FAULT DIAGNOSIS OF GARMENT AND TEXTILE SPINNING FRAME BASED ON SUPPORT VECTOR MACHINE

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ABSTRACT: The purpose is to study the automatic diagnosis of garment textile spinning frame fault based on support vector machine. Combining the four common faults of the spinning frame, the support vector machine is used to classify and identify the fault. The extracted feature vectors are entered. The feature vector is trained and identified by multi - classification method. The optimal parameters of the support vector machine are searched by trial and error method and cross validation method. Then, the support vector machine is compared with BP neural network. The results show that the support vector machines are short in time and high in classification accuracy. It is more suitable for the research of fault diagnosis in spinning frame. Therefore, it can be concluded that the training speed of support vector machines (SVM) is fast and the performance is good.

Key Words—fault diagnosis, support vector machine, eigenvector, one-to-one algorithm, one-to-many algorithm

1 INTRODUCTION

In the past, for garment spinning equipment, engineers generally judged the cause of equipment failure based on experience. However, this kind of artificial judgment has some limitations and errors [5]. At the same time, it will consume a certain amount of human resources. In view of this, a new technology - mechanical fault diagnosis technology is introduced [4]. With the rapid development of computer technology, fault diagnosis technology has become the technical basis of modern equipment management [3]. It is beneficial to improve the comprehensive benefits of enterprises. At present, many signals can be used in mechanical condition monitoring and fault diagnosis, which mainly include temperature, noise, vibration, light, electromagnetism, flow, light, pressure, and so on [2]. It has been involved in many fields such as national defense, aerospace, civil engineering, petrochemical, hydraulic power, metallurgy, automobile production, shipbuilding [1].

2 STATE OF THE ART

At present, more and more attention has been paid to fault diagnosis. The main technical means of mechanical fault diagnosis has the vibration diagnosis method, noise diagnosis technology, spectral diagnosis technology and ferrography analysis method, nondestructive testing technology, temperature and infrared thermal imaging diagnostic methods and diagnostic technology [6].

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On the whole, modern fault diagnosis technology mainly includes fault mechanism research, state signal detection, fault characteristic analysis, fault diagnosis method, fault monitoring and diagnosis system [7]. The support vector machines (SVM) method is used to diagnose four common faults in the spinning frame of the textile spinning machine, such as the bending failure of rollers, the elliptical trouble of rollers, the unbalance of the main drive gear rotation, the unbalance of the transmission gear and the defects of the transmission gear [8]. At present, the research of support vector machines (SVM) has achieved some achievements both at home and abroad. However, there are still some problems that need to be studied deeply [9]. It is important to select the appropriate kernel functions and kernel function parameters. The support vector machine performance depends on kernel functions as well as the choice of parameters in kernel functions [10]. In this respect, there is no complete theoretical basis for it yet. The appropriate multi class algorithm is chosen to meet the needs of multiple fault classifiers. The support vector machines (SVM) are concerned with two kinds of problems. For many kinds of problems, the support vector machines are still in the phase of algorithm research [12]. Further research needs to be done to improve the slow training algorithm of support vector machines, in order to meet the real-time requirements of equipment fault diagnosis. The integration of other knowledge-based fault diagnosis methods, such as fuzzy diagnosis method, neural network diagnosis method, and support vector machines (SVM), should be further studied [13]. The application of the support vector machine in the field of fault diagnosis should continue to be popularized [11].

3 METHODOLOGY

3.1 Multivariate classification algorithm of support vector machine

The solution of the multi-classification problem is mainly to classify the multi-valued classifier by combining the two types of classifiers [14]. The typical multi-class classification method mainly has the following two kinds. The first is the l-1 algorithm (referred to as l-v-1). The 1-to-1 algorithm is presented by Kressel. The algorithm traces a classifier between two classes [15]. Thus, for a k-type problem, there will be k(k-1)/2 classification functions. When classifying an unknown sample, each classifier evaluates its category and votes for the corresponding category. Finally, the most popular category is the category of the unknown sample, which is called the "voting law". The one-to-many algorithm is proposed by Vapink. The basic idea is to construct N classifiers for class N problems. The i-th classifier uses the i-th class of training samples as positive training samples, and other classes of training samples are negative training samples [17]. At this point, the decision function of the classifier does not take the symbolic function sgn $(\cdot)$. The final output is the largest of the two classes of classifier output.

