

An Identification Method for Dynamic Systems with SCNs Hysteresis Compensator: Application to the Inchworm Piezo Motor

Shuo Han¹, Yunlang Xu¹, Jianbo Yu¹, Xiaofeng Yang^{1,2*†}

¹*State Key Laboratory of Integrated Chips and Systems, School of Microelectronics, Fudan University, Shanghai, 200433, China.

²Shanghai Engineering Research Center of Ultra-Precision Motion Control and Measurement, Academy for Engineering and Technology, Fudan University, Shanghai, 200433, China.

*Corresponding author(s). E-mail(s): xf_yang@fudan.edu.cn;

Contributing authors: 20112020011@fudan.edu.cn;

xuyunlang@fudan.edu.cn; jb_yu@fudan.edu.cn;

[†]These authors contributed equally to this work.

Abstract

It is widely known that inchworm piezo motors are being used in ultra-precision detection platforms where high clamping force and nano-precision are required. This paper examines and proposes a dynamic model of the inchworm piezo motor to improve the performance and controller. Traditional identification strategies have not been adopted for calculating parameters for the dynamic model exhibiting hysteresis nonlinearity. In addition, hysteresis deteriorates the accuracy of positioning of inchworm piezo motors. It has been proposed to solve these problems using a feedforward controller, a hysteresis compensator based on a stochastic configuration networks algorithm (SCNs). Using the SCNs algorithm, both voltage and displacement inputs can be used to describe the nonlinear memory of hysteresis, and the kernel function provides a flexible and accurate representation of this behavior. This method enables the dynamic model parameters of the inchworm piezo motor to be identified using frequency sweeps. A proportional-integral (PI) controller is used to verify the positioning accuracy, and experimental results show that an inchworm piezo motor has a positioning accuracy of about **1nm** when the laser interference is low with a **10MHz** adoption rate and **0.1nm** resolution.

Keywords: Inchworm piezo motor, Hysteresis nonlinearity, Dynamic modeling, SCNs modeling

1 Introduction

For ultra-precision detection and motion systems dedicated to super-resolution microscopy for semiconductor tests [1], ultra-precision micro-machines for manufacturing[2, 3], and microrobots for medical assistance technology[4], inchworm piezo motors are commonly used. It should be noted that inchworm piezo motors are particularly useful in semiconductor chip detection systems due to their advantages in terms of their long travel ranges (millimeter scale), nanometer resolution (nanometer scale), and heavy forces (tens of N scale)[5, 6]. The modeling and identification of inchworm piezo motors remain a challenging problem even though numerous previous studies have focused on their applications[7–9].

The inchworm piezo motor poses a challenge in modeling because of its coupled linear dynamic and nonlinear hysteresis systems, which make its parameters more difficult to calculate using methods for identifying linear dynamic systems[10–12]. There are two general types of linear dynamic identification methods: sweep frequency identification and noise identification[13, 14]. By increasing the input frequency, the sweep identification proposes to calculate the parameters of the modeling, resulting in a rate-dependent behaviour for the inchworm piezo motor[15]. In order to determine the noise, the voltage amplitude is changed, which allows the hysteresis loop to show amplitude-dependent behavior for the inchworm piezo motor[16]. This paper presents the results of the Frequency Response Function (FRF) of the inchworm piezo motor in Fig.1, which presents an undesirable hysteresis behavior which makes linear dynamic identification difficult. For inchworm piezo motors with hysteresis behavior, it is difficult to compute the parameters and highlight their characteristics using traditional identification methods. As a result, the problem of hysteresis modeling and compensation has generated considerable interest in the development of an identification system to deal with this phenomenon[17, 18].

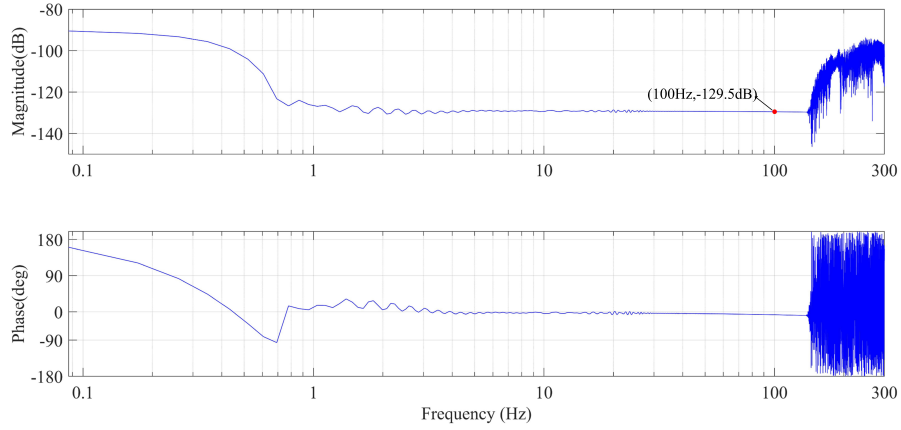


Fig. 1 Result of FRF for the inchworm piezo motor with hysteresis behavior in the identification system (Figure shows that magnitude and phase of the FRF)

