Multi-feature entropy distance approach with vibration and acoustic emission signals for process feature recognition of rolling element bearing faults

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Abstract

To accurately reveal rolling bearing operating status, multi-feature entropy distance method was proposed for the process character analysis and diagnosis of rolling bearing faults by the integration of four information entropies in time domain, frequency domain and time–frequency domain and two kinds of signals including vibration signals and acoustic emission signals. The multi-feature entropy distance method was investigated and the basic thought of rolling bearing fault diagnosis with multi-feature entropy distance method was given. Through rotor simulation test rig, the vibration and acoustic emission signals of six rolling bearing faults (ball fault, inner race fault, outer race fault, inner ball faults, inner–outer faults and normal) are gained under different rotational speeds. In the view of the multi-feature entropy distance method, the process diagnosis of rolling bearing faults was implemented. The analytical results show that multi- feature entropy distance fully reflects the process feature of rolling bearing faults with the change of rotating speed; the multi-feature entropy distance with vibration and acoustic emission signals better reports signal features than single type of signal (vibration or acoustic emission signal) in rolling bearing fault diagnosis; the proposed multi-feature entropy distance method holds high diagnostic precision and strong robustness (anti-noise capacity). This study provides a novel and useful methodology for the process feature extraction and fault diagnosis of rolling element bearings and other rotating machinery.

Keywords

Rolling element bearing, process fault recognition, information entropy, multi-feature entropy distance method

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Introduction

As the most common machine elements, rolling bearings are playing an exceptionally vital role in almost all kinds of rotating machinery.[1,2] Rolling bearings are as such used in industries at length due to their relatively lower price and operational ease. The manoeuvre of rotating machinery, just like an aeroengine, is entirely dependent upon the health state of rolling bearings which accounts for almost 45%–55% of these equipment failures.[3] The presence of bearing faults, such as galling, spalling, subcase fatigue or failure of the bearings due to misalignment, high extent of waviness and inclusions, causes a catastrophic collapse of the system, which thereby reduces the reliability and usability of mechanical systems.[4] Thus, it becomes a requisite to implement and expand effective maintenance strategiesto minimize the impact of failures due to the malfunction of the rolling bearings. Herein, it is crucial to seek an effective measure for failure prediction and faultdiagnosis in earlier to promptly reduce and prevent rolling bearing faults.[5]

Various fault diagnosis approaches of rolling bearing and their diagnostic capabilities were discussed for the past few decades. Before the years 2001, the earliest work on the signal processing techniques related to bearings is quite simple and mainly dependent upon simple time domain methods,[6–11] frequency domain methods[12–14] and time-frequency domain methods.[15,16] Moreover, the signature analysis methods were ineffi-cient to minimize the effect of noises and interferences due to other sources of vibration such as gears or the varying speed of the shaft.5 Modern signal processing approaches developed during the period 2001–2010 include wavelet transform based techniques,[17–19] entropy[20–22] and empirical mode decomposition.[23,24] After the years 2011, more advanced fault diagnosis tools were developed by information fusion technique to avoid uncertainty and the shortcomings of single technique and single information, and thereby improve the diagnostic precision and effect. These methodologies comprise spectral kurtosis and kurtogram,[25] wavelet-based approaches,[26,27] ensemble empirical mode decom- position[28,29] and so forth. In fact, the objective of signal processing in rolling bearing fault diagnosis is to extract the feature information of fault signals, which is called feature extraction, and as such to distinguish different signal caused by different kinds of faults.

As one of the key programmes of rolling bearing fault diagnosis, actually, feature extraction directly influences diagnosis results. Along with ever increasing on the accuracy of fault diagnosis, feature extraction technique is increasingly valued and thereby leads to the prevalence of information entropy,30 and in consequence emerges various entropy methods by combining singular spectrum in time domain, power spectrum in frequency domain, wavelet space spectrum and wavelet energy spectrum in time–frequency domain, which are defined by singular spectrum entropy,[31] power spectrum entropy,[32] wavelet space spectrum entropy[33] and wavelet energy spectrum entropy,[34] respectively. Due to the complicacy of rolling bearing signals of rotating machinery herein accompanying with a lot of ambient noise and other superfluous signals, the fault diagnosis techniques based on information entropy still confront with unavoidable questions: (a) the signal characters of rolling bearing faults are insufficiently reflected by the extracted information features; (b) the real fault features of rolling bearings are hardly described by single type of fault signal like vibration signals[35–37] or acoustic emission (AE) signals,[38–40] in spite of a large amounts of works studied by single type of fault signal for the related machinery; and (c) the process features of rolling bearing signals cannot be reasonably expressed and reflected in fault diagnosis so that the diagnostic precision is unacceptable. Therefore, it is obviously urgent to require proposing an effective method to innovatively address the above issues and thereby improve the effect of rolling bearing fault diagnosis.

The objective of this article, along with information fusion method and many signals for fault diagnosis, is to propose multi-feature entropy distance (MFED) method by four information entropies, which are the information features of the vibration signals and AE signals of rolling bearing faults under different rotating speeds. The developed MFED method was vali- dated by the four information entropies of two types of (vibration and AE) signals for six kinds of process faults of rolling bearings simulated on rotor system test rig.

In what follows, section 'Basic theory and methodologies' discusses the MFED method with the auxiliary presentation on four information entropies and gives the basic thought of the process diagnosis of rolling bearing faults based on the MFED method with vibration and AE signals. In section 'Rolling bearing faults simulation experiment', rolling bearing simulation experiments are investigated to collect the failure data of rolling bearings. Process fault diagnoses of rolling bearing based on the MFED method are studied including the diagnoses with single type of vibration or AE signal and two kinds of signals (vibration and AE signals), and the validation of the robustness of the MFED method as well in section 'Rolling bearing fault diagnosis with MFED method'. Section 'Conclusion' summarizes some conclusions on this study.

Basic theory and methodologies

To perform the fault diagnosis of rolling bearings, this section is to discuss the feature extraction method with information entropy theory, MFED method and the basic thought of the process feature extraction and diagnosis of rolling bearing faults in this article.

