Research Article

Identification Method of Shaft Orbit in Rotating Machines Based on Accurate Fourier Height Functions Descriptors

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In this paper, an algorithm based on two novel shape descriptors and support vector machine (SVM) is proposed to improve the recognition accuracy and speed of shaft orbits of rotating machines. Firstly, two novel shape descriptors, respectively, named accurate Fourier height functions 1 (AFHF1) and accurate Fourier height functions 2 (AFHF2) are presented based on height function (HF) and Fourier transformation. Both AFHF1 and AFHF2 shape descriptors are constant to similarity transforms and also have intrinsic invariance to the starting point change and are more compacted than HF. Therefore, they perform well on the global or local features of the contours of shaft orbits. Then, the AFHF1 and AFHF2 shape descriptors are utilized to extract features of shaft orbits in the simulated dataset and measured dataset. Taking extracted feature vectors as the input, SVM is adopted in order to classify the fault types according to the shapes of shaft orbits. Finally, a series of descriptors including shape context (SC), inner-distance shape context (IDSC), triangular centroid distances (TCDs), and HF were compared to verify the performance of the proposed AFHF1 and AFHF2 shape descriptors. The average accuracy of our method in simulated dataset and measured dataset are all higher than 99.83%, the average recognition time of each sample is no more than 19 milliseconds. The experiments demonstrate that the proposed method has the best recognition accuracy and real-time and antinoise performance.

1. Introduction

Rotating machines play a critical role in industrial production [1]. Once failure occurs, it may cause the enterprise to suffer huge economic losses, and even catastrophic accidents. Therefore, the condition monitoring and fault identification of rotating machines are of great significance to improve productivity and reduce maintenance costs and prolong the service life of equipment [2].

The shaft orbit [3–8] is a two-dimensional representation synthesized by shaft vibration signals [9, 10], which presents a snapshot of the rotor actual motion at its centre [11] and contains a lot of fault information [12]. In the last ten years, many researchers have regarded the identification of shaft orbits as pattern recognition of two-dimensional images and put forward many methods.

Identification methods of shaft orbits mainly include two fundamental procedures: feature extraction and classification. In the first procedure, the quality of the extracted features could directly determine the accuracy of the identification on shaft orbits [1]. Many scholars have proposed many efficient methods for feature extraction of shaft orbits, such as Fourier descriptors (FD) [13], chain code [14, 15], Walsh descriptor (WD) [16], seven improved invariant moment [17], histogram of oriented gradients (HOG) [18], fractal theory [19], and comprehensive geometric characteristic (CGC) [1]. Each of them can extract feature of shaft orbits well, but has its disadvantages.

Fourier descriptors [13] are selected to extract features of shaft orbits because of its simplification and high efficiency, but sensitive to the starting point and indirectly

sensitive to similarity transforms. Although chain code [14, 15] feature had low computation complexity and the correlation between local feature points was also preserved, lots of global features were lost. Xiang et al. calculated the distance vector between the points of shaft orbits and the centre point and adopted Walsh orthogonal matrix to transform the distance vector [16]. The Walsh descriptor was obtained with rotation invariance and scale invariance, but it often adopts floating-point operation, which leads to complex calculation. Yan et al. proposed seven improved invariant moment based on Hu invariant moment to extract the features of shaft orbits well [17]. But the ability of invariant moment to represent complex graphics is limited, because the dimension of its features is only 7. Bao et al. applied HOG as the low-level local shape descriptor to extract feature vectors from shaft orbits [18]. But HOG is sensitive to translation and rotation. Chang et al. proposed fractal theory to extract features of shaft orbits [19]. Although the dimension of the feature extracted by the fractal theory is small, the recognition rate is not high enough. Chen et al. proposed a method of comprehensive geometric characteristics [1], which extracted features of shaft orbits from three different aspects: structure, region, and boundary. Although it can achieve satisfactory accuracy, its real-time performance is not good enough, extraction time of which is longer than chain code and Walsh descriptor.

In recent year, Height Function (HF) [20] method is proposed to extract features of 2D images well, and constant to similarity transforms. Several improvement algorithms have been proposed based on the HF method. Multiscale arch height (MARCH) description [21] is a method for mobile retrieval of leaf images, which is based on the K-scale arch height as a measure of the curvature surrounding a contour point. This method utilizes arch height features instead of the height values for leaf shape representation. Nanni et al. [22] presented an approach of a matrix descriptor based on the local phase quantization to improve the performance of shape context (SC) [23], inner-distance shape context (IDSC) [24], and HF [20]. Shekar and Pilar [25] proposed a combined classifier model based on HF and two-dimensional discrete cosine transform (2D-DCT) to exact shape representation and classification [26]. All of these methods are achieved by combining HF with other algorithms. However, there is little work on improving the principle of HF descriptor itself. The principle of the HF algorithm and its deficiencies are shown in the following paragraphs.

