Fault Diagnosis of Rotating Machinery based on the Minutiae Algorithm

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ABSTRACT

Rotary machinery plays an important role in industry. Combined faults can be observed in rotating machinery, making fault classification difficult. In this paper, the Minutiae algorithm is used to classify the faults from the frequency domain of a particular fault. This paper provides a fault classification technique based on image processing for fault analysis of rotating machinery, recognizing function extraction automatically. Minutiae algorithm, a rising method within the discipline of image processing for characteristic extraction, is utilized in this paper to classify specific faults from the converted recurrence plot. The results reveal the effectiveness of the proposed method, providing a rather powerful tool for fault diagnosis of rotating machinery. The proposed model achieved an accuracy of 100% for combined faults, 98.33% for loosened faults, and 95% for unbalanced faults proving its applicability.

Keywords-rotating machinery; fault diagnosis; Minutiae algorithm

I. INTRODUCTION

Rotary machines, also known as rotor bearing systems, play an important role in industry. With the rapid development of science and technology, critical machines in industry are becoming faster and more complex. Critical and essential machines are machines that have high capital costs, require high or moderate costs to repair, take more time, and require skilled personnel. In addition, the unexpected shutdown or failure of critical and essential machinery affects plant safety and causes significant production losses. Therefore, accurate and reliable diagnosis of critical and important machine faults is of utmost importance. In this concern, single and multiple fault diagnostics of rotating machines have become important among researchers and operators. Condition monitoring and failure diagnostics of rotating machines are extremely important for the safety and reliability of industrial production [1]. During the recent decades, many signal processing techniques, such as symplectic geometry mode decomposition [2], variational mode decomposition [3], neural network and wavelet transform [4], wavelet packet decomposition, Fourier transform, artificial neural networks [5], and empirical wavelet transform and fuzzy entropy [6], have been widely used to analyze the nonlinear and nonstationary signals. Authors in [7] used BP-ANN for the identification of bearing cap looseness with an overall success rate of 90%. Authors in [4] successfully predicted the effects of unbalance and shaft bow combined faults on the frequency components of the FFT spectrum of rotating machinery using ANN and Wavelet Transform (WT). Their method was successfully tested for single and combined unbalance and shaft bow. Authors in [8] developed a finite element model of a rotor system with a loose pedestal, and they examined the effects of pedestal displacement and looseness clearance on the system dynamic properties. Authors in [9] employed ANNs to detect pedestal looseness and imbalance in the rotor bearing system. Their findings demonstrated that statistical characteristics gave better results than frequency domain. Authors in [10] used a combined time series analysis algorithm and ANNs to detect and diagnose the fault. Authors in [11] used time series analysis and ANNs for fault diagnosis of rotating machinery. Authors in [12] divided vibration signals into many product functions using the local mean decomposition method, and then they calculated the multi-scale entropy of each product function as feature vectors. These feature vectors subsequently served as the input for the fault classifier, which completes the fault classification. All these technologies, however, primarily rely on 1-dimensional vibration signal processing methods. Authors in [13] proposed an effective fault diagnosis method based on Multi-Scale Dimensionless Indicator (MSDI) and random forests. They reported that their approach can accurately identify various fault types with an average precision of 95.58%. Authors in [14] used Support Vector Machine (SVM), ANNs, and k-Nearest Neighbor (kNN) for fault diagnosis of rotating machinery. Different vibration signals may be categorized based on the extracted characteristics using various classification techniques, including Logistic Regression (LR), SVMs, and ANNs [15]. Authors in [16] used FFT of IMFs from the Hilbert-Huang Transform process to utilize the efficiency of Hilbert Transform in the frequency domain. Authors in [17] utilized a SVM with a Genetic Algorithm (GA) to diagnose a power transformer fault, with the GA being used to choose the proper SVM free parameters. Authors in [18] used amino acid sequences to address challenges with the categorization of macromolecules using deep learning models such as Convolution Neural Networks (CNNs), LSTM, and Gated Recurrent Units (GRU). Authors in [19] used a neural network-based model to classify the state of the gearbox into good (unbroken tooth) condition and poor (broken tooth). They claimed that BLSTM accuracy with an incomplete autoencoder is extremely reliable and suitable for time series data-based health monitoring of wind turbine gearbox systems. Authors in [20] studied metallic clutch damper springs included in the 1-D modeling of the powertrain system that was subjected to vibration optimization using the Simulated Annealing (SA) technique. This cutting-edge technology expedites the optimization of the engine system's vibration and offers presumptions that save money and time during actual vehicle testing.

