Dynamic Model of Hysteresis in Piezoelectric Actuator Based on Neural Networks

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Abstract: A dynamic hysteresis model based on neural networks is proposed for piezoelectric actuator. Neural network has been widely applied to pattern recognition and system identification. However, it is unable to directly model the systems with multi-valued mapping such as hysteresis. In order to handle this problem, a novel hysteretic operator is proposed to extract the dynamic property of the hysteresis. Moreover, it can construct an expanded input space to transform the multi-valued mapping of hysteresis into one-to-one mapping. Then neural networks can directly be used to approximate the behavior of dynamic hysteresis. Finally, the experimental results are presented to illustrate the potential of the proposed modeling method.

Key words: hysteretic operator; modeling; neural networks

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0 Introduction

Piezoelectric actuators are widely used in micro-positioning and ultra-precision manufacturing systems. However, one of the drawbacks of the piezoelectric actuator is the existence of hysteresis. Hysteresis has the multi-valued and non-differentiable properties, which cannot be treated as the conventional nonlinearities. It often severely limits system performance such as giving rise to undesirable inaccuracies or oscillations, even leading to instability[1]. Therefore, it is necessary to develop a model to describe the behavior of hysteresis so that the corresponding model-based controller can be designed to eliminate the harmful effect of hysteresis.

For decades, there have been several hysteresis models such as the Preisach model[2-3], the KP model[4], the PI model[5], the Bouc-Wen model[6]. These models can be classified into two categories: rate-dependent model and rate-independent model. Most of the above-mentioned models are based on the assumption that the hysteresis is rate-independent.

Hysteresis combined with rate-dependent phenomena is also called dynamic hysteresis, while rate-independent hysteresis is referred to by the term "static". When excited by voltage excitation with frequency content covering a wide range, the hysteresis phenomena are often rate-dependent which cannot be described by static model.

Research on dynamic model of hysteresis has received great attention. Some dynamic Preisach models[7-9] are proposed by reforming the density functions of the classical Preisach model. Those models have the common problem that it is difficult to determine the values of the density functions. Ref. [10] proposed a dynamic Prandtl-Ishlinskii (PI) model to describe the rate-dependent hysteresis using a linear function to express the relationship between the slopes of the hysteretic loading curve and the rate of the input. In Ref. [11], a dynamic PI model is developed by integrating rate-dependent play operator and density functions formulated on the basis of the change

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rate of input. Alternatively, Ref. [12] also proposed semi-linear Duhem model for the rate-dependent hysteresis as the input rate function was not positively homogeneous.

In recent years, some research about the use of neural networks for the modeling of the hysteresis has also been published[13-16]. These neural models are only useful for identification of rate-independent hysteresis such as classical Preisach-type hysteresis. Ref. [17] proposed a neural model for rate-dependent hysteresis in piezoceramic actuators. In this approach, both a so-called generalized gradient of the output with respect to the input of hysteresis and the derivative of the input that represents the frequency change of the input are introduced into the input space. However, introduction of the gradient of hysteresis output against its input may be sensitive to the measurement noise.

The main contribution of this paper is to develop a dynamic model based on neural networks for rate-dependent hysteresis. In this method, to solve the problem that the feed-forward neural networks cannot be directly used to approximate the hysteresis which is multi-valued and non-differentiable at the turning points of the input, a special hysteretic operator is proposed for the transformation of the one-to-one mapping. The hysteretic operator can describe the change tendency of the hysteresis to its input and extract the dynamic property of the rate-dependent hysteresis. Moreover, two parameters included in the hysteretic operator can be adjusted to adapt to the change of operating condition.

1 Dynamic Hysteretic Operator

One of the advantages of using neural networks for modeling is that the parameters of the neural network model can be updated on-line to track the change of the environment or operating condition. However, it is known that neural networks can only be available for the approximation of the continuous systems with one-to-one and multi-to-one mappings. It is unable to directly model the systems with multi-valued mapping such as hysteresis[18]. Moreover, the rate-dependent hysteresis is related to the change rate of input. In order to handle this problem, a transformation operator is proposed to extract main feature of variation information of rate-dependent hysteresis and to transform the multi-valued mapping into a one-to-one mapping. The proposed hysteretic operator $f(x)$ is defined as

$$f(x) = (1-\alpha e^{-|x-x_p|}) \cdot (x-x_p)(1+\beta e^{-|\dot{x}|}) + f(x_p) \tag{1}$$

where x is the current input, $f(x)$ the current output, and x_p the dominant extreme adjacent to the current input x. $f(x_p)$ is the output of the operator when the input is x_p. α, β are the turning parameters, $\alpha>0$, $\beta>0$.

