An Intelligent Classification Model based on Statistical and Recursive Quantitative Analyses for Bearing Transfer Diagnosis

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***Abstract*—Bearing is an important component in rotating machinery, and their failure will affect the operation of the machine and even cause losses. Data-driven fault diagnosis methods for vibration-based analyses in bearings are studied widely. However, the success of fault classification is based on sophisticated and complete training data. In this paper, an intelligent classification method based on statistical analysis and recursive quantitative analysis (RQA) is designed, which is trained and tested by different data sets containing artificial or real damage. In addition, the use of statistical indexes and/or RQA indexes are also compared by calculating its classification accuracy. Two classification structures, i.e. a multi-class SVM classifier and a multi-level two-class SVM classifier, are also compared. Through experimental comparison and analyses, the combination of statistical indexes and RQA indexes is useful for improving the classification accuracy, and the knowledge obtained by sample training can be applied to bearing fault diagnosis from other source data.**

***Keywords*—bearings; recursive quantitative analysis; support vector machine; classification; fault diagnosis.**

I. INTRODUCTION

Rolling bearings are important machine parts in various rotating machines, and its importance is self-evident. The failures of the bearing often have a large proportion that leads to the failure of the whole rotating machinery [1, 2]. It is reported that the failure of bearings will cause mechanical downtime and increase unnecessary maintenance man-hours. Therefore, it is essential to monitor the bearings' conditional states and identify its fault at its early fault stage so that appropriate maintenance and decisions can be made according to their real-time states. The technologies based on the temperature detection, oil debris sample detection and vibration signal detection are well developed, the last of which is proven to be useful for online condition monitoring and prognosis of bearings. Vibration based analyses has changed from the qualitative analysis, i.e. whether there is faulty component, to the quantitative analysis, i.e. the evaluation of the fault severity level. No matter which kind of analyses is used, the health indexes play an important role when analyzing the fault state and severity of bearings. There are many such indexes, including statistical indicators and multi-domain indexes from single sensor, composite indexes from multiple sensors, and so on. Huang *et al*. [3] used three time-domain and frequency-domain based features to extract characteristics from vibration signals and then predicted the remaining life of a bearing. Yan *et al*. [4] extracted multi-domain indicators of bearings and optimized the extracted feature indicators using the Laplace score algorithm, finally used a support vector machine-based classification model optimized by the particle swarm so as to identify the faulty states of bearings.

Yan and Jia [5] used statistical analysis, fast Fourier transform and variational mode decomposition to extract features in multi-domains for the purpose of obtaining the intrinsic information in raw vibration signals. Vakharia *et al*. [6] extracted 40 features, including common statistical indicators, kurtosis, skewness, root mean square, etc. and some complexity measurement, e.g. Shannon entropy in time domain, characteristic frequencies and wavelet transform for representing four states of bearings. After that, they used feature ranking methods to pick out most informative features in order to reduce the number of features. Gupta and Pradhan [7] described the trends of the research and applications in vibration measurement techniques in the multiple domains.

As for too many health indexes, some representive and sensitive features are chosen from features in multi-domain. Methods for feature selection and feature weighting are then presented. Some commonly used feature selection methods include distance evaluation technique [8], attribute weighting filter based on decision tree [9] and Relief-F-based attribute estimation with [10], as well as adaptive feature selection, e.g. [11]. Feature weighting includes improved fuzzy kernel clustering [12], iterative relief [13], etc.

Machine learning and deep learning are also involved to combine with the feature selection to enhance classification performance and efficiency, meanwhile, remove the heavy burden of corresponding computation cost. Cui *et al*. [14] presented a modified matching pursuit algorithm to adaptively extract the characteristic fault components from noisy signals by this algorithm, which helps to make the extraction steady, rapid and controllable. Lu *et al*. [15] firstly applied some common statistical features along with energies of intrinsic

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mode functions of the analyzed signal and then used the principal component analysis to obtain representative features. Helmi *et al*. [16] used an adaptive neuro-fuzzy interface system to process the extracted features of a vibration signal. Zhang *et al*. [17] constructed a deep auto-encoder model based on subset to automatically extract features from different fault patterns. Hoang and Kang [18] provided a review on research and applications of three deep learning algorithms in the field of bearing fault diagnosis, as well as some problems to be solved. The combination of traditional features of vibration signals and artificial neural networks makes it easier to identify faults in bearings [19-21].