It has been proposed that hysteresis modeling and compensators can be used to reduce the complexity of the inchworm piezo motor caused by its hysteresis behavior. It is currently possible to classify hysteresis modeling into two main categories[19]. A hysteresis model-based approach is primarily used[20, 21]. It has been shown that Prandtl-Ishlinskii(PI) hysteresis modeling is one method often used to describe hysteresis[22], and it typically describes a continuous loop of hysteresis that is rate-independent [23]. This PI hysteresis modeling has the advantage of being simple, and its hysteresis compensator can be calculated analytically[24]. In spite of this, the hysteresis loop formed by the PI operator did not return to zero along the input cycle voltage[25]. Following this, Preisach hysteresis modelling was used to model a complete rate-independent hysteresis loop due to its simplicity and calculation speed[26], which proved superior to PI modeling. The Preisach hysteresis model had merit in that it was capable of describing a greater number of hysteresis loop characteristics (i.e., significant and inner loops)[27]. Nevertheless, it was difficult to apply the exact solution of the Preisach hysteresis compensator[28]. Inchworm piezo motors exhibit hysteresis characteristics that can be difficult to compensate. For obtaining a more accurate expression of the hysteresis compensator function, Bouc-Wen hysteresis modeling has been proposed. As well as its computational simplicity, it only required one differential equation with a few parameters to describe the hysteresis behavior[29]. It is possible to describe both rate-dependent and amplitude-dependent hysteresis behavior using Bouc-Wen's hysteresis model. It should be noted, however, that the classical Bouc-Wen hysteresis model can only be applied to symmetric and rate-independent hysteresis descriptions[30, 31]. Additionally, the Duhem hysteresis modeling presents a static model with outputs independent of the input frequency and, therefore, cannot provide accurate descriptions of rate-dependent hysteresis nonlinearity. Based on the results of this study, the model-based hysteresis methods do not meet the nonlinearity of the hysteresis loop for the inchworm piezo motor. As a result, the methods of model-free hysteresis are suggested to resolve the problem of hysteresis.

Using the second type of hysteresis model-free method, hysteresis modeling can be trained using data-driven algorithms[32]. For example, the Radial Basis Function (RBF) neural network was proposed for application in the nonlinear system[33], which incorporated a dynamic RBF neural network to model the hysteresis of the plant. In the approach mentioned above, auxiliary hysteresis descriptions were utilized in order to extract the change tendency of the nonlinear effect, thus producing expanded inputs for solving the multivalued problem. In previous studies, artificial neural networks (ANNs) were demonstrated to be an effective means of modeling the hysteresis loop[34]. In the context of hysteresis modeling, the ANN provided advantages due to its universality and robustness[35, 36]. The support vector machine (SVM) is superior to the artificial neural network (ANN) in terms of global optimization and generalization ability for the hysteresis loop to model. Therefore, the SVM is widely employed to estimate nonlinear systems accurately[37], especially that involving hysteresis loops[38].

It is further proposed to use the Least-Squares Support-Vector Machine (LSSVM) in order to train the nonlinearity parameters to compensate for hysteresis modeling, and its advantage lies in being a more accurate compensator of hysteresis by

fitting[39]. To resolve the hysteresis loop, this paper presents a SCNs hysteresis modeling approach. Using SCNs algorithm trains, hysteresis modeling can be fitted and compensated directly via multivalued input. As a result of the redundancy of neural network nodes, the calculation time can be reduced. The SCNs algorithms are more appropriate for precision systems. By using the SCNs inverse hysteresis model, the hysteresis compensator for the inchworm piezo motor needs to be completed.

In the paper, the inverse hysteresis modeling of SCNs is used in order to compensate for the hysteresis behavior, and finally, the dynamic system of the inchworm piezo motor is identified. There are three major contributions to this paper. First of all, the techniques of dynamic modeling of the inchworm piezo motor are presented. Secondly, the nonlinearity hysteresis compensator must be put into the inchworm piezo motor system in order to make an accurate identification of the motor. In addition, the SCNs hysteresis model converts into a feedforward controller in order to compensate for hysteresis by using the SCNs algorithm. It is necessary to identify the inchworm piezo motor in order to calculate the parameters of the dynamic modeling in the experiment. Lastly, the feedback controller (PI Controller) and feedforward controller are introduced to verify the accuracy of positioning in the experiment using the inchworm piezo motor.

