Research on nonlinear calibration model of sensor based on wavelet support vector machine

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Abstract

In view of the sensor due to factors such as aging, drift, temperature change caused by the sensor input and output of nonlinear problems, the support vector machine (SVM) based on wavelet kernel data correction, the nonlinear data correction method and constructed based on wavelet support vector machine (SVM) model for the nonlinear data correction.Through the Matlab simulation results show that the calibration results based on the wavelet support vector machine (SVM) is better than RBF and polynomial kernel correction, provides a very good method for sensor nonlinear correction,which has extensive promotion of significance.

Keywords

Sensors, wavelet kernel, support vector regression machine, nonlinear correction.

1. Introduction

At present, when correcting the nonlinear data processing, there are two types of methods which are often used, one kind is the traditional method, this method is divided into hardware compensation method and look-up table method, least square method, and the curve fitting method, etc;Another is a modern processing methods, including neural network, support vector machine (SVM) and wavelet analysis, as well as the genetic algorithm and so on[1].For smooth data,using the traditional method of curve fitting can make the input and output and has a good linearity,for non-stationary data,usually adopt modern processing method,with the appropriate selection of kernel function,mapped the low dimensional nonlinear data to high-dimensional space linearization can be realized.In this paper, the method based on support vector regression machine is based on VC dimension theory and structure risk minimum principle is derived based on income,has a solid mathematical foundation,uses the finite sample information have a better fitting effect can be achieved.Correction based on data processing, the wavelet kernel as the kernel function of support vector regression machine, by comparing the gaussian kernel and radial basis kernel function, the results show that the wavelet kernel correction results are more accurate, and error is smaller.

2. Research on wavelet kernel function method

2.1 construct the wavelet kernel function

As for wavelet transform,framework F is usually the $Riesz$ base,so F is a framework of H,make Q as the framework operator of F,there are:

(1) Q is positive definite, and the existence of the dual framework F.

$$F^d = \{ f_i^d = Q^{-1} f_i \} \tag{2-1}$$

(2)for any and all $f \in H$,it can be written as the following forms of decomposition nucleosynthesis

$$f = \sum_i \langle f, Q^{-1} f_i \rangle f_i = \sum_i \langle Q^{-1} f, f_i \rangle f_i \tag{2-2}$$

(3)because F is the $Riesz$ base, F and F^d are $\langle f_i, f_j^d \rangle = \delta_{i,j}$ meaning dual.

According to the above properties, for any function $f \in H$,frame operator with the expansion of the form $QF = \sum_i \langle f, f_i \rangle f_i^d$.

This article selected m order B spline function as the wavelet kernel function, as follows:

$$k_{m,J}(x,y) = \sum_i \varphi_{m,0,j}(x)\varphi_{m,0,j}(y) + \sum_{0 \le j \le J} \sum_i 2^{-2j} \psi_{m,j,i}(x)\psi_{m,j,i}(y) \tag{2-3}$$

In the form: J is truncated length factor, it can be determined by the length of the input signal is the only.Figure 1 is when $m=4$, the wavelet kernel function with the change of the input.

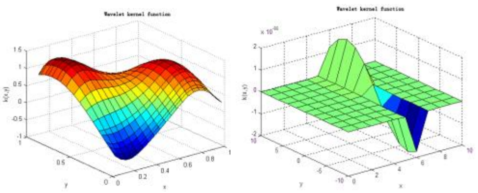

Figure 1.when m=4 the wavelet kernel function is changing with the input

At present, based on the wavelet kernel function has been constructed,it is different from RBF, linear kernel, the kernel function is sparse change kernel function,have good performance for multi-scale interpolation.

3. based on wavelet support vector regression machine nonlinear correction model is established

In this article wavelet support vector regression modeling method based on nonlinear correction, in essence, after the wavelet kernel function as a support vector regression nuclear, after nonlinear mapping, and then the data is linearized so fitting error between the data and the input data to achieve as small as possible.