Information entropy theory

Information entropy is used to measure the uncertainty of system. Remarkable chaotic system has large information entropy value while orderly system corresponds to small information entropy.[30]

When a measurable set H garners the Lebesgue space M with the measure μ (μ(M) = 1), which is denoted as the incompatible set (Ai ∩ Aj = 0, i ≠ j) with a limited partitioning A = {Ai}, we gain

$$M = \bigcup_{i=1}^{n} A_i \tag{1}$$

the information entropy E of the set A is defined as

$$E(A) = -\sum_{i=1}^{n} \mu(A_i) \log \mu(A_i) \tag{2}$$

where $\mu(A_i)$ is the measurement of the ith sample A_i, $i = 1, 2, \ldots, n$.

By the delay embedding technique, an arbitrary signal $\{x_i\}(i = 1, 2, \ldots, n)$ is mapped to an embedded space to obtain the $m \times n$ matrix, denoted by B, that is

$$\boldsymbol{B}=\begin{bmatrix} x_1 & x_2 & \cdots & x_m \\ x_2 & x_3 & \cdots & x_{m+1} \\ \vdots & \vdots & \cdots & \vdots \\ x_{n-m} & x_{n-m+1} & \cdots & x_n \end{bmatrix} \tag{3}$$

where m is the length of the embedded space and n is the number of samples.

With the singular value decomposition in time domain, the singular values $\{\sigma_i\}_{i=1}^{m}$ of the matrix $\boldsymbol{B}$ are gained. Based on information entropy thought, the singular spectrum entropy (SSE) E_{ss} of the signal is defined as

$$\begin{cases} E_{ss} = -\sum_{i=1}^{m} p_{ss,i} \log(p_{ss,i}) \\ \text{s.t. } p_{ss,i} = \frac{\sigma_i}{\sum_{i=1}^{m} \sigma_i} \end{cases} \tag{4}$$

where $p_{ss,i}$ is the ratio of the ith singular spectrum to the whole spectrum.[31]

SSE describes the measure of the disorder or randomness of signals in time domain by singular values, which is used to reflect the time domain features of signals in this study.

When $X(\omega)$ in frequency domain is the discrete Fourier transform of a time domain signal $\{x_t\}$, its power spectrum is as follows

$$S(\omega) = \frac{1}{2\pi N} |X(\omega)|^2 \tag{5}$$

Due to the conservation of energy on the transformation from time domain to frequency domain,[32] namely

$$\sum x^2(t)\Delta t = \sum |X(\omega)|^2 \Delta\omega \tag{6}$$

$s = \{s_1, s_2, \ldots, s_n\}$ may be regarded as the partition of original signal $\{x_t\}$ in line with the basic thought of information entropy; hence, the power spectrum entropy (PSE) E_{ps} is defined by

$$\begin{cases} E_{ps} = -\sum_{i=1}^{n} p_{ps,i} \log(p_{ps,i}) \\ \text{s.t. } p_{ps,i} = \frac{s_i}{\sum_{i=1}^{n} s_i} \end{cases} \tag{7}$$

where $p_{ps,i}$ is the ratio of the ith power spectrum to the whole spectrum.[32]

PSE expresses the measure of the disorder or randomness of signals in frequency domain by discrete Fourier transform from time domain. The PSE method is adopted to reflect and extract the frequency domain features of signals in this article.

The limited energy of time domain function $f(t)$ is conserved by the wavelet transform from time domain to frequency domain, which follows

$$\int_{-\infty}^{+\infty} |f(t)|^2 \mathrm{d}t = \frac{1}{C_\psi} \int_0^{\infty} e(a) \mathrm{d}a$$

$$\text{s.t.} \begin{cases} C_\psi = \int_{-\infty}^{+\infty} \frac{|\psi(\omega)|^2}{\omega} \mathrm{d}\omega \\ e(a) = \int_{-\infty}^{+\infty} \left|W_f(a,b)\right|^2 \mathrm{d}b \end{cases} \quad (8)$$

where C_ψ is the admissible condition of the wavelet function; $e(a)$ is the energy of the function f(t) (wavelet energy spectrum) on the scale a; $\psi(\cdot)$ is the wavelet mother function and $W_f(a,b)$ is the amplitude of wavelet transformation on scale a.

The objective of wavelet transform is to isometrically map the one-dimensional (1D) signal into two- dimensional (2D) space. Thus, the energy distribution matrix of signal on 2D wavelet space is as follows

$$\mathbf{W} = \left[\frac{\left|W_f(a,b)\right|^2}{C_\psi a^2} \right] \quad (9)$$

Through the singular value decomposition of the matrix **W** similar to SSE, the singular values are gained and denoted by $\{\upsilon_i\}_{i=1}^n$. The singular values $\{\upsilon_i\}_{i=1}^n$ may be considered as the feature partition of original time domain function $f(t)$. Therefore, in the light of the heuristic idea of information entropy, the wavelet space spectrum entropy (WSSE) E_{ws} of the signal is expressed[33] as follows

$$\begin{cases} E_{ws} = -\sum_{i=1}^{n} p_{ws,i} \log(p_{ws,i}) \\ \text{s.t. } p_{ws,i} = \frac{\upsilon_i}{\sum_{i=1}^{n} \upsilon_i} \end{cases} \quad (10)$$

where $p_{ws,i}$ is the ratio of the ith feature spectrum to the whole spectrum.

WSSE is the measure of the disorder or randomness of signals in time domain and frequency domain by wavelet transform from time domain to frequency domain and then singular value decomposition on the energy distribution matrix of signal. Thus, the entropy method is applied to capture one time –frequency domain features of signals in this investigation.

According to wavelet transform, when the wavelet spectrum of signal $f(t)$ on n scales is explained by $e = \{e_1, e_2, \ldots, e_n\}$ similar to PSE, $\{e_1, e_2, \ldots, e_n\}$ can be regarded as the partition of signal energy. Thus, wavelet energy spectrum entropy (WESE) E_{we} is[34]

$$\begin{cases} E_{we} = -\sum_{i=1}^{n} p_{we,i} \log(p_{we,i}) \\ \text{s.t. } p_{we,i} = \frac{e_i}{\sum_{i=1}^{n} e_i} \end{cases} \quad (11)$$

where $p_{we,i}$ is the ratio of the ith wavelet energy spectrum to the whole wavelet energy spectrum.

