A neural networks based model for rate-dependent hysteresis for piezoceramic actuators

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Abstract

A method for the identification of the rate-dependent hysteresis in piezoceramic actuators is proposed. In this approach, both a so-called generalized gradient of the output with respect to the input of the hysteresis and the derivative of the input that represents the frequency change of the input are introduced into the input space. Then an expanded input space is established. Thus, the multi-valued mapping of the rate-dependent hysteresis can be transformed into a one-to-one mapping based on the expanded of the input space. In this case, the neural network method can be applied to the modeling of the rate-dependent hysteresis. Finally, the experimental results are presented to illustrate the performance of the proposed approach.

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1. Introduction

Piezoceramic actuators, with their high stiffness, fast frequency response, and high resolution are increasingly being used in micropositioning applications [1–3]. However, piezoceramic actuators also exhibit a form of hysteresis between the output displacement and the input voltage. The hysteresis often leads to oscillation, vibration and even instability of systems if the closed-loop control is implemented. Hence, how to obtain an accurate and tractable model of the hysteresis behavior has become one of the hot topics in precision manufacturing engineering.

Until today, there have been several methods concerning modeling of hysteretic phenomena. The Preisach model is one of the typical and the most popular models. Although the Preisach model does not provide physical insight into the hysteretic system, it provides a basic tool for phenomenological modeling of the system that is producing observed hysteretic characteristics [4,5]. There are some applications of Preisach model to describe or control the Preisach typed hysteresis [3–12]. Refs. [10–12] proposed the techniques to decompose the multi-valued mapping of the hysteresis into a one-to-one mapping between the input and the output so as to enable the neural networks to model hysteresis. However, most of the above-mentioned methods are based on the assumption that the hysteresis is rate-independent. As the matter of fact, the hysteretic phenomena are often rate-dependent, i.e. the output of the hysteresis also relies on the frequency of the input. In Refs. [7–9], the modified Preisach models were employed to describe the characteristic of the rate-dependent hysteresis. However, those methods also have the problem that it is difficult to determine the values of the distribution functions of the models. Ref. [13] combined the so-called hysteretic operator based on the first order differential equation with a diagonal recurrent neural networks to identify the rate-independent hysteretic model, unfortunately this kind of model has led to obvious modeling residual at the tuning points of the hysteresis, for the rate-dependent hysteresis is a kind of non-smooth nonlinearity, i.e., the gradient of the hysteresis output with respect to the input at the tuning points does not exist.
The shape of the hysteresis relies upon the gradient of the hysteresis output with respect to the input. However, the gradient of the output with respect to the input will not exist at the non-smooth points of the hysteresis. Therefore, to construct a simple and on-line adjustable model for the rate-dependent hysteresis is a real challenge in engineering.

In this paper, the so-called generalized gradient [14–16] of the output with respect to the input is introduced to construct the expanded input space for the rate-independent hysteresis. The function of the introduced generalized gradient is to extract the main features such as the moving tendency of the hysteresis. In order to handle the rate-dependent characteristic of the hysteresis, the derivative of the input is also introduced into the expanded input space. Moreover, it is proved that the derivative of the input is proportional to the frequency change of the input if the case of the frequency change of the input happens. On the proposed expanded input space, the one-to-one mapping between the output and the input of the hysteresis is realized. So, the neural networks can be utilized for the modeling of the rate-dependent hysteretic systems. Finally, the experimental results on the hysteresis in a piezoelectric actuator are illustrated.

2. The concept of generalized gradient

In this section, the concepts about the generalized gradient are briefly described.

**Definition 1** ([14]). For a locally Lipschitz function $V: \mathbb{R}^n \times \mathbb{R} \to \mathbb{R}$, define the generalized gradient of $V$ at $x$ by

$$\partial V(x) \triangleq \varnothing \left( \lim \nabla V(x_i) | x_i \to x, x_i \not\in \Omega_V \cup N \right)$$

where $\Omega_V$ is the set of Lebesgue measure zero where $\nabla V$ does not exist, $\nabla V$ denoting the gradient of $V$, and $N$ is an arbitrary set of zero measure, $\varnothing$ denoting convex closure.

Consider the vector differential equation [15]:

$$\dot{x} = f(x, t)$$

where $f: \mathbb{R}^n \times \mathbb{R} \to \mathbb{R}$ is defined a.e. (almost everywhere with respect to Lebesgue measure), and is measurable in an open region $Q \subset \mathbb{R}^{n+1}$. Moreover, $\forall$ compact $D \subset Q$. $\exists$ integral $A(t)$ such that $|f(x(t))| \leq A(t)$ a.e. in $D$.

