Chapter 71
Application of LS-SVM by GA for Reducing Cross-Sensitivity of Sensors

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Abstract Least square support vector machine (LS-SVM) is widely used in the regression analysis, but the prediction accuracy greatly depends on the parameters selection. In this paper, Simple Genetic Algorithm is applied to optimize the LS-SVM parameters; correspondingly, the prediction accuracy is improved. Sensors are always sensitive to several parameters, and this phenomenon is called cross-sensitivity which restricts the application of sensors in engineering. In order to reduce cross-sensitivity, the model of multi-sensor system measurement is established in this paper. For solving the nonlinear problems in the model, LS-SVM is used to establish the inverse model. It proves that the method has a high forecasting precision. It is beneficial to the application of sensors.

Keywords Multi-sensorsystem • Nonlinear system • Simple genetic algorithm • LS-SVM

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Introduction

Interest has been growing in the use of multiple sensors to increase the capabilities of intelligent systems. The issues involved in integrating multiple sensors into the operation of a system are presented in the context of the type of information these sensors can uniquely provide.

Sensors are usually sensitive to several parameters in the testing system. This phenomenon is called cross-sensitivity. For example, with the help of Bragg grating equation we know that the cross-sensitivity of strain and temperature is the key problem of FBG sensors. When using the sensor, it is difficult to distinguish the change of the output caused by the strain or the temperature separately. How to reduce the cross-sensitivity is the hot topic of the application of FBG sensors. It restricts the development of the sensor (Xu et al. 1994).

With the importance of sensors in Automated Testing and Control system, the research for reducing the cross-sensitivity is very popular. The domestic and foreign researchers all make great efforts to suppress the cross-sensitivity of the sensors. For instance, since 1993, the solutions proposed to reduce the cross-sensitivity are based on three kinds of thoughts roughly: first, double wavelength matrix calculation method; Second, double parameters matrix calculation method; Third, strain (temperature) compensation method. But, solving this problem by hardware either makes sensors system more complex and costly or causes high measuring error by material, changes of light source, precision of adding impurities in fiber. On the basis of sufficient study and comparison of a variety of methods for reducing cross-sensitivity of sensors, a data fusion method based on software is proposed for eliminating the affection of non-objection parameters (Luo et al. 1998). This method will no longer rely excessively on sensor's selectivity and it doesn't change the sensor's manufacturing process, but effectively reduces the cross-sensitivity of the sensors. It can weak the affection of non-objection parameters to measurement and enhance the affection of objection parameter to measurement. Finally, it can improve the measurement precision, stability and reliability of sensors (Luo and Key 1989; Suykens et al. 2000, 2002).

In this paper, we concisely review the basic principles of LS-SVM for regression. SVM is a new study method which developed from the statistics theory and structural risk minimization principle. Experimental results indicate that the SVM can solute the problems, such as small samples, nonlinear, high dimension, and local minimum and so on. It has comprehensive applications in pattern recognition, signal processing and function approximation already.

We can see that LS-SVM is formulation of the principles of SVM, which involves quality instead of inequality constraints. Furthermore, LS-SVM uses the least squares loss function instead of thee-insensitive loss function. In this way, the solution follows from a linear KKT system. Therefore it is easier to optimize and the computing time is short. At the same time, the dual problem of LS-SVM corresponds to solve a linear KKT system which is a square system with a global and possibly unique solution if the matrix has full rank.

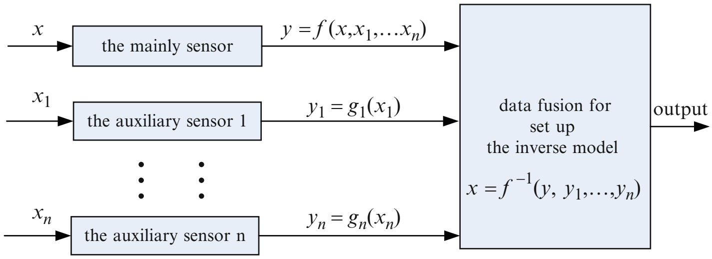

Fig. 71.1 Multi-sensor system measurement model

Therefore, the intelligent sensor system simulation model is set up. Use the method of LS-SVM to set up the inverse model (Suykens 2003) and use Simple Genetic Algorithm to optimize the parameters of LS-SVM.

