Hindawi
Shock and Vibration
Volume 2018, Article ID 7546128, 8 pages
https://doi.org/10.1155/2018/7546128

Research Article

Fault Diagnosis of Intershaft Bearings Using Fusion Information Exergy Distance Method

Jing Tian,[1] Yanting Ai,[2] Chengwei Fei,[3] Ming Zhao,[1] Fengling Zhang,[2] and Zhi Wang[2]

[1]*School of Power and Energy, Northwestern Polytechnical University, Xi'an 710072, China*
[2]*Liaoning Key Laboratory of Advanced Test Technology for Aeronautical Propulsion System, Shenyang Aerospace University, Shenyang 110136, China*
[3]*School of Transportation Science and Engineering, Beihang University, Beijing 100191, China*

Correspondence should be addressed to Chengwei Fei; feicw544@163.com

Received 17 April 2018; Revised 3 July 2018; Accepted 1 August 2018; Published 29 August 2018

Academic Editor: Daniele Baraldi

For the fault diagnosis of intershaft bearings, the fusion information exergy distance method (FIEDM) is proposed by fusing four information exergies, such as singular spectrum exergy, power spectrum exergy, wavelet energy spectrum exergy, and wavelet space spectrum exergy, which are extracted from acoustic emission (AE) signals under multiple rotational speeds and multi-measuring points. The theory of FIEDM is investigated based on four information exergy distances under multirotational speeds. As for rolling bearings, four faults and one normal condition are simulated on a birotor test rig to collect the AE signals, in which the four faults are inner ring fault, outer ring fault, rolling element fault, and inner race-rolling element coupling fault. The faults of the intershaft bearings are analyzed and diagnosed by using the FIEDM. From the investigation, it is demonstrated that the faults of the intershaft bearings are accurately diagnosed and identified, and the FIEDM is effective for the analysis and diagnosis of intershaft bearing faults. Furthermore, the fault diagnosis precision of intershaft bearings becomes higher with increasing rotational speed.

1. Introduction

In the birotor system of an aeroengine, the intershaft bearing is widely used to connect high- and low-pressure rotors in a rotor supporting system. The outer and inner rings of intershaft bearing rotate with the high- and low-pressure rotor, respectively. It is easy for an intershaft bearing to produce a fault owing to the extreme operation environment under a high temperature, high speed, large dynamic load, and poor lubrication. As an essential component of rotors, therefore, the intershaft bearing is an important fault source of rotor system and seriously affects the safety and reliability of aeroengines and even aircrafts [1]. Due to the aeroengine operation in so severe environments, the faults of the intershaft bearings always contain noise, low signal to noise ratio (S/N) signals, and coupling fault signals, so that it is difficult to efficaciously analyze and identify the faults of intershaft bearings [2]. Acoustic emission (AE) signals possess high-frequency fault characteristics and are widely considered as the objective of study in intershaft bearing fault diagnosis. However, the sampling frequency of an AE signal is required to be very high, so that it is problematic to reflect the process characteristics of the intershaft bearing operation by adopting only one transient signal. In addition, the coupling fault of the bearing is difficult to be accurately identified because of the interactions of two or numerous faults.

In the past, various scholars investigated fault diagnosis techniques for rolling bearings based on AE signals using theory and experiments. Al-Ghamdi and Mba [3] validated that AE signal was superior to vibration signal in the analyses and diagnoses of rolling bearings incipient faults. Safizadeh [4] adopted a multisensor data integration method for the vibration fault diagnosis of rolling element bearings utilizing an accelerometer and a load cell. Purushotham et al. [5] proposed the hidden Markov model to conduct the diagnoses

of single and coupling faults based on simulation experiments. Al-Bugharbee and Trendafilova [6] researched the fusion approach based on a singular spectrum analysis and an autoregressive (AR) model, to improve the S/N of bearing fault signals, and then to accurately identify the fault categories and defect sizes. Yang et al. [7] extracted the early features of bearing faults and effectively restrained the noise signals for a wind turbine based on the ART-2-information fusion technique. Shakya et al. [8] improved fault diagnosis by obtaining different physical parameters from different sensors. Moosavian et al. [9] utilized the wavelet technique and D-S evidence inference to process the noise and vibration signals in a mechanical fault diagnosis with a diagnostic precision of 98.56%. The above works show that the multiclass information fusion of multiple sensors is promising to improve the fault diagnostic accuracy. However, a bearing fault always couples with noise signals and thus is often the weak and low S/N fault. In respect of complex bearing fault signals, it is difficult for the above methods to process the bearing fault signals because the effective features of weak faults cannot be recognized and extracted.

Chen et al. [10] used the D-S theory and fusion information entropy method to study the diversity and uncertainty of rotating machinery fault signals using the simulation data rather than the effective test data. Xu et al. [11] developed a multifuzzy ARTMAP classifier based on the Bayes criterion for bearing fault recognition with the time- and frequency-domain features of the fault signals. Zhao et al. [12] employed the global empirical decomposition mode to analyze single and coupling faults of bearings. Zhao et al. [13] combined approximate entropy and empirical mode decomposition to discuss the defect sizes of the rolling elements in bearings. He and Zhang [14] utilized the approximate entropy and wavelet analysis method to manage the AE signals in rolling bearing fault diagnosis. Herein, the technique in which the approximate entropy is regarded as a feature parameter of the signal was verified to be feasible and effective in the defect detection of rolling element bearings. Vazifeh and Hosseinabadi [15] investigated the wavelet entropy and kernel function to analyze the fault categories of gears. Li et al. [16] also demonstrated the validity of the information entropy for reflecting the fault condition in rolling bearings by using the multiscale fuzzy entropy and bearing experimental data. Cheng et al. [17] proposed an information entropy fusion method with the ensemble empirical mode decomposition (EEMD) for gear fault diagnosis.

