Fault diagnosis method for switch control circuit based on SVM-AdaBoost

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Abstract: In order to realize the fault diagnosis of the control circuit of all-electronic computer interlocking system (ACIS) for railway signals, taking a five-wire switch electronic control module as an research object, we propose a method of selecting the sample set of the basic classifier by roulette method and realizing fault diagnosis by using SVM-AdaBoost. The experimental results show that the proportion of basic classifier samples affects classification accuracy, which reaches the highest when the proportion is 85%. When selecting the sample set of basic classifier by roulette method, the fault diagnosis accuracy is generally higher than that of the maximum weight priority method. When the optimal proportion 85% is taken, the accuracy is highest up to 96.3%. More importantly, this way can better adapt to the critical data and improve the anti-interference ability of the algorithm, and therefore it provides a basis for fault diagnosis of ACIS.

Key words: all-electronic computer interlocking system (ACIS); switch control circuit; support vector machine (SVM); AdaBoost; fault diagnosis

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0 Introduction

Nowadays, the railway station signal control system have entered the stage of vigorous development of the fourth generation all-electronic computer interlocking system (ACIS)[1], which can implement the interlocking function of station signal equipment by electrical or electronic equipment. In this research, taking the control circuit of five-wire switch all-electronic control module (switch module)[2] in ACIS as a research object, the fault diagnosis method is studied by using a large amount of historical operation and debug fault data.

As an important part of ACIS, switch module can realize all-electronic real-time control of the switch. Because of large operation current and electromagnetic interference, the fault frequency of the control circuit of switch module is high. In ACIS, switch module acts as real-time security systems, in which the relationship between multiple performance parameters is complex and the fault has random uncertainty and fuzziness, therefore the fault is difficult to distinguish. At present, diagnosis of the ACIS mainly relays on artificial experience. Researchers also have paid attention to intelligent diagnosis methods of control circuit[3], such as neural network[4-5], support vecotr machine (SVM)[6], Bayesian network[7], etc. However, there is no successful application in fault diagnosis of ACIS. Therefore, it is of great significance to study the intelligent fault diagnosis method of control circuit based on multi-performance parameters for production debugging and fault repairing of ACIS, as well as to improve the intelligence of railway signal control system.

Adaboost[8] can adaptively adjust the accuracy of the classifier by choosing the samples of the basic classifier in the way of maximum weight priority, which changes the data distribution of training samples. Each iteration will obtain a basic classifier with the best classification and its weight in the overall classifier. As iterations increase, the final strong classifier generated by the basic classifier iteration has the smallest classification error, while SVM[9] has greater advantages in solving small sample, non-linear and high-dimensional problems. In this paper, based on the fault data accumulated by switch module in ACIS for a couple of years, a

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method of selecting basic classifier samples by roulette method and diagnosing them by combining the advantages of SVM and AdaBoost algorithm[10] is proposed, and then the fault diagnosis simulation of switch module control circuit is carried out. The results show that it can provide a basis for fault diagnosis of ACIS.

1 Analysis of switch module control circuit

Switch module drives AC five-wire switch machine to control the switch. The operation circuit structure is shown in Fig. 1. The circuit interfaces X1, X2, X3, X4 and X5 are control wires connected with the switch machine through the distributor to realize switch driving and state acquisition. A, B and C are three-phase power source, K1 to K7 are electronic control switches. Besides, main switch breakdown inspection circuit, phase supervision device and current detection circuit are set up to monitor the working state of the circuit in real time.

