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A Study of Vibration Parameter Image for Rotating Machinery Based on Multi-scale Morphological Transformation Edge Detection Method

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Abstract. The 3d vibration parameter images were obtained from rotor's normal state, fault of unbalance, misalignment, steam exciting vibration and bearing pedestal looseness which were examined on the modeling of 600 MW turbine rotor experimental bench. These 3d images of different faults were pretreated and transformed to 2d gray-scale images. Multi-scale enhancement processing method was adopted to enhance available information of parameter images based on the theory of Top-Hat transformation and Bottom-Hat transformation. The results show that this method can effectively filter out the noise of parameter image and obtain high-quality edge features from the fault image.

Keywords: rotating machinery, vibration parameter image, Top-Hat, Bottom-Hat, edge detection

1. Introduction

Rotating machinery is the main production tool in petrochemical industry, metallurgy, electric power, aerospace industry and so on. Usually, the failure for rotating machinery is the vibration. A lot of information which reflects the running state of equipment is contained in 3d vibration parameter images for rotating machinery, such as 2d amplitude-frequency or phase-frequency characteristic curve, trend image, wavelet map, 3d spectrum, 3d step correlation chart and so on. Nowadays, the monitoring and diagnosis according to vibration signal is the primary means for rotating machinery maintenance management. According to incomplete statistics, fault diagnosis methods based on vibration occupy more than 70% in rotating machinery fault diagnosis, because there is a wealth of equipment running state information in the vibration signal, and it is important research field of fault diagnosis at present [1~5].

The information of vibration parameter images has not been applied to fault diagnosis for rotating machinery well, the main reason is that extracting the features of images is difficult, because the features can be described with language hardly [4]. The edge is the most basic feature of parameter images, which contains most available information of the images, and how to extract available information is the key for rotating machinery fault diagnosis. Generally speaking, the vibration signals of rotating machinery are seriously interference by noise because of construction environment and other reasons, the ideal effect is often difficult to achieve in its edge detection so that the follow-up fault diagnosis work is greatly affected. Mathematical morphology is mathematical tool which analyzes image by study the morphological features as object. The basic idea of mathematical morphology is to measure and extract the corresponding morphology of image with structural element with certain morphology in order to achieve the purpose of analyzing and recognizing image [6]. Therefore, this paper is based on the experiments of literature [1]. Firstly, rotating machinery vibration parameter images are filtered by multi-scale opening and closing filter to gain low-frequency images which are enough smooth. Secondly, the multi-scale morphological Top-hat transformation and Bottom-hat transformation are applied to extract detail features of images which are

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smaller than the scale. So the original images are decomposed into low-frequency smoothing images and multi-scale high-frequency detail images. And then get the enhanced images by fusion processing. Lastly, detect their edges with multi-scale edge detection method. The results show that this method makes the fusion images contain both excellent noise immunity and abundant detail information. Therefore, the edges of rotating machinery vibration parameter images can be well detected with this method.

2. Basic principle of mathematical morphology

The main contents of morphological morphology are the description of the basic features and structure of image with a full set of transformations. The most basic transformations are the erosion and dilation. Other transformations are defined by the combination of these two transformations.

2.1. Morphological erosion and dilation operations

Let A be an input image, B be a structure element. Then the erosion and dilation operations of image A with image B are defined as:

$$A\Theta B=\min\{A(s+x,t+y)-B(x,y) \mid (s+x),(t+y)\in D_{\mathrm{A}},(x,y)\in D_{\mathrm{B}}\} \tag{1}$$

$$A\oplus B=\max\{A(s-x,t-y)+B(x,y) \mid (s-x),(t-y)\in D_{\mathrm{A}},(x,y)\in D_{\mathrm{B}}\} \tag{2}$$

Among of which $x,y\in Z^2$ represent space vector, $A\rightarrow Z$ represent integer gray-scale image, $B\rightarrow Z$ represent gray-scale structure element, $A,B\in Z^2$ represent the thresholds of gray-scale image and structure element. D_{A} and D_{B} are the domains of the function A and B respectively. The displacement parameters must be included within the domain of the function A.