The above methods reveal that regarding the information entropy as a fault feature index is feasible and efficacious in reflecting and describing the conditions of the bearing operation and other machinery. However, the above investigations mainly focused on the single faults in the machinery by adopting the single information entropy under one analytical domain such as time domain or frequency domain. In addition, most of the above studies mainly focused on ordinary rolling bearings. However, a few investigations pertained to intershaft bearing fault analysis and diagnosis. In contrast with an ordinary bearing, the intershaft bearing connects high-pressure rotor and low-pressure rotor, and the signals of the faults have to be transmitted from the fault sources to the sensors. In this process, fault signals significantly attenuate, and then have a low S/N owing to the interference in the complex and long path. Therefore, it is impossible to accurately extract the features of the intershaft faults by using the traditional extraction methods. It is of tremendous significance to develop an effective method to extract the useful feature information in an intershaft bearing fault diagnosis. We have found a preliminary solution in the investigation of the above documents at depth.

In conclusion, the objective of this study is to develop the fusion information exergy distance method (FIEDM) for intershaft bearing fault diagnosis by the AE signals of five condition (rolling element fault, inner ring fault, outer ring fault, inner ringrolling element coupling fault, and normal) and four information exergies (singular spectrum exergy (SSE), power spectrum exergy (PSE), wavelet energy spectrum exergy (WESE), and wavelet space spectrum exergy (WSSE)) from different analytical domains (time, frequency, and time-frequency domains). Herein, AE signals of the four faults and normal condition are acquired from the simulation experiments performed on a birotor test rig. The fault diagnoses of intershaft bearings are completed by obtaining the fusion information exergy distance curve under multiple speeds.

The rest of this paper is structured as follows. Section 2 introduces information exergy theory, including the information exergy concept and four information exergies (SSE, PSE, WESE, and WSSE) under different analytical domains including the time domain, frequency domain, and time-frequency domain. In Section 3, the FIEDM is developed based on the information exergies of the AE signals for the intershaft bearing fault diagnosis, with the emphasis on the establishments of information exergy matrix, information exergy distance, and fusion information exergy distance. The intershaft bearing fault diagnosis is performed based on the FIEDM with the assistance of fault simulation experiments conducted on a rotor test rig in Section 4. Section 5 gives some conclusions on this study.

2. Information Exergy Theory

2.1. Concept of Information Exergy. Information entropy is a measure of the order degree of a system. For an intershaft bearing fault, low order degree of the fault information indicates large information entropy. Owing to the different order degrees corresponding to different faults, the information entropy is often considered as an index to evaluate the states of the intershaft bearing faults. However, it is difficult to apply it to identify the operation process of the bearings. To entirely consider the fault information to timely diagnose the fault of the weak signal in early stages, the other measurement as the index-information exergy is developed [18].

For one measuring point, the AE signal is Lebesgue space M. A measure of the space is μ satisfying $\mu(M) = 1$, in which M is an incompatible set with a limited partition $A = \{A_i\}_{i=1}^{n}$ subjected to both $M = \cup_{i=1}^{n} A_i$ and $A_i \cap A_j = 0, \forall i \neq j$. The information entropy of A is expressed [19] as

$$S(A) = -\sum_{i=1}^{n} \mu(A_i) \log \mu(A_i), \tag{1}$$

in which $\mu(A_i)$ is a measure of set $\{A_i\}_{i=1}^{n}$.

Exergy was first proposed from a thermodynamics perspective and thus is also called thermodynamic exergy. The exergy is defined as the maximum theoretical useful work produced by a thermodynamic system, when the system works in the reversible process, which varies from the initial state to a thermodynamic equilibrium state with the surrounding environment [14]. In this definition, thermodynamic exergy is a quantity of process and similar to the thermodynamic entropy. The information exergy is a time-based process function, which describes the active components of a state signal that reflects a feature within a period of time.

In line with the process information of an AE signal in the time domain $[t_1, t_2]$, the information exergy is gained by integrating information entropy S of the measuring point in $[t_1, t_2]$, i.e.,

$$E_p(t) = \int_{t_1}^{t_2} S(A, t)\, dt, \tag{2}$$

where t_1 and t_2 are the upper and lower boundary of the time, respectively.

Information exergy reflects the degree of ordering of an AE signal in the running process. In view of the working process of the rotating machinery just like an aeroengine, the integrating range may be discretized by the speed.