In Figure 1, let $\mathbf{X} = \{\mathbf{x}_i\}$ ($i = 1, 2, \dots, N$) denote the sequence of equidistant sample points along the outer contour in a given shape, and the sampling point i follows the contour in an ordered counterclockwise direction. [20] For each sample point $\mathbf{x}_i$, its tangent line l_i is used as the reference axis, which inherits its orientation from the contour orientation. The distance between the j th ($j = 1, 2, \dots, N$) sample point $\mathbf{x}_j$ and the tangent line l_i is defined as the height value $H_{i,j}$, and it is calculated for every sample point. The feature vector of point $\mathbf{x}_i$ for shape $\mathbf{X}$ is the ordered sequence of height values:

FIGURE 1: The Height Functions for the sample point $\mathbf{x}_i$.

$$H_i = (H_i^1, H_i^2, \dots, H_i^N)^T \\ = (H_{i,i}, H_{i,i+1}, \dots, H_{i,N}, H_{i,1}, H_{i,2}, \dots, H_{i,i-1})^T, \quad (1)$$

where $H_{i,j}$ ($j = 1, 2, \dots, N$) denotes the height value of the j th sample point $\mathbf{x}_j$ according to the reference axis l_i of the point $\mathbf{x}_i$.

Feature vectors of each sampling point are calculated, and they are composed of the feature matrix of the shape $\mathbf{X}$ according to the sampling sequence. Then the dimension of the feature matrix is reduced from $N \times N$ to $M \times N$ by smoothing [20], where $M = \lfloor N/k \rfloor$ (the integer part of N/k). Feature matrix is normalized row by row to make the shape representation scale invariant.

However, there are three obvious deficiencies of HF shape descriptor according to its definition. (1) In HF descriptor, the reference axis direction of the point $\mathbf{x}_i$ is starting from $\mathbf{x}_{i-1}$ to $\mathbf{x}_{i+1}$. Therefore, the line of $\mathbf{x}_{i-1}$ to $\mathbf{x}_{i+1}$ is defined as the reference axis instead of the real tangent line, as shown in Figure 2. For the image with a large shape contour or strong edge noise, the small error of shape feature description will greatly influence the retrieval accuracy, anti-noise property, and robustness of the algorithm. (2) For the same contour, the HF descriptors are different when the starting points of the shape contour are different. When HF shape descriptor is used in image matching, it is necessary to find the best corresponding points, so the dynamic programming (DP) is used to find the best corresponding points between different shape contours, which may reduce the retrieval efficiency. (3) Although smoothing process decreases the dimensions of the HF descriptor matrix, it also reduces the local feature characterization performance of the descriptor, and the dimension of the descriptor is still high, and the compactness of HF descriptor is not good enough. Therefore, when using HF descriptors, it is imperative to improve the three deficiencies above to improve its performance.

The second key procedure of identification of shaft orbit is classification. The main methods of classification are support vector machine (SVM) and the neural network. SVM performs better in accuracy and real time than the neural network when the samples are few and has been

FIGURE 2: Accurate height values for the sample point x_i .

successfully applied in many different fields such as fault diagnosis [15, 27].

In this paper, two novel descriptors called accurate Fourier height functions (AFHFs) including accurate Fourier height function 1 (AFHF1) and accurate Fourier height function 2 (AFHF2) are proposed based on HF and Fourier transformation to improve the accuracy, starting point invariance, and compactness. Then, we take advantage of AFHFs and SVM, and a novel recognition method for the shaft orbits is proposed in Section 2. Experiments are shown in Section 3. And the conclusion is shown in the final section.

2. Shaft Orbit Identification Method Based on AFHFs and SVM

In this section, a new identification method of shaft orbit in rotating machine based on improved HF descriptors is introduced. Firstly, AFHFs shape descriptors are presented in detail. Then, the orbit identification method based on AFHFs shape descriptors and support vector machine (SVM) is proposed.

2.1. Accurate Fourier Height Functions Shape Descriptor. In order to decrease the error of the HF shape descriptor in contour representation, the HF shape descriptor is corrected by using an accurate height value of the contour point.

