RBF Neural Network Modeling of Rate-dependent Hysteresis for Piezo-ceramic Actuator

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Abstract: This paper deals with the model identification problem of a piezo-ceramic actuator (PZT) based on a radial basis function (RBF) neural network. The phenomenon referred to as the rate-dependent hysteresis of a piezo-ceramic actuators can be a cause of considerable performance degradation in the applications. This paper proposes the RBF neural network as a model of hysteresis which characterizes the rate-dependent hysteresis of PZT. In order to increase precision of the adaptive RBF neural network modeling, the particle swarm optimization (PSO) algorithm is applied to optimize the parameters of the RBF neural network model. Several experiments have been additionally performed to demonstrate the precision and response of the proposed modeling for a wide variety of operating conditions. Analysis and comparison show that the proposed RBF neural network modeling for our PZT performed quite well.

Key-Words: *Piezo actuator, rate-dependent hysteresis, RBF neural network; adjustment, PSO*

1. Introduction

Piezo-ceramic actuator is a kind of smart material which is widely used in many fields, such as ultra-precise machining, optical alignment and biotechnology. Although piezo-ceramic actuator has many advantages in applications, the property of rate-dependent hysteresis of the PZT might cause nonlinearity and instability of the system, which will lead to considerable deterioration of positioning accuracy without appropriate compensation [1-2].

Many researchers have researched the hysteresis modeling, such as well-known phenomenological mathematical model-Preisach model [3]. In the previous research, Hata et.al., proposed a feed-forward positioning control system of PZT which suffers rate-dependent hysteresis. They used the inverse distribution function which is generated off-line by an interpolation of two inverse distribution functions identified at two different operating conditions corresponding to a certain driving frequency to cancel out the influence of hysteresis [4]. However, the identification of distribution functions require plenty of computations. The method cannot achieve the on-line modeling and performance is not good enough as a numerical model of rate-dependent hysteresis.

In the present research, in order to characterize the property of rate-dependent hysteresis of PZT, an RBF neural network (RBFNN) modeling is proposed for modeling of rate-dependent hysteresis. Particle swarm optimization algorithm is utilized to optimize parameters of neural network, and adjusting of iterations is done to get more precise and better performance in our rate-dependent hysteresis modeling.

2. RBFNN Modeling for hysteresis

This section describes the details of rate–dependent hysteresis modeling of PZT using RBF neural network.

2.1 Descriptions of RBFNN modeling

Here we design a 3-7-1 layers RBF neural network for the modeling shown in Figure 1 which is given as follow:

Received: 15, 11, 2014, Accepted: 01, 12, 2014
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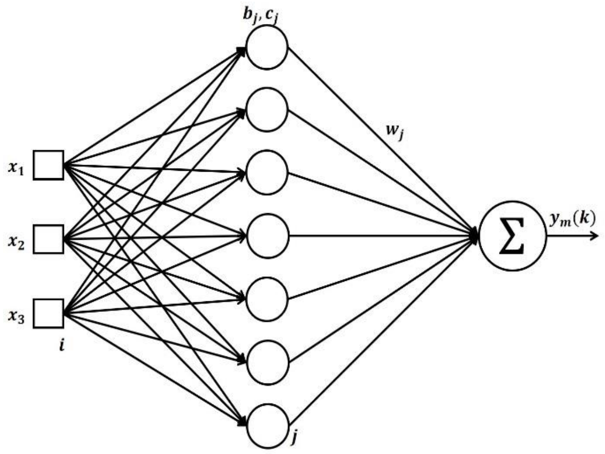


Figure 1 Structure of neural network

Input layer: the input nodes denoted by $x_1, x_2,$ and x_3, are given by

$$x_1 = r(k) \quad (1)$$

$$x_2 = r(k-1) \quad (2)$$

$$\mathrm{x}_3 = \mathrm{y}(\mathrm{k}-1) \quad (3)$$

respectively, where $r(k)$ represents the current value of training input, $r(k - 1)$ is the value of training signal at previous time instant and $y(k-1)$ amounts to the previous output displacement of the actuator.

Hidden layer: nodes at hidden layer utilize the multiple radial basis function units necessary to capture the input-output dynamics of PZT. The output of hidden layer can be denoted by the following equations:

$$\mathrm{x} = [x_1, x_2, x_3] \quad (4)$$

$$h_j = \exp\left(\frac{-\|x-c_j\|^2}{2b_j}\right) \qquad j = 1, \cdots, 7\ , \quad (5)$$

Where x is the input of hidden layer, h is the output, and c, b is the center and width of the Gaussian RBF.