Multiple Sensors System Simulation Model

Generally, the sensors are influenced by multiple parameters; the expression of input/output of sensors is as follow (Suykens et al. 2001; Hackett and Shah 1990):

$$y = f(x, x_1, \ldots, x_n) \tag{71.1}$$

Where x is an objection parameter; $x_1, \ldots x_n$ are non-objection parameters; y is the output of sensor.

In order to restrain the cross-sensitivity of sensor and improve the static characteristics, an intelligent sensor system model is set up. The model is consisted of the mainly sensor (the sensor which measures the objection parameter) and the auxiliary sensors (the sensors which measure the non-objection parameters. See Fig. 71.1).

Inputs of the model are the outputs of the mainly sensor and the auxiliary sensors. Using the intelligence software for data fusion in PC, set up the inverse model by the output of the mainly sensor and the auxiliary sensors and the mainly sensor's objection parameter.

$$x = f^{-1}(y, y_1, \ldots, y_n) \tag{71.2}$$

Set Up the Inverse Model by Using the Method of LS-SVM

In order to get the outputs which are obtained under the influence of reducing non-objection parameters, in this paper, setting up an inverse model by using the intelligent software. At present the neural network technology is widely applied in data fusion, but the neural network must have been trained by a lot of samle data, only then it can have strong generalization performance, in addition, it is easy to fall into local minima and over fitting (Hall and Llinas 1997; Suykens and Vandewalle 1999).

It has good generalization capacity, and has been the research hotspot in the machine learning field after neural network. Different with neural network, SVM bases on the principle of structural risk minimization, which realized the compromise of given data between approximation accuracy and approximation function complexity. Through choice nesting function subset, and compromised consideration of the experience risk and confidence interval, it chooses the minimum structural risk and then gets the best real risk boundary.

LS-SVM is proposed by Suykens. LS-SVM uses quadratic loss function, which changes quadratic programming problem in SVM into linear equation group resolving. It reduced computing complexity, but still with the high accuracy, and increased the solving speed, and it is more suitable for the cross-sensitivity. But the LS-SVM parameters impact prediction accuracy seriously, therefore, this paper uses genetic algorithm to solve the parameter choice problem of SVM model during forecasting process. Genetic algorithm uses selection, crossover and mutation operation to search the model parameter global optimal solution, with the optimized parameters. LS-SVM increased the forecasting accuracy.

Extensive empirical comparisons show that LS-SVM obtains good performance on various regression problems, but two obvious limitations still exist. First, the training procedure of LS-SVM amounts to solving a set of linear equations. Although the training problem is, in principle, solvable, in practice, it is intractable for a large data set by the classical techniques, Gaussian elimination, because their computational complexity usually scales cubically with the size of training samples. Second, the solution of LS-SVM lacks the sparseness and, hence, the test speed is significantly slower than other learning algorithms such as support vector machine and neural networks.

The algorithm of function approximation based on LS-SVM regression algorithm is described as follows. In a regression problem, we are given a training set of samples $D = \{(x_i, y_i)\}_{i=1}^{l}$. $x_i \in X \subseteq R^n$ is the input vector, and $y_i \in R^m$ is the output data of corresponding goal. The problem of linear regression is that seeking the linear function f is to model data:

$$f(x_i) = \omega^T \varphi(x_i) + b \tag{71.3}$$

Where the input data are projected to a higher dimensional feature space. The nonlinear mapping function $\varphi(\bullet)$ maps the input space to a so-called higher dimension feature space whose dimension can be infinite. The term $\boldsymbol{b}$ is a bias term. ω is a $l \times m$ matrix. The optimization problem can be described as:

$$minJ(\omega, e) = 0.5\omega^T \omega + 0.5\gamma \sum_{i=1}^{l} \sum_{j=1}^{m} e_{ij}^2 \tag{71.4}$$

γ is a positive real constant and should be considered as a tuning parameter in the algorithm. According to optimization function (71.4), it defines Lagrange function as:

$$L(\omega, b, e, \alpha) = J(\omega, e) - \sum_{i=1}^{l}\sum_{j=1}^{m} \alpha_{ij}\{\omega_{ij}^{T}\varphi(x_i) + b_{ij} + e_{ij} - y_{ij}\} \tag{71.5}$$

With Lagrange multipliers α_{ij}. It is well-known from the *Karush-Kuhn-Tucher* optimization theory that the solution can be expressed as a linear system of equations:

$$\begin{pmatrix} 0 & I^T \\ I & \left[\varphi(x_p)^T\varphi(x_i)_{l\times l}^T\right] \end{pmatrix}\begin{pmatrix} b \\ A \end{pmatrix} = \begin{pmatrix} 0_{l\times m} \\ Y \end{pmatrix} \tag{71.6}$$