As shown in Figure 2, we draw the parallel line l_i of line l that is the actual axis of the original height function at the reference point x_i , and set line l_i as the new axis of improved HF. Therefore, the height error ΔH of original HF can be eliminated and the height value H can be rectified with the exact height value H' . At the same time, the distance from the sample point x_i to its own axis l_i is always 0, so height value $H_{i,i}$ can be removed. Finally, the improved HF vector of point x_j which is named as Accurate Height Function (AHF) shape descriptor can be expressed as follows:

$$\begin{aligned} H'_i &= (H'_i, H'_i, \dots, H'_i)^T \\ &= (H'_{i,i+1}, \dots, H'_{i,N}, H'_{i,1}, \dots, H'_{i,i-1})^T, \end{aligned} \quad (2)$$

where $H'_{i,j}$ ($j = 1, 2, \dots, i-1, i+1, \dots, N$) denotes the exact height value of the j th sample point x_j .

In our method, two improvement algorithms are compensated for the second and the third deficiencies. (1)

Fourier transformation is performed on each row of the AHF shape descriptor that is not smoothed, and the phase information is discarded to get the new shape descriptor Accurate Fourier Height Function 1 (AFHF1). (2) Fourier transformation is performed for each row of the AHF shape descriptor that is smoothed, and the phase information is discarded to get the new shape descriptor Accurate Fourier Height Function 2 (AFHF2). The above specific algorithms will be showed in the following two subsections.

2.1.1. AFHF1 Shape Descriptor. Firstly, let g_t denote the t th row of the feature matrix of AHF shape descriptor that is not smoothed, where $t = 1, 2, \dots, N-1$. The Fourier transformation for g_t is given by

$$F_t(i) = \frac{1}{N} \sum_{u=1}^N g_t(u) \exp\left(\frac{-j2\pi(u-1)i}{N}\right), \quad i = 1, 2, \dots, N, \quad (3)$$

where $j^2 = -1$ and $\text{abs}(F_t(i))$ is the absolute value of $F_t(i)$ and represents the modulus of the discrete Fourier transform coefficient $F_t(i)$. It is easy to prove that $\text{abs}(F_t(i))$ is invariant to the starting point of the contour for a given shape [28]. Therefore, the value of Fourier transform coefficient is used to describe the shape contour. In order to make the generated shape descriptors robust and compact, the lowest order coefficients P is used, where $P \ll N$. So the final AFHF1 shape descriptor can be defined as follows:

$$\text{AFHF1}(S) = \begin{pmatrix} \text{abs}(F_1(1)) & \cdots & \text{abs}(F_1(\nu)) \\ \vdots & \ddots & \vdots \\ \text{abs}(F_t(1)) & \cdots & \text{abs}(F_t(\nu)) \end{pmatrix}, \quad (4)$$

where $t = 1, 2, \dots, N-1$; $\nu = 1, 2, \dots, P$. $F_t(\nu)$ is the discrete Fourier transform coefficient.

It can be seen from the definition of AFHF1 that its feature matrix dimension is $(N-1) \times P$. The feature matrix of AFHF1 is more compact than that of the original HF shape descriptor whose matrix dimension is $N \times M$, where P is less than M .

2.1.2. AFHF2 Shape Descriptor. AFHF1 removes the smoothing process from the original HF, while AFHF2 reserves the HF smoothing process and directly improves it on the basis of the AHF descriptor. By applying Fourier transforms in each row of the AHF shape descriptor and discarding the phase information, a new descriptor AFHF2 can be obtained. Similarly, the final AFHF2 shape descriptor can be defined as follows:

$$\text{AFHF2}(S) = \begin{pmatrix} \text{abs}(F_1(1)) & \cdots & \text{abs}(F_1(\nu)) \\ \vdots & \ddots & \vdots \\ \text{abs}(F_t(1)) & \cdots & \text{abs}(F_t(\nu)) \end{pmatrix}, \quad (5)$$

where $t = 1, 2, \dots, M$; $\nu = 1, 2, \dots, P$. $F_t(\nu)$ is the discrete Fourier transform coefficient.

From the definition of AFHF2 shape descriptor, it is not difficult to know that its matrix dimension is $M \times P$, which is lower than that of AFHF1. However, the smoothing process takes the average height values of multiple adjacent points, which may affect the invariance of starting point on AFHF2 shape descriptor. Compared to the original HF shape descriptor, the choice of starting point may have a much smaller impact on AFHF2 shape descriptor.