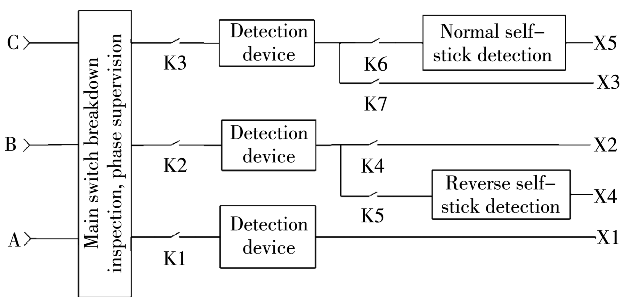

Fig. 1 Structure diagram of switch module main operation circuit

The operating flow of switch operation circuit is as follows: When the switch is in reverse position and the switch module receives the normal operation command from interlocking system, switches K1, K2, K3, K4 and K6 are turned on and then X1, X2 and X5 are connected, which drives the switch machine to rotate towards normal position. When the switch is in normal position and the switch module receives reverse operation command, switches K1, K2, K3, K5 and K7 are turned on and then X1, X3 and X4 are connected, which leads to phase conversion and drives the switch machine to reverse position.

Switch module indication circuit structure is shown in Fig. 2. It consists of transformer, current limiting resistance R1, normal indication detection circuit, reverse indication detection circuit, power source for switch indication, etc. It can monitor the switch position in real time.

Indication diode, usually connected to the distributor, is the main component of the whole circuit. When it breaks down and is reversely connected, switch indication is lost, which can also effectively prevent X2 and X3 from reversing and resulting in error indication. Therefore, indication diode is an important component to ensure the normal operation of switch indication circuit, but its component characteristics lead to frequent faults of the whole circuit, therefore it should be included in the whole control circuit for fault analysis.

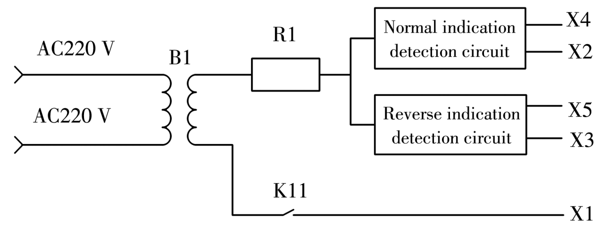

Fig. 2 Structure diagram of switch module indication circuit

According to the features of the control circuit of switch module, the fault tree[11] is drawn, as shown in Fig. 3. Ten types of failure modes are defined from A1 to A10, as listed in Table 1, which are represented by labels −5 to 5, respectively.

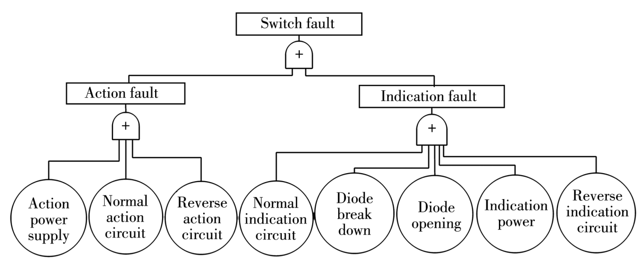

Fig. 3 Fault tree of Switch module control circuit

Table 1 Fault modes of Switch module control circuit

ID	Label	Failure mode
A1	−5	Operation fault free
A2	−4	Indication fault free
A3	−3	Normal operation circuit fault
A4	−2	Reverse operation circuit fault
A5	−1	Indication diode open
A6	1	Normal indication circuit fault
A7	2	Reverse indication circuit fault
A8	3	Indication diode breakdown
A9	4	Switch operation power fault
A10	5	Switch indication power fault

In order to diagnose switch module control circuit, 13 separated fault features are selected from ACIS and monitoring machine according to fault mode and cause analysis, as listed in Table 2, which are recorded as B1 to B13.

Table 2 Fault features description of switch module control circuit

ID	Features Description
B1	A phase current
B2	Switch K4,K6 state
B3	Switch K5,K7 state
B4	B phase current
B5	C phase current
B6	Switch normal indication
B7	Switch reverse indication
B8	Abnormal normal indication signal
B9	Abnormal reverse indication signal
B10	Phase disordering
B11	Operation voltage
B12	Indication voltage
B13	Switch operation state

Therefore, the fault diagnosis of switch module control circuit takes the fault features shown in Table 2 as inputs and the fault modes shown in Table 1 as outputs.

