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Numeral eddy current sensor modelling based on genetic neural network*

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This paper presents a method used to the numeral eddy current sensor modelling based on the genetic neural network to settle its nonlinear problem. The principle and algorithms of genetic neural network are introduced. In this method, the nonlinear model parameters of the numeral eddy current sensor are optimized by genetic neural network (GNN) according to measurement data. So the method remains both the global searching ability of genetic algorithm and the good local searching ability of neural network. The nonlinear model has the advantages of strong robustness, on-line modelling and high precision. The maximum nonlinearity error can be reduced to 0.037% by using GNN. However, the maximum nonlinearity error is 0.075% using the least square method.

Keywords: modelling, numeral eddy current sensor, functional link neural network, genetic neural network

PACC: 0630L, 0620D, 8730

1. Introduction

The numeral eddy current sensor finds extensive applications in various systems such as instrumentation and process control. These applications demand that the sensor has an easy digital interface for direct readout, the response characteristics of the sensor should be linear and independent of variations in the environmental conditions such as temperature, humidity, etc. However, the response characteristic of the sensor is nonlinear.

To convert the nonlinear output into linear digital output the main methods have been proposed. In the first method, a read-only memory (ROM)-based look-up table is employed for the entire dynamic range of the sensor. The conversion table for the data is stored in the ROM. The digital equivalent of the data under measurement is obtained by addressing the ROM by an m-bit counter. In the second method, a nonlinear scheme is utilized with the help of the least square method (LSM).[1]

These methods have the following limitations. Firstly, in the case of extreme change of environmental conditions, such as temperature, humidity, etc., the look-up table or the nonlinear encoding function needs modification to adapt to the new nonlinear sensor output. Secondly, in the care of replacement and aging of the sensor, the data stored in the ROM requires updating. Further, in spite of the advanced manufacturing technology, the response characteristics of sensor of the same manufacturer differ from sample to sample. As a result, in the case of replacement, aging or extreme change in environmental conditions, frequent calibration of the sensor is required.[2] In this paper, we propose a different method that circumvents the problems associated with existing methods. The problems have been solved by an adaptive technique using an genetic neural network (GNN) for the shortcoming of conventional methods.

The artificial neural network (ANN) has been widely applied in science and engineering.[3−15] The majorities of these applications are the gradient technique and back propagation (BP) for optimizing the networks. BP has unquestionably been a major technique, but it is plagued with long practicing and unpredictable performance.

The genetic algorithm (GA) is based on natural selection and genetic mechanism is a global search that moves from one population of points to another.[16,17] As the algorithm continuously samples the parameter

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space, the search is directed toward the area of the best solution. The combination of ANN and GA is a potential and effective method.[18]

2. Principle of eddy current sensor

The detailed construction of an eddy current sensor is depicted in Fig.1.[1] If the eddy current sensors are designed for measuring displacement δ, the response characteristic of the sensor is nonlinear. The response of sensor may be expressed as follows:

$$f(\delta) = w_0 + w_1\delta + w_2\delta^2 + \cdots + w_n\delta^n + \cdots, \quad (1)$$

where f (frequency) is the sensor output and δ (displacement) is the input. w represents estimated value of coefficient. The unknown coefficients represent the characteristic parameters of the sensor.[1]

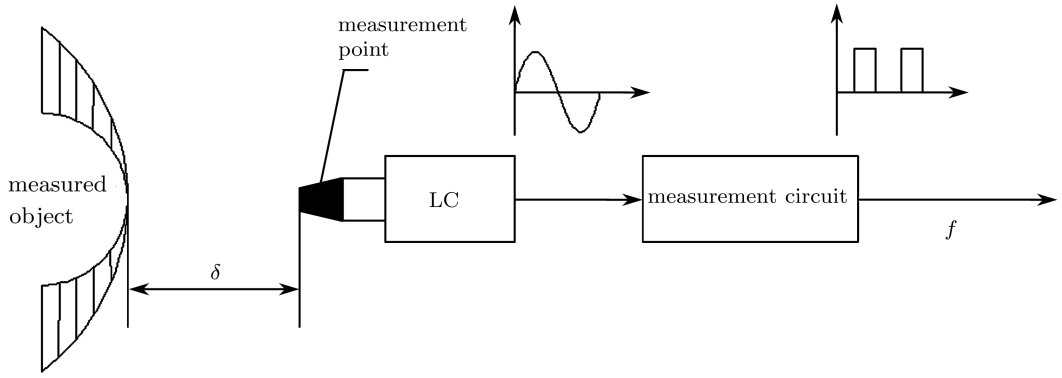


Fig.1. Principle of an eddy current sensor.

