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The Entropy Algorithm and Its Variants in the Fault Diagnosis of Rotating Machinery: A Review

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ABSTRACT Rotating machines have been widely used in industrial engineering. The fault diagnosis of rotating machines plays a vital important role to reduce the catastrophic failures and heavy economic loss. However, the measured vibration signal of rotating machinery often represents non-linear and non-stationary characteristics, resulting in difficulty in the fault feature extraction. As a statistical measure, entropy can quantify the complexity and detect dynamic change through taking into account the non-linear behavior of time series. Therefore, entropy can be served as a promising tool to extract the dynamic characteristics of rotating machines. Recently, many studies have applied entropy in fault diagnosis of rotating machinery. This paper aims to investigate the applications of entropy for the fault characteristics extraction of rotating machines. First, various entropy methods are briefly introduced. Its foundation, application, and some improvements are described and discussed. The review is divided into eight parts: Shannon entropy, Rényi entropy, approximate entropy, sample entropy, fuzzy entropy, permutation entropy, and other entropy methods. In each part, we will review the applications using the original entropy method and the improved entropy methods, respectively. In the end, a summary and some research prospects are given.

INDEX TERMS Entropy, fault diagnosis, fault feature extraction, rotating machinery, condition-based maintenance.

NOMENCLATURE

ApEn	Approximate entropy
SampEn	Sample entropy
FE	Fuzzy entropy
REN	Rényi entropy
PE	Permutation entropy
SpEn	Spectral entropy
WaEn	Wavelet entropy
IMFs	Intrinsic mode functions
EMD	Empirical mode decomposition
MSE	Multiscale sample entropy
CMSE	Composite multi-scale sample entropy
MMSE	Modified multiscale sample entropy
HSE	Hierarchical sample entropy
MFE	Multiscale fuzzy entropy
CMFE	Composite multi-scale fuzzy entropy
RCMMFE	Refined composite multivariate multiscale fuzzy entropy
MMFE	Modified multiscale fuzzy entropy
HFE	Hierarchical fuzzy entropy
SVM	Support Vector Machine
MPE	Multiscale permutation entropy
CMPE	Composite multiscale permutation entropy
GCMPE	Generalized composite multiscale permutation entropy
MHPE	Modified hierarchical permutation entropy
SDE	Symbolic dynamic entropy
HCM	Health condition monitoring
CWRU	Case Western Reserve University

I. INTRODUCTION

Rotating machinery is one of the most widely used mechanical equipment of modern industry, for example in helicopters, airplanes, machining centers, tracked loaders, mining tracks, and wind turbines as shown in Figure 1. Subjected to the harsh working condition, the rotating machines are vulnerable

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FIGURE 1. Some applications of rotating machinery [10].

to various damages [1]–[5]. In order to guarantee the production security and minimize the unexpected breakdowns and economic loss, it is important to detect these damages as early as possible [6]–[9]. Due to the rich fault-related information embedded in contaminated vibration signals, the vibration-based fault diagnosis method has become a mainstream in the field of health condition monitoring (HCM) [3], [4].

The collected vibration signals of rotating machinery often represent non-linear and non-stationary characteristics and the fault features are usually weakened and disturbed by the strong environment noises and other neighboring components. However, most of the existing methods are based on a stationary assumption, which is inefficient to analyze these complex vibration signals [11]. Therefore, how to extract these periodic features is the crucial issue in HCM of rotating machinery [12].

As a statistical measure, entropy can quantify the complexity and detect dynamic change through taking into account non-linear behavior of time series [7], [13]–[17]. Recently, entropy-based method has been widely applied in the fault diagnosis of rotating machinery [17]–[21]. Known that the vibration signal collected from a healthy machine has a larger entropy value due to its high irregularity, while that collected from a faulty rotating machine has a smaller entropy value due to its low irregularity caused by the localized damage [22], [23]. Compared with traditional methods, entropy-based method has several advantages, such as good cluster ability, high classification accuracy, robust to noise, independent on prior knowledge, etc [24]. Therefore, entropy can be served as a promising tool to extract the dynamic characteristics of rotating machines, which shows considerable potential for HCM of rotating machinery.

Entropy, as a measure of uncertainty or irregularity of time series, was first proposed by Shannon in 1948 [25]. Shannon entropy estimates the complexity using the probability distribution of its states. For a given time series, if the probability values of different states are similar, it is difficult to determine the future status, thus the time series has its maximum entropy value. In contrast, if there is only one state, the time series has its minimum entropy [26]. After that, other forms of Shannon entropy are conducted and the most representative one is rényi entropy [27]. Inspired by Shannon entropy, Pincus introduced approximate entropy (ApEn) to quantify the irregularity and self-similarity of time series [28], [29]. However, a very long data is required in ApEn, and if the data length is short, the obtained value is often smaller than the real one [30]. To address this problem, Richman and Moorman [30] proposed sample entropy (SampEn). SampEn, though powerful, has two main shortcomings. First, SampEn utilizes a jumping self-similarity function (Heaviside function) to measure the complexity of time series, resulting in inaccurate estimated value in real applications [13], [21]. Second, SampEn has lower calculation efficiency, especially for long time series [23]. To address the first problem, fuzzy entropy (FE) was developed by Chen *et al.* [31], which replaced the Heaviside function with a kind of fuzzy membership function. To address the second problem, a new irregularity indicator, permutation entropy (PE) was proposed by Bandt and Pompe [32]. PE assesses the dynamical characteristics by considering the order of the amplitude value, which has a higher calculation efficiency compared with SampEn.

Entropy-based method has been widely used in many fields such as biology [30], [33], [34], medicine [35], geography [36], image-processing [30], and engineering [18], [37], [38]. In this paper, we will give a comprehensive review on entropy-based methods and their applications in fault diagnosis of rotating machinery. For each entropy method, we will review the mathematical theorem, improved entropy methods, and applications in the fault diagnosis of rotating machinery, respectively.

The organization of the rest of this paper is as follows: Section II to VII presents the fundamentals of six main entropy methods, their variants and engineering applications. Section VIII reviews the other four entropy methods and their applications in the fault diagnosis of rotating machinery. Section IX gives a summary of the entropy-based methods and their applications. Section X describes some prospects of entropy in fault diagnosis of rotating machinery.

II. SHANNON ENTROPY

A. DESCRIPTION OF SHANNON ENTROPY

Entropy is first introduced by Shannon to evaluate the irregularity and self-similarity of time series in information theory [25]. For a given time series $\{x_1, x_2, \ldots, x_n\}$, the definition of Shannon entropy $H(x)$ is given as follows.

$$H(x) = -\sum_{i=1}^{n} p(x_i) \log_2 (p(x_i)) \tag{1}$$

where p represents the probability of the time series $\{x_i\}$. The physical meaning of $\log_2(p(x_i))$ denotes the length of the binary encoding. It can quantify the information of the time series $\{x_i\}$ and its unit is bits.

In mathematics, the Shannon entropy represents the expectation of the shortest average coding length according to the probability distribution of its states [25]. In other words, it is the expectation of the quantity of information. This expectation can be regarded as an indicator to measure the complexity of information. Shannon not only defines entropy, but also defines three properties as follows. First, Shannon entropy should be continuous; Second, Shannon entropy should be a monotonic increasing function. A bigger entropy indicates a more uncertainty or irregularity of time series; Third, if a probability can be divided into the sum of several individual values, so does the Shannon entropy [25].

B. APPLICATIONS USING SHANNON ENTROPY

This section describes the applications of Shannon entropy in the fault diagnosis of rotating machinery. For convenience, the applications of Shannon entropy are listed in Table 1. Table 1 provides the authors, Shannon entropy-combined method, application object and database source.

TABLE 1. Applications of Shannon entropy in fault diagnosis of rotating machinery.

Authors	Method	Applications	Database
P. K. Kankar et al. [39]	SVM-LVQ-SOM + Shannon Entropy	Bearings	Indian Institute of Technology Roorkee
M. Hernandez-Vargas et al. [40]	Singular value decomposition + Shannon Entropy	Broken-rotor-bars	Universidad de Guanajuato
Jiang et al. [41]	Singular value decomposition + Shannon Entropy	Bearings	Northwestern Polytechnical University
Jiang et al. [42]	Probabilistic Neural Network+Shannon Entropy	Single-span rotors	Suzhou University of Science and Technology
Wang et al. [43]	Shannon Entropy	Gas turbines	Harbin Engineering University
He et al. [44]	adaptive redundant multiwavelet packet+ Shannon Entropy	Gears	Xi'an Jiaotong University
F. Hemmati et al. [45]	WPT + Shannon Entropy	Bearings	University of British Columbia
F. Hemmati et al. [46]	WPT + Shannon Entropy	Bearings	University of British Columbia
H. Heidari Bafroui et al. [47]	CWT[1] + Shannon Entropy	Gears	Amirkabir University of Technology
Chen et al. [48]	ensemble multiwavelet+ Shannon Entropy	Aero-engine rotor and planetary gearboxes	Xi'an Jiaotong University
L. Cui et al. [49]	WPD+ WaEn	Bearings	CWRU

1. CWT is a time-frequency representation of signal proposed by J.D. Wu et al. [50]

C. IMPROVED SHANNON ENTROPY METHODS

Based on Shannon entropy, many researchers have devoted to enhance the performance of Shannon entropy for more accurate complexity estimation, such as spectral entropy, wavelet entropy and energy entropy.