2.1.3. Characteristic of the Improved Accurate Fourier Height Functions. The matrix dimensions of improved AFHF1 and AFHF2 shape descriptors and related descriptors are shown in Table 1, where N is the number of contour sample points and equal to 128, and the number of inner-distance bins N_d is equal to 8, the number of inner-angle N_θ is equal to 12, the number of Fourier coefficients P is equal to 16, and the smoothed vector dimension M is equal to 20. The descriptors for comparison include IDSC [24], HF [20], and triangular centroid distances (TCDs) [28].

As shown in Table 1, the dimension of the feature matrix of the improved AFHF1 and AFHF2 descriptor is much lower than that of the original HF descriptor. In particular, AFHF2 descriptor is more compact than HF and other descriptors.

Compared to the original HF descriptor, the contour starting point has almost no significant influence on AFHF1 and AFHF2 descriptor. In order to determine the influence of the starting point on the descriptors, the shape descriptors extracted from the contours A and B can be defined as $F_A = \{H_t^A(v) | t = 1, 2, \dots, M; v = 1, 2, \dots, N\}$ and $F_B = \{H_t^B(v) | t = 1, 2, \dots, M; v = 1, 2, \dots, N\}$, respectively. The similarity of them is measured by the distance L_1 . The smaller the distance is, the more similar they are. The distance is defined as follows:

$$L_1(A, B) = \frac{1}{N \cdot M} \sum_{t=1}^{N-1} \sum_{v=1}^M |H_t^A(v) - H_t^B(v)|. \quad (6)$$

In order to estimate the influence of the starting point on three descriptors, HF, AFHF1, and AFHF2, 100 sample points are sampled at equal intervals in the clockwise direction on the outline of a petal-shaped shaft orbit, as shown in Figure 3. Different points are selected as the starting point, as shown in Figures 3(b) and 3(c), the red points represent the sample points of each shape contour, and the blue point represents the starting point of each shape contour. Then the feature matrices corresponding to HF, AFHF1, and AFHF2 are calculated, respectively, which are shown in Figures 3(d)–3(i). When the starting point is different, HF feature matrix changes greatly, but the AFHF1 and AFHF2 description matrices are almost unchanged.

In order to describe the influence of the starting point on the above three shape descriptors quantitatively, the similarities of three sets of feature matrices are calculated individually by using Equation (6). The similarity between two HF feature matrices in Figures 3(d) and 3(e) is 0.5348, the similarity between two AFHF1 feature matrices in

TABLE 1: Dimension comparison of different descriptors feature matrices.

Shape descriptor	Feature dimension
IDSC	$N \times N_d \times N_\theta = 128 \times 8 \times 12 = 12288$
HF	$M \times N = 20 \times 128 = 2560$
TCDs	$(N-1) \times P = 127 \times 16 = 2032$
AFHF1	$(N-1) \times P = 127 \times 16 = 2032$
AFHF2	$M \times P = 20 \times 16 = 320$

Figures 3(f) and 3(g) is 7.0968×10^{-16} , and the similarity between two AFHF2 feature matrices in Figures 3(h) and 3(i) is 7.5922×10^{-16} . The results show that the starting point has a great impact on HF shape descriptor, while it has almost no effect on AFHF1 and AFHF2 shape descriptors. Moreover, starting points have slightly less impact on AFHF1 than on AFHF2, which is due to the smoothing process in AFHF2.

2.2. Identification Method of Shaft Orbit Based on AFHFs. Since the starting point has almost no influence on AFHF1 and AFHF2 shape descriptors, there is no need to use the DP method, which is used by the original HF shape descriptors to obtain the matching result. The SVM, which is a classification algorithm based on statistical learning theory, is adopted as the classifier in this paper. SVM has unique advantages in solving a small amount of samples: nonlinear and high-dimension classification and recognition.

It is the most important for SVM to choose the proper kernel function and its parameters δ and the optimal penalty factor c . Different kernel functions of SVM are used to test on the shaft orbit dataset, and the experimental results show that the recognition rate of the linear kernel function is much higher than that of the others. Since the linear kernel function requires few parameters to be set specifically, and the dimension of feature matrices is high, the linear kernel function is adopted.

Combined with the AFHF1 and AFHF2 descriptors proposed in Section 2.1, a shaft orbit identification method for fault diagnosis of rotating machine is proposed based on AFHF1, AFHF2, and SVM. The specific process is shown in Figure 4.

