Fault Diagnosis and Classification of Mine Motor Based on RS and SVM

Xianmin Ma, Xing Zhang and Zhanshe Yang

Abstract A fault diagnosis method that based on Rough Sets (RS) and Support Vector Machine (SVM) is proposed, because of the diversity and redundancy of fault data for the mine hoist motor. RS theory is used to analyze the stator current fault data of mine hoist machine in order to exclude uncertain, duplicate information. For getting the optimal decision table, the equivalence relationship of positive domains of between decision attributes and different condition attributes is analyzed in the decision tables to simplify condition attributes. The optimal decision table is as the SVM input samples to establish the SVM training model. And the mapping model which reflects the relation of the characteristics between condition attribute and decision attribute is obtained by SVM training model in order to realize the fault diagnosis of the mine hoist machine. The simulation results show that the fault diagnosis method based on RS and SVM ca accuracy of fault diagnosis.

Keywords Fault diagnosis · Fault classification · Mine hoist motor · RS · SVM

1 Introduction

Mine hoist is one of the "big four operating equipment" of coal mine and is called "throat" of mine, because it is the only hub connected to ground and underground. Mine hoist motor often runs under condition of frequent starting up, rotation, braking and variable loads, so motor often occurs to fault. If mine hoist motor can not be guaranteed to operate normally, not only affects the operation of the entire system, and also threaten the safety of personnel [1].

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Common types of motor fault have rotor fault, stator fault, bearing fault. The practice results show that the rotor fault rate is the highest, and the rotor bar breaking fault is the most common in rotor fault, and the rotor bar breaking fault reaches more 48.4 % [2]. When the rotor of mine hoist machine goes wrong, the stator current will produce fault frequency characteristic component corresponding with the rotor fault [3]. The Fast Fourier Transform is used to analysis the spectrum of stator current in order to obtain mine hoist machine rotor fault data. The common set theories have classical set theory, fuzzy set theory and RS theory. RS becomes the most commonly used set theory, because membership function of RS can be obtained directly in the processing data without any additional information, so it has more stronger objective analysis capabilities and fault tolerance. Equivalence relation of domain of RS theory is used to judge the collection which is made up by the similar elements in positive domain of concept, these collections are used to establish decision table of mine hoist machine fault data, and the decision table is used to search rules to predict and classify the new data. But these rules are mostly dependent on the logical reasoning of knowledge base, and there is no any relationship can be found among these rules, so the diagnosis rate is low and the efficiency is not high for this method [4, 5]. Therefore, in this paper, the intelligent algorithms are introduced, because of the limitations of expert system and the existence of empirical risk minimization principle of artificial neural network, the SVM algorithm with the feature of achieving structural risk minimization principle is used and it can also solve the small sample problem. Then the optimal decision table after reduction is as the input samples of SVM to diagnose and classify the mine hoist machine fault [6].

2 Stator Current Fault Analysis

When the rotor of mine hoist machine goes wrong, the stator current will produce fault frequency characteristic component corresponding with the rotor fault, the side frequency characteristics of the fault can be shown [7]:

$$f_b = (1 \pm 2ks)f_1 \tag{1}$$

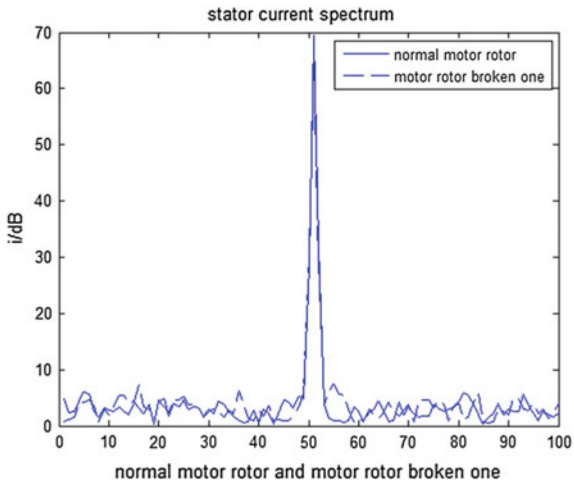
where s is slip; f_1 is power supply frequency (50 Hz).

