Support vector machine regression modeling of nonlinear pressure sensor

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Abstract

In the process of the use of the sensor, there are various environmental factors, which lead to the error of measurement. A nonlinear correction model of the sensor based on support vector machine is proposed for the nonlinear characteristics of the influence factors and the output of the sensor. Through the establishment of training set and test set which can compare the study accuracy with correction accuracy to selections the optimal kernel function, nuclear parameters, control error and penalty factor for the support vector machine (SVM). Taking the pressure sensor as an example, the relative error of the current model compare with the BP neural network algorithm is reduced from 2.78% to 0.77%. The model significantly improves the accuracy of the sensor calibration, and has a very good application effect..

Keywords

Sensor; support vector machine; kernel function; control error; penalty factor.

1. Introduction

Sensor as a key component in the data measurement system, whose accuracy affects the quality of the measurement of the system[1].However, due to a number of environmental factors, there is a nonlinear problem in input and output of the sensor, so correcting the sensor is of great significance. Over the past often used hardware compensation methods, such as hardware Compensation Act by Zhou Shenghai[2], but debug the hardware compensation is difficult and the circuit is complexity so that is not easy to achieve full compensation. With the widespread use of computer technology the software correction method has been applied, neural networks have been proposed by many scholars, as BP neural network method proposed by Tian Feng[3] , Generalized Regression Neural Network proposed by Duan Songjie[4], RBF neural network proposed by Yu Along[5], but the neural network algorithm is difficult to simultaneously achieve empirical risk and expected risk minimization, and thus cannot achieve good classification performance[6].Therefore, this article based on the nonlinear characteristics of the sensor output, put forward a model of non-linear calibration sensor based on support vector machine [7].

This model uses the structural risk minimization principle, along with good accuracy and generalization ability. Through the correction accuracy of the analysis, preferably the optimal kernel function, kernel parameters, control error and penalty factor. Establish test set to validate the model's achieve results in the actual application process, and compared with BP neural network , reflecting the advantage of support vector machine method in terms of non-linear calibration sensor.

2. Model of SVM

2.1 Modeling

Based on the classification and learning theory, support vector machine is commonly used in pattern recognition, prediction of probability density function approximation and many other fields, nonlinear correction of sensor belongs the field on function approximation of SVM, support vector regression (SVR, Support Vector Regression) is a regression algorithm of support vector machine function approximation and the form of regression function is [8, 9]:

$$f(\mathrm{x}) = \sum_{s.v.} (\mathrm{a_i} - \mathrm{a_i}^*)\,\mathrm{K}(\mathrm{x}, \mathrm{x_i}) + \mathrm{b} \tag{1}$$

In the formula, $s.v.$ is the support vector (Support Vector); $s.v. = \mathrm{s}$ (s is the number of support vectors); a_i^*, a_i, b are undetermined coefficients of the model; $K(\mathrm{x}, \mathrm{x_i})$ is the kernel function of the support vector machine; x is the to be predictors vector; x_i is the sample factor vector of support vectors. $i = 1, 2, \cdots, s$

2.2 Factors and calibration indicators of sensor

Most of the sensors meet the following relationship:

$$y = f(\mathrm{x}, \mathrm{t_1}, \mathrm{t_2}, ..., \mathrm{t_n}) \tag{2}$$

In the formula: $t_1, t_2, ..., t_n$ are the n impact factors, x is the input of sensor, y is the output of sensor. $t_1, t_2, ..., t_n$ and y have a nonlinear relationship. In the case of pressure sensor, the output of the sensor y is not only related to pressure being measured x, but also the working temperature T and the power fluctuation. Thus establishing the support vector machine correction model put the measure pressure as output parameter, and put the sensor output voltage, operating temperature, power fluctuations as the input parameters of correction model. Establishing calibration process is shown in figure 1.