In the remainder of the paper, the following sections are provided: Section 2 introduces dynamic modeling of the inchworm piezo motor; Section 3 discusses hysteresis using SCNs hysteresis modeling, and a feedforward controller is described; Section 4 describes experiments, training and identification of SCNs hysteresis models; and finally, the study concludes with constraints and ideas for future research.

2 Dynamic modeling and analysis

2.1 Dynamic modeling

As shown in Fig.2 (a), the inchworm piezo motor is composed of two pairs of bender-type PEAs which symmetrically distribute with the runner. In a square-shaped distribution, phalanx bender-type PEAs include all four bender-type PEAs. To better explain the model of the inchworm piezo motor, the one phalanx bender-type PEAs names p_1 , consisting of bender-type PEAs [1],[2],[3]and [4], another phalanx bender-type PEAs names p_2 , consisting of bender-type PEAs [1'],[2'],[3']and [4']. Fig.2 (b)illustrates the simultaneous introduction of voltages $u_1(t)$ and $u_2(t)$ to produce displacements along the X and Z axes. There are two piezo stacks in the inchworm piezo motor, each with a separate deformation. By supplying voltage to the two piezo stacks, the piezo stacks extend along the z-axis and bend along the x-axis when they are charged. An overview of the schematic deformation of the side view and the working principle of an inchworm piezo motor can be found in Fig.2. By accomplishing the supply voltages, the bender-type PEA can be put in a working region in the X, Z plane, which is spanned by the periodic waveforms $u_i(t)$, $i \in \{1,2\}$, with $\min(u_i) = -250V$ and $\max(u_i) = +250V$.

It is assumed that every bender-type PEA contains the same deformation, then the displacement of bender-type PEAs in X and Z directions(see Fig.2 (b)) can be

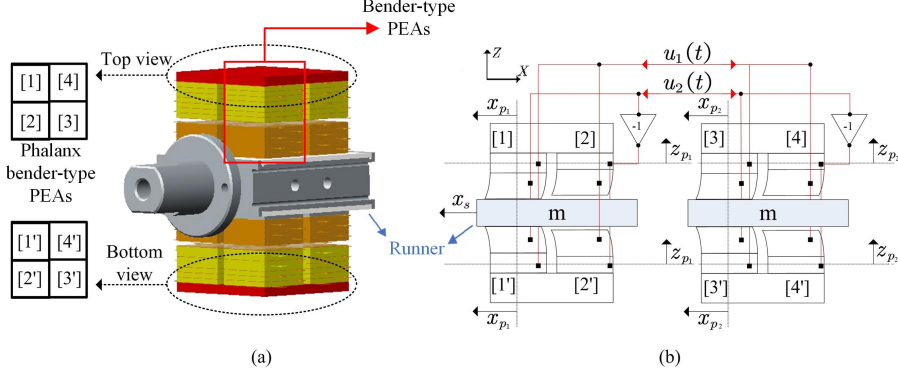


Fig. 2 Schematic modeling of the inchworm piezo motor. (a) Modeling of the inchworm piezo motor. (b) Working modeling.

described as follows:

$$\begin{cases} x_{p1} = x_{p2} = c_1 u_1(t) - h_x(t) \\ z_{p1} = z_{p2} = c_2 u_2(t) - h_z(t) \end{cases} \quad (1)$$

Where t is the time variable; c_1 and c_2 are the bending and extending piezoelectric coefficient, respectively; x_{p_i} and z_{p_i} , $i \in \{1,2\}$ represent the displacement, respectively; u_i , $i \in \{1,2\}$ denotes the input voltage; h_x and h_z indicate the hysteretic loop in terms of displacement of bender-type PEAs along X-axis and Z-axis, respectively; and x_s is the displacement of inchworm piezo motor. Accordingly, the dynamic modeling of the inchworm piezo motor, shown in Fig.2 (b), can be expressed as follows:

$$m\ddot{x}_s = \begin{cases} k(x_{p1} - x_s) + b(\dot{x}_{p1} - \dot{x}_s), & \text{if } z_{p1} \geq z_{p2} \\ k(x_{p2} - x_s) + b(\dot{x}_{p2} - \dot{x}_s), & \text{if } z_{p1} < z_{p2} \end{cases} \quad (2)$$

The heights of the pair of the bender-type ($z_{p1}(t)$ and $z_{p2}(t)$) determine which pair of the bender-type drives the runner. Parameters m , k and b represent the mass, damping coefficient, and stiffness. Therefore, the dynamic model of the inchworm motor can be expressed in the following manner:

$$m\ddot{x}_s = k(X_p - x_s) + b(\dot{X}_p - \dot{x}_s) \quad (3)$$

Where, X_p defines the bending displacement. When (1) is substituted for (3), the following results are obtained:

$$m\ddot{x}_s(t) + b\dot{x}_s(t) + kx_s(t) = c_1 [b\dot{u}_1(t) + ku_1(t)] - [kh_x(t) + b\dot{h}_x(t)] \quad (4)$$

Based on equation (4), we can conclude that a linear dynamic system and a non-linear dynamic system are included in any dynamic modeling of the inchworm piezo motor. A piezo motor driven by inchworms exhibits a relationship between displacement and input voltage. Therefore, we assumed that the hysteresis behavior was only dependent on the input voltage.

