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Review

A review on empirical mode decomposition in fault diagnosis of rotating machinery

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ABSTRACT

Rotating machinery covers a broad range of mechanical equipment and plays a significant role in industrial applications. It generally operates under tough working environment and is therefore subject to faults, which could be detected and diagnosed by using signal processing techniques. Empirical mode decomposition (EMD) is one of the most powerful signal processing techniques and has been extensively studied and widely applied in fault diagnosis of rotating machinery. Numerous publications on the use of EMD for fault diagnosis have appeared in academic journals, conference proceedings and technical reports. This paper attempts to survey and summarize the recent research and development of EMD in fault diagnosis of rotating machinery, providing comprehensive references for researchers concerning with this topic and helping them identify further research topics. First, the EMD method is briefly introduced, the usefulness of the method is illustrated and the problems and the corresponding solutions are listed. Then, recent applications of EMD to fault diagnosis of rotating machinery are summarized in terms of the key components, such as rolling element bearings, gears and rotors. Finally, the outstanding open problems of EMD in fault diagnosis are discussed and potential future research directions are identified. It is expected that this review will serve as an introduction of EMD for those new to the concepts, as well as a summary of the current frontiers of its applications to fault diagnosis for experienced researchers.

Contents

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1. Introduction

Rotating machinery is one of the most common classes of mechanical equipment and plays an important role in industrial applications. It generally operates under tough working environment and is therefore subject to failures, which may cause machinery to break down and decrease machinery service performance such as manufacturing quality, operation safety, etc. With rapid development of science and technology, rotating machinery in modern industry is growing larger, more precise and more automatic. Its potential faults become more difficult to be detected. Therefore, the need to increase reliability against possible faults has attracted considerable interests in fault diagnosis of rotating machinery in recent years. Adopting effective signal processing techniques to analyze the response signals and to reveal fault characteristics is one of the commonly used strategies in fault diagnosis of rotating machinery [1,2]. However, it is a challenge to develop and adopt effective signal processing techniques that can discover crucial fault information from the response signals [3].

Traditional signal processing techniques, including time-domain and frequency-domain analysis, are based on the assumption that the process generating signals is stationary and linear. They may result in false information once they are applied to mechanical fault signals, as the mechanical faults may be non-stationary and generate transient events [4,5]. To deal with non-stationary signals, several advanced time-frequency analysis techniques have been introduced and applied to fault diagnosis of rotating machinery [6,7].

Empirical mode decomposition (EMD) [8] is one of the most powerful time-frequency analysis techniques. It is based on the local characteristic time scales of a signal and could decompose the signal into a set of complete and almost orthogonal components called intrinsic mode function (IMF). The IMFs indicate the natural oscillatory mode imbedded in the signal and serve as the basis functions, which are determined by the signal itself, rather than pre-determined kernels. Thus, it is a self-adaptive signal processing technique that is suitable for nonlinear and non-stationary processes. Since EMD was introduced in 1998, it has been extensively studied and widely utilized in various areas, for example, process control [9,10], modeling [11–13], surface engineering [14], medicine and biology [15], voice recognition [16], system identification [17,18], etc. The number of publications on EMD has been increasing steadily over the past decade.

Since EMD is suitable for processing nonlinear and non-stationary signals, it has attracted attention from researchers in the field of fault diagnosis of rotating machinery as well. Studies on EMD applied to fault diagnosis of rotating machinery grow at a very rapid rate in the past few years. Many publications on this topic, including theory and applications, appear every year in academic journals, conference proceedings and technical reports. Huang and Wu [19] provided a thorough review on EMD and Hilbert–Huang transform applied to geophysical studies, while a survey on the use of EMD to fault diagnosis of rotating machinery has not been reported based on the authors' literature search.

This paper attempts to summarize and review the recent research and development of EMD in fault diagnosis of rotating machinery. It aims to synthesize and place the individual pieces of information on this topic in context and provide comprehensive references for researchers, helping them develop advanced research in this area. The paper surveys the applications of EMD in fault diagnosis based on the diagnosis objects such as rolling element bearings, gears and rotors, which are the common and key components of rotating machinery. Moreover, for each kind of the diagnosis objects, we review the research in terms of different methodologies, namely the original EMD method, improved EMD methods, EMD combined with other techniques, etc.

The remaining part of the paper is organized as follows. Section 2 introduces the EMD algorithm and its problems, and the EEMD algorithm. Section 3 reviews the applications of EMD to fault diagnosis according to the key components and the methodologies used for each component. Section 4 provides a brief summary by synthesizing the papers in a table and points out some existing problems of EMD in fault diagnosis. Section 5 describes prospects of EMD in fault diagnosis and identifies possible research directions in future. Concluding remarks are given in Section 6.

