A hopfield neural network-based Bouc-Wen model for magnetic shape memory alloy actuator

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ABSTRACT

Magnetic shape memory alloy (MSMA) actuator has potential application value in the aerospace, robotics and precision positioning due to the advantages such as small size, high precision, long stroke length and large energy density. However, the asymmetrical rate-dependent hysteresis between input and output of the MSMA actuator makes it difficult to build precise model of the MSMA actuator-based micropositioning system, so that the application of the MSMA actuator is seriously hindered. In this paper, a Bouc-Wen (BW) model is adopted to describe the hysteresis of the MSMA actuator. The parameters of BW model are identified online by Hopfield neural network (HNN). Then, the effectiveness of HNN-based BW model is fully certified using the experiments. The experimental results show that the BW model identified in this paper can accurately describe the hysteresis of the MSMA actuator at different input excitation.

I. INTRODUCTION

As frontier of modern science, most of the equipment in micro-nano positioning technology employs micro-actuator as actuation.1 Smart materials, such as giant magnetostri ctive alloy, piezoceramic material and magnetic shape memory alloy (MSMA),2,3 are widely used in the development of micro-actuators devoted to micro-nano positioning applications. As one of the smart material actuators, MSMA actuator, which is capable of positioning with the nanometer resolution and small volume, has attracted much research interest. However, the same as other smart material actuators, there are some difficulties in application of the MSMA actuator, namely, 1) asymmetric loop between ascending and descending branches and 2) the output displacement depends on the input frequency,4,5 which causes the deterioration of positioning accuracy. This phenomenon is called asymmetrical rate-dependent hysteresis. Therefore, in order to describe the complex hysteresis characteristics of the MSMA actuator, it is very meaningful to establish the accurate hysteresis model of the MSMA actuator.

In order to promote the application of smart material actuators, several models have been drawing considerable attention to describe the hysteresis phenomenon. Prandtl-Ishlinskii (PI) model,6 Krasnosel’skii-Pokrovskii (KP) model,7 Duhamel model,8 Bouc-Wen (BW) model,8 nonlinear autoregressive moving average with exogenous inputs (NARMAX) model10 and neural network-based model11 are the common models, which are adopted to describe the hysteresis of smart material actuators. The Preisach model is widely used to represent the hysteresis of the MSMA actuator. Chiang et al.12 used classical Preisach model to capture the hysteresis from input signals and output responses of MSMA actuator. But the experiment result only show that Preisach model has the ability to describe the static hysteresis characteristic of the MSMA actuator. In general, the accuracy of the static hysteresis models is gradually deteriorated while the input frequency of the actuator is increased. To increase the accuracy of the static hysteresis models, some modified models have been proposed, such as modified rate-dependent PI model, dynamic Preisach model and rate-dependent Duhamel model. In the Ref. 13, Shakiba et al. adopted two models, namely rate-independent and rate-dependent generalized PI, to characterize the MSMA actuator. The experimental results show compared with the rate-independent PI model, the rate-dependent PI model, which considered the effect of input frequency by defining a time-dependent operator, can describe dynamic non-linearity of MSMA actuator. Oh et al.1 proposed a rate-dependent...
semi-linear Duhem model to describe the rate-dependent hysteresis and a least squares method was adopted to identify the parameters of the Duhem model. However, as a kind of classical identification methods, the least squares method required a number of iterations. In order to omit this drawback of classical identification methods, Zhou et al. established the KP model and PI model with their density function expressed by the Elman neural network and internal time-delay recurrent neural network, respectively. Nevertheless, the number of operators in KP model and PI model is large, which increased the difficulty of calculating. Fu et al. proposed a non-linear autoregressive with external input (NARX) neural network to represent the hysteresis of magnetorheological elastomer isolator. Yu et al. implemented neural networks-based NARMAX models to represent the hysteresis of the MSMA actuator, and the effectiveness of NARMAX model was proven through the experiments. However, the structure of the above neural networks were complex.

From the above research, because of the excellent nonlinear approximation ability of neural network, many scholars have applied it to identify the hysteretic system. Especially feedforward neural network is widely used. However, in addition to feedback connection between neurons, feedback neural network establishes feedback connection between neurons on the basis of feedforward neural network. So that compared with feedforward neural networks, besides the ability of approximate nonlinear function, the capability of computing power, associative memory and optimization for feedback neural network is further improved. As a kind of fully interconnected recursive neural network, Hopfield neural network (HNN) has feedback connections from output to input and each neuron in HNN is connected to others. Gao et al. adopted HNN to identify the PI model, but the integration of play-operators increases the complexity of computation. Adly et al. proposed a HNN approach for the implementation of Stoner Wohlfarth-like operators to establish hysteretic model, and this method could lead to a significant enhancement in the computational efficiency of the vector Preisach-type hysteresis model. However, the experimental results in Ref. 20 only demonstrated the static hysteresis.