However, most of success of classification models depend on the fact that training and testing samples are homogenous. That is to say, they share the same fault information. If the training samples cover fault types as many as possible, the testing samples can succeed to identify the same faults collected from the same bearing under the same condition. This limited the application of the training classification model. Therefore, we tried to investigate how to improve the performance of the training model and then apply it to new bearing data collected from other experiments, different from those for training, so that the training models can be used in different cases and their classification knowledge can be transferred to analyze the states of other bearings. In this paper, a classification model is designed based on feature extraction and normal support vector machine (SVM), the former of which uses some statistical indexes and recursive quantitative analysis (RQA) to represent the states of the tested bearing, and then the latter of which is trained and tested by different experimental data. The performance on the classification is then analyzed and compared to generalization ability of the classification.

The remaining of this paper is organized as follows. Section II briefly introduces the features extracted from vibration signal in this paper. Section III introduces the experiment data and their analysis results, and then compares the classification results on different source data and classification models. Finally, some conclusions are given in the last section.

II. Statistical and Recursive Quantitative Analyses For Evaluating Bearing Health State

A. *Statistical analysis*

The statistical analysis provides many useful health indexes for the feature extraction and bearing diagnosis. Here, some popular statistical indicators, including Peak-to-Peak, Root mean square, Variance, Kurtosis, are extracted from the analyzed signal $x(k)$, k = 1, 2, ⋯, n, and n is the number of samples. They can be calculated by Eqs. (1)-(4). These four indicators are selected according to its sensitive property to faults, which was verified in some references. Their performances are also individually compared and analyzed in Section III.

$$x_{\text{P-P}} = \max\{x(k)\} - \min\{x(k)\} \ , \tag{1}$$

$$x_{\text{RMS}} = \sqrt{\frac{1}{n}\sum_{k=1}^{n} x^2(k)} \tag{2}$$

$$x_{\text{Var}} = \frac{\sum_{k=1}^{n}(x(k)-\overline{x})^2}{n} \tag{3}$$

$$x_{\text{Kurtosis}} = \frac{\frac{1}{n}\sum_{k=1}^{n}\left(x(k)-\frac{1}{n}\sum_{k=1}^{n}x(k)\right)^4}{\left(\sqrt{\frac{1}{n}\sum_{k=1}^{n}(x(k)-\frac{1}{n}\sum_{k=1}^{n}x(k))^2}\right)^4} \tag{4}$$

B. *Recursive quantitative analysis*

It is proven that bearing vibration signals are nonlinear and non-stationary, and they are always contaminated by noise and other signals, which makes the identification of the real bearing signal difficult. Recursive graph is a useful method for analyzing the periodicity, chaos, and non-stationarity of time series, and can reveal the internal structure in time series. Faure and Korn [22] calculated the KOLMOGORV of the system from the perspective of recursive quantitative analysis, establishing a link between recursive graph analysis and system nonlinear characteristic parameters. Webber *et al*. [23] proposed the recursive quantitative analysis (RQA), which quantifies the recursive phenomenon exhibited in recursive graphs and provides favorable conditions to extract the features to indicate the states of the tested bearing. After using the RQA, the extracted characteristics hidden in the noisy signal is more reliable than those directly obtained from raw signals. Based on the previous study, the recursive quantitative analysis is introduced to extract corresponding faulty indexes.

The recursive quantitative analysis [23] of a signal is based on phase space reconstruction. For a signal $x_k(k=1,2,\cdots,n)$, the m-dimensional reconstructed phase space is:

$$\begin{Bmatrix} X_1 \\ X_2 \\ \cdots \\ X_N \end{Bmatrix} = \begin{Bmatrix} x_1, x_{1+\tau}, \ldots, x_{1+(m-1)\tau} \\ x_2, x_{2+\tau}, \ldots, x_{2+(m-1)\tau} \\ \cdots \\ x_{n-(m-1)\tau}, x_{n-(m-2)\tau}, \ldots, x_n \end{Bmatrix} \tag{5}$$

where m represents the embedded dimension, τ is the delay time and $N = n-(m-1)\tau$ is the number of reconstructed vectors. In general, m must be greater than twice the dimension of the power system attractor. The choice of τ must ensure that the reconstructed embedded vectors are not related to each other. X_j represents the motion track of the m-dimensional space dynamic system trace.

