorted according to the increases in their speed of contraction and extension, and in the mass of a weight suspended by the AMA. Here, we tested whether the proposed LS-SVM model could capture the hysteretic behavior of the water-hydraulic AMA.

The length, pressure, and force of the water-hydraulic AMA were measured using the above experimental setup for modeling. For the measurements, sinusoidal signals with time periods of 5 s, 10 s, and 15 s were inputted into the pressure controller as reference values. The amplitudes were increased from 50 kPa to 150 kPa at a constant interval of 50 kPa. The mass of a weight lifted by the water-hydraulic AMA was 1 kg, 2 kg, and 3 kg. In all, the measurements were conducted under 27 different experimental conditions. The experimental data of the water-hydraulic AMA were recorded at a sampling frequency of 200 Hz.

Figure 3 shows some of the measured data used for modeling. The values of the pressure and force were detected by the corresponding sensors. The contraction rate $\epsilon$ was calculated...
lated by $\epsilon = L - l$ with the length $l$ acquired by the sensor and the prerecorded initial length $L$ after loading under each experimental condition. The $x$-axis indicates the internal pressure, the $y$-axis the contraction rate, and the $z$-axis the force of the water-hydraulic AMA. As may be seen, hysteretic characteristics exist in the water-hydraulic AMA. This leads to the principal difficulty in modeling the AMA. As described above, in the proposed LS-SVM model, the input includes the contraction rate, contraction velocity, and internal pressure of the water-hydraulic AMA, and the output is its force. The contraction velocity was calculated with the backward difference of the measured contraction rate. According to the equation of motion mentioned below, $f_m L = F$ is used as the output instead of $f$ ($m$ is the mass of a weight). Strictly, $f$ contains friction force and gravity.

The accuracy of the LS-SVM-based hysteresis modeling was assessed using the experimental data. Before the model assessment, datasets were created from the experimental data. They were divided into two groups: datasets for modeling, and datasets for verification. A computer program of our modeling approach was developed with Matlab software (The MathWorks, Inc). First, a modeling experiment was conducted to investigate the dependence of the modeling error on the number of modeling datasets. The number of datasets for modeling $N$ was varied from 100 to 5000. On the other hand, the number of verification datasets was fixed at 50000. The LS-SVM-based modeling was carried out with the $N$ datasets for modeling, and the MAE (mean absolute error) was computed using the datasets for testing. Here, the MAE is defined as

$$\text{MAE} = \frac{1}{N_v} \sum_{i=1}^{N_v} |f_{ei} - f_i|, \quad (8)$$

where $f_{ei}$ is the measured force, $N_v$ is the total number of the verification datasets, and $f_i$ is the force obtained by multiplying the LS-SVM model output by $mL$. Each value is the average obtained from 500 modeling iterations because the modeling datasets were randomly selected. Modeling results are shown in Fig. 4. The vertical axis denotes the MAE calculated by Eq. (8) and the horizontal axis the number of the modeling datasets. In this figure, the MAE is smallest around $N = 750$ and almost constant over 750.

### 2.4.2 Model accuracy

Using the experimental setup shown in Fig. 1, additional experimental data were acquired for the 1.5 kg and 2.5 kg masses. Sinusoidal reference signals with amplitudes of 60 kPa, 110 kPa, and 170 kPa and time periods of 7 s, 12 s, and 17 s were inputted to the pressure controller, and time responses of the length, pressure, and force of the AMA were measured. Note that these conditions are different from the 27 experimental conditions in Section 2.4.1. All these additionally acquired data were used as the datasets for testing to examine the approximation accuracy of unknown data. In the same way as described in Section 2.4.1, modeling datasets were selected randomly from the total datasets obtained from the abovementioned experimental data under the 27 conditions.

After training the LS-SVM model with the $N$ datasets for modeling, input vectors generated from the testing datasets were fed to the LS-SVM model and output was computed. The number of modeling datasets $N$ was varied from 100 to 5000. Figure 5 demonstrates the relation between the MAE calculated from the model output with Eq. (8) and the number of modeling datasets. Similar to the result of Fig. 4, the MAE was smallest around $N = 750$. Hence, we fix $N$ at 750 hereafter.