2.2. Morphological opening and closing operations

Opening and closing operations are defined as:

$$A\circ B=(A\Theta B)\oplus B \tag{3}$$

$$A\bullet B=(A\oplus B)\Theta B \tag{4}$$

Opening operation can eliminate the scattered points and the burrs which are smaller than the structure element. It plays the role of separation by cutting off slender lap, which is smoothing the image. Closing operation can fill on the gaps and the holes which are smaller than the structure element. It plays the role of connection by repairing the short intermittent, which is filtering the external image can burnish the cusps convex to the inside image [7].

2.3. Morphological transformation

Some important markers can be gained from the difference between original image and its result of opening operation. This method is very effective in seeking the dark pixel aggregates (particles) in bright background or seeking the bright pixel aggregates in dark background. Morphological Top-Hat and Bottom-Hat transformations can meet the above two requirements respectively, so they can be used to detect the peaks and valleys of the image of signal which are smaller than structure element [8].

Top-Hat transformation operation is defined as:

$$\mathrm{Top-Hat}(A)=A-(A\circ B) \tag{5}$$

Bottom-Hat transformation operation is defined as:

$$\mathrm{Bottom-Hat}\ (A)\ =(A\bullet B)-A \tag{6}$$

3. Multi-scale morphological transformation edge detection

Morphological filter operation can be the combinations in series and parallel which are composed of one or two individuals chose from erosion, dilation, opening and closing operations. Multi-scale opening and closing filter operation deals with the image in many times with the different shapes or sizes structure elements, which is better than multi-scale erosion and dilation filter operation in maintaining the details of image, eliminating noise, improving SNR and so on. This method optimizes the available information of original image to some extent so that the follow-up edge detection result is more real and reliable. Therefore, it is used more frequently in the morphological filter.

3.1. Multi-scale enhancement

Because the multi-scale opening and closing filter operation has space invariance, the effect is better than the multi-scale erosion and dilation filter operation. So it is used for the enhancement processing of image in this paper. In order to get enough smoothing image, the largest scale structure element B_n is adopted firstly in multi-scale filter, then the opening and closing smoothing processor $\overline{G}(\omega, x, y)$ is expressed as follows:

$$\overline{G}(\omega, x, y) = \omega G \circ B_n(x, y) + (1-\omega)\, G \bullet B_n(x, y) \tag{7}$$

where ω represents the weight of the opening and closing smoothing processor, G represents the input gray image, B_n represents the structure element, n represents the filter scale. Among of which ω has a greater impact on the final filtering result, let it be 0.5 generally.

The low-frequency image enough smooth are gained by the processing with opening and closing smoothing processor, and the high-frequency detail information also wants to be extracted for more comprehensive available information of image. In multi-scale enhancement method, morphological Top-hat transformation can extract the highlights smaller than corresponding scale between adjacent scales, morphological Bottom-hat transformation can extract the scotomas smaller than corresponding scale between adjacent scales, which are expressed with E_j and F_j respectively. Because the noise is more likely to occur in the image which is processed with the small scale structure element, the effect of noise is reduced with the increase of scale. Therefore, the Top-hat transformation and Bottom-hat transformation with correction coefficient are chose in this paper. Let the correction coefficient be the geometric progression with the common ratio 0.5. In this case the effect of noise is reduced for the image. This process completes the smoothing processing of small scale features of the image in different scales. The specific formulas are expressed as follows [9]:

$$E_j = k_j\, [g \circ B_{j-1} - g \circ B_j]; \quad j = 1, 2, 3, \cdots, n \tag{8}$$

$$F_j = k_j\, [g \bullet B_{j-1} - g \bullet B_j]; \quad j = 1, 2, 3, \cdots, n \tag{9}$$

$$k_j = \left(\frac{1}{2}\right)^{n+1-j}; \quad j = 1, 2, 3, \cdots, n \tag{10}$$

