FAULT DIAGNOSIS OF RELEVANCE VECTOR MACHINE BASED ON HARMONIC WAVELET PACKET

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Monitoring the vibration signals of roller bearings is important indirect mean for that they reveal the characteristics and feature of roller bearing faults. Therefore, monitor the vibration signals and diagnose the working states of roller bearings are widely used to ensure the safety operation of the machines. In view of the traditional rolling bearing fault diagnosis methods are affected by human factors, the causes of the faults are relatively complex. On the basis of the existing research, a new method is proposed which is based on wavelet packet analysis and acyclic graph relevance vector machine. It disassembles and reconstructs signal of fault diagnosis under different fault conditions which uses vibration harmonic wavelet packet. At the same time, frequency band energy is extracted as a feature vector. Through the application of acyclic graph relevance vector machine, the mapping between the feature vector and fault model are developed. In this way, the fault diagnosis of rolling bearing is solved. Experimental results shows that the proposed method can diagnose rolling bearings' faults rapidly and accurately, its validity and stability are verified; moreover the superiority of RVM in intelligent fault diagnosis is revealed through the comparative analysis between DAG-RVM and SVM.

Keywords: Harmonic wavelet packet; directed acyclic graph; relevance vector machine; fault diagnosis

1. Introduction

Rolling bearing is the key component of large mechanical equipment, and its ability to work directly affects the safety of the whole mechanical equipment. Therefore, it is very necessary and significant to study the fault characteristics of large scale mechanical rolling bearings. The research on fault diagnosis of rolling bearing is essentially a problem of pattern recognition. It mainly consists of a series of faults, such as cracks in the outer ring, pitting corrosion in the inner ring, and pitting corrosion [1]. The appearance of these faults is the result of the

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interaction of many different factors, and the relationship between them is complex and nonlinear. At present, fault diagnosis methods of large-scale machinery mainly include fuzzy evaluation method, artificial neural network method and so on [2-6]. The ambiguous evaluation method can effectively express the fuzzy knowledge, but because it is often required to set the weights of evaluating factors according to the experience of experts, so the evaluation results may be affected to some extent. Artificial neural network in a strong self-learning ability and better to do the ability to approximate any nonlinear function have great advantages. At the same time, it is also a kind of human brain nervous system physical structure simulation, with a lot of network structures, its disadvantages is the expression ability is weak for the fuzzy information [7-9].

Rolling bearing in the collected data with the fault sample size is relatively small and fault information exists a lot of uncertain factors. The result of classification is also uncertain. The research results about the reform are: Chen Tie Hua et al. [10] put forward a kind of using fuzzy method to detect rolling bearing fault causes and the method can also apply fuzzy theory the concept of subordinate degree to evaluate the uncertainty of the classification results.

The results can be seeing with mechanical failure trends. The paper [11-13] also gives the method of using the support vector machine to carry out the high dimensional projection of the fault data in order to locate the source of the fault accurately. In order to achieve the objective evaluation of the uncertainty of the experimental results, the concept of rough set is introduced to give the boundary of the similarity between the experimental results and the classification results.

This paper presents a will harmonic wavelet packet and fault diagnosis method of combining RVM of directed acyclic graphs and the relevance vector machine knowledge applied to the rolling bearing fault diagnosis problems. Firstly, the data of the rolling bearing are decomposed by harmonic wavelet packet, and the wavelet decomposition coefficients of each frequency band are obtained. Secondly, using a directed acyclic graph and the multi class classification problem into a RVM binary classification problem is decomposed into. Finally, the RVM classification achieves fault type identification.

1. Introduction to related concepts

1.1 Classification model description of relevance vector machine

Relevance vector machine (RVM) the concept of was first proposed by E. Tipping Michal. Its most typical method is to use the kernel function to map the low latitude and nonlinear sample data to the high latitude space. Bayesian theory is the precondition of the training of relevance vector machine. Based on the prior distribution, the automatic correlation decision theory (Determination Automatic

Relevance, ARD) was used to eliminate the irrelevant points, so that the classification model was diluted [14]. Therefore, Bias theory is the most critical part of the relevance vector machine.

RVM is proposed to solve the two classification problem, sample target value $t_i \in \{0,1\}$. Assume that the training sample set is $\{x_i, t_i\}_{i=1}^{N}$, $x_i \in R^d$ is training samples. RVM model predictive function as shown in formula (1):

$$y(x;\omega) = \sum_{i=1}^{N} \omega_i K(x, x_i) + \omega_0 \quad (1)$$

The formula: N for the sample number; ω_i is the weight of the model; $K(x, x_i)$ is the kernel function.