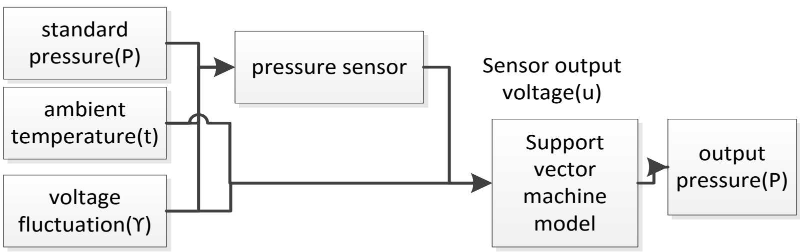

Figure 1 flow chart of support vector machine correction

2.3 The establishment of the training set and test set

In order to check and adjust model, using standard pressure effect on the pressure sensor, and placed in the incubator. Temperature from $20 \sim 70^oC$, every10°C do a set of tests, and each group of 6($0 \sim 5\times10^4 Pa$) do different pressure test. 6 sets of data can be divided into two parts: a training set (1 ~ 3 sets of data) and test set (4 ~ 6 sets of data). The training set established is to obtain nonlinear relationships and the test set established is to test the accuracy of the model and the generalization ability.

Training set and testing set is made up of two parts, namely the input parameters and output parameters. The sensor output voltage, ambient temperature and voltage fluctuation as input parameters of the model, and output pressure as output parameters of the model, and specific data are shown in table 1. T is the environment temperature, u is the sensor output voltage, γ is the power supply fluctuation, P is the output pressure.

Table1 training set of correction model and testing set

sample classification	serial number	input parameter			output parameter
		$T/^oC$	u/mV	$\gamma/\%$	$P/10^4Pa$
training sample	1	20	0	3	0
			⋮		
			100.11	3	5
	2	40	0	-1	0
			⋮		
			84.22	-1	5
	3	60	0	-2.5	0
			⋮		
			79.83	-2.5	5
testing sample	4	30	0	1	0
			⋮		
			91.24	1	5
	5	50	0	-1.6	0
			⋮		
			80.72	-1.6	5
	6	70	0	-3	0
			⋮		
			78.37	-3	5

Because of the characteristic parameters of the physical significance and dimension is different. If directly use the original data, which will lead to the result error increase, and the original sample data is needed to preliminary deal. The data will be translated into values [0, 1], which adopt linear normalization method. The linear normalized transformation:

$$\overline{x}_i = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \tag{3}$$

In the formula, x_i、$\overline{x}_i$、$x_{\min}$ and $x_{\max}$ respectively represent groups of initial sample data of the sample information, after the normalization of data, the minimum and maximum initial sample data.

2.4 The parameters discussed of training model and the calibration.

How to achieve the desired model by selecting parameters, this problem does not exist theoretically effective way. In the practical process of parameter selection process is gradually change the parameter values, through different training set is adopted to establish the support vector machine model of the correction, and use set of correction to correct and calculate testing set .By the average relative error of the result calculated, one of the most optimal value chose as model parameters.

In order to measure the effect of training and prediction, average relative error was used as evaluation index [10]

$$e = \frac{1}{n}\sum_{i=1}^{n}\left|y_i' - y_i\right| \times \frac{100}{y_i} \tag{4}$$

In the formula, y_i' represents the ith a sample support vector machine calculated value; y_i represents the ith a sample of the sample values. In assessing the training accuracy and the correction precision, n represents the number of training set and test set number respectively.

Apply the support vector machine training algorithm to study and train after the normalization of the three groups of training samples in table 1 (the number 1 ~ 3).Then the three groups of test samples in table 1 (i.e., serial number 4 ~ 6)has been corrected with the model after training, adjusting the types of kernel function, the parameters of kernel function, the size of control error and penalty factor constantly, the entire modeling process finished until the relative error of the results and the actual value reached to the minimum.

As shown in table 2, taking the polynomial kernel function, Gauss radial basis kernel function and Sigmod kernel function into the training set and testing set and then doing contrastive analysis of them.

Table 2 comparison and analysis for kernel function of SVM

Kernel function type	Learning accuracy（e/%）	The correction precision（e/%）
Polynomial kernel function	1.53	1.88
Gauss radial basis kernel function	0.69	0.77
Sigmod kernel function	0.97	1.31

Selecting the Gauss RBF kernel function according to the result of comparative analysis.

The specific form of the Gauss radial basis kernel function is [11]:

$$K(x, x_i) = \exp(-\frac{\|x - x_i\|^2}{\gamma^2}) \tag{5}$$

In the formula, γ is the width parameters of the Gauss radial basis kernel function, the generalization ability of the kernel function is weakened with the increase of parameters.

