2005 年 第 19 卷 第 4 期 测 试 技 术 学 报 Vol. 19 No. 4 2005
(总第 54 期) JOURNAL OF TEST AND MEASUREMENT TECHNOLOGY (Sum No. 54)

文章编号: 1671-7449(2005)04-0453-06

Application of Back Propagation Artificial Neural Networks on Dynamic Compensation of Measurement Systems

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Abstract: Nonlinear dynamic compensation of measurement systems is an important aspect in the field of instrument technique. The back propagation (BP) neural network is proposed for nonlinear dynamic compensation of measurement systems, as its architecture is determined only by the number of nodes in the input, hidden and output layers. With the nonlinear mapping behavior, the BP neural network can catch up with the dynamic response of the system. A recursive prediction error algorithm which converges fast is applied to train the BP neural network. Experimental results show that the performance of the BP neural network model conforms to the measurement system to be compensated, proving the method is not only effective but of high precision.

Key words: dynamic compensation; neural networks; recursive prediction error algorithm

BP 神经网络在测试系统动态补偿中的应用

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摘 要: 测试系统的非线性动态补偿是仪器技术的一个重要方面. 采用 BP 神经网络对测试系统进行动态补偿. BP 神经网络的结果决定于网络输入、隐层和输出节点. 由于其非线性映射特性, BP 神经网络完全能够反映测试系统的动态响应特性. 采用了收敛速度较快的递推预报误差算法训练神经网络. 试验结果表明, BP 神经网络的特性完全能够满足测试系统的动态补偿要求, 表明本文的方法是有效的.

关键词: 动态补偿; 神经网络; 递推预报误差算法

中图分类号: TP212 **文献标识码**: A

When the measurand varies with time, the relationship between the input and output of a measurement system also shows dynamic properties. Ideal dynamic performance of a measurement system meets the non-distortion demand, that is[1]

$$y(t) = kx(t - \tau_0), \tag{1}$$

where: $x(t)$, $y(t)$ is the input and output of the measurement system respectively; k is the measurement system gain, constant; τ_0 is the time-delay, constant.

To find a non-distorted measurement system in a practical circumstance is very difficult. For a considerably good one, its amplitude-frequency performance is flat, namely k keeps stable only within a limited frequency scope, otherwise it will decline. As to the phase frequency performance, the linear scope even narrower than the bandpass. So, the dynamic error is inevitable in practical measurement.

In addition, to avoid the complexity brought out by nonlinear modeling of measurement system, the transfer properties of the measurement system are always expected to be linear, steady and non-time

* **收稿日期**: 2004-11-19
基金项目: 国家自然科学基金资助项目(30270382)
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varying. But in practical cases, this ideal system doesn't exist. Therefore, meeting certain precision, measurement system is regarded as linear and non-time varying system and resulting in the dynamic measurement errors.

Neural networks, as general tools for implementing nonlinear mapping between inputs and outputs, can play an important role in measurement systems[2]. Many researches have presented successful results on modeling measurements or sensors[3~5]. Little has been done on correcting dynamical errors of measurement systems by neural networks. Arpaia et al have proposed an artificial neural network-based solution for the compensation of differential active transducers subject to several error sources, but two sensors should be used in the correcting structure[6].

To eliminate or reduce dynamic errors of a measurement system, it is necessary to model the system based on its actual properties and compensate it dynamically. Artificial neural networks are applied in modeling of measurement system. An inverse artificial network model is used to dynamically compensate the measurement errors. Experiment results show that the measurement system after dynamic compensation meets non-distortion demand and possesses ideal properties.

1 Dynamic Compensation of Measurement System Based on Artificial Neural Networks

A discrete time nonlinear system can be represented by NARMAX (Nonlinear AutoRegressive Moving Average models with eXogeneous inputs)[7]. This model describes the nonlinear process, depending on the fact that the output at a certain time is a nonlinear function of the input, the output and the lag. A measurement system model can be represented as the NARMAX model below.

$$y(t+1) = f(y(t), \cdots, y(t-n+1), x(t), \cdots, x(t-m+1)), \tag{2}$$

where: $y(t)$, $x(t)$ is the output and the input of the system respectively; n, m is the maximum lag of the output and the input; $f(.)$ is a nonlinear function.