In this paper, a BW model is innovatively identified online by HNN to describe the hysteresis of MSMA actuator. BW model is a kind of differential equation model. Compared with other models, such as PI model and KP model, it has fewer parameters to be identified. Nevertheless, BW model is rate-independent, identifying the applicable parameters is a significant part of modeling BW model. HNN has the features of the nonlinear mapping property to be applied to adjust the model parameters online. Hence, it has more computing power and better global searching capability compared with feedforward neural network. In this paper, HNN is used to identify the parameters of BW model online. To verify the effectiveness of the HNN-based BW model, the contrast experiments of the model in Ref. 7 are adopted. Experimental results demonstrate that the proposed model in this paper has capable of capturing the hysteresis of the MSMA actuator at different input signals.

II. IDENTIFICATION OF BOUC-WEN MODEL

A. Bouc-Wen model

BW model was initially proposed and subsequently modified by Bouc and Wen in the 1970s, respectively. Due to its capability to characterize the hysteresis and the advantage of simple structure, it has been extensively used in various applications of piezoelectric micro-positioning platform, giant magnetostrictive actuator, and MSMA actuator. The general expression of BW model is given as:

\[
\begin{align*}
\dot{y}_d(t) &= pu(t) + H(t) \\
H(t) &= a\dot{u}(t) + \beta\dot{u}(t)H(t) + y\dot{u}(t)H(t)
\end{align*}
\]

(1)

where \(y_d(t)\) and \(u(t)\) are the output displacement and input voltage of the MSMA actuator at \(t\) time, respectively. \(H(t)\) is the hysteresis state, \(\alpha\) is the weighting parameter of the system. \(\alpha\), \(\beta\) and \(\gamma\) are the parameters, which determine the amplitude and shape of the BW model. By the definition of derivative, \(\dot{H}(t)\) and \(\ddot{u}(t)\) can be approximately expressed as follows, respectively:

\[
\dot{H}(t) = \frac{H(t) - \eta_1H(t - \Delta t)}{\Delta t}
\]

(2)

\[
\ddot{u}(t) = \frac{u(t) - \eta_2u(t - \Delta t)}{\Delta t}
\]

(3)

where \(\Delta t\) is the sampling period. \(\eta_1\) and \(\eta_2\) are the parameters which are equal to 1 when \(\Delta t\) is sufficiently small. Thus, at the \(k\)th (\(k > 1\) and \(k\) is integer) sampling instant, Eq. (1) can be re-expressed as:

\[
\begin{align*}
\dot{y}_d(k) &= pu(k) + H(k) \\
H(k) &= a\frac{u(k) - u(k - 1)}{\Delta t} + \beta\frac{\Delta u(k) - u(k - 1)}{\Delta t}H(k - 1) \\
+ \gamma\Delta u(k)H(k - 1)
\end{align*}
\]

(4)

Then Eq. (4) can be further simplified as:

\[
\begin{align*}
\dot{y}_d(k) &= pu(k) + H(k) \\
\Delta H(k) &= a\Delta u(k) + \beta\Delta u(k)H(k - 1) \\
+ \gamma\Delta u(k)H(k - 1)
\end{align*}
\]

(5)

where \(\Delta H(k) = H(k) - H(k - 1)\) and \(\Delta u(k) = u(k) - u(k - 1)\).

B. Model identification based on the HNN

Owing to the asymmetrical rate-dependent hysteresis of the MSMA actuator, it is difficult to identify the unknown parameter. Neural network has the strong capability of nonlinear approximation and online adjustment. Therefore, it can identify the parameters of BW model online.

In 1982, Hopfield proposed HNN and established the HNN structure to solve the optimization calculation problem. HNN is a feedback neural network, which is composed of nonlinear elements connection. Different with feedforward neural network, such as BP neural et al., each neurons in HNN transmits its output value to all other neurons via connection weights, and receives all the information from other neurons at the same time. An important feature of the HNN is that it can converge to a steady state. According to the Refs. 23 and 24, the asymptotically stable of HNN is proved. That is the state of HNN always moves in the direction...
to decrease its energy function, and the stable state is the minimum value for its energy function. Different with some neural networks, whose weights are adjusted by negative gradient descent method, the weights of HNN are identified by the method that the objective function and the energy function of HNN are got the minimum at the same time. Besides the energy function of HNN equal to the objective function of this identification method. Therefore it effectively avoids the local minimum during training the neural network by negative gradient descent method. In addition, HNN is a kind of fully interconnected recursive neural network, it has the ability of associative memory compared with feed-forward neural network. Therefore, it is suitable to describe the dynamic nonlinearity and can adjust the parameters of BW model adaptively.

