A New Robust Rolling Bearing Vibration Signal Analysis Method

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Abstract. As bearing vibration signal is of nonlinear and nonstationary characteristics, and the condition-indicating information distributed in the rolling bearing vibration signal is complicated, a new rolling bearing health status estimation approach using holder coefficient and gray relation algorithm was proposed based on bearing vibration signal in the paper. Firstly, the holder coefficient algorithm was proposed for extracting health status feature vectors based on the bearing vibration signals, and secondly the gray relation algorithm was developed for achieving bearing fault pattern recognition intelligently using the extracted feature vectors. At last, the experimental study has illustrated the proposed approach can efficiently and effectively recognize different fault types and in addition different severities with good real-time performance.

Keywords: Vibration signal processing · Holder theory · Gray relation theory Fault diagnosis

1 Introduction

Rolling element bearings are commonly used in rotational machines, and usually their failure leads to the machine breakdown, which causes substantial economic losses [1–3]. Vibration-based bearing fault diagnosis approaches have attracted broad attention in the near past as vibration signal holds rich bearing health status information. As the result of the nonlinear factors, such as stiffness, friction and clearance, bearing vibration signals always bear nonlinear and nonstationary performance [4]. what's more, bearing vibration signals involve not only the working information related to the bearing itself, but also plentiful information related to other rotating parts of the machine, which in comparison with the former is usually taken as the background noise [5]. Thus the common time domain or frequency domain signal processing approaches may not easily obtain an accurate estimation result about the bearing health status [6].

Recently, the procedure of bearing fault diagnosis is gradually taken as a process of fault pattern recognition with the aid of artificial intelligence (AI) approaches [7], and its reliability is essentially determined by the effectiveness of the fault feature

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extraction. Nowadays, Some entropy based feature extraction methods (e.g., hierarchical entropy [8], fuzzy entropy [9], sample entropy [10] and approximate entropy [11, 12]), were used for extracting fault feature vectors based on bearing vibration signals. Here, we exploit a holder coefficient algorithm, for extracting fault feature vectors based on the vibration signals, so as to improve the performance of traditional feature extraction approaches in the paper.

When the fault feature extraction is ready, a fault pattern recognition method is required to implement the fault diagnosis automatically. The most common approaches are support vector machines [13] and artificial neural networks [14–16]. However, the training of artificial neural networks requires a lot of faulted samples, which are difficult to obtain in practice. The support vector machines are based on statistical learning theory, and have better generalization than artificial neural networks under a smaller number of samples [17]. However, the accuracy of support vector machines is essentially determined by the choice of their optimum parameters [18]. Thereafter, complex multi-class concept [19] or optimization algorithms [14, 18] has been used to improve the effectiveness of SVMs. In this paper, so as to keep a balance between generality and accuracy, a gray relation algorithm was used to achieve fault pattern recognition.

2 Holder Coefficient Algorithm

Holder coefficient can be used to measure the similar degree of two sequences, which may extract signals' features. It is evolved from Holder inequality and the definition of Holder inequality can be described as follows:

For any vector $X = [x_1, x_2, \ldots, x_n]^T$ and $Y = [y_1, y_2, \ldots, y_n]^T$, they satisfy:

$$\sum_{i=1}^{n} |x_i \cdot y_i| \leq \left(\sum_{i=1}^{n} |x_i|^p\right)^{1/p} \cdot \left(\sum_{i=1}^{n} |y_i|^q\right)^{1/q} \tag{1}$$

where $\frac{1}{p} + \frac{1}{q} = 1$ and $p, q > 1$.

Based on the Holder inequality, for two discrete signals $\{f_1(i) \geq 0, i = 1, 2, \ldots, n\}$ and $\{f_2(i) \geq 0, i = 1, 2, \ldots, n\}$, if $\frac{1}{p} + \frac{1}{q} = 1$ and $p, q > 1$, then Holder coefficient of these two discrete signals is obtained as follows:

$$H_c = \frac{\sum f_1(i) f_2(i)}{\left(\sum f_1^p(i)\right)^{1/p} \cdot \left(\sum f_2^q(i)\right)^{1/q}} \tag{2}$$

where $0 \leq H_c \leq 1$.