Where $p, i = 1, 2, \ldots, l$, $A = (\alpha_1, \alpha_2, \ldots, \alpha_m)$, $\alpha_j = (\alpha_{j1}, \alpha_{j2}, \ldots, \alpha_{jl})$, $Y = (y_1, y_2, \ldots, y_m)$, $y_j = (y_{j1}, y_{j2}, \ldots, y_{jl})$, $I = (1, \ldots, 1)$, $i = 1, 2, \ldots, l, j = 1, 2, \ldots, m)$.

$\boldsymbol{A}^*$and $\boldsymbol{b}^*$ are the optimized parameters consequently,

$$y_j(x) = \sum_{i=1}^{l} \alpha_{ij}^{*} K(x, x_i) + b_{ij}^{*} \tag{71.7}$$

$j = 1, 2, \ldots, m)$. According to Mercer's theory, any positive-definite kernel function can be expressed as the inner produce of two vectors in some feature space and, therefore, can be used in LS-SVM. Among all the kernel functions, Gaussian kernel is the most popular choice. We have used a Gaussian kernel for LS-SVM

$$K(X_i, X_j) = \exp\left(-\frac{\|X_i - X_j\|}{\sigma^2}\right) \tag{71.8}$$

The concept of Genetic Algorithms (GA), first formalized by Holland (1975) and extended to functional optimization by De Jong (1975), involves the use of optimization search strategies patterned after the Darwinian notion of natural selection and evolution. During a GA optimization, a set of trial solutions is chosen and "evolves" toward an optimal solution under the "selective pressure" of the object function.

GA optimizers are robust, stochastic search methods modeled on the concepts of natural selection and evolution. GA optimizers efficiently search for and locate global maxima in high dimension, multimodal function domains in a near optimal manner. GA is a direct search method which does not depend on the concrete problem. It can use the existing information to search the data string, which need to improve quality. Similar to the natural evolution, through the effect to the gene in chromosome, genetic algorithm searches the better chromosome to solve problem. Similar to the nature, genetic algorithm knows nothing about solution question. It only needs appraisal to every chromosome produced by algorithm. And it changes the chromosome based on the adaptation value, and makes better adaptability chromosomes have more propagation opportunities than the worse. Simple genetic algorithm (SGA) only uses three simple genetic operators, such as selection operator, cross over operator and mutation operator. Its genetic evolution is simple operation, easy understand, and it also is the rudiment and foundation to other genetic algorithm. Simple genetic algorithm mainly consists of elements, as follows: chromosome coding, individual fitness evaluation, genetic operator (selection operator, crossover operator and mutation operator), and genetic parameter setting and so on. The problem solving process utilized simple genetic algorithm. The main feature of genetic algorithm is that it carries on structural object directly, and it has better ability of global optimization. Genetic algorithm used the probability optimization method, which adjusts search direction adaptively without fixed regulation. It starts form initial population which is randomly generated or specify created. Then according to an operation rule (select, duplicate, crossover, mutation and so on),it uses iterative calculation, according to the individual adaptation value, it retained the improved variety and guides searching process approach to optimal solution.

Used SGA and LS-SVM to reduce cross-sensitivity we establish nonlinear model between input and output. Both γ and σ are optimized in paper through using SGA in the model of LS-SVM. The parameter controls the penalty degree to the sample, which surpassed the error, and the parameter σ is the kernel function parameter. Research showed that the parameters greatly affect the prediction accuracy, so to seek the best combination about γ and σ is the problem about optimization model parameter choice.

Experiment and Analysis

For solving the nonlinear problems in the model, multiple-input multiple-output least square support vector machine is used to establish the inverse model. Using the Simple Genetic Algorithm to optimize the parameters of LS-SVM, finally, it can eliminate the sensors' output influence caused by non-objection parameters.

Therefore, simulation model of the intelligent sensor system is set up. Utilizing the method of least square support vector machine to set up the inverse model and using simple Genetic Algorithm to optimize the parameters of LS-SVM.

The percentages of the left hemisphere resistance and the total value of the two slide rheostats (u_1 and u_2) are inputs of the system. The outputs of the system (y_1 and y_2) are the voltage value of multi meters 1 and 2. We can get 64 groups of simulation data. Among them the serial numbers 1–48 are training set, 49–64 are predicted set. The inputs signals u_1 and u_2 are cross-sensitivity by analyzing the model. For example, regression for u_1 using output data is affected by u_2, and vice versa (Fig. 71.2).