WESE indicates the measure of the disorder or randomness of signals in time–frequency domain by wave- let transform and the partition of wavelet energy spectrum on original signal. WESE values are employed to reflect other time–frequency domain features of the signal.

MFED method with vibration and AE signals

When each type of entropy on SSE, PSE, WSSE and WESE is regarded as one feature of signal, the space comprising four entropies is a four-feature space. Therefore, one fault point m in four-feature space is composed of four entropies (E_{ss}, E_{ps}, E_{ws} and E_{we}), which vary in a small range. The mean of the varying values on one kind of information entropy of this type of fault is the centre of this information entropy. The centre is called information entropy point.[41–43] When the jth kind of information entropy E_{ij} has k values for the ith type of fault, the information entropy point $\bar{E}_{ij}$ of the jth information entropy E_{ij} on the ith fault is expressed as

$$\bar{E}_{ij} = \frac{1}{k}\sum_{p=1}^{k} E_{ij}^{p} \tag{12}$$

where p ($p = 1, 2, \ldots, k$) is the pth value in the jth information entropy E_{ij} on the ith fault; k is the total number of the jth information entropy E_{ij} on the ith fault.

Thus, for the jth kind of entropy of the ith type of fault, its information entropy distance d_i on one unknown fault is defined by the distance between the jth kind of entropy value E_{aj} of this unknown fault and the information entropy point $\bar{E}_{ij}$ of the jth kind of information entropy in the ith type of fault in four- feature space, that is

$$d_i = \sqrt{\sum_{j=1}^{4} (E_{aj} - \bar{E}_{ij})^2} \tag{13}$$

where i is the ith category of fault; j ($j = 1, 2, 3, 4$) expresses the jth entropy category (SSE, PSE, WSSE and WESE).

For as such many kinds of entropies used in reflecting the features of signals by information entropy distance, we call this method as MFED method. The size of MFED shows the proximity degree of an unknown fault to the ith fault, namely, the small MFED d_i indicates the large probability of the unknown fault belonging to the ith fault, and vice versa. Therefore, the fault diagnosis of the unknown fault is conducted by the minimum value of the entropy which is the minimum entropy error (or difference) between the unknown fault and the corresponding fault. It should be noted that the diagnosed fault (unknown fault) must have one corresponding fault type in the selected referencing types of faults when MFED method is applied to fault diagnosis.

The MFED approach is promising in the use of one kind of vibration or AE signal in fault diagnosis.[35–40] Sometimes, multiple types of signals are simultaneously required, however, to master the characters of faults more accurately. Under the circumstances, based on the thought of the MFED method, the four MFED values of each fault from one kind of signals may be regarded as the feature indexes of the fault signals. If all the four MFED values of one fault from many kinds of signals are calculated as the feature indexes of the fault according to fall into place, the MFED of this fault is gained based on multiple kinds of signals. When P_{ij} is the jth parameter (entropy category) of the ith fault, the MFED d_i of the jth type of information entropy E_{aj} of an unknown fault point $\boldsymbol{\lambda}_a$ and the jth entropy value $\overline{E}_{ij}$ of the information entropy point $\boldsymbol{\lambda}_i$ of the ith fault is as follows

$$d_i = \sqrt{\sum_{j=1}^{\theta} (E_{aj} - \bar{E}_{ij})^2} \tag{14}$$

where θ is the number of the feature indexes of fault signal.

When vibration and AE signals are considered synchronously, there are eight feature indexes to reflect this fault in the light of the idea of MFED method for multiple kinds of signals. This method is called MFED-method-based vibration and AE signals.

For the process signals under different rotating speeds, the MFED values of all rotational speeds and all types of information entropies are calculated. Therefore, we can sketch MFED graphs under different rotational speeds and different fault modes to judge the fault type of unknown fault. Besides, the unknown fault may be diagnosed by the minimum value of the sum of MFED data under different rotating speeds. Assuming that a process rotational speed comprises l speed points for process faults, the total MFED value for the unknown fault belonging to the ith fault under different rotational speeds is as follows

$$d_{i,total} = \sum_{r=1}^{l} d_i^r \tag{15}$$

where d_i^r is the MFED value on rth rotating speed point, expressed by

$$d_i^r = \sqrt{\sum_{j=1}^{n} \left(E_{aj}^r - \bar{E}_{ij}^r\right)^2} \tag{16}$$

where E_{aj}^r is the jth type of information entropy value of unknown fault on rth rotating speed point; $\bar{E}_{ij}^r$ is the jth type of information entropy value of the ith fault on rth rotating speed point, obtained by equation (12).

The fault diagnosis method based on MFED with multiple types of signals and multi-speed is called as the MFED method with multiple types of signals for process fault diagnosis. The basic thought of the MFED method with AE signal and vibration signal for process fault diagnosis is illustrated in Figure 1.

Basic thought of process fault diagnosis on rolling bearings based on MFED method

Regarding the above discussion, the basic diagnosis process based on MFED method for an unknown fault of rolling bearing is structured in Figure 2. The fault diagnosis of rolling bearing comprises of rotor simulation experiment, collection of fault signals, extraction of signal features and fault diagnosis. Herein, fault signals contain vibration and AE signals which are from six faults of rolling bearing (ball fault, inner race fault, outer race fault, inner ball fault, inner–outer fault and normal) from multi-channel multi-speed sampling on rotor simulation test rig. Signal features are the MFEDs of vibration and AE signals for an unknown fault signal from four information entropies.

Rolling bearing faults simulation experiment

In this article, rotor system test rig adopted is a double rotor system as shown in Figure 3(a), which can run with positive and negative rotational speeds. An intermediary bearing connects the two rotors. The testing system contains vibration testing system and AE testing system. Herein, the testing system of vibration signals in this rotor system test rig is LMS Test Lab system as shown in Figure 3(b), which includes signal collecting device, signal amplifier, speed regulator, speed display and computer. The testing system of AE signals is SAEU2S system as shown in Figure 3(c), which comprises hardware setup, analysis and sampling control,[43] in which the related parameters of this system are set as shown in Table 1.

In the test system of vibration signals, the used sensors are PCB acceleration sensor (model no.: 333H30), which measures the acceleration of rolling bearing vibration from 0 to 3000 Hz.[43] The sensors in the test system of AE signals are piezoelectric sensor (model no.: SR150 M), measuring frequency from 0 Hz to 500 kHz. The two types of sensors are used to acquire the signals of the rolling operation.