The BW model structure identified by the HNN for MSMA actuator is shown in Fig. 1. As shown in Fig. 1, the HNN is a kind of full meshed single-layer neural network, where $y(k)$ is the real output of MSMA actuator. $e(k)$ is the model error at $k$ time. The structure of nodes is shown in Fig. 3, which can be described as an analog circuit. The mathematic formulas of HNN can be written as:

$$
\begin{align*}
\text{FIG. 1} & \quad \text{BW model identified by the HNN.} \\
\end{align*}
$$

where $x_i(k)$ is the $i$th neuron output of network, and the output vector of the network is $X(k) = [a(k), \beta(k), y(k), \rho(k)]$. $f(U_j(k))$ is the activation function of $j$th neuron, and $f(U_j(k)) = \frac{1-\exp(-aU_j(k))}{\exp(-aU_j(k))}$ $i = 1, 2, \ldots, 4$, $j = 1, 2, \ldots, 4$. For simplicity, $R_j$ is denoted as infinite. Then Eq. (6) can be written as:

$$
\begin{align*}
E(k) = \frac{1}{2} \sum_j \left[ y_j(k) - y_d(k) \right]^2
\end{align*}
$$

where $\alpha_j = \frac{1}{R_j C_j}$ and $\theta_j = -\frac{1}{C_j}$ are the weight and threshold of HNN.

In order to acquire appropriate the parameters of BW model, the energy function $E_k$ of HNN and the objective function $E$ of the model must reach minimums at the same time. Where

$$
\begin{align*}
\text{FIG. 2} & \quad \text{The structure of HNN nodes.} \\
\end{align*}
$$

$$
\begin{align*}
\text{FIG. 3} & \quad \text{Experimental platform of the MAMS actuator.} \\
\end{align*}
$$

the weight and threshold of 1th neuron turning algorithm is calculated as follows:

$$
\begin{align*}
\frac{\partial E_k}{\partial \alpha_i(k)} = 0, \quad \frac{\partial E_k}{\partial \beta_i(k)} = 0, \quad \frac{\partial E_k}{\partial \gamma_i(k)} = 0, \quad \frac{\partial E_k}{\partial \rho_i(k)} = 0
\end{align*}
$$

In view of Eq. (5) and Eq. (9), the turning algorithm can be expressed as:
FIG. 4. Comparison experimental results with different input signals. (a) 0.2Hz. (b) 0.4Hz. (c) 0.8Hz.

\[
\begin{align*}
-\omega_{11}(k)\alpha - \omega_{12}(k)\beta - \omega_{13}(k)\gamma - \omega_{14}(k)\rho - \theta_1(k) &= 0 \\
-\Delta u(k)\left[y(k) - \rho u(k) - H(k-1) - \alpha \Delta u(k)\right] - \beta |\Delta u(k)|H(k-1) - \gamma |\Delta u(k)|H(k-1)] &= 0
\end{align*}
\] (10)

If the coefficients in the equations are corresponding, the optimal parameters of BW model based on HNN can be obtained. From Eq. (10), the coefficients can be given as:

\[
\begin{align*}
\omega_{11}(k) &= -\Delta u^2(k) \\
\omega_{12}(k) &= -\Delta u(k)\Delta u(k)H(k-1) \\
\omega_{13}(k) &= -\Delta u^2(k)H(k-1) \\
\omega_{14}(k) &= -\Delta u(k)u(k) \\
\theta_1(k) &= \Delta u(k)[y(k) - H(k-1)]
\end{align*}
\] (11)

Similarly, define \(\Delta u(k) = \Delta u(k)|\Delta u(k)|\), \(\phi(k) = H(k-1)\), so the weights and thresholds of the neural network shown in Fig. 2 can be updated by Eq. (12) and Eq. (13).

| Frequency of the KP model of the HNN-based BW model (Hz) | MAX/RMS errors of the KP model in Ref. 7 (μm) | MAX/RMS errors of the HNN-based BW model (μm) |
|---------------------------------------------------------|-----------------------------------------------|-----------------------------------------------|
| 0.2                                                     | 1.0643/0.3484                                 | 0.3248/0.0525                                 |
| 0.4                                                     | 0.9571/0.2233                                 | 0.2120/0.0918                                 |
| 0.8                                                     | 1.1263/0.2589                                 | 0.3078/0.1726                                 |

TABLE I. MAX error and RMS error of the KP model proposed in Ref. 7 and the BW model in this paper.
With the proposed algorithm of identification, the parameters of BW model can adjust by the HNN automatically.