1) SPECTRAL ENTROPY

Spectral entropy (SpEn) is a normalized form of Shannon entropy. SpEn utilizes the power spectrum amplitude of time series to assess its regularity [61]. SpEn is obtained by multiplying the power in each frequency p_f by the logarithm of the same power, and the product is multiplied by -1. The definition of SpEn is expressed as follows.

$$SpEn = \sum_{f} p_f \log\left(\frac{1}{p_f}\right) \tag{2}$$

For convenience, Table 2 summarizes the applications of SpEn in fault diagnosis of rotating machinery.

TABLE 2. Applications of SpEn in fault diagnosis of rotating machinery.

Authors	Method	Applications	Database
R. Hao et al. [51]	SVM+pattern spectrum entropy	Bearings	Tsinghua University
S.-D. Wu et al. [52]	SVM+Multi-Band Spectrum Entropy	Bearings	CWRU
G. Cheng et al. [53]	EEMD+ SpEn	Gears	China University of Mining and Technology
S. Luo et al. [54]	VPMCD+ SpEn	Rotating machinery	Hunan University
C.-W. Fei et al. [55]	SVM+Process Power Spectrum Entropy	Rotor	Beijing University of Aeronautics and Astronautics
Y.-T. Ai et al. [56]	Information fusion+ SpEn + wavelet entropy	Bearings	Shenyang Aerospace University
J. Chen et al. [57]	ARMP[1]+ SpEn	Bearings	Xian Jiaotong University
H. Tang et al. [58]	Complexity Spectrum Entropy	Bearings	Shanghai JiaoTong University
R. Shao et al. [59]	SEC[2]	Gears	Northwestern Polytechnical University
H. SU et al. [60]	SpEn	Rotating machinery	Huazhong University of Science and Technology

1. The adaptive redundant multiwavelet packet (ARMP) is a development of the wavelet theory proposed by Yuan et al. [61]
2. Spectrum entropy clustering (SEC) is a data mining method of statistics, extracting useful characteristics from a mass of nonlinear and nonstationary data.

2) WAVELET ENTROPY

Wavelet entropy (WaEn) estimates the complexity of time series by quantifying the degree of similarity between different fractions of signals. In other words, WaEn is a indicator of the disorder degree associated with the multi-frequency signal response [73]. WaEn can recognize the underlying episodic dynamic behavior of a signal. Also, WaEn can provide an accurate complexity estimation for a periodic mono-frequency signal [62]. The definition of wavelet entropy is given in Eq. (3).

$$WaEn = -\sum_{i<0} p_i \ln p_i \tag{3}$$

where p_i denotes the probability distribution of time series. i represents different resolution levels.

WaEn has three main advantages as follows: high calculation efficiency, better noise elimination and no pre-determined parameters [62].

For convenience, a summary of applications of WaEn in fault diagnosis of rotating machinery is listed in Table 3.

TABLE 3. Applications of WaEn in fault diagnosis of rotating machinery.

Authors	Method	Applications	Database
M. Kang et al. [63]	SVD+ WaEn	Bearings	University of Ulsan
N. Rodriguez et al. [64]	KELM+ WaEn	Bearings	CWRU
G. Cheng [65]	SOM+ WaEn	Gears	China University of Mining and Technology
Y.-B. Jing et al. [66]	LMD+ WaEn	Rotating machinery	Tianjin University
C.-W. Fei and G.-C. Bai [67]	FSVM+ WaEn	Aeroengine	An aeroengine research unit of China
M. S. Islam et al. [68]	WaEn	Rotating machinery	University of Ulsan
T. Liu and Z. Wu [69]	WaEn	Scroll compressor	Lanzhou University of Technology

3) ENERGY ENTROPY

Energy entropy quantifies the regularity of time series with the help of intrinsic mode functions (IMFs). Assume that we have obtained n IMFs, three steps are required to obtain the energy entropy as follows [70]:

(1) Calculate the energy of ith IMF

$$E_i = \sum_{j=1}^{m} \left|c_{ij}\right|^2 \tag{4}$$

where m represents the length of IMF.

(2) Calculate the total energy of these n efficient IMFs

$$E = \sum_{i=1}^{n} E_i \tag{5}$$

(3) Calculate the energy entropy of IMFs

$$H_{en} = -\sum_{j=1}^{n} p_i \log\left(p_i\right) \tag{6}$$

where H_{en} denotes the energy entropy in the whole of the original signal and $p_i = E_i/E$ denotes the percentage of the energy of the IMF number i relative to the total energy entropy.

For convenience, Table 4 summarizes the applications of energy entropy in fault diagnosis of rotating machinery.

TABLE 4. Applications of energy entropy in fault diagnosis of rotating machinery.

Authors	Method	Applications	Database
P. K. Kankar et al. [71]	Energy to Shannon Entropy Ratio[1] + Shannon Entropy	Bearings	Indian Institute of Technology Roorkee
P. Kankar et al. [72]	Energy to Shannon Entropy Ratio[1] + Shannon Entropy	Bearings	Indian Institute of Technology Roorkee
P. K. Kankar et al. [39]	Energy to Shannon Entropy Ratio1 + Shannon Entropy	Bearings	Indian Institute of Technology Roorkee
Z. Su et al. [73]	EMD + Energy Entropy	Bearings	Henan University of Technology
S. Dong et al. [74]	LMD + Energy Entropy	Bearings	CWRU
S. Dong et al. [75]	LMD + Energy Entropy	Bearings	CWRU
M. Y. Asr et al. [76]	EMD + Energy Entropy	Gears	University of Tabriz
X. Qin et al. [70]	EEMD+Energy Entropy	Bearings	CWRU
J. Ben Ali et al. [77]	EMD+Energy Entropy	Bearings	Center for Intelligent Maintenance Systems (IMS)
Y. Yu et al. [78]	EMD+Energy Entropy	Bearings	Hunan University
H. Xu and G. Chen [79]	EMD+Energy Entropy	Bearings	CWRU
Y. Xie and T. Zhang [80]	EMD+Energy Entropy	Bearings	CWRU
S. Dong et al. [81]	EMD+Energy Entropy	Bearings	CWRU
J. Ben Ali et al. [82]	EMD+Energy Entropy	Bearings	Center for Intelligent Maintenance Systems (IMS)
S. Dong et al. [83]	EMD+Energy Entropy	Bearings	CWRU
A. Rai and S. H. Upadhyay [84]	EMD+Energy Entropy	Bearings	Indian Institute of Technology
X. Zhang and J. Zhou [85]	EEMD+Energy Entropy	Bearings	CWRU
H. Ao et al. [86]	LCD+Energy Entropy	Bearings	UCI benchmark, the Iris, Tyroid, and Seed data sets
W. B. Xiao et al. [87]	WPT+Energy Entropy	Bearings	Shanghai Jiao Tong University
J. Ma et al. [88]	WPT+Energy Entropy	Bearings	CWRU
A. Brkovic et al. [89]	WT+Energy Entropy	Bearings	CWRU
J. Yuan et al. [90]	WT+Energy Entropy	Bearings	Xian Jiaotong University
C. Zhang et al. [91]	EMD+Energy Entropy	Gears	University of Science and Technology of the Inner Mongol
J. Zhang and Y. Liu [92]	CEITD+Energy Entropy	Diesel engine	Tianjin University
M. Varanis and R. Pederiva [93]	WPT+Energy Entropy	Induction motors	University of Campinas
Y. Xiao et al. [94]	IEMD[3]+Energy Entropy	Gears and generator shaft	Beijing Jiaotong University
Yu et al. [95]	EMD+Energy Entropy	Gears and bearings	Their own experiment

1. The detail of energy to Shannon entropy ratio can be seen in [71], [96].
2. Complete ensemble intrinsic time-scale decomposition (CEITD) is a self-adaptive time-frequency analysis method proposed by J. Zhang and Y. Liu [92].
3. The improved EMD (IEMD) is an adaptive time-frequency analysis method proposed by Y. Xiao et al. [94].