The following tables part of the experimental data through the simulation (see Table 71.1). Firstly, preprocess the input/output data by (71.9).

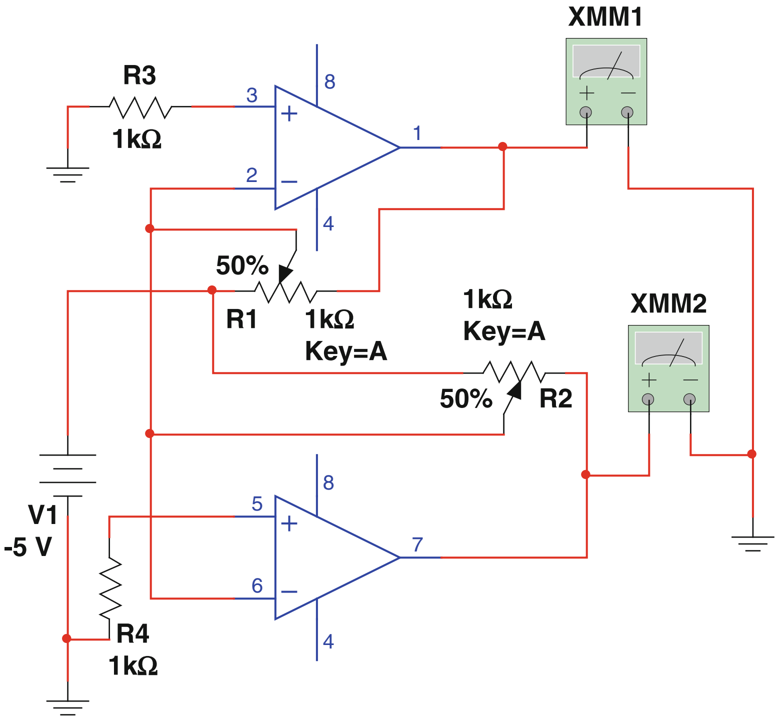

Fig. 71.2 Circuit simulation model of two-input two-outputs

Table 71.1 Simulation data of model for training and predicting

Number	u_1	u_2	y_1	y_2
1	5	15	5.812	3.855
2	5	20	6.739	4.966
…	…	…	…	…
8	5	35	9.22	7.926
9	10	15	3.023	2.016
10	10	20	3.511	2.601
…	…	…	…	…
16	10	35	4.842	4.185
…	…	…	…	…
57	40	15	0.874	0.612
58	40	20	1.016	0.790
…	…	…	…	…
64	40	35	1.426	1.294

$$\bar{x}_i = \frac{x_i - x_{min}}{x_{min} - x_{max}} \tag{71.9}$$

Where x_i is the sample data. x_{max} is the maximum of sample data and x_{min} is the minimum of sample data. $\bar{x}_i$ is the preprocessing data. In order to more close to the

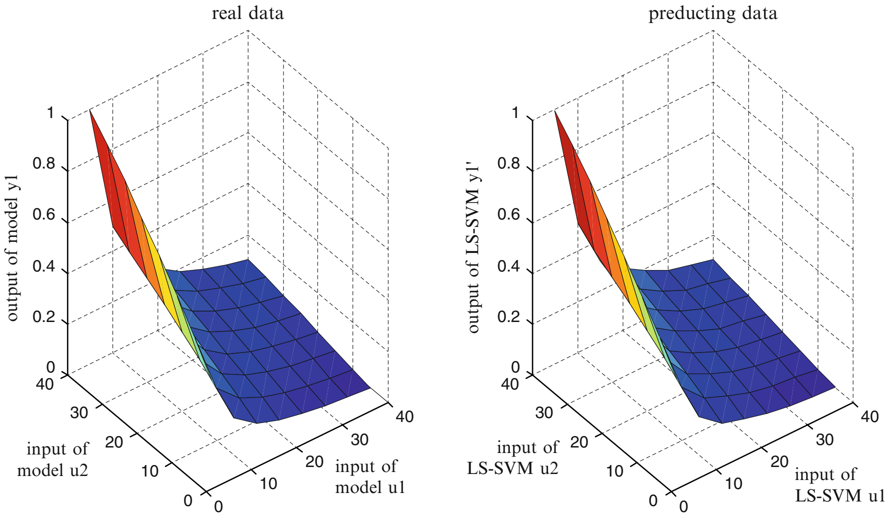

Fig. 71.3 The comparison of the real data and the predicted data for regression

physical truth, superimpose white noise with mean value of 0, standard deviation of 0.03 based on the preprocessing data.

