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Fault Extraction and Identification on Transmission Components of Mechanical Equipment

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Abstract

In order to solve the problem of nonlinear, nonstationary, complex components and redundant information of rolling bearing vibration signal in single scale, a rolling bearing fault feature extraction method based on wavelet packet decomposition and permutation entropy and sample entropy is proposed. Firstly, wavelet packet decomposition is used to decompose the original signal of rolling bearing into several subbands with different frequencies, and the permutation entropy and sample entropy of signal data at different frequencies are calculated. Secondly, the sample entropy and permutation entropy of different frequency signals after decomposition and reconstruction are extracted to form a high-dimensional feature vector to complete the initial fault feature extraction. Finally, the extracted feature samples are randomly arranged for fault recognition. The experimental data of rolling bearing processed by this method are identified by extreme learning machine. The results show that the method can effectively identify the fault types of rolling bearing, and the classification effect is better than that of the original data set training, and the classification accuracy reaches 99.8.

Keywords: Rolling Bearing, Wavelet Packet Decomposition, Entropy Characteristics, ELM, Feature Extraction

Introduction

With the continuous progress of science and technology in modern society, the automation and integrated production equipment in various industries of machinery and electric power also make the various industries more closely connected. In the process of equipment production, if a key equipment failure suddenly occurs, the operation of the system may be interrupted, and even more serious, it may hurt people and cause huge property losses. Such accidents happen again and again, so the urgency and importance of equipment fault detection and fault isolation are paid more and more attention. With the application of new technologies and new materials, the production reliability is improved and the safety is guaranteed. Real-time monitoring of production status and strengthening quality control of working status have also become important measures. Under such production environment and background, fault diagnosis theory came into being. In order to ensure the safety of mechanical production, protect personal and production safety, and find, deal with and prevent faults effectively and quickly, it has become an essential and important link [1].

The transmission part of mechanical equipment is the core part of fault diagnosis, and the transmission shaft, one of the important parts of the transmission part, is used in all kinds of mechanical equipment. As a transmission shaft which plays an important role in fixing and restricting the movement in the operation of mechanical equipment, most mechanical equipment failures occur here, which is often the most prone to failure. According to incomplete statistics, the faults related to the transmission shaft account for more than 20 of the faults in which the mechanical equipment cannot operate normally. In July 2017, a pendulum fracture accident occurred at the Carnival Playground in Ohio, USA. The on-site accident is shown in Figure 1.1; Figure 1.2 shows the broken shaft accident of wind power generation in Brandenburg, Germany in 2014. The normal operation of industrial production is closely related to the quality of transmission shaft. The failure of the transmission shaft will cause the vibration of the mechanical equipment, and it will often be accompanied by mechanical damage, and even worse, the mechanical equipment will cause accidents and damage. Therefore, the higher the precision standard of the machine, the stricter the standard of the transmission shaft. Minor faults may cause great damage to the normal operation of the machine, the precision of the equipment and personal safety [2].

With the continuous development of China's economic construction, the manual diagnosis method of regular inspection by professionals not only takes a long time, but also requires maintenance and inspection of all equipment. Its flexibility, economic cost and time cost can no longer meet the normal industrial demand. With the development of artificial intelligence and signal processing technology, coupled with the rapid development of electromagnetic detection, vibration detection, infrared measurement, image processing, pattern recognition, wavelet analysis, neural network and other technologies, the fault diagnosis theory continues to develop.

Real-time detection of equipment production status, identification of fault location and damage degree, diagnosis. Eliminating conventional vibration to diagnose faults, creating a microcomputer system for real-time monitoring and fault diagnosis of transmission shaft, "failure mechanism", "detection, diagnosis and prediction technology", "reliability design" and "material durability evaluation" are all the research results obtained by the mechanical fault prevention team of the National Bureau of Standards [3].

George Georgoulas and others from the Department of Computer Science and Electrical and Space Engineering of Swedish Control Engineering Group introduced a simple method to detect and diagnose faults by fusing information from two accelerometers. Under the three visual features extracted from the accelerometer data located at two different points in the diagnosed environment, the test proves that the fault diagnosis accuracy of this method reaches 98.91 percentage.

Scheme Design

Moment function

Moment function is widely used as a means of image analysis in image type recognition and model recognition. Moment is a numerical feature, which distinguishes random variables in statistics and probability. Through calculation and analysis, the rich geometric characteristics contained in each picture, such as the size and shape of the image; Different kinds of geometric features, such as the direction and position of the image, can be extracted, and the moment set can be obtained [4]. It plays an important role in image target coding, azimuth estimation and image pattern recognition.

