Sensors & Transducers, Vol. 176, Issue 8, August 2014, pp. 38-42

Sensors & Transducers

http://www.sensorsportal.com

Immune Algorithm Complex Method for Transducer Calibration

*** YU Jiangming, ZHANG Lin, WANG Wenfeng, WANG Jun, SUN Anquan, ZHANG Jiali and LIU Tao**

Air and Missile Defense College, AFEU, Xi'an, 710051, China

* Tel.:+86029-84789203, fax: +86029-84789203

* E-mail: wwf98161201@163.com

Received: 17 May 2014 /Accepted: 31 July 2014 /Published: 31 August 2014

Abstract: As a key link in engineering test tasks, the transducer calibration has significant influence on accuracy and reliability of test results. Because of unknown and complex nonlinear characteristics, conventional method can't achieve satisfactory accuracy. An Immune algorithm complex modeling approach is proposed, and the simulated studies on the calibration of third multiple output transducers is made respectively by use of the developed complex modeling. The simulated and experimental results show that the Immune algorithm complex modeling approach can improve significantly calibration precision comparison with traditional calibration methods. *Copyright © 2014 IFSA Publishing, S. L.*

Keywords: Transducer, Complex calibration, Least square method, Immune algorithm.

1. Introduction

Sensor is a component or a device can be able to feel what is predetermined to be measured and convert it into output signal in accordance with certain rules. Although it is usually the output signal and the measured physical are designed of a linear relationship, but in actual measurement error of the measurement system are often affected by the external environment interference, sensor aging and install a number of uncertainties affecting the properties. When the sensor is a multi-input and multi-output, sometimes there is a nonlinear input-output coupling between the dimensions with them so that the sensor output signals will actual show non-linear relationship with the measured physical quantity. To do this, an effective sensor calibration methods need to be developed.

Different scholars have studied sensor calibration, and have achieved some results. X. U. Fengxia [1] with a total least squares identification such as gyro accelerometer error, but the method exist contradiction between precision and storage space, the sensor can't describe nonlinear factors and multiple sets of data to calculate the cumulative error and cause errors exist, the impact of the accuracy of the calibration results; Bahadorimehr A. R. [2], etc. apply the neural network algorithm is to the sensor calibration, but the method need large network, long learning curve, and severe dependence of sample data, poor in promotion of generalization; Zhang Chun [3] used genetic algorithm in accelerometer sensor for auto calibration system, but the convergence speed in this method is slow, easy to fall into local optimum.

Artificial Immune System (Artificial Immune System, AIS) is an intelligent algorithm inspired by the human immune system, its properties are mainly six [4]: distributed, self-organizing, lightweight, multi-level, diversity, time use disposable. Compared with neural network algorithm, immune algorithm can learn new knowledge and recall previously learned information, ensuring rapid convergence to global optimal solution; compared to the genetic algorithm, immune algorithm based on affinity and concentration integrated Antibodies reproductive strategy role, maintaining the diversity of the solutions.

This article will introduce artificial immune algorithm to the process of calibrating sensor, while combine the artificial immune algorithm with traditional methods and give composite calibration method based on artificial immune algorithm.

2. Artificial Immune Algorithm

2.1. A Summary of Artificial Immune Algorithm

Artificial immune algorithm consider antigens and antibodies, respectively, as corresponding objective function optimization problem of feasible solution, and the affinity between them is considered a match extent feasible solution with objective function [5]. Ensure the diversity of feasible solutions through affinity between antibodies; expected to promote antibody and genetic variation in optimum antibody by anticipant survival rate; preservation feasible solution similar to the preferential inhibition continues to produce a feasible solution to accelerate the search for a global optimal solution by the memory of a cell unit and again when a similar problem occurs even faster to find the optimum solution optimal solution.

Development of artificial immune system focused on clone selection, negative selection and immune network theory [6]. Among them, the clone selection theory is thinking: only those able to recognize a specific antigen reproduce cells, and the memory cells remain in the body to provide fast secondary response; negative selection idea is: while randomly generated detector delete those can be detected by the detector body to ensure stay detectors have the ability to detect any non-antilogous; thought immune network model are: the immune system by simulating the mutual stimulation and coordination between the antibody and achieve dynamic update of the network.

2.2. Steps of Artificial Immune Algorithm

The basic steps of artificial immune algorithm include: antigen identification, the initialization of the antibody, calculation affinity, using selection, crossover and mutation operators to generate new antibodies and updating the antibody group, the basic process is shown in Fig. 1.