Six typical faults (ball fault, inner race fault, outer race fault, inner ball faults, inner–outer faults and normal) were simulated to obtain fault data on rotor system test rig under multi-rotating speeds and multi- measuring points in which the cylindrical roller bearing (model no.: NU202) is regarded as the test bearing.[43] Ten sensors are mounted on the casing and bearing. Herein, six acceleration sensors are used to monitor the vibration signals on the X-, Y- and Z-directions of casing and pedestal, as illustrated in Figure 4(a). The four voltage sensors are to check the AE signals on the X- and Y-directions of casing and pedestal, as shown in Figure 4(b). The signal data are sampled by the interval speed of 100 r/min from 800 to 2000 r/min. Therefore, 78 groups of vibration signals and 52 groups of AE signals are acquired for up or down rotation speed. Based on the basic principles of four information entropies, the values of four information entropies for vibration and AE signals are calculated, which are used to accomplish the fault diagnosis of rolling bearing with MFED method.

Rolling bearing fault diagnosis with MFED method

Rolling bearing fault diagnosis by MFED method with single kind of signals

Based on four information entropy methods (SSE, PSE, WSSE and WESE) and equation (12), the entropy values of vibration and AE signals for six kinds of rolling bearing faults are shown in Table 2. Based on the testing data for six faults under different rotational speeds from rolling bearing experiments and MFED method in equation (13), the diagrams of MFEDs are gained for the six faults as shown in Figure 5. Regarding equation (15), the total MFEDs of each unknown faults for vibration signals and AE signals are listed in Table 3 where the minimum total MFEDs are the bolded data in the same signal in same columns.

Rolling bearing fault diagnosis with MFED method by vibration and AE signals

As shown in section 'Rolling bearing fault diagnosis by MFED method with single kind of signals', the MFED- method-based single type of signal is revealed to be imprecise in distinguishing process faults from Figure 5, although the types of unknown faults can be identified by the minimum total MFEDs (bolded data) with single kind of signals in Table 3. The reason is that it is difficult to fully reflect the process characters of faults by single vibration or AE signals. To overcome this issue, we improve the process diagnosis method–MFED method based on the combination of vibration and AE signals.

Process fault diagnosis of rolling bearing with vibration and AE signals. From the analysis of information entropy, vibration and AE signals contain four information entropies, respectively. If eight information entropies for the vibration and AE signals of rolling bearing under multi-speed are regarded as the characteristic parameters, based on equation (14), the MFEDs under different rotating speeds are shown in Figure 6.

To satisfy the application of practical engineering, these diagrams are turned into MFED data and the total MFED values by superposing the MFED data of all rotation speeds by adopting equation (15), which is called as a judgement of rolling bearing fault diagnosis for each fault of unknown faults. The results are listed in Table 4. In line with MFED method, the unknown fault belongs to the fault with the minimum value in each column in Table 4. As shown in Table 4, the MFED method is demonstrated to be effective in identifying the fault category with minimum value (bolded numbers) in each column, to which the unknown faults belong simply, intuitively and clearly.

Precision validation of rolling bearing fault diagnosis. To further support the validation of MFED method, four sets of test data were gained under the same simulation conditions of six faults of rolling bearing from 800 to 2000 r/min. Each group of the vibration and AE data was processed to gain the corresponding total MFED data by the MFED method. The results obtained are shown in Table 5. The bolded data are the minimum values in each column which demonstrated that the unknown fault belongs to the fault in the corresponding line.

Robustness validation of MFED method

In the real-work environment of rolling bearings, the (vibration or AE) signals generated from bearing faults are always disturbed by noise signals and outliers. To highlight the effectiveness of MFED method in rolling bearing fault diagnosis with noise and outliers, the robustness of the proposed MFED method was checked by adding Gaussian white noise to the vibration and AE signals of rolling bearing faults. First, based on the rotor simulation test rig, 20 groups of signals under different rotational speeds (800 and 2000 r/min), including vibration and AE signals, for each fault of rolling bearings, were collected as fault data. The number of collected process data for six faults of rolling bearings is 120 groups. And then these signals (120 groups) were overlapped by Gaussian white noise with mean value 0 and variance 5 to acquire the fault signals with noise. Finally, based on the fault diagnosis programme with the developed MFED method similar to section 'Rolling bearing fault diagnosis with MFED method by vibration and AE signals', 120 groups of signals with/ without the noise signal were diagnosed for six rolling bearing faults. The results are listed in Table 6.

Discussion

From the process fault diagnosis of rolling bearings with MFED method, some results are drawn as follows:

As illustrated in Figure 5, unknown fault belongs to the fault with the closest curve of feature entropy distance to horizontal axis. Therein, the MFED between the unknown fault and the fault is smallest. However, the fact of curve overlapping in Figure 5 shows that the fault category cannot be accurately judged by single type of fault signals, although the categories are judged in Table 4. Thus, one alternative is to apply MFED method with multi-speed and multi-point data to diagnose the faults from vibration and AE signals.

As revealed from Figures 5–6, the same fault has the same trend in the curves of the MFEDs with single signal

(AE or vibration signal) and the MFED with AE and vibration signals for all unknown fault. In addition, the overlapping in these curves has been obviously improved by the MFED method with vibration and AE signals. And thereby the curve of unknown fault is significantly separated from other fault signals because the MFED method with vibration and AE signals better reflects signal feature than single vibration or AE signals. The results demonstrate that the accuracy and effect of rolling bearing fault diagnosis are markedly improved by the proposed MFED method.

From Tables 4–5, it is demonstrated that each unknown fault in the four groups of rolling bearing fault data are accurately diagnosed by the MFED method, which further confirms the feasibility and availability of the proposed MFED method with high precision. As shown in Table 6, when the fault signals of rolling bearings were not disturbed by noise, the correct identification number of fault samples is 116 and the corresponding diagnostic precision is 0.967. Nevertheless, the correct number of fault samples is 114 and its diagnostic precision is 0.95 when the signals are with noise. Comparing with the diagnosis results without noise, the correct samples and precision of fault diagnosis with noise only reduce by 2 and 0.017, respectively. The results indicate that the proposed MFED method holds strong robust- ness and capacity of resisting disturbance (anti-noise capacity) in the fault diagnosis of rolling bearings and is promising to be applied to the condition monitoring and fault diagnosis of complex turbomachinery just like an aeroengine, working on severe environment.