$f(x)$ can be written as

$$f(x) = (1-\alpha e^{-|x-x_p|})(x-x_p) + f(x_p) + \beta(1-e^{-|x-x_p|})(x-x_p)e^{-|\dot{x}|} = \bar{f} + \tilde{f} \tag{2}$$

where $\bar{f} = (1-\alpha e^{-|x-x_p|})(x-x_p) + f(x_p)$ stands for the static components of hysteresis. $\tilde{f} = \beta(1-e^{-|x-x_p|})(x-x_p)e^{-|\dot{x}|}$ represents the dynamic term of rate-dependent hysteresis.

A neural rate-independent hysteresis can be derived based on $\bar{f}(x)$. The detailed property of the hysteretic operator in special form is discussed in Ref. [15]. As an extension of the work in Ref. [15], a novel hysteretic operator $\tilde{f}$ is proposed and $e^{-|\dot{x}|}$ is embedded in the proposed operator to describe the dynamic property of rate-dependent hysteresis. Moreover, two parameters α, β included in the operator can be adjusted to adapt to the change of operating condition.

In Fig. 1, the inputs fed into the proposed hysteretic operator are sinusoidal inputs. The frequencies of the input are $0.1/2\pi$, $1/2\pi$, and $10/2\pi$ Hz, respectively. It is noticed that the peak amplitude decreased with the increase of the input frequency as similar to rate-dependent hysteresis. It is shaped like the hysteresis in piezoelectric actuator, i. e., multi-valued and non-smooth property. Hence the proposed hysteretic operator can extract the dynamic property of the rate-dependent hysteresis.

Fig. 2 shows that the hysteretic operator loop

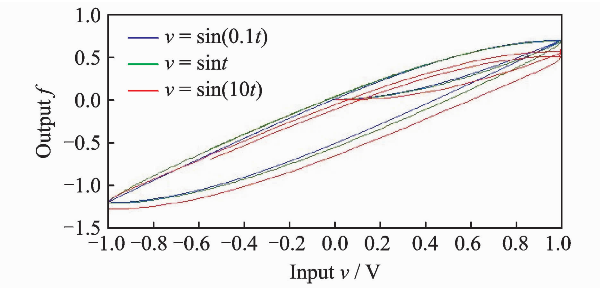

Fig. 1　Hysteresis operator with different frequency input

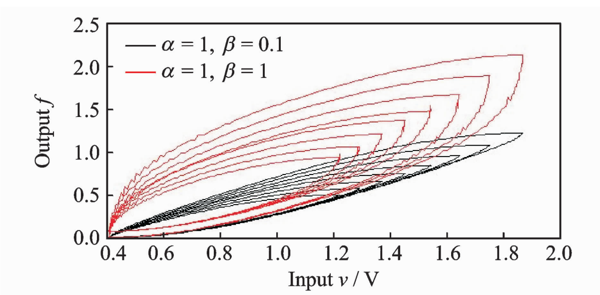

Fig. 2　Hysteresis operator with different α and β

varies by adjusting α and β. In the next section, the output of hysteresis operator is used to model the hysteresis. It is a key component of the hysteresis model. Hence it is essential to select the proper value of α and β when the hysteresis nonlinear system is excited by voltage excitation with frequency content covering a wide range.

Remark 1　The hysteretic operator can describe the change tendency and extract the dynamic property of rate-dependent hysteresis.

Remark 2　Proper selection of α and β may improve the precision of hysteresis model.

2　Hysteresis Model Based on Neural Network

As in the previous work of Ref. [15], the special form of $\bar{f}$ is introduced to transform the multi-valued mapping of Preisach-type hysteresis into one-to-one mapping. In the rate-dependent hysteresis, $\tilde{f}$ is embedded to describe the dynamic property. The hysteretic operator f is introduced into the constructed expanded input space. Then the modeling procedure for the rate-dependent hysteresis will be implemented on this expanded input space. Hence, the following Theorem 1 is obtained.