Output layer: output of the RBF neural network can be calculated by

$$y_m = \sum_{j=1}^{7} w_j \cdot h_j \qquad j = 1, \cdots, 7 \quad (6)$$

Where the w is the weight corresponding to h.

2.2 Training process of modeling

The training of parameters in the RBF neural network is an important and difficult point for our design, so in order to get better performance for this neural network modeling, particle swarm optimization intelligent algorithm which is a global optimization proposed by Eberhart and Kennedy in 1995 is used for the parameters training of RBF neural network modeling [5].

The training process based on PSO begins with initializing a group of random particles corresponding to the variables to be sought, and then finds out the optimal solution through iteration. Particles track two extreme value to update their own in each iteration, one is the optimal solution called the individual extreme value p that particles themselves find, the other is the present global optimal solution called the global extreme values are found, the speed and the position of the particles will be updated by utilizing the equation

$$v_n = w \cdot v_c + c_1 \cdot \mathrm{r} \cdot (\mathrm{p} - p_c) + c_2 \cdot r \cdot (g - p_c) \quad (7)$$

for the speed and

$$p_n = p_c + v_n \quad (8)$$

where v_n represents the new speed of particles, v_c is the current speed, p_n is the new position of particles, p_c is the current position, the coefficient $r \in (0, 1)$is the random number generated for increasing the randomness of motion, c_1 and c_2 are acceleration constants, and the w is the inertia weight.

In this training of RBFNN, the objective function is defined by

$$g(k) = \frac{1}{2}e(k)^2 = \frac{1}{2}(y(k) - y_m(k))^2 \quad (9)$$

Where y is the actuator output and y_m is the model output. The training will be performed to make the value of g as small as possible. In our pervious experimental design of RBFNN modeling for PZT, though the number of initial population is selected to be 100, individuals' length to be 35 and the maximum number of iterations to be 100, each of which is determined by experience, we did not pay enough attention to the setting of iterations, then we increase the maximum number of iterations to be 200 and increase the setting of initial population to 150.

When model output y_m approaches to the real actuator response y, g must decrease gradually. In order to visualize the progress of PSO training of RBF-NN for capturing PZT dynamics, the accumulated criterion as defined by

$$J = \sum_{k=1}^{N} g(k) \tag{10}$$

is calculated over one specific iteration, where N represent the number of signal samples contained in a single iteration.

The 3-7-1 RBF-NN contains the parameters of center c, widths of function b at hidden layer and the weights w for the output layer in equation (6) are trained based on the PSO.

3. Result

The PZT used for our experiment is PZBA-00030 by FDK Corporation which has the dynamic range of ±1000μm and positioning resolution of 20nm.