When the rotor of mine hoist machine goes wrong, the expression of stator current can be written:

$$\begin{aligned} i = I\cos(wt - \varphi_0) + I_1 \cos[(1-2s)wt - \varphi_1] \\ + I_2[(1+2s)wt - \varphi_2] \end{aligned} \tag{2}$$

where I_1, I_2 are the amplitude of the stator current fault component feature after the rotor broken bars; φ_1, φ_2 are the characteristic initial phase corresponding to fault current component.

Fig. 1 Spectrum of normal rotor and rotor broken one

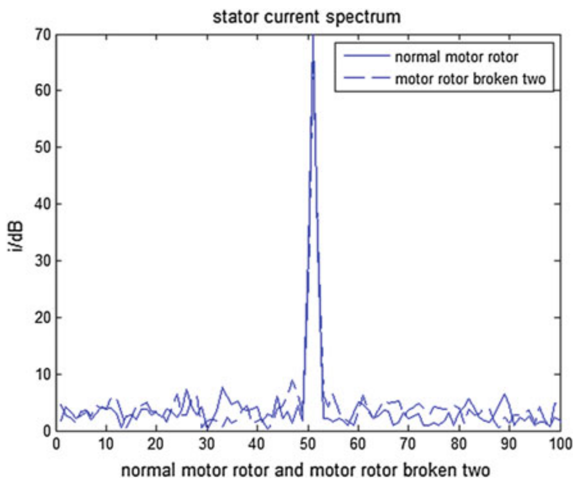


The simulation spectrum of stator current is obtained. But the stator current amplitude $(1 \pm 2ks)f_1$ is small, in order to prevent the component is affected by the magnitude of the fundamental current, the Hamming window function is used. When the slip is 0.02, the simulation spectrum of normal rotor and rotor broken one is shown in Fig. 1. The solid line represents stator current spectrum of motor rotor broken bars, the dotted line represents stator current spectrum of normal motor rotor.

From the Fig. 1 can be seen that when the rotor broken one the side frequency (the fault characteristic frequency components) of fundamental appears on the alongside. The side frequency appears on the frequency of 48 and 52 Hz.

When the motor rotor broken two, the stator current spectrum is shown in Fig. 2.

Fig. 2 Spectrum of normal rotor and rotor broken two



From Fig. 2 can be seen that when the rotor broken two the side frequency (the fault characteristic frequency components) of fundamental appears on the alongside, the side frequency appears on the frequency of 48, 52, 47, and 53 Hz.

The fault data that is extracted in spectrogram maybe has the features of duplicate, defects, redundancy, it will affect the result of diagnosis. In order to remove redundant condition attributes, eliminate duplicate samples to obtain the optimal decision table, the rough set theory is used to have the data sample pre-treatment before fault data is diagnosed.

3 RS Basic Theory

RS theory in 1982 was proposed by Polish mathematician Pawlak, RS theory is a mathematical tool to be used to analyze uncertain and redundant data, then to reveal potential rules by finding the implicit knowledge [8–11].

3.1 Knowledge Base and no Clear Relationship

Setting a non-empty finite set (theory domain)U, for any subset $X \subseteq U$ is known as the a concept or category of theory of domain, R is gens equivalence relation of $U, K = (U, R)$ is a knowledge base or approximate space, for an equivalence relation P, if $P \subseteq R$ and $P \neq \phi$, then all the intersection $(\cap P)$ of equivalence relation is also the equivalence relation on the theory of domain U, and the intersection is not clear on the relationship for an equivalence relation P, denoted $IND(P)$, further:

$$[X]_{IND(P)} = \bigcap\nolimits_{\forall R \in P} [X]_R \quad \forall x \in U \tag{3}$$

3.2 Approximation Set and Dependence

Upper and lower approximation set of subset $X \in U$ can be defined:

$$\begin{cases} \bar{R}(X) = \{x | (\forall x \in U) \wedge ([X]_R \cap X \neq \phi)\} \\ \underline{R}(X) = \{x | (\forall x \in U) \cap ([X]_R \subseteq X)\} \end{cases} \tag{4}$$

The positive domain of X about R s equal to the lower approximation set about$R$, according to the equivalence relation to judge the collection that is made up by the elements which must belong to theory domain of X.