Theorem 1　For any rate-dependent hysteresis, v and H are defined as the input and output of hysteresis, respectively. $v \in C(0, t_E)$, there exists a continuous one-to-one mapping Γ: $R^2 \to R$, such that $H[v(t)] = \Gamma[v(t), f(v(t))]$.

Proof　Firstly, it is proved that Γ is a one-to-one mapping.

Assume that v_1 and v_2 are defined as the input with different frequency, i. e. , $|\dot{v}_1| \neq |\dot{v}_2|$.

For two different sampling time instances m and n, $v_1(m) = v_2(n) = v$, but $H[v_1(m)] \neq H[v_2(n)]$.

As $|\dot{v}_1| \neq |\dot{v}_2|$, according to definition of $f(x)$, we have $f[v_1(m)] \neq f[v_2(n)]$. Then

$$[v_1(m), f(v_1(m))] \neq [v_2(n), f(v_2(n))]$$

Therefore, the coordinate $[v(t), f(v(t))]$ is uniquely corresponding to the output of hysteresis $H[v(t)]$. It is obtained that Γ is a one-to-one mapping.

Next, it will be verified that Γ is a continuous mapping.

$$v_1 - v_2 \to 0 \Rightarrow H(v_1) - H(v_2) \to 0 \quad (3)$$

$$v_1 - v_2 \to 0 \Rightarrow f(v_1) - f(v_2) \to 0 \quad (4)$$

Therefore, it can be concluded that there exists a continuous one-to-one mapping $\Gamma: R^2 \to R$, such that $H[v(t)] = \Gamma[v(t), f(v(t))]$

Theorem 1 indicates that the multi-valued mapping of hysteresis can be transformed into a one-to-one mapping by the proposed transformation operator. It is also proved that the obtained mapping is a continuous mapping.

Based on what is stated above, the neural networks can be now applied to the modeling of the hysteresis since the hysteresis transformation operator is introduced to construct a coordinate in order to realize the decomposition of multi-valued mapping of hysteresis into a one-to-one mapping. It is known that multilayer feed-forward neural networks (MFNN) are capable of approximating any continuous function on a compact set in arbitrary accuracy. Therefore, the MFNN used to identify the hysteresis is shown as follows

$$\Gamma(v(t), f(v(t))) = NN(v(t), f(v(t))) + \varepsilon \quad (5)$$

where $NN(\cdot)$ represents the multilayer feedforward neural networks. ε is the approximation error, for any $\varepsilon_N>0$, $|\varepsilon|\leqslant\varepsilon_N$.

The neural-networks-based hysteresis model is shown in Fig. 3.

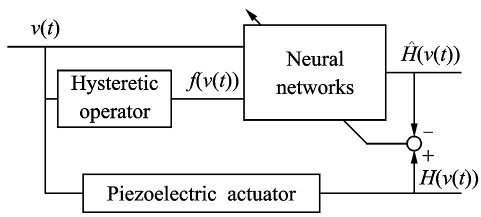

Fig. 3 Neural-networks-based hysteresis model

Remark 3 The proposed modeling structure is totally different from the operator-superposition of the conventional hysteresis models. With introduction of such hysteretic operator into the input space, the multi-valued hysteresis can be transformed into a one-to-one mapping on a newly constructed expanded input space which enables neural networks to approximate the behavior of rate-dependent hysteresis.

3 Experimental Results

The proposed approach is applied to the identification of the neural model for hysteresis in a piezoelectric actuator (PZT-753. 21C, a product of PI Company). The actuator has a nominal expansion of 0—25 μm under the input voltage within 0—100 V.

The architecture of the neural model consists of two input nodes, twelve hidden neurons and one output neuron. The input of the neural model is $(v(t), f(v(t)))$. The sigmoid and linear functions are used as the activation function in the hidden layer and in the output layer, respectively. The Levenberg-Marquardt algorithm is used to train the neural networks. The data is separated into two parts. One is used for model identification and the another is for model validation. After 438 epochs, the training procedure is accomplished.