2.2 Model analysis

As shown in equation (4), the inchworm piezo motor is dynamically modeled with a nonlinear hysteresis system. During identification, hysteresis causes both amplitude and rate dependence, undermining the results. Therefore, the Hammerstein model[40], as shown in Fig.3, and can be introduced in the inchworm piezo motor with the coupling between hysteresis and linear dynamics. Since $W(t)$ and $U(t)$ are not measurable, $u(t)$ and $x(t)$ represent the input voltage and output displacement, respectively. The linear voltage converter $D(\cdot)$, hysteresis $H(\cdot)$, and linear dynamics $G(\cdot)$ are coupled.

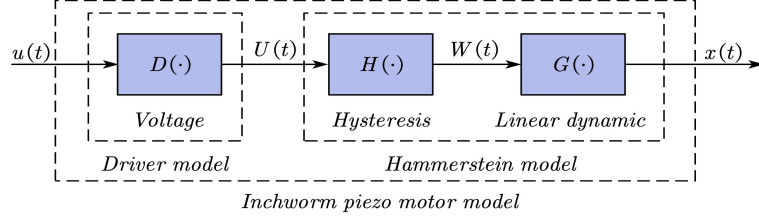


Fig. 3 Dynamical modeling of the inchworm piezo motor

The dynamic modeling of the inchworm piezo motor can be described as follows:

$$x_s(t) = G(f[D(u(t)), H(u(t))]) \quad (5)$$

then, we split equation (4) as follows:

$$\begin{cases} G(t) = m\ddot{x}_s(t) + b\dot{x}_s(t) + kx_s(t) \\ D(t) = c_1(b\dot{u}_1(t) + ku_1(t)) \\ H(t) = kh_x(t) + b\dot{h}_x(t) \end{cases} \quad (6)$$

To realize the parameter identification of the inchworm piezo motor using conventional identification methods, it is vital to model and compensate $H(t)$. From formula (1), we can get

$$H(t) = c_1(ku_1(t) + b\dot{u}_1(t)) - (kx_{p2}(t) + b\dot{x}_{p2}(t)) \quad (7)$$

So, the SCNs hysteresis modeling is proposed to solve the problem.

3 Hysteresis modeling using SCNs algorithm

In contrast to developing an inversion of the constructed hysteresis model, the nonlinear hysteresis can be directly modeled using the SCNs algorithm. Wang et al. proposed the SCNs algorithm in 2017[41], and it is a randomly configured neural network using the single-layer forward neural network structure (SLFNN). The SCNs algorithm has the main advantage of reducing the node redundancy of a neural network, thus facilitating accurate fitting.

As shown in Fig.4 (a), hysteresis modeling uses an SCNs algorithm that has a structure where only three input nodes, including the input voltage at the previous time instant $k-1$ (i.e. $u(k-1)$, $H(k-1)$) and at the current time instant k (i.e. $u(k)$, $\hat{H}(k)$), are used for multivalued nonlinearity. then,

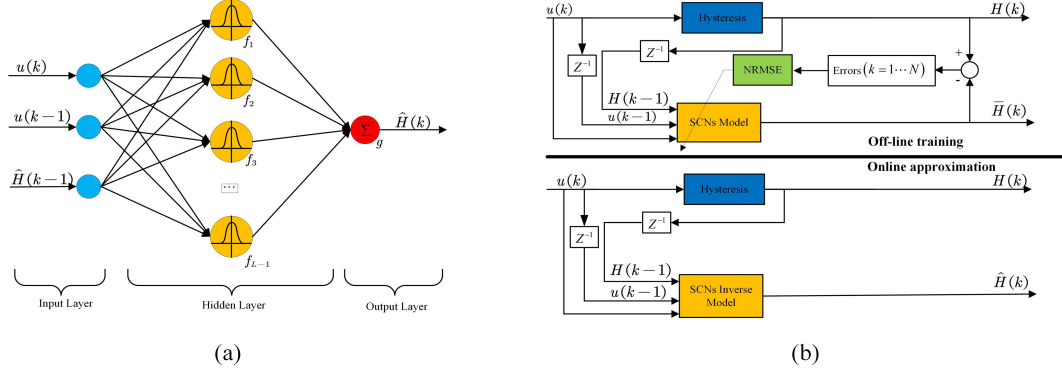


Fig. 4 Diagram of SCNs hysteresis modeling. (a)Diagram of SCNs, (b) Diagram of SCNs hysteresis modeling training and evaluation.