3. Experiment and Analysis of Shaft Orbit Identification

3.1. Experiments and Analysis on Simulation Data

3.1.1. Simulated Shaft Orbit Dataset. Using MATLAB software, the shaft orbits are simulated according to the following equation (6).

$$\begin{cases} x(t) = A_1 \sin(\omega t + \alpha_1) + A_2 \sin(2\omega t + \alpha_2), \\ y(t) = B_1 \cos(\omega t + \beta_1) + B_2 \cos(2\omega t + \beta_2), \end{cases} \quad (7)$$

where A_1 , B_1 and A_2 , B_2 are the first and second frequency components, respectively, ω is the angular velocity, and α and β represent the initial position of x and y , respectively. The corresponding relationship between the faults and the graphs is shown in Table 2 [16, 29]. In addition, petal-shaped

FIGURE 3: Comparison of HF, AFHF1, and AFHF2 descriptor from different starting points. (a) Petal-shaped shaft orbit; (b) shape contour 1 of (a); (c) shape contour 2 of (a); (d) HF shape descriptor of (b); (e) HF shape descriptor of (c); (f) AFHF1 shape descriptor of (b); (g) AFHF1 shape descriptor of (c); (h) AFHF2 shape descriptor of (b); (i) AFHF2 shape descriptor of (c).

shaft orbit corresponds to Oil whirl [29], which increases the type of shaft orbit and increases the difficulty of identification compared to many researches [1–3, 13–19]. Although both banana-shaped and outer “8” shaft orbit correspond to misalignment faults, they correspond to different severity of misalignment faults [30]. When the severity of the misalignment of the shaft is small, the shaft orbit is an ellipse. But the short axis of ellipse shaft orbit will gradually become shorter when the severity of the fault is increasing, and when the fault is increased to a certain extent, the shaft will become an outer “8” shape.

200 images of shaft orbits are simulated by MATLAB for each fault type, of which 100 images are for training and the remaining 100 images are for testing. The typical samples of shaft orbit dataset are shown in Figure 5.

3.1.2. Feature Extraction and Identification of Simulated Shaft Orbit Datasets. Firstly, a series of descriptors including SC, IDSC, TCDs, and HF were compared to verify the performance of the proposed AFHF1 and AFHF2 shape descriptors. Secondly, in order to illustrate the superiority of SVM, it is compared with BP neural network.

All algorithms selected 100 feature points as samples. SC, IDSC, TCDs, HF, AFHF1, and AFHF2 shape descriptors are used to extract the feature of shaft orbits, respectively. And the parameter P of AFHF1 and AFHF2 is set to 16 in all experiments. The smoothed vector dimension M of AFHF2 is set to 19. Then half of the feature vectors extracted by each shape descriptor are randomly selected as training samples, and the rest are selected as testing samples. The training samples are used to train SVM

FIGURE 4: Process of shaft orbit identification method based on AFHFs and SVM.

TABLE 2: Shaft orbit shapes of different faults.

Fault types	Shapes of shaft orbits
Misalignment	Banana-shaped
Unbalance	Ellipse
Oil whip	Inner “8”
Misalignment	Outer “8”
Oil whirl	Petal-shaped

and BP neural network, and the testing samples are used to test the trained SVM and BP neural network for verifying the performance of each algorithm. The experiment flowchart is shown in Figure 6.

The parameters of SVM are set as follows: the “linear kernel function” is selected and the other parameters are the default. The parameters of BP neural network in MATLAB toolbox are set as follows: the period is set to 1000, the target error is set to 0.0001, the node number of hidden layer is set to 15, S-type function “logsig” is selected as the excitation function, and linear function “Purelin” is adopted as the output layer excitation function.

Experimental results of simulated shaft orbit dataset are shown in Tables 3 and 4, where SVM and neural network are used as the classifier, respectively. The accuracy comparison of all algorithms is intuitively shown in Figure 7. The conditions of all experiments are the same.

From the perspective of shape descriptors, the accuracies of the algorithms using the AFHF1 and AFHF2 shape descriptors are higher than 99.57%, but the highest accuracy of the algorithms using other shape descriptors is 98.03%.

From the perspective of the classifier, the performance of the algorithms using SVM as classifier are slightly better than using BP neural network as classifier in accuracy and real

time when AFHF1 and AFHF2 shape descriptors are used to extract feature in the experiments of simulated shaft orbit identification. Therefore, the proposed method has the best performance, its average time for identifying a shaft orbit is less than 19 milliseconds, and the average accuracy is higher than 99.88%.