Taking the SVM model of pressure sensor nonlinear correction as examples, discussing the selection process and method of the model parameters. It has been found that correct selection of three parameters plays a crucial role on the output pressure of the model by adjusting the parameters in the calculation process of correction:①Gauss radial basis kernel function parameter γ; ②The control error ε; ③Penalty factor C(positive constant,controlling the values of a_i, a_i^* in formula(1), $a_i, a_i^* \in [0, C]$).

Figure 2 describes the change of learning precision and prediction precision when fixing two parameters of γ ,C, ε ,selecting the rest of the parameters.

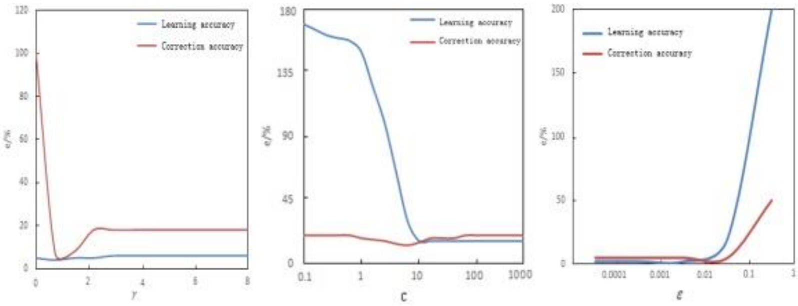

Figure 2.The change of the learning precision and prediction precision when selecting the parameters

The learning precision and prediction precision should be minimized simultaneously when doing the parameter optimization, for the observation in figure 2,the learning precision and calibration accuracy reach to the minimum at the same time when the γ=0.87.Therefore, selecting γ=0.87 as the parameter of Gauss radial basis kernel function in the correction model. Similarly, selecting the penalty factor $C=10$; the control error $\varepsilon=0.01$.

2.5 Application effect

Table 3 lists the the relative error when using the model to calculate testing set, formula (6) obtains the calculation method of the relative error of the output pressure. Results show that the average relative error of the test sample calculated value is less than 1%; the accuracy can meet engineering needs.

$$\sigma=\frac{|X-X_i|}{X}\times 100\% \tag{6}$$

In the formula, σ is the relative error, X is the total number of current sample points, X_i is the calculating value.

Table 3 the test sample results calculated table

sample number	T/℃	γ/%	calibration value	calculated value	relative error/%
4	30	1	1	1．02	2
			⋮	⋮	⋮
			5	4.97	0.6
5	50	-1.6	1	1	0
			⋮	⋮	⋮
			5	4.98	0.5
6	70	-3	1	0.99	1
			⋮	⋮	⋮
			5	5.03	0.6
Average					0.77

Figure 3 to figure 5 is the calculated value line chart of the sample 4 ~ 6 which use the SVM to correct the pressure sensor. We can find that calculated value showed a good linear characteristic, the output pressure and the calibration pressure error is very small. It can be seen that the effect of the sensor nonlinear correction model based on SVM is good, reaching the accurate calibration purposes for sensor nonlinear environmental factors. Its accuracy and generalization ability can meet the practical needs.