2 SVM-AdaBoost fault diagnosis method

The problem studied in this paper has the characteristics of small sample size, non-linearity and high dimension, therefore SVM is used as the basic classifier. AdaBoost[12] method can enhance the performance of classifier adaptively by superposition, but in the process of Adaboost training, the training is too biased towards such difficult samples, which makes the Adaboost algorithm vulnerable to noise interference. Because roulette algorithm can ensure that each sample has a certain probability of being selected to form a subset of the basic classifier, it can improve the anti-interference ability of the classifier. Therefore, roulette algorithm is used as the selection method of training sample subset of basic classifier, SVM-AdaBoost is used as fault diagnosis method, and switch module control circuit is taken to study the fault diagnosis method of control circuit of ACIS.

2.1 SVM

SVM[13] is a machine learning method based on statistical learning theory. It improves the generalization ability of learning machine by seeking the smallest structured risk, realizes the minimization of experience risk and confidence range, and achieves the goal of good statistical law in the case of fewer samples.

For a set of training samples

$$S = \{(\boldsymbol{x}_i, y_i)\},\ \boldsymbol{x}_i \in \mathbf{R}^n,\ y_i \in \{1, -1\}, \tag{1}$$

where $\boldsymbol{x}_i$ is the data point, y_i represents the sample category. To classify the vast majority of samples correctly, the hyperplane should satisfy the requirement of maximizing the sum of the minimum distances from two types of sample points to the hyperplane. The expression of the hyperplane is given by

$$\boldsymbol{w}^{\mathrm{T}}\boldsymbol{x} + b = 0. \tag{2}$$

where $\boldsymbol{w}$ is the weight vector and b is bias of hyperplane. The distributions of $\boldsymbol{w}$ and b are essentially linear, and non-linearity is caused by noise, that is, there are very few outliers far from the normal position. Using soft interval, good results can be obtained as

$$\begin{gathered} \min \frac{1}{2}\|\boldsymbol{w}\|^2 + c\sum_{i=1}^{n}\xi_i \\ \text{s.t. } y_i(\boldsymbol{w}^{\mathrm{T}}\boldsymbol{x}_i + b) \geqslant 1 - \xi_i, \\ \xi_i \geqslant 0,\ i = 1, 2, \cdots, n, \end{gathered} \tag{3}$$

where ξ_i is a slack variable and represents the number of function intervals of the data point $\boldsymbol{x}_i$ allowed to deviate from the hyperplane; $c>0$ is a penalty factor and presents the tolerance allowed to make mistakes.

For linear non-separable problems, the data are mapped to high-dimensional space by kernel function, and the SVM is extended to the non-linear separable case. Since Eq. (3) satisfies the karush-kuhn-tucher (KKT) condition, the above problem is transformed into

$$\begin{gathered} \max_{\alpha} \sum_{i=1}^{n}\alpha_i - \frac{1}{2}\sum_{i,j=1}^{n}\alpha_i\alpha_j y_i y_j K(\boldsymbol{x}_i, \boldsymbol{x}_j), \\ \text{s.t. } 0 \leqslant \alpha_i \leqslant c, \\ \sum_{i=1}^{n}\alpha_i y_i = 0, \end{gathered} \tag{4}$$

where α_i and α_j are Lagrange coefficients and $K(\boldsymbol{x}_i, \boldsymbol{x}_j)$ is the kernal function. Here, linear and Gaussian kernels are used, and their expressions are given by

$$K(\boldsymbol{x}_i, \boldsymbol{x}_j) = \langle \boldsymbol{x}_i, \boldsymbol{x}_j \rangle, \tag{5}$$

$$K(\boldsymbol{x}_i, \boldsymbol{x}_j) = \exp\left(\frac{-\|\boldsymbol{x}_i - \boldsymbol{x}_j\|^2}{2\delta^2}\right). \tag{6}$$

The decision function can be obtained by

$$f(x) = \mathrm{sign}\left(\sum_{i,j=1}^{n}\alpha_i y_i K(\boldsymbol{x}_i, \boldsymbol{x}) + b\right). \tag{7}$$

The above parameters c and δ are determined by grid optimization method.