III. RÉNYI ENTROPY

A. DESCRIPTION OF RÉNYI ENTROPY

Rényi entropy is a generalized form of Shannon entropy, which can quantify the irregularity, uncertainty, or randomness of time series [27]. The definition of REN with order is expressed as follows.

$$REN_\alpha\left(X\right) = -\frac{\alpha}{1-\alpha} \sum \log_2 p_i^\alpha \tag{7}$$

where p_i represents the probability of a time series $\{x_1, x_2, \ldots, x_n\}$ and the order $\alpha \neq 1$. For $\alpha \geq 2$, REN provides a lower bound for its smooth entropy [97]. For $\alpha = 1$, REN equals to Shannon entropy.

REN has two main advantages. Frist, REN changes by an additive constant at the rescaling of the variables; Second, REN remains unchanged for the different density functions. In other words, REN does not vary irrespective of the density functions used. Also, REN has its own shortcoming. REN is not a sub-additive, recursive, nor it possess the branching and sum properties [33].

B. APPLICATIONS USING RÉNYI ENTROPY

This section aims to describe the applications of REN in the fault diagnosis of rotating machinery. For convenience, the applications of REN are summarized in Table 5. It can be observed that Table 5 provides the authors, REN-combined method, application object, and database source.

TABLE 5. Applications of REN in fault diagnosis of rotating machinery.

Authors	Method	Applications	Database
P. Bokoski et al. [98]	REN	Bearings	IEEE PHM 2012 Data Challenge
B. Tao et al. [99]	REN	Bearings	Huazhong University of Science and Technology
J. Singh et al. [100]	EEMD+REN	Bearings	University of Cincinnati
P. Bokoski and . Jurii [101]	WPT+REN	Gears	Jozef Stefan Institute

C. IMPROVED RÉNYI ENTROPY METHODS

Based on REN, Robert Jenssen developed a novel information-theory-based method for data transformation and dimensionality reduction, called kernel entropy component analysis (KECA) [102]. KECA attempts to maintain the maximum estimated Rényi quadratic entropy of the input data set via a kernel-based estimator [103]. Zhou *et al.* developed two fault diagnosis methods based on KECA: supervised kernel entropy component analysis [103] and weight kernel entropy component analysis [104] for the fault diagnosis of rolling bearings.

IV. APPROXIMATE ENTROPY

A. DESCRIPTION OF APPROXIMATE ENTROPY

Approximate entropy (ApEn) was first proposed by Pincus [28], [29] to quantify the irregularity and unpredictability of time series. ApEn evaluates the probability of occurrence of a new pattern through observing the embedding dimension m and similarity coefficient r. Since the similarity criterion is equivalent to the standard deviation of time series, ApEn is a scale invariant indicator [29]. A larger ApEn value means a higher probability of a new pattern occurring of time series, and a smaller ApEn value indicates the time series has lower irregularity. The concept of ApEn is defined as follows.

$$ApEn = \phi^{m}(r) - \phi^{m+1}(r) \tag{8}$$

where $\phi^m(r)$ represents the mean value of logarithm pattern mean count. $\phi^m(r)$ and $\phi^{m+1}(r)$ can be calculated using Eq. (9).

$$\phi^m(r) = \frac{1}{N-m+1} \times \sum_{i=1}^{N-m+1} ln\left[\frac{1}{N-m+1} num\{d[x(i), x(j)] < r\}\right] \tag{9}$$

where r represents the tolerance of the time series, m represents the pattern length, N represents the length of time series, and $num\{d[x(i), x(j)] < r\}$ represents the count of the distance between $x(i)$ and $x(j)$ lower than the tolerance r. Here, the distance is defined as the maximum absolute difference of their corresponding scalar components. In mathematics, ApEn is an approximate value of the negative average natural logarithm of the conditional probability. To achieve an accurate complexity estimation performance, the parameters of ApEn are recommend as follows: pattern length $m = 2$ and similarity coefficient $r = 0.2{*}SD$ (SD represents the standard deviation) [28], [29]. A flowchart of the ApEn method is shown in Figure 2.

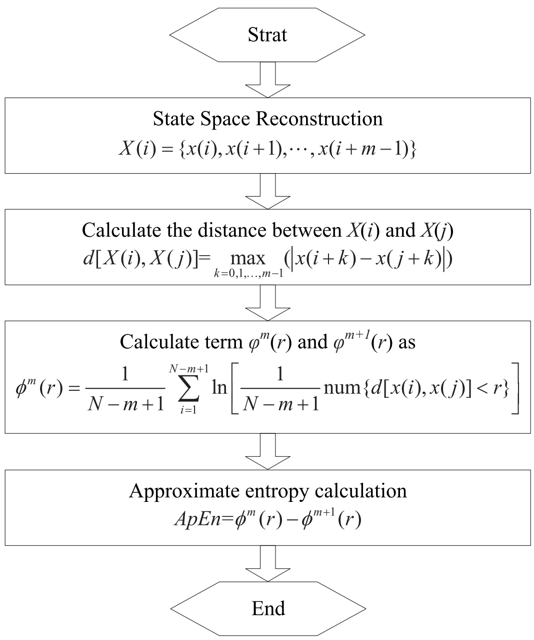

FIGURE 2. Flowchart of the ApEn method.

ApEn has three main advantages as follows. Frist, ApEn has some ability to resist interference and noise, especially the transient anti-interference ability [28]; Second, ApEn has a stable estimation with relatively short data; Third, ApEn is suitable for random signal, certain signal and their combinations [30]. In addition, ApEn has five main shortcomings as follows. First, ApEn is biased statistic and heavily dependent on the input signal length. Signals with short length lead to a lower value than expected.

Second, ApEn lacks of consistent results for different values of m and r; Third, ApEn is susceptible to strong noises [105]; Fourth, ApEn counts self-matches which is against the basic definition of entropy; Last, ApEn has a low calculation efficiency.

B. APPLICATIONS USING APPROXIMATE ENTROPY

This section aims to describe the applications of ApEn in fault diagnosis of rotating machinery. For convenience, the applications of ApEn are summarized in Table 6. It can be observed that Table 6 provides the authors, ApEn-combined method, application object, and database source.

TABLE 6. Applications of ApEn in fault diagnosis of rotating machinery.

Authors	Method	Applications	Database
K. Li et al. [23]	VMD + ApEn	Bearings	Huazhong Jiangnan University
Y. He et al. [106]	EMD + ApEn	Bearings	Tsinghua University
S. Zhao et al. [107]	EMD + ApEn	Bearings	CWRU
Y. Imaouchen et al. [108]	CEEMD[1] +ApEn	Bearings	CWRU
X. An et al. [109]	ALIF[2] + ApEn	Bearings	Tsinghua University

1. CEEMD is a signal processing techniques method proposed by J.-R. Yeh et al. [110]
2. ALIF is a new time-frequency analysis method proposed by Cicone et al. [111].

V. SAMPLE ENTROPY

A. DESCRIPTION OF SAMPLE ENTROPY

As discussed above, ApEn has certain disadvantages in the complexity estimation of time series. To address this problem, Richman and Moorman [30] proposed sample entropy (SampEn). Unlike ApEn, SampEn can measure the irregularity of time series independent of the embedding dimension m and similarity coefficient r. Therefore, SampEn is relatively consistent and eliminating the bias of ApEn [30]. A larger SampEn value indicates the time series with higher complexity, while a samller SampEn value implies the time series with lower irregularity [74]. The definition of SampEn is given as follows.

$$SampEn = -\ln\left(\frac{B^{m+1}(r)}{B^m(r)}\right) \tag{10}$$

where $B^m(r)$ is the mean value of pattern mean count. $B^m(r)$ and $B^{m+1}(r)$ can be expressed as:

$$B^m(r) = \frac{1}{N-m+1}\sum_{i=1}^{N-m+1}\left[\frac{1}{N-m} num\{d[x(i),x(j)] < r\}\right]$$
$$i = 1, 2, \cdots, N-m+1, \quad i \neq j \tag{11}$$

where r represents the tolerance of the time series; m represents the embedding dimension; N represents the length of time series. $num\{d[x(i), x(j)] < r\}$ represents the count of the distance between $x(i)$ and $x(j)$ lower than the tolerance r. Noted that the $i \neq j$ means the SampEn can not contain self-matches. In SampEn method, it is recommended to set $m = 2$ and $r = (0.1 \sim 0.25) * SD$ (SD represents the standard deviation) [112], [113].

A flowchart of the SampEn method is illustrated in Figure 3.

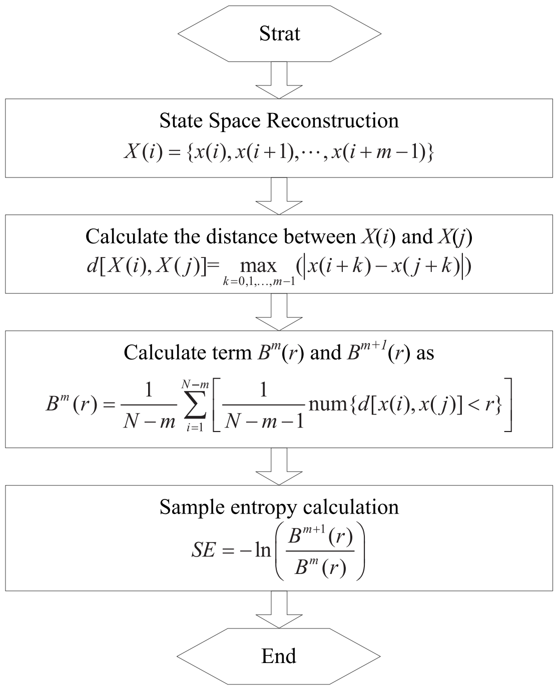

FIGURE 3. Flowchart of the SampEn method.