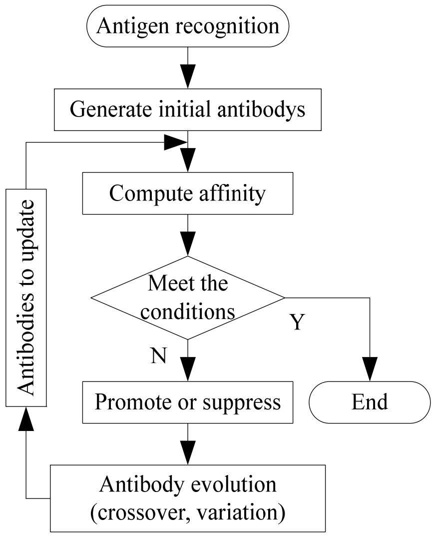

Fig. 1. Basic flow chart of artificial immune algorithm.

2.2.1. Generating Initial Antibody Group

It randomly generated a certain number of antibodies in the solution space, and use real number encoding.

2.2.2. Affinity

Assuming $AB = \{Ab_i \mid i = 1, 2, \cdots, n\}$, is a set of antibodies; $AG = \{Ag_i \mid i = 1, 2, \cdots, n\}$ is a set of antigen. Then the affinity a_{ij} of antibody Ab_i to the antigen Ag_j can be expressed in the formula of the following form:

$$a_{ij} = 1 - \frac{\| Ab_i - Ag_j \|}{\max\limits_{\substack{1<i\le n \\ 1<j\le m}} \| Ab_i - Ag_j \|}, \quad i = 1,2,\cdots,n \quad j = 1,2,\cdots,m \tag{1}$$

where $\| Ab_i - Ag_j \|$ is the norm of two vectors Ab_i and Ag_j in space and the norm, the smaller the distance between them, the higher of their affinity [7].

The calculation formula of the affinity of antibody Ab_i and antibody Ab_j can be expressed in the following form:

$$s_{ij} = 1 - \frac{\| Ab_i - Ab_j \|}{\max\limits_{\substack{1<i\le n \\ 1<j\le n}} \| Ab_i - Ab_j \|} \quad i = 1,2,\cdots,n \quad j = 1,2,\cdots,n \tag{2}$$

We can be seen from the above equation: the more similar antibodies are, the greater the affinity and the inhibition of antibodies will be.

2.2.3. Cloning and Mutation

The number of monoclonal antibodies N_c is determined by the degree of affinity, which is expressed as:

$$N_c = \sum_{i=1}^{n} round(N - norma \| Ag_i - Ab_j \|)N, \tag{3}$$

where N is the number of antibodies; $round(\cdot)$ is the function of selecting the nearest integer; $round(\cdot)$ is the normalized function.

The probability of antibodies mutation can be expressed as the following formula:

$$Ab^*_i = Ab_i - \alpha(Ab_i - Ag_j), \tag{4}$$

where $\alpha = 1 - e^{\|Ab_i - Ag_j\|}$ is the antibody mutation rate.

3. Complex Modeling Methods of Artificial Immune

While there is error in traditional parameter fitting method when establishing the knowledge-based model, the model parameters describes the main characteristics of the sensor system. The nonlinear parts of system can be characterized by the artificial immune algorithm. Since the nonlinear characteristic characterized by the artificial immune is weaker and partial with respect to the general feature of system, so it can effectively reduce the workload of the network model and improve the accuracy of modeling. Meanwhile, the complex model of artificial immune contains knowledge base model, so it is more transparent than artificial immune pure black box model, and you can usually get better generalization ability. The complex model of artificial immune can be reflected by equation (5)

$$f(x) = f_1(x) + f_2(x), \tag{5}$$

where $f(x)$ means the measured m dimension physical quantities, $f(x) \in R^m$; x means n dimension output signal of sensor, $x \in R^n$; $f_1(x)$ is the knowledge-based model, which is based on the characteristics of the sensor and the variation of measurement data by assuming an appropriate form of the model structure, and by obtained data fitting. It is the main characteristic of function relationship between the measured physical data and the sensor output signal; $f_2(x)$ is artificial immune model, it is the error between knowledge-based model and the actual model, which is weak, partial, in complex and unknown form and difficult to parametric modeling.

Thus, knowledge-based model and the artificial immune model will form a composite artificial immune model. It can describe the actual variation of the measured physical data and sensor output signals, the modeling process is shown in Fig. 2 [8].