The generalized linear model of $y(x;\omega)$ is applied to the prediction function sigmoid, and the sample set of the maximum likelihood function of the form (2) can be obtained:

$$p(t|\omega) = \prod_{i=1}^{N} \sigma[y(x_i;\omega)]^{t_i}\{1 - \sigma[y(x_i;\omega)]\}^{1-t_i} \quad (2)$$

Among them:$\sigma(\blacksquare)$ was expressed as sigmoid function.

In order to avoid learning phenomenon and ensure that the sparsely of the models, sparse Bayesian method to weight and mean zero Gaussian distribution restrictions, such as (3) shown:

$$p(\omega|\alpha) = \prod_{i=1}^{N} N(\omega_i|0, \alpha_i^{-1}) \quad (3)$$

In the formula: $N(\blacksquare)$ is normal distribution function; α_i is a super parameter; α is the super parameter vector, $\alpha = (\alpha_0, \alpha_1, \dots, \alpha_N)^T$.

Due to $p(t|\omega)$ is not a normal distribution, cannot solve this integral directly. Therefore, the Laplace's method to estimate the hyper parameters α values of a weights ω, specific process is as follows:

(1) Fix the current valueα; calculate the weight valueω_{MP}. According to $P(\omega|t,\alpha) \in p(t|\omega)p(\omega|\alpha)$, find the maximum value of the type (4) in the ω_{MP}:

$$\log\{p(t|\omega)p(\omega|\alpha)\} = \sum_{i=1}^{N}[t_i \log y_i + (1-t_i)\log(1-y_i)] - \frac{1}{2}\omega^T A\omega \quad (4)$$

In the formula: $y_i = \alpha[y(x_i;\omega)]$, $A = \mathrm{diag}(\alpha_0, \alpha_1, \dots, \alpha_N)$.

(2)Application of Newton method to findω_{MP}, the Laplace method is used to approximate the log posterior probability in the vicinity of its ω_{MP}.The Hessian matrix is obtained by the transformation of the covariance matrix of the weight of $\sum$.

Using the Gauss approximation of statistical covariance $\sum$ and weight ω_{MP}, the model (5) is carried out to obtain the optimal weight value.

$$\alpha_i^{new} = \frac{\gamma_i}{\omega_{Mp}^2} \quad (5)$$

Among: $\gamma_i \equiv 1 - \alpha_i \sum_{ii}$, $\sum_{ii}$ is the i-the element of the weight covariance $\sum$ diagonal.

After finding out the α_i^{new}, the mean and variance of the posterior distribution of the weights are calculated again. In the iterative process, some weight ω_i is not zero, and the corresponding x_i is called the correlation vector. The weight of the type (5), and finally get the prediction sample point probability, determine which samples belong to.

1.2 Analysis of acyclic graph model

RVM was originally proposed to solve the problem of two classifications, however, the actual life of the problem encountered is relatively complex, mostly belong to the multi classification problem. Therefore, a combination of correlation vector machine method is needed to solve this problem. And the traditional uses of more classification methods mainly include: one to one, one to many, DT-RVM, and DAGRVM, etc. Comprehensive comparison of the advantages and disadvantages of these methods can be drawn: the classification method is superior, not only the classification accuracy is high, but also sets aside time, is suitable for the reference to the large-scale machinery fault diagnosis research, therefore this article uses this method.

Decision oriented non cyclic graph (DDAG) [15] method is based on a classification algorithm based on the new algorithm idea. At the same time of classification knowledge of graph theory in the relevance vector machine to a large number of optimized combination and build a new multi classification relevance vector machine, namely DAGRVM multi class classification relevance vector machine. On a C class of multi classification problem, DAG structure, including a total of C nodes, there should be RVM C, distributed in the C layer structure. The number of layers and nodes are the same, which is to say that the first layer has a node, the corresponding layer i also contain an i node. The bottom layer also contains a leaf node with the same number of classes C, while the first i node of the j layer points to the first i and i+1 nodes of the j+1 layer, wherein the top node is called the root node. According to the characteristics of bearing fault, the fault of bearing is divided into 4 typical states: normal (1), rolling element fault (2), inner fault (3) and outer ring fault (4). The design of DAGRVM topology is shown in figure 1.which includes 4 internal nodes (at the top of the root node) and 4 leaf nodes. Decision-making oriented to non-decision, as shown in figure 1.