Given $IND(K) = \{IND(P) | \phi \neq P \subseteq S\}$, it represents all equivalence relation in the knowledge base $K = (U, R)$, $\forall P, Q \in IND(K)$, the both exist the dependence of knowledge that is denoted:

$$\gamma_P(Q) = \frac{|pos_P(Q)|}{|U|} \tag{5}$$

where $pos_P(Q)$ is positive domain of Q about P.

3.3 Attribute Reduction

RS reduction is divided into attribute reduction and attribute value reduction, the attribute reduction is more complicated, methods of attribute reduction have resolution matrix reduction method and data analysis reduction method, etc.

Resolution matrix reduction method, in information systems $S = (U, B, V, f)$ of decision collection, among $B = C \cup D$ is collection of attributes, C is condition property, D is decision properties, V is value of the property, f expressed a kind of mapping: $U \times B \rightarrow V$, commonly used distinguish matrix to be expressed for:

$$M_D(i,j) = \begin{cases} \{b_k \in B \wedge b_k(x_i) \neq b_k(x_i)\} & d(x_i) \neq d(x_j) \\ 0 & d(x_i) = d(x_j) \end{cases} \tag{6}$$

where i expresses line, j says column, $i, j = 1, 2, 3, \ldots, n$, $M_D(i,j)$ represents elements of resolution matrix.

The resolution function is only defined by M_D, attributes $b \in B$, if $b(x,y) = \{b_1, b_2 \ldots, b_k\} \neq \phi$, specified a resolution function $b_1 \wedge b_2 \wedge \ldots \wedge b_k$, using $\sum b(x,y)$ to express it.

Data analysis reduction method, according to the information of the decision table (U, B) to carry on attribute reduction of attribute set B in turn, when a property is reduced to check the decision table whether to generate new rules, if it not to generate new rules, then the property can be reduced, or can not be reduced.

Delimited $r \in R$, if $IND(R) = IND(R - \{r\})$, then r is irreducible knowledge for R, if $P = (R - \{r\})$ is independent, P is a reduction about R, all irreducible relationship is called nuclear in R, denoted $CORE(R)$.

P and R are all equivalent relation cluster:

$$POS_{IND(P)}(IND(Q)) = pos_{IND(P-\{R\})}(IND(Q)) \tag{7}$$

If $R \in P$, then Q can be reduced for P, otherwise Q can not be reduced about P, equivalence relation set of all Q not about to go in P is called nuclear about Q for P, denoted $CORE_Q(P)$.

3.4 Data Decentralization

RS theory is applied only to deal with discrete data, but the collected data in the actual project is mostly continuous data, continuous attribute needs to be discrete into limited semantic symbol before to realize the processing of RS of continuous data attributes. The discrete methods commonly have discrete equidistant method, equal frequency method, and minimum entropy method, etc. But the easiest discrete way is dependent on the user own experience and knowledge to divided the area of continuous attributes into a plurality of are not mutually superimposed interval. Although rough set theory can be used to classify the new data according to the potential rules of the data reduction, this rule is more dependent on the logical reasoning of knowledge base and there will be no rules can be found among these rules, but speed is low and efficiency is not high for this diagnosis method. And when the rough set algorithm is introduced, the large number of sample data is reduced, because of the data sample is too small, the false positive rate will be greatly increased for expert systems with limitations and the artificial neural network with the principle of minimum empirical risk. Therefore, the Support Vector Machine (SVM) algorithm is applied with the principle of structural risk minimization, this algorithm can better be used to diagnose and classify small samples, nonlinear data.

4 Classification Principle of SVM Theory

SVM gets minimal actual risk and constructs statistical learning machine of optimal hyperplane based on structural risk minimization principle, SVM topology is determined by SV, and it can solve the issues which not easy to distinguish, such as small sample, non-linearity and low-dimensional space [11–15].

SVM is proposed from the case of linearly separable of the optimal hyperplane. There are training samples are assumed $E = \{(x_i, x_j), i = 1, 2, \ldots, n\}, x \in R^d$, $y_i \in \{1, 2, \ldots, k\}$, they can be correctly classified categories by established hyperplane, and the sample set should satisfy:

$$y_i[(w \cdot x_i) + b] - 1 \geq 0, i = 1, 2, \ldots, n \tag{8}$$

where w is weight, b is threshold.