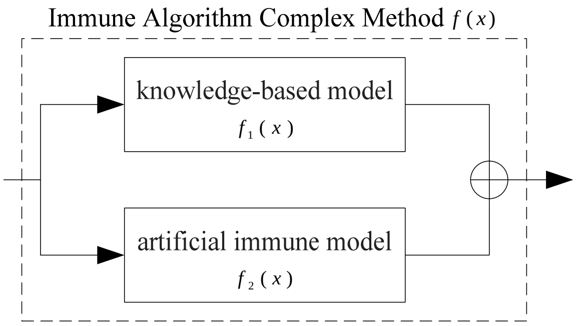

Fig. 2. Immune Algorithm Complex Method.

4. Sensor Calibration Simulation

The structure of the three-dimensional micro force sensor is shown schematically in Fig. 3, the semi-square cantilever structure is connected by silicon, and the sides of each wafer are integrated using a photolithography process LIGA strain gages.

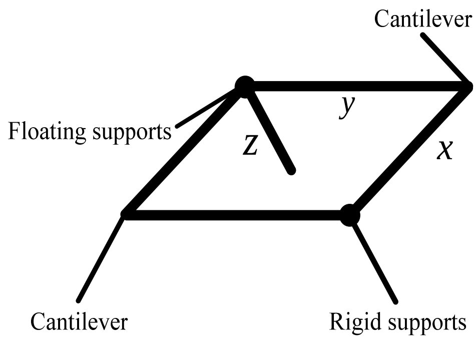

Fig. 3. Schematic three-dimensional micro-force sensor.

The front and back gages connected to the external signal amplification and processing circuitry after forming H-bridge. When both sides of a silicon strain gauge beam generated by squeezing or stretching strain displacement, H-bridge strain resistance will change slightly changed and the output voltage, which can realize the measurement of force in accordance with the calibration of the micro-conversion relationships [9]. Because the force in the direction of the sensor is most important, so the sensor is fixed at the opposite ends of the support using a floating support (a low-friction ball-point contact) to ensure that the measuring z direction of the sensor in the external force, the direction of the silicon beam strain will not output signals because of x, y torsional deformation.

Let the three-dimensional micro force sensor output force vector be $F=[F_x,F_y,F_z]^T$, the output signal vector is $U=[u_1,u_2,u_3]^T$, the three-dimensional relationship between the input and output of the three-dimensional sensor, the sensor output signal is measured between the physical quantity is expressed as

$$F=CU+\varepsilon(U), \tag{6}$$

where $\varepsilon(U)$ means that the nonlinear coupling term between the dimensional output, C is the calibration coefficient matrix.

According to the calibration principle, load F_x, F_y and F_z in accordance with equally spaced step (5 g) into 50 g, then uninstall, measure and record the actual load value and three dimensional micro-force sensor output voltage value [10] simultaneously in each load step. It gets 30 sets of data in total. Then the linear portion of the sensor input and output (i.e., the knowledge base model part) can be expressed as

$$F_1=\begin{bmatrix}F_{x1}\\F_{y1}\\F_{z1}\end{bmatrix}=CU=\begin{bmatrix}c_{11}&c_{12}&c_{13}\\c_{21}&c_{22}&c_{23}\\c_{31}&c_{32}&c_{33}\end{bmatrix}\begin{bmatrix}u_1\\u_2\\u_3\end{bmatrix} \tag{7}$$

Based on obtained calibration data, fit the calibration coefficient matrix C in formula (7) using the least squares method, there is

$$C=\begin{bmatrix}-8.33&20.48&-6.04\\-25.67&35.75&-45.91\\9.75&-8.82&8.16\end{bmatrix} \tag{8}$$

Fit the coefficient matrix C obtained by the method of least squares into the formula (7). Fig. 4 the curve of error between the least square method and actual load, it can be seen from Fig. 4 that there is visible warp between F_1 in the formula (7) and the measured results obtained in significant deviation of the force, i.e. $F\neq F_1$, indicating the presence of the nonlinear coupling of the sensor error.

The $\varepsilon(U)$ part of the knowledge base for the error model and the actual sensor input force vector (i.e. $F-CU$ part), artificial immune algorithm to segment 30 sets of sample data is loaded as artificial immune training set, the output voltage U is the input signal of the training set, inter-dimensional nonlinear coupling error is the output part of the training set, the size of the antibody population is 100, the maximum number of iterations is 1000.

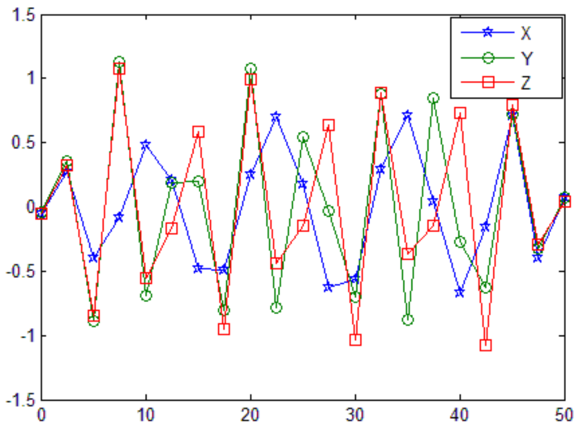

Fig. 4. Errors of least-squares method and the actual load.