The Minutiae algorithm approach is recognized as an attractive descriptor for practical usage and for matching features with strong resilience and high accuracy due to the advancement of the image automated feature extraction technology during the recent decades. It is used in this study to extract defect characteristics from recursive graphs. Once the Minutiae features are extracted, they can be used for fault classification and pattern recognition. By comparing the extracted patterns with known fault signatures, the algorithm can identify the type and severity of the fault. The effectiveness of the suggested method is tested through the use of fault diagnosis cases, such as unbalanced, loosened, and combined fault.

II. METHODOLOGY

A. Experimental Setup

The tests were conducted on the test rig shown in Figure 1. The test-rig consists of a shaft of 25 mm diameter and 700 mm length which is supported on two double row deep groove ball bearings (SKF1205). At the midpoint of the bearings, a single 130 mm-diameter, 18 mm-thick rotor disc is mounted. Eight evenly distributed 12 mm diameter holes with a 45 mm radius are present on the rotor disc, which can be used to produce unbalance by adding weight. A 1 hp DC motor drives the rotor, and a DC controller regulates its speed. The rigid flange coupling is used to connect the rotor shaft (driven shaft) and motor shaft (driving shaft). The parallel misalignment of 0.2 mm in vertical direction was created in coupling by placing shims below DE and NDE bearings housing. Pedestal looseness is obtained by loosening the pedestal bolts. The rotor operating speed was kept at 1000 rev/min.

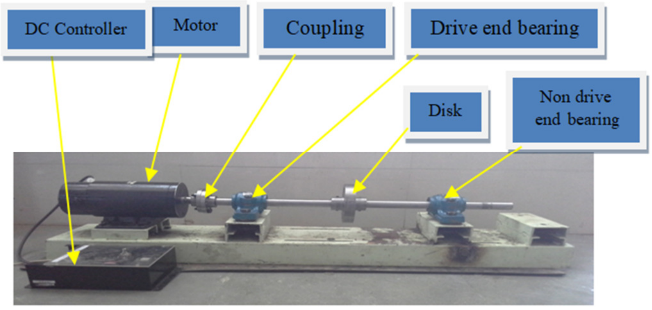


Fig. 1. The rotor test rig.

Fig. 2. The FFT analyzer.

A four channel FFT analyzer (Make: Adash; Model: VA4Pro) is used to measure and analyze the vibrations (Figure 2). The vibration signals in the Horizontal (H), Vertical (V), and Axial (A) direction at a bearing-housing are collected using three piezoelectric accelerometers (Make: CTC; Model: AC102-1A) with 100 mV/g sensitivity. The data acquisition parameters are given in Table I. The frequency spectra of unbalanced (Figure 3), loosened (Figure 4), and combined (Figure 5) faults were obtained. Figure 3 shows one peak and Figure 4 shows two peaks higher than the others. In Figure 5, multiple peaks are observed. A total of 60 testing signals of unbalanced, loosened and combined faults were obtained under our experimental conditions.