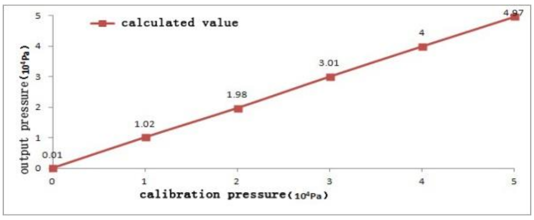

Figure 3.Sample 4 sensor output pressure contrast

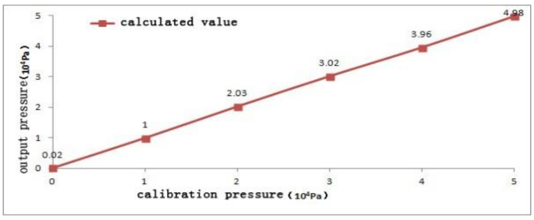

Figure 4.Sample 5 sensor output pressure contrast

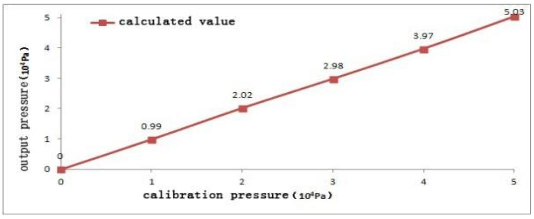

Figure 5. Sample 6 sensor output pressure contrast

3. The contrastive analysis of SVM and the BP neural network

In order to study the superiority that using support vector machine (SVM) model compared with the BP neural network, taking the three groups of data respectively as the input parameters of the support vector machine (SVM) method and BP neural network. The BP neural network input layer consists of three nodes, and the output layer adopts 1 node, at the same time, there are 7 hidden layer neurons node. The transfer function of the BP neural network hidden layer is the tansig function, and the transfer function of the output layer is linear function. Taking 1000 times repeated training through the training set, controlling the permissible error within 0.001.Comparing the relative error of the modification value after the BP neural network training with the modification value of the SVM, the comparison results as shown in figure 6 to figure 8.

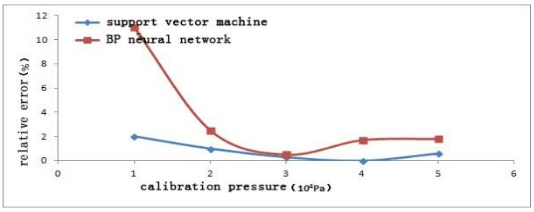

Figure 6.In contrast with different method of corrections' relative error of sample 4

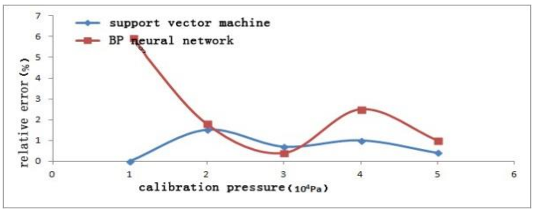

Figure 7.In contrast with different method of corrections' relative error of sample 5

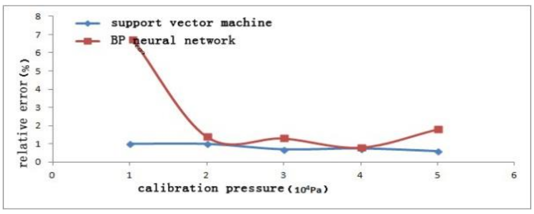

Figure 8.In contrast with different method of corrections' relative error of sample 6

Table 4 shows the calculated value and the relative error data.

It can be seen from the comparison results, the support vector machine (SVM) method is superior to the BP neural network. When the sensor data be nonlinear corrected. It attributed to the BP neural network is difficult to realize high precision and good generalization ability concurrently. The generalization ability declines while the accuracy rally, and vice versa. The support vector machine (SVM) method is inferred by VC dimension theory and structure risk minimum principle; and it could achieve the optimal balance of accuracy and generalization ability and make it have a good performance at the sensor nonlinear correction.

Table 4. In contrast with different method of corrections' relative error calculated value

sample number	calibration value	support vector machine (SVM) method		BP neural network method	
		calculated value	fractional error/%	calculated value	fractional error/%
4	1	1．02	2	0.89	11
	:				
	5	4.97	0.6	5.09	1.8
5	1	1	0	1.06	6
	:				
	5	4.98	0.5	4.95	1
6	1	0.99	1	1.07	7
	:				
	5	5.03	0.6	4.91	1.8
Average			0.77		2.78

4. Conclusions

Sensor nonlinear correction model is established based on support vector machine (SVM). Contrasting and analyzing study accuracy and calibration accuracy through the test; choosing the Gauss radial basis kernel function to summarized three parameters which can control the results of the model, Gauss radial basis kernel function parameter σ, error control ε and penalty factor C, selecting the parameter of Gauss radial basis kernel function γ=0.87 ,penalty factor C=10 ;The control error ε=0.01 from training set and test set

Using the testing set to examine support vector machine (SVM) calibration accuracy, and the test results show that the relative error less than 1%, the output result and calibration value of support vector machine (SVM) which emerge good linear features and the correction effect is obvious.

By comparing and analyzing the BP neural network and support vector machine (SVM) method which found that the support vector machine (SVM) method is superior to BP neural network, the relative error reduced from 2.78% to 0.77% which to show the superiority in the aspect of sensor software calibration, and it has advantages of good accuracy and generalization ability.

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