Holder coefficient characterizes the similar degree of two discrete signals, if and only if $f_1^p(i) = k f_2^q(i)$, $i = 1, 2, \ldots, n$, in which n denotes the length of discrete signal and k is a real number, H_c will be the biggest value. In this case, the similar degree of two signals is biggest, which indicates that the two signals belong to the same type of signals; if and only if $\sum_{i=1}^{n} f_1(i) f_2(i) = 0$, H_c get the minimum value, and in this case, the similarity of two signals is smallest, which indicates the signals are irrelevant, and belong to different types of signals.

Rectangular sequence $s_1(i)$ and triangular sequence $s_2(i)$ are selected as reference sequences, and then the Holder coefficient value of the vibration signals to be identified with the two reference signal sequences is obtained as follows:

$$H_1 = \frac{\sum f(i)s_1(i)}{\left(\sum f^p(i)\right)^{1/p} \cdot \left(\sum s_1^q(i)\right)^{1/q}} \tag{3}$$

where the rectangular sequence $s_1(i)$ is as follows:

$$s_1(i) = \begin{cases} s, & 1 \le i \le N \\ 0, & else \end{cases} \tag{4}$$

Similarly, H_2 is obtained as follows:

$$H_2 = \frac{\sum f(i)s_2(i)}{\left(\sum f^p(i)\right)^{1/p} \cdot \left(\sum s_2^q(i)\right)^{1/q}} \tag{5}$$

where the triangular sequence $s_2(i)$ is as follows:

$$s_2(i) = \begin{cases} 2is/N, & 1 \le i \le N/2 \\ 2s - 2is/N, & N/2 \le i \le N \end{cases} \tag{6}$$

3 Gray Relation Algorithm

As the basis of gray system theory, the gray relation algorithm is to calculate the gray relation coefficient and relation degree between each comparative feature vector and reference feature vectors based on the basic theory of space mathematics [20–23].

Suppose the fault feature vectors (i.e., the two-dimensional feature vector extracted based on Holder coefficient algorithm) extracted based on vibration signals, to be identified are as follows:

$$B_1 = \begin{bmatrix} b_1(1) \\ b_1(2) \end{bmatrix}, B_2 = \begin{bmatrix} b_2(1) \\ b_2(2) \end{bmatrix}, \ldots, B_i = \begin{bmatrix} b_i(1) \\ b_i(2) \end{bmatrix}, \ldots \tag{7}$$

where B_i(i = 1,2,...) is a certain fault pattern to be recognized (i.e., fault types and in addition severities).

Suppose the knowledge base between the health status patterns (i.e., fault type as well as severity) and fault signatures (i.e., the feature vectors) from a part of samples is as follows:

$$C_1 = \begin{bmatrix} c_1(1) \\ c_1(2) \end{bmatrix}, C_2 = \begin{bmatrix} c_2(1) \\ c_2(2) \end{bmatrix} \ldots, C_j = \begin{bmatrix} c_j(1) \\ c_j(2) \end{bmatrix}, \ldots \tag{8}$$

where $C_j(\mathrm{j} = 1, 2, \ldots)$ is a known health status pattern (i.e., fault type as well as severity); $C_j(\mathrm{j} = 1, 2, \ldots)$ is a characteristic parameter.