2.2 SVM-AdaBoost method

The core idea of AdaBoost algorithm is to increase the weight of error sample and to reduce the weight of correct samples, so as to train a new basic classifier under the new sample distribution. Thus several basic classifiers are obtained, and a strong classifier is formed by superimposing certain weights.

To improve the anti-interference ability of AdaBoost, the proportional coefficient K is set, and K-ratio samples are selected by roulette algorithm to form a subset of basic classifier samples in each iteration.

The basic idea of roulette algorithm is that the probability of a sample being selected is proportional to the value of its fitness function. If the sample size is N and $fit(\boldsymbol{x}_i)$ is the fitness of sample $\boldsymbol{x}_i$, the selection probability of $\boldsymbol{x}_i$ is calculated by

$$p(\boldsymbol{x}_i) = \frac{fit(\boldsymbol{x}_i)}{\sum_{i=1}^{n} fit(\boldsymbol{x}_i)}. \tag{8}$$

Roulette process is as follows.

1) Produce a random number R with uniform distribution in an interval of $[0,1]$.

2) If $R \leqslant q_1$, sample $\boldsymbol{x}_1$ is selected;

3) If $q_{n-1} \leqslant R \leqslant q_n$ $(2 \leqslant n \leqslant N)$, sample $\boldsymbol{x}_n$ is selected, where $q_n = \sum_{j=1}^{n} p(\boldsymbol{x}_j)$ is called the accumulation probability of $\boldsymbol{x}_n$.

The training process of the SVM-AdaBoost algorithm[14] for selecting the sample set of the basic classifier by roulette method is as follows.

1) According to the training sample set

$$S = \{(\boldsymbol{x}_i, y_i)\},\ i = 1,2,\cdots,N, \tag{9}$$

we choose the proportion p of basic classifier samples to total samples, the iteration number M, the exit accuracy A, and the individual fitness $fit(\boldsymbol{x}_i)$ of smaple $\boldsymbol{x}_i$, where $fit(x_i)$ is the current weight of the sample x_i.

2) Initialize sample weights

$$\boldsymbol{v}_1 = (v_{1,1},\cdots,v_{1,i},\cdots,v_{1,N}),\ v_{1,i} = \frac{1}{N}. \tag{10}$$

3) For the number of iterations $m=1,2,\cdots,M$,

① According to the current sample weight $v_{m,i}$, the training sample subset $S_m \subset S$ of basic classifier $G_m(\boldsymbol{x})$ is obtained by roulette algorithm;

② Using the training data set with weight distribution $\boldsymbol{v}_m$, the basic classifier $G_m(\boldsymbol{x})$ is obtained by SVM learning.

③ The classification error rate e_m of $G_m(\boldsymbol{x})$ on the training data set is calculated by

$$e_m = \sum_{i=1}^{N} v_{m,i} I_{m,i}, \tag{11}$$

where $I_{m,i} = \begin{cases} 1, & G_m(x_i) \neq y_i, \\ 0, & G_m(x_i) = y_i. \end{cases}$

④ The weight of $G_m(\boldsymbol{x})$ in the final classifier is calculated by

$$\alpha_m = \frac{1}{2} \ln \frac{1-e_m}{e_m}, \tag{12}$$

where α_m denotes the importance of $G_m(\boldsymbol{x})$ in the final classifier, and its purpose is to obtain the weight of the basic classifier in the final classifier.