3.1 supports the theoretical basis vector regression

Let the presence of the training sample set as (x_i, y_i), $i = 1, 2, ..., n$, $x_i \in R^n$ are the input sample, y_i is the output sample, after the non-linear mapping, linear regression function can be expressed as:

$$f(x) = (w \bullet x) + b \tag{3-1}$$

Among them, w and b are the normal vector and offset linear regression function, this time hyperplane equation can be expressed as:

$$\omega \bullet x + b = 0 \tag{3-2}$$

To make the classification of all samples can be correctly classified, required to meet the following constraints:

$$y_i(\omega \bullet x + b) - 1 \geq 0 \tag{3-3}$$

It can be calculated based on analytic geometry, classification intervals is $2/\|\omega\|$, in order to make the classification interval reaches the maximum, that is to take the minimum $\|\omega\|$, to solve the optimal hyperplane actually be transformed into the meet (3-3) to minimize the objective function under the conditions of:

$$\min \frac{1}{2}\|\omega\|^2 = \frac{1}{2}(\omega \bullet \omega) \tag{3-4}$$

In order to solve the formula (3-4), using the Lagrange multiplier method using KKT condition theory, linking vertical (3-3), (3-4) can be obtained by Lagrange objective function:

$$L(\omega, \mathrm{b}, \mathrm{a}) = \frac{1}{2}\|\omega\|^2 - \sum_{i=1}^{n} \alpha_i \left(y_i\left(\omega^T x_i + b\right) - 1\right) \tag{3-5}$$

α_i is the Lagrange multiplier, the problem is a convex quadratic programming problem, there is a unique optimal solution, in order to obtain a unique solution of ω、b partial derivative and make partial derivative is 0, that is:

$$\frac{\partial L}{\partial \omega} = 0 \Rightarrow \omega = \sum_{i=1}^{n} \alpha_i y_i x_i$$
$$\frac{\partial L}{\partial b} = 0 \Rightarrow \sum_{i=1}^{n} \alpha_i y_i = 0 \tag{3-6}$$

Take the formula (3-6) into the formula (3-5) can be obtained:

$$L(\omega, b, a) = \frac{1}{2}\sum_{i=1}^{n} \alpha_i - \frac{1}{2}\sum_{i,j=1}^{n} \alpha_i \alpha_j y_i y_j x_i^T x_i \tag{3-7}$$

Above is derivation linearly separable case, for linearly inseparable case, which usually involves a penalty factor of misclassification point penalty function it is actually misclassification point to its correct location from the classification. To illustrate the significance of the penalty factor, Figure 2 is a penalty function to define a discrete form.

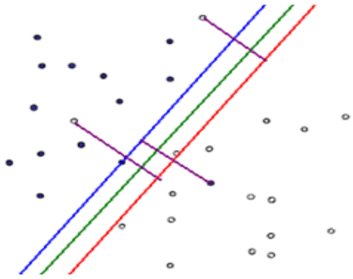

Figure 2.penalty function is defined in the form of discrete

The blue and red are respectively in support of the position vector of the straight line where the green line is the decision-making function, the purple line represents the misclassification point to distance its corresponding decision surface. In this case, the original function plus a penalty function, its optimal objective function can be expressed as:

$$\min \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{R} \varepsilon_i, s.t., y_i\left(\omega^T x_i + b\right) \geq 1 - \varepsilon_i, \varepsilon_i \geq 0 \tag{3-8}$$

Among them, ξ_i is the slack variable, indicating that whether the point classification is correct, then, that support vector number is 0, C for the penalty coefficient, showing how much was added to misclassification point penalty, when C is large, divide the wrong point will be less , but the situation is more serious over-fitting, when C is small division wrong point may be a lot,but the model established at this time is not very correct, and thus how to select the penalty coefficient C, most of the cases resulting from the experience.