SampEn method has four main advantages as follows. First, SampEn is an accurate value of negative average of logarithm of conditional probability, which doesn't rely on the length of data; Second, SampEn doesn't contain self-matches; Third, SampEn has better performance in the consistency; Last, SampEn is insensitive in data length. In addition, the main shortcomings of SampEn lies in its inconsistency for the sparse data and low calculation efficiency.

B. APPLICATIONS USING SAMPLE ENTROPY

This section aims to describe the applications of SampEn in fault diagnosis of rotating machinery. For convenience, the applications of SampEn are summarized in Table 7. It can be observed that Table 7 provides the authors, SampEn-combined method, application object, and database source.

C. IMPROVED SAMPLE ENTROPY METHODS

This section aims to describe the improved sample entropy methods: multiscale sample entropy, modified multiscale sample entropy, composite multiscale sample entropy and hierarchical sample entropy. In addition, there are some other improved SampEn methods, such as refined composite multiscale entropy [14], multivariate sample entropy [119],

TABLE 7. Applications of SampEn in fault diagnosis of rotating machinery.

Authors	Method	Applications	Database
J. Liang et al. [114]	EEMD[1] + SampEn	Bearings	Fuzhou University
L. Zhang et al. [115]	LWPT[2] + SampEn	Bearings	CWRU
M. Seera et al. [116]	Power spectrum + SampEn	Bearings	Swinburne University of Technology
G. Cheng et al. [53]	EEMD + SampEn	Gears	China University of Mining and Technology

1. EEMD is a signal processing techniques method proposed by Z. Wu et al. [117].
2. LWPT is a time-frequency representation of signal proposed by Sweldens. [118].

generalized multiscale entropy [120] refined multiscale entropy [121]. Such improved will not be described in this paper due to they are not applied in the fault diagnosis of rotating machinery until now.

1) MULTISCALE SAMPLE ENTROPY

The measured vibration signals from the rotating machinery and the fault information often embedded in multiple scale structures. However, SampEn only analyzes the vibration signal from single scale and much useful information will be ignored. This limits its performance in extracting the embedded fault features [122]. In order to avoid such disadvantage, Costa *et al.* put forward a multiscale procedure and combined it with SampEn, called multiscale sample entropy (MSE), to estimate the complexity of the original time series over a range of scales [131]. MSE can enhance the physical meanings and statistical sense of SampEn. There are two steps in MSE method [123].

(1) For a given time sereis $\{x_1, \ldots, x_i, \ldots, x_N\}$, the coarse-graining procedure for scale i is obtained by averaging the samples of the time series inside consecutive but non overlapping windows of length i. Therefore, it can be divided into several coarse-grained time series $\{y^{(\tau)}\}$ using Eq. (12) as follows. Figure 4 gives an example of the coarse-grained procedure.

$$y_j^{(\tau)} = \frac{1}{\tau} \sum_{i=(j-1)\tau+1}^{j\tau} x_i, \quad 1 \leq j \leq N/\tau \tag{12}$$

where τ is the scale factor and τ should be a positive integer. When $\tau = 1$, the time series $\{y^{(1)}\}$ is the original time series.

(2) Compute the SampEn for each coarse-grained time series and then plotted as the function of the scale factor τ. The definition of MSE is given as follows.

$$MSE(x, \tau, m, r) = SampEn(y_j^{(\tau)}, m, r) \tag{13}$$

A flowchart of the MSE method is shown in Figure 5. For convenience, the applications of MSE in fault diagnosis of rotating machinery are summarized in Table 8.

MSE can estimate the dynamical characteristics of time series over different scales. However, MSE has three main

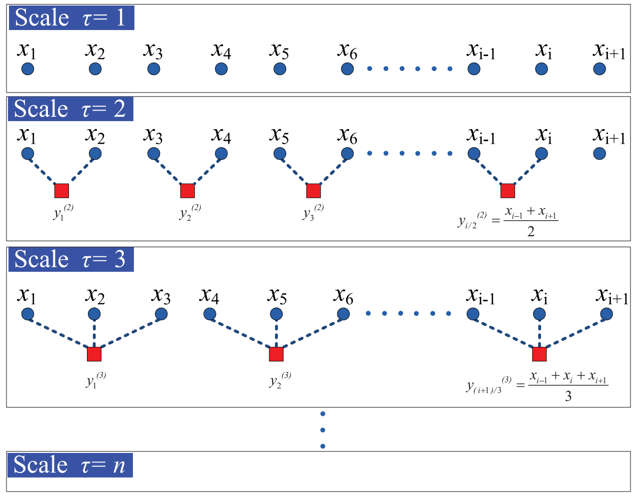

FIGURE 4. Procedure of coarse graining process.

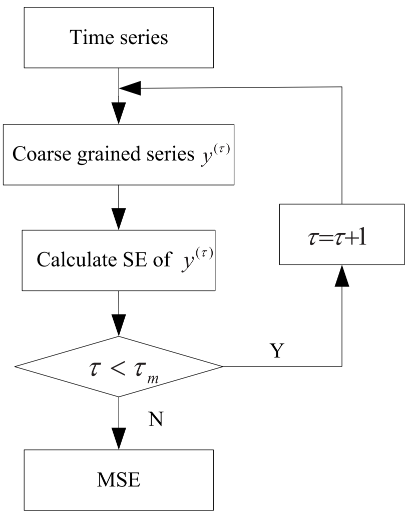

FIGURE 5. Flowchart of the MSE method.

TABLE 8. Applications of MSE in fault diagnosis of rotating machinery.

Authors	Method	Applications	Database
H. Liu et al. [124]	LMD+MSE	Bearings	CWRU
G. Cheng et al. [125]	LMD+MSE	Gears	China University of Mining and Technology
N.-K. Hsieh et al. [126]	EMD+MSE	High-speed spindle	National Taiwan University
A. Verma et al. [127]	GRA[1]+MSE	Motors	Indian Institute of Technology Patna
Y.Li et al. [128]	Improved VKF+MSE	Planetary gearboxes	University of Electronic Science and Technology of China

1. GRA(Grey relational analysis) is a statistical approach for the optimization of complex processes.

shortcomings as follows. First, the coarse-graining procedure reduces the data length with the scale factor increasing, which may lead an inaccurate estimation; Second, MSE can be regarded as a low-pass filter, which cannot prevent aliasing when the downsampling procedure is applied [121]; Third, the standard deviation of time series may become lower with the scale factor increasing. This would cause the patterns becoming closer, resulting a decreasing entropy value.

2) COMPOSITE MULTISCALE SAMPLE ENTROPY

To address such issues of MSE, the composite multi-scale sample entropy (CMSE) is proposed by Wu *et al.* [113]. Since the composite multiscale analysis considers SampEn values of all coarse-grained time series with the same scale factor, a more reliable estimation of SampEn values can be obtained. The concept of CMSE is expressed as follows.

(1) For the time series $\{X(i)\} = \{x_1, x_2, \cdots, x_N\}$, the composite multiscale time series $y_u^\tau = \left\{y_{u,1}^\tau, y_{u,2}^\tau, \cdots, y_{u,(i+1)/2}^\tau\right\}$ is shown as:

$$y_{k,j}^{(\tau)} = \frac{1}{\tau}\sum_{i=(j-1)\tau+k}^{j\tau+k-1} x_i, \quad 1 \le j \le \frac{N}{\tau},\ 1 \le k \le \tau \tag{14}$$

(2) Calculate the SampEn of each coarse-grained time series $\{y_u^\tau\}$ for a given τ and k.

$$CMSE(X, \tau, m, n, r) = \frac{1}{\tau}\sum_{u=1}^{\tau} SampEn(y_k^{(\tau)}, m, n, r) \tag{15}$$

The composite multisacle time series can be seen in Figure 6. Reference [113] applied CMSE and artificial neural network to recognize the bearing fault types using the CWRU data. The simulation and experimental results demonstrate that the CMSE can enhance the linear distinguishability compared with MSE method.