This type of nonlinearity in Eq. (2) is too complex to be represented by a uniform model. As shown in fig. 1, if the input of the measurement system is $x(t)$, dynamic measurement error will exist between $y(t)$ and $x(t)$. To compensate for the dynamic errors, it can be deduced from equation (2) as

$$x(t) = g(y(t+1), \cdots, y(t-n+1), x(t-1), \cdots, x(t-m+1)), \tag{3}$$

where: $g(.)$ is some kind of nonlinear function which is relevant to $f(.)$.

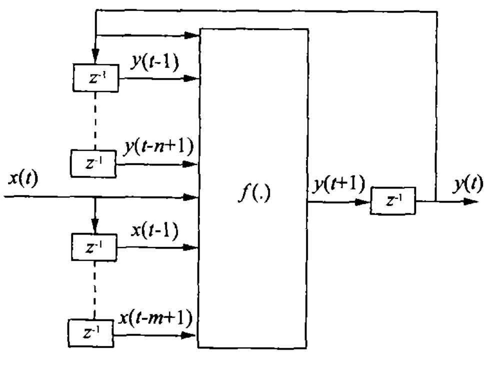

Fig.1 Mesaurement system model

图1 测试系统模型

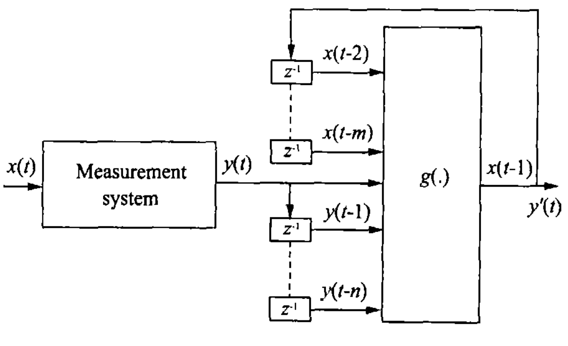

Fig.2 Mesaurement system after dynamic compensatipn

图2 动态补偿后的测试系统

Link the system which is represented by equation (3) to the measurement system and realize the dynamic compensation, as shown in fig. 2. It is obvious that the input and output relationship of the measurement system after compensation is

$$y'(t) = x(t-1), \tag{4}$$

where: $y'(t)$ is the output of the measurement system after compensation.

Comparing Eq. (4) with Eq. (1), we can conclude that if $g(.)$ is known, the measurement system after dynamic compensation meets non-distortion demand and possesses ideal input and output properties.

To compensate dynamic errors of measurement system, it is necessary to use some kind of model to approach $g(.)$. Fortunately, the emergence of neural networks provides a satisfactory solution to model for this type of complex system. It has been proven that any continuous function in a closed interval can be approached by one hidden layer BP network model. Therefore, a three layer BP network model is competent for mapping an arbitrary function from one multi-dimension space to another multi-dimension space freely.

Fig. 3 presents the principles of dynamic compensation of measurement system based on artificial neural networks. N_f is used to approach the properties of the measurement system while N_g is used to compensate the dynamic properties of the measurement system. As the input of N_g is the output of the measurement system, and the output of the measurement system is up to its input and can't be chosen randomly, the input signal of N_g can't be chosen randomly when Ng is being trained. In practical application, N_f is used to train N_g. As Nf is a mathematical model, any training signal can be chosen when Nf is used to train N_g. Then appropriate N_g model can be obtained.

Fig. 4 illustrates the structure of a neural network with single hidden layer, which describes the nonlinear system with single input and output[7,8]. The model structure of N_g can be represented by the equation below

$$\hat{y} = \sum_{j=1}^{n_1} w_j^2 x_{fj}^1(t) = \sum_{j=1}^{n_1} w_j^2 g\left(\sum_{k=1}^{n_0} w_{jk}^1 x_{fk}(t) + b_j^1\right), \tag{5}$$

where: $\hat{y}$ is output of the neural network; $x_{fj}^1, w_j^2 (j = 1, 2, \cdots, n_1)$ is outputs of the hidden layer neurons and the weights for connection between neurons in hidden layer and output layer respectivelyl; $w_{jk}^1, b_j^1 (j = 1, 2, \cdots, n; k = 1, 2, \cdots, n_0)$ is weights for connection between the output of the kth neurons and the jth neurons in the hidden layer and threshold values of neurons in hidden layer respectively; $x_{fk} (k = 1, 2, \cdots, n_0)$ is inputs of the neural network N_g.