$$\begin{aligned} \hat{H}(k) &= f(\mathbf{u}(k)), \\ \mathbf{u}(k) &= [u(k), u(k-1), H(k-1)]^T \end{aligned} \quad (8)$$

Where $\hat{H}(k)$ and $\mathbf{u}(k)$ are the actual hysteresis output and the input vector at the current time instant k , respectively. According to the definition of the SCNs algorithm, the unknown hysteresis modeling function is approximated by:

$$\begin{aligned} f_{L-1}(\mathbf{u}(k)) &= \sum_{j=1}^{j=L-1} \beta_j g_j[\omega_j \mathbf{u}(k) + b_j], \\ (L &= 1, 2, \dots, f_0 = 0) \end{aligned} \quad (9)$$

Where $g_j(\cdot)$ denotes the activation function, L represents the number of hidden nodes, β_j is the output weight, ω_j is the input weight, and b_j is the offset value. Especially, $g_j(\mathbf{u}(k))$ is designed as:

$$g_j(\mathbf{u}(k)) = \exp\left(-\frac{1}{2\sigma_j^2} \|\mathbf{u}(k) - \mathbf{c}_j\|^2\right) \quad (10)$$

Where σ_j and $\mathbf{c}_j = [c_{1,j}, c_{2,j}, c_{3,j}]^T$ ($j = 1, 2, \dots, L-1$) denote the Gaussian distributed width and the center vector at the j^{th} hidden node, respectively. The SCNs hysteresis modeling consists of the offline training stage and the online approximation

stage, as shown in Fig.4 (b). In this paper, we obtain the activation function parameter values through offline training and the output results through online estimation.

Generally, the normalized root-mean-squared error (NRMSE) is chosen to evaluate the SCNs hysteresis model.

$$e_{\text{NRMSE}} = \frac{\sqrt{1/n \sum_{i=1}^n (H(k) - \bar{H}(k))^2}}{\max_i H(k) - \min_i H(k)} \quad (11)$$

Where n is the length of input voltage, $H(k)$ and $\bar{H}(k)$ denote the output hysteresis and the model predictions of hysteresis for the inchworm piezo motor, respectively.

4 Experiments and discussions

4.1 Experimental setup

There are four main components to the overall experimental setup. Firstly, the experiments are carried out on an inchworm piezo motor, whose size is $\phi 40mm \times h50mm$ and total traveling length is $19.42mm$. Secondly, a controller with 16-bit digital-to-analog converters (DACs) and a high-speed quadrature decoder (QAD) is used to form a hardware-in-the-loop (HIL) controller. Thirdly, a multichannel voltage amplifier operates at a drive frequency exceeding $1.5KHz$ with a voltage range of $\pm 600V_{pp}$ and a current output of $40mA$. Finally, the measuring system is laser interference with a $10MHz$ adoption rate and $0.1nm$ resolution. The hysteresis modeling and identifying algorithms are programmed in the MATLAB/Simulink environment, and Fig.5 illustrates the experimental setup.

4.2 SCNs model training and compensator design

This section aims to determine the hysteresis compensation factor of the inchworm piezo motor based on input displacement and output voltage. Firstly, the SCNs model training of the output displacement is accomplished in this paper, and we finally adopt an input voltage signal [see Fig.6 (a)] for this purpose to calculate the parameters of the SCNs model. The input voltage signal is designed as follows:

$$u(t) = 3.5 \sin(10\pi t) e^{-t} \quad (12)$$

By inputting the voltage signal $u(t)$ into the multichannel voltage amplifier, the result of the inchworm piezo motor was shown in Fig.6 via laser interference. The result of SCNs modeling training is shown in the experiment. The hysteresis loop is plotted in Fig.6 (c) by the input voltage and output displacement. Finally, the error is calculated to contrast experimental displacement and SCN model output displacement in Fig.6 (d).

In this experiment, we set a time interval of $0.0001s$ and 35001 training data sets. Then, the parameters β_j, w_j and b_j in the SCNs model are obtained. So, the SCNs

