Study on a Fire Detection System Based on Support Vector Machine

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Abstract: It is very important to research the prediction of fire, which is significant to the people and nation. The traditional fire detection system based on neural network has the disadvantages of over learning, trapped in local minimum, etc. This paper proposes a new fire detection system based on support vector machine (SVM). Gas sensors, smoke sensor and temperature sensor are composed to be a sensor array. The fire detection model is established, including sample selection, prediction model training prediction, output modules, etc. The SVM transform the complicated nonlinear problem into the linear problem in the high dimensional plane. The experimental results show that fire detection system based on support vector machine had high recognition rate and reliability, it overcomes the disadvantages of traditional methods. Copyright © 2014 IFSA Publishing, S. L.

Keywords: Support vector machine, Fire detection, Sensor array, Pattern recognition.

1. Introduction

Fire extremely harm to the life safety, property, environment and ecological balance. The accurate prediction in the early is very important for the control of fire. Fire alarm is the key technology in fire-fighting domain of various countries. The traditional fire alarm methods such as threshold method and process method, mostly according to single parameter of the fire, the recognition technique of which had disadvantages of simplification, poor adaptability and high false alarm rate [1]. Recently, the intelligent multi-parameter fire alarm methods is been risen. The artificial neural network as the main technology is researched widely. The artificial neural network can be affected by the complexity of samples and network structure which lead to problems of over learning, poor generalization ability and low fire recognition rate [2].

Support vector machine (SVM) is a new intelligent learning method, which is based on structural risk minimization of statistical learning theory [3-5]. Sample vectors are mapped to high dimensional feature space. Nonlinear problem of primary spaces is transformed into a linear problem of high dimensional feature space. Inner product operation of high dimensional feature space is transformed into kernel function calculation, which avoids the complex nonlinear calculation of high dimensional feature space and the dimension disaster. SVM which can avoid over learning and local minimum is more generalized performance and
convergence speed as compared to artificial neural network which is based on the empirical risk minimization principle.

This paper proposes a new fire alarm model based on support vector machine and multi-sensor information fusion. The experimental results show that multi-sensor data can be disposed intelligently and realize the fire prediction. The prediction accuracy of SVM fire alarm model is more than neural networks. The reliability and accuracy of fire alarm system are increased.

2. Support Vector Regression (SVR)

2.1. SVR Algorithm

The initial research of SVM is classification. Recently the application of SVM is extended to regression and time series prediction. Support vector regression (SVR) is used to extend the conclusion of pattern recognition classification to the real function.

In the case of less statistical samples, SVR algorithm based on structural risk minimization principle can increase the learning generalization and minimize the empirical risk and confidence interval, which has good statistical law.

The given training sample set is \( S = \{(x_i, y_i)\} \), the input and output are \( x_i \in R^*, y_i \in R \) respectively. \( \Phi \) makes the input data be mapped to high dimensional feature space through nonlinear mapping. It realizes the linear regression in this new space. The regression function is

\[
 f(x) = \sum_{i=1}^{n} \alpha_i \Phi_i(x) + b
\]  

Based on estimation risk minimization, construct the minimization objective function:

\[
 \min \frac{1}{2} \sum_{i,j=1}^{n} (\alpha_i - \alpha_j)^2 (\alpha_i - \alpha_j) K(x_i, x_j) + \varepsilon \sum_{i=1}^{n} (y_i - (\alpha_i - \alpha_j)^2) 
\]

\[
+ C \left( \sum_{i=1}^{n} \xi_i + \sum_{i=1}^{n} \xi_i^* \right)
\]  

(4)

The constraint condition is

\[
\sum_{i=1}^{n} (\alpha_i - \alpha_j) = 0, i = 1, 2, \cdots, n \\
\alpha_i \leq C, \xi_i \geq 0, i = 1, 2, \cdots, n
\]  

(5)

According to duality theory, Formula (2) is transformed into quadratic programming problem, which is solved by Lagrange optimization method.