**Definition 2.** A vector function $x(\cdot)$ is called a solution of (2) on $[t_0, t_1]$, if $x(\cdot)$ is absolutely continuous on $[t_0, t_1]$, and for almost all $t \in [t_0, t_1]$, it has

$$x \in K[f](x)$$

where

$$K[f](x) \triangleq \bigcap_{\tau > 0} \bigcap_{N=0} \varnothing \left( B(x, \tau) - N, t \right)$$

and $\bigcap_{\mu N=0}$, $\varnothing$ and $B(x, \tau)$ denote the intersection over all the sets $N$ of Lebesgue measure zero, convex closure and the open ball of radius $\tau$ centered at $x$, respectively.

3. The phenomena of rate-dependent hysteresis in piezoelectric actuators

In this section, an experimental example of a piezoelectric actuator is illustrated to show the phenomena of rate-dependent hysteresis. The input (voltage)-to-output (displacement) curve of the hysteresis in a piezoceramic actuator (PZT-753.21C) is shown in Fig. 1. The input signal is $u(t) = \sin(2\pi ft) + b$, where $b$ is a constant so as to guarantee the amplitude of the input of the piezoceramic actuators is positive. The output of the hysteresis of the piezoceramic actuator has a nominal expansion of $0–20 \, \mu m$ under the input voltage within $0–10 \, V$. From Fig. 1, it is noticed that the width of the voltage-to-displacement curve of the hysteresis increases as the frequency of the input increases; moreover, the curve circumvolves in the clockwise direction with the increase of the input frequency. Hence, Fig. 1 indicates that the shape of the voltage-to-displacement curve is related to the change of the input frequency. Usually, piezoceramic actuators are expected to be excited by the voltages with the frequency covering a wide range [7]. In next section, it can be proved that the change of the input frequency is proportional to the derivative of the input if the frequency of the input is changed.

4. Construction of an expanded input space

It is well known that hysteresis is a non-smooth nonlinearity with multi-valued mapping. In this case, the conventional technique of the identification cannot directly be applied to model the hysteretic system. Therefore, it is necessary to construct a one-to-one mapping to realize the modeling of hysteresis. One of the methods is to introduce the gradient of the output with respect to the input into the model since the gradient of the output with respect to the input represents the shape feature of the hysteresis. However, in hysteresis, the gradient of the output with respect to the input do not exist at the extremum points [3–9]. Hence, in this section the so-called generalized gradient is applied.

Note that hysteresis is a locally Lipschitz function [3–9]. Therefore, the generalized gradient of the output with respect
to the input in the hysteresis can be obtained. In the smooth
segments, the generalized gradient is the same as the traditional
gradient, i.e.

$$\nabla H(u(t)) = \frac{H(u(t + \Delta)) - H(u(t))}{u(t + \Delta) - u(t)} \quad (5)$$

where $|\Delta| < \gamma$, $\gamma$ is an arbitrary small positive number; $u(t)$ is a continuous input signal; and $H(u(t))$ is the output of the hysteresis.

The generalized gradient of the output with respect to the input in hysteresis can be defined as

$$K[f](u(t)) = \partial H(u(t)) = \begin{cases} \text{co}(\lim \nabla H(u(t_1))) | t_1 \rightarrow t, u(t_1) \rightarrow u(t), u(t_1) \notin \Omega_F \cup N \}, \text{extrema} \\ \nabla H(u(t)), \text{else} \end{cases}$$

where $\Omega_F$ is the set of the Lebesgue measure zero where
$\nabla H(u(t))$ does not exist; $N$ is an arbitrary set of zero measure; $\text{co}$ denoting the convex closure.

The generalized gradient at extremum point is a bounded set based on Eq. (6). If the gradient actually does not exist at the extremum point, based on the properties of the rate-dependent hysteresis, the generalized gradient at the extremum point can be defined as:

$$\tilde{K}[f](u(t)) = \nabla H(u(t - \xi)) \quad (7)$$

where $\xi$ is an arbitrary small positive number.

Based on Eqs. (6) and (7), it leads to:

$$\tilde{K}[f](u(t)) \in K[f](u(t)). \quad (8)$$

According to formula (8), it is known that $\tilde{K}[f](u(t))$ is bounded as $K[f](u(t))$ is bounded. Rewrite Eq. (6):

$$K[f](u(t)) = \begin{cases} \tilde{K}[f](u(t)), \text{extrema} \\ \nabla H(u(t)), \text{else} \end{cases} \quad (9)$$

Hence, Eq. (9) presents the special generalized gradient of the output with respect to the input used in this paper to extract the change tendency of the hysteresis.