3. Functional link ANN

ANN techniques have emerged to become highly successful in solving numerous complex and intractable problems in science and engineering. There are many types of ANN. In this section we discuss one model, which is called a functional link ANN model (FLANN model).[19,20] FLANN is a single-layer nonlinear network. In contrast to the linear weighting of the input pattern produced by the linear links of a multilayer perceptron (MLP), the functional link acts on an element of a pattern or on the entire pattern itself by generating a set of linearly independent functions, then evaluating these functions with the pattern as the argument. Thus, separability is possible in the enhanced space. Further, the FLANN structure offers less computational complexity compared with that of MLP because of its single-layer structure. A FLANN structure is shown in Fig.2.

Using the actual input u, a nonlinear set of data $\{u^n\}$, $n = 0, 1, \cdots, N-1$ is generated. These are used as input to the FLANN. It is assumed that the neuron of the FLANN does not contain any nonlinearity. Based on the above and referring to Fig.2 we may write a set of equations describing the neural algorithm as

$$\hat{y_i}(k) = \sum_{j=0}^{n} u_i^j w_j(k), \quad (2)$$

$$e_i(k) = y_i(k) - \hat{y_i}(k). \quad (3)$$

The weight updated equation for $n = 0, 1, 2, \cdots, N-1$ is given by

$$w_j(k) = w_j(k+1) + \eta e_i(k) u_i^j \quad (4)$$

$$J = \sum_{i=1}^{m} e_i^2, \quad (5)$$

where $y_i(k), \hat{y}_i(k), e_(k), w_j(k)$ represent the desired output, estimated output, error, and the interconnection weights of the FLANN. η denotes the learning constant, which gives the stability and the rate of convergence. m denotes the sample numbers.

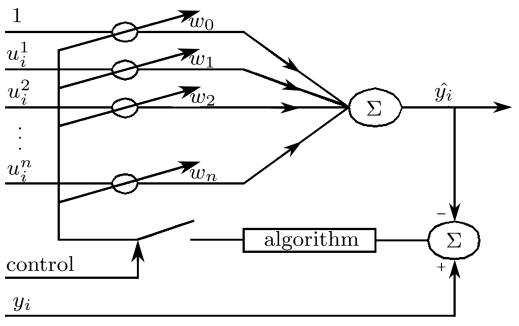


Fig.2. Functional link neural network.

4. GA

The GA combines Darwinian survival of the fittest and the crossover operation and accelerates the optimizing speed and capability. It starts with the initial population by randomly choosing, and each answer is expressed as a string. These candidates go along for better answer by the combination of strings. The general GA is composed of reproduction, crossover and mutation, which simulate propagating, mating and gene mutation of natural selecting and inheritance course. The steps of GA are as follows:[21−23]

Step 1 Define an objective function.

Step 2 Initialize population.

Step 3 Calculate the values of evaluating function of each chromosome. These values are then used in assigning probabilities for each of the points in the population.

Step 4 Randomly choose the points by the probability of selection equal to its assigned probability value to generate a new population.

Step 5 Randomly pair the points from the new population for the crossover operation and mutation operation to generate offspring.

Step 6 Repeat the steps 3, 4 and 5 until the chromosome satisfies the given probabilities.

5. Optimizing ANN by GA

There are three steps in the course of optimizing the weights of FLANN by GA. First, define the structure of the FLANN; second, define the encoding of the interconnection weights; third, optimize the interconnection weights of the FLANN by GA. Structure of the neural networks is depicted in Fig.2. The input of FLANN, u, represents δ (displacement). The output y represents f (frequency).