2.2. Time-Domain Information Exergy of the AE Signals. For the AE signals with a discrete time series, assuming that a certain AE signal is $\{x_i\}_{i=1}^{N}$, where N is the number of sampling points for the time series analysis using the time delay embedded space, and the length of a certain mode window is M and the delay constant is 1, signal $\{x\}$ can be divided into $N-M$ segments mode data. In line with N sample points and M mode window length, pattern matrix A may be structured as

$$A = \begin{bmatrix} x_1 & x_2 & \cdots & x_M \\ x_2 & x_3 & \cdots & x_{M+1} \\ \vdots & \vdots & \cdots & \vdots \\ x_{N-M} & x_{N-M+1} & \cdots & x_N \end{bmatrix}. \tag{3}$$

The singular value decomposition of the matrix A is used to obtain singular value spectra $\{\sigma_i\}_{i=1}^{M}$ of the AE signals. The number of nonzero singular values reflects the number of patterns contained in each column of matrix A, and the size of the nonzero singular value indicates the proportion of the corresponding mode to total modes. Thus, a singular value is a time-domain division of the AE signal [20]. The singular spectrum entropy H_t of an AE signal in the time domain is

$$H_t = -\sum_{i=1}^{M} p_i \ln p_i, \tag{4}$$

in which $p_i = \sigma_i / \sum_{i=1}^{M} \sigma_i$ is the proportion of the i-th singular value to the entire singular value spectrum. With regard to calculation, the signal may be normalized by white noise signal. The maximum singular spectral entropy of white noise is $H_{t,\max} = \log M$. Hence, the singular spectrum entropy can be normalized by the white noise with respect to the maximum, i.e.,

$$H_t = \frac{-\sum_{i=1}^{M} p_i \log p_i}{\log M}. \tag{5}$$

The information exergy of the singular spectrum of the AE signal, i.e., singular spectrum exergy (SSE), is

$$E_{h.t}(t) = \int_{t_1}^{t_2} H_t(t)\, dt. \tag{6}$$

From the above analysis, the SSE is the time frequency feature of an AE signal regarding information exergy.

2.3. Frequency-Domain Information Exergy of AE Signals. By transforming the time-domain AE signal $\{x_t\}$ of a certain measuring point into the frequency-domain signal $X(\omega)$ by a discrete Fourier transform, we gain the power spectrum $S(\omega) = 1/2\pi N |X(\omega)|^2$. In the process of the time-frequency conversion, the energy of the AE signal is conserved in light of

$$\sum x^2(t)\Delta t = \sum |X(\omega)|^2 \Delta\omega. \tag{7}$$

Therefore, $S = \{S_1, S_2, \cdots, S_N\}$ may be regarded as a division of the original AE signal. Power spectrum entropy H_f [21] of the AE signal in the frequency domain is defined as

$$H_f = -\sum_{i=1}^{N} q_i \ln q_i, \tag{8}$$

where $q_i = S_i / \sum_{i=1}^{N} S_i$ is the proportion of the ith spectrum value to the entire power spectrum. The white noise signal is used to normalize the power spectrum entropy [22, 23] in view of Equation (9), in which the maximum power spectral entropy of the white noise is $H_{f,\max} = \log N$:

$$H_f = \frac{-\sum_{i=1}^{N} q_i \log q_i}{\log N}. \tag{9}$$

In line with the definition of information exergy, the power spectrum exergy (PSE) is

$$E_{h.f}(t) = \int_{t_1}^{t_2} H_f(t)\, dt. \tag{10}$$

In terms of the above analysis, the PSE reflects the frequency-domain features of the AE signals in respect of information exergy.

2.4. Time-Frequency Domain Information Exergy of AE Signal. Wavelet analysis is a time-frequency analysis method that is developed based on overcoming the shortcomings of the Fourier transform [24, 25]. For an AE signal $f(t)$ of

a measured point, the energy conservation of the limited energy contained in the function before and after the wavelet transform is

$$\begin{cases} \int_{-\infty}^{+\infty} \left|f(t)\right|^2 dt = \dfrac{1}{C_\psi} \int_0^{\infty} E(a)\mathrm{d}a, \\ C_\psi = \int_{-\infty}^{+\infty} \dfrac{\left|\psi(\omega)\right|^2}{\omega} \mathrm{d}\omega, \\ E(a) = \int_{-\infty}^{+\infty} \left|W_f(a,b)\right|^2 \mathrm{d}b, \end{cases} \tag{11}$$

where C_ψ is the admissible condition of the wavelet function and $E(a)$ is an energy value of function $f(t)$ at a.

$E = \{E_1, E_2, \ldots, E_n\}$ is considered as the wavelet energy spectrum of a signal $f(t)$ at n scales. Therefore, according to the definition of the information entropy, E is a type of signal energy, so that wavelet energy spectrum entropy H_{we} [22] in the time-frequency domain can be denoted as

$$H_{we} = -\sum_{i=1}^{n} s_i \ln s_i, \tag{12}$$

where $s_i = E_i / \sum_{i=1}^{n} E_i$ is the percentage of the ith spectrum value to the entire wavelet energy spectrum value.

According to the definition of the exergy information, the wavelet energy spectrum exergy (WESE) is

$$E_{h.we}(t) = \int_{t_1}^{t_2} H_{we}(t)\, dt. \tag{13}$$

Wavelet transform is a method of mapping a one-dimensional signal onto a two-dimensional space. $W = [|W_f(a,b)|^2 / C_\psi a^2]$ is the energy distribution matrix of the signal in the two-dimensional wavelet space. Similar to the singular spectrum entropy in the time domain, the singular value decomposition for W determines the time-frequency characteristic spectrum of wavelet space spectrum entropy H_{ws} [26, 27] which is expressed as

$$H_{ws} = -\sum_{i=1}^{n} r_i \ln r_i, \tag{14}$$

where $r_i = \sigma_i / \sum_{i=1}^{n} \sigma_i$ is the proportion of the ith eigenvalue to the entire characteristic spectrum.