Moment invariants are a set of characteristic parameters, which are unique to each picture and correspond one to one. It has great reference significance in judging image shape. Whether the image is enlarged or reduced, rotated at different angles and translated in position, its invariance will not change. This characteristic makes the recognition of images reference and is more conducive to image classification, which is a very important characteristic. Mathematically, each picture is actually compared to a thin block with uneven thickness. Because of its different thickness, the mass density at each position is also uneven and its size is different.

When it changes, the pixel size and the center of gravity of the image are virtually unchanged. Only in this way can the calculation be carried out, and the moment invariants of each order moment will not change. Therefore, in this paper, aiming at the axis track of the failure, typical pictures are selected. By rotating the pictures by 90 degrees, 180 degrees and doubling and shrinking the images, the standard invariant distance of each image is obtained, and the invariant moment database is established, so that the fault types can be quickly identified [5].

Invariant moment

As a feature extraction method, the geometric invariant moment method uses mathematical matrix to express the geometric features of the image. In fact, moment invariants draw lessons from moment method, pixel points are regarded as image particles, and pixel coordinates are regarded as force arms [6]. If the size of digital image f (i; j) is $M \times N$, its $p + q$ moment is:

$$M_{pq} = \sum_{i=1}^{M} \sum_{j=1}^{N} i^p j^q f(i,j) \tag{1}$$

The corresponding $p + q$ order center distance is:

$$M_{pq} = \sum \sum (i - \bar{i})^p (j - \bar{j})^q f(i,j) \tag{2}$$

Generally, the first moment of an image is about the shape, and the second moment is used to show the expansion level of the average value between lines. The third moment is used to calculate the symmetry of the average value.

Gray Processing

Color image is composed of R component, G component and B component, which are not equal in most cases. Gray processing can make the three components equal. Images can be converted into grayscale images [7]. Pixel is the smallest unit of each image. What we call image processing is actually processing and operating the image composed of pixels. Every pixel is represented by r vector, g vector and b vector, that is, it corresponds to three vector matrices of r, g and b, namely r matrix, g matrix and b matrix. Each image has different pixel values, and the larger the gray value, the brighter the pixels. Generally, the processing of pixel color is the process of assigning different values to three vectors: R, G and B. After grayscale processing, the axis track images prepared in advance are converted into their own grayscale images. This makes a good preparation for the next step of processing, and then carries out the calculation of image recognition. The efficiency of extracting different fault images is improved. Especially, in the recognition of fault images of outer eight and inner eight and quincunx, it is obviously improved and the calculation time is greatly reduced.

Image Recognition based on Hu Invariant Moment Method

M.K.Hu extended the moment theory in 1970s, and Hu invariant moments were summarized and sorted out. It includes seven values, which are normalized by the image and then combined nonlinearly to get the processed values. Its theoretical basis is Papoulis's uniqueness theorem. If f (x; y) is a continuous piecewise function with finite values in the plane, the unique ordered moment can be deter- mined. On the contrary, the moment sequence $\{\mu_{p,q}\}$ can also uniquely determine f (x; y):

$$f(x,y) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \exp\left[-j2\pi (ux + vy)\right] \cdot \left[\sum_{p=0}^{\infty} \sum_{q=0}^{\infty} m_{p,q} \frac{(2j\pi)^{p+q}}{p!q!}\right] \tag{3}$$

For each complete image, in a fixed area, it is a function that satisfies the condition of continuous segmentation. The uniqueness theorem also confirms that the moments of different orders of each image are fixed and can be extracted as features. Therefore, all the information represented by each image can be uniquely expressed by the moment sequence. In theory, we need to find all the moments of different orders of the image, but in practice, we only need to select one subsequence. As a part of moment sequence, the effective features and other information expressed by subsequence are enough to describe and express an image.

The following is Hu invariant moment formula:

$$I_1 = y_{20} + y_{02} \tag{4}$$

$$I_2 = (y_{20} + y_{02})^2 + 4y_{11}^2 \tag{5}$$

$$I_3 = (y_{30} + 3y)^2 + (3y_{21} - y_{03})^2 \tag{6}$$

$$I_4 = (y_{30} + y_{12})^2 + (y_{21} + y_{30})^2 \tag{7}$$

These seven invariant moments are all related to specific regions, which are also called regional moments by scholars. Among the above moment invariants, the image invariance is the last one that is not possessed, and the image of I_7 is -I_7.