Conclusion

The objective of the efforts is to propose the MFED method for the process fault diagnosis of rolling bearing with single and coupling faults, by integrating four information entropies (SSE in time domain, PSE in frequency domain, WSSE and WESE in time–frequency domain) and two kinds of signals (vibration and AE signals), respectively. Through this investigation, some conclusions are summarized as follows:

1. Information entropy is able to reflect the uncertainty of signal and the process of signal variation.
2. The diagnostic result based on many kinds of signals is superior to that based on single type of signal in the process fault diagnosis of rolling bearing by the MFED method.
3. MFEDs effectively reflect the process characters of rolling bearing fault signals under different rotational speeds.
4. The MFED approach can distinguish the fault types of rolling bearings with high precision comprehensively and intuitively and is proved to be a promising diagnostic approach, for catering to the increasing characteristic parameters and feature information as well.
5. The proposed MFED method is demonstrated to hold strong robustness and capacity of resisting disturbance (anti-noise capacity) in the process fault diagnosis of rolling bearings.
6. By integrating many types of signal information, the advanced approach, MFED method, is promising to accurately monitor and estimate the operation status of turbomachinery working in the extreme environments with messy noises.

Acknowledgements

The authors would like to thank General Research Grant from Hong Kong SAR government, the Funding of Hong Kong Scholars Program and China's Post-doctoral Science Fund.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship and/or publication of this article.

Funding

The author(s) disclosed receipt of the following financial sup- port for The research, authorship, and/or publication of this article: The article is co-supported by General Research Grant from Hong Kong SAR government (grant no. B- Q39B), the Funding of Hong Kong Scholars Program (grant nos G-YZ90 and XJ2015002) and China's Post-doctoral Science Fund (grant no. 2015M580037).

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Figures

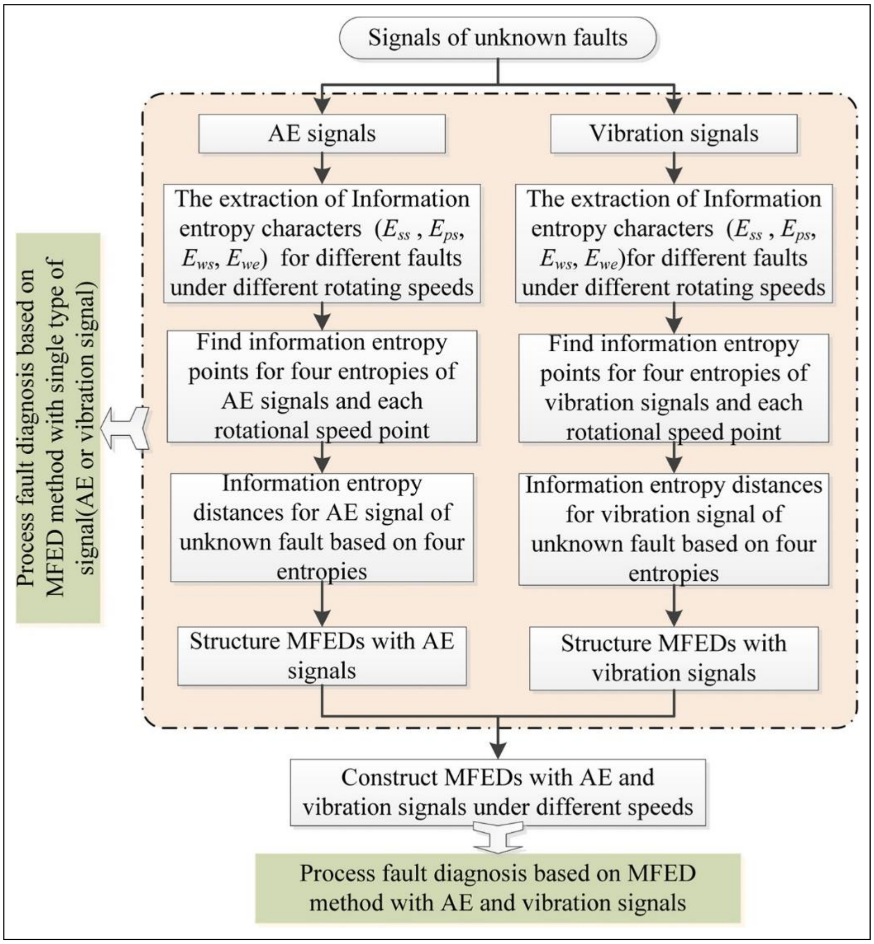

Figure 1. The basic thought of the MFED method with AE signal and vibration signals for process fault diagnosis.

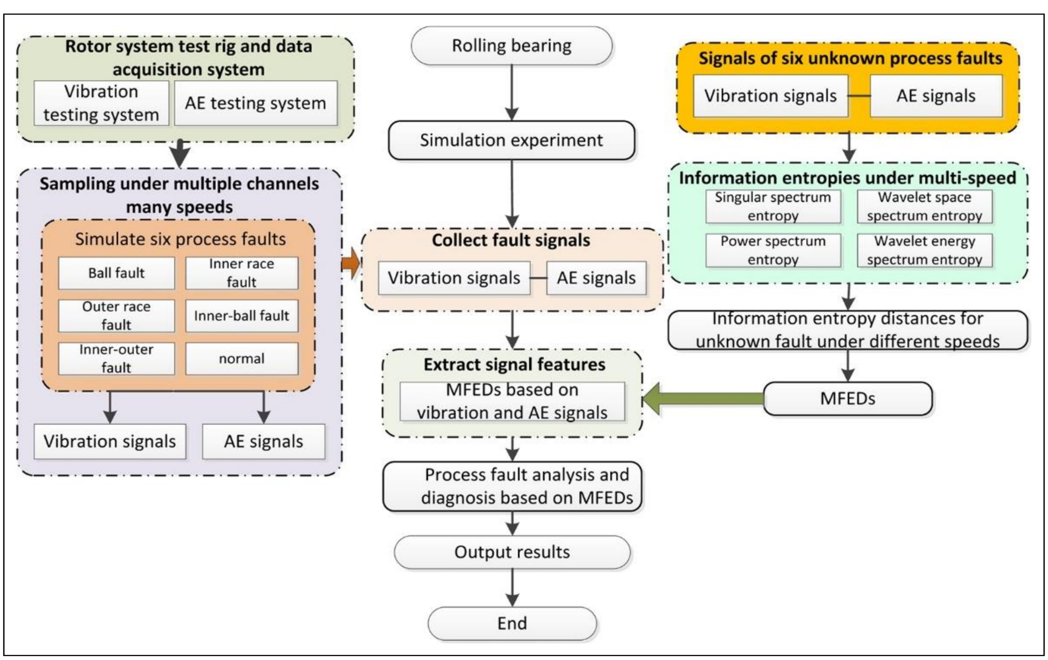

Figure 2. Flow chart of rolling bearing faults diagnosis with MFED-method-based vibration and AE signals.