The classification interval distance in this case from the above formula is $2/\|\omega\|$, when $\|w\|^2$ is minimized to get the maximum hyperplane. The Lagrange multipliers are used to solve objective function that establishes optimal hyperplane under $\sum_{i=1}^{n} \alpha_i y_i = 0$ and $\alpha_i \geq 0$ (α_i is Lagrange multipliers $i = 1, 2, \ldots, n$).

$$\sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i=1}^{n} \sum_{i=1}^{n} \alpha_i \alpha_j y_i y_j (x_i, x_j) \tag{9}$$

When α_i gets optimal solution, then optimal decision of classification function can be gotten:

$$F(x) = \mathrm{sgn}\left\{ \sum_{i=1}^{n} \alpha_i^* y_i (x_i \cdot x) + b^* \right\} \tag{10}$$

where sgn$\{\cdot\}$ is sign function.

For linear inseparable issues, a slack variable $\xi_i \geq 0$ on the basis of linear problem is introduced, sample collection should meet:

$$y_i[(w \cdot x_i) + b] - 1 + \xi_i \geq 0, i = 1, 2, \ldots, n \tag{11}$$

When the formula satisfies the constraints $\sum_{i=1}^{n} \alpha_i y_i = 0$ and $0 \leq \alpha_i \leq C$, the α_i gets optimal solution, then optimal decision of classification function can be gotten:

$$F(x) = \mathrm{sgn}\left\{ \sum_{i=1}^{n} \alpha_i^* y_i (x_i \cdot x) + b^* \right\} \tag{12}$$

There are given a multivalued classifier that "one to one" combined with "One to many" algorithms, then the classification function of the multi-fault classifier can be established, the function can be written:

$$F^{\mathrm{m}}(x) = sign\left\{ \sum_{SV} \alpha_i^m y_i^m k(x_i, x) + b^m \right\} \tag{13}$$

5 Case Analysis

There are basic steps based on RS theory and SVM algorithm:

(1) The collected data is analyzed to do the normalization process
(2) The data after the normalization processing is discrete to form a decision Table
(3) For duplicate sample or redundant rules doing reduction in the decision Table
(4) Optimal decision table is gotten
(5) The optimal decision table is as input samples of SVM to establish SVM training model, samples have been treated by RS compare with the SVM simulation results of the samples which have not been treated by RS.

In this paper, these four fault types that rotor broken one (1), rotor broken two (2), rotor broken three (3) and rotor broken four (4) of mine hoist machine rotor are as an example for fault diagnosis, according to the spectrum analysis of stator current to extract the section frequency band data is as the mine hoist machine fault

Table 1 Mine hoist machine data

Sam.	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8	Type
c1	0.045	0.032	0.018	0.764	0.104	0.029	0.079	0.011	1
c2	0.038	0.019	0.027	0.875	0.076	0.034	0.049	0.009	1
c3	0.052	0.029	0.048	0.796	0.087	0.073	0.073	0.006	1
c4	0.062	0.041	0.452	0.258	0.074	0.055	0.058	0.083	2
c5	0.023	0.061	0.163	0.843	0.239	0.042	0.042	0.007	2
c6	0.039	0.021	0.072	0.782	0.068	0.065	0.060	0.018	2
c7	0.044	0.072	0.033	0.812	0.169	0.028	0.022	0.017	2
c8	0.078	0.051	0.003	0.852	0.091	0.048	0.014	0.004	3
c9	0.057	0.042	0.053	0.524	0.259	0.100	0.097	0.031	3
c10	0.058	0.069	0.017	0.777	0.075	0.069	0.016	0.088	3
c11	0.022	0.036	0.054	0.432	0.226	0.255	0.551	0.020	4
c12	0.014	0.030	0.249	0.344	0.265	0.132	0.225	0.026	4
c13	0.037	0.026	0.020	0.701	0.053	0.044	0.213	0.005	4
c14	0.052	0.035	0.043	0.810	0.066	0.032	0.149	0.016	4