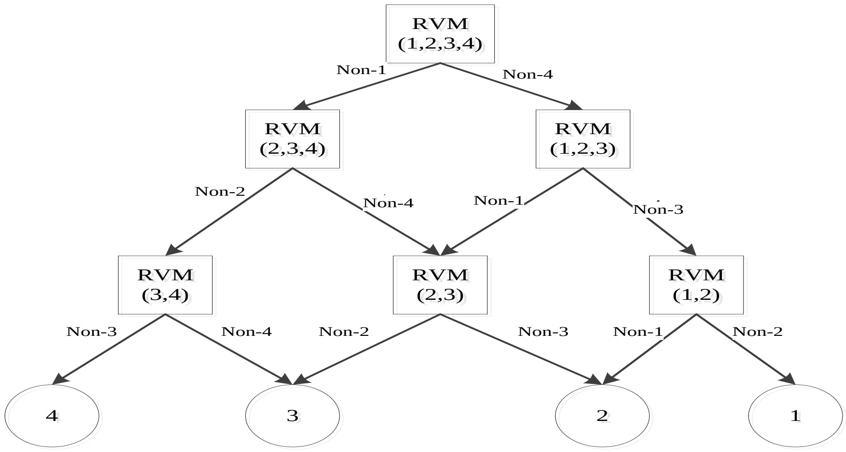


Fig. 1. Directed acyclic graph model

1.3 Analysis of harmonic wavelet packet method

1.3.1 Principle of harmonic wavelet packet

On the basis of the analysis of the harmonic wavelet signal, the new form of Newland is constructed, that is, the harmonic wavelet. The frequency band of the wavelet is given by layer by layer. With the decomposition of the signal, the same decomposition layer cannot get all the frequency bands. There are still some frequency bands which need to be decomposed. Harmonic wavelet has the characteristics of box shaped spectrum, and the analytical expression is relatively simple, the corresponding frequency domain of the general expression is:

$$\mathrm{W}_{m,n}(\omega) = \begin{cases} \frac{1}{2\pi(\mathrm{n}-\mathrm{m})}, & \omega \in [2\mathrm{m}\pi, 2n\pi] \\ 0, & \text{other} \end{cases} \tag{6}$$

For inverse Fourier transform of (6), the time domain expression of harmonic wavelet packet is:

$$\psi_{\mathrm{m,n}}(\mathrm{t}) = [\exp(\mathrm{i}2\pi\mathrm{nt}) - \exp(\mathrm{i}2\pi\mathrm{mt})]/[\mathrm{i}2\pi(\mathrm{n}-\mathrm{m})\mathrm{t}] \tag{7}$$

In the formula: m, n are the scale parameters, $\mathrm{m} = 2^j, \mathrm{n} = 2^{(j+1)},\ j \in Z^+$, i is the imaginary part and $\mathrm{i} = \sqrt{-1}$.

Therefore, the binary harmonic wavelet packet decomposition is used to achieve arbitrary refinement of frequency. Assuming that the bandwidth of the analysis band B is $\mathrm{B} = f_h/2^j$, the corresponding upper and lower bounds of the analysis band is:

$$\begin{cases} \mathrm{n} = (\mathrm{s}+1)\mathrm{B} \\ m = sB \end{cases} \qquad \mathrm{s}=0,1,2,\ldots,2^j - 1 \tag{8}$$

1.3.2 Implementation of harmonic wavelet packet in frequency domain

According to the principle of harmonic wavelet analysis, article can draw the harmonic wavelet packet frequency domain analysis, as shown in figure 2.

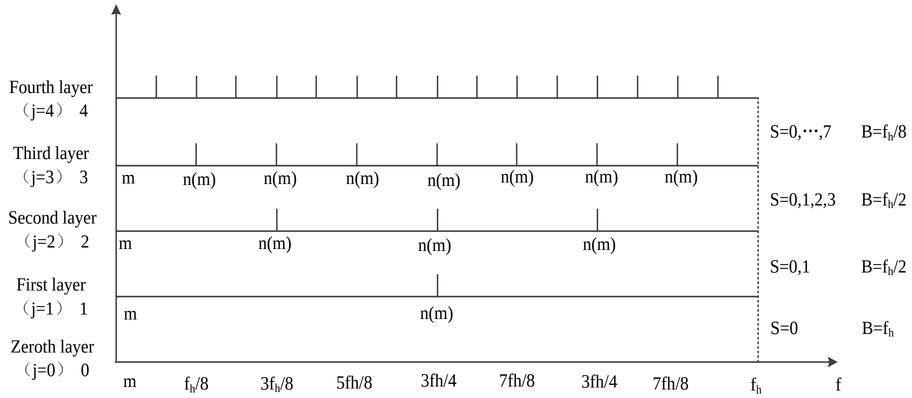


Fig. 2. Frequency domain analysis of harmonic wavelet packet

From the figure can be drawn, regardless of the frequency of the vibration signal, as long as the signal is decomposed to a certain layer, and according to m, n value to determine the upper and lower bounds of the frequency band, the following steps to achieve the transformation algorithm [16].