Figure 6 exemplifies the measured data for the 7 s time period sinusoidal reference signal with an amplitude of 110 kPa for the 1.5 kg mass, and the output data from the LS-SVM model. In this figure, the measured values are indicated by · and the model output data by the symbol ◦. In Fig. 6(a), the $x$-axis indicates the internal pressure, the $y$-axis the contraction rate, and the $z$-axis the force of the water-hydraulic AMA. Figure 6(b) shows the relation between the contraction rate and internal pressure, obtained by mapping all the data in Fig. 6(a) onto the $y$-$x$ plane (both the contraction rate and internal pressure are included in the input vectors to the LS-SVM model).
Similarly, Fig. 6 (c) shows the relation between the force and internal pressure, obtained by mapping all the data in Fig. 6 (a) onto the $z$-$x$ plane, and Fig. 6 (d) shows the relation between the force and the contraction rate, obtained by mapping all the data in Fig. 6 (a) onto the $z$-$y$ plane. These relations have hysteresis characteristics. In these figures, it is confirmed that the proposed LS-SVM model can capture the hysteretic behavior of the water-hydraulic AMA, although the model accuracy was not very high.

### 3. Control of a Water-Hydraulic AMA

#### 3.1 State-Space Model

The equation of motion of an AMA, the continuity equation, and the flow characteristics of a valve are expressed as follows [4],[11]:

$$m \frac{d(L v)}{dt} = f,$$

$$Q = \frac{V}{K_b} \frac{dP}{dt} + \frac{dV}{dt},$$

$$Q = S \sqrt{\frac{2(P_u - P_d)}{\rho}},$$

where $m$ is the mass of a weight, $f$ is the force, $Q$ is the flowrate, $V$ is the volume of an AMA, $K_b$ is the bulk modulus, $S$ is the valve opening area, $P_u$ is the upstream pressure, $P_d$ is the downstream pressure, and $\rho$ is the density.

The relation between the volume $V$ and the contraction rate $\epsilon$ is represented by the following equation [6]:

$$V = D_1 \epsilon^2 + D_2 \epsilon + D_3,$$

where $D_1$, $D_2$, and $D_3$ are the constants. The values of the parameters $D_1$, $D_2$, and $D_3$ were the same as those used in [4].

In that study, the pressure control for several step reference signals was executed for a water-hydraulic AMA, and the diameter and length of the AMA in the steady state were recorded. The volume of the AMA was then calculated from the diameter and length, regarding the AMA as approximately cylindrical in shape. The parameter values were determined based on the relationship between the volume and contraction rate.

Before training the LS-SVM model, since the range of each input variable was different, preprocessing was executed to avoid the deterioration of modeling accuracy due to this factor; i.e., all the input and output data were standardized using their means and standard deviations (after training, postprocessing was conducted to convert them back to their original values). Therefore, $\alpha$ and $\beta$ in Eq. (6) were determined for the standardized input and output data. Taking this standardization into account, a state-space model of the water-hydraulic AMA system is derived here. We express the standardized variable of an arbitrary variable $x$ as $\bar{x}$, the mean of $x$ as $\bar{x}_m$, and the standard deviation of $x$ as $\sigma$. The standardization is represented as $\bar{x}_m = x - \bar{x}_m \sigma$.

By linearizing Eq. (10) in the vicinity of the mean values, we get

$$\Delta Q = \frac{V_m}{K_b} \frac{d(P)}{dt} + \frac{d(\Delta V)}{dt},$$

where we define that $\frac{d(\Delta V)}{dt} = \frac{d(\Delta V)}{d(\Delta x)} \frac{d(\Delta x)}{dt} = \frac{d(\Delta V)}{d(\Delta x)} \Delta x = D_m \cdot \Delta x$. For $V_m$ and $D_m$, we use the average values obtained from Eq. (12).

Similarly, linearizing the valve flow characteristics (11) gives

$$\Delta Q = \left( \frac{\partial Q}{\partial S} \right)_m \Delta S + \left( \frac{\partial Q}{\partial P} \right)_m \Delta P = k_o \Delta S - k_o \rho \Delta P,$$
where we assume that \( P_d = P \) and \( P_u = P_f \) (\( P \) is the pressure of tap water).

By substituting Eq. (14) into Eq. (13), we then have

\[
\frac{d(\Delta P)}{dt} = \frac{K_b}{V_m}(-D_m\Delta v + k_v\Delta S - k_p\Delta P).
\]  

(15)

Here we approximate the dynamics of the control valve with \( S = k_u u \), where \( u \) is the operating voltage of the valve and \( k_u \) is approximately determined from the experimental relation between the flowrate and operating voltage [4].

