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A Fault Diagnosis Scheme for Rotating Machinery Using Recurrence Plot and Scale Invariant Feature Transform

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Abstract. Condition monitoring and fault diagnosis of rotating machinery has gained wide attention for its significance in preventing catastrophic accidents and guaranteeing sufficient maintenance. The traditional fault diagnosis methods usually need manually extracting the features from raw sensor data before classifying them with pattern recognition models. This paper presents a method based on image processing for fault diagnosis of rotating machinery, who can realize feature extraction automatically. The proposed method mainly includes the following steps. First, the vibration signal is transformed into a recurrence plot utilizing recurrence quantification analysis technology, which provides a basis for the following image-based feature extraction. Then, an emerging approach in the field of image processing for feature extraction, scale invariant feature transform (SIFT) is employed to automatically exact fault features from the transformed recurrence plot and finally form the feature vector. The case study results demonstrate the effectiveness of the proposed method, thus providing a highly effective means to fault diagnosis for rotating machinery.

Keywords: recurrence plot; scale invariant feature transform (SIFT); style; rotating machinery; fault diagnosis.

1. Introduction

Rotating machinery has been widely used in many engineering fields, such as power system, petroleum, aviation and so on[1, 2]. Generally, rotating machinery has a high operating speed, and is often the key equipment of enterprises, such as aero-engine, large rolling mills, turbines, large centrifugal compressor units, etc. Once the fault occurs in this equipment, it will cause huge economic loss, and may even lead to catastrophic accidents. Therefore, the condition monitoring and fault diagnosis of rotating machinery is very important.

In order to solve the problem of rotating machinery fault diagnosis, researchers have attempted to introduce image analysis techniques for fault diagnosis of rotating machinery, therefore visualized fault diagnosis methods have emerged[3, 4].

Based on the idea of image analysis, this paper proposes a fault diagnosis based on recurrence plot and scale invariant feature transform (SIFT). Recurrence plot analysis, a new non-stationary, nonlinear signal analysis method is introduced in this paper. In addition, traditional recurrence plot analysis method is recurrence quantification analysis (RQA), which describes recurrence plot of signals under different state by nonlinear feature quantity such as recursion rate, determination rate, recursive entropy, stratification rate. This method requires the observer to judge and screen the selected feature quantities by themselves, so it will miss the important feature information due to human factors, who lack the adaptability of feature extraction.

Since the recurrence plot[5, 6] is essentially an image, the recurrence plots of the different state signals will exhibit different textures. Image feature extraction method is introduced in this paper. Owing to the development of the image automatic feature extraction technique in recent decades, the scale invariant feature transform (SIFT) method is recognized as the most appealing descriptor for

practical uses and for matching features with good robustness and high accuracy[7-9]. This paper introduces SIFT operator to extract fault features from recursive graphs.

By analyzing the recurrence plot of gearbox under different fault modes, the result proves that the recurrence plot has strong characterization ability for different fault mode of gearbox and SIFT can extract texture feature information of recurrence plot with better performance. Finally, a classical neural network, probabilistic neural network (PNN)[10, 11] is introduced for identification of fault modes. The combination of recurrence plot and SIFT and effectively diagnosis fault mode of gearbox.

This paper is organized as follows: Section 2 introduces the related algorithms, Section 3 describes the case study performed to validate the method, and Section 4 presents the conclusions and related future work.

2. Methodology

2.1 Recurrence Plot

MARWAN et al. [12] proposed the phase space reconstruction to describe system dynamics in 1987, which called a recurrence plot (RP). The texture information of the RP can characterize the related information of system time domain, which is a description of the global topology characteristics from the whole image. RP can be used to describe the steady-state characteristics of the system. When the system is completely stable, the texture of the RP is evenly distributed; well when the system is non-stationary, the RP's detail texture will show relevant information in the time domain. As the unevenness increases, the detail texture becomes more significant [9]. Since the RP has a strong ability to portray the system, RP can used to analyze gearbox signals under different fault modes.