According to Equation (8), the wavelet space spectrum exergy (WSSE) is

$$E_{h,ws}(t) = \int_{t_1}^{t_2} H_{ws}(t)\, dt. \tag{15}$$

The basis function of a wavelet is a type of division of the signal energy in the scale space that reflects the energy distribution of the signal in both time domain and frequency domain. Based on the WSSE, the information ordering degree of the intershaft bearing AE signal in the acceleration or deceleration process can be accurately measured.

3. Information Exergy Distance Method for Fault Diagnosis

3.1. Information Exergy Matrix. For a typical intershaft bearing fault, the information entropy matrix **A** of the AE signals is expressed by

$$\mathbf{A} = \begin{pmatrix} S(1,1) & S(1,2) & \cdots & S(1,n) \\ S(2,1) & S(2,1) & \cdots & S(2,1) \\ \vdots & \vdots & & \vdots \\ S(m,1) & S(m,1) & \cdots & S(m,n) \end{pmatrix}, \tag{16}$$

in which m indicates the number of sampling speeds of the AE signal in the process of speed up or speed down; n is the number of measuring points of the AE signal; and $S(i, j)$ in matrix **A** represents the AE information entropy of the jth measuring points at the ith sampling speeds.

Assuming that two matrices **A** in any two sampling intervals are equal and an interval is a sequence section of the units, m sampling points of the rotating speed process might be evenly divided into $m-1$ sequence intervals. Each measuring point of AE signals has one information exergy, i.e.,

$$E_p(t) = \int_{t_1}^{t_2} S(t)\, dt = \sum_{i=1}^{m-1} \frac{S(i) + S(i+1)}{2}. \tag{17}$$

Equation (17) reflects the changing regularity of the information ordering degree of an AE signal at the measuring point in the process of speed up and speed down.

3.2. Information Exergy Distance Method of Fault Diagnosis. As illustrated from the above analysis, the SSE, PSE, WESE, and WSSE reflect the complexity of an AE signal in the process of acceleration or deceleration of an intershaft bearing in different analytical domains. If the four information exergies are fused to reflect the fault features from different analytical domains, the information features of the intershaft bearing faults can be fully described synthetically, so that it is promising to improve the accuracy of the fault analysis and recognition. If one information exergy for the faults is regarded as one-dimensional space, four-dimensional (4-D) space can be structured by the four information exergies from different domains. For one process fault of the intershaft bearing, its four information exergies can be extracted in the form of four information exergy bands. Each information exergy band covers a narrow range in which the information exergy values vary. The information exergy center, also called information exergy point, is obtained by computing the mean value of each information exergy of each fault. For one fault, four information exergies points structure a single 4-D space.

Information exergy distance d_i is defined by the distance between the information exergy point e_a of an unknown fault and the information exergy point e_i of ith type of fault, i.e.,

$$d_i = \sqrt{\sum_{j=1}^{4} \left(E_{aj} - E_{ij}\right)^2}, \tag{18}$$

where i is the ith fault category, $j = 1, 2, 3, 4$ denotes the jth category of information exergy, E_{aj} is the jth information exergy value of an unknown fault e_a, and E_{ij} expresses the jth information entropy value of the ith type of fault e_i.

Regarding the existence of multiple faults in the intershaft bearings as a fault domain $E = \{e_i\}_{i=1}^{n}$, the fault diagnosis of the intershaft bearing is to determine to which known fault the unknown fault e_a belongs to. Namely, information exergy point e_a of the unknown fault is closest to information exergy point e_i in the known fault in the 4-D space according to the minimum information exergy distance. Based on Equation (18), the calculation accuracy of the information energy can be improved by increasing the number of sampling points with the rotational speed. All information exergy distances between the unknown fault and all known faults under multiple speeds in the bearing operation can be depicted as one curve. The curve is called information exergy curve. In line with this curve, it is promising to clearly judge to which known fault the unknown fault belong by the minimum information exergy distance. The method based on numerous information exergies under multiple speeds is called the fusion information exergy distance method (FIEDM) in this paper.

4. Fault Diagnosis of Intershaft Bearing

4.1. Simulation Experiment of Intershaft Bearing Fault. In the speed up or speed down process of rotating machinery like an aeroengine, the state of the intershaft bearing constantly varies with low S/N, noise, weak signals, and coupling signals. To validate the accuracy and practicability of FIEDM in the fault diagnosis of the intershaft bearings, the simulation experiment was conducted in a birotor test rig to collect sufficient sample data. The double rotor (birotor) system is shown in Figure 1, which can run with positive and negative rotational speeds. An intershaft bearing connects two rotors. The testing system of AE signals is the SAEU2S system as shown in Figure 2, which comprises hardware setup, analysis, and sampling control [15]. The related parameters of this system are listed in Table 1. The sensors in the test system of the AE signals are piezoelectric sensors (model no. SR150M) with a sampling rate range between [0 Hz, 500 kHz].