3.2. Experiments and Analysis on Actual Measured Data. In order to verify the performance of the proposed algorithm, a rotor test bench is used to produce different faults, and the same methods which are used in the simulation experiment are adopted for contrast. The measured database of shaft orbits is created on the bearing rotor test bench as shown in Figure 8. The rotor test bench consists of the rotor table, the sensors, the DC motor controller, the signal acquisition card, and the analysis software. Different state experiments were performed on the rotor test bench, 200 shaft orbits were collected in each state, 100 samples of each type were randomly selected as training samples, and the remaining 100 samples were used as testing samples.

As shown in Figure 9(a), the original measured shaft orbit has much noise, so the features of the shaft orbit cannot be extracted directly and the image must be preprocessed. The preprocessing method used in this paper includes two steps, wavelet filtering and binarization. Figure 9(b) shows a shaft orbit image after preprocessing. The same processing is applied to different types of shaft orbits, and then the features of these images are extracted and classified. And experimental results of measured shaft orbit dataset are shown in Tables 5 and 6, where SVM and neural network are used as the classifier, respectively.

By comparing experimental results on simulated shaft orbits and actual measured shaft orbits in Tables 3–6, the accuracy of identification on the measured shaft orbit is lower than the simulation shaft orbit with the same algorithm. This is because simulated shaft orbits are noiseless. However, the reduction in the accuracies of the algorithms using the AFHF1 and AFHF2 shape descriptors is small, not exceeding 0.3%, and the accuracies of the algorithms using other shape descriptors decreased greatly, ranging from 0.7% to 3.3%. It shows that the AFHF1 and AFHF2 shape descriptors proposed in this paper have a great antinoise performance.

Similar to the analysis of simulation result in section 3.1.2, the following conclusions can be drawn:

- (1) From the perspective of shape descriptors, AFHF1 and AFHF2 shape descriptors are more suitable for identification on actual measured shaft orbit than SC, IDSC, TCDs, and HF shape descriptors.
- (2) From the perspective of the classifier, the performance of the algorithms using SVM as classifier is slightly better than that using BP neural network as classifier in accuracy and real time when AFHF1 and AFHF2 shape descriptors are used to extract feature in the experiments of actual measured shaft orbit identification.

FIGURE 5: The typical samples of simulated shaft orbit dataset. (a) Banana-shaped; (b) petal-shaped; (c) inner “8”; (d) outer “8”; (e) ellipse.

FIGURE 6: The experiment flowchart.

TABLE 3: Experimental results on simulated shaft orbit dataset by SVM.

Algorithms	Average accuracy (%)	Average feature extracting time of single sample (ms)	Training time (s)	Average testing time of single sample (ms)
SVM + AFHF1	99.93	16.214	0.246	0.143
SVM + AFHF2	99.88	18.172	0.045	0.031
SVM + SC	98.03	23.063	3.456	7.648
SVM + IDSC	96.46	46.426	3.592	7.631
SVM + TCDs	96.04	16.187	0.407	0.457
SVM + HF	95.81	18.016	0.563	0.778

4. Conclusions and Future Works

An algorithm based on two novel shape descriptors and SVM is proposed. In the algorithm, two novel shape descriptors, respectively, named AFHF1 and AFHF2 based on HF and Fourier transformation are presented to extract features from shaft orbits. Both AFHF1 and AFHF2 shape descriptors are constant to similarity transforms, also have

intrinsic invariance to the starting point change and are more compacted than HF. Therefore, they perform well on the global or local features of the contours of shaft orbits. SVM is adopted as the classifier to efficiently identify the extracted feature. In our experiments, AFHF1 and AFHF2 are compared with SC, IDSC, HF, and TCDs, and BP neural network is compared with SVM. The identification accuracies on the simulated and actual measured shaft orbit

TABLE 4: Experimental results on simulated shaft orbit dataset by BP neural network.

Algorithms	Average accuracy (%)	Average feature extracting time of single sample (ms)	Training time (s)	Average testing time of single sample (ms)
BP + AFHF2	99.66	18.172	27.39	0.380
BP + AFHF1	99.57	16.214	61.40	0.869
BP + HF	96.50	18.016	70.16	0.924
BP + TCDs	94.10	16.187	57.17	0.726
BP + SC	87.84	23.063	368.55	3.044
BP + IDSC	83.38	46.426	364.79	3.013

FIGURE 7: Accuracy comparison of different algorithms on simulated shaft orbits.

FIGURE 8: Structure of bearing rotor test bench.