Compare the actual measured value with the results of the immune complex-type artificial calibration model, test the accuracy of the results of calibration, the error to the standard load is shown in Fig. 5. Table 1 shows the variances of calibration results obtained by different methods, it can be seen that, the artificial immune complex calibration method compared to the least squares method has a higher calibration accuracy, because the human immune composite calibration method can dimensional nonlinear coupling between the sensor error compensation.

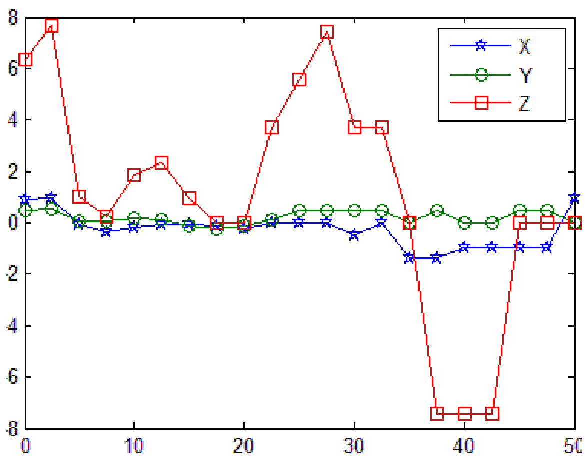

Fig. 5. Errors of artificial immune complex calibration.

Table 1. Compares the variance of the different calibration results.

Output	**Least Square Method**	**Immune Algorithm Complex Method**
F_X	3.9919	0.0104
F_Y	9.2839	0.0216
F_Z	9.6074	0.0405

5. Conclusions

The relationship between measured physical quantity and the sensor output signals often contains complex and unknown nonlinear characteristics, which affected the accuracy and reliability of test results. This paper offers the calibration methods and procedures of artificial immune complex-type of sensor, and simulates the calibration of the three-dimensional micro-force sensor. Simulation results show that the calibration method of the artificial immune complex-type sensor can effectively compensate for the complex nonlinear characteristics of sensor and significantly improve the accuracy of the calibration of the sensor.

References

[1]. Xu Fengxia, Xia Gang, Su Baoku, Zhao Xuezeng, Study on identifying error model of PIGA by total least squares method, *Transducer and Microsystem Technologies*, 26, 9, 2007, pp. 20-22.

[2]. Bahadorimehr A. R., Hamidon M., Hezarjaribi Y. A., Novel Neural Network Model of Capacitive MEMS Accelerometers, *Semiconductor Electronics*, 11, 2008, pp. 174-178.

[3]. Zhang Chun, The Research and Realization of Accelerometer Automatic Calibration System, *Hunan University*, Changsha, 5, 2012.

[4]. Cheng Xiang, Feng Jie, Wang Yuling, Application of immune algorithm in intrusion detection, *Science & Technology Information*, 1, 11, 2008, pp. 68-69.

[5]. Shi Jiangang, Chen Gang, Gao Zhe, Summary of immune algorithm, *Software Guide*, 7, 11, 2008, pp. 68-69.

[6]. Deng Zelin, Tan Guanzheng, Fan Bishuang, Fu Ming, Research progress on immune classification, *Computer Engineering and Applications*, 47, 16, 2011, pp. 8-11.

[7]. Xiong Xiaobo, Gui Guoqing, Zheng Mingxin, Xu Jiancong, Ma Shuzhi, Research on deformation prediction for deep foundation pit based on the artificial immune RBF neural network, *Rock and Soil Mechanics*, 28, 11, 2008, pp. 598-602.

[8]. Xie Shilin, Chen Shenglai, Zhang Xinong, Zhu Changchun, Neural Network Hybrid Modeling Method For Transducer Calibration, *Journal of Mechanical Engineering*, 46, 22, 2010, pp. 6-15.

[9]. Chen Haichu, Zhang Ruihua, Research on 3 Dimentional Micro Force Sensor for Micro Assembly, *Piezoelectectrics & Acoustooptics*, 29, 3, 2007, pp. 280-282.

[10]. Ma Yingkun, Zhang Xinong, Support vector machine complex method for multi-dimensional sensor calibration, *Journal of Aerospace Power*, 26, 6, 2011, pp. 1274-1281.