In order to solve the formula (3-8), by the Lagrange multiplier method using KKT condition theory, and seek its dual problem:

$$\max_{\alpha,\alpha^*}\sum_{i=1}^{l}\left[\alpha_i^*\left(y_i-\varepsilon\right)-\alpha_i\left(y_i+\varepsilon\right)\right]-\frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l}\left(\alpha_i-\alpha_i^*\right)\left(\alpha_j-\alpha_j^*\right)\left(x_i\cdot x_j\right) \tag{3-9}$$

$$s.t.\begin{cases}\sum_{j=1}^{l}\left(\alpha_i-\alpha_i^*\right)=0 \\ 0\le\alpha_i\le C \quad ,i=1,2,\cdots,l \\ 0\le\alpha_i^*\le C\end{cases} \tag{3-10}$$

Formula (3-10) linear representation of the situation cannot be separated and the formula (3-7) linear representation of separable case except that ranges from changes to increase penalties and to increase computational complexity.

By the formula (3-30), according to partial differential minimum, obtain the normal vector and regression function regression function:

$$w=\sum_{i=1}^{l}\left(\alpha_i-\alpha_i^*\right)x_i \tag{3-11}$$

$$f\left(x\right)=\left(w\cdot x\right)+b=\sum_{i=1}^{l}\left(\alpha_i-\alpha_i^*\right)\left(x_i\cdot x_j\right)+b \tag{3-12}$$

Above are introduced linearly separable and inseparable linear problem,as for nonlinear problem cannot be separated, ideas and concrete solutions to solve linear non are the same, except that the selected kernel function. In the case of linear low-dimensional space cannot be divided, by selecting the appropriate kernel function, the spatial mapping from the original linear space to a high-dimensional space, in this high-dimensional linear space,then can achieve super-plane division.

3.2 based on wavelet support vector regression modeling nonlinear correction

When using wavelet support vector regression nonlinear data correction, usually need to preprocess the data, the processed data as input support vector regression, the mapping process by wavelet kernel function after the low-dimensional non-linear data is mapped into a high dimensional linear space, so that the output vector machine approach and expectations as much as possible, and ultimately achieve the purpose of correction of non-linear data. When using wavelet support vector regression model for correcting nonlinear data, usually it takes the following steps:

Determine the sample data

Under normal circumstances, the sensor can be used as $y=f(x),x\in(\xi_a,\xi_b)$, where y represents the sensor output, x sensor input, ξ_a,ξ_b as signal input range. Ideally, the sensor input and output into a linear relationship, but in most cases, the output of the sensor is non-linear; in order to eliminate the non-linear characteristics of the sensor, the sensor needs to be added at the output of a correction links, making the final output of the sensor input a linear relationship. In this paper, wavelet support vector regression nonlinear data correction, is the use of nonlinear characteristics wavelet support vector regression, the vector regression linear compensation as part of its training sample (y_i, x_i), that is the formula, y_i expressed support vector regression input, x_i expressed fitting target.

2) Select the kernel function K

SVR is due to the introduction of kernel function only has better nonlinear processing ability in the use of support vector regression to solve practical problems, kernel function commonly used include linear kernel, polynomial kernel, RBF kernel, Sigmoid nuclear, Fourier nuclear, anova nuclear, erbf nuclear, spline nuclear, and bspline nucleus, but this paper wavelet kernel as SVR kernel function, because the wavelet multiscale having nuclear sparse interpolation characteristic change feature, you can improve support generalization and noise immunity vector Regression. Wavelet kernel function used in this paper, the expression can be expressed as:

z= cos(1.75*(u-v)/0.6)*exp(-(abs(u-v))^2/(2*0.6^2)) (3-13)

establish a data correction diagnostic model

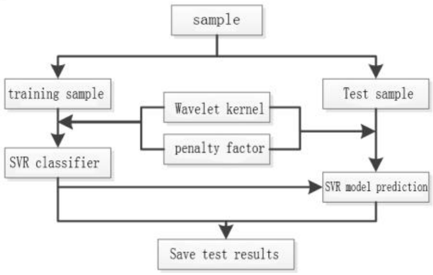

Figure 3.based on wavelet support vector regression data calibration model

(1) Select the sample data as feature vectors, in order to achieve a linear relationship between the sensor input-output, this paper is the sensor output data and sensor data as input data sample;