TABLE I. DATA ACQUISITION PARAMETERS

Sampling Frequency	4096 Hz
No. of Samples	4096
Window	Hanning
No. of lines	1600
Frequency range	10 Hz -1600 Hz
Time	1 s

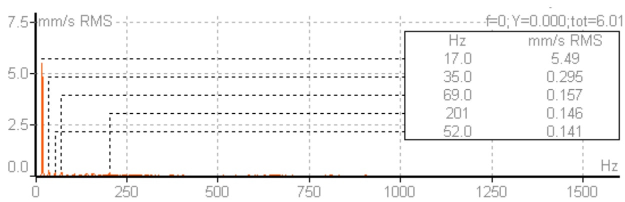


Fig. 3. Frequency spectrum of unbalanced fault.

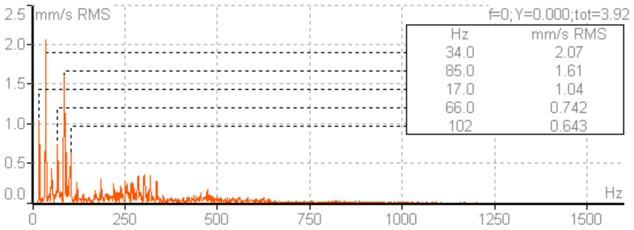


Fig. 4. Frequency spectrum of loosened fault.

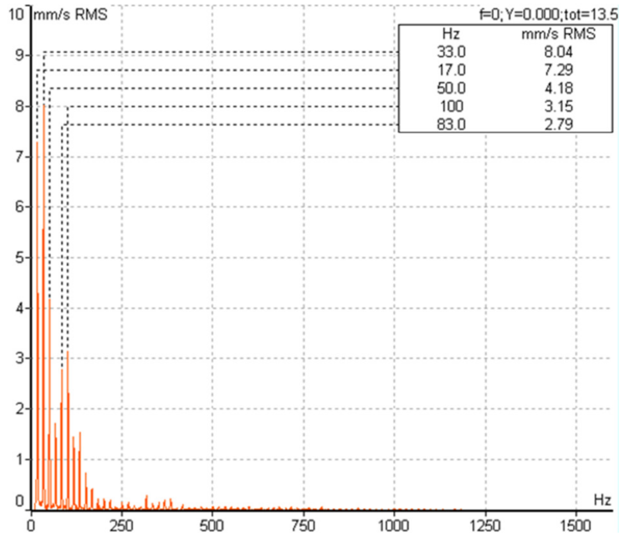


Fig. 5. Frequency spectrum of combined fault.

B. The Minutiae Algorithm

Minutiae algorithms can be adapted to various types of machinery and different kinds of sensor data, making them versatile tools for fault diagnosis in a wide range of industrial applications. Minutiae algorithms enable data-driven decision making, where maintenance actions are based on the analysis of actual machine performance data rather than predetermined schedules. This approach, known as predictive maintenance, optimizes maintenance efforts and reduces unnecessary downtime. The flow chart of the fault diagnostic system with the use of the Minutiae Algorithm is shown in Figure 6. The steps of the followed method are:

Represent the mechanical system as a graph: Each node in the graph represents a component of the system, and each edge represents a connection or interaction between two components.

Define the rotating faults to be detected: For example, faults such as misaligned gears or bearings, unbalanced loads, or irregular vibrations.

Extract features from the graph: Graph analysis techniques can be used to extract various features from the graph, such as node degree, betweenness centrality, and clustering coefficient. These features can capture different aspects of the graph's structure and dynamics.

Application of the Minutiae algorithm: Compare the extracted features from the graph at different time points to identify any small, unique features that are indicative of the rotating faults defined in step 2.

Train a machine learning model: Use the identified features as input to a machine learning model that can learn to detect the rotating faults automatically. You can train the model using labelled data, where you have examples of the system both with and without the faults.