⑤ The weight distribution of the training data set is update by

$$v_{m+1,i} = \frac{v_{m,i}}{z_m} \exp(-\alpha_m y_i G_m(\boldsymbol{x}_i)), \tag{13}$$

$$z_m = \sum_{i=1}^{N} v_{m,i} \exp(-\alpha_m y_i G_m(\boldsymbol{x}_i)), \tag{14}$$

where z_m is the normalization factor, making v_{m+1} obey a probability distribution. The updating increases the weights of the samples misclassified and reduces the weights of the samples correctly classified by the basic classifier. Thus, the AdaBoost method can focus on the more difficult samples. Then Eq. (12) is reduced to

$$v_{m+1,i} = \begin{cases} \dfrac{v_{m,i}}{2e_m}, & y_i G_m(\boldsymbol{x}_i) = -1, \\ \dfrac{v_{m,i}}{2(1-e_m)}, & y_i G_m(\boldsymbol{x}_i) = 1, \end{cases} \tag{15}$$

where $y_i G_m(\boldsymbol{x}_i) = -1$ represents that the sample is misclassified by the basic classifier, and $y_i G_m(\boldsymbol{x}_i) = 1$ represents that the sample is correctly classified.

⑥ The training process is completed after the classification accuracy reaches the established threshold A or iteration has performed M times.

4) The decision function $F(\boldsymbol{x})$ of the final classifier is obtained as

$$F(x) = \operatorname{sign}\Big(\sum_{m=1}^{M} \alpha_m G_m(\boldsymbol{x})\Big). \tag{16}$$

The algorithm classification process is described as follows.

1) Weak classifiers are cascaded into strong classifiers as

$$F(x) = \sum_{m=1}^{M} \alpha_m G_m(\boldsymbol{x}). \tag{17}$$

2) Substituting the sample values into Eq. (16), classification results are obtained as

$$f(\boldsymbol{x}) = \begin{cases} 1, & F(\boldsymbol{x}) > 0, \\ -1, & F(\boldsymbol{x}) < 0. \end{cases} \tag{18}$$

The above process is a binary classification problem. To solve the multi-classification problem, a pair of multi-classification methods are used to construct a multi-classifier. The approach is to design a classifier between any two classes of samples, therefore the l-class samples need to design $l(l-1)/2$ classifiers. When classifying an unknown sample, the category that gets the most votes is the category of the unknown sample.

Selceting the samples of basic classifier by using roulette algorithm can ensure that the algorithm pays attention to the difficult samples, while smaller weight samples can also have a certain probability to participate in the training process, which improves the integrity of the basic classifier samples, makes the basic classifier after several iterations not completely concentrated on the difficult samples, and improves the anti-interference ability of the classifier. At the same time, the different sample sets ensure the heterogeneity of the basic classifier.

3 Simulation and analysis

Fault diagnosis is carried out by using 1 784 fault data accumulated from more than 400 railway stations and production debugging. The sample distribution is shown in Table 3.

Table 3 Samples distribution of switch module control circuit faults

ID	Label	Number of total samples	Number of training samples	Number of test samples
A1	−5	300	250	50
A2	−4	300	250	50
A3	−3	177	127	50
A4	−2	148	98	50
A5	−1	252	202	50
A6	1	170	120	50
A7	2	182	132	50
A8	3	165	115	50
A9	4	50	35	15
A10	5	40	25	15

3.1 Samples acquisition of basic classifier

The basic classifier samples are selected by the maximum weight priority and roulette method, respectively. The two methods select all the unified samples and use SVM-AdaBoost to classify faults. The strategies are as follows.

1) When sample proportion p is 55%, 65%, 75%, 85%, 95% and 100%, respectively, the samples are trained.

2) The maximum weight priority method ranks the samples according to their weights, and takes the top p data as the subset of the basic classifier. The roulette method chooses the sample subset in the roulette method described in Section 2.2.

3) SVM-AdaBoost is used to train the two way, and results are verified by test data, as shown in Fig. 4.