After the processing by multi-scale opening and closing filter operation, the final image is composed of three parts: the first part is the low-frequency smoothing image which is generated by the processing with opening and closing smoothing processor with the largest scale structure element, this part contains the large scale information of the smoothing image. The second part is the high-frequency features of highlight image which are smaller than the filter scale. The third part is the high-frequency features of scotoma image which are smaller than the filter scale. Thus, after the fusion and enhancement processing, the image is expressed as follows:

$$y = \overline{G}(\omega, x, y) + \sum_{j=1}^{n} E_j - \sum_{j=1}^{n} F_j \tag{11}$$

3.2. Multi-scale edge detection operation

The selection of structure element is very important in the principle of mathematical morphology. The function of structure element is equal to probe. There are many structure elements with different shapes and sizes can be chose. The selection of structure element will affect the erosion and dilation operations greatly so that affecting the final outcome of edge detection [10]. Different structure elements can be used to extract different features of image. The noise reduction ability of small scale structure elements is weak, but their edge detail of detection is good. In contrast, the noise reduction ability of large scale structure elements is strong, but the edge of detection is rough. In fact, it is needed to determine the point value of each window when the window size is definite, because the structure element is a small window of gray-scale form. This process can be carried through according to the specific purpose and testing effect. Generally speaking, the 3×3, 5×5 and 7×7 windows are usually used, among of which 3 × 3 window is the fastest whose edge is the most exquisite [11].

After analysis and comparison, the multi-scale structure element used here is defined as:

$$B_{\mathrm{n}} = B \oplus B \oplus B \oplus \cdots \oplus B \tag{12}$$

where B is cross 3×3 structure element, the meaning of upper type is that large-scale structure element is gained by small-scale structure element dilates in many times [12].

Detect the edge of above enhanced image by multi-scale edge detection method, the edge detection operator is expressed:

$$H = \sum_{\mathrm{j}=1}^{\mathrm{n}} a_{\mathrm{j}} H_{\mathrm{j}} \tag{13}$$

Among of which a_{j} represents the weight coefficient.

$$\begin{aligned} H_{\mathrm{j}} = {} & A \oplus B_{\mathrm{j}} - A + 0.5\{\max(A \oplus B_{\mathrm{j}} - A,\ A - A\Theta B_{\mathrm{j}}, A \oplus B_{\mathrm{j}} - A\Theta B_{\mathrm{j}}) - \\ & \min(A \oplus B_{\mathrm{j}} - A,\ A - A\Theta B_{\mathrm{j}}, A \oplus B_{\mathrm{j}} - A\Theta B_{\mathrm{j}})\} \end{aligned} \tag{14}$$

Weight coefficient a_{j} can be decided according to the ratio between information entropy after detection and total information entropy:

$$a_{\mathrm{j}} = H(\mathrm{j}) \ / \sum_{\mathrm{j}=1}^{\mathrm{n}} H(\mathrm{j}) \tag{15}$$

Among of which $H(j)$ represents the information entropy of the edge detection operator H_{j} for the corresponding structure element B_{j}, which is defined as follows:

$$H(j) = -\sum_{\mathrm{i}=0}^{255} p(i)\mathrm{lb}p(i) \tag{16}$$

Among of which $p(i)$ representing the probability of the part whose gray value is i in the image, namely the ratio between total number of every gray value and the total number of the pixel of image [13].