**Remark 1.** $\tilde{K}[f](u(t))$ is utilized to estimate the gradient of the hysteresis at the extremum points since the conventional gradient of the hysteresis at the extremum point does not exist.

Considering the dynamic behavior of the rate-dependent hysteresis also relies on the frequency change of the input, it is necessary to find a way to construct a relationship between the response of the hysteresis and the frequency change of the input. As the frequency change of the input is not easy to be measured on-line, in the following, it will be illustrated that the derivative of the input is proportional to the frequency change of the input if the frequency of the input is changed. Therefore, it is possible to extract the information of the frequency change from the derivative of the input.

**Lemma 1.** Suppose both $u(t)$ and $u_1(t) \in C^2$, which are smooth and bounded functions which have the same form but the frequencies of each function are different. Thus, it is considered that the frequency of $u(t)$ is $f$ while the frequency of $u_1(t)$ is $af$, where $a$ is an arbitrary bounded positive number. Then, it yields

$$\dot{u}(t) = au(t) \quad (10)$$

where $\dot{u}(t)$ and $\dot{u}(t)$ are respectively the derivative of $u(t)$ and $u_1(t)$.

The proof of Lemma 1 is provided in Appendix A.

Based on Lemma 1, it is known that the derivative of the input is proportional to the frequency of input. Also, Section 3 indicated that the characteristic of the rate-dependent hysteresis is significantly affected by the change of the frequency of the input. In order to describe the behavior of the rate-dependent hysteresis, the derivative of the input which is proportional to the frequency change of the input is introduced to 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 will be obtained.

**Theorem 1.** For the rate-dependent hysteresis, if the input satisfies the conditions given by Lemma 1, and there exists a continuous one-to-one mapping $T: R^1 \rightarrow R$, such that

$$H(u(t)) = T(H(u(t - \Delta t)), K[f](u(t - \Delta t)), \dot{u}(t), u(t)) \quad (11)$$

where $t - \Delta t$ and $t$ denote the two adjacent time points and $t - \Delta t < t$. Moreover, $t - (t - \Delta t) < \delta$, where $\delta$ is an arbitrary small positive number.

The proof of the Theorem 1 can be presented in Appendix B.

### 5. Neural network based identification for rate-dependent hysteresis

It is known that neural networks have great potential for modeling of hysteresis. Refs. [10–12] have applied the multilayer feed-forward neural networks (MFNN) to the approximation of the rate-independent hysteresis. Ref. [18] used the MFNN to approximate the Preisach-hysteretic model that is also a kind of rate-independent hysteresis. Although the above-mentioned examples have shown that the MFNN can be used to model rate-independent hysteresis effectively, the modeling of rate-dependent hysteresis is seldom found in literatures.

Based on Eq. (9), $K[f](u(t - \Delta t))$ is bounded. Moreover, $\dot{u}(t)$ and $H(u(t))$ are bounded if $u(t)$ is bounded. As $T(H(u(t - \Delta t)), K[f](u(t - \Delta t)), \dot{u}(t), u(t))$ is a continuous one-to-one mapping, thus, the neural networks can be employed to model the rate-dependent hysteresis. The MFNN used to identify the hysteresis is shown as

$$T(H(u(t - \Delta t)), K[f](u(t - \Delta t)), \dot{u}(t), u(t)) = \text{NN}(H(u(t - \Delta t)), K[f](u(t - \Delta t)), \dot{u}(t), u(t)) + \xi \quad (12)$$
where $\text{NN}(-)$ represents multilayer feed-forward neural networks, and $\xi$ is the approximation error, for any $\xi_N > 0$, $|\xi| \leq \xi_N$.

6. Experimental results

In this section, the proposed approach is applied to the modeling the hysteresis inherent in a piezoceramic actuator. It is known that if the piezoceramics is polarized by an electric field, the corresponding strains along with resulting stresses are created. In terms of such phenomena, piezoceramics actuator can be used for precision positioning.

In this experiment, the sampling frequency of the data is 30 KHz. The input is the sinusoid function plus a constant to guarantee the input to be always larger than zero, i.e. $u(t) = e^{-w_1 t}[\sin(2\pi f e^{-w_2 t}) + 1.1]$, where $w_1$ and $w_2$ are bounded positive numbers; $a$ and $f$ are respectively frequency and amplitude of the input signal. The architecture of the neural model in this example consists of 4 input nodes, 10 hidden neurons and 1 output neuron. The inputs of the neural model are $\{H[u(t - \Delta t)], K[f][u(t - \Delta t)], \dot{u}(t), u(t)\}$. The sigmoid function and the linear function are respectively used as the activation functions in the hidden and output layers. The conjugate gradient algorithm with Powell-Beale restarted method [17] is used to train the neural model.