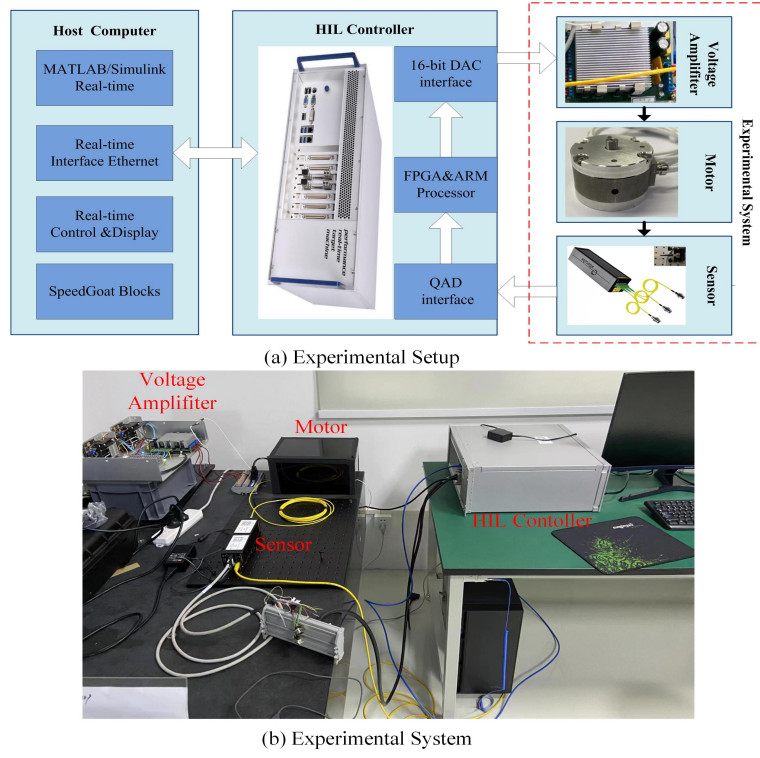


Fig. 5 Experimental setup

modeling compensator can be expressed as:

$$\hat{u}(k) = \frac{1}{1 + e^{-(w_j x(k) + b_j)}} \times \beta_j \quad (13)$$

Where verifying the accuracy of the SCNs model output under this experimental condition. We conducted tests of $f = 1Hz$ and $f = 10Hz$, respectively, for experimental verification in Fig.7.

4.3 Dynamics model identification

As shown in Fig.8, a hysteresis model is introduced to the identification system at first. A linear dynamics model of the inchworm piezo motor is identified by the swept-sine waves, whose amplitude range of $5V$ and the frequency range of $0.1 \sim 800Hz$. The inchworm piezo motor position responses are recorded using a sampling rate of $1kHz$.

Where $u(t)$ is the input voltage value along the variable t . f_0 is the starting frequency of $0.1Hz$, f_e is the ending frequency of $800Hz$, and T is a whole time cycle. The swept-sine signal can be expressed in Formula(14), $u(t)$ is the input voltage value along the variable t . f_0 is the starting frequency of $0.1Hz$, f_e is the ending frequency

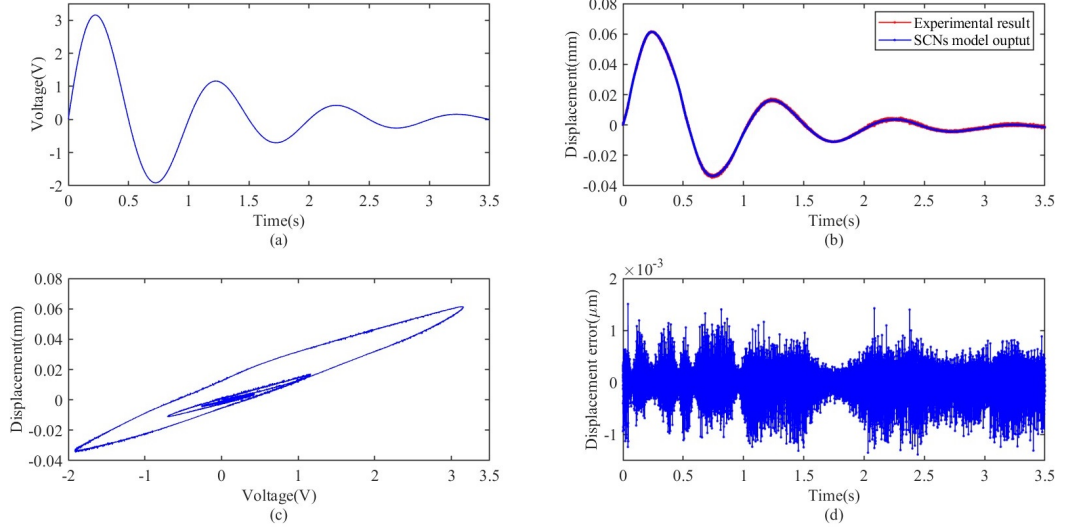


Fig. 6 Results of the SCNs hysteresis model training. (a)Input voltage. (b)Experimental result and SCNs hysteresis model output. (c) Experimental result of hysteresis loop between input voltage and output displacement. (d)Error between experimental result and SCNs hysteresis model output.