III. EXPERIMENTAL RESULTS

In this section, a number of experiments are conducted to identify the effectiveness of the HNN-based BW model. The experimental data is collected from the experimental platform as shown in Fig. 3. The MSMA actuator is driven by a voltage amplifier (PSW 30-36). Then, the actual displacement is measured by a micrometer (MDSL-0500M6-1A). The data format transformation between

\[
W(k) = \begin{bmatrix}
\omega_{11}(k) & \omega_{12}(k) & \omega_{13}(k) & \omega_{14}(k) \\
\omega_{21}(k) & \omega_{22}(k) & \omega_{23}(k) & \omega_{24}(k) \\
\omega_{31}(k) & \omega_{32}(k) & \omega_{33}(k) & \omega_{34}(k) \\
\omega_{41}(k) & \omega_{42}(k) & \omega_{43}(k) & \omega_{44}(k)
\end{bmatrix}
\]

\[
\Theta(k) = \begin{bmatrix}
\Delta u(k) \\
\Delta u(k)H(k-1) \\
\Delta u(k)H(k-1) \\
\Delta u(k)H(k-1)H(k-1)
\end{bmatrix}
\]

(12)

(13)
To verify the performance of the BW model identified in this paper, the model proposed in Ref. 7 is implemented as comparison. The output of the BW model is closer to the actual displacement of the MSMA actuator compared with the KP model. The maximum (MAX) modeling error and root-mean-square (RMS) modeling error listed in Table I are used to assess the modeling precision. From the quantitative comparison, the Table I show that the HNN-based BW model can accurately describe the hysteresis of MSMA actuator with different frequencies of input signals.

In order to further validate the effectiveness of the proposed model, the sinusoid reference with different amplitudes at 1Hz and the sinusoid reference with mixed frequency (0.6Hz and 1Hz) are employed. Fig. 5 demonstrates the comparison experimental results between KP model proposed in Ref. 7 and BW model proposed in this paper. The MAX/RMS errors of HNN-based BW model at the variable amplitude signal of 1Hz and the mixed frequency signal are 2.6174μm/0.5504μm and 5.0701μm/0.8153μm, respectively. Compared with the KP model, the MAX/RMS errors at the two sinusoid references are reduced by 15.96%/23.24% and 22.20%/44.09%, respectively. In contrast to the proposed model in Ref. 7, the HNN-based BW model can obtain better modeling performance. In addition, the proposed method can precisely describe both major hysteresis loops and minor hysteresis loops shown in Fig. 5.

The merit of high computing efficiency for HNN-based BW model is verify by repeated experiments under the same experimental conditions. The experiments results are shown in Table II. The input signal values shown in Fig. 4 and Fig. 5 are adopted for repeated experiments. Ten sets of experimental results are selected randomly, and their average time, MAX time and minimum (MIN) time are listed in Table II. Compared with the identification time of Elman neural network-based KP model proposed in Ref. 7, the identification time of HNN-based BW model is far less. Identification time of the proposed method for each experiment is less than 0.5s. The high computing efficiency of HNN is proved.

IV. CONCLUSION

In this paper, a BW model is established to describe hysteresis of the MSMA actuator, and the HNN is first adopted to adjust the parameters of BW model online. The asymmetric and rate-dependent problem of hysteresis for MSMA actuator is solved by this method. A battery of experiments are presented with different input signals to testify the effectiveness of the HNN-based BW model compared with the KP model in Ref. 7. The experimental results show that both asymmetry and rate-dependent hysteresis of the MSMA actuator can be represent completely by the proposed modeling method. In comparison with the existing Ref. 7, the BW model identified by HNN has a better performance not only with the input signals of signal frequency, but also with the input signals of mixed frequency and variable amplitude. In addition, many times experiments show that it takes a short time to identify BW model by HNN, which proved the high computing efficiency capability of this method. Therefore, the proposed method has the ability of precise modeling for the asymmetrical rate-dependent hysteresis of the MAMS actuator.

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