4. Multi-scale morphological transformation edge detection for rotating machinery parameter images

4.1. Rotating machinery fault simulation

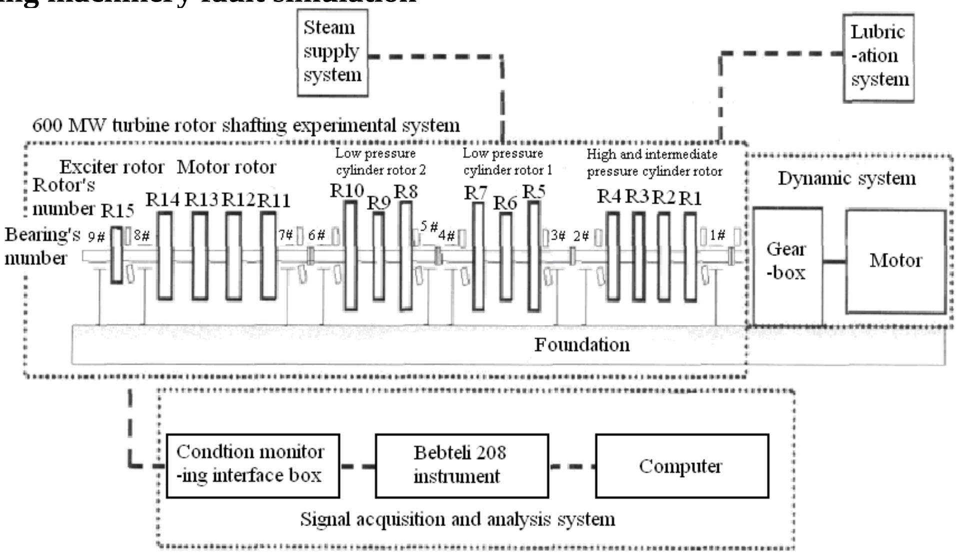
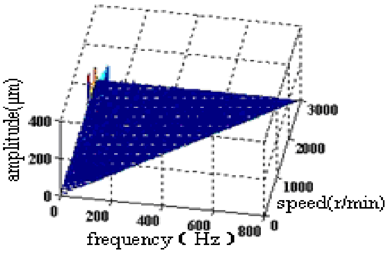


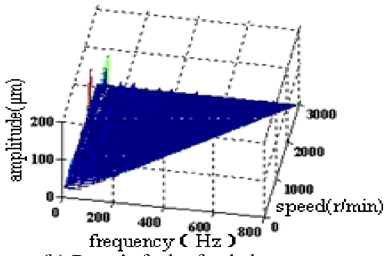
Fig. 1. Equipments and connections of the modeling of 600 MW turbine rotor experimental bench

On the modeling of 600 MW turbine rotor shafting experimental bench, rotor's normal state, fault of unbalance, misalignment, steam exciting vibration and bearing pedestal looseness were examined and researched in this paper. The equipments and connections of the experimental bench are shown in figure 1, which mainly include five parts, modeling of 600 MW turbine rotor shafting, dynamic system, lubrication system, steam supply system and signal acquisition and analysis system. There are 9 bearings and 5 spans in the modeling of 600 MW turbine rotor shafting (the number of bearings and rotors are shown in figure 1). The 55 KW variable-frequency motor was adopted which outputted rotational speed and power with the FRENIC converter in dynamic system of experimental bench. HG0G-C2-type gearbox was also used in this paper. Each bearing was supplied lubricating oil by independent oil circuit in lubrication system. BENTLY3000XL8mm eddy current sensors were installed at every bearing chock whose output was 7.87V/mm. In the experiment, the sampling frequency was as 32 times as the rotational speed, the sampling time was 0.64s and the maximum rotational speed was 3200 r/min. Then the collecting signals were transferred to the computer by A/D card for the following data analysis.

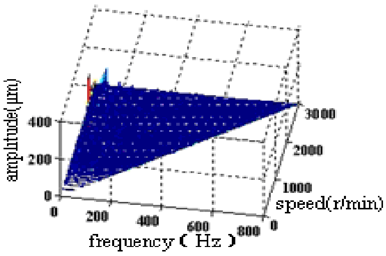
The experiment collected 40 samples in each state of rotor's normal state, fault of unbalance, misalignment, steam exciting vibration and bearing pedestal looseness for a total of 200. In this paper, firstly the collection samples of original vibration signals were pretreated and then they were transformed to the 3d vibration parameter images (3 coordinate were frequency, speed and amplitude). Then the vibration data information was added to these images. The 3d spectrums of 5 states are shown in figure 2 respectively.