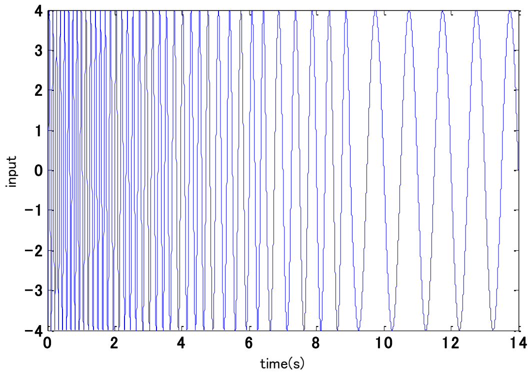


Figure 2 Input signal

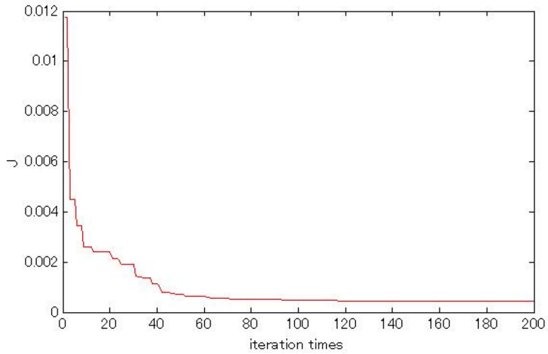


Figure 3 Training for RBF neural network

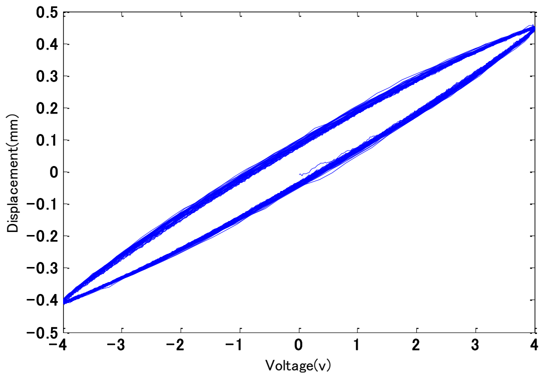
The input shown in Figure 2 for our modeling of piezo-ceramic actuator is a sinusoidal voltage signal with frequency from 10 to 1Hz. The frequency of the voltage signal varies to capture the property of rate-dependent hysteresis.

Figure 3 shows training proceeds J, we can see that the training results are good and the proposed neural network acquire the dynamic relation of our PZT in the end of process. And with the help of comparison in Table 1, after tuning the number of iteration, the results become better in the proposed modeling.

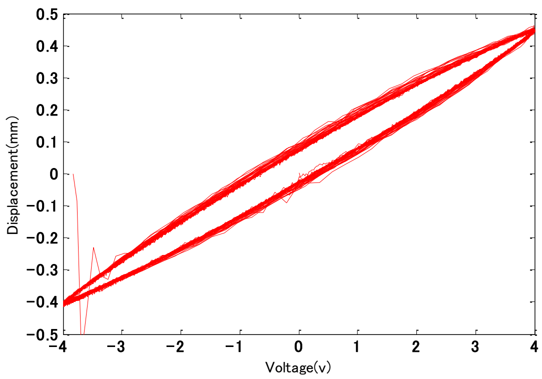
In order to see the performance of rate-dependent hysteresis modeling based on the proposed RBFNN, Figure 4-6 shows the results of the proposed rate-dependent RBFNN modeling.

Table 1 How number of iteration affect the modeling accuracy

Times	50	200
Minimum of J	0.00057	0.00045



(1) Experimental data



(2) NN model data

Figure 5 Result of rate-dependent hysteresis

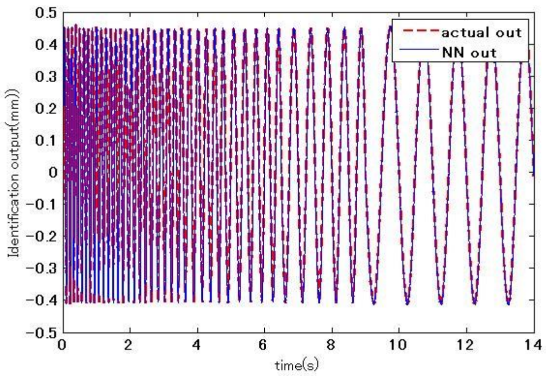


Figure 6 Output of modeling

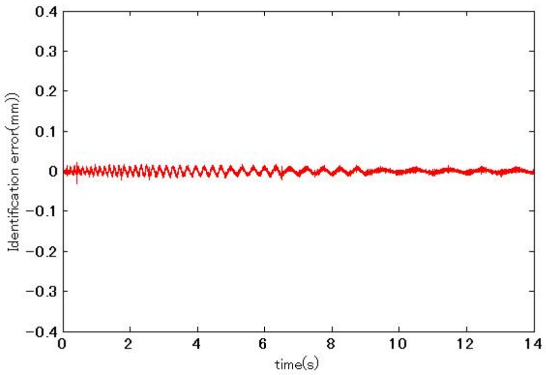


Figure 7 Modeling error

As shown in Figure 7, the root mean square of error e defined by

$$e = \sqrt{(\sum_{k=1}^{n}(y(k) - y_m(k)^2))/n} \qquad (11)$$

is 0.006mm which is smaller than 1-2% of the amplitude of motion, results validate that the proposed RBFNN modeling is very efficient for catching the behavior of rate-dependent hysteresis in the piezo-ceramic actuator.

4. Conclusion

In this paper, an RBF neural network model based on PSO algorithm is proposed for characterizing rate-dependent hysteresis for the piezo-ceramic actuator. With the help of proposed neural network based on the improved initial setting and experiment data, the results illustrate that this proposed RBF neural network model performance very well for the modeling of rate-dependent hysteresis in our PZT. The additional compensation design of our PZT will continue be performed based on this work in the future.

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