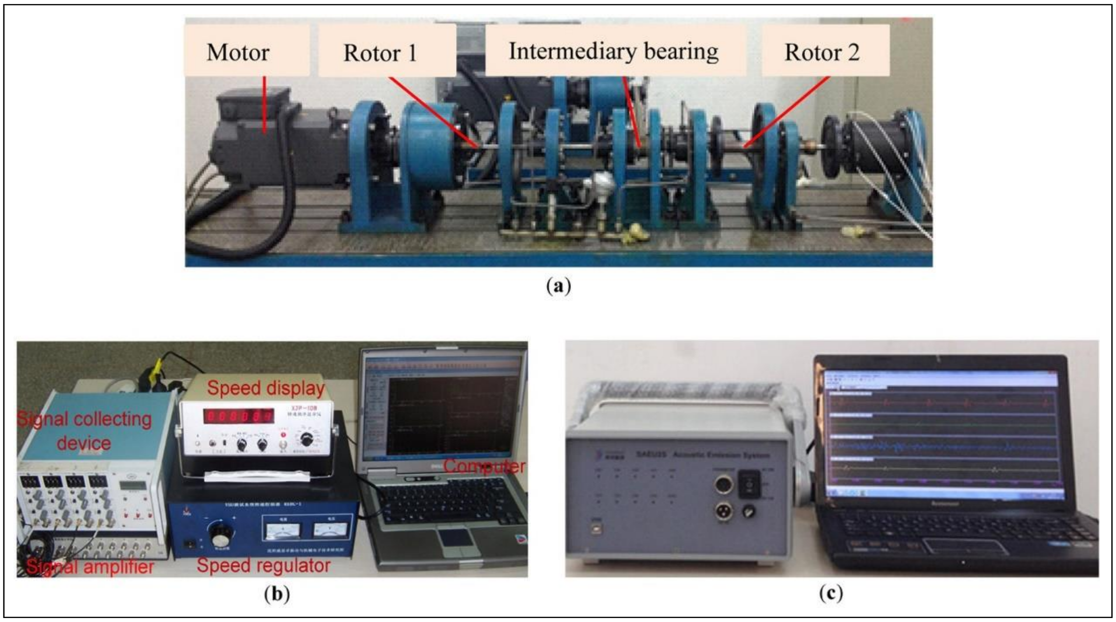

Figure 3. Simulation system of rotor test rig for six faults: (a) rotor simulation test rig, (b) vibration testing system and (c) AE testing system.

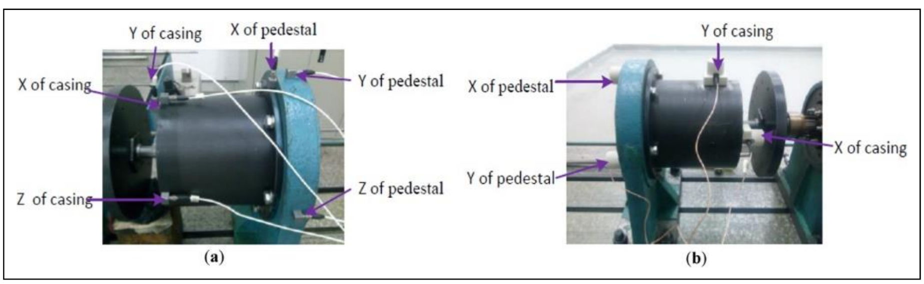

Figure 4. Distributions of vibration sensor and AE sensor: (a) vibration sensor distribution and (b) AE sensors distributions.