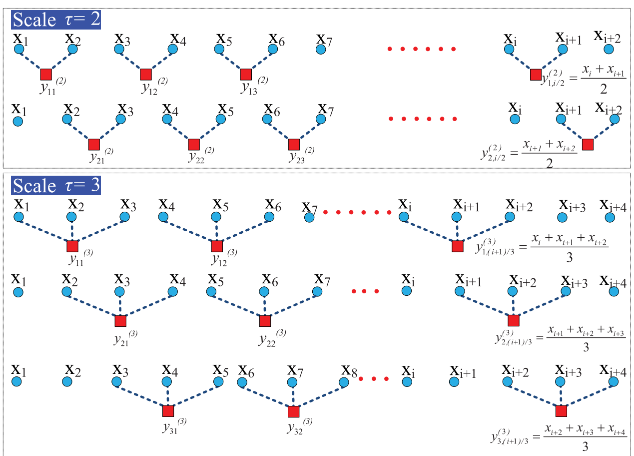

FIGURE 6. The schematic illustration of the composite multiscale time series for scale factor $\tau = 2$ and $\tau = 3$.

3) MODIFIED MULTISCALE SAMPLE ENTROPY

Modified multiscale is another way to overcome the defect of data length decreasing during the coarse-graining procedure. Wu *et al.* [129] proposed modified multiscale sample entropy (MMSE), which utilizes a moving-averaging procedure to replace the traditional coarse-graining procedure.

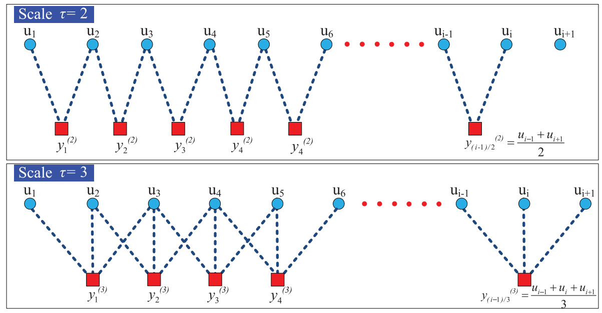

FIGURE 7. The schematic illustration of the modified multiscale time series for scale factor $\tau = 2$ and $\tau = 3$.

Figure 7 illustrates the moving-averaging procedure. The definition of MMSE is given as follows.

(1) For a given time series $\{X(i)\} = \{x_1, x_2, \cdots, x_N\}$, the moving-averaging procedure can be obtained by following:

$$y_j^\tau = \frac{1}{\tau}\sum_{i=j}^{j+\tau-1} x_i, 1 \le j \le N - \tau + 1 \tag{16}$$

(2) Calculate the SampEn for each improved coarse-grained time series.

$$MMSE(x, \tau, m, r) = SampEn(y^{(\tau)}, m, r) \tag{17}$$

In [129], MMSE is able to provide a more precise estimation of entropy compared with MSE when analyzing a short-term time series. The experimental bearing signals from CWRU are used to validate the advantages of MMSE in the fault feature extraction.

4) HIERARCHICAL SAMPLE ENTROPY

MSE can provide a comprehensive analysis of vibration signals, however, it may discard the fault information hidden in the high frequency components because the multiscale analysis in MSE only considers the fault information in low frequency components [15], [130]. To address this problem, Zanin *et al.* [20] developed the hierarchical decomposition and proposed the hierarchical sample entropy (HSE). Hierarchical decomposition has been demonstrated to be more effective than multiscale analysis [131]. There are two main steps in HSE method in Eq. (20).

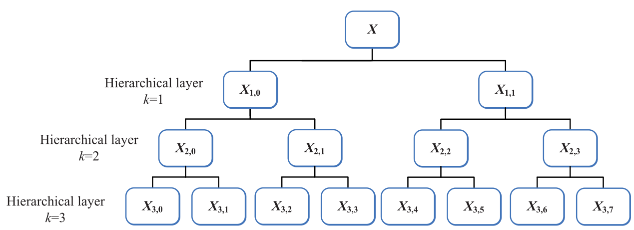

FIGURE 8. Illustration of hierarchical decomposition process with 3 hierarchical layers.

(1) Construct the hierarchical tree. Figure 8 illustrates the hierarchical tree with 3 hierarchical layers. For a given time

series $X\{x(i), i = 1, 2, \cdots, N\}$, the hierarchical component Z_k^e can be obtained by the averaging operator Q_0 and difference operator Q_1 as follows:

$$Q_0(x) = \frac{x(i) + x(i+1)}{2} \quad i = 1, 2, \cdots, N-1 \tag{18}$$

$$Q_1(x) = \frac{x(i) - x(i+1)}{2} \quad i = 1, 2, \cdots, N-1 \tag{19}$$

(2) Calculate the SampEn of each layers of the hierarchical component and then plotted as the function of hierarchical lay k. The definition of HSE is given as follows.

$$HSE(x, k, e, m, r) = SampEn(Z_k^e, m, r) \tag{20}$$

The calculation process of the HSE is shown in Figure 9.

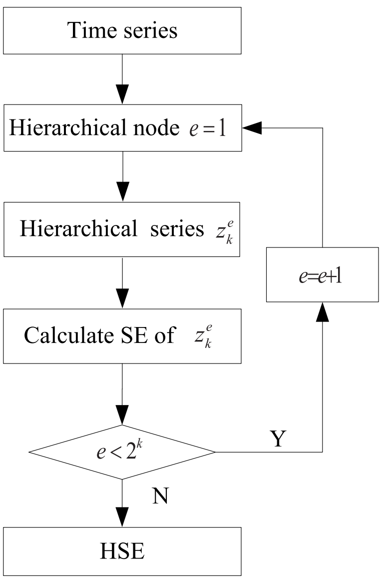

FIGURE 9. Flowchart of the HSE method.

In the application of HSE, only one reported paper was found. Zhu *et al.* [132] applied the HSE combining with SVM in fault diagnosis for bearings. The data source is from CWRU and the final classification accuracy using HSE is 100%.

VI. FUZZY ENTROPY

A. DESCRIPTION OF FUZZY ENTROPY

Because SampEn measures the similarity between the two vectors using the Heaviside function, which is jumping. However, the boundaries of the two classes are mostly ambiguous in real applications, thereby, the Heaviside function is unsuitable to measure the similarity of two vectors [21], [133]. To avoid this shortcoming, fuzzy entropy (FE) was developed by Chen *et al.* [31], which replaces the Heaviside function with a Gaussian function. As the continuity of the exponential function, FE can overcome the drawbacks of SampEn effectively.

For a time series $\{x(i), i = 1, 2, \cdots, N\}$, the similarity of FE is defined as follows.

$$D_{ij}^m = \mu\left(d_{ij}^m, n, r\right) = e^{-\ln 2\left(d_{ij}^m / r\right)^n} \tag{21}$$

where, r represents the similarity tolerance. The d_{ij}^m represents the distance between X_i^m and X_j^m. Define the function φ^m as:

$$\varphi^m(n, r) = \frac{1}{N-m} \sum_{i-1}^{N-m} \left(\frac{1}{N-m-1} \sum_{j=1, j\neq i}^{N-m} D_{ij}^m \right) \tag{22}$$

Then, FE can be expressed as:

$$FE(m, n, r, N) = \ln \varphi^m(n, r) - \ln \varphi^{m+1}(n, r) \tag{23}$$

A flowchart of the FE method is shown in Figure 10.

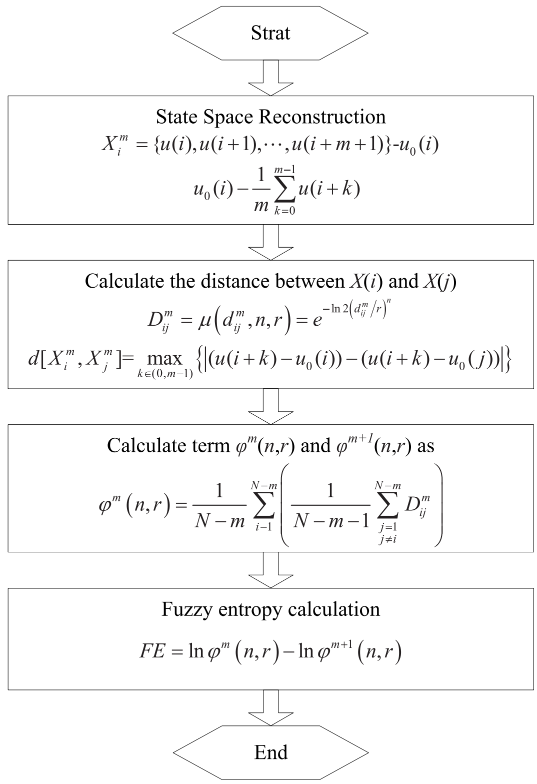

FIGURE 10. Flowchart of the FE method.

Compared with SampEn method, FE has a better performance in robustness to noise because FE evaluates ambiguous uncertainties from the highly irregular signals. Therefore, the advantage of FE is that FE is insensitive to background noises and highly sensitive to the dynamical change [16], [21]. In addition, the main shortcoming of FE lies in its low calculation efficiency.