(2) to step (1) of the sample data is input to SVR classifier. Grid-search methods using SVM parameters were optimized, training optimal penalty coefficient C, the loss parameters and kernel function parameters are not sensitive;

(3) completing the steps above, after determining support vector regression parameters, the parameters determined together with sample data for testing, and finally get the output corrected;

(4) After completion of data correction, the corrected data were compared with the actual data, and save the model.

4. Examples of non-linear calibration sensor

In this paper, the effects of different types of kernel functions and their parameters for sensor nonlinearity correction accuracy will function as three different types of SVM kernel function, and the results obtained by different correction Matlab programming language to analyze the type of kernel function select parameters and their impact on the sensor calibration accuracy.

The figure is the penalty coefficient different kernel functions under different calibration results.

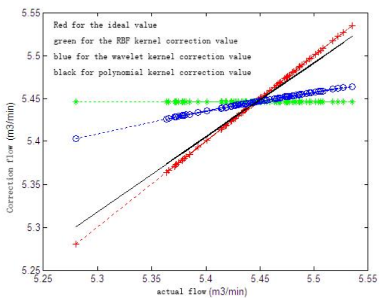

Figure 4.C = 1 during calibration results under different kernel functions

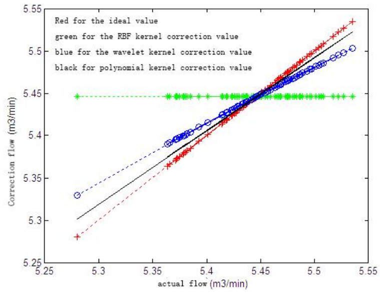

Figure 5.C = 3 during calibration results under different kernel functions

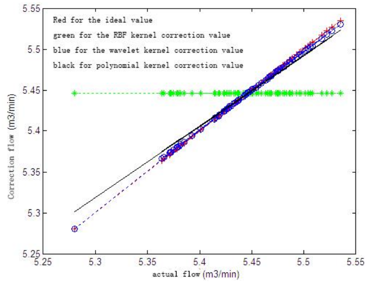

Figure 6.C = 5 during calibration results under different kernel functions

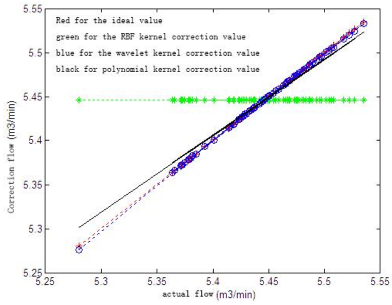

Figure 7.C = 7 during calibration results under different kernel functions

From 4 to 7 it can be seen in a different penalty coefficient, using different kernel function of the sensor output nonlinear correction, the different calibration results obtained. For the RBF kernel function, when using this correction method corrects penalty factor increases, no significant change in its output, the input and output satisfy a linear relationship, but the larger the value of the corrected output and the actual output value difference; when using polynomial kernel nonlinear correction factor coefficients increase with the penalty, and its input and output without significant changes, and the correction of the output value of the sensor output value under ideal conditions there is a big error; and in the use of wavelet kernel function sensor nonlinear data correction, with the penalty increasing the factor, the non-linear correction effect is more obvious, when the penalty factor is greater than or equal to 5, the calibration results no significant changes, and the output value of the output value and the ideal situation corrected under can better fit.

5. Conclusions

By comparison Matlab simulation results based on wavelet support vector regression Linear Rectification better. The simulation results show that the improved output characteristics and performance of the sensor by this method for non-linear calibration sensor provides a very good way, with extensive promotion significance.

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