FIGURE 9: Measured shaft orbit. (a) Original shaft orbit. (b) Shaft orbit after preprocessing.

datasets and the comparisons with the algorithms mentioned above are obtained. The experiments show that the proposed algorithm can quickly and accurately identify shaft orbits. As for simulated and measured shaft orbits, the

TABLE 5: Experimental results on actual measured shaft orbit dataset by SVM.

Algorithms	Average accuracy (%)	Average feature extracting time of single sample (ms)	Average training time (s)	Average testing time of single sample (ms)
SVM + AFHF2	99.86	18.521	0.048	0.041
SVM + AFHF1	99.83	16.374	0.270	0.244
SVM + SC	96.16	23.542	4.954	9.594
SVM + TCDs	95.34	16.354	0.385	0.457
SVM + IDSC	94.21	46.592	4.823	8.907
SVM + HF	92.52	18.539	0.650	1.050

TABLE 6: Experimental results on actual measured shaft orbit dataset by BP neural network.

Algorithms	Average accuracy (%)	Average feature extracting time of single sample (ms)	Average training time (s)	Average testing time of single sample (ms)
BP + AFHF2	99.49	18.521	26.04	0.345
BP + AFHF1	99.34	16.374	58.13	0.756
BP + HF	93.34	18.539	68.77	0.879
BP + TCDs	92.84	16.354	57.33	0.724
BP + SC	84.59	23.542	369.91	3.044
BP + IDSC	76.30	46.592	376.39	3.051

average time of identifications is all less than 19 milliseconds and the average of accuracies are all higher than 99.83%. The proposed method has the best recognition accuracy, and real-time and antinoise performance.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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References

- [1] X. Chen, J. Zhou, H. Xiao, E. Wang, J. Xiao, and H. Zhang, "Fault diagnosis based on comprehensive geometric characteristic and probability neural network," *Applied Mathematics and Computation*, vol. 230, pp. 542–554, 2014.
- [2] X. Zhang, J. Zhou, J. Guo, Q. Zou, and Z. Huang, "Vibrant fault diagnosis for hydroelectric generator units with a new combination of rough sets and support vector machine," *Expert Systems with Applications*, vol. 39, no. 3, pp. 2621–2628, 2012.
- [3] H. T. Xue, Z. X. Li, H. Q. Wang, and P. Chen, "Intelligent diagnosis method for centrifugal pump system using vibration signal and support vector machine," *Shock and Vibration*, vol. 2014, Article ID 407570, 14 pages, 2014.
- [4] Y. Meng, L. Lu, and J. Yan, "Shaft orbit feature based rotator early unbalance fault identification," *Procedia CIRP*, vol. 56, pp. 512–515, 2016.
- [5] L. F. Villa, A. Reñones, J. R. Perán, and L. J. D. Miguel, "Statistical fault diagnosis based on vibration analysis for gear test-bench under non-stationary conditions of speed and load," *Mechanical Systems and Signal Processing*, vol. 29, pp. 436–446, 2012.
- [6] Z. Huang, J. Zhou, M. Yang, and Y. Zhang, "Vibration characteristics of a hydraulic generator unit rotor system with parallel misalignment and rub-impact," *Archive of Applied Mechanics*, vol. 81, no. 7, pp. 829–838, 2011.
- [7] L. M. Zhai, Y. Y. Lou, Z. W. Wang, S. Kitauchi, and K. Miyagawa, "Nonlinear vibration induced by the water-film whirl and whip in a sliding bearing rotor system," *Chinese Journal of Mechanical Engineering*, vol. 29, no. 2, pp. 260–270, 2016.
- [8] M. A. Jordan, "What are orbit plots, anyway?," *Orbit*, vol. 4, pp. 8–15, 1993.
- [9] D. E. Bently, "Vibration analysis techniques for detecting and diagnosing shaft cracks," *Orbit*, vol. 7, no. 1, 1986.
- [10] A. Muszynska, "Misalignment and shaft crack-related phase relationship for 1 X and 2 X vibration components of rotor responses," *Orbit*, vol. 10, pp. 4–8, 1989.
- [11] A. Muszynska, "Vibrational diagnostics of rotating machinery malfunctions," *International Journal of Rotating Machinery*, vol. 1, no. 3-4, pp. 237–266, 1995.
- [12] A. Yunusa-Kaltungo, A. D. Nembhard, and J. K. Sinha, "Experimental observations of rotor orbit analysis in rotating machines," *Mechanisms and Machine Science*, vol. 21, pp. 1551–1560, 2015.
- [13] B. Fu, J. Z. Zhou, W. Q. Chen, and B. H. Yu, "Identification of the shaft orbits for turbine rotor by modified fourier descriptors," in *Proceedings of Third International Conference on Machine Learning and Cybernetics*, vol. 2, pp. 1162–1167, Shanghai, China, August 2004.
- [14] C. Wang, J. Zhou, P. Kou, Z. Luo, and Y. Zhang, "Identification of shaft orbit for hydraulic generator unit using chain code and probability neural network," *Applied Soft Computing*, vol. 12, no. 1, pp. 423–429, 2012.
- [15] J. Zhou, H. Xiao, C. Li, J. Xiao, W. Zhang, and W. Fu, "Shaft orbit identification for rotating machinery based on statistical fuzzy vector chain code and support vector machine," *Journal of Vibroengineering*, vol. 16, pp. 713–724, 2014.