Table 2 Fault decision table

Sam.	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8	D
c1	0	0	0	1	1	0	0	0	1
c2	0	0	0	1	0	0	0	0	1
c3	0	0	0	1	0	0	0	0	1
c4	0	0	1	1	0	0	0	0	2
c5	0	0	1	1	1	0	0	0	2
c6	0	0	0	1	0	0	0	0	2
c7	0	0	0	1	1	0	0	0	2
c8	0	0	0	1	0	0	0	0	3
c9	0	0	0	1	1	1	0	0	3
c10	0	0	0	1	0	0	0	0	3
c11	0	0	0	1	1	1	1	0	4
c12	0	0	1	1	1	1	1	0	4
c13	0	0	0	1	0	0	1	0	4
c14	0	0	0	1	0	0	1	0	4

data, such as $\leq 0.125 f_1(a_1)$,$(0.125\sim 0.5)f_1(a_2)$,$(0.625\sim 0.75)f_1(a_3)$,$(0.875\sim 1) f_1(a_4)$,$(1.125\sim 1.5)f_1(a_5)$,$(1.625\sim 1.75)f_1(a_6)$, $(1.875\sim 2)f_1(a_7)$, $> 2f_1(a_8)$, the f_1 is speed frequency. Data is shown in Table 1, and the data has been normalized.

The data in Table 1 is dispersed by utilization frequency method, if the mine hoist machine occurs fault in the corresponding bands, the data is marked 1, otherwise the data is marked 0. Fault type is denoted D. The decision table is shown in Table 2.

Table 3 The first reduction of the decision table

Sam.	a_3	a_5	a_6	a_7	D
c1	0	1	0	0	1
c2	0	0	0	0	1
c4	1	0	0	0	2
c5	1	1	0	0	2
c6	0	0	0	0	2
c8	0	0	0	0	3
c9	0	1	1	0	3
c11	0	1	1	1	4
c12	1	1	1	1	4
c13	0	0	0	1	4

In the decision Table 2, the same fault type has duplicate samples c2, c3, the sample c3 is removed; duplicate samples c5, c7, the sample c7 is removed; duplicate samples c8, c10, the sample c10 is removed; duplicate samples c13, c14, the sample c14 is removed.

In the condition properties, a_1, a_2, a_3, a_8 are belong to the same state for all decision attribute, and they are unable to correctly distinguish the decision attributes, so these conditions attributes are eliminated. Decision table after reduction is shown in Table 3.

Theory domain is U = (c1, c2, c4, c5, c6, c8, c9, c11, c12, c13), condition property is (a_3, a_5, a_6, a_7) in the Table 3.

The equivalence of theory domain for condition attribute can be described:

$$U/C = \{\{\text{c1}\}, \{\text{c2}, , \text{c6}, \text{c8}\}, \{\text{c5}\}, \{\text{c4}\}, \{\text{c9}\}, \{\text{c11}\}, \{\text{c12}\}, \{\text{c13}\} \tag{14}$$

The equivalence of theory domain for decision property can be denoted:

$$U/D = \{\{\text{c1}, \text{c2}\}, \{\text{c4}, \text{c5}, \text{c6}\}, \{\text{c8}, \text{c9}\}, \{\{\text{c11}, \text{c12}, \text{c13}\}\} \tag{15}$$

The similar equivalence relationships can be wrote:

$$U/a_3 = \{\{\text{c1}, \text{c2}, \text{c6}, \text{c8}, \text{c9}, \text{c11}, \text{c13}\}, \{\text{c4}, \text{c5}, \text{c12}\}\} \tag{16}$$

$$U/a_5 = \{\{\text{c2}, \text{c4}, \text{c6}, \text{c8}, \text{c13}\}, \{\text{c1}, \text{c5}, \text{c9}, \text{c11}, \text{c12}\}\} \tag{17}$$

$$U/a_6 = \{\{\text{c1}, \text{c2}, \text{c4}, \text{c5}, \text{c6}, \text{c8}, \text{c13}\}, \{\text{c9}, \text{c11}, \text{c12}\}\} \tag{18}$$

$$U/a_7 = \{\{\text{c1}, \text{c2}, \text{c4}, \text{c5}, \text{c6}, \text{c8}, \text{c9}\}, \{\text{c11}, \text{c12}, \text{c13}\}\} \tag{19}$$

The positive domain of D about C is:

$$pos_C(D) = \{c1, c4, c5, c9, c11, c12, c13\} \quad (20)$$

$$\gamma_C(D) = \frac{|pos_C(D)|}{|U|} = \frac{7}{14} = 0.5 \quad (21)$$

The dependence of D for C is 0.5, so uncertain Sample is {c2, c6, c8}, they can be discarded.