The course of FLANN, which is based on GA, is learning, applying, then learning. First, define the interconnection weights of the network, after then optimize the interconnection weights by GA until the result of the output meets the demand of the evaluating function. The steps of GA used in training FLANN are as follows:[24,25]

Step 1 Define the weights encoding project, then initialize the points.

Step 2 Define the structure of the network by the given input and output specimens.

Step 3 Calculate the evaluating function in the light of some criteria.

Step 4 Generate new point by crossover operation and mutation operation.

Step 5 Repeat step 3 until the optimized weights satisfies the evaluating function.

6. Experimental

The characteristics of an eddy current sensor may be mathematically represented with sufficient accuracy by the first five terms of the power series as

$$f(\delta) = w_0 + w_1\delta + w_2\delta^2 + w_3\delta^3 + w_4\delta^4, \qquad (6)$$

where w represent the estimated values of the coefficients. To validate our assumption of using the first five terms of the power series, a simulation study is carried out by taking data from Table 1.

Table 1. Input and output data of sensor.

δ/mm	f/Hz	δ/mm	f/Hz	δ/mm	f/Hz
0.00000	382014	4.1666	389096	8.3333	392951
0.4167	382079	4.5833	389587	8.7500	393151
0.8333	383750	5.0000	389986	9.1666	393308
1.2500	384594	5.4167	390467	9.5833	393410
1.6667	3835386	5.8333	390855	10.0000	393501
2.0833	386136	6.2500	391305	10.4167	393592
2.5000	386812	6.6666	391734	10.8333	393694
2.9166	387479	7.0833	392097	11.2500	393782
3.3333	388057	7.5000	392387	11.6667	393861
3.7500	388650	7.9166	392655	12.0833	393957

The parameter setting of the GA used in the simulations are tabulated in Table 2.

Table 2. Parameter setting of the GA.

chromosome representation	16-bit per variable (binary string)
population size	50
fitness assignment	ranking
selection	roulette wheel selection
crossover	multi-point crossover
crossover rate	0.5
mutation	bit mutation
mutation rate	0.001

Eddy current sensor mathematical model is given by

$$f(\delta) = 382086.8 + 2119.34\delta - 104.125\delta^2 + 0.0642\delta^3 - 0.06094\delta^4. \tag{7}$$

The measurement error is given by Table 3.

Table 3. The measurement error.

δ/mm	a/%	b/%	δ/mm	a/%	b/%
0.00000	−0.051	−0.0191	6.2500	0.016	−0.0176
0.4167	−0.038	−0.0117	6.6666	0.004	0.0017
0.8333	−0.027	−0.0079	7.0833	0.014	0.0118
1.2500	−0.028	0.0053	7.5000	0.013	0.0108
1.6667	−0.029	0.0144	7.9166	0.014	0.0114
2.0833	−0.030	0.0218	8.3333	−0.029	0.0262
2.5000	−0.023	0.0192	8.7500	−0.026	0.0234
2.9166	−0.025	0.0234	9.1666	−0.020	0.0162
3.3333	−0.013	0.0136	9.5833	−0.008	0.0013
3.7500	−0.016	0.0166	10.0000	0.000	−0.0102
4.1666	0.010	−0.0094	10.4167	0.001	−0.0160
4.5833	0.015	−0.0152	10.8333	−0.009	−0.0135
5.0000	0.035	−0.0360	11.2500	−0.023	−0.0093
5.4167	0.026	−0.0275	11.6667	−0.043	−0.0025
5.8333	0.033	−0.0345	12.0833	−0.075	−0.0132

7. Results and discussion

This paper discusses application of GA and FLANN in the numeral eddy current sensor modelling. From the experimental results, we learn that the maximum nonlinearity error can be reduced to 0.037% by using GNN. However, the maximum nonlinearity error is 0.075% using LSM.[1] So the model has the character of high precision and strong robustness. At the same time, this method can simultaneously search into many directions, thus greatly increases the probability of finding a global optimum. The new modelling method has a potential future in the field of measurement and control.

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