In image processing, morphological operations are used to analyze and manipulate the shapes and structures within an image. These operations are typically applied to binary images and involve the use of a structuring element, which defines the neighborhood around each pixel. The function cv2.getStructuringElement() is used to create a structuring element of a specific shape and size. In this case, cv2.MORPH_ELLIPSE is used as the shape argument (equation for getting the kernel: cv2.getStructuringElement (cv2.MORPH_ELLIPSE, (3, 3))). The size of the structuring element is specified as (3, 3), indicating a 3×3 matrix. The resulting kernel variable represents the generated structuring element and can be used in various morphological operations, such as erosion, dilation, opening, and closing, to modify and enhance the shape and structure of the image.

$$\text{Element}=\begin{cases}1, \text{ if } \left(\dfrac{x-1}{1.5}\right)^2+\left(\dfrac{y-1}{1.5}\right)^2 \leq 1 \\ 0, \text{ otherwise}\end{cases}$$

Morphological operations in image processing involve the manipulation of shapes and structures within an image. These operations are commonly used for tasks such as noise removal, feature extraction, and image enhancement. In this specific code snippet, the dilation() function is applied to the input_image using the kernel structuring element. This operation expands or enlarges the regions in the image based on shape and size defined by the kernel. The resulting image is stored in the output_image variable. Dilation is used to enhance or enlarge features, fill in gaps, and fuse nearby structures:

$$\text{dilation }(I, B)(x, y) = \max \{ I(x-i, y-j) : b(i, j) = 1 \}$$

where (x, y) represents a pixel position in the output dilated image, and (x-i, y-j) represents the corresponding pixel positions in the input image I based on the structuring element B.

Next, the erosion() function is applied to the output_image using the same kernel structuring element. Erosion is a fundamental morphological operation in image processing that aims to shrink or erode the regions of an image based on the shape and size defined by the structuring element. It is used to remove small details, smooth the boundaries, and separate overlapping structures. This operation removes or shrinks the regions in the image, complementing the previous dilation operation. The resulting image after erosion is not stored in a separate variable, but the operation is directly applied to the output_image itself. The combined effect of dilation followed by erosion is known as the opening operation. It helps to smooth out the image, remove small isolated regions, and refine the boundaries of objects in the image.