(1)With the prior knowledge of the signal, bandwidth and frequency band width to determine the corresponding frequency bands and layers, According to $\mathrm{B} = f_h/2^j$ and formula (9) to determine the value of the frequency band, and the corresponding number of layers j.

$$\mathrm{m} = \mathrm{sB}, \mathrm{n} = (\mathrm{s}+1)\mathrm{B}, \mathrm{s} = 0,1,2,\dots,2^{\mathrm{j}}-1 \tag{9}$$

(2) The frequency band value of the expression in the formula:

$$\mathrm{W}_{m,n}(\omega) = \begin{cases} \frac{1}{2\pi(\mathrm{n}-\mathrm{m})}, & \omega \in [\mathrm{mN}/f_s, nN/f_s] \\ 0, & \text{other} \end{cases} \tag{10}$$

In the formula: N is the signal length and f_s is the sampling frequency of the signal.

(3) Discrete signal f(r) to do FFT, to obtain spectrum F(ω

(4) The wavelet transform of the frequency band, according to the formula:

$$\widehat{\mathrm{W}}_{\mathrm{f}}(\mathrm{m},\mathrm{n},\omega) = 4\pi(\mathrm{n}-\mathrm{m})\mathrm{F}(\omega)\mathrm{f}^{\mathrm{d}}(\omega)\mathrm{W}_{m,n}(\omega) \tag{11}$$

(5) If the signal is analyzed in the time domain, the inverse FFT can be done.

1.3.3 Characteristics of the fault of rolling bearing based on Harmonic Wavelet

Harmonic wavelet packet has good performance in fault feature recognition, so it is a good tool to extract fault features in fault diagnosis field, and the specific process of fault feature extraction is as follows:

(1) Harmonic wavelet packet decomposition of the test data to obtain the wavelet coefficients;

(2) The energy values of wavelet coefficients at different scales are calculated by the formula (12):

$$E_{H_{Nj}} = \sqrt{|H_{N,i}|^2}\,dx = \sqrt{\sum_{j=1}^{M} |H_{N,i,j}|^2} \tag{12}$$

Among them, N represents the number of frequency bands; M represents the number of wavelet coefficients of each band. (3)

To get the energy for standardization:

$$\overline{E_{H_{Nj}}} = \frac{\left[E_{H_{N,j}} - \mathrm{mean}\left(E_{H_{N,j}}\right)\right]}{D_\sigma\left(E_{H_{N,j}}\right)} \tag{13}$$

In the formula, mean represents the wavelet frequency band energy mean; D_σs represents the standard deviation of the wavelet frequency band energy.

(4) The fault feature vectors are obtained as follows:

$$\overline{E_{H_N}} = \left[\ \overline{E_{H_{N,1}}}\ \ \overline{E_{H_{N,2}}}\ \ \cdots \overline{E_{H_{N,M}}}\ \right] \tag{14}$$

Harmonic wavelet packet has strong decomposition ability and localization ability, and the harmonic wavelet packet has a concise expression and operation process. According to the four typical state of the rolling bearing, namely, the normal rolling bearing, the rolling element fault, the inner fault of the inner ring and the outer ring fault, the analysis signal is divided into any frequency band.

2. Fault diagnosis of rolling bearing based on harmonic wavelet packet and dag-rvm

Based on the - based multi - classifier model, a new type of rolling bearing identification method is designed based on the DAG-RVM - based multi - classifier model, which is shown in Figure 3:

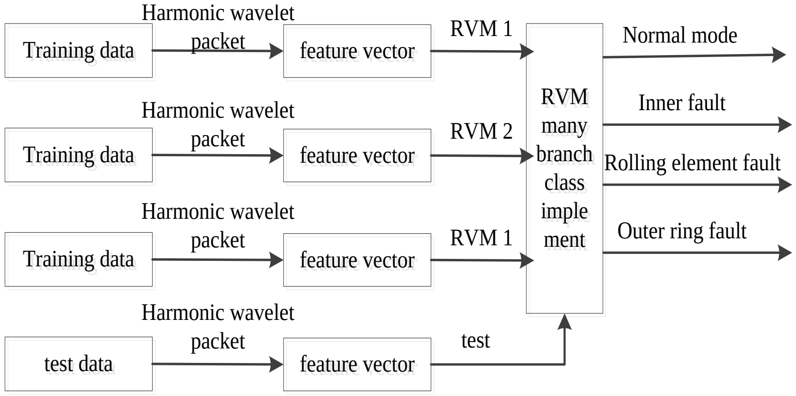


Fig. 3. Fault diagnosis model of rolling bearing

The diagnostic steps of the model are shown below:

(1) selected the rolling bearings of different modes of experimental data, the experimental data set is divided into training and test data and the training data for the RVM multimodal classifier training and test data realization of rolling bearing performance of fault diagnosis model of discrimination.