The first method uses k(k-1)/2 classifiers. However, the number of training samples in each classifier is lower than the latter. The second method is easier to implement, but the robustness is not strong. The misclassification of any classifier will bring about the ambiguity of classification [16]. From the point of view of classification effect, the latter should distinguish the single class data from other classes, and the classification hyperplane is more complex than the former. It is prone to error.

3.2 The roller fault diagnosis based on support vector machines

The fault diagnosis block diagram is shown in Figure 1.

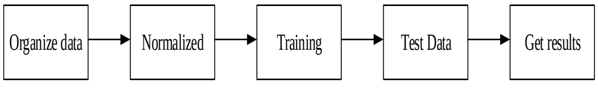

Fig. 1. The fault diagnosis block diagram

Data organization is to sum up the characteristic parameters of each fault. Normalization is the elimination of dimensional effects. At the same time, it can also speed up the simulation. The training sample data are trained to get the model. In the test sample, the trained model is entered for testing and the test results are obtained. The resulting test results are sorted out. Finally, the conclusion is obtained.

3.3 The selecting methods of vibration measuring parameters

The first method is cut-and-trial. After the model (SVM, kernel function) is selected, the initial value is first assigned to the parameter (C, γ). Then, the experimental tests are carried out. the parameter values are adjusted repeatedly, according to the test accuracy until satisfactory test accuracy is achieved. The experimental results show that the testing accuracy increases with the increase of C. When it exceeds a certain value, the accuracy begins to decrease. At the same time, as the number of C increases, the number of support vectors decreases strictly, and the number of support vectors at the boundary decreases rapidly until it becomes 0. The cut-and-trial method is the most common and effective method at present. However, it is based on experience and lacks sufficient theoretical basis. For different kernel functions, different samples may be adjusted differently. Therefore, in the process of parameter adjustment, there is a certain blindness. In addition, when the magnitude of the adjustment is large, the adjustment times are more frequent, and the experiment is more complicated.

The second is the cross-validation method. The so-called cross validation method, that is, training samples M are randomly divided into roughly equal to each other disjoint subset [18]. That is to say, $M = M_1 \cup M_2 \cup \cdots \cup M_k$, it conducts k times training and testing. The approach of i-th iteration is: M_i is chosen as the test set, and the sum of its remaining subsets is the training set. After the decision function is obtained from the training set, the algorithm tests the test set M_i and records the correct rate l_i of the test. Thus, after the k iteration was completed, the correctness of the k tests was obtained, that is, l_1, l_2, ... l_k. Comparing the cross-validation accuracy of parameters, the parameters with high accuracy are chosen.

4 RESULT ANALYSIS AND DISCUSSION

4.1 Simulation analysis of roller fault diagnosis based on support vector machines

The four faults in spinning frame are studied. Among them, the roller elliptical fault is different from the other three faults. As a result, the data corresponding to their normal signals vary greatly. Here, the data of these two normal signals are processed separately, so a multi class fault classifier is constructed in six states. A total of 8 samples were taken from each state, and 48 samples were used as training samples. All classifiers use radial basis functions. In order to compare the classification performance of the two algorithms, the fault data will be trained and tested by "one to one" and "one to many". One-to-one algorithm: eight samples of the two states are used as two types of input for the classifier, which are identified as + l and -1, respectively. A total of 15 types of classifiers are built into six kinds of working states. They are SVM12, SVM13, SVM14, SVM15, SVM16, SVM23, SVM24, SVM25, SVM26, SVM34, SVM35, SVM36, SVM45, SVM46 and SVM56. Among them, SVMmn represents the two kinds of support vector machines that established between m class and n class sample. One-to-many algorithm: eight states of a state and 8 * 5 = 40 states of the remaining five states are used as two types of input for the classifier, which are identified as + l and -1, respectively. A total of six types of classifiers are established for six kinds of working states. They are SVM1, SVM2, SVM3, SVM4, SVM5 and SVM6. Among them, SVMn denotes the two kinds of support vector machines that established between n class and the other kinds of samples. The characteristic frequency of the four faults is taken as the training sample of the support vector machine. Among them, each set of training samples or test samples consists of 6Hz, 69Hz, 84Hz, 97Hz and 103Hz amplitude, and the power spectrum in the 125Hz~180Hz frequency section and the peak value in the time-domain characteristic parameters. For each type of problem, 10 sets of samples are used. It consists of 8 sets of training samples and 2 sets of test samples. As shown in Table 1.