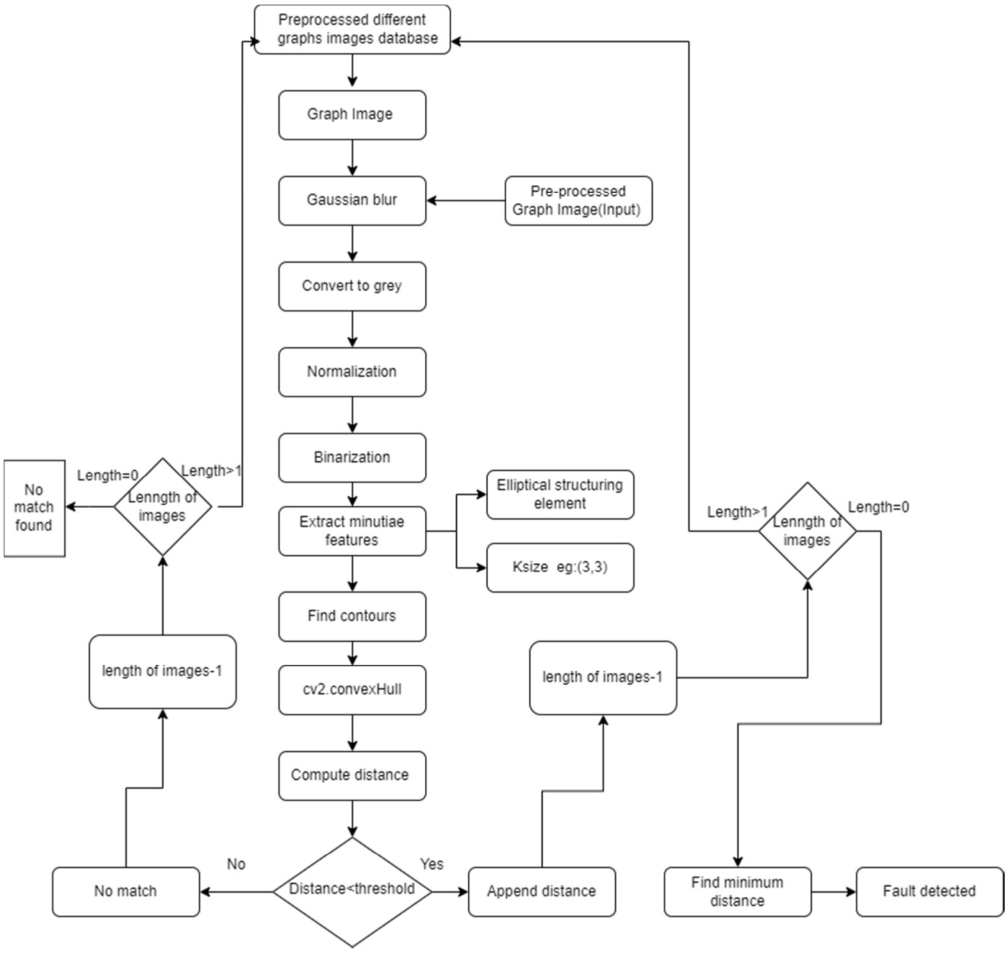


Fig. 6. Flow chart of the fault diagnostic system with the use of the Minutiae algorithm.

erosion (I, B)(x, y) = min { I(x+i, y+j) : b(i, j) = 1 }

where (x, y) represents a pixel position in the output eroded image, and (x+i, y+j) represents the corresponding pixel positions in the input image I based on the structuring element B.

The final ouput image is acquired as:

output_image = dilation (input_image, kernel) followed by erosion (output_image, kernel)

III. RESULTS AND DISCUSSION

In order to exhibit the superiority of the proposed diagnosis system, an experiment is conducted on a testing dataset to evaluate its performance. An enhanced testing image from the testing dataset is shown in Table II.

As mentioned above, a total of 60 testing signals were obtained. Table III shows the classification accuracy of all the testing signals. The experiment results indicate that each fault category can get high classification accuracy and the proposed system is effective in fault diagnosis of rotating machinery.

Accuracy measures the proportion of correctly classified instances out of the total number of instances in the dataset. Our model achieved an accuracy of 100% for the combined fault type. For the loosened fault type, the achieved accuracy is 98.33% and for the unbalanced fault type, the achieved accuracy is 95%, indicating the ability of the proposed method to make correct predictions.

Minutiae algorithms are capable of capturing subtle changes in the data that may indicate the early stages of a fault or degradation in a machine. Early detection is essential for proactive maintenance, preventing catastrophic failures, reducing downtime, and minimizing repair costs. Minutiae algorithms can achieve high precision in fault diagnosis, thus reducing false alarms and ensuring that the identified faults are accurate and reliable.

IV. CONCLUSION

In this paper, the proposed Minutiae algorithm provides effective fault classification in rotating machinery diagnosis based on image recognition. The suggested image-recognition-based fault diagnostic technique for rotating machines first provides an image interest point extraction method to achieve feature extraction of RP automatically and to offer fault diagnosis. The results showed that this method can improve robustness and generalization ability while maintaining classification accuracy.