2. Empirical mode decomposition

2.1. EMD algorithm

The EMD method was introduced by Huang et al. [8] and is able to decompose a signal into some IMFs. An IMF is a function that satisfies the following two conditions: (1) in the whole data set, the number of extrema and the number of zero-crossings must either equal or differ at most by one, and (2) at any point, the mean value of the envelope defined by local maxima and the envelope defined by the local minima is zero. An IMF represents a simple oscillatory mode imbedded in the signal. Based on the simple assumption that any signal contains different simple IMFs, the EMD method was introduced to decompose a signal into IMF components. In this paper, the EMD method proposed by Huang et al. [8], is hereafter referred as the original EMD method. Table 1 summarizes the EMD process of a signal $x(t)$ and Fig. 1 shows the steps of the original EMD method.

At the end of the procedure we obtain a residue r_I and a collection of I IMFs $c_i(i=1,2,\ldots,I)$. Summing up all IMFs and the final residue r_I, we get $x(t)=\sum_{i=1}^{I} c_i+r_I$. Therefore, we can decompose a signal into I IMFs and a residue r_I, which is the mean trend of$x(t)$. The IMFs, $c_1,c_2,\ldots,c_I$, include different frequency bands ranging from high to low. The frequency components contained in each frequency band are different and they change with the variation of the signal $x(t)$, while r_I represents the central tendency of the signal$x(t)$. A more detailed explanation about EMD can be found in Ref. [8].

A simulation is carried out here to illustrate the usefulness of the EMD method. A signal including two sine waves with different frequencies and a trend component is generated, and then the EMD method is applied to decompose this signal following the steps described in Fig. 1. The decomposition result is presented in Fig. 2, from which it is observed that two IMFs c_1 and c_2 and a residue r_2 are produced. The two IMFs correspond to the two sine waves and the residue reflects the trend component embedded in the simulated signal.

After introducing EMD, we compare it with classical time-frequency analysis methods, such as short time Fourier transform (STFT) and wavelets as follows.

(1) Although STFT can overcome the disadvantages of FFT-based methods in processing non-stationary signals, it produces constant resolution for all frequencies because it adopts the same window for the whole signal. This implies that if we want to obtain a good frequency resolution using wide windows, which is desired for the analysis of low-frequency components, we would not be able to obtain good time resolution (narrow window), which is desired for the analysis of high-frequency components. Therefore, STFT is suitable for the analysis of quasistationary signals instead of real non-stationary signals [20].

(2) Comparing with STFT, wavelets can be utilized to analyze multi-scale signals through dilation and translation, and extract time-frequency characteristics of the signals effectively. Therefore, wavelets are more suitable than STFT for analyzing non-stationary signals. Wavelets being non-adaptive, however, have its own disadvantage that their analysis results depend on the choice of the wavelet base function. This may lead to a subjective and a priori assumption on the characteristics of the signal. As a result, only the signal characteristics that correlate well with the shape of the wavelet base function have a chance to produce high value coefficients. Any other characteristics will be masked or completely ignored.

(3) Different from wavelets, EMD is a self-adaptive signal processing method. It is based on the local characteristic time scales of a signal and could decompose the signal into a set of IMFs. The IMFs represent the natural oscillatory mode embedded in the signal and work as the basis functions, which are determined by the signal itself, rather than pre-determined kernels. Of course, EMD has weaknesses as well. For example, EMD produces end effects; the IMFs are not strictly orthogonal each other; mode mixing sometimes occurs between IMFs. In conclusion, each time-frequency analysis method suffers various problems. It is hard to say that one can always exceed others for any case.

Table 1
The EMD algorithm.

(1) Initialize: $r_0=x(t)$, and $i=1$
(2) Extract the ith IMF c_i
(a) Initialize: $h_{i(k-1)}=r_{i-1}$, $k=1$
(b) Extract the local maxima and minima of $h_{i(k-1)}$
(c) Interpolate the local maxima and the minima by cubic spline lines to form upper and lower envelops of $h_{i(k-1)}$
(d) Calculate the mean $m_{i(k-1)}$ of the upper and lower envelops of $h_{i(k-1)}$
(e) Let $h_{ik}=h_{i(k-1)}-m_{i(k-1)}$
(f) If h_{ik} is an IMF then set $c_i=h_{ik}$, else go to step (b) with $k=k+1$
(3) Define the remainder $r_{i+1}=r_i-c_i$
(4) If r_{i+1} still has least 2 extrema then go to step (2) with $i=i+1$ else the decomposition process is finished and r_{i+1} is the residue of the signal