For $\rho \in (0, 1)$:

$$\xi\big(b_i(k), c_j(k)\big) = \frac{\min\limits_j \min\limits_k \left|b_i(k) - c_j(k)\right| + \rho \cdot \max\limits_j \max\limits_k \left|b_i(k) - c_j(k)\right|}{\left|b_i(k) - c_j(k)\right| + \rho \cdot \max\limits_j \max\limits_k \left|b_i(k) - c_j(k)\right|} \tag{9}$$

$$\xi(B_i, C_j) = \frac{1}{2} \sum_{k=1}^{2} \xi\big(b_i(k), c_j(k)\big), j = 1, 2, \ldots \tag{10}$$

where ρ is a distinguishing coefficient; $\xi\big(b_i(k), c_j(k)\big)$ is the gray relation coefficient for k_{th} feature parameter for B_i and C_j; $\xi(B_i, C_j)$ is the gray relation degree for B_i and C_j. Thereafter B_i is categorized to the health status pattern where the maximal $\xi(B_i, C_j)(j = 1, 2, \ldots,)$ is calculated.

4 Proposed Approach

Totally, the proposed approach for rolling bearing health status estimation is as follows:

a. The vibration signals from the object rolling element bearing in a rotating machine are sampled under different working conditions, including normal operating condition and faulty operating condition with various fault types and severities, for the establishment of the sample knowledge base.

b. Through a two-dimensional feature extraction algorithm based on Holder coefficient theory, the health status feature vectors are extracted from the sample knowledge base.

c. The sample knowledge base for GRA is established based on the fault symptom (i.e., the extracted feature vector) and the fault pattern (i.e., the known fault types and severities).

The feature vectors extracted based on bearing vibration signals to be identified are input into GRA, and the diagnostic results (i.e., fault types and severity) are output.

5 Experimental Validation

All the rolling element bearing vibration signals for analysis are from Case Western Reserve University Bearing Data Center [24] in the paper. The related experimental device consists of a torque meter, a power meter and a three-phase induction motor, and the load power and speed measured by the sensor, seen in Fig. 1. Over controlling

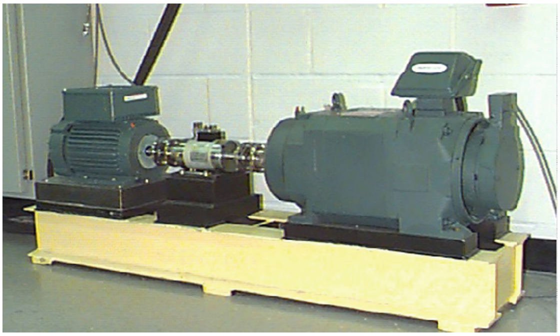

Fig. 1. Experimental setup

the power meter, the desired torque load can be obtained. The motor drive end rotor is supported by a test bearing, where a single point of failure is set through discharge machining. The fault diameters (i.e., fault severities) include 28 mils, 21 mils, 14 mils and 7 mils, and the fault types include outer race fault, the inner race fault and the ball fault. An accelerometer is installed on the motor drive end housing with a bandwidth up to 5000 Hz, and the vibration data for the test bearing in different operating conditions is collected by a recorder, where the sampling frequency is 12 kHz.

The bearing vibration data used for analysis was obtained under the load of 0 horsepower and the motor speed of 1797 r/min. The test bearing is a deep groove rolling bearing of 6205-2RS JEM SKF. Totally 11 types of vibration signals considering different fault categories and severities are analyzed, seen in Table 1. Each data sample from vibration signals is made up of 2048 time series points. For those 550 data samples, 110 data samples are randomly chosen for establishment of knowledge base, with the rest 440 data samples as testing data samples.

Table 1. Description of experimental data set

Bearing condition	Fault diameter (mils)	The number of base samples	The number of testing samples	Label of classification
Normal	0	10	40	1
Inner race fault	7	10	40	2
	14	10	40	3
	21	10	40	4
	28	10	40	5
Ball fault	7	10	40	6
	14	10	40	7
	28	10	40	8
Outer race fault	7	10	40	9
	14	10	40	10
	21	10	40	11

The fault feature vectors extracted from bearing normal operating condition and different fault conditions with 7 mils fault diameter over the two-dimensional feature extraction algorithm using Holder coefficient were shown in Fig. 2.