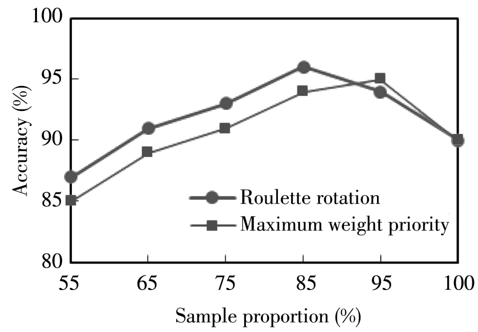

Fig. 4 Impact of sample acquisition methods on basic classifiers

The experimental results show that the diagnosis accuracy of the classifier which uses roulette method is generally higher than that of the maximum weight priority method when the proportion of samples is less than 85%. When $p > 85\%$, the diagnosis accuracy of the maximum weight priority method is slightly higher than that of the roulette method, and when $p = 85\%$, the SVM-AdaBoost algorithm has the highest diagnosis accuracy when the roulette method is used to select the basic classifier samples. Therefore, the optimal proportion is $p=85\%$.

3.2 Analysis of fault diagnosis accuracy

The diagnosis experiments are carried out by using the methods shown in Table 4. Because of small sample size, SVM shows better accuracy than BP neural network. The average fault diagnosis rate of linear kernel SVM and BP neural network are approximately equal, about 80%. For Gauss kernel SVM, the optimal classification parameters c and δ are chosen by grid optimization method. When $C_{\text{best}} = 4$ and $\delta_{\text{best}} = 12.8$, the classification result is the best, and the accuracy is 89.4%.

Linear kernel SVM has a strong ability to classify single feature fault such as operation power fault represented by A9 and indication power fault represented by A10, and all of them are classified correctly. Compared with linear kernel SVM, Gauss kernel SVM, which has higher fault diagnosis rate for other non-single feature faults. For A6, A7 and A8 fault modes, Gauss kernel SVM shows lower resolution than other modes because based on train station fault data, experienced engineers can hardly distinguish these three types of faults from the monitor data and curves. The average accuracy of Gauss kernel SVM is higher than that of linear kernel SVM and BP neural network method.

Table 4 Fault rate of Switch module control circuit

Diagnosis methods	Accuracy (%)										Average accuracy(%)
	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	
BP Neural Network	78	82	72	80	84	78	76	84	86.7	93.3	80
Linear kernel SVM	82	76	74	76	82	78	76	80	100	100	79.5
Gauss kernel SVM	96	92	92	94	90	86	82	82	93.3	86.7	89.4
SVM-AdaBoost	94	100	96	100	96	92	94	98	93.3	100	96.3

For the SVM-AdaBoost method, it uses roulette algorithm to select basic classifier samples. Taking into account the fact that linear kernel SVM has a high fault diagnosis rate for single fearture faults, the first basic classifier uses linear kernel SVM, and subsequently uses Gaussian kernel SVM. Each Gaussian kernel SVM uses grid optimization method to determine parameters c and δ.

Let the accuracy threshold $A=95\%$, the number of iterations $M=10$, and then the experiment is carried out. When iteration performs 4 times, the accuracy meets the loop iteration exit request. At this point, the SVM-AdaBoost fault diagnosis result is shown in Fig. 5, and the accuracy is up to 96.3% (414/430), which is much better than other methods. It is proved that this method has better resolution in Switch module control circuit fault diagnosis.