A recursive graph is then defined as a matrix:

$$R_{ij} = \theta(\xi - r_{ij}), i, j = 1,\cdots,N \tag{6}$$

where $\theta(x)$ is the Heavside function, and ξ is the distance threshold.

$$r_{ij} = \| X_i - X_j \|, i, j = 1,\cdots,N \tag{7}$$

where r_{ij} is the Euclidean distance between the vector i and the vector j in the reconstructed vector space.

For recursive quantitative analysis, the choice of embedding dimensions m, delay time τ, and thresholds ξ is critical. The parameters vary for rolling bearings with different status. According to Refs. [24-26], the parameters are set as shown in Table I. The selected reference threshold ξ is 10 times of the standard deviation of time series.

Further, the following formula can be obtained:

$$R_{ij}=\begin{cases}1 & \xi > r_{ij}\\ 0 & \xi \le r_{ij}\end{cases} \tag{8}$$

TABLE I. SUGGESTED RQA PARAMETERS

status	Best embedded dimension m	Optimal delay time τ
Healthy	4	5
Outer ring fault	3	4
Inner ring fault	1	4

The use of recursive quantitative analysis (RQA) is to refine the changing features of data and transform the visual recursive graph information into data. RQA quantifies the characteristics of the system by quantitatively analyzing the proportion of recursive points and regular line segments in the recursive graph, and then four indexes based on RQA [23] are then obtained as follows:

(1) Recursion rate (RR)

RR is defined as the proportion of recursive points occupied on the graph.

$$\mathrm{RR}=\frac{1}{N^2}\sum_{i,j=1}^{N}R_{ij} \tag{9}$$

where N is the number of embedded vectors.

(2) Determinism (DET)

DET represents as the ratio of the number of recursive points parallel to the main diagonal line segment in the recursive graph to the total number of recursive points.

$$\mathrm{DET}=\frac{\sum_{l=l_{\min}}^{N} lp(l)}{\sum_{i=1}^{N}\sum_{j=1}^{N}R_{ij}} \tag{10}$$

where l is the length of the line segment and $l_{\min}$ is the minimum number of points parallel to the diagonal segment and usually is set to a value of 2. N is the number of embedded vectors. $p(l)$ is the diagonal distribution probability of length l. The value of DET is related to the certainty of the system structure. The larger the value, the more certain the system structure is.

(3) Laminar (LAM)

It analyzes the vertical structure in the recursive graph, which refers to the sum of ratio of recursive point contained in each vertical line to the recursive points contained in all vertical lines in the recursive graph. It is defined as:

$$\mathrm{LAM}=\frac{\sum_{v=v_{\min}}^{N} vp(v)}{\sum_{v=1}^{N} vp(v)} \tag{11}$$

where $p(v)=\{v_i, i=1, \dots, N\}$, $p(v)$ is a frequency distribution of length v in the vertical structure, $v_{\min}$ is the threshold of the vertical line length and the threshold $v_{\min}$ is usually set to 2.

(4) Recursive entropy (ENTR)

ENTR represents the Shannon entropy of the length distribution of the line segment parallel to the main diagonal in the recursive graph. Entropy characterizes the complexity of the system, and the value of ENTR increases as the complexity of the system increases. Its definition is:

$$\mathrm{ENTR}=-\sum_{l=l_{\min}}^{N} p(l)\ln p(l) \tag{12}$$

where $p(l)$ is the diagonal distribution probability of length l. The RQA indexes are calculated by using the CRP TOOL [27]. In the following Section III, the performance of statistical analysis and RQA will be compared.

C. *Procedure for an intelligent fault classification model*

Based on these features, the support vector machine (SVM) proposed by Vapnik *et al*. [28] is used to classify bearing faults. For the bearing fault classification, the feature extraction based on the statistical analysis and recursive quantitative analysis is firstly applied to extract features from raw vibration signals and then the SVM is used to classify the bearing states. Therefore, the procedure for this intelligent fault classification model is described as follows:

(1) Feature vector generation: Four indexes based on the statistical analysis, including Peak-to-Peak (P-P), Root mean square value (RMS), variance (Var), and kurtosis are obtained from the vibration signal in time domain. Another four indexes based on the RQA, i.e. Recursion rate (RR), Determinism (DET), laminarity (LAM) and Recursive entropy (ENTR), are obtained. Thus, eight indexes are formed as one feature vector.