Hu moment invariants can be used to measure the axis trajectory image as a whole. Moreover, the calculation of these seven moment invariants is different in complexity and the amount of information expressed is different. The low-order moments of images often contain most valuable information. The high-order moment is not meaningless, and the axis rail. The regional features and detail features of trace images can be expressed. For example, the twist degree can be expressed by the third-order moment, and the peak state can be expressed by the fourth-order moment [8]. In this paper, according to the above formula, the Hu moment invariant program is written. Hu moment invariants of the detected image after rotating and scaling are calculated. In order to test the correctness and invariance of Hu moment invariants, the Hu moment invariants of a normal image are calculated and tested. After rotating, shrinking and doubling, six groups of values are obtained. I_1 - $I_7$is the calculated values of 7 Hu moments, and the data are shown in Table 1.

Table 1: Hu moment invariant data of normal axis trajectory

I1	I2	I3	I4	I5	I6	I7
1.0000	1.0107	2.2123	2.8620	4.7858	7.4172	3.6747
1.0000	1.0107	2.2123	2.8620	4.7858	7.4172	3.6747
1.0000	1.0107	2.2123	2.8620	4.7858	7.4172	3.6747
1.0000	1.0107	2.2123	2.8620	4.7858	7.4172	3.6747
1.0000	1.0110	1.0110	3.4158	5.3004	8.2237	4.1767
1.0000	1.0107	2.2123	2.8620	4.7858	7.4172	3.6747

Simulation Experiment

The goal of the program is to complete the detection of axis trajectory, that is, the identification of fault types. Firstly, each axis track image is read, and the image is grayed to complete the image preparation. Then run the program to calculate Hu moment invariant data. The program rotates each image, completes the transformation of different angles, and calculates the Hu invariant moment value of different angle transformation [9]. After that, double the size of the picture, get and extract the value again. Each group of Hu invariant moment of each image corresponds to 7 values. Finally, the cyclic calculation of Hu invariant moment of each image of different fault types is completed. Save six sets of Hu moment invariant data of each image in the data set until all images are calculated. Complete the establishment of data set. After the test image is normalized, the accuracy detection of each image is started. Firstly, read the image to be detected. You can choose to add salt and pepper noise to increase the recognition difficulty. After rotating, reducing and amplifying, calculate the Hu invariant moment data of the detected image after various transformations. When calculating the feature distance between the image and each data image, the image with the smallest feature distance is selected as the final detection result by Euclidean criterion. The detected image type is output in real time on the program interface. Finally, the detection accuracy is counted.

- Read data image
- Rotate dataset
- Scale dataset
- Extracting Hu moments
- Create dataset
- Read the image to be detected choose to add salt and pepper noise to increase the difficulty of recognition.
- When calculating the feature distance between the image and each data image, the image with the smallest feature distance is selected as the final detection result by Euclidean criterion.
- Detect the image type and count the detection accuracy.

Normalization processing

Image normalization is widely used in visual science and image recognition. Its principle is to transform the image to processed into a fixed standard form after various transformations.

At this time, the image is subject to various affine transformations, such as rotation Scaling and so on have invariant properties []. The first step of normalization is to determine the parameters, transform the moment of the function, and affine transformation also has invariance. The second step is to use the transformation function to construct the standard form and get the final image. Normalization can improve the convergence speed of the target. Generally speaking, no matter how far you go, you will ensure that the direction is right and will not deviate from the main road.

Normalization can also improve the accuracy of the target. Let the different features of the image have equal influence and contribution to the final recognition result. Normalization can make different fault images go through different geometric transformations and still find image invariants. This improves the classification speed of various images. In this way, not only the standard image can be recognized. Subsequently, according to the Hu invariant moments of different images, the influence of various transformations is eliminated. It can quickly identify and obtain a class or type of fault image.

Euclidean Distance Determination

First, detect the normal image, and the program can correctly identify the image1:

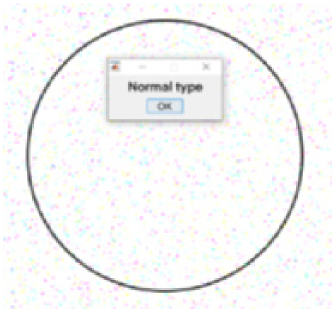

Figure 1: Normal image detection

In the classification of images, Euclidean distance is used to determine the distance. It can calculate the real distance between points in n-dimensional space, which is a widely used distance definition.

The formula of Euclidean distance is as follows:
N-dimensional space formula:

$$d(x,y)=\sqrt{(x_1-y_1)^2+(x_2-y_2)^2+\cdots+(x_n-y_n)^2} \tag{8}$$

P is the Euclidean distance between point (x_1; y_1) and (x_2; y_2) point |X| is the Euclidean distance from point (x_2; y_2) to the origin.

