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The faults detection methods for embedded equipment

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Abstract: Due to the objects in the embedded control procedure are difficult to obtain a variety of fault data and fault features, it's necessary to establish simulation models in accordance with the operational mechanisms of the embedded equipment to simulate and diagnose the practical faults. This paper proposes a SVM integrated diagnostic method and further proposes the faults classification model with improved neural network. The faults diagnose performance is greatly improved by analyzing the types of the faults in different facets. For the embedded valve failure modes, the simulation results of the proposed method are compared with that of the previous mature independent element analysis method. The simulation results show that the fault diagnosis method in this paper can effectively improve the speed and accuracy of fault diagnosis for the embedded equipment.

1 Introduction

The embedded equipment normally works in the environment with high temperature and pressure or extreme low temperature vacuum. The improper operation or system failures will cause dangerous. To improve the security of the production process, the effective system fault detection and diagnosis is very necessary[1]. This paper presents the neural networks method with improved neuron and the output from Support Vector Machine is used to divide the overall classification which is in strict accordance with the concept of rough set theory. Therefore the networks have clear physical meanings and have better generalization abilities than the improved BP neural network. The performance of the proposed method is better than the mature technology of independent element in the simulation researches of embedded faults detection[2-5].

2 The construction of improved neural network of Support Vector Machine

Because the formats of the classification functions from SVM is similar to a neural network, the front parts of the neural networks can be designed to multiple sub-neural networks in which each corresponds to a proximal Support Vector Machine classifier.

Given a classification problem with m faults, m two-class classifiers can be designed and each classifier can distinguish one type of mode from other modes. The given sample set is as follows.

$$\Theta(\chi_i, y_i^k), i = 1 \cdots n, \chi \in \Re^d, y^k \in \{-1,1\}, k \in \{ 1,\cdots,m \}$$

Then the classification function is

$$f^k(\chi) = \sum_{i=1}^{n} \alpha_i^k \ y_i^k K(\chi, \chi_i) + b^k \quad , \quad k = 1,2,\cdots m \tag{1}$$

When $f^k(\chi) > 0$, k type of fault happened. In order to increase the output reliability of the classifiers, there is one stricter constrain, that is when $f^k(\chi) > \tau$, k type of fault happened.

The results from the Support Vector Machine are used as the positive domain, negative domain and boundary of some category which is designed as a rough neuron. The activation function of the neuron is called *sigmoid*. In order to better detect the embedded faults, the training algorithm is gradient method which revises the variable weights by output errors.

$$K(\chi, \chi_i) = \exp(\frac{|\chi - \chi_i|^2}{\sigma^2}) \tag{2}$$

The difference from the traditional radial basis function method is that the center of each basis function corresponds one support vector in which σ^2 is width parameter determined by experiences.

3 Simulations

DAMADICS model is a classic embedded valve faults simulation model which can generate every type of faults with varied strengths. The actual industrial data can also be imported to the model to simulate. The actual data in this paper imported to the model is from the operational data of Lublin Sugar Factory within one hour in one day. There are 19 typical valve faults integrated in the simulation model as follows.

F1：Valve blockage failure； F2：Valve plug or sink failure；

F3：Valve corrosion failures；

F4：Valve bearing friction increase failure；F5：External leakage failure；

F6：Internal leakage fault; F7: Carrier evaporation and overheating fault;

F8: Motor rod twisted failure; F9: Rack loose failure;

F10: Film perforation faults; F11: Spring elasticity fault;

F12: Electric-gas converter fault; F13: Rod displacement sensor failure;

F14: Pressure sensor failure; F15: Locator feedback fault;

F16: Supply pressure drop fault;

F17: Unpredictable pressure changes failure;

F18: Bypass valve failure; F19: Flow sensor failure.

Each faults data is added to obtain 100 failure points to form a data sample with 2000 points which contain normal operation and features of 19 types of faults.

The measured samples are imported into the established two-dimension classification model and the detection performance with the proposed method is shown in Table 1. The SVM method fails to detect the fault of F9 and F17 because there is no more detailed failure information. The collected data is processed by ICA to extract 2-dimension vectors from 5-dimension data and 200 points are selected with equal spaces which can decrease the burdens of the classifier with the proposed method.

Table 1 Faults detection rates

Faults	F1	F2	F3	F6	F7	F13	F16	F19
Detection rates%	79.2	66.8	79.4	27.1	61.2	35.1	50.2	92.1

The faults detection performance for F1, F2, F3, F7, F10, F16, F18, and F19 is satisfactory. However the faults of F6 and F13 cannot be accurately diagnosed because the dimensions of the detected variables are not very much and faults feature information extracted is not enough to distinguish the two faults which can only detect one of the two faults. The further detection and identification performance is evaluated by the real data from Lublin Sugar Factory and the description of the data is as shown in Table 2.

Table 2 The actually measured valve failure rates with LS Factory process

Faults types	F16	F13	F19
Faults data description	November 9,2001 (60650–60700)s	October30,2001 (57340–57890)s	November 17, 2001 (58150–58325)s
Faults detection rates %	82.9	77.1	91.0

From the above simulation results, the proposed method can quickly detect and diagnose the faults with high accuracy. However there are also some limitations for the method. It strongly depends on the data. With the increase of the feature information extracted from the detected data, the classification performance will be improved and the faults detection rates will be increased. When 5-dimesion detected data is used to extract 2-dimension, the classification performance with independence element method is not satisfied and there are some error detections. The further improvement is proposed which applies 3-dimension independent elements multi-slice to train the Support Vector Machine classification model. The proposed method can well solve the issues that the faults of F6 and F16 cannot be diagnosed.

Table 3 The faults detection rates comparison after improvement

w/ faults	w/o faults	F1	F2	F3	F6	F7	F13	F16	F19
Independent elements	87.3	79.2	88.8	90.4	30.1	66.2	40.1	59.2	90.9
Proposed method	88.6	84.5	92.3	91.1	53.6	70.7	50.1	66.9	91.3

The simulation results in Table 3 illustrate the proposed method can quickly and accurately detect and diagnose the faults. The method can solve the issues that the traditional methods cannot extract the faults information completely and the diagnosis performance is not satisfied. The proposed method can well identify the faults that cannot be detected with independent elements method. However the proposed method depends on the original data. The valve features should be deeply researched in the following work and the faults features should be specifically selected in the detection data during the analysis of the relation between the faults features and detection variables.

4 Conclusions

This paper proposes a faults detection method integrating the methods of Support Vector Machine and Rough Neural Network which can not only increase the faults detection accuracy, but also solve the issues of the embedded equipment that the faults can be detected but cannot be diagnosed. The structure of the rough neural network based on Support Vector Machine is determined and each neuron and weight has physical meanings. Thus the network can be well described. The proposed method is well applicable for the small scale data classification issue which can increase the learning accuracy in the samples training and improve the prediction capability for the unknown samples.

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