- [16] X. Xiang, J. Zhou, X. An, B. Peng, and J. Yang, "Fault diagnosis based on Walsh transform and support vector machine," *Mechanical Systems and Signal Processing*, vol. 22, no. 7, pp. 1685–1693, 2008.
- [17] C. Yan, H. Zhang, and L. Wu, "Automatic recognition of orbit shape for fault diagnosis in steam turbine generator sets," *Journal of Computational Information Systems*, vol. 6, pp. 1995–2008, 2010.
- [18] J. Bao, Z. Zhu, H. Tang, T. Lu, and Q. Zhang, "Apply low-level image feature representation and classification method to identifying shaft orbit of hydropower unit," in *Proceedings of Sixth International Conference on Intelligent Human-Machine Systems and Cybernetics*, vol. 2, pp. 165–168, Hangzhou, China, August 2014.
- [19] H. C. Chang, S. C. Lin, C. C. Kuo, C. Y. Lin, and C. F. Hsieh, "Using neural network based on the shaft orbit feature for online rotating machinery fault diagnosis," in *Proceedings of 7th IEEE International Conference on System Science and Engineering*, pp. 26–28, Beijing, China, July 2016.
- [20] J. Wang, X. Bai, X. You, W. Liu, and L. J. Latecki, "Shape matching and classification using height functions," *Pattern Recognition Letters*, vol. 33, no. 2, pp. 134–143, 2012.
- [21] B. Wang, D. Brown, Y. Gao, and J. L. Salle, "MARCH: multiscale-arch-height description for mobile retrieval of leaf images," *Information Sciences*, vol. 302, pp. 132–148, 2015.
- [22] L. Nanni, S. Brahmam, and A. Lumini, "Local phase quantization descriptor for improving shape retrieval/classification," *Pattern Recognition Letters*, vol. 33, no. 16, pp. 2254–2260, 2012.
- [23] S. Belongie, J. Malik, and J. Puzica, "Shape matching and object recognition using shape contexts," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 24, no. 4, pp. 509–522, 2002.
- [24] H. Ling and D. W. Jacobs, "Shape classification using the inner distance," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 29, no. 2, pp. 286–299, 2007.
- [25] B. H. Shekar and B. Pilar, "Discrete cosine transformation and height functions based shape representation and classification," *Procedia Computer Science*, vol. 58, pp. 714–722, 2015.
- [26] B. H. Shekar and B. Pilar, "An ensemble of morphology based pattern spectrum and height functions for shape representation and classification," in *Proceedings of 2014 International Conference on Advances in Computing, Communications and Informatics*, pp. 2264–2272, Delhi, India, September 2014.
- [27] J. Zheng, J. Cheng, and Y. Yang, "Multiscale permutation entropy based rolling bearing fault diagnosis," *Shock and Vibration*, vol. 2014, Article ID 154291, 8 pages, 2014.
- [28] C. Yang, H. Wei, Q. Yu, C. Yang, H. Wei, and Q. Yu, "A novel method for 2D nonrigid partial shape matching," *Neurocomputing*, vol. 275, pp. 1160–1176, 2018.
- [29] X. Chen, H. Yan, and J. Sun, "Research on the identification of axis orbit in hydro-generator unit base on pso-bp and combined moment invariants," *Journal of Vibration Measurement and Diagnosis*, vol. 1, pp. 108–114, 2016.
- [30] Z. Jiang and Y. Li, "Research on feature extraction of shaft orbit for rotating machine," *Journal of Vibration Measurement and Diagnosis*, vol. 27, pp. 98–101, 2007.