(1) Suppose that a given discrete time series $x=\{i=1,2,\cdots,N\}$ is reconstruct Pseudo phase space with delay constant τ and an embedding dimension *m,* that is:

$$Y_i=\left\{x_i,x_{i+\tau,},x_{i+\tau},,x_{i+(m-1)\tau}\right\},i=1,2,,N-(m-1)\tau \tag{1}$$

(2) Calculate the distance between the jth point and the ith point, that is**:**

$$dist(i,j;m)=\left\{\sum_{k=0}^{m-1}\left|x_{i+k\tau}-x_{j+k\tau}\right|\right\}\Big/\sum_{k=0}^{m-1}x_{i+k\tau} \tag{2}$$

(3) Construct a square map of N*N points, N is noted as the length of the discrete time series, the abscissa and ordinate represent the sequence number of the point on the pseudo phase orbit, as shown is figure 1.

$$\left\{\begin{array}{l} coordinate\ (i,j)\ is\ blank, \\ \qquad\qquad when\ dist(i,j;m)>r \\ coordinate\ (i,j)\ is\ \text{a Solid point}, \\ \qquad\qquad when\ dist(i,j;m)\le r \end{array}\right\} \tag{3}$$

Where *r* is the neighborhood radius and will be set in advance.

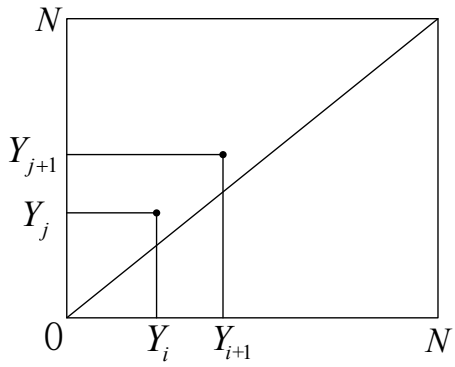

Fig. 1 The construction of RP

From the construction principle, the detail texture in the recurrence plot reflects the time-related information contained in the corresponding system, while the whole plot shows the global topological properties of the system. Therefore, a recurrence plot can be used to describe the smoothness of the system. When the behavior of the system is completely stable, its recursive graph is a uniformly distributed graph; when the system is in an unsteady state, the time-related information will show a subtle texture structure on the recurrence plot. As the unevenness increases, the texture structure shown on the recurrence plot will be more prominent.

Figure 2 shows a recurrence plot of the white noise signal with a signal length of 1000. From a macro perspective, figure 2 shows a distinct uniform pattern, indicating that this signal is a stationary process; well from a microscopic perspective observe, you can see that figure 2 shows the characteristics of independent recursive points, which demonstrate the signal is a stationary process.

Combining the above two characteristics, it is easy to judge that the signal expressed by the recurrence plot is a random stationary process, which is consistent with the characteristics of the white noise signal.

2.2 SIFT Descriptor

The basic steps of the SIFT image registration algorithm are as follows: (1) Feature point extraction; (2) Generate feature descriptors; (3) feature point matching. The feature point extraction mainly includes generating a Difference of Gaussian (DOG) scale space, finding local extremum points, screening feature points, and determining the direction of feature points.

2.2.1 Feature Point Extraction

The feature point extraction step using the SIFT algorithm is shown in Figure 1

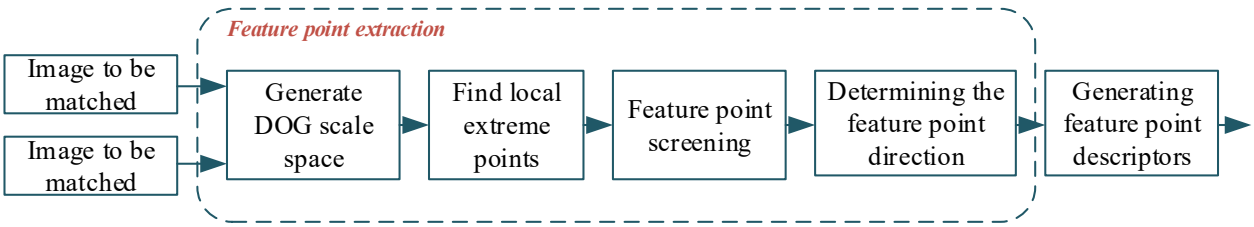

Fig. 2 SIFT descriptor

(1) Generate DOG scale space. The convolution of Gaussian function and image can generate scale space. σ Is set as scale parameter. Therefore, scale space $L(x,y,\sigma)$ of $I(x,y)$ can be describe as:

$$L(x,y,\sigma)=G(x,y,\sigma)*I(x,y) \tag{4}$$

Where $I(x,y)$ is the input image, $*$ is the convolution symbol, $G(x,y,\sigma)$ is a Gaussian smooth kernel function whose expression is:

$$G(x,y,\sigma)=\frac{1}{2\pi\sigma^2}e^{-(x^2+y^2)/2\sigma^2} \tag{5}$$

In actual calculation, the DOG is obtained by subtracting the upper and lower two images of the same scale in the Gaussian pyramid image. The formula is:

$$D(x,y,\sigma)=\left(G(x,y,k\sigma)-G(x,y,\sigma)\right)*I(x,y)=L(x,y,k\sigma)-L(x,y,\sigma) \tag{6}$$

Where k is treated as a constant, who is the scale ratio of two adjacent scale images.

(2) Find local extreme points. After generating the DOG scale space, each sample point is scanned and compared with the surrounding 26 pixels to determine whether it is an extreme point. The local extremum points found in this way are the rough feature points (key points) of the image.

(3) Feature point screening. After the rough feature points of the image are selected, the difference algorithm is used to determine the position and scale of the key points, and then the extreme points with low contrast are eliminated. Optimize feature point detection results by removing the edge response interference caused by Gaussian difference operation with Hessian matrix.

(4) Determining the direction of feature point. In addition to the coordinate values (plane position and scale) of the vector, the eigenvector also determines its direction value according to the gradient direction of the neighborhood pixels of the feature point. The modulus *m (x, y)* and direction *θ (x, y)* of the gradient at Gaussian smooth image L at point *(x, y)* can be expressed b

$$m(x,y)=\sqrt{f_x^2(x,y)+f_y^2(x,y)} \tag{7}$$

$$\theta(x,y)=\tan^{-1}\frac{f_y(x,y)}{f_x(x,y)} \tag{8}$$

Where $f_x(x,y)=L(x+1,y)-L(x-1,y)$, $f_y(x,y)=L(x,y+1)-L(x,y-1)$.

2.2.2 Generating a Local Descriptor

A 16×16-pixel size region is taken as the center of the feature point, and the region is divided into 4×4 sub-blocks. The gradient direction histogram of each sub-block is counted in eight directions to obtain a seed point. Each feature point is composed of 4×4 seed points, and each seed point has 8 directions, thus forming a feature vector of 4×4×8=128 dimensions, which has rotation invariance, scale invariance.

To ensure the vector has a certain degree of illumination invariance, normalization is need for the vectors.

3. Case Study

In order to verify the effectiveness of the proposed method, the bearing fault vibration data of the Western Reserve University was used for verification. The fault bearing model is a KF6205 deep groove ball bearing, in which the number of rolling elements is 9, the rolling diameter is 7.94 mm, the bearing pitch diameter is 39.04 mm, and the contact angle is 0°.

The vibration signal used is 2048 in length. Vibration data are collected under normal conditions and fault conditions, including bearing roller wearing, inner race wearing, and outer race wearing fault conditions, as well as impeller wearing fault. The sampling time is 2s for each set, and one set is collected every 5 seconds.

A recurrence plot of the signal is obtained using RP. Figure 3 (a) ~ (d) correspond to four failure modes, that is bearing inner race, bearing outer race, bearing rollers wearing and normal. The top of each picture is the time domain waveform of the signal, and the lower part is the corresponding recursive picture.