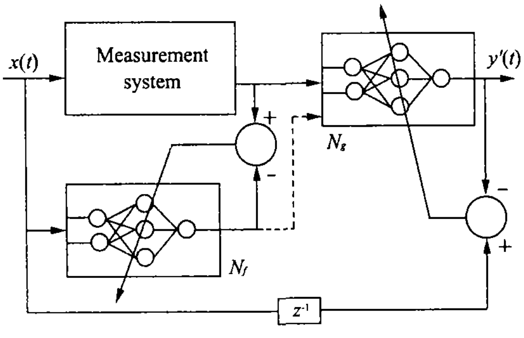

Fig. 3 Dynamic compensation of measurement system by neural networks

图 3　基于神经网络的测试系统动态补偿

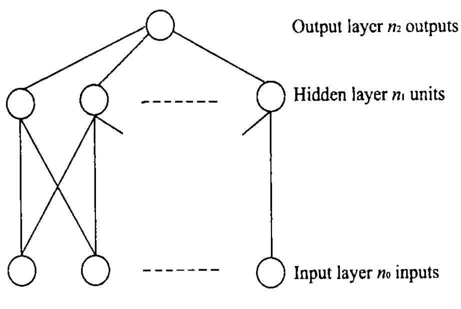

Fig. 4 A neural network with one hidden layer

图 4　单隐层神经网络

As for neurons in hidden layer, the excitation function is defined as

$$g(z) = 1/[1 + \exp(-z)]. \tag{6}$$

Similarly, The expression of N_g is

$$\hat{y}'(t) = \sum_{j=1}^{\tilde{n}_1} \tilde{w}_j^2 x_{gj}^1(t) = \sum_{j=1}^{\tilde{n}_1} \tilde{w}_j^2 g\left(\sum_{k=1}^{\tilde{n}_0} \tilde{w}_{jk}^1 x_{gk}(t) + \tilde{b}_j^1\right), \tag{7}$$

where: $\widetilde{w}_j^2$, $\widetilde{w}_{jk}^1$, $\widetilde{b}_j^1$ is the weight and threshold of N_g, respectively; $\widetilde{n}_0$, $\widetilde{n}_1$ is the number of the input nodes and hidden nodes of N_g, respectively.

In order to model the system using neural networks, it is necessary to train the neural network model and assign appropriate values to weights and thresholds. This paper adopts the recursive prediction error (RPE) algorithm to train the neural network[9]. Compared with BP algorithm, the RPE algorithm has such characteristics as simple structure, high convergence speed and avoiding being trapped in the choice of learning rate and inertia factors.

First, define the prediction error as

$$\epsilon(t, \theta) = x(t-1) - y'(t, \theta), \tag{8}$$

where: $x(t-1)$, $y'(t, \theta)$ is delayed input of measurement system and output of the neural network model respectively; θ is vector of weights and thresholds.

After N data have been recorded, a criterion function can be expressed by the following sum of squared prediction errors

$$J(\theta) = \frac{1}{2N}\sum_{t=1}^{N}\epsilon^T(t, \theta)\epsilon(t, \theta). \tag{9}$$

The unknown vector θ are updated along the Gauss-Newton search direction of $J(\theta)$ to make $J \to \min$. The basic equation is

$$\theta(t) = \theta(t-1) + s(t)\mu(\theta(t-1)), \tag{10}$$

where: $s(t)$ is step size; $\mu(\theta)$ is gauss-Newton search direction.

$$\mu(\theta) = -[H(\theta)]^{-1}\nabla J(\theta), \tag{11}$$

where the gradient of $J(\theta)$ towards θ is denoted as $J(\theta)$, $H(\theta)$ is the second order derivative of $J(\theta)$, namely the Hessian matrix of $J(\theta)$.