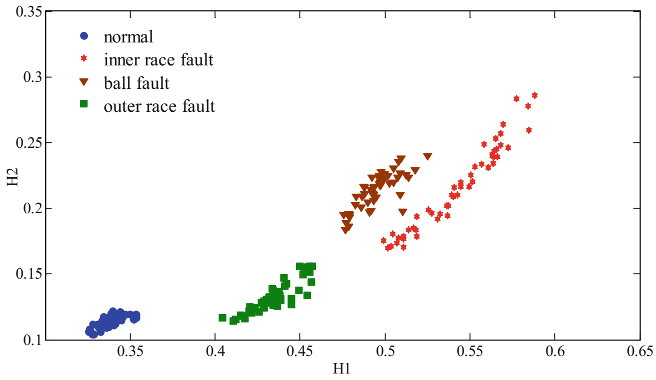

Fig. 2. Holder coefficient features of a random chosen sample from bearing normal operating condition and different fault conditions with fault diameter 7 mils

And the fault feature vectors extracted from bearing inner race fault condition with different severities over the two-dimensional feature extraction algorithm using Holder coefficient were shown in Fig. 3.

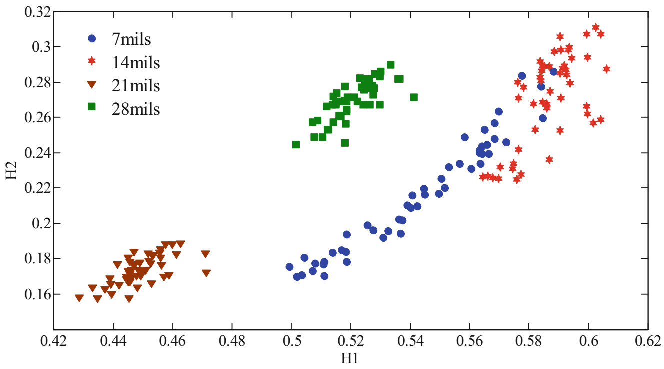

Fig. 3. Holder coefficient features of a random chosen sample from bearing inner race fault condition with various severities

From Figs. 2 and 3, it can be seen that the fault feature vectors extracted from the bearing vibration signals with different fault types and in addition different severities through the two-dimensional feature extraction algorithm using Holder coefficient show apparent differences.

The sample knowledge base for GRA is established based on the fault symptom (i.e., the extracted feature vectors) and the fault pattern (i.e., the known fault types and severities). The feature vectors extracted from the testing bearing vibration signals to be identified are input into GRA, and the diagnostic results (i.e., fault types and severities) are output, shown in Table 2.

Table 2. The diagnostic results by GRA

Label of classification	The number of testing samples	The number of misclassified samples	Testing accuracy (%)
1	40	0	100
2	40	6	85
3	40	0	100
4	40	0	100
5	40	6	85
6	40	6	85
7	40	0	100
8	40	13	67.5
9	40	0	100
10	40	0	100
11	40	0	100
In total	440	31	92.95

The diagnostic results from Table 2 show that the fault pattern recognition success rate for detecting bearing faulty conditions can reach 100%, and the total fault pattern recognition success rate can reach almost 93%. The time cost by the proposed diagnostic approach for one Test Case is within 1.6 ms by using a laptop computer with a 2.0 GHz dual processor.

6 Conclusion

A novel rolling element bearing vibration signal analysis approach using holder coefficient and gray relation algorithm was proposed in the paper. The experimental results have demonstrated that the holder coefficient algorithm is very suitable for rolling bearing fault feature extraction, which can obtain more distinguishing information imaging different health status. And the gray relation algorithm as a pattern recognition technique is very suitable for implementing the rolling bearing fault pattern recognition intelligently under a small number of base samples. Moreover, the proposed approach can efficiently and effectively recognize different fault types and in addition different severities with good real-time performance.

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