(2) Using the harmonic wavelet packet to process the multi group training data of different states, and the signal is decomposed and calculated. The characteristic vectors of rolling bearings under different fault conditions are obtained by normalizing the average and standard deviation of the wavelet frequency band energy.

(3) The different types of feature vectors are used to train the RVM two classification models, which makes the RVM multi classification model have the ability to diagnose the faults of the rolling bearings.

(4) on the test data of harmonic wavelet packet feature vector extraction processing, will get the fault characteristic vectors RVM multi classification rolling bearing diagnosis model, complete recognition judgments and output testing data type.

At the same time, article need to point out that the RVM classifier can not only make a single fault diagnosis, but also can put a set of samples into a number of combinations of RVM classifier for decision-making training, to achieve multiple fault diagnosis. Decision directed acyclic graph method, which is based on the data distribution and the diagnostic results of the path selection. Each classifier is only to determine a class of the difference between the same and other categories, equivalent to a category as a separate category. The rest as a whole as a class, so as to form a multi classifier to identify multi class fault problem, complete the identification of samples to be tested X. Its class model diagram is shown in Fig. 4:

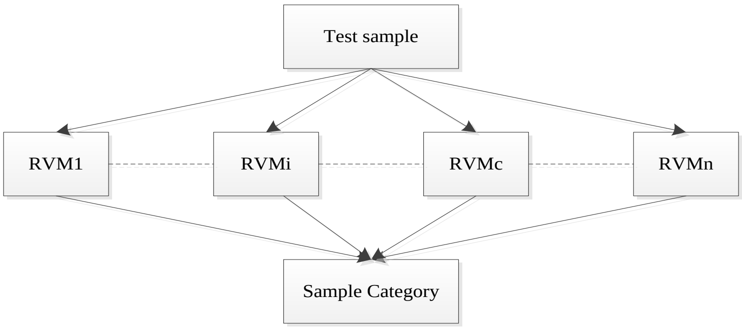
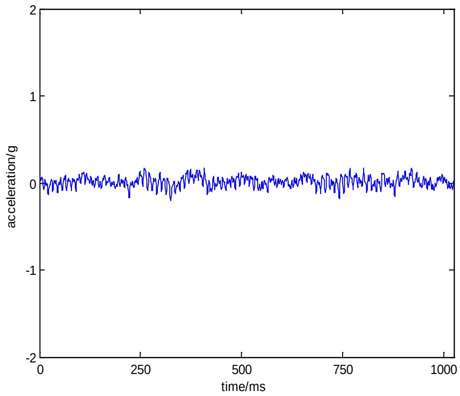
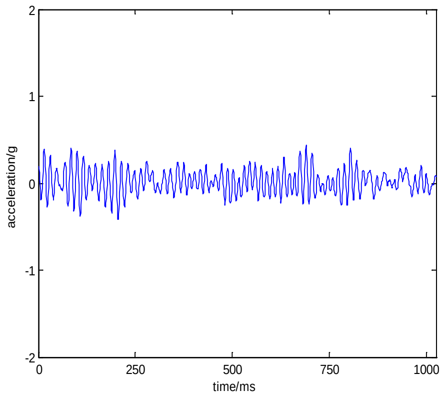


Fig. 4. RVM multi class diagnostic model chart

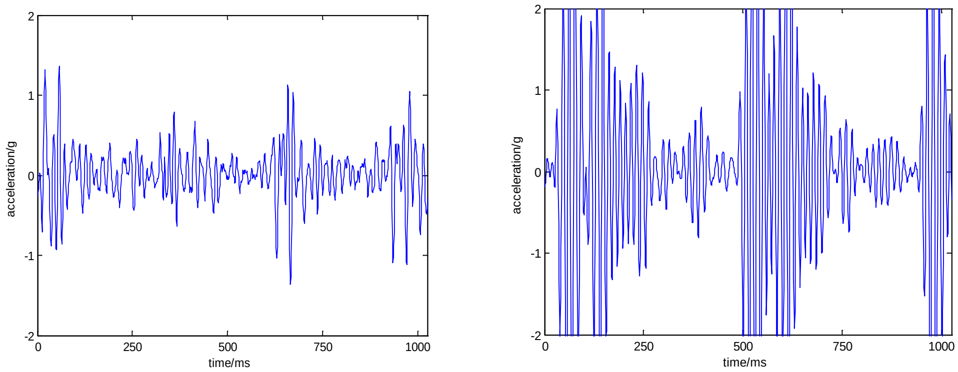
3. Simulation experiment and result analysis

Based on the relevant vector machine, this paper applied to acyclic graph multi classification problem. In this paper, the experimental data of the Western Reserve University of the United States are selected. The obtained experimental data are extracted by the method of harmonic wavelet packet. The extraction process is: firstly, the test data are decomposed by multi harmonic wavelet packet, and the wavelet coefficients of different frequency bands are obtained. Then according to the wavelet coefficients, the wavelet coefficients can be calculated, and the corresponding fault feature vectors can be obtained. In the fault diameter is 7mil and speed 1750r / min, time domain waveform graph as shown in Fig. 5.