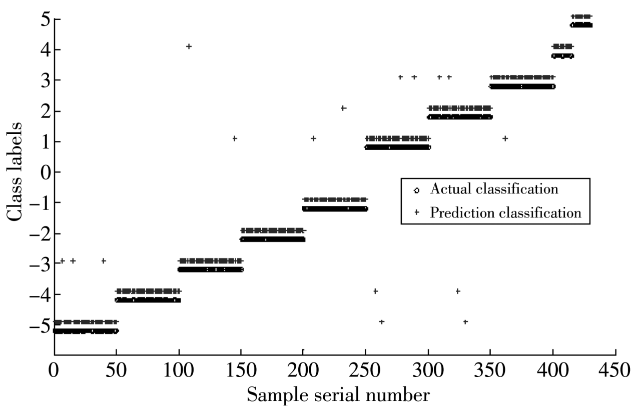

Fig. 5 Fault diagnosis results of SVM-AdaBoost

3.3 Analysis of anti-interference capability

In the process of Adaboost training, the weight of difficult samples increases exponentially, and the training is too biased towards difficult samples, which makes the Adaboost algorithm vulnerable to noise interference. Furthermore, the control circuit is vulnerable to external complex environment interference, component performance degradation and other factors, which easily causes fault feature offset and fault feature data being at the edge of normal operating conditions, while such data are vulnerable to the performance of the algorithm.

As shown in Fig. 6, non-switching features of switch module are selected to analyze the distribution of fault feature data. The data marked with circle is part of the data deviating from the normal value. The classification results show that this kind of data are easy to be misjudged by various classification methods in Table 4. Therefore, outliers far away from the most points in Fig. 6 and the similar outliers artificially simulated are selected to form a test sample set with a total of 100 data.

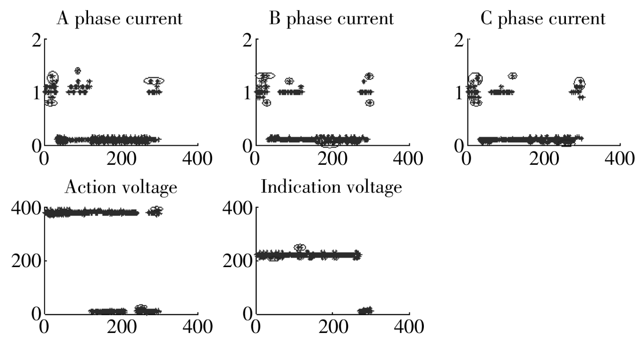

Fig. 6 Characteristic data distribution of switch module control circuit

The experimental results are shown in Table 5. For this kind of samples, the accuracy of sample selection by roulette method is 14% higher than that by maximum weight priority way.

Table 5 Analysis of anti-interference ability of SVM-AdaBoost

	Maximum weight priority	Roulette block method
Accuracy	74%	88%

Experimental results show that the method of fault diagnosis based on SVM-AdaBoost can better adapt to critical data and improve anti-interference ability when the sample set of basic classifier is selected by using roulette method.

4 Conclusion

In this paper, the SVM-AdaBoost method is used to diagnose the switch module control circuit of the ACIS.

The acquisition way of basic classifier sample set affects the diagnosis accuracy of SVM-AdaBoost. The diagnosis accuracy is generally higher than the maximum weight priority method by using the roulette method to obtain samples. Simultaneously, this method can better adapt to critical data and improve the anti-interference ability of the algorithm.

The proportion of basic classifier samples has a great influence on the accuracy of SVM-AdaBoost fault diagnosis. The proportion of samples can be determined by experiment according to the sample data. The fault diagnosis method based on SVM-AdaBoost for switch module control circuit has better accuracy. The research content can be applied to the fault diagnosis of ACIS.

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基于 SVM-AdaBoost 的道岔控制电路故障诊断方法研究

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摘　要： 为实现铁路信号全电子计算机联锁系统控制电路的故障诊断，以五线制道岔全电子控制模块为例，提出了采用轮盘赌转法选择基本分类器的样本集，采用 SVM-AdaBoost 算法实现故障诊断的方法。实验结果表明，基本分类器样本占比影响分类准确率，样本占比为 85%时准确率最高；轮盘赌转法选择基本分类器的样本集后故障诊断准确率普遍高于最大权重优先的方式，准确率达 96.3%；同时该方法能更好地适应临界数据，提高算法抗干扰能力。因此本论文的研究内容可为全电子计算机联锁系统的故障诊断提供依据。

关键词： 全电子计算机联锁系统；开关控制电路；支持向量机；AdaBoost；故障诊断

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