According to the sensors system model, optimize the parameters by Simple Genetic Algorithm. Set the population size for 50, evolution generation for 100, penalty factor for 0.1, calculating fitting value by 15-traverse crosscheck, threshold value of sharing function for 10. From the SGA we can see that after the 50 generation the parameters converging to the global optimal solution probable.

To build the multiple sensors model, the proper parameters γ and σ^2 choosing of LS-SVM regression is very important. In this paper, we take advantage of the Root Mean Square Error (RMSE) minimization in the testing samples as the criterion. If the LS-SVM regression matches this criterion, the parameters are fixed as the sensing parameters. As a result, the parameters of LS-SVM regression are chosen $\sigma^2 = 12467.9, \gamma = 5.170$. The prediction results of LS-SVM estimator for training data and the prediction results of LS-SVM estimator for testing data are shown in Fig. 71.3. Figure 71.4 is the relative error of the predicted data.

$$\mathrm{Error} = (\mathrm{b} - \mathrm{a})/\mathrm{a}^{*}100\,\% \tag{71.10}$$

Where Error is relative error, *a* is a real data, *b* is a predicted data.

This suggests that the method of support vector regression can get very good predictive effect in the case of small sample data (See Fig. 71.3).

From Fig. 71.4 we know that the maximal relative error of predicted data is less than 2%, so the result is satisfactory.

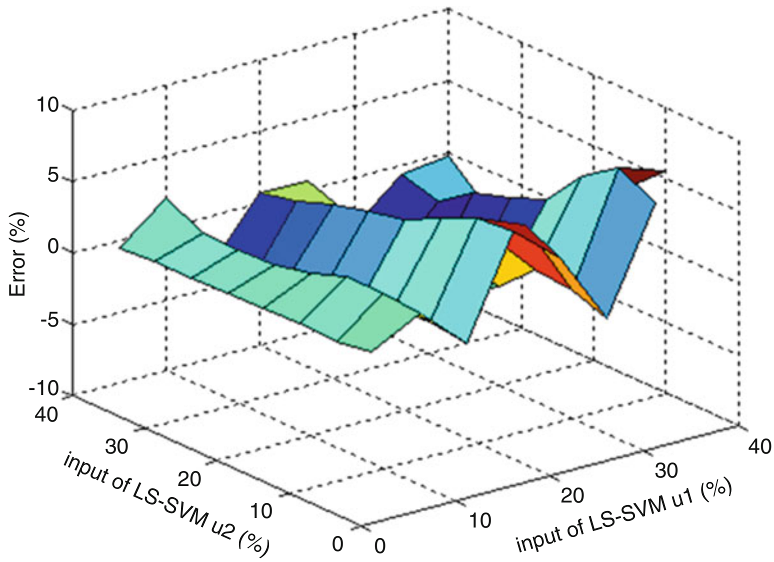

Fig. 71.4 The relative error of the predicting data

Conclusion

Through analyzing the regression of simulation data, LS-SVM is suit for modeling for the data. It also achieves predicted results that are relatively accurate in the case of existing noise. This research uses LS-SVM to reduce the affection of cross-sensitivity to nonlinear multi-sensor signals. The simulation result is satisfactory. It demonstrates that the method has a high forecasting precision. Results show that the method is effective. LS-SVM is prior especially for large scale problem, because of its procedure is high efficiency and its performance is eminent compared with SVM.

Result shows that the cross-sensitivity of sensor is restrained and the stability and precision of the sensor are increased. The proposal is suit for measuring of sensors at high precision. Measurement sensitivity and stability of the whole sensor system have a large enhancement, so the sensor system can get high measurement accuracy under the condition of changing greatly of non-objection parameter. The outputs of the sensor system without cross-sensitivity are more abundant and optimized, and operative modes of sensors are more transparent and open. So that it has great advantages in system maintaining, choosing control strategies and ensuring system reliability.

It improves the prediction accuracy of regression analysis by using genetic algorithm optimize LS-SVM parameters. It proves that the LS-SVM has a high forecasting precision, increasing the security and stability of sensors operation.

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