Four typical faults (rolling element fault, inner ring fault, outer ring fault, and inner ring-rolling element coupling faults) and normal condition were simulated on the rotor system test rig to obtain the fault data under multirotating speeds and multimeasuring points. Thereafter, the cylindrical roller bearing (model no. NU202) is regarded as the test bearing. The defects with the width of 0.1 mm are machined on the surfaces of inner ring, outer ring and roller of the bearing via wire cutting. Four voltage sensors are used to measure the AE signals in X and Y directions of the casing and pedestal, which are displayed in Figure 3. The signal data

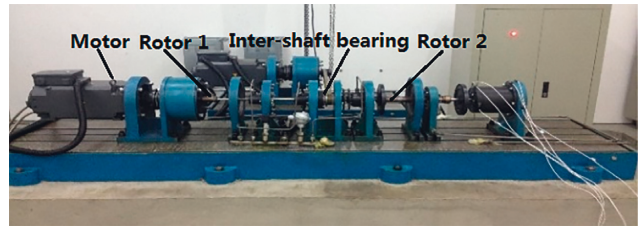

Figure 1: Rotor simulation test rig for intershaft bearing faults.

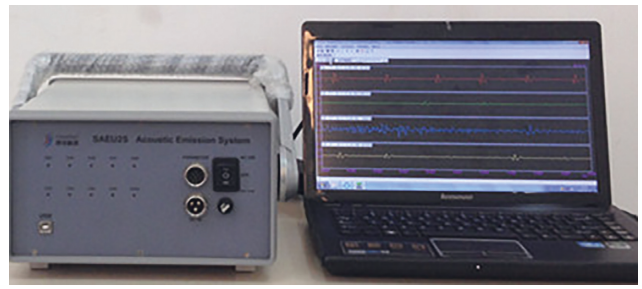

Figure 2: AE testing system.

are sampled from 800 rpm to 2000 rpm with an interval speed of 100 rpm. Therefore, 52 groups of AE signals are acquired for one speed up or speed down. Based on the theory of four information exergies, the values of four information exergies for the AE signals are calculated for the fault diagnosis of the intershaft bearings with the FIEDM method.

4.2. Intershaft Bearing Fault Diagnosis. Based on the fault simulations, we acquire the AE signals of four types of faults (i.e., rolling element fault, inner ring fault, outer ring fault, inner ring-rolling element, and coupling fault) and normal condition. In terms of Equations (6), (10), (13), and (15), the four information exergies $(E_{h\cdot t}, E_{h\cdot f}, E_{h\cdot we}, E_{h\cdot ws})$ were extracted for all the acquired AE signals of the bearing faults to structure a 4-D space. In light of Equation (16), the information exergy distance between an unknown fault and known faults was computed to draw the information exergy curve.

In the process of fault simulation, we specifically simulated the faults of outer ring with four sizes of deflects (0.06 mm, 0.08 mm, 0.1 mm, and 0.12 mm) and collected their AE signals. Similarly, in line with the Equation (18), we achieve the fusing information exergy points of AE signals under different rotational speeds as shown in Figure 4. As revealed in Figure 4, the four information exergy curves of four outer ring faults are obviously deferent and increase with the increase of information exergy values. Although the information exergy curve cannot completely separate the faults with different sizes, the separability of fault data based on information exergy has revealed. Based on this case, therefore, the FIEDM method is proposed for bearing fault diagnosis in this paper.

The information exergy distance curves between rolling element fault (unknown) and the five condition of intershaft

Table 1: Related parameters of the AE data acquisition system.

Sampling frequency (kHz)	Parameter interval (μs)	Lockout time (μs)	Filter (kHz)	Waveform threshold (dB)	Parameter threshold (dB)	Preamplifier gain (dB)
1000	20	50	20–400	40	40	40

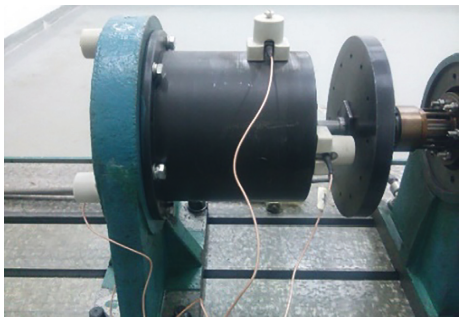

Figure 3: AE sensor distributions.

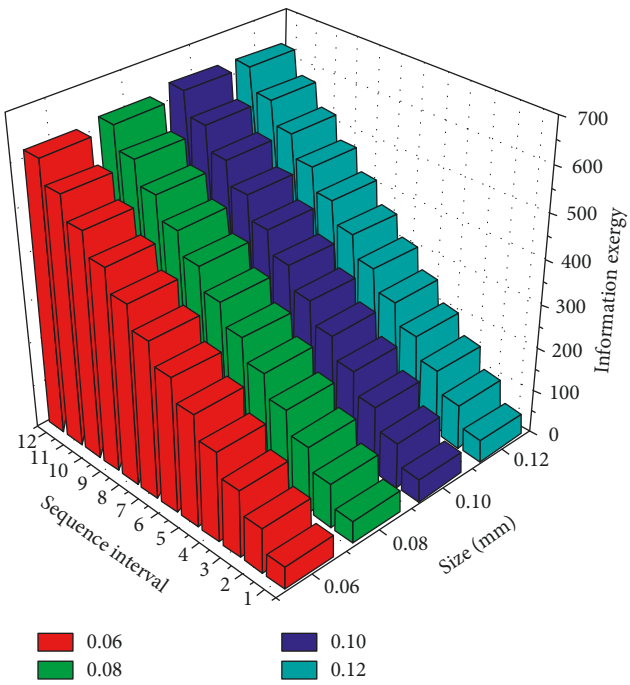

Figure 4: Information exergy of different fault sizes.