TABLE II. FREQUENCY SPECTRA IN THE TRAINING DATASET AND THEIR ENHANCED IMAGES

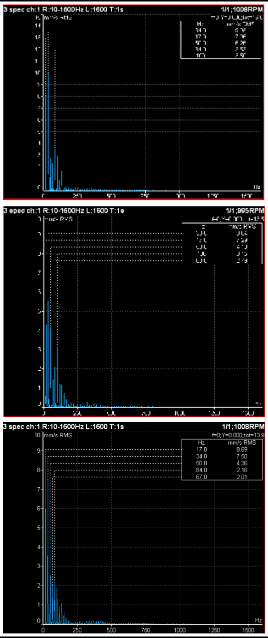
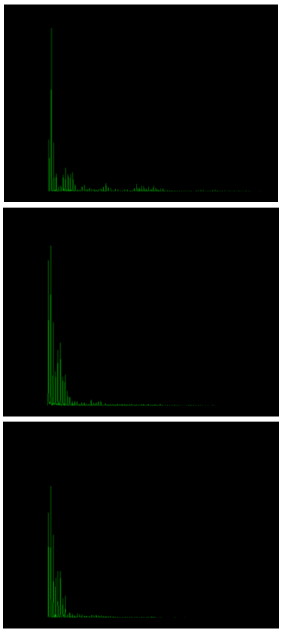
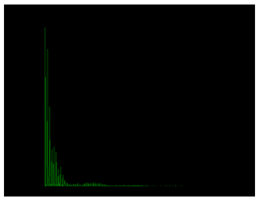
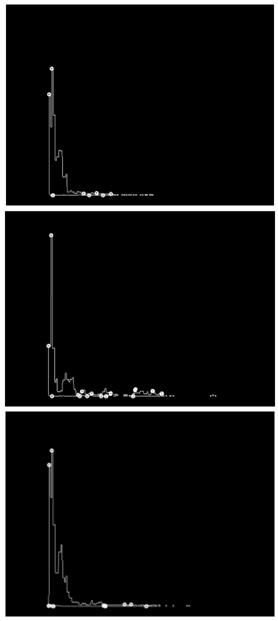
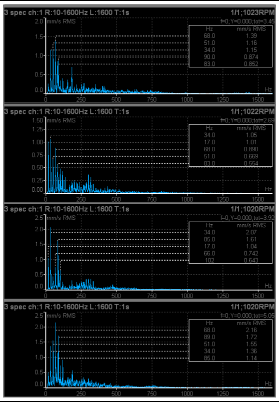
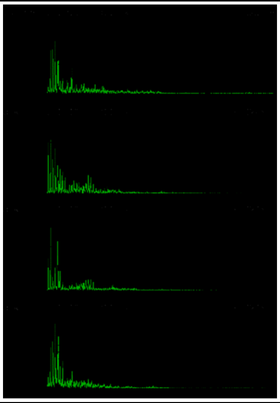
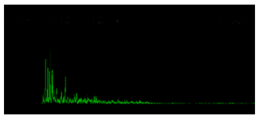
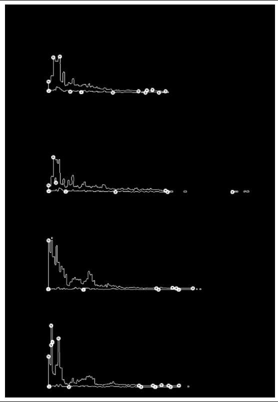
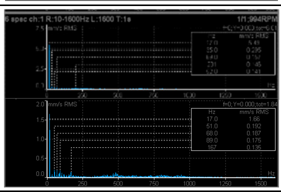
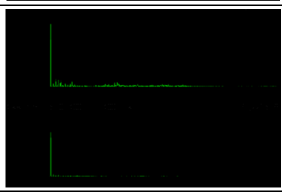
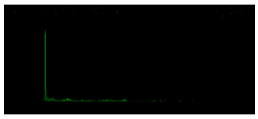
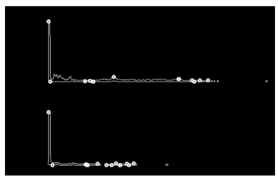
Fault type	Original	Processed image	Input image	Output images
Combined				
Loosened				
Unbalanced				

TABLE III. DIAGNOSIS RESULTS

Fault types	Testing samples	Correct results	Accuracy
Combined	60	60	100%
Looseness	60	59	98.33%
Unbalanced	60	57	95%

Minutiae algorithm is helpful in accurate early fault detection so that corrective action can take place to avoid failure of machines. Minutiae algorithms are essential components of modern machine fault diagnosis systems, providing the necessary tools to monitor, analyze, and predict faults in machinery, leading to improved reliability, safety, and productivity in industrial settings. The performance of the suggested proposed on benchmark data sets is quite promising.

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