The positive regions can be computed:

$$pos_{C-a_3}(D) = \{c4,\ c5,\ c12\} \neq pos_C(D) \quad (22)$$

$$pos_{C-a_5}(D) = \{c1,\ c5,\ c9,\ c11,\ c12\} \neq pos_C(D) \quad (23)$$

$$pos_{C-a_6}(D) = \{c9,\ c11,\ c12\} \neq pos_C(D) \quad (24)$$

$$pos_{C-a_7}(D) = \{c11,\ c12,\ c13\} \neq pos_C(D) \quad (25)$$

Therefore, reduction of the final condition property is (a_3, a_5, a_6, a_7).

The optimal decision table eventually can be gotten which is shown in Table 4.

The optimal decision table data samples {c1, c4, c5, c9, c11, c12, c13} are established matrix of the condition attributes and the fault types {1, 2, 3, 4} are established matrix of decision attribute, those matrix are as the input sample of SVM to train the SVM model.

Choosing different the inner product kernel functions to form different algorithms, there are four kernel functions are more commonly useful in the classification: linear kernel, polynomial kernel function, RBF kernel function and sigmoid kernel function. After several tests, the RBF is used.

$$k(x, y) = \exp\left[-\|x-y\|^2/(2s)^2\right] \quad (26)$$

where x, y are training data; s is the width of the RBF. In the paper s takes 0.5, error penalty factor C takes 10.

Table 4 Optimal decision table

Sam.	a_3	a_5	a_6	a_7	D
c1	0	1	0	0	1
c4	1	0	0	0	2
c5	1	1	0	0	2
c9	0	1	1	0	3
c11	0	1	1	1	4
c12	1	1	1	1	4
c13	0	0	0	1	4

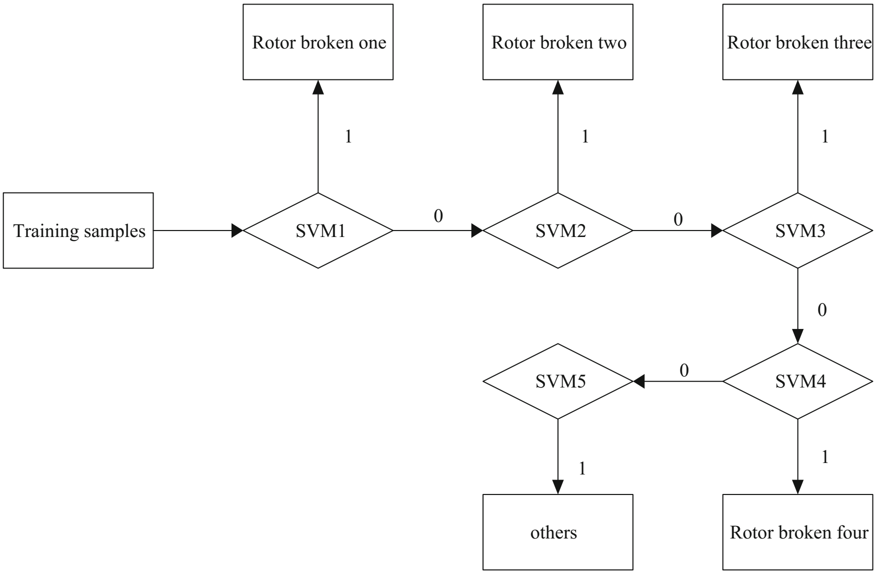


Fig. 3 The flowchart of multiple fault classifiers

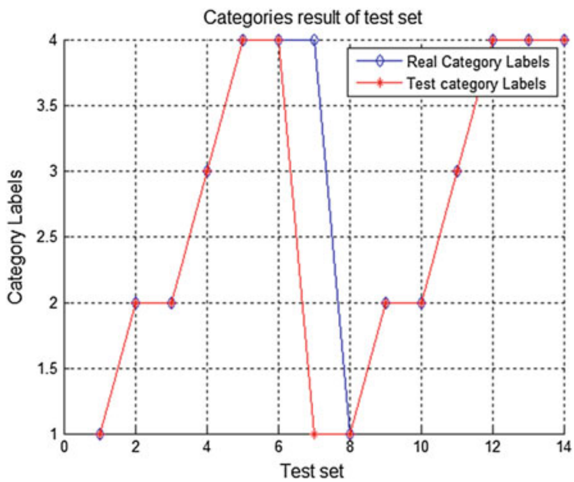


Fig. 4 SVM training results is treated by RS

The fault characteristic is as the input sample of multi-fault classifier, then the flowchart can be obtained of multiple fault classifier, as the Fig. 3 is showed.