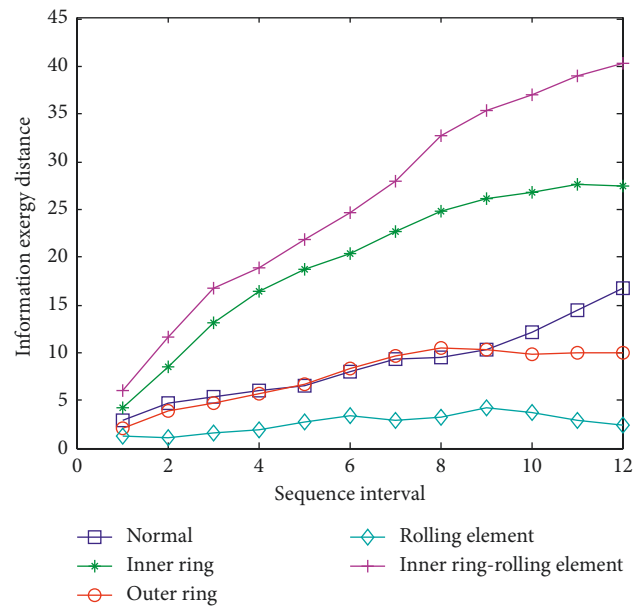

Figure 5: Information exergy distance of the rolling element fault.

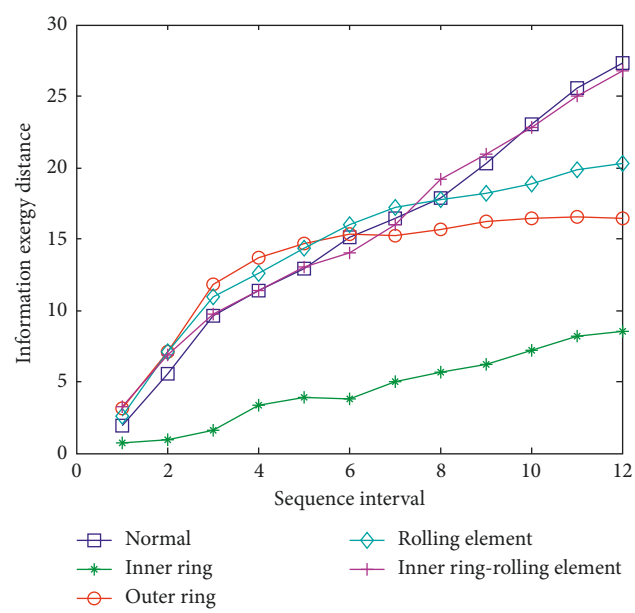

Figure 6: Information exergy distance of inner ring fault.

bearing are shown in Figure 5. Although the information exergy distance curves of the unknown faults (inner ring fault, outer ring fault and inner ring-rolling element coupling fault) are shown in Figures 6–8, respectively.

Based on the theory of the information exergy distance, the minimum information exergy distance (closest to the abscissa axis in the curves) for an unknown fault indicates that the unknown fault belongs to the corresponding known fault. As illustrated in Figure 5, a separation obviously exists between the information exergy distance curves, in which the information exergy distance curve of the rolling element fault is closest to the abscissa axis. Therefore, the unknown fault is ascertained as a rolling element fault, which is consistent with the physical examination. Furthermore, the separation of the information exergy distance curves is more obvious as speed up. Based on Equation (17), a larger sequence interval indicates more rotational information in the information exergy point, so that it is more probable to precisely identify the bearing faults.

As revealed from Figures 6 and 7, the inner and outer faults of the intershaft bearing are also diagnosed successfully

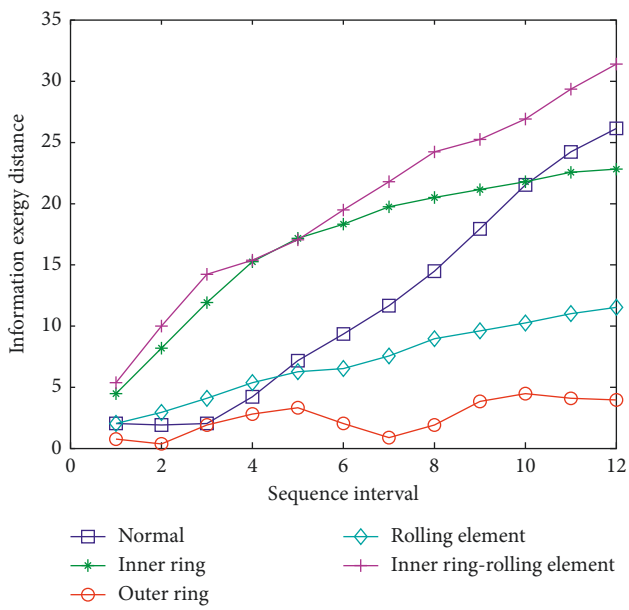

Figure 7: Information exergy distance of the outer ring fault.