B. APPLICATIONS USING FUZZY ENTROPY

This section describes the applications of FE in fault diagnosis of rotating machinery. For convenience, the applications of FE are listed in Table 9. Table 9 provides

TABLE 9. Applications of FE in fault diagnosis of rotating machinery.

Authors	Method	Applications	Database
J. Zheng et al. [24]	LCD+FE	Bearings	CWRU
J. Zheng [134]	PEEMD[1]+FE	Bearings	China CWRU
Y. Yang et al. [135]	ITD[2]+FE	Bearings	CWRU
J. Ye [136]	Fuzzy cross entropy	Turbines	Shaoxing College of Arts and Sciences

1. Partially ensemble EMD (PEEMD) is an adaptive timefrequency analysis method proposed by [137].
2. The intrinsic timescale decomposition(ITD) is a adaptive time-frequency analysis method put forward by Mark and Ivan [138].

the authors, FE-combined method, application object and database source.

C. IMPROVED FUZZY ENTROPY METHODS

1) MULTISCALE FUZZY ENTROPY

Because applying FE of single scale entropy may generate the unreliable results, MFE method was proposed by combining multiscale analysis and FE method [13]. MFE algorithm contains two steps as follows [13], [21].

(1) For a given original time series $\{X_i\} = \{X_1, X_2, \cdots, X_N\}$, it can be divided into several coarse-grained time series y_j^τ using Eq. (24).

$$y_j^\tau = \frac{1}{\tau} \sum_{i=(j-1)\tau+1}^{j\tau} x_i, \quad 1 \le j \le \frac{N}{\tau} \tag{24}$$

where $\tau = 1, 2, \cdots, N$ is a positive integer.

(2) Calculate FuzzyEn of each coarse-grained time series y_j^τ using Eqs. (21)-(23) and describe FuzzyEn as a function of scale factor τ using Eq. (25) [21].

$$MFE\,(x, \tau, m, n, r) = FuzzyEn\left(y_j^\tau, m, n, r\right) \tag{25}$$

A flowchart of the MFE method is shown in Figure 11. For convenience, the applications of MFE in fault diagnosis of rotating machinery are summarized in Table 10.

TABLE 10. Applications of MFE in fault diagnosis of rotating machinery.

Authors	Method	Applications	Database
J. Zheng et al. [13]	VPMCD+MFE	Bearings	CWRU
H. Zhao et al. [139]	EEMD+MFE	Bearings	Dalian Jiaotong University

However, there are two main problems in the MFE method. First, the statistical stability of MFE is poor for the analysis of short time series. Since the coarse-graining procedure in the multi-scale analysis shortens the length of the time series as the scale factor τ increases, it may generate the inaccurate or undefined estimation of entropy and loose statistical reliability at larger scale factors [21]. Second, the averaging operation used in the coarse-graining procedure to generate a new time series only considers the fault information embedded in

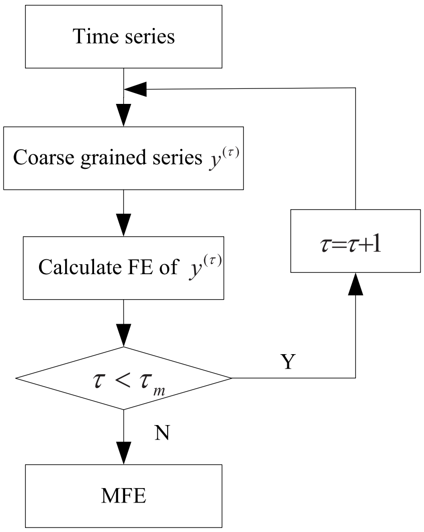

FIGURE 11. Flowchart of the MFE method.

the low frequency region, which loses fault information in the high frequency part [17], [140].

2) COMPOSITE MULTISCALE FUZZY ENTROPY

Based on the composite multiscale analysis and FE method, the composite multi-scale fuzzy entropy (CMFE) is developed by Zheng *et al.* [16]. CMFE considers the FuzzyEn values of all coarse-grained time series with the same scale factor, thereby, it can minimize the variance of FuzzyEn values at large scales. The definition of CMFE is given as follows.

(1) For the time series $\{X(i)\} = \{x_1, x_2, \cdots, x_N\}$, the composite multiscale time series $y_u^\tau = \left\{y_{u,1}^\tau, y_{u,2}^\tau, \cdots, y_{u,(i+1)/2}^\tau\right\}$ is expressed as:

$$y_{k,j}^{(\tau)} = \frac{1}{\tau} \sum_{i=(j-1)\tau+k}^{j\tau+k-1} x_i, \quad 1 \le j \le \frac{N}{\tau}, \ 1 \le k \le \tau \tag{26}$$

(2) Calculate the FE of each coarse-grained time series $\left\{y_u^\tau\right\}$ for a given τ and k.

$$CMFE(X, \tau, m, n, r) = \frac{1}{\tau} \sum_{u=1}^{\tau} FE(y_k^{(\tau)}, m, n, r) \tag{27}$$

Reference [16] applied CMFE and ensemble support vector machines to achieve the fault pattern identification. The experimental data from CWRU is used for validation and the final classification result achieves 100%.

3) REFINED COMPOSITE MULTIVARIATE MULTISCALE FUZZY ENTROPY

Recently, Azami and Escudero extended the MFE to multivariate signals (mvMFE) [119]. mvMFE measures each sequence in multi-channel data by taking into account their mutual predictability. However, mvMFE will have some fluctuations at larger scale. To address this issue, refined composite multivariate multiscale fuzzy entropy (RCMMFE) was proposed by Zheng *et al.* [141]. Because the multivariate multiscale analysis has a better fault feature extraction ability than mono channel analysis, RCMMFE has a better performance for fault feature extraction. In [141], the CWRU bearing data is applied to verify the effectiveness of the RCMMFE method and the final classification accuracy is 100% [141]. Li *et al.* [142] combined Vold-Kalman filter and RCMFE to conduct the fault diagnosis of rolling bearing under speed fluctuation condition. Results demonstrated that their method is able to recognize the localized damage on the inner race, outer race, and rolling element under variable speed conditions. The definition of RCMMFE is expressed as follows.

(1) For a given normalized p variate multi-channel time series $X = \{x_{k,i}\}_{i=1}^{N}, k = 1, 2, \cdots, p$, the coarse-graining time series is similar as MSE:

$$y_{k,j}^{(\tau)} = \frac{1}{\tau} \sum_{i=(j-1)\tau+1}^{j\tau} x_{k,i} \tag{28}$$

(2) Compute the average $\bar{\varphi}_{\tau}^{m}(r)$ of all $\varphi_{\tau q}^{m}(r)$ and the average $\bar{\varphi}_{\tau}^{m+1}(r)$ of all $\varphi_{\tau q}^{m+1}(r)$ values of $y_{k,j}^{(\tau)}$ under $q = 1, 2, \cdots, \tau$, respectively.

(3) The definition of RCMMFE is expressed as

$$RCMMFE(X, M, \tau, n, r) = -\ln\left[\frac{\bar{\varphi}_{\tau}^{m+1}(r)}{\bar{\varphi}_{\tau}^{m}(r)}\right] \tag{29}$$

4) MODIFIED MULTISCALE FUZZY ENTROPY

Modified multiscale fuzzy entropy (MMFE) is proposed by Li *et al.* [21] to overcome the data length decreasing during the coarse-graining procedure in MFE method. Combined local mean decomposition (LMD) and SVM, the LMD-MMFE method is demonstrated to be effective in recognizing 10 bearing fault types and severities [21]. The concept of MMFE is defined as follows.

(1) The modified multiscale time series can be obtained using Eq. (30).

$$y_{j}^{(\tau)} = \frac{1}{\tau} \sum_{i=j}^{j+\tau-1} x_i, \quad 1 \le j \le N - \tau + 1 \tag{30}$$

(2) Calculate the FE for each improved coarse-grained time series.

$$MMFE(x, \tau, m, r) = FE(y^{(\tau)}, m, r) \tag{31}$$

5) HIERARCHICAL FUZZY ENTROPY

Similar with MSE, MFE only considers the fault information embedded in the low frequency region, which loses fault information in the high frequency part. To tackle this problem of MFE, hierarchical fuzzy entropy (HFE) is proposed by Li *et al.* [140] by combing hierarchical decomposition analysis with FE. Because the averaging and differential processes are both utilized in the hierarchical decomposition, the HFE can characterize more information than the MFE. The effectiveness of HFE is validated using experimental signals from CWRU. The results demonstrate that the HFE has a better performance than MFE. Meanwhile, Zhu and Li [143] combined with HFE with SVM to recognize bearing fault types and a satisfactory classification accuracy (100%) was achieved. The concept of HFE is given as follows.