(a) The time domain waveform of the normal data (b) The time domain waveform of rolling element fault



(c) The time domain waveform of inner fault (d) The time domain waveform of the outer ring fault

Fig. 5. time domain waveforms of various states

It can be seen from the above figure: time domain waveform is the direct reflection of the normal or fault type of the rolling bearing in the case of the amplitude of the signal at a certain stage. Fig. (a) in the amplitude of the signal acceleration with time scale changes in the mean around no significant fluctuations and notes that the normal operation of the bearing. In fig. (b), there is a slight impact on the amplitude of signal acceleration with time scale, which indicates that there is a fault in the rolling body. In fig. (c), there is a significant fluctuation in the amplitude of the acceleration of the signal with the time scale change, which indicates that there is a fault in the inner ring. Fig. (d), the signal acceleration amplitude changes with time, there is a violent cyclical fluctuation condition. You can judge the fault of the outer ring. Based on the extraction principle of the last section, the experimental data are processed by harmonic wavelet packet, and the four characteristic energy distribution graphs are obtained in Fig. 6.

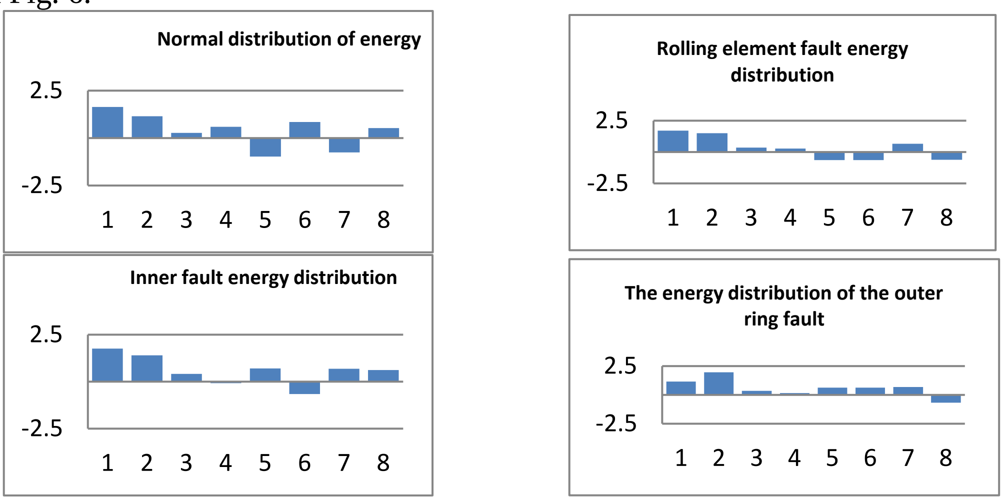


Fig. 6. energy distribution of feature extraction

As can be seen from the graph, there is a distinct difference in the energy distribution of different fault states, which is very favorable for the classification and identification of faults. At the same time, it can be seen that the energy distribution of the vibration signal is relatively average in the normal state. When the fault occurs, the corresponding frequency band will appear the corresponding resonance frequency. At this point, the energy will be concentrated in this frequency band, with respect to the rolling body and inner fault, the outer ring fault degree is more serious and energy concentration is even more powerful. Therefore, in the outer ring fault energy distribution diagram, the outer ring fault signal high frequency energy and other low frequency band energy ratio is smaller, while the other low frequency band energy ratio is smaller. This is basically the same as the fault condition of the frequency response of the 5 signals in the frequency domain.

In order to verify the performance of this method, this paper uses the training and test samples obtained above to compare DAG-RAM, DT-RAM and OAO-RVM. The results of test samples are shown in table 1.

Table 1

Diagnosis results of different methods

	DT-RVM	OAR-RVM	DAG-RVM
Diagnostic time	0.30s	0.35s	0.293s
Diagnostic standard Accuracy	89.5%	92.5%	92.5%

The diagnosis results show that the DAG-RVM method has the advantage of the diagnostic accuracy and the efficiency of the DT-RVM. Compared with DAG-RVM, OAR-RVM has the advantage in diagnosis time.

In order to better verify the proposed diagnosis method for rolling bearing performance, this paper selects the fault diameter under different test data. The following is based on the DAG-RVM and method of diagnosis and DT-RVM OAR-RVM tested.