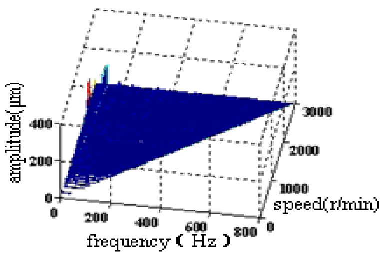
(a) Rotor's normal state



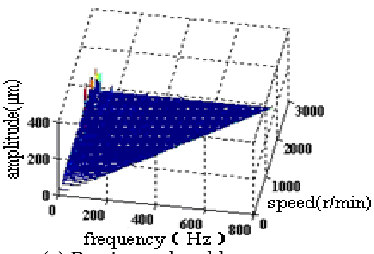
(b) Rotor's fault of unbalance



(c) Rotor's misalignment

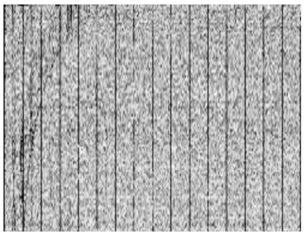


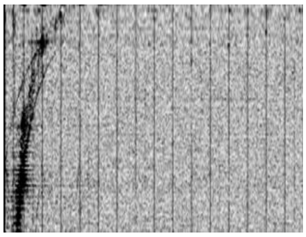
(d) Steam exciting vibration

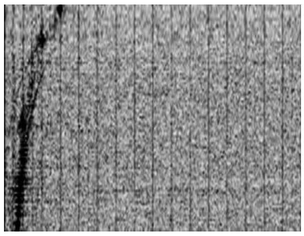


(e) Bearing pedestal looseness

Fig. 2: 3d spectrums of 5 states


(a) Rotor's normal state


(b) Rotor's fault of unbalance


(c) Rotor's misalignment


(d) Steam exciting vibration

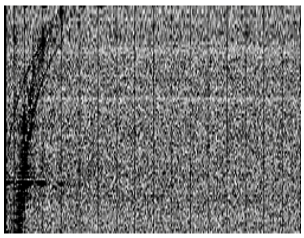

(e) Bearing pedestal looseness

Fig. 3: Gray-scale images of 5 states


(a) Rotor's normal state


(b) Rotor's fault of unbalance


(c) Rotor's misalignment


(d) Steam exciting vibration


(e) Bearing pedestal looseness

Fig. 4: Edge detection images of 5 states

4.2. Multi-scale morphological transformation edge detection

If the edge of 3d images wants to be detected, it must be transformed into 2d gray-scale images firstly. According to the feature that the frequency doubling of 3d spectrum was obvious, the frequency was looked as the horizontal axis, the rotational speed was looked as the vertical axis, and the gray value of pixel point was looked as the size of amplitude under the corresponding rotational speed and frequency in the conversion. The manifest vertical line in gray-scale image was frequency doubling line which corresponds to the frequency doubling line in the 3d spectrum. The results are shown in Figure 3.

In order to extract effectively the edge features of gray-scale images, the various states of figure 3 were pretreated such as de-noising and smoothing in this paper. The structure element was selected as follows: *B*=[1 2 1; 2 6 2; 1 2 1]. Their edges were detected with the multi-scale morphologi-cal transformation edge detection method designed in this paper. The results are shown in figure 4. As can be seen from the figure 4, after multi-scale enhancement processing, there is a substantial increase of SNR in the corresponding images for rotating machinery vibration parameter, the detection outcomes show that the edges are bright and the outlines are clear, these prove that multi-scale morphological transformation edge detection method can not only eliminate the noise but also enhance the available information under preserving the detail features of image fully. It is manifested that the effect of the method designed in this paper is better than classical edge detection operators and suit to detect the edges and eliminate noise of parameter images under 5 states for rotating machinery. This paper also provides a good foundation for the further fault diagnosis.

5. Ending words

In this paper, multi-scale morphological transformation edge detection method is used to enhance the available information of rotating machine vibration parameter images according to Top-Hat transformation and Bottom-Hat transformation, the edge detections of rotating machine vibration parameter images are realized, too. The edge texture is clear and the noise is filtered out completely in the results of edge detection. This method can extract the edge features of rotating machinery vibration parameter images which contain noise. In the practical application of engineering, multi-scale morphological transformation edge detection method can well solve the coordination problems between edge detection precision and anti-noise performance combining with the features of engineering parameter images and the noise. This paper provides an efficient method to extract the features of image for the fault diagnosis for rotating machinery based on 3d vibration images.

6. Acknowledgements

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