(1) Calculate the hierarchical component Z_k^e through the hierarchical decomposition analysis (details are given in Section V. C. 4).

(2) Calculate the FE value of each hierarchical component and the HSDE can be obtained using Eq. (32).

$$HFE\left(x, k, e, m, \varepsilon\right) = SDE_{norm}\left(z_k^e, m, \varepsilon\right) \tag{32}$$

VII. PERMUTATION ENTROPY

A. DESCRIPTION OF PERMUTATION ENTROPY

As a statistical measure, permutation entropy describes complexity of a time series or signal measured on a physical system through phase space reconstruction, and takes into account non-linear behavior of the time series, as often seen in vibration signals of rotary machines. Thus, PE can be served as a viable tool for dynamic changes detection of the machine working status.

Permutation entropy (PE) was proposed by Bandt and Pompe [32] to measure the irregularity of time series. Different from ApEn, SampEn and FE, PE only utilizes the order of the amplitude of time series [37]. Therefore, PE has a corresponding higher calculation efficiency [144] and is robust under non-linear distortion of time series [37]. PE has been widely applied into the fault diagnosis of rotating machinery due to its sensitivity to the dynamical change [37], [145]. The concept of PE is defined as follows.

$$PE = -\sum p(\pi) \log_2 p(\pi) \tag{33}$$

$$p(\pi) = \frac{num\{i | i \le T - n, (x_{i+1}, \cdots, x_{i+n})\ has\ type\ \pi\}}{T - n + 1} \tag{34}$$

where $p(\pi)$ denotes the relative frequency for each permutation π. $num\{i | i \le T - n, (x_{i+1}, \cdots, x_{i+n})\ has\ type\ \pi\}$ indicates the number of permutation π under order m. The calculation process of the PE is shown in Figure 12.

PE is an appropriate complexity measure for chaotic time series, especially in the presence of dynamical and observational noise. PE has four main advantages as follows. First, PE has a high calculation efficiency, which can be used to compute huge data set [37]; Second, PE has a good performance of complexity estimation; Third, PE has good robust ability to noise [32]; Last, PE does not require any model assumption and is suitable for the analysis of nonlinear processes. The main shortcoming of PE lies in its inability to classify well defined patterns of a particular design [146].

B. APPLICATIONS USING PERMUTATION ENTROPY

This section aims to investigate the usage of PE for fault diagnosis of rotating machinery. For convenience, the applications of PE are listed in Table 11. Table 11 provides the authors, FE-combined method, application object and database source.

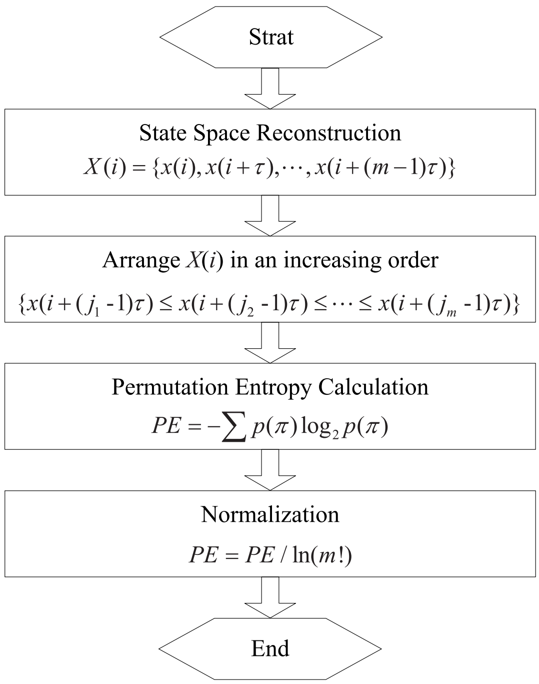

FIGURE 12. Flowchart of the PE method.

TABLE 11. Applications of PE in fault diagnosis of rotating machinery.

Authors	Method	Applications	Database
X. An et al. [147]	VMD+PE	Bearings	Tsinghua University
X. Xue et al. [148]	EEMD+PE	Bearings	CWRU
X. Zhang et al. [149]	EEMD+PE	Bearings	CWRU
L. Zhao et al. [150]	CEEMD+PE	Gears	Southeast University
M. Kuai et al. [151]	CEEMD+PE	Gears	China University of Mining and Technology
J. Zhou et al. [152]	EEMD+PE	Bearings	CWRU
R. Yan et al. [37]	PE	Bearings	Southeast University
Y. Wang et al. [153]	WPT+PE	Bearings	CWRU
C. Yi et al. [154]	TSSA[1]+PE	Bearings	Wuhan University of Science and Technology
Y. Zhang et al. [155]	SVD +PE	Bearings	Hangzhou Bearing Test and Research Center (HBRC)
Y. Wang et al. [156]	SVD+PE	Bearings	CWRU
Z. Shi et al. [157]	LMD+PE	Bearings	CWRU
J. Dang et al. [158]	PE	Rotating machinery	Xian University of Technology

1. Tensor-based singular spectrum algorithm (TSSA) is a method for analysing real-valued time series proposed by Saeid. [159].

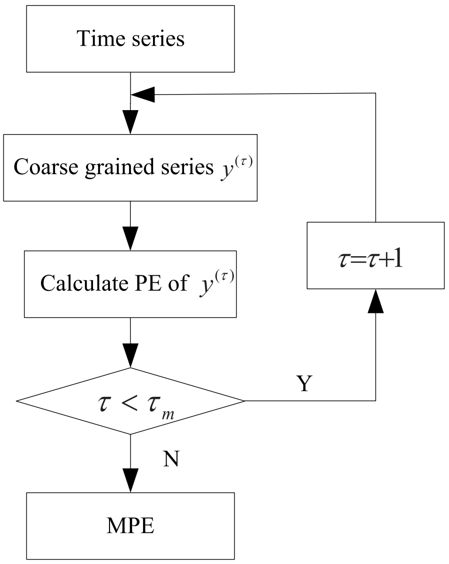

FIGURE 13. Flowchart of the MPE method.

TABLE 12. Applications of MPE in fault diagnosis of rotating machinery.

Authors	Method	Applications	Database
D. Yao et al. [160]	EEMD+MPE	Bearings	Beijing University of Civil Engineering and Architecture
J. Liu et al. [161]	VMD+MPE	Bearings	CWRU
Y. Li et al. [21]	LMD+MPE	Bearings	CWRU
Y. Gao et al. [162]	LMD+MPE	Bearings	CWRU
R. Tiwari et al. [163]	ANFC[1]+MPE	Bearings	CWRU
L. Zhao et al. [164]	WPD[2]+MPE	Bearings	CWRU
J. Zheng et al. [165]	SVM+MPE	Bearings	CWRU
V. Vakharia et al. [166]	SVM+MPE	Bearings	CWRU
V. Vakharia et al. [167]	SVM+MPE	Bearings	PDPM Indian Institute of Information Technology
S.D. Wu et al. [52]	SVM+MPE	Bearings	CWRU
S.D. Wu et al. [7]	SVM+MPE	Bearings	CWRU

1. The adaptive neuro fuzzy classifier (ANFC) is such a system in which neural network will provide learning ability to fuzzy logic algorithm..
2. The wavelet packet decomposition (WPD) is an extension of the wavelet transform..

C. IMPROVED PERMUTATION ENTROPY METHODS

1) MULTISCALE PERMUTATION ENTROPY

Like MSE and MFE, two steps are required in MPE method as follows: (1) obtain the multiple series using the coarse-graining analysis; (2) calculate the PE value of each coarse-grained time series. A flowchart of the MPE method is shown in Figure 13. For convenience, the applications of MPE in fault diagnosis of rotating machinery are summarized in Table 12.

2) COMPOSITE MULTISCALE PERMUTATION ENTROPY (CMPE)

Like CMSE and CMFE, the composite multi-scale permutation entropy (CMPE) is also developed to overcome the shortcomings of MPE. Because PE has better performance in the fault feature extraction and high calculation efficiency, CMPE also show outstanding merits in the fault diagnosis of rotating machinery. Tang *et al.* [168] proposed a bearing fault diagnosis method based on CMPE and Dual Tree Complex Wavelet Packet Transform, the final classification accuracy using CWRU data can achieve 98.79%. Li *et al.* [23] developed a bearing fault diagnosis method based on EEMD and CMPE and a satisfactory classification result with 98.79% can be achieved using CWRU experimental data.

3) GENERALIZED COMPOSITE MULTISCALE PERMUTATION ENTROPY (GCMPE)

Because MPE may produce uncertain and unsatisfactory analysis for short-length data, especially at larger scales [17]. In addition, the averaging procedure used in the MPE will cause loss of useful information [17] to some extent. Generalized composite multi-scale permutation entropy (GCMPE) is proposed by Zheng *et al.* [17] to estimate the complexity of time series. Compared with MPE, GCMPE has two main advantages. First, GCMPE uses the composite multiscale analysis to reduce the large variance of PE values at large scales. Second, GCMPE adopts the second-order moment (unbiased variance) to replace the first-order moment in the coarse graining procedure, which enhances the fault signature extraction ability [17]. The concept of GCMPE is given as follows.