If the output of discriminant $F^1(x)$ is 1, the sample belongs to class 1(rotor broken one), the training is finished; otherwise, training samples will go in the classifier 2 automatically, then the output of discriminant $F^2(x)$ is 1, the sample belongs to class 2 (rotor broken two), the test is finished, otherwise, test samples

Table 5 Analysis simulation result

L	1	2	3	4	5	6	7	8	9	10	11	12	13	14
M	1	2	2	3	4	4	**4**	1	2	2	3	4	4	4
N	1	2	2	3	4	4	**1**	1	2	2	3	4	4	4

will go in the classifier 3 automatically. And so on, for classifier k, if the output of discriminant $F^k(x)$ is 1, the sample belongs to class k, the output of the discriminant is 0,the sample does not belong to the any classifier.

Some test samples are selected, according to the above processing of RS reduction to carry on the reduction of test samples to get the optimal decision table of tested sample, the optimal decision table of tested sample is applied to the SVM training model, the simulation results is shown in Fig. 4.

The Table 5 is established to analyze simulation results of the test samples that have been treated by RS in Fig. 4. There L represents sample number; M represents real category; N represents test category.

In Table 5, there is an error classification sample, the classification accuracy is up to 92.857 %.

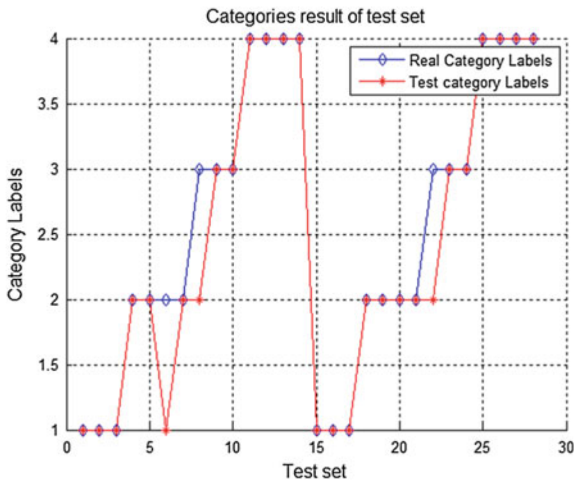


Fig. 5 SVM training results without being treated by RS

Table 6 Analysis simulation result

L	1	2	3	4	5	6	7	8	9	10	11	12	13	14
M	1	1	1	2	2	**2**	2	**3**	3	3	4	4	4	4
N	1	1	1	2	2	**1**	2	**2**	3	3	4	4	4	4
L	15	16	17	18	19	20	21	22	23	24	25	26	27	28
M	1	1	1	2	2	2	2	**3**	3	3	4	4	4	4
N	1	1	1	2	2	2	2	**2**	3	3	4	4	4	4

The SVM simulation result of test samples that had not been processed by RS is shown in Fig. 5.

The Table 6 is established to analyze simulation results of the test samples that have not been treated by RS in Fig. 5.

In Table 6, there are three error classification samples, the classification accuracy is up to 89.285 %.

The results of Table 5 compares to the results of Table 6, the accuracy of data which treated by RS to carry on fault diagnosis online has been greatly improved.

6 Conclusion

This article discusses the fault diagnosis method of mine hoist machine based on RS theory and SVM. There are some repeat and interference information of fault data which has been extracted from mine hoist machine. In order to reduce decision table and simplify diagnostic information, the RS theory is used to eliminate the uncertainty or repeated samples and to simply redundant attributes. The SVM is conducive to extract the data rapidly and raise the speed of fault diagnosis classification; in the simulation results, the fault diagnosis method based on RS and SVM is more accurate than the fault diagnosis method only based on SVM, so the fault diagnosis method has a certain practical value for the occasions of fault diagnosis needing online.

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