It can be easily derived out that

$$\nabla J(\theta) = \frac{\partial J(\theta)}{\partial\theta} = -\frac{1}{N}\sum_{t=1}^{N}\Psi(t, \theta)\epsilon(t, \theta), \tag{12}$$

$$\Psi(t, \theta) = \left[\frac{dy'(t, \theta)}{d\theta}\right]^T. \tag{13}$$

The RPE algorithm for training N_g is described by following equations[3,4]

$$\epsilon(t) = x(t-1) - y'(t), \tag{14a}$$

$$p(t) = \frac{1}{\lambda(t)}\left[p(t-1) - p(t-1)\Psi(t)[\lambda(t)I + \Psi^T(t)p(t-1)\Psi(t)]^{-1}\Psi^T(t)p(t-1)\right], \tag{14b}$$

$$\theta(t) = \theta(t-1) + p(t)\Psi(t)\epsilon(t), \tag{14c}$$

where: $\theta(t)$ is vector estimation of the weights and thresholds of N_g when the time is at t.

$p(t)$ is called the middle matrix, representing the covariance matrix of parameters when $t \to \infty$, whose initial value $p(0)$ is usually chosen from the range of $10^4 I$ to $10^5 I$, where I is the identity matrix. $\lambda(t)$ is called the forgetting factor. It is desirable to set $\lambda(t) < 1$ at the initial stage so that rapid adaptation takes place and then to let $\lambda(t) \to 1$ as $t \to \infty$. Following equation can meet the above requirements

$$\lambda(t) = \lambda_0\lambda(t-1) + (1-\lambda_0). \tag{15}$$

The RPE algorithm for training Nf are similar to Eqs(14).

2 Experiment Results

From the analysis above, the process of applying artificial neural networks to dynamic compensation of a measurement system can be summarized as follows: ① Based on the properties of measurement system, determine the number of input nodes and hidden nodes of N_f and N_g. And determine relevant initial values. ② Acquire relevant experimental data, apply RPE algorithm to train the model N_f. ③ Choose appropriate training signal and input it into N_f. Apply the output of N_f as the input of N_g. Error signals can be obtained by the comparison of the output of N_g and training signal. Apply Eq. s (14) in training N_g. ④ Link N_g to the measurement system to realize its dynamic compensation.

For example, compensate the measurement system below.

$$y(t+1) = \frac{0.8}{1 + \exp[-0.5x(t) - 0.6y(t) - 0.9]}$$

Determine the structure of the model N_f and N_g by setting $n_0 = 2$, $n_1 = 1$ and $\tilde{n}_0 = 2$, $\tilde{n}_1 = 5$, respectively.

Set $\theta = [\theta_1, \theta_2, \cdots, \theta_{20}]^T = [\tilde{w}^1_{11}, \tilde{w}^1_{12}, \cdots, \tilde{w}^2_5]^T$, then

$$\Psi = \frac{d\hat{y}'}{d\theta} = \begin{cases} x^1_{gk} & \text{if } \theta_i = \tilde{w}^2_k,\ 1 \le k \le 5 \\ x^1_{gk}(1 - x^1_{gk})\tilde{w}^2_k & \text{if } \theta_i = \tilde{b}^1_k,\ 1 \le k \le 5 \\ x^1_{gk}(1 - x^1_{gk})\tilde{w}^2_k x_{gm} & \text{if } \theta_i = \tilde{w}^1_{km},\ 1 \le k \le 5,\ 1 \le m \le 2 \end{cases}.$$

Pseudo random binary sequences (PRBS) whose amplitude is ± 1 and length is 64 is utilized to train N_f for 800 iterations. In order to obtain correct model, PRBS whose amplitude is ± 0.1, ± 0.2, $\cdots$, ± 1 and and length is 64 is utilized to train N_g for 3 200 iterations. Table 1 presents the weights and thresholds of N_g. Link N_g to the measurement system to realize dynamic compensation. Fig. 5 shows the experiment results, whose input signal is

$$x(t) = \sin(\pi t/32) + \sin(\pi t/16) + e(t).$$

where: $e(t)$ is irrevelant noise with mean value of 0 and standard variance of 0.05.