(2) State label setting: Labels 1, 2, and 3 are marked for bearings with healthy state, outer race defect, and inner race defect, respectively.

(3) Feature vector normalization.

(4) SVM based classification: Experimental data are used to the SVM algorithm and then the intelligent classification model is obtained. Testing sets are used to test the generalization ability and classification accuracy.

III. EXPERIMENTS AND ANALYSES

A. *Brief Introduction on Expaerimental Data* [29]

The experimental data used in this paper were obtained by Lessmeier *et al*. [29] in Paderborn University. Experimental data were recorded at a test rig consists of several modules, as shown in Figure 1. It includes five main components: (1) an electric motor, (2) a torque-measurement shaft, (3) a rolling bearing test module, (4) a flywheel, and (5) a load motor.

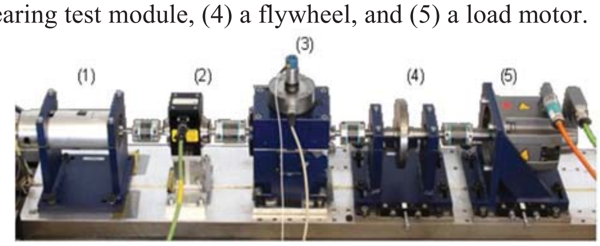

Figure 1. Modular test rig [29].

Two types of damage are generated on the tested rolling ball bearing (6203): the outer race defect and the inner race defect, which are introduced by manually using machine tools or with apparatus for accelerated lifetime tests, that is to say, the defects are artificial or real damage. The common experiment settings for data collection are: the rotation speed 1500 rpm with a load torque 0.7Nm, a radial force on the bearing 1000N, and temperature roughly at 45-50 °C. For each bearing state, 20 measurements of 4 seconds were recorded and the corresponding sampling frequency is 64kHz.

To analyze the performance of the bearing transfer diagnosis, training and testing sets are chosen from different experimental data, which are shown in Table II. As shown in this table, the data K004 and K005 are collected from healthy bearings and are used for training and testing. KA08, KA09 and KA15 are collected from bearings with outer race defects. It is noted that data KA08 are generated by the artificial damage and used for testing, while data KA09 and are KA15 are generated by the artificial and real damages, respectively, and both are used for training. Data KI16 and KI18 are collected from bearing with inner race defects in the Accelerated lifetime tests, and they are used for testing and training, respectively. More details on these data are shown in Table III.

TABLE II. INFORMATION ON TRAINING AND TESTING SETS

Label	Status	Train set	Test set	Sample No.
1	Health	K004		40
			K005	20
2	Outer race defect		KA08	20
		KA09		20
		KA15		20
3	Inner race defect		KI16	20
		KI18		40

TABLE III. DAMAGE DESCRIPTION ON TRAINING AND TESTING SETS

Bearing code	Extent of damage	Damage method	Generation method
K004 (Health)	Run-in Period: 5h, Radial Load: 3000N, Speed: 3000min^{-1}		
K005	Run-in Period: 10h, Radial Load: 3000N, Speed: 3000min^{-1}		
KA08	2	Drilling	Artificial damage
KA09	2	Drilling	Artificial damage
KA15	1	Plastic deformation: Indentations	Accelerated lifetime test
KI16	3	Fatigue: pitting	Accelerated lifetime test
KI18	2	Fatigue: pitting	Accelerated lifetime test

B. *Recursion graphs of some experimental data*

To train the classification, the RQA is applied to the experimental data to get four RQA indexes. Here part of results is shown. Figure 2 shows the temporal waveform and frequency spectrum of the data set K004 from a healthy bearing, along with its recursion graph. Figures 3 and 4 also show the waveforms and graphs of the data sets KA15 and KI16. The former is from a bearing with an outer race defect.

As shown in Table III, its damage is deformation indentation on the outer race and the damage extent is smaller. The latter is from a bearing with pitting on the inner race and its extent is large. Both of them are generated in the accelerated lifetime tests and thus belong to real damages. Based on these, eight indexes in Eqs. (1)-(4) and Eqs. (9)-(12) are calculated for bearing classification.