In this study, we assume that the force of the AMA \( f \) depends on the contraction rate \( \epsilon \), the contraction velocity \( v \), and the internal pressure \( P \). Equation (9) is rewritten as

\[
\frac{dv}{dt} = \frac{f}{mL} = F(\epsilon, v, P),
\]

(16)

where \( F \) is the LS-SVM model output, because the LS-SVM model is trained with the input vector \( x = [\epsilon, v, P]^T \) and the output \( F = \frac{dE}{dt} \). Here, we consider very small changes in the neighborhood of the average values, and consequently Eq. (16) becomes \( \frac{dv}{dt} = \Delta F \), as all the input and output data are standardized during training. Since \( \Delta F \) is represented as \( \Delta F = \sigma_F \bar{F} \) (\( \sigma_F \) is the standard deviation of \( F \)), \( \bar{F} \) can be expressed in the same form as Eq. (7). Therefore, the equation of motion can be rewritten as

\[
\frac{d(\Delta v)}{dt} = \sigma_F \left( \frac{A_1}{\sigma_x}, \sigma_\epsilon \Delta \epsilon + \frac{A_2}{\sigma_y}, \sigma_\bar{v} \Delta \bar{v} + \frac{A_3}{\sigma_p}, \sigma_p \bar{F} \right),
\]

(17)

where \( \sigma_x, \sigma_\epsilon, \sigma_\bar{v}, \) and \( \sigma_p \) are the standard deviations of \( \epsilon, v, \) and \( P \), respectively. In this work, because all the data are standardized during training, \( b \) in Eq. (7) becomes \( b \approx 0 \).

We here define the state variables as \( x = [x_1, x_2, x_3]^T = [\Delta \epsilon, \Delta v, \Delta P]^T \) and define the control input as the valve operating voltage \( u \). From Eqs. (15) and (17), the state equation is derived as

\[
\dot{x}(t) = Ax(t) + Bu(t),
\]

(18)

\[
A = \begin{bmatrix} 0 & 1 & 0 \\ a_1 & a_2 & a_3 \\ 0 & b_1 & b_2 \end{bmatrix}, \quad B = \begin{bmatrix} 0 \\ 0 \\ b_3 \end{bmatrix},
\]

where \( a_1 = \frac{\sigma_F A_1}{\sigma_x}, a_2 = \frac{\sigma_F A_2}{\sigma_y}, a_3 = \frac{\sigma_F A_3}{\sigma_p}, b_1 = -\frac{K_b D_m}{mL}, b_2 = \frac{k_p}{mL}, \) and \( b_3 = \frac{K_b k_v}{V_m} \).

This state equation contains the proposed LS-SVM model directly, and is capable of representing the hysteretic characteristics in the water-hydraulic AMA, as experimentally demonstrated in Section 2.4.2. In the experiments described below, the state variables \( x_1 \) and \( x_3 \) can be calculated from the sensor output data, and \( x_2 \) can be obtained by the backward difference of \( x_1 \).

### 3.2 Control System

In this paper, we propose a model predictive control (MPC) system [25] of the water-hydraulic AMA with the state equation (18), including our developed LS-SVM model. This system provides optimal control by predicting the system’s future state using the state-space model that can deal with the hysteresis in the water-hydraulic AMA.

| Table 1 Model parameters. |
|---------------------------|
| \( D_1 \) (m\(^3\)) | -6.2 \times 10^{-4} | \( D_2 \) (m\(^3\)) | 3.7 \times 10^{-4} |
| \( D_1 \) (m\(^3\)) | 7.9 \times 10^{-4} | \( D_3 \) (m\(^3\)) | 3.4 \times 10^{-4} |
| \( K_b \) (Pa) | 2.2 \times 10^5 | \( k_p \) (m\(^3\)/Pa-s) | 7.0 \times 10^{-11} |
| \( k_v \) (m/s) | -29 | \( k_v \) (m/s) | 4.0 \times 10^{-7} |
| \( P_s \) (Pa) | 0.37 \times 10^6 | \( \sigma_\epsilon \) (-) | 0.043 |
| \( \sigma_p \) (Pa) | 5.7 | \( \sigma_x \) (Pa) | 6.1 \times 10^4 |
| \( \sigma_x \) (-) | 0.018 | \( V_m \) (m\(^3\)) | 8.7 \times 10^{-5} |

For the experimental setup shown in Fig. 1, we designed an MPC system to enable the contraction rate of the water-hydraulic AMA to be followed as a reference contraction rate. A computer program of the control system was made using Matlab and the Model Predictive Control toolbox (The MathWorks, Inc). The constants \( A_1, A_2, \) and \( A_3 \) in the state equation (18) were found by training the LS-SVM model beforehand. For this training, 750 modeling datasets were selected from the experimental data acquired for the modeling verification described in Section 2.4.1. We utilized the experimental system’s parameter values determined in our previous work [4], [24] to calculate the state equation (18). The parameter values are summarized in Table 1. The sampling frequency was set at 200 Hz. An MPC system was designed with a discrete-time version of Eq. (18). As a result of preliminary experiments, we chose 100 discrete-time steps as the prediction horizon in the MPC system and three discrete-time steps as the control horizon by a trial-and-error approach. We also set the cost function’s weight for the control variables at 25, and that for the control input at 0.05. Since the range of the control input \( u \), i.e., the valve operating voltage, is \(-10 \text{V} \leq u \leq +10 \text{V}\), the constraint was imposed on it. All the initial values were set at zero.