800Hz, and T is a whole time cycle.

$$u(t) = 5 \sin \left(2\pi \left(f_0 \times t + 0.5 \times \frac{f_e - f_0}{T} \times t^2 \right) + 0.5\pi \right) \quad (14)$$

The input swept-sine and output position set data are used to identify the system by estimating the model from the frequency response data. Fig.8 (a) illustrate the experiments and the associated model. These results show that the first resonant mode occurs around 138.8Hz. So, the inchworm piezo motor frequency responses can be expressed as:

$$G(s) = \frac{6.664e^{-6}s + 0.2657}{3.04s^2 + 58s + 2.312e^6} \quad (15)$$

It is observed that the second-order model that has been identified matches the system dynamics well in terms of magnitude at frequencies below 500Hz. As a result, the estimated second-order model cannot accurately describe high-frequency dynamics. This paper proposes a simple second-order model to demonstrate the linear dynamics system of the inchworm piezo motor.

4.4 FF compensation Plus FB controller

As described in Section 4.2, the inchworm piezo motor model was decoupled as a linear system identified by the hysteresis modeling compensator. The FRF of the inchworm piezo motor was obtained in Section 4.3. To further suppress the existence of residual tracking errors and other disturbances, it cannot be processed by FF compensation. Hence, proportional-integral (PI) controller is introduced to the system as an FB

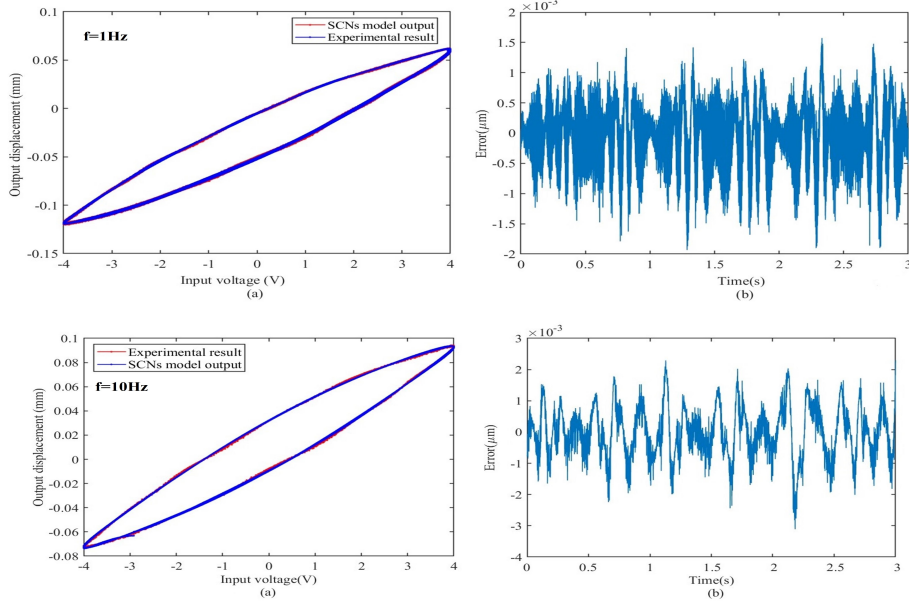


Fig. 7 Results of the SCNs hysteresis modeling testing. (a) $f = 1\text{Hz}$ and $f = 10\text{Hz}$, hysteresis loop from the SCNs hysteresis modeling and experiment between input voltage and output displacement. (b) $f = 1\text{Hz}$ and $f = 10\text{Hz}$, the error between the SCNs hysteresis modeling output and experimental hysteresis output.

controller, which improves the accuracy of positioning the inchworm piezo motors. The whole block diagram is presented in Fig.9.

In Fig.9, $K_p = 10$ and $K_i = 145.836$ are the proportional and integral gains, respectively. The positioning displacement error $e(t) = x_r(t) - x_{out}(t)$, $x_r(t)$ is reference tracking and $x_{out}(t)$ is actual displacement by the measuring system. The experimental results showed that the target displacement of $1\mu\text{m}$ and 2mm , the actual displacement, and the positioning displacement error were plotted in Fig.10 under the FF compensation plus FB controller.

Based on the environment's influence and the feedback displacement of the laser interference, damage positioning displacement of around 5nm is observed, and long-term testing will result in large fluctuations. In this section, we take the reference displacement as step tracking.

5 Conclusion

The goal of this study was to develop a model and identification of a piezo motor that operates with nonlinear hysteresis. We found that the SCNs hysteresis model can be used as a sound model for describing nonlinear hysteresis behavior. In this experiment, we calculated the parameters of the SCNs hysteresis model through the process of data training. It was further demonstrated that the error between the SCNs hysteresis model output and the experimental result could be controlled within the range of 2nm . In addition, a SCNs hysteresis compensator is included in this