For modeling training, the measured data are obtained from the system excited by the signal:

$$u(k) = e^{-1.6 \times 10^{-3} k}[\sin(4.0 \times 10^{-5} \pi f e^{-4.0 \times 10^{-4} k}) + 1.1],$$

where $k$ is the sampling instant; $a$ and $f$ are respectively chosen as 2.4 V and 800 Hz. On the other hand, for model validation, the data are measured from the system that is excited by the signal, i.e.

$$u(k) = e^{-1.3 \times 10^{-3} k}[\sin(4.0 \times 10^{-5} \pi f e^{-3.0 \times 10^{-4} k (0.5\pi) + 1.1}],$$

where amplitude $a$ and frequency $f$ are respectively selected as 1.6 V and 750 Hz. With 365 epochs, the training procedure is finished. The corresponding mean squared error (MSE) is $1.48403 \times 10^{-5}$. The derived model validation results are shown in Fig. 2(a–c). In Fig. 2(a and b), the prediction of the obtained neural model is compared with the measured data. It is illustrated the generalization capability of the neural model. The correspond-

Fig. 2. The validation of the proposed model for dynamic hysteresis in piezoceramic actuator: (a) comparison between the real output data and the prediction of the proposed model; (b) model validation of the proposed model; (c) model error of the proposed model.

Fig. 3. The validation of the PI model for dynamic hysteresis in piezoceramic actuator: (a) comparison between the real output data and the prediction of the PI model; (b) model validation of PI model; (c) model error of the PI model.
The maximum model residual is less than 0.026 μm.

In order to make comparison, the modified Prandtl–Ishlinskii (PI) [19] with 200 backlash operators is implemented to model the hysteresis. The derived PI modeling results are shown in Fig. 3(a and b). The corresponding model error is shown in Fig. 3(c). The least squares algorithm is applied to the estimate of the coefficients of the backlash operators. The maximum error of the PI model is less than 0.86 μm. Fig. 2 indicates that the proposed model can obtain more accurate modeling results for the rate-depended hysteresis in piezoceramic actuator.

7. Conclusions

In this paper, the approach to identify the rate-depended hysteresis is presented. In this scheme, the generalized gradient of output with respect to input is introduced into the input space to extract the moving tendency of the hysteresis. Moreover, the derivative of the input is also introduced into the input space to represent the frequency change of the input. It has been proved that the mapping from the obtained input space to the output space is a one-to-one mapping. In this case, the neural networks can be employed on this expanded input space to model the rate-dependent hysteresis. Finally, the experimental results on a piezoelectric actuator demonstrate promising results of the proposed approach.

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Appendix A

In this appendix, the proof of Lemma 1 is given as follows:

**Proof.** Assume that both \( u(t) \) and \( u_1(t) \) are the same type of the periodic signals only their frequencies are different, i.e., the frequency of \( u(t) \) is defined as \( f \) while the frequency of \( u_1(t) \) is \( af \). Then

\[
u(t) = u(t) \left( \frac{t}{\alpha f} \right), \quad (A1)
\]

and the corresponding Fourier series of \( u(t) \) is described by:

\[
u(t) = \frac{a_0}{2} + \sum_{n=1}^{\infty} (a_n \cos(n2\pi ft) + b_n \sin(n2\pi ft)), \quad (A2)
\]

where the coefficients \( a_n \) and \( b_n \) are respectively defined as:

\[
a_n = 2f \int_{-1/(2f)}^{1/(2f)} u(t) \cos(n2\pi ft) \, dt \quad (n = 0, 1, 2, \cdots) \quad (A3)
\]

and

\[
b_n = 2f \int_{-1/(2f)}^{1/(2f)} u(t) \sin(n2\pi ft) \, dt \quad (n = 1, 2, 3, \cdots) \quad (A4)
\]

On the other hand, the Fourier series of \( u_1(t) \) is:

\[
u_1(t) = \frac{c_0}{2} + \sum_{n=1}^{\infty} (c_n \cos(n2\pi af t) + d_n \sin(n2\pi af t)) \quad (A5)
\]

where the corresponding coefficients \( c_n \) and \( d_n \) are respectively defined as:

\[
c_n = 2a\alpha f \int_{-1/(2af)}^{1/(2af)} u_1(t) \cos(n2\pi af t) \, dt \quad (n = 0, 1, 2, \cdots) \quad (A6)
\]

and

\[
d_n = 2a\alpha f \int_{-1/(2af)}^{1/(2af)} u_1(t) \sin(n2\pi af t) \, dt \quad (n = 1, 2, 3, \cdots) \quad (A7)
\]