(1) When the sampling rate is 12K, fault diameter is 7mil, and the DAG-RVM, DT-RVM and OAR-RVM are used to diagnose the fault of the obtained feature sets. The diagnostic results are shown in table 2.

Table 2

Diagnostic results of different methods for fault diameter 7mil

<table>
<tr><th colspan="2"></th><th>DT-RVM</th><th>OAR-RVM</th><th>DAG-RVM</th></tr>
<tr><td rowspan="2">1730r/min</td><td>Diagnostic time (s)</td><td>0.25</td><td>0.27</td><td>0.20</td></tr>
<tr><td>accuracy rate</td><td>93%</td><td>93%</td><td>93%</td></tr>
<tr><td rowspan="2">1750r/min</td><td>Diagnostic time (s)</td><td>0.30</td><td>0.35</td><td>0.293</td></tr>
<tr><td>accuracy rate</td><td>89.5%</td><td>92.5%</td><td>92.5%</td></tr>
<tr><td rowspan="2">1772r/min</td><td>Diagnostic time (s)</td><td>0.27</td><td>0.29</td><td>0.23</td></tr>
<tr><td>accuracy rate</td><td>92%</td><td>91.5%</td><td>92%</td></tr>
</table>

1797r/min	Diagnostic time (s)	0.31	0.35	0.27
	accuracy rate	93%	91.5%	94.5%

(2) When the sampling rate is 12K, fault diameter is 14 mil, the DAG-RVM, DT-RVM and OAR-RVM algorithms are applied to the fault diagnosis of the obtained feature sets, and the results are shown in table 3.

Table 3

Diagnostic results of different methods for fault diameter 14mil

		DT-RVM	***OAR-RVM***	***DAG-RVM***
1730r/min	Diagnostic time (s)	0.29	0.32	0.27
	accuracy rate	93.5%	93.5%	93.5%
1750r/min	Diagnostic time (s)	0.28	0.30	0.25
	accuracy rate	93.5%	92.5%	94.5%
1772r/min	Diagnostic time (s)	0.30	0.34	0.25
	accuracy rate	92.5%	92.5%	92.5%
1797r/min	Diagnostic time (s)	0.28	0.31	0.28
	accuracy rate	93.5%	93.5%	93.5%

(3) When the sampling rate is 12K, fault diameter is 21 mil, and the DAG-RVM, DT-RVM and OAR-RVM are used to diagnose the fault of the obtained feature sets. The diagnostic results are shown in Table 4.

Table 4

Diagnosis results of different methods when the fault diameter is 21mil

		DT-RVM	***OAR-RVM***	***DAG-RVM***
1730r/min	Diagnostic time (s)	0.30	0.33	0.29
	accuracy rate	92.5%	92.5%	92.5%
1750r/min	Diagnostic time (s)	0.31	0.34	0.30
	accuracy rate	93.5%	93.5%	93.5%
1772r/min	Diagnostic time (s)	0.27	0.31	0.25
	accuracy rate	93.5%	92.5%	93.5%
1797r/min	Diagnostic time (s)	0.34	0.36	0.30
	accuracy rate	92.5%	92.5%	93.5%

From the above table can be obtained for the diagnosis of DAG-RVM is better than the diagnosis method based on DT-RVM and OAR-RVM. According to the test data of rolling bearing, the DAG-RVM diagnosis time is short and the rate is higher, and the diagnosis efficiency is higher. For rolling bearings with different rotation rates, the DAG-RVM algorithm has better stability, and maintains a high diagnostic accuracy rate.

In addition, the inner fault of the inner ring, outer ring fault, the rolling body fault directly different but the same rate, the DAG-RVM algorithm is verified, and the DT-RVM and OAR-RVM algorithm are compared. Among them, the sampling rate is 12K, the speed is 1750r/min, and the performance of the speed data is compared with the results shown in table 5.

Table 5

Comparison of different sizes and different methods of diagnosis

Inner fault diameter (mil)	***Ball fault diameter (mil)***	***Outer ring fault diameter (mil)***		***OAR-RVM***	***DT-RVM***	***DAG-RVM***
7	14	7	accuracy rate	92.5%	92.5%	94%
			time	0.29	0.29	0.26
14	7	21	accuracy rate	92%	93%	94.5%
			time	0.31	0.28	0.26

From the table can get: in different fault diameter, DAG-RVM algorithm is shorter than other algorithms, the rate is high; the same time, the accuracy of the diagnosis is also the highest.