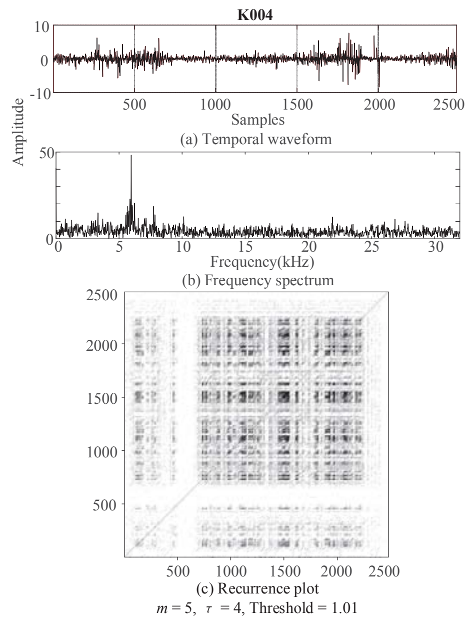

Figure 2. Data K004: the temporal waveform in (a), frequency spectrum in (b), and the recursion graph in (c).

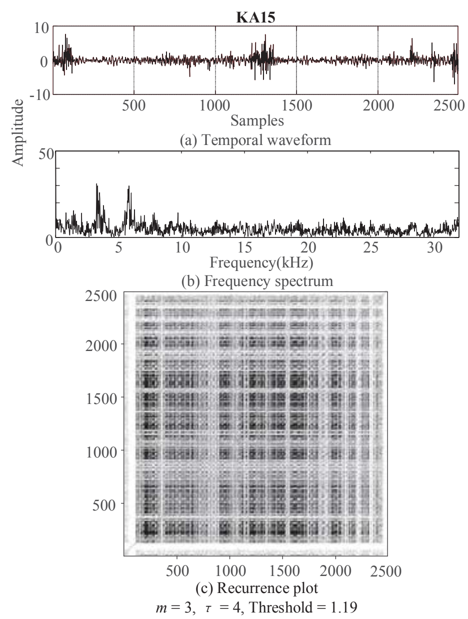

Figure 3. Data KA15: the temporal waveform in (a), frequency spectrum in (b), and the recursion graph in (c).

C. *SVM multi-classification*

Using above indexes and choosing radial basis function (RBF), the SVM algorithm is available for fault classification. It is used as a multi-label classifier, that is to say, the indexes are inputted into the SVM and then three labels are determined at the same time, where '1' corresponds to the healthy state, '2' indicates the samples from the bearing with an outer race defect, and '3' indicates the samples from the bearing with an inner race defect. The classification results are shown in Figures 5, 6, and 7 that are obtained by using all eight indexes, only 4 statistical indexes, and 4 RQA indexes, respectively.

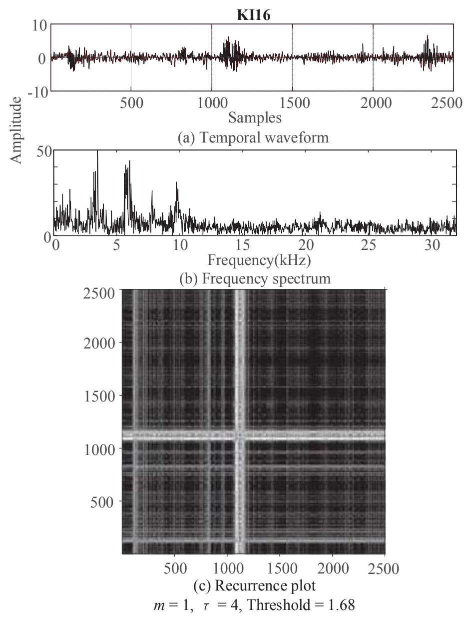

Figure 4. Data KI16: the temporal waveform in (a), frequency spectrum in (b), and the recursion graph in (c).

The classification accuracy of 95% is calculated based on the ratio between the number of correct classification samples and all the number of testing samples. Taking Figure 5 as an example, three samples in 60 testing samples are wrongly classified into the outer race defect (Label 2), while its real label should be 1.

In Figures 5-7, 60 testing samples are used to test the classification accuracy, in which the real label and the classification results are marked by two symbols, so that their difference is easily identified. To compare the fault sensitivity, two types of indexes are also used to compare with the case using all indexes. The results indicate that their performance are similar, and the classification only using RQA indexes is not as good as those using all indexes or 4 statistical indexes.