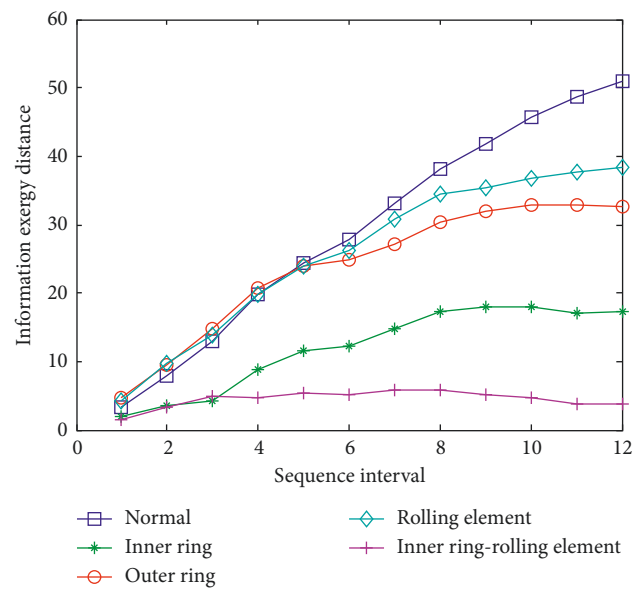

Figure 8: Information exergy distance of the inner ring-rolling element coupling fault.

by the information exergy distance curve. In the low-sequence interval in Figure 7, the information exergy distance of the outer ring fault is close to that of the normal state of the bearing. The reason is that in the low-sequence interval, the speed increase is not very high so that the outer ring fault is not aroused and the fault feature is not too obvious. With an increase in the speed, the feature of the outer ring fault is excited and contains more process information. Thus, the information exergy distance curves can be obviously separated. The results in Figures 5–7 fully illustrate that the proposed FIEDM can accurately diagnose the single fault of intershaft bearing.

Figure 8 displays the information exergy distance curve between the inner ring-rolling element coupling fault (unknown) and five known faults (state). As exhibited by Figure 8, the information exergy distance curve of the inner ring-rolling element coupling fault is closest to the abscissa axis, which clearly indicates that the unknown fault is the inner ring-rolling element coupling fault. However, in the sequence interval 1–3 as the speed increases from 800 r/min to 1000 r/min, the information exergy distance curves of the inner ring-rolling element coupling fault and inner ring fault overlap. This is because the coupling fault contains the inner ring fault, whereas the feature of the rolling element fault does not appear (or not obvious) in the 1–3 increasing interval. With the increase in the sequence interval, the two fault information exergy distance curves begin to separate, and the information exergy distance curve of the coupling fault approaches the abscissa axis.

In summary, the information exergy distance curve accurately indicates the fault to which the single fault of the intershaft bearing belongs. Relative to a single fault, the coupling fault is difficultly diagnosed. However, with the increase in the sequence interval, the coupling fault can be also efficiently diagnosed by the proposed FIEDM.

5. Conclusions

The objective of this study is to propose an efficient method by using four information exergies of acoustic emission (AE) signals for the intershaft bearing fault diagnosis from an information fusion perspective. This method is called fusion information exergy distance method (FIEDM) in this paper. The FIEDM is investigated by extracting four information exergy features such as singular spectrum exergy (SSE), power spectrum exergy (PSE), wavelet energy spectrum exergy (WESE), and wavelet space spectrum exergy (WSSE), from the acoustic emission (AE) signals of intershaft bearings under multimeasuring points and multirotational speeds. Consequently, the information features based on the FIEDM comprehensively reflects the exergy features of the bearing faults from different analytical domains. The AE signals of the intershaft bearings are acquired based on the simulating experiments on the rotor test rig. According to the intershaft bearing fault diagnosis with the FIEDM, it is revealed that the proposed method (FIEDM) can effectively handle the low S/N fault signals. In addition, the FIEDM with the AE signals can not only clearly identify the unknown single faults such as rolling element fault, inner ring fault, and outer ring fault, but also accurately diagnose the coupling faults of inner ring-rolling element coupling fault with the increasing sequence interval for the intershaft bearings. Additionally, with the increase in the rotational speed, the proposed FIEDM makes the effect of the intershaft bearing fault diagnosis with high accuracy more obvious.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This research is supported by the National Natural Science Foundation of China (grant nos. 11702177 and 51605016). The authors would like to thank them.

References

[1] A. Rai and S. H. Upadhyay, "A review on signal processing techniques utilized in the fault diagnosis of rolling element bearings," *Tribology International*, vol. 96, pp. 289–306, 2016.

[2] W. Caesarendra, B. Kosasih, A. K. Tieu et al., "Acoustic emission-based condition monitoring methods: review and application for low speed slew bearing," *Mechanical Systems and Signal Processing*, vol. 72-73, pp. 134–159, 2016.

[3] A. M. Al-Ghamdi and D. A. Mba, "Comparative experimental study on the use of acoustic emission and vibration analysis for bearing defect identification and estimation of defect size," *Mechanical Systems and Signal Processing*, vol. 20, no. 7, pp. 1537–1571, 2006.

[4] M. S. Safizadeh and S. K. Latifi, "Using multi-sensor data integration for vibration fault diagnosis of rolling element bearings by accelerometer and load cell," *Information Fusion*, vol. 18, pp. 1–8, 2014.

[5] V. Purushotham, S. Narayanan, and S. A. N. Prasad, "Multi-fault diagnosis of rolling bearing elements using wavelet analysis and hidden Markov model based fault recognition," *NDT & E International*, vol. 38, no. 8, pp. 654–664, 2005.