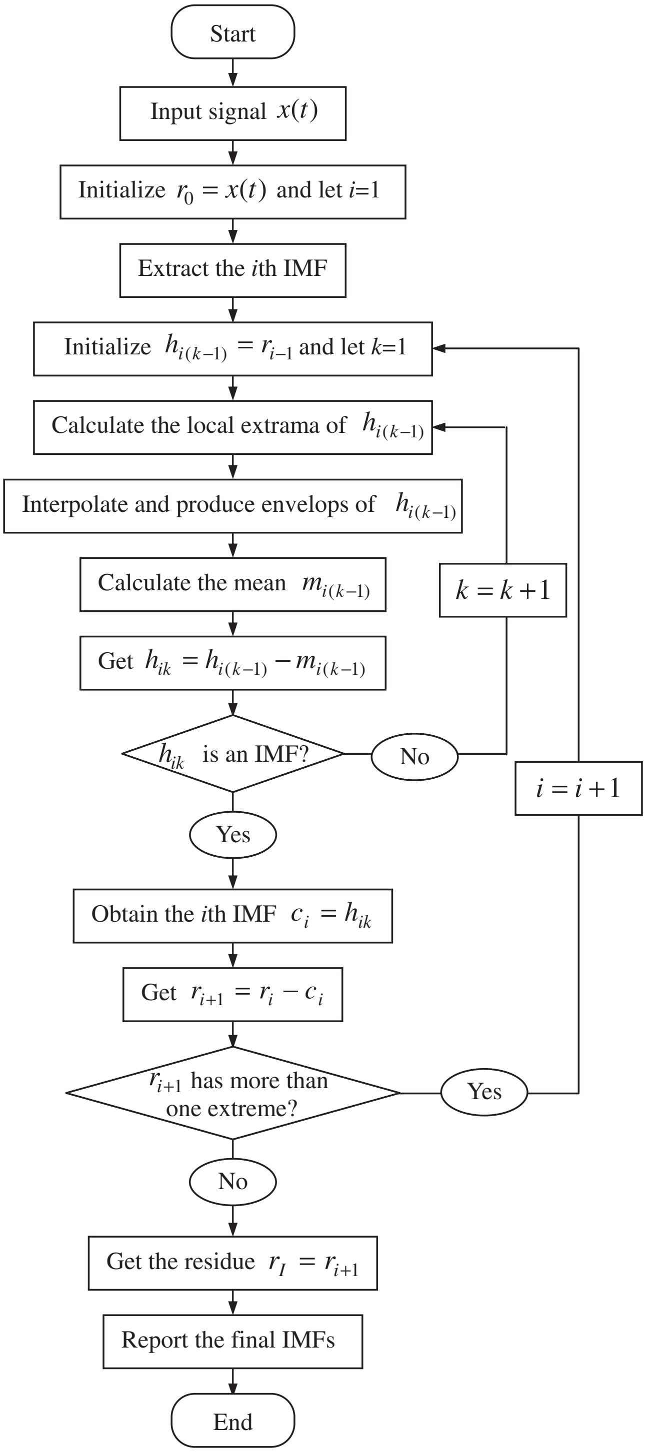

Fig. 1. Flow chart of EMD.

2.2. Problems of EMD and solutions

Although the EMD method shows outstanding performance in processing nonlinear and non-stationary signals, the algorithm itself has some weaknesses. Rato et al. [21], Chen and Wang [22] and Rilling et al. [23] thoroughly discussed the issues of EMD such as lacking a theoretical foundation, end effects, sifting stop criterion, extremum interpolation, etc.

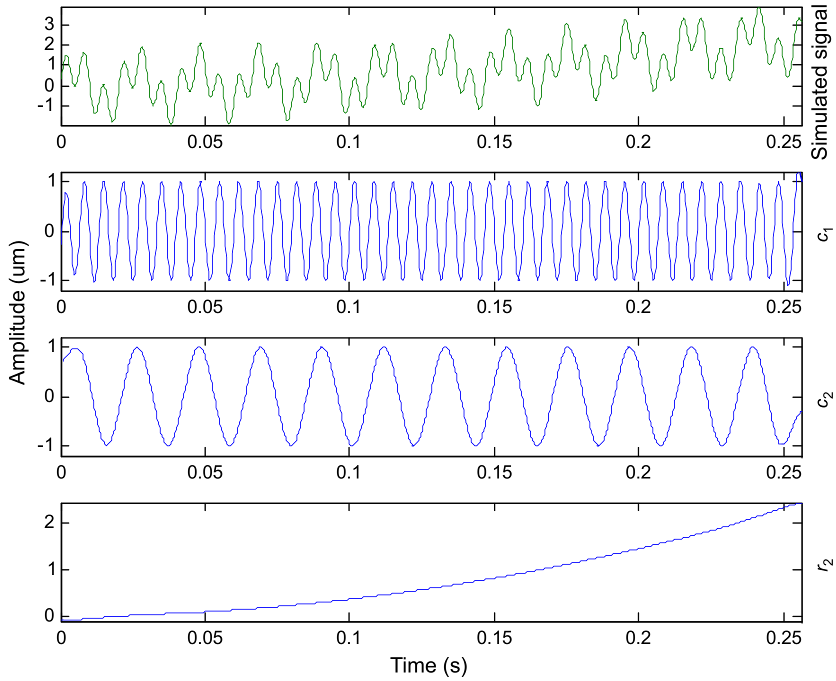

Fig. 2. Illustration of the EMD method.