Tab 1 Weights and thresholds of the model N_g

表 1 模型 N_g 的权值和阈值

$\tilde{w}^1_{11}$	$\tilde{w}^1_{12}$	$\tilde{b}^1_1$	$\tilde{w}^1_{21}$	$\tilde{w}^1_{22}$	$\tilde{b}^2_1$	$\tilde{w}^1_{31}$	$\tilde{w}^1_{32}$	$\tilde{b}^3_1$	$\tilde{w}^1_{41}$
-7.374692	1.243797	2.762024	-17.709556	0.339096	13.274070	-11.992602	-4.498916	9.083950	4.471686
$\tilde{w}^1_{42}$	$\tilde{b}^4_1$	$\tilde{w}^1_{51}$	$\tilde{w}^1_{52}$	$\tilde{b}^5_1$	$\tilde{w}^2_1$	$\tilde{w}^2_2$	$\tilde{w}^2_3$	$\tilde{w}^2_4$	$\tilde{w}^2_5$
-0.826207	-2.607716	4.149208	-0.243093	-1.275178	-2.202395	-4.253382	-0.056839	1.941558	4.803375

In fig. 5, $x(t)$ is shown by curve 1. Curve 2 represents the outputs without compensation while curve 3 shows the outputs after compensation. It is obvious that the measurement system after compensation meets the non-distortion demand and possesses very good properties.

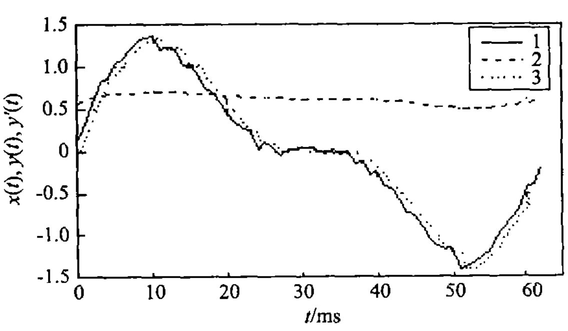

Fig 5 Dynamic compensation results

图 5 动态补偿结果

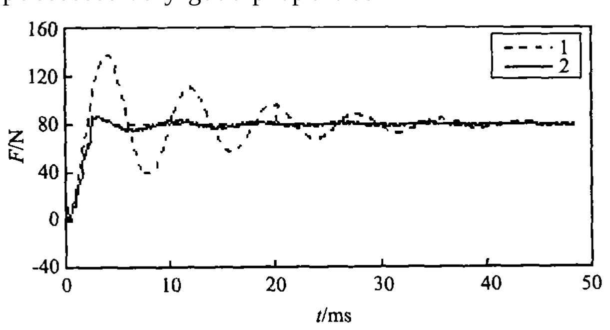

Fig 6 Dynamic compensation of mechanical sensor

图 6 力传感器的动态补偿

Fig. 6 gives the compensation results of a mechanical sensor which can be regarded as a measurement system. Curve one represents the step response. The model of the sensor is drawn by means of system identification. When the order of the model is set seven, the result is satisfactory.

Because of the high order, it's not easy to realize dynamic compensation of the system. In order to compensate the sensor, determine the structure of the model N_f and N_g by setting $n_0 = 14$, $n_1 = 20$ and $\tilde{n}_0 = 14$, $\tilde{n}_1 = 20$, respectively. Curve 2 in fig. 5 illustrates the compensation result. The steady state time after compensation becomes less than 5 ms. It shows that the dynamic performance has been improved greatly.

It is a common problem to choose suitable structure of the neural networks. A feasible way is to select different nodes of input and hidden layers. A optimal network can be acquired by comparing the performances of different neural networks.

3 Concusions

① This paper discusses application of artificial neural networks in dynamic compensation of measurement system. From the experimental results, we learn that the performance of measurement system after compensation meets the non-distortion demand, proving the method is effective. ② Based on the analysis above, the model N_g undertakes the function of reversible mapping of the measurement system. Therefore, in order to get reliable N_g, the measurement system is requested to be reversible. This paper doesn't discuss the reversibility of nonlinear systems. Readers who are interested in it can refer to reference[10,11]. ③ The generalization of neural network model should be considered in the training of the model N_g. In order to secure the dynamic properties of the measurement system to be compensated correctly, the training data must be representative. In fact, when the model N_g is being trained, only using PRBS (pseudo random binary sequences) with single amplitude usually results in wrong results. ④ It is assumed that the structure of measurement system (such as the order values m, n) is known. If the values m, n are unknown, it is necessary to apply different values of m and n in modeling the measurement system, and choose the values of m and n with relatively high precision. ⑤ Increasing the number of nodes in the hidden layer is also helpful to improve the precision of dynamic compensation, but will be at the cost of training time.

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