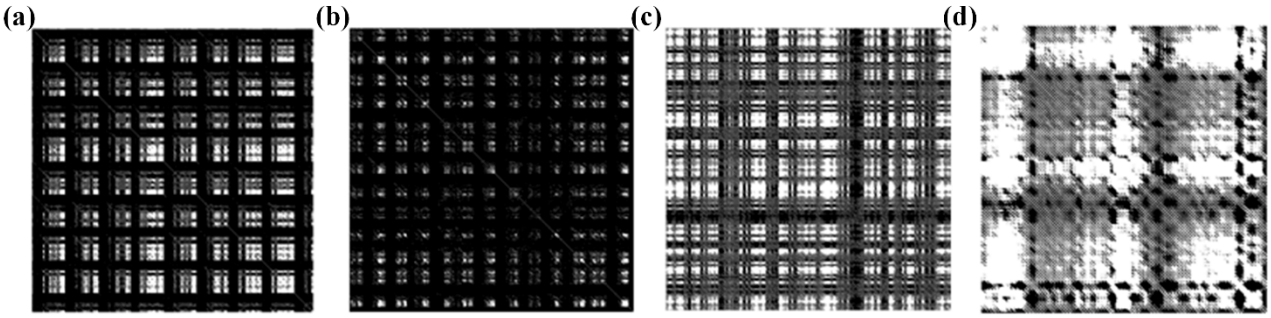

Fig. 3 The RP of (a) bearing inner race (b) bearing outer race (c) bearing rollers wearing and (d) normal

In the experiment, the SIFT descriptor extracts the feature point of the bi-spectrum with 128-dimension form. By using PCA, the origin features of the datasets are reduced automatically to 20 dimensions.

The input eigenvector of PNN is extracted by SURF and t-SNE. To display the result visually, the classification result is contrasted with the actual result. The accuracy rate is defined as the odds ratio of the correct results and the total results.

Four set cross validation is adopted to verify the accuracy of the proposed method. For each fault mode, 60 sets of data are collected. The length of the data is 2048. Divide the 60 sets into 4 groups; each group is selected as training data in turn, whereas the others are selected as test data. The composition of the data is shown as Table 1:

Table 1. The data composition

Fault types	Number of data points	Amount of training data	Amount of test data
Normal	60	15	45
Bearing roller wearing	60	15	45
Bearing inner race wearing	60	15	45
Bearing outer race wearing	60	15	45
Total amount	240	60	180

The fault diagnosis of PNN is shown as follows. Table 2 show the results of 4 set cross validation. The red circle is the actual fault category, and the blue triangle is the fault diagnosis result. Annotations 1~4 in vertical axis represent the bearing roller wearing, the bearing inner race wearing, the normal condition, the centrifugal pump impeller wearing and the bearing outer race wearing. Table 2 presents a summary of the cross-validation results.

Table 2. The diagnosis results

Fault types	Testing Samples	Correct Results of 4 sets				Accuracy				Total accuracy
		1	2	3	4	1	2	3	4	
Normal	60	60	58	60	59	100%	96.7%	100%	98.3%	98.75%
Bearing roller wearing	60	59	60	59	59	98.3%	100%	98.3%	98.3%	98.75%
Bearing inner race wearing	60	60	58	58	59	100%	96.7%	96.7%	98.3%	97.91%
Bearing outer race wearing	60	58	60	59	57	96.7%	100%	98.3%	95%	98.23%

From the diagnosis of PNN we can conclude that all of the accuracy rates exceed 96%. The cross-validation results of the first, second, third, and fourth sets are 98.75%, 98.75%, 97.91%, and 97.5%, respectively. Average classification accuracy is as high as 98.33%, which verifies the effectiveness of the proposed method.

4. Conclusion

In this paper, we present a novel rotating machinery diagnosis method based on image recognition that contains four major steps: First, the RQA is employed to transform the initial vibration signal into an image (RP). Next, SIFT is first introduced to extract feature points of the image automatically. Based on the feature vectors extracted by RP and SIFT, PNN is applied to enable fault mode recognition. The proposed image-recognition-based fault diagnostic method for rotating machine first introduces the image interest point extraction method to provide a fault diagnosis and achieve feature extraction of RP automatically. Thus, the method avoids the limitations of relying on a diagnostician for feature extraction. Favorable results demonstrate that our method can improve robustness and generalization ability while maintaining accuracy of classification.

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