Table 1. A brief description of the data set

Data sheet	Category	Number of training samples	Number of test samples
The main roller is normal	1	8	2
The main roller is bent	2	8	2
The gear rotation quality is imbalance	3	8	2
Gear defect	4	8	2
Deputy roller normal	5	8	2
Deputy lara oval	6	8	2

The penalty parameter C = 100 and the nuclear parameter γ= 0.05 are adjusted. The fault is identified by using the one-to-one classification algorithm. The results are shown in Table 2

Table 2. The simulation results of one-to-one algorithm

Test sample (each group has two test samples)	Normal 11	Bending 22	Unbalanced 33	Defect 44	Deputy roller normal 55	Oval 66
SVM12	11	22	11	11	11	11
SVM13	11	11	33	11	11	11
SVM14	11	11	11	44	11	11
SVM15	11	11	55	11	55	55
SVM16	11	11	11	11	11	66
SVM23	33	22	33	33	33	33
SVM24	44	22	44	44	44	44
SVM25	55	22	55	55	55	55
SVM26	22	22	66	22	26	66
SVM34	44	44	33	44	44	44
SVM35	55	55	33	55	55	55
SVM36	33	33	33	33	33	66
SVM45	55	55	55	44	55	55
SVM46	44	44	44	44	44	66
SVM56	55	55	55	55	55	66
The final category	11	22	33	44	55	66

For each SVM classifier, the appropriate penalty parameters C and the kernel parameters γ are selected. By using a one-to-many classification algorithm, the fault is identified. The results are shown in Table 3.

Table 3. The simulation results of one-to-many algorithm

Test sample (each group has two test samples)	Normal 11	Bending 22	Unbalanced 33	Defect 44	Deputy roller normal 55	Oval 66
SVM1	11	-1-1	-1-1	-1-1	-1-1	-1-1
SVM2	-1-1	11	-1-1	-1-1	-1-1	-1-1
SVM3	-1-1	-1-1	1-1	-1-1	-1-1	-1-1
SVM4	-1-1	-1-1	-1-1	11	-1-1	-1-1
SVM5	-1-1	-1-1	-1-1	-1-1	11	-1-1
SVM6	-1-1	-1-1	-1-1	-1-1	-1-1	11
The final category	11	22	3 others	44	55	66

As can be seen from Table 2 and Table 3, the one-to-one algorithm is more accurate. This is due to the fact that each classifier in the one-to-many algorithm is classified between the class and the rest, and the number of sample data of the other classes is often several times the number of sample data. So, when n is large, a classifier of the two types of data vary widely. This may affect the classification of the model, resulting in an increase in the likelihood of misjudgment during testing. Therefore, this paper uses a one-to-one classification algorithm.

4.2 Comparison between support vector machine and BP neural networks

The BP neural network is used to design the automatic recognition program. It is composed of four modules, namely, input module, training module, diagnosis module and output module. The simulation results of support vector machine and BP neural network are compared. The results are shown in Table 4.

Table 4. Comparison of simulation results between support vector machines and BP neural networks

Algorithm	Accuracy	Execution time
Support vector machine	100%	0.05
BP neural networks	87.5%	26.73

As can be seen from Table 4, the support vector machine has the characteristics of high accuracy and fast diagnosis. In addition, it has more advantages than other methods in the failure of the spinning frame, and it can get more accurate classification results.

5 CONCLUSION

This paper makes a basic research on the application of roller vibration detection and fault diagnosis. The method of support vector machine is used to classify and identify faults. According to the experimental results, the following conclusions can be obtained. The training speed of the support vector machine is fast and the performance is good. After training, the model has a high accuracy in testing the sample and remains the same results for the same test sample. It is much faster than the BP neural network, and the accuracy rate can reach 100% in the case of small samples. It can identify several faults very accurately. However, the BP neural network cannot achieve such a high accuracy rate. Compared with the neural network, the generalization ability is strong. For multiple classification problems, the impact of different classification algorithms on classification results needs to be considered. At present, the two commonly used types of algorithms are "one-to-one" and "one-to-many". These two methods have their own advantages and disadvantages. The example shows that for the same samples and training parameters, the one-to-one algorithm is less likely to be misjudged than the one-to-many algorithm.

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