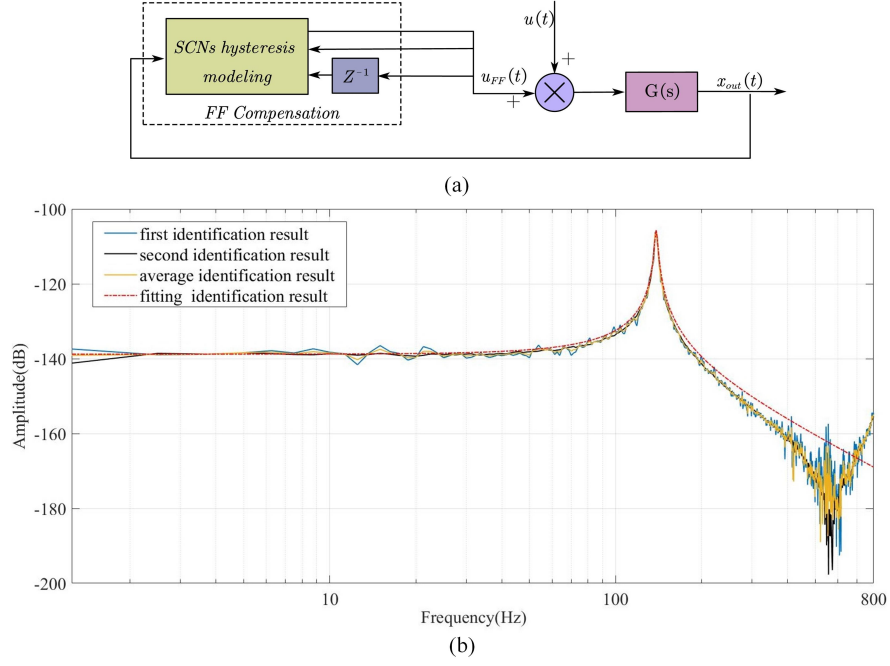


Fig. 8 Identification system of the inchworm piezo motor.(a) Block diagram of identification, (b) Result of identification system.

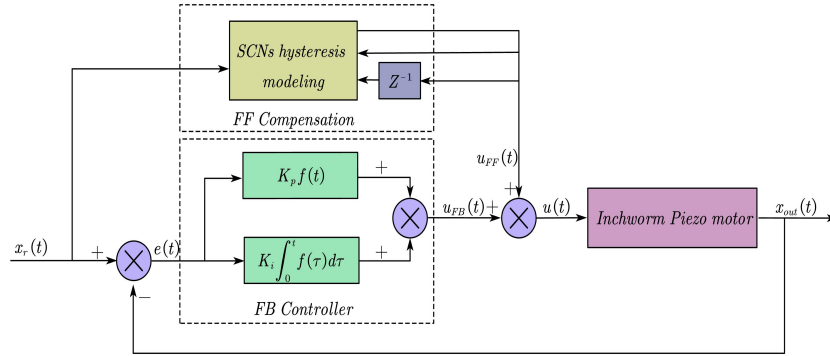


Fig. 9 Close-loop controller and hysteresis compensator system

paper in order to identify the inchworm piezo motor through linear identification. This controller system generates a second-order model of the inchworm piezo motor. The closed-loop PI experiment assisted us in determining that the positioning accuracy error is approximately $1nm$. It will be the subject of future research to investigate the application of the inchworm piezo motor to the electron microscope platform.

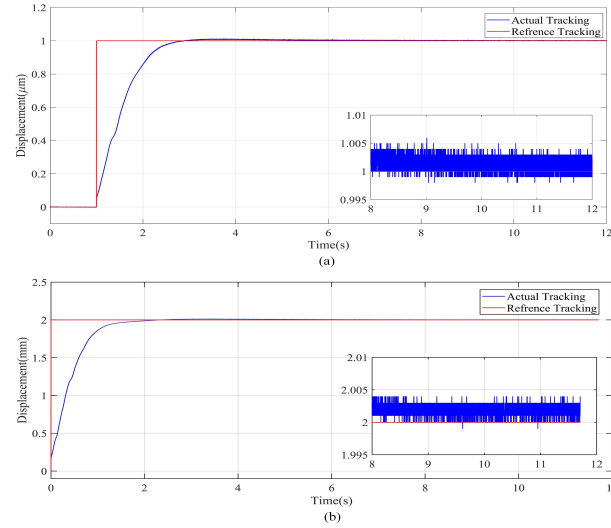


Fig. 10 Results of the positioning displacement under the FF compensation and FB controller. (a) Target displacement is $1\mu m$. (b) Target displacement is $2mm$.

Authors' Contributions. Shuo Han's contribution is writing the manuscript of our work, doing some experiments and analyzing data, and calculating and derivating formulas. Yunlang Xu, Jianbo Yu, and Xiaofeng Yang contributed to revise the manuscript and the central idea of the manuscript and proposed some recommendations for the manuscript.

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Data Availability Statement. The data that support the findings of this study are available from [20112020011@fudan.edu.cn]. Restrictions apply to the availability of these data, which were used under licence for this study. Data are available [from the authors: Shuo Han] with the permission of [20112020011@fudan.edu.cn].

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