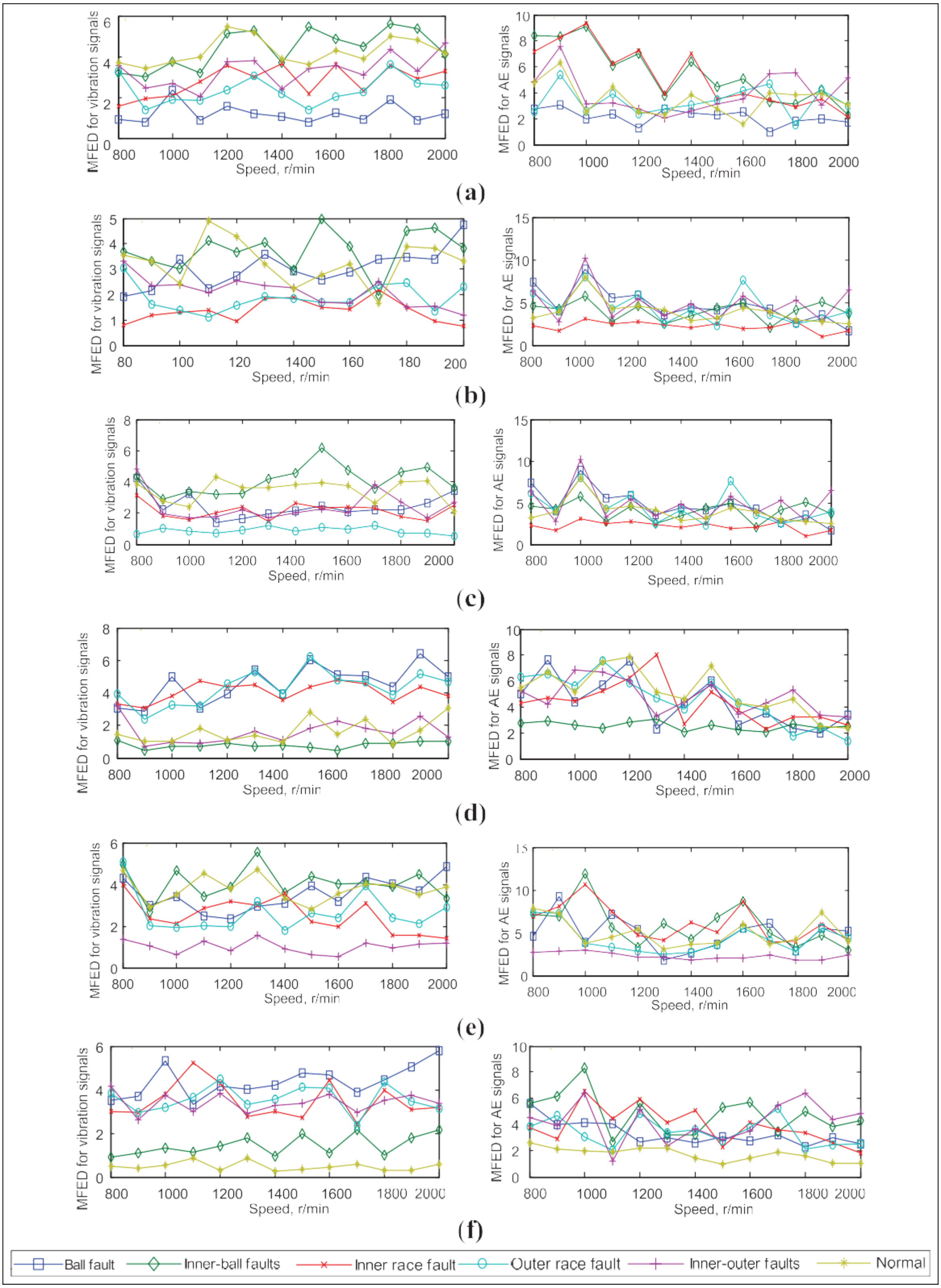

Figure 5. MFED graphs of six unknown faults for vibration and AE signal under multi-speed: (a) unknown fault 1 (ball fault), (b) unknown fault 2 (inner race fault), (c) unknown fault 3 (outer race fault), (d) unknown fault 4 (inner ball faults), (e) unknown fault 5 (inner–outer fault) and (f) unknown fault 6 (normal).

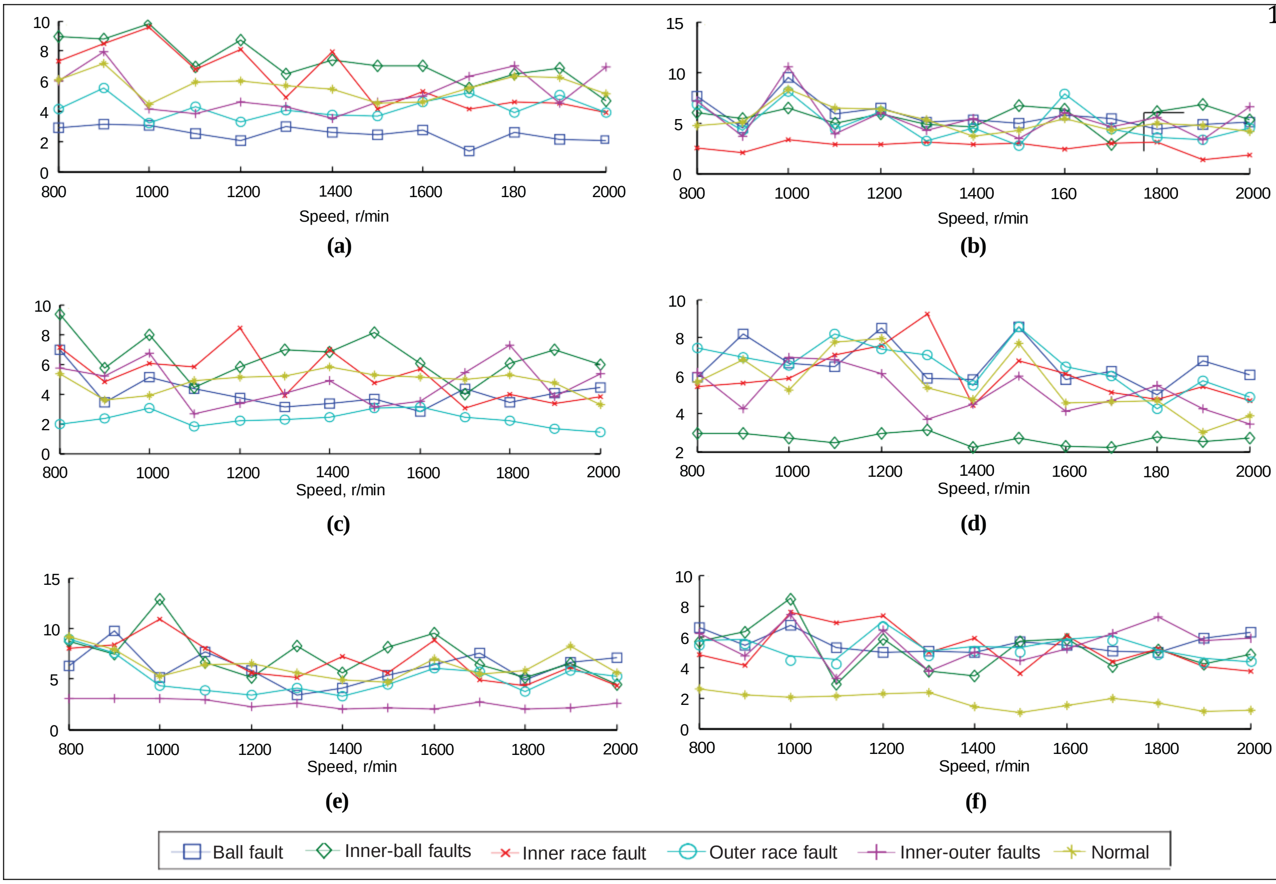

Figure 6. MFEDs of unknown faults with vibration and AE signals: (a) unknown fault 1 (ball fault), (b) unknown fault 2 (inner-race fault), (c) unknown fault 3 (outer-race fault), (d) unknown fault 4 (inner-ball fault), (e) unknown fault 5 (inner-outer fault) and (f) unknown fault 6 (normal)

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

AE: acoustic emission.