Define \( t = \frac{t_1}{\alpha} \). Thus, Eqs. (A6) and (A7) can be respectively rewritten as:

\[
c_n = 2a\alpha f \int_{-1/(2f)}^{1/(2f)} u_1 \left( \frac{t_1}{\alpha} \right) \cos(n2\pi f t_1) \, dt_1 \quad (n = 0, 1, 2, \cdots) \quad (A8)
\]

and

\[
d_n = 2a\alpha f \int_{-1/(2f)}^{1/(2f)} u_1 \left( \frac{t_1}{\alpha} \right) \sin(n2\pi f t_1) \, dt_1 \quad (n = 1, 2, 3, \cdots) \quad (A9)
\]

According to Eqs. (A1), (A3), (A4), (A8) and (A9), it is known that

\[
a_n = c_n, \quad \text{and} \quad b_n = d_n. \quad (A10)
\]

Based on Eq. (A10), Eqs. (A2) and (A5) can rewritten as:

\[
u(t) = \frac{a_0}{2} + \sum_{n=1}^{\infty} A_n \cos(n2\pi ft + \varphi_n) \quad (A11)
\]

and

\[
u_1(t) = \frac{c_0}{2} + \sum_{n=1}^{\infty} A_n \cos(n2\pi af t + \varphi_n). \quad (A12)
\]

where \( A_n = \sqrt{a_n^2 + b_n^2} \), and \( \varphi_n = -\arctan(b_n/a_n) \). The derivatives of both \( u(t) \) and \( u_1(t) \) exist is:

\[
\dot{u}(t) = -\sum_{n=1}^{\infty} (2n\pi f A_n) \sin(n2\pi ft + \varphi_n) \quad (A13)
\]

and

\[
\dot{u}_1(t) = -\sum_{n=1}^{\infty} (2n\pi af A_n) \sin(n2\pi af t + \varphi_n). \quad (A14)
\]
Appendix B

In this appendix, the proof of the Theorem 1 is given as follows:

**Proof.** Let any \( t_1, t_2 \in [t_0, t] \) where \( t_1 \neq t_2 \).

Then

\[
H(u(t_1 - \Delta t)) = H(u(t_2 - \Delta t)), \quad K[f](u(t_1 - \Delta t)) = K[f](u(t_2 - \Delta t)).
\]

(B3)

Then

\[
H(u(t_1)) \neq H(u(t_2)).
\]

(B4)

\( t - (t - \Delta t) < \delta \), where \( \delta \) is an arbitrary small positive number, it will lead to:

\[
\dot{u}(t_1) = \frac{u(t_1) - u(t_1 - \Delta t)}{\Delta t}
\]

(B5)

and

\[
\dot{u}(t_2) = \frac{u(t_2) - u(t_2 - \Delta t)}{\Delta t}.
\]

(B6)

It is assumed that Eqs. (B1) and (B2) are held. Then

\[
u(t_1 - \Delta t) = u(t_2 - \Delta t).
\]

(B7)

As \( u(t) \) is a continuous and single-valued function and \( t - (t - \Delta t) < \delta \), hence,

\[
|u(t_1) - u(t_1 - \Delta t)| < \varepsilon
\]

where \( \varepsilon \) is a sufficiently small positive number.

Considering Eq. (B8), \( H(u(t)) \) is continuous and \( K[f](u(t - \Delta t)) \) is bounded, it leads to

\[
H(u(t_1)) = H(u(t_1 - \Delta t)) + K[f](u(t_1 - \Delta t))(u(t_1) - u(t_1 - \Delta t)) + o(u(t_1) - u(t_1 - \Delta t))
\]

(B9)

and

\[
H(u(t_2)) = H(u(t_2 - \Delta t)) + K[f](u(t_2 - \Delta t))(u(t_2) - u(t_2 - \Delta t)) + o(u(t_2) - u(t_2 - \Delta t))
\]

(B10)

Based on Eqs. (B1)–(B3), (B7), (B9) and (B10), it derives:

\[
H(u(t_1)) = H(u(t_2)).
\]

It is clear that there is a conflict between Eq. (B11) and the assumption given by Eq. (B4). Thus, Eq. (B11) is held. Moreover, considering that \( K[f](u(t)) \) is utilized to estimate the gradient of the hysteresis at the extremum points since the conventional gradient of the hysteresis at the extremum point does not exist. If Definitions 1 and 2 are held, then \( T(\cdot) \) should be a continuous and one-to-one mapping.

References


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