First of all, in order to test the performance of the algorithm, this paper selects the sampling rate and motor speed under the same conditions, the fault diameter is the same test data. The data samples of each group were extracted to train the RVM classifier, which is used to train the RVM classifier, and also to extract the fault energy of the four patterns features samples. In this paper, article select a set of 100*4 in the experimental data of the rolling bearing of the Western Reserve University of the United States as the characteristic sample data. The first 50 sets of data of different fault samples are selected; the 200 groups of sample data is used as the training data of the experiment to train the RVM classifier, so as to achieve the ability to identify different kinds of faults. Then, the other 50 sets of data of different fault states are selected, and the data of the 200 groups are tested on the RVM. Finally, the recognition accuracy rate of RVM is 98.5070, which proves that the fault judgment ability is very prominent. This paper selects a set of test data, the test data with harmonic wavelet packet decomposition to get the wavelet coefficients. Then the packet coefficients are obtained and the square root of the square and the square root of the square are obtained. In the end, the fault feature vectors are obtained by the standard treatment of the coefficient energy, and then the feature samples are obtained. The data feature and test results are shown in table 6.

Table 6

Data diagnosis results

Test data description	***Characteristic sample***	***Diagnostic results***
normal	1.64650009663691 1.15160016125762 0.272209034866068 0.592586262126531 -0.982188931127097 0.843887683937407 -0.759352411623381 0.533048458467114	Normal *
Inner fault	1.75928930062677 1.39765979630193 0.421238087353046 -0.079559377990064 0.70282494465181 -0.653008031042351 0.680821477071988 0.619497178819452	Inner fault *

Outer ring fault	1.15644935250639 1.95475100810408 0.347029377418803 0.161904858168439 0.642501006510469 0.617938417794412 0.674514779227451 -0.667311921490908	Outer ring fault
Rolling element fault	1.70104529227735 1.5017056355096 0.356182044653735 0.281728252980344 -0.649110159255831 -0.635545310807668 0.654052835117208 -0.626132324972175	Rolling element fault *

From the above table, the training data can be used to obtain the feature samples and feature vectors. Then the feature vector is input into the RVM classifier to test, and then the corresponding fault type can be obtained, so as to realize the fault diagnosis.

In order to verify the performance of the design and diagnosis method, the configuration of the computer is Core (R) Intel (TM) Duo () 2 CPU E7500@2.93GZHz 2.93GHz 4G, memory, 3006 hard disk. The classification method based on SVM is compared in this paper. Because most of the traditional SVM method can only realize the division of two classification, it can combine multiple classifiers to achieve multiple classification problems such as "against all one" and other types. According to the experimental data collected from the 400 groups of samples, 200 groups of samples were taken out for data training. Then this paper select 200 sets of sample data for testing. Compare the results with different methods and compare the results as shown in table 7.

Table 7

Comparison results of different methods

Classification method	***Diagnostic time***	***accuracy rate***
DAG-RVM	0.293s	92.5%
one against all-SVM	0.576s	74 %

Because the RVM multi classifier model constructed in this paper is similar to the construction of SVM (against all one), it has comparability. Visible design of the RVM method than the traditional SVM (against all one) method to improve the efficiency of nearly doubled, and has a relatively high diagnostic accuracy. When the rolling bearing fault diameter is the same as 7mil and speed in 1750r / min, using Figure 4 classification model to construct the dag-svm diagnosis method, the sparsely of differences diagnostic methods were compared. Results are shown in Table 8 shows.

Table 8

Comparison results of different methods

Classification method	***accuracy rate***	***RV or SV number of classifier at all levels***
DAG-RVM	98.6%	2/2/2
DAG-SVM	96.5 %	151/92/83

By comparison of RVM and SVM, article can see that RVM has better sparsely. Multi classification model using two different classifier of fault diagnosis categories, DAG-RVM relevance vector machine (RVM) the number of about 1 / 50 of the number of support vector dag-svm, but in terms of precision DAG-RVM diagnostic accuracy significantly higher than DAG SVM and reach 98.6%.

4. Conclusions

RVM in essence is a kind of combination of statistical learning theory and the principle of Bayes framework together with a new classifier. Compared with the traditional SVM method and RVM has more advantages including: the selection of parameters is relatively simple, the calculation process is relatively simple, and can provide relatively reliable information to ensure the implementation of classification and so on. At the same time, this paper also introduces the DAG into the RVM to integrate, to realize the fault diagnosis of large-scale machinery.

In addition, the method also has the following characteristics: (1) the decision-making structure can be selected automatically according to the distribution of the training samples, which can obtain a higher diagnostic accuracy. (2) The decision structure introduced DAG to model construction, which has a very low complexity, and is more effective at the same time. (3) The main point is, this method after the diagnosis can give a good fault classification results, at the same time, the analysis and diagnosis and to be assessed, the large machinery bearing fault diagnosis results was reasonable but also the reliability of the classification results. The experimental results show that the method is correct, effective and reasonable.

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