Fig. 4 shows the results of model validation. Fig. 5 shows the hysteretic operator. Fig. 6 demonstrates the model validation error. The maximum error is 0.019 1. The mean square error is 0.003 5. The validation error comparison between the proposed model and Ref. [15] are shown in Fig. 7. The architecture is the same as the proposed model. The derived maximum error of the model is 0.044 5 and the mean square error is 0.007 9.

Thus, the proposed neural model can lead to more accurate modeling results for rate-dependent hysteresis in the piezoelectric actuator.

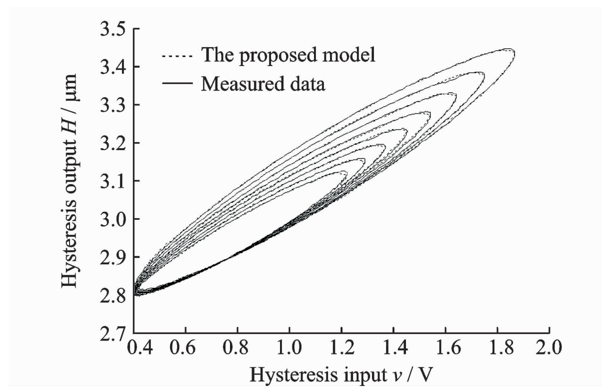

Fig. 4 Results of model validation

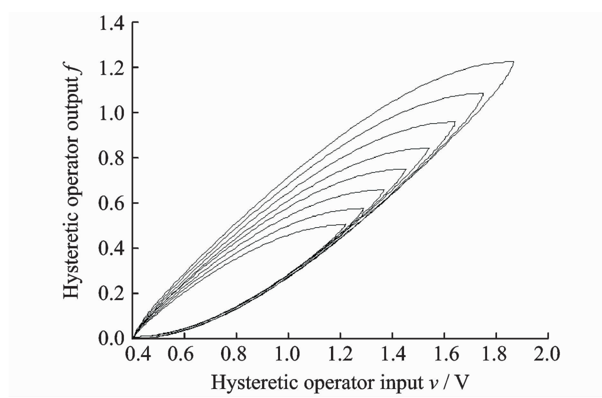

Fig. 5 Hysteretic operator

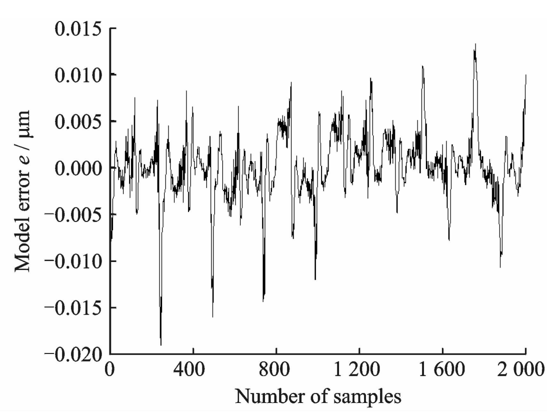

Fig. 6 Model validation error

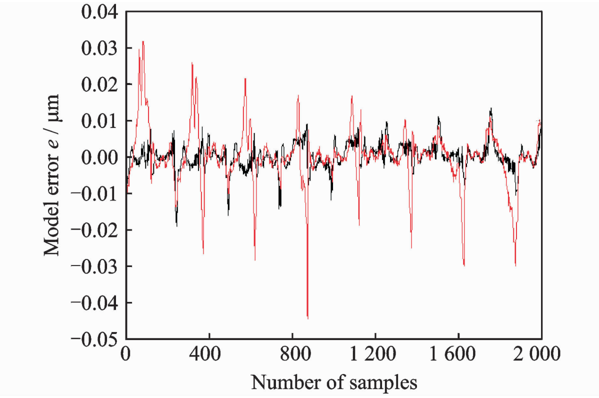

Fig. 7 Error comparison between the proposed method and Ref. [15]

4 Conclusions

The approach to identify the rate-dependent hysteresis based on neural networks is presented. In order to transform the multi-valued mapping of the rate-dependent hysteresis into one-to-one mapping so that the neural networks can be utilized for the approximation, a novel hysteretic operator is introduced to the input space of the hysteresis. The hysteretic operator can describe the change tendency and extract the dynamic property of rate-dependent hysteresis. Moreover, two parameters included in the operator can be adjusted to adapt to the change of operating condition. The experimental results have illustrated the potential of the proposed modeling technique.

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