Table 1. Related parameters of AE data acquisition system.

Fault types	SSE		PSE		WSSE		WESE	
	Vibration	AE	Vibration	AE	Vibration	AE	Vibration	AE
Ball fault	92.857	85.191	48.875	60.052	5.714	5.688	18.127	13.974
Inner race fault	92.656	84.018	49.131	58.584	5.717	5.676	18.187	15.212
Outer race fault	93.076	84.572	48.709	60.019	5.704	5.687	17.838	14.049
Inner ball fault	93.188	82.965	52.641	57.533	5.697	5.682	18.816	14.281
Inner–outer fault	92.535	84.348	49.647	58.854	5.714	5.714	18.060	14.742
Normal	93.176	85.717	51.847	60.972	5.712	5.675	18.893	14.902

AE: acoustic emission; SSE: singular spectrum entropy; PSE: power spectrum entropy; WSSE: wavelet space spectrum entropy; WESE: wavelet energy spectrum entropy.

Table 2. Four entropy values of vibration and AE signal for rolling bearing typical faults.

Fault types	Signal types	Unknown 1	Unknown 2	Unknown 3	Unknown 4	Unknown 5	Unknown 6
Ball fault	Vibration	**15.509**	39.461	31.866	56.937	59.412	45.736
	AE	**27.882**	60.734	41.2531	42.724	56.752	63.665
Inner race fault	Vibration	36.454	**17.65**	27.889	44.915	52.753	32.803
	AE	68.601	**28.757**	60.904	50.512	55.672	79.956
Outer race fault	Vibration	30.393	24.279	**11.446**	46.476	56.047	34.338
	AE	43.647	57.609	**27.593**	44.278	59.858	55.939
Inner ball fault	Vibration	55.067	42.491	44.925	**6.271**	21.009	49.329
	AE	45.776	50.671	42.556	**22.444**	67.482	64.729
Inner–outer fault	Vibration	57.189	48.701	53.333	18.726	**10.227**	52.976
	AE	71.437	52.226	63.322	62.353	**32.993**	76.581
Normal	Vibration	42.995	27.374	31.425	44.274	20.935	**13.206**
	AE	52.028	63.624	50.768	54.683	62.047	**29.499**

MFED: multi-feature entropy distance; AE: acoustic emission.

Table 3. Diagnostic results of unknown faults with MFED method and single signals.

Fault types	Unknown 1	Unknown 2	Unknown 3	Unknown 4	Unknown 5	Unknown 6
Ball fault	**32.680**	74.756	52.674	85.627	80.228	72.256
Inner race fault	79.826	**34.148**	67.644	77.825	87.46	68.418
Outer race fault	54.79	63.523	**29.97**	84.946	66.568	65.279
Inner ball fault	94.663	72.082	84.134	**34.647**	94.511	65.712
Innerouter fault	68.783	70.11	61.162	66.437	**32.544**	71.347
Normal	73.105	67.5	62.446	71.964	82.541	**23.427**

MFED: multi-feature entropy distance.

Table 4. Diagnostic results of first unknown faults data by MFED method with two types of signals.

Data sets	Fault types	Unknown 1	Unknown 2	Unknown 3	Unknown 4	Unknown 5	Unknown 6
1st	Ball fault	**35.449**	71.027	54.703	94.975	75.725	74.491
	Inner race fault	75.893	**54.56**	67.855	88.643	84.824	72.657
	Outer race fault	48.509	61.208	**33.733**	91.02	59.671	71.87
	Inner-ball fault	90.29	79.102	81.777	**54.17**	84.289	69.117
	Inner–outer fault	63.602	68.878	59.725	86.574	**45.763**	68.617
	Normal	71.444	71.11	64.912	81.798	72.377	**34.985**
2nd	Ball fault	**36.034**	70.791	53.136	89.988	70.637	73.763
	Inner race fault	69.293	**53.022**	70.684	78.798	80.755	71.322
	Outer race fault	52.943	68.363	**32.271**	82.388	54.925	63.022
	Inner-ball fault	86.794	79.331	85.083	**53.755**	84.642	68.468
	Inner–outer fault	63.461	68.882	60.132	78.917	**44.205**	68.838
	Normal	71.3	78.524	61.716	74.612	68.397	**28.979**
3rd	Ball fault	**39.083**	73.395	53.925	85.529	74.87	72.875
	Inner race fault	80.362	**51.97**	69.386	78.63	83.956	71.593
	Outer race fault	54.842	62.993	**35.501**	80.449	61.906	68.361
	Inner-ball fault	93.026	74.65	78.267	**52.943**	84.409	69.081
	Inner–outer fault	68.177	67.016	56.694	78.342	**50.69**	74.82
	Normal	73.261	79.053	64.582	65.108	70.223	**33.487**
4th	Ball fault	**34.154**	72.745	54.356	86.769	67.059	70.077
	Inner race fault	78.741	**48.812**	69.002	75.123	80.309	71.801
	Outer race fault	53.881	69.707	**35.653**	76.768	70.873	62.718
	Inner-ball fault	93.746	71.711	85.224	**51.194**	82.36	68.869
	Inner–outer fault	68.444	76.131	59.812	78.065	**45.443**	70.188
	Normal	72.926	82.716	64.34	65.509	71.328	**29.533**

MFED: multi-feature entropy distance.

Table 5. Diagnostic results of unknown faults by MFED method with two types of signals.

Fault types	Sample number	Sum	Signals without noise		Signals with noise	
			Correct number (precision)	Correct sum (precision)	Correct number (precision)	Correct sum (precision)
Ball fault	20	120	20 (1.0)	116 (0.967)	19 (0.95)	114 (0.95)
Inner race fault	20		19 (95)		20 (1.0)	
Outer race fault	20		20 (1.0)		19 (0.95)	
Inner ball fault	20		18 (0.9)		18 (0.9)	
Inner–outer fault	20		19 (0.95)		18 (0.9)	
Normal	20		20 (1.0)		20 (1.0)	

MFED: multi-feature entropy distance.

Table 6. Robustness validation of MFED method in rolling bearing fault diagnosis.