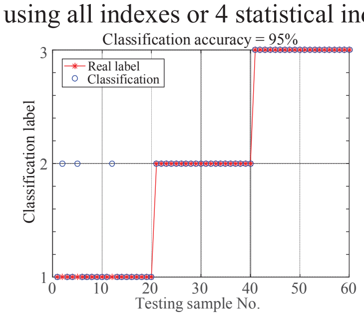

Figure 5. Classification results using SVM multi-classification and all indexes.

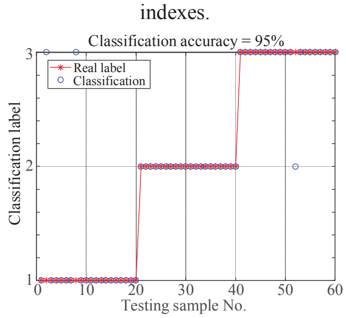

Figure 6. Classification results using SVM multi-classification and 4 statistical indexes.

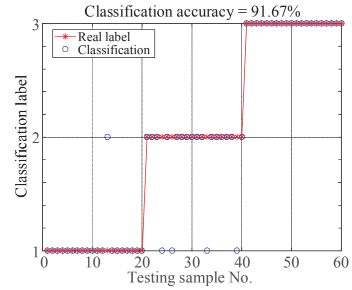

Figure 7. Classification results using SVM multi-classification and 4 RQA indexes.

D. Comparisons

To evaluate the influences caused by the health indexes and classification model structures, two comparisons are conducted, one of which is to compare the results using multiple or single health index, the other of which is to compare the multi-classification model with multi-level two-class SVM classification model. In the latter model, the first level is to classify the healthy and faulty states and then the second level is to classify the outer and inner race defects. The comparison results are shown in Tables IV and V.

Table IV shows the classification accuracies when using different health indexes and SVM multi-classification method. As shown in this table, single index cannot provide rich information and thus its corresponding classification accuracy is much lower.

TABLE IV. CLASSIFICATION RESULTS FOR SVM MULTI-CLASSIFICATION MODELS

Health index	Overall accuracy	Health	Outer race defect	Inner race defect
All eight indexes	95.00%	85.00%	100.00%	100.00%
Statistical indexes	95.00%	90.00%	100.00%	95.00%
RQA indexes	91.67%	95.00%	80.00%	100%
Peak-to-Peak	33.33%	0.00%	100%	0.00%
RMS	33.33%	0.00%	0.00%	100%
Var	33.33%	0.00%	0.00%	100%
Kurtosis	33.33%	0.00%	0.00%	100%
RR	11.67%	25.00%	10.00%	0.00%
DET	33.33%	100.00%	0.00%	0.00%
LAM	33.33%	100.00%	0.00%	0.00%
ENTR	41.67%	15.00%	10.00%	100%

TABLE V. CLASSIFICATION RESULTS FOR SVM MULTI-LEVEL TWO-CLASS CLASSIFICATION MODELS

Health index	1st classification	2nd classification	Health	Outer race defect	Inner race defect
All eight indexes	95.00%	93.02%	85.00%	86.96%	100.00%
Statistical indexes	93.33%	90.91%	80.00%	86.96%	95.00%
RQA indexes	88.33%	87.17%	85.00%	78.94%	90.00%

Table V shows the classification accuracies when using three different health index sets and different classification structures. These comparisons demonstrate that although the classification performance only using the RQA indexes is lower than those using the statistical indexes, the RQA indexes really make positive effect on classification and provide richer information in the raw bearing signals.

IV. CONCLUSIONS

In this paper, the intelligent classification based on the statistical analysis and recursive quantitative analysis is designed for bearing fault diagnosis. Health states of bearings are represented by 4 statistical indexes and 4 RQA indexes. Different index sets and classification structures are compared. The corresponding results show that the classifier using all eight indexes has higher classification accuracy than those using single or part of 8 indexes.

In the experiments, the bearing faults from artificial damage and real damage generated in the accelerated life tests are chosen as training and testing samples, the latter of which are not chosen the same data sets as the former. After training the classifier, testing samples from other data sets show a successful transfer diagnosis. The classification results indicate that the knowledge learned from some samples can be further used to identify the states of other samples. It extends the applications of intelligent classification. Further introducing the transfer learning theory is useful for improving the accuracy of bearing fault diagnosis; meanwhile, it can help to solve the limitation of limited samples from real damages.

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