[6] H. Al-Bugharbee and I. Trendafilova, "A fault diagnosis methodology for rolling element bearings based on advanced signal pretreatment and autoregressive modelling," *Journal of Sound and Vibration*, vol. 369, pp. 246–265, 2016.

[7] D. Yang, H. Li, Y. Hu et al., "Vibration condition monitoring system for wind turbine bearings based on noise suppression with multi-point data integration," *Renewable Energy*, vol. 92, pp. 104–116, 2016.

[8] P. Shakya, A. K. Darpe, and M. S. Kulkarni, "Bearing diagnosis using proximity probe and accelerometer," *Measurement*, vol. 80, pp. 190–200, 2016.

[9] A. Moosavian, M. Khazaee, G. Najafi et al., "Spark plug fault recognition based on sensor integration and classifier combination using Dempster–Shafer evidence theory," *Applied Acoustics*, vol. 93, pp. 120–129, 2015.

[10] J. Chen, F. Ye, and Y. Li, "A robust rotary machinery fault diagnosis approach based on entropy fusion and DS theory," in *Proceedings of 13th International Conference on Signal Processing*, pp. 1424–1428, IEEE, Chengdu, China, November 2017.

[11] Z. Xu, Y. Li, Z. Wang et al., "A selective fuzzy ARTMAP ensemble and its application to the fault diagnosis of rolling element bearing," *Neurocomputing*, vol. 182, pp. 25–35, 2016.

[12] M. Zhao, J. Lin, X. Xu et al., "Multi-fault detection of rolling element bearings under harsh working condition using IMF-based adaptive envelope order analysis," *Sensors*, vol. 14, no. 11, pp. 20320–20346, 2014.

[13] S. F. Zhao, L. Liang, G. H. Xu et al., "Quantitative diagnosis of a spall-like fault of a rolling element bearing by empirical mode decomposition and the approximate entropy method," *Mechanical Systems and Signal Processing*, vol. 40, no. 1, pp. 154–177, 2013.

[14] Y. He and X. Zhang, "Approximate entropy analysis of the acoustic emission from defects in rolling element bearings," *Journal of Vibration and Acoustics*, vol. 134, no. 6, pp. 969-970, 2012.

[15] M. Vazifeh and F. A. Hosseinabadi, "Fault diagnosis based on wavelet entropy feature extraction and information fusion," in *Proceedings of 2nd International Conference on Information Science and Control Engineering*, pp. 234–238, IEEE, Shanghai, China, April 2015.

[16] Y. Li, M. Xu, R. Wang et al., "A fault diagnosis scheme for rolling bearing based on local mean decomposition and improved multiscale fuzzy entropy," *Journal of Sound and Vibration*, vol. 360, pp. 277–299, 2016.

[17] G. Cheng, X. Chen, H. Li et al., "Study on planetary gear fault diagnosis based on entropy feature fusion of ensemble empirical mode decomposition," *Measurement*, vol. 91, pp. 140–154, 2016.

[18] F. Chen, L. Huang, Y. Han et al., "Fault diagnosis method of information exergy based on space-time feature spectrum in frequency domain," *Journal of Vibration Measurement & Diagnosis*, vol. 34, no. 5, pp. 898–904, 2014.

[19] Y. Ai, J. Guan, C. Fei et al., "Integration information entropy method of rolling bearing fault diagnosis based on n-dimensional characteristic parameter distance," *Mechanical Systems and Signal Processing*, vol. 88, pp. 123–136, 2017.

[20] H. Cui, L. Zhang, R. Kang et al., "Research on fault diagnosis for reciprocating compressor valve using information entropy and SVM method," *Journal of Loss Prevention in the Process Industries*, vol. 22, no. 6, pp. 864–867, 2009.

[21] C. Fei, G. Bai, W. Tang et al., "Quantitative diagnosis of rotor vibration fault using process power spectrum entropy and support vector machine method," *Shock and Vibration*, vol. 2014, no. 10, pp. 269–278, 2014.

[22] A. Rai and S. H. Upadhyay, "A review on signal processing techniques utilized in the fault diagnosis of rolling element bearings," *Tribology International*, vol. 96, pp. 289–306, 2016.

[23] C. W. Fei and G. C. Bai, "Wavelet correlation feature scale entropy and fuzzy support vector machine approach for aeroengine whole-body vibration fault diagnosis," *Shock and Vibration*, vol. 20, no. 2, pp. 341–349, 2013.

[24] H. Qiu, J. Lee, J. Lin et al., "Wavelet filter-based weak signature detection method and its application on rolling element bearing prognostics," *Journal of Sound and Vibration*, vol. 289, no. 4-5, pp. 1066–1090, 2006.

[25] D. Paliwal, A. Choudhury, and G. Tingarikar, "Wavelet and scalar indicator based fault assessment approach for rolling element bearings," *Procedia Materials Science*, vol. 5, pp. 2347–2355, 2014.

[26] G. S. Hu, F. F. Zhu, and Z. Ren, "Power quality disturbance identification using wavelet packet exergy entropy and weighted support vector machines," *Expert Systems with Applications*, vol. 35, no. 1-2, pp. 143–149, 2008.

[27] C. W. Fei, Y. S. Choy, W. Z. Tang, and G. C. Bai, "Multi-feature entropy distance approach with vibration and AE signals for process feature extraction and diagnosis of rolling bearing faults," *Structural Health Monitoring*, vol. 17, no. 2, pp. 156–168, 2018.