\[
\min \frac{1}{2} \sum_{i,j=1}^{n} (\alpha_i - \alpha_j)(\alpha_i - \alpha_j) K(x_i, x_j) 
\]

\[
+ \varepsilon \sum_{i=1}^{n} (y_i - (\alpha_i - \alpha_j)^2) 
\]

(4)

The optimal solution is \( \hat{\alpha} = (\hat{\alpha}_1, \hat{\alpha}_2, \cdots, \hat{\alpha}_n)^T \). In Formula (4) and (5), \( \alpha_i \) and \( \alpha_i^* \) are Lagrange multiplier. \( K(x_i, x_j) \) is kernel function.

Select a \( 0 < \alpha_i < C/n \) components of \( \hat{\alpha} \). Calculate \( b = y_i - \sum_{j=1}^{n} (\hat{\alpha}_j - \hat{\alpha}_j) K(x_i, x_j) + \varepsilon \); Or Select a \( 0 < \alpha_i^* < C/n \) components of \( \hat{\alpha} \). Calculate

\[
 b = y_i - \sum_{j=1}^{n} (\hat{\alpha}_j - \hat{\alpha}_j) K(x_i, x_j) - \varepsilon 
\]

(5)

Construct support vector linear regression function:

\[
 f(x) = \sum_{i=1}^{n} (\alpha_i - \alpha_j) K(x_i, x_j) + b
\]  

(6)

Complex nonlinear samples are mapped to high dimensional feature space. It is no need to calculate nonlinear function for regression function. It is known from formula (6) that the calculation of kernel function can avoid complicated operations of high dimension.

According to Hilbert-Schmidt theorem, \( K(x_i, x_j) \) satisfies the Mercer condition is inner product kernel.

\[
 K(x_i, x_j) = \Phi(x_i) \cdot \Phi(x_j)
\]  

(7)

There are some common kernel functions.

I. Linear kernel function

\[
 K(x_i, x_j) = (x_i, x_j)
\]  

(8)

II. M order polynomial kernel function

\[
 K(x_i, x_j) = (x_i, x_j + 1)^n
\]  

(9)

III. Neural network kernel function

\[
 K(x_i, x_j) = \tanh[c_1(x_i, x_j) + c_2]
\]  

(10)
IV. RBF kernel function

\[ K(x_j, x_i) = \exp\left(-\frac{\|x_j - x_i\|^2}{2\sigma^2}\right) \]

2.2. SVR Machine Learning

Based on structural risk minimization principle, SVR machine learning make the learning model with given limited training samples, which can obtain the relationship between input and output, predict and judge the unknown sample data. The algorithm steps of SVR machine learning is shown as Fig. 1.

Fig. 1. The steps of SVR machine learning.

3. SVR Recognition of Fire Alarm

There are smoke, toxic and harmful gas, the change of Oxygen Content and the risen temperature in fire. The traditional recognition method of fire was to monitor one parameter of fire, or only some certain parameters, the relationship between which was independent without fusion processing. So false alarm always happened. In this paper temperature sensor, smoke sensor and gas sensor of CO and O₂ were adopted to compose the sensor array fire alarm system. SVR was adopted to realize the data fusion processing of fire parameters and fire alarm.

The identification principle of fire alarm based on SVR was shown as Fig. 2. Fire parameters of the detecting point including temperature, smoke concentration and concentration of CO and O₂ were monitored by experiment. Some related data were outputted by the sensor array made up of temperature sensor, smoke sensor and gas sensor. Output data of sensor array were sent to computer to standardization and normalization process through signal processing circuit and multi-function data acquisition card. Training samples and test samples were selected from the processed output data. Training samples were trained by SVR learning machine. During the course of training, parameters were designed and compared to choose the optimal parameters. Test samples were used to test the trained SVR learning machine and verify training results.

Fig. 2. Identification principle of fire alarm based on SVR.