For comparison, we also tested our previous control system based on the inverse model of the water-hydraulic AMA [24]. The previous system was composed of a basic feedback part and an LS-SVM model-based feedforward part. The feedback part was comprised of an inner PID (proportional-integral-derivative) pressure control loop and an outer PID contraction control loop. The inner loop was introduced to reduce the time delay in internal pressure change in response to a control command signal because the contraction motion depends on the responsiveness of the internal pressure. The role of the feedforward part was to restrain performance deterioration arising from the hysteresis by canceling it out with an inverse model. This control system outperformed a standard PID control system. In our previous study [24], the LS-SVM model was used in the control system only to cancel out hysteresis characteristics in the water-hydraulic AMA, and the principal PID controllers were not designed based on the LS-SVM model. Therefore, the LS-SVM model was independent of the controller. The MP controller in this study was designed based on the state-space model containing the proposed LS-SVM model; thus, the proposed LS-SVM model is indispensable to the calculation of the MP controller.

As mentioned above, the valve voltage has the limits, and thus an input constraint was introduced into the MPC system. Hence, the MPC system does not need any anti-integral windup techniques. We introduced an anti-integral windup technique [27] into the previous control system only.
3.3 Experimental Results

Finally, we performed experiments to validate the control performance of the water-hydraulic AMA control system. In order to test the effect of prediction with the proposed state-space model, we used a rectangular reference contraction rate. In the experiments, both the control performance of the proposed MPC system and that of the previous control system [24] were investigated under the following three experimental conditions:

- **Condition 1**: the height of the rectangular reference $r_h = 0.24$, the width of the rectangular reference $r_w = 10$ s, and the mass $m = 1$ kg
- **Condition 2**: $r_h = 0.24$, $r_w = 10$ s, and $m = 2.5$ kg
- **Condition 3**: $r_h = 0.24$, $r_w = 5$ s, and $m = 2.5$ kg
- **Condition 4**: $r_h = 0.12$, $r_w = 5$ s, and $m = 2.5$ kg

Figure 7 exemplifies the control results under Condition 1. In Fig. 7 (a), the dashed line indicates the reference contraction rate, and the solid line a measured time response of the contraction rate with the proposed MPC system. In Fig. 7 (b), the dashed line indicates the reference, and the solid line a measured time response of the contraction rate with the previous control system. By comparing these results, we could confirm that the proposed MPC system exhibits quicker rising and a smaller tracking error than the previous control system.

For each experimental condition, the control trial was repeated five times. The error between the reference and the actual contraction rate was evaluated using a mean absolute error (MAE). The MAEs are summarized in Fig. 8. From this figure, it may be seen that the proposed MPC control system could reduce the MAEs more than the previous control system under all experimental conditions. According to both the time responses shown in Figs. 7 (a) and 7(b) and the MAEs in Fig. 8, it was verified that the control system with the proposed LS-SVM model achieves higher control accuracy than the control system with the previous LS-SVM model [24].

Figure 9 shows a simulation result of the proposed MPC system with the state-space model (18) for Condition 1. Although there was a time lag and a difference in responsiveness between the experimental and simulated responses, the response simulated with the model could approximate the experimental response (e.g., the MAE between the experimental and simulated responses was 0.015 for Condition 1). The performance of MPC greatly depends on the accuracy of the model used for prediction. As the state-space model (18) includes the proposed LS-SVM model, which can represent the hysteretic behavior shown in Section 2.4.2, the prediction accuracy of the model is relatively high even though it is linear, and our MPC system based on the model could attain higher control performance.

4. Conclusions

In this paper, we proposed an LS-SVM-based modeling approach for a water-hydraulic AMA. Modeling test results with the experimental data showed that the proposed model could capture the hysteretic characteristics of the water-hydraulic AMA. In addition, we constructed a state-space model of the water-hydraulic AMA system that incorporated the LS-SVM model and proposed an MPC system based on the state-space model. Experimental comparisons of the control performance of the MPC system with that of our previous control system including the LS-SVM-based inverse model demonstrated that the proposed MPC system performs with higher accuracy than the previous one.

In our future work, the proposed control approach will be applied to a power-assist device driven by water-hydraulic AMAs.

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