For multiple types of faults, select a vector for each type of fault as the standard reference. During detection, calculate the distance through equation 4.8, and the minimum distance is obtained to find out the corresponding category, that is, the corresponding fault type. The i-dimensional coordinates of the nth point are expressed, and the invariant moment of the image is calculated. Then the Euclidean distance between the invariant moment and the image invariant moment in the standard library is calculated, and the pixel value of the detected image is transformed into the distance from the point to the nearest fault type image. By comparing the similarity between the image and the standard image, the program can automatically identify whether it is a kind of image and output the fault type. The function of fault image recognition can be realized.

In this program, several groups of different types of images are input to calculate their Hu invariant moments. After graying and normalization, the image invariant moment and the values in the database are calculated by Euclidean distance. The accuracy rate reached 100.

Detection of images of different fault types 2345:

Figure 2: Inner eight type image detection

Figure 3: External eight type image detection

Through the identification and detection of various images, various fault types and their axis trajectory images are summarized, as shown in table 2. The program rotates each image, completes the transformation of different angles, and calculates the Hu invariant moment value of different angle transformation. After that, the image is doubled and magnified, and the Hu moment invariant value of each image is obtained and extracted again.

Figure 4: Plum blossom image detection

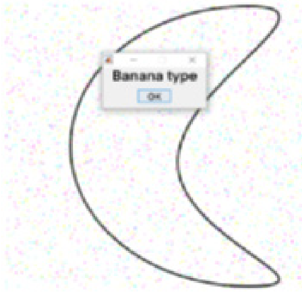

Figure 5: Banana image detection

Table 2: Axis trajectories of different fault types

Fault classification	Axis trajectory image
Rotor unbalance	amp; elliptic
Rotor misalignment	amp; outer eight or banana type
Oil film oscillation	amp; irregular quincunx
Whirl of oil film	amp; inner eight type
Friction between moving and stationary parts	amp; regular or irregular quincunx
Mechanical looseness	amp; irregular ellipse
Shaft crack	amp; Banana type

Each image is classified by Euclidean distance. The images of each fault type are tested for 30 times. Finally, the accuracy of the program is 100, which fully shows the effectiveness of the method. The test results are shown in table3.

Table 3: Axis trajectories of different fault types

Test group	Test quantity / time	Accuracy Banana type 30 100
Normal type	30	100
Inner eight types	30	100
Outer eight type	30	100
Plum blossom type	30	100
Banana type	30	100

Conclusion

With the rapid development of fault diagnosis technology, fault types can be identified accurately and efficiently, and the safety of mechanical equipment, property and personal safety can be protected. In this paper, the Hu moment invariant data are analyzed for different types of axis tracks, and the fault types and causes are summarized. Finally, the validity and accuracy of the program are tested by using the test data. This paper mainly summarizes the following aspects:

1. Studying the related documents of the subject background, understanding the development status at home and abroad, and making a more in-depth study on the subject. Understand the importance of fault diagnosis in national economic construction, and learn and master more knowledge about the subject.
2. Some basic information of transmission components is introduced, including the structure of transmission shaft, the classification of transmission shaft and the types of fault causes, and the basic axis track types and related fault causes are also introduced. The knowledge of transmission parts and axis track is understood, which lays a foundation for the identification and classification of axis track.
3. The theoretical knowledge needed in image processing is introduced, including moment function, invariant moment and gray processing. Moment function is a basic mathematical method for image recognition, while invariant moment is a mathematical theory. Graying is to convert an image into usable pixels. All these are ready for the follow-up program.
4. Based on Hu moment invariants, combined with Euclidean criterion and other mathematical methods, the function of image recognition is realized on Matlab platform. Through repeated experiments, it can be seen that the image recognition program based on Hu moment invariants has the characteristics of high recognition rate and high speed, which proves the advantages of Hu moment invariants in image recognition.

Although some achievements have been made in this study, there are some inadequacies in the process of running the program. The following problems should be paid attention to in the future study and research:

1. For the fault types, only a few typical faults are selected, and the fault types with low frequency and few times in other mechanical equipment are not studied and identified.
2. The relevant knowledge of Hu moment invariants theory has not been thoroughly studied, and its theoretical knowledge has only been partially used for reference and application, and it is impossible to deal with and identify more complex fault types of axis trajectory. It is hoped that in the future study and work, we can conduct deeper research and identify more fault types.
3. Lack of real-time analysis of actual working conditions, less involvement in actual working environment and work interference factors of mechanical equipment, and the program needs to be tested according to actual working conditions. It is hoped that in the future work, combining with the actual work situation, we will analyze the work, combine the theory with the actual work situation, and further improve the procedures and papers.

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