4. Experimental Results

The experimental data were temperature, smoke concentration, CO concentration and O₂ concentration. A temperature sensor, a smoke sensor and a CO sensor and an O₂ sensor were adopted to compose the sensor array for the measurement of fire parameters.

For the comparison between two measurement results of SVR and artificial neural network, BP algorithm is a common algorithm of artificial neural network, which was selected to establish neural network model in this paper. This Neural Network was a 3 layers BP network of 4-10-3 Structure. Input layer had 5 nodes that were temperature (°C), smoke concentration (mg/m³), CO concentration (mg/m³) and O₂ concentration (mg/m³) from input sensor array. Output layer had 3 nodes that were of probability values of smoldering stage, developing stage and open fire stage. The experiment measured 30 data sets, 20 data sets of which were selected as training samples to train the network; the rest 10 data sets were selected as test samples to verify the learning effect of the network. Analysis result of BP neural network with 5 random data sets was shown as Table 1.
Table 1. Analysis result with BP neural network.

<table>
<thead>
<tr>
<th>Groups</th>
<th>Temperature</th>
<th>Smoke</th>
<th>CO</th>
<th>O₂</th>
<th>Expected output</th>
<th>Predicted output</th>
</tr>
</thead>
<tbody>
<tr>
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<td></td>
<td></td>
<td></td>
<td></td>
<td>Smoldering stage</td>
<td>Developing stage</td>
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<td></td>
<td></td>
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<td></td>
<td>Smoldering stage</td>
<td>Developing stage</td>
</tr>
<tr>
<td>1</td>
<td>25</td>
<td>0.0</td>
<td>5.0</td>
<td>200</td>
<td>0.7</td>
<td>0.1</td>
</tr>
<tr>
<td>2</td>
<td>30</td>
<td>0.5</td>
<td>18.0</td>
<td>280</td>
<td>0.9</td>
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<tr>
<td>3</td>
<td>40</td>
<td>1.2</td>
<td>27.5</td>
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<tr>
<td>4</td>
<td>50</td>
<td>2.1</td>
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Type of kernel functions, parameters, penalty parameter C and error requirement parameter ε are needed in the SVR model. In common kernel functions, the model of polynomial kernel function is relatively complicated, and operational speed is slow.

While neural network kernel functions sometimes has the problem of no convergence results. RBF kernel function has the balance between the computing time and prediction accuracy. Complex nonlinear samples are mapped to high dimensional feature space by the RBF kernel function, which is failed for the linear kernel function. So RBF kernel function was picked for the SVR kernel function in this paper. It is important for the establishing of SVR model that the different kernel width was chosen for the control of the constant σ, penalty parameter C and error requirement parameter ε. Based on the theoretical analysis and the comparison of experimental results, the optimal parameter combination was determined by the minimum error, when C=350, σ=2.2, ε=0.001, prediction accuracy was higher. Analysis result of SVR compared with the analysis result of BP neural network with 5 random data sets was shown as Table 2.

Table 2. Analysis result with SVR.

<table>
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From the Table 1 and Table 2, the prediction average error in smoldering stage of BP neural network is 5.28 %, the prediction average error in developing stage is 5.38 %, and the prediction average error in open fire stage is 6.8 %. The prediction average error in smoldering stage of SVR is 2.4 %, the prediction average error in developing stage is 2.7 %, and the prediction average error in open fire stage is 2.4 %. Experiments showed that recognition accuracy of BP neural network that intelligent fire alarm system is always adopted currently was significantly lower than the SVR method. Error convergence curve of SVR training is shown as Fig. 3. After training, the prediction fitting precision is 9.99995×10⁻³, the mean square error achieved the request of training precision, the whole training process is convergent and the network learning precision is high.

5. Conclusions

This paper presents SVR fire alarm system that has good recognition effect from the fire alarm experiment.
better role in the field of quantitative identification and lays a solid foundation for the further research.

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