(1) For a discrete time series $\{x_1, \ldots, x_i, \ldots, x_N\}$ of length N, the coarse-grained time series $\left\{y_k^{(\tau)}\right\}$ is computed as:

$$y_k^{(\tau)} = \frac{1}{\tau} \sum_{i=(j-1)\tau+k}^{j\tau+k-1} (x_i - \bar{x}_i), \quad 1 \le j \le N/\tau,\ 2 \le j \le \tau \tag{35}$$

(2) Calculate the PE values of all coarse-grained time series $\left\{y_k^{(\tau)}\right\}$ for the scale factor τ.

(3) The GCMPE can be calculated as follows:

$$GCMPE(X, \tau, m, \lambda) = \frac{1}{\tau} \sum_{k=1}^{\tau} PE(y_k^{(\tau)}, m, \lambda) \tag{36}$$

Zheng *et al.* [17] applied the GCMPE in bearing fault diagnosis. Experimental results show that the proposed method performs best in recognizing bearing fault types and fault severities with testing accuracy of 100%.

4) MODIFIED HIERARCHICAL PERMUTATION ENTROPY

Another improved permutation method is called modified hierarchical permutation entropy (MHPE), which is proposed by Li *et al.* [15] to address the drawbacks of MPE. MHPE has two main advantages. First, MHPE utilizes the moving-averaging and moving-difference procedure to replace the original hierarchical procedure. The length of time series will not be shortened as hierarchical layer increases, thereby, MHPE has a higher stability comparing with HPE. Second, MHPE method gets rid of the requirement of the data length of $N = 2n$ (n is a positive integer) in conventional hierarchical procedure. Simulation and experimental signals show that MHPE performs better to recognize the various fault types of planetary gearboxes.

VIII. OTHER ENTROPY METHODS

A. SYMBOLIC DYNAMIC ENTROPY

Recently, Li *et al.* [23] proposed a new entropy method, namely symbolic dynamic entropy (SDE), to assess the dynamical characteristics of time series. Known that SampEn and PE are two most widely used entropy methods. However, SampEn is not fast enough especially in the analysis of long time duration signals. PE, though faster than SampEn, only utilizes the amplitude information of the time series, which is easily affected by the noises [38]. To fill this research gap, SDE utilizes the symbolization procedure to eliminate background noise. Also, SDE reserve the fault information using the probability of state pattern and the state transition [23]. SDE has been demonstrated to have better performance in detecting the dynamical change of time series using both simulated and experimental signals. SDE has obvious advantages, such as high calculation efficiency and robust to noise. The main calculation steps can be seen in Figure 14. Details about SDE can refer to [23].

In addition, SDE is extended to multiscale symbolic dynamic entropy (MSDE) [23], refined composite multiscale symbolic dynamic entropy [15], hierarchical symbol dynamic entropy [38], and generalized multiscale symbolic dynamic entropy (GCMSDE) [18] for comprehensive analysis of vibration signals of rotating machinery. Until now, SDE and its various improvements have been successfully applied in the fault diagnosis of rolling bearings and gearboxes.

B. BELIEF ENTROPY

Belief entropy was first proposed by Deng *et al.* [169] to measure the uncertain information of time series. A larger belief entropy value means the evidence contains more information [170]. Xiao [171] proposed a hybrid methodology based on belief entropy and fuzzy preference relation analysis to accomplish the motor rotor fault diagnosis. Details about symplectic entropy can refer to [169].

C. FREQUENCY BAND ENTROPY

Liu *et al.* [172] proposed frequency band entropy to extract fault features of rolling bearings. Frequency band entropy is developed based on short-time Fourier transform, which can provide the complexity of each frequency component. Frequency band entropy provides a way of blindly designing optimal band-pass filters. The effectiveness of the frequency band entropy is demonstrated using both simulated and experimental signals. Results show that frequency band entropy is sensitive to the incipient fault of rolling bearings [172].

D. SYMPLECTIC ENTROPY

Lei *et al.* [173] proposed symplectic entropy based on the energy distribution of the attractor X in symplectic space. The symplectic entropy can better describe the properties of the system using the symplectic transform, even for the

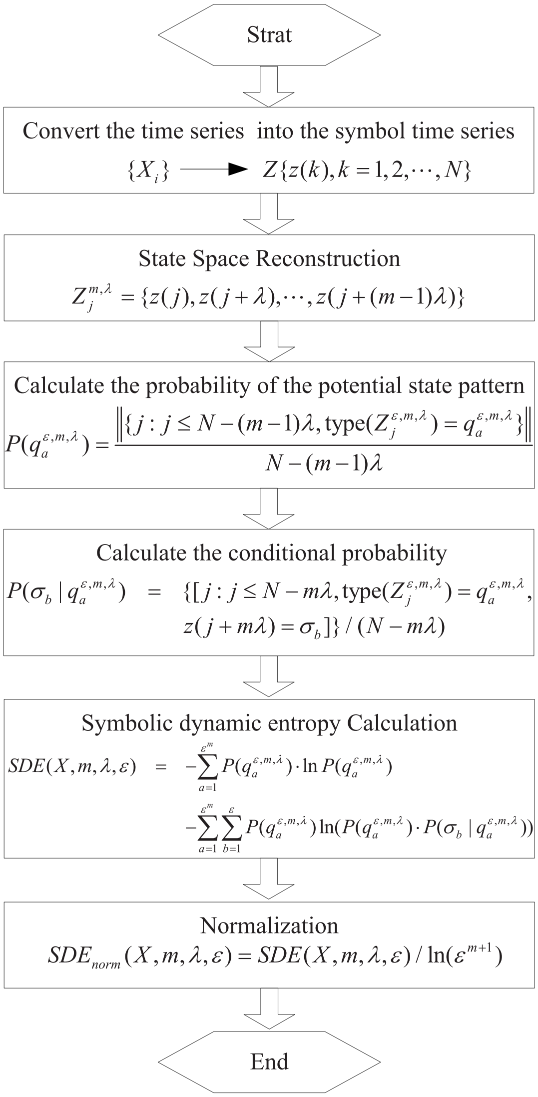

FIGURE 14. The main calculation steps of SDE.

nonlinear dynamic systems. Based on its merits in the extraction of the dynamic characteristics, symplectic entropy has been successfully applied to diagnose the various faults of rolling bearings. Details content about symplectic entropy can refer to [173].

IX. SUMMARY

Based on the above review, we can see that entropy has achieved many successful applications in fault diagnosis of rotating machinery such as gears, rotors, and bearings. We have tried our best to include all the related papers in this review. But, omission of some papers may still be inevitable due to kinds of possible reasons. Based on the above review, a summary of our observations is given below.

(1) The applications of entropy and its variants have successful applied in fault diagnosis of rotating machinery. Compared with traditional methods, entropy has several advantages, including better detection ability of dynamical changes, suitable for the non-linear time series, independent on prior knowledge and better cluster ability.

(2) To make accurate fault diagnosis, the existing problems of entropy cannot be ignored, such as low calculation efficiency, vulnerable to parameters and the noise robust ability. Many researchers have attempted to address these problems and obtained good results.

(3) Entropy methods perform well in detecting dynamic change of rotating machinery. However, it is hard to complete the fault diagnosis of rotating machinery only through the complexity estimation using entropy methods. The combination entropy with dimensional reduction methods and machine learning methods offers a promising tool for fault diagnosis of rotating machinery. However, as many parameters are involved in these entropy-based combination methods, expert experiences are required to select the optimal parameters.

X. PROSPECTS

Entropy algorithm has been successfully applied in fault diagnosis of rotating machinery and its variants and improvements have been made to enhance the performance in detecting the dynamic change of time series. However, some issues should be further studied in-depth for better performance. Some research prospects are given below based on our review and our research experience in this field.

(1) The development of multivariate version of entropy should be considered. In real applications, multiple channel signals may be collected simultaneously. The multivariate entropy will contain richer fault information than univariate. Although this problem has been preliminarily studied [141], it is still worthy of further research.

(2) Fault diagnosis of rotating machinery is facing the challenge of the variable speed influence. To complete the fault diagnosis of rotating machinery under variable speed conditions will have great significance.

(3) Computational efficiency deserves attention of researchers in development of entropy methods. Although PE is proposed to improve computational efficiency, it is still inefficient for online monitoring. Further improvements are still needed in computational efficiency of PE and other entropy-based methods to satisfy online HCM requirements.

(4) The unsuitable selected parameters of entropy cannot detect dynamic changes effectively, leading to extremely bad classification results. Further studies should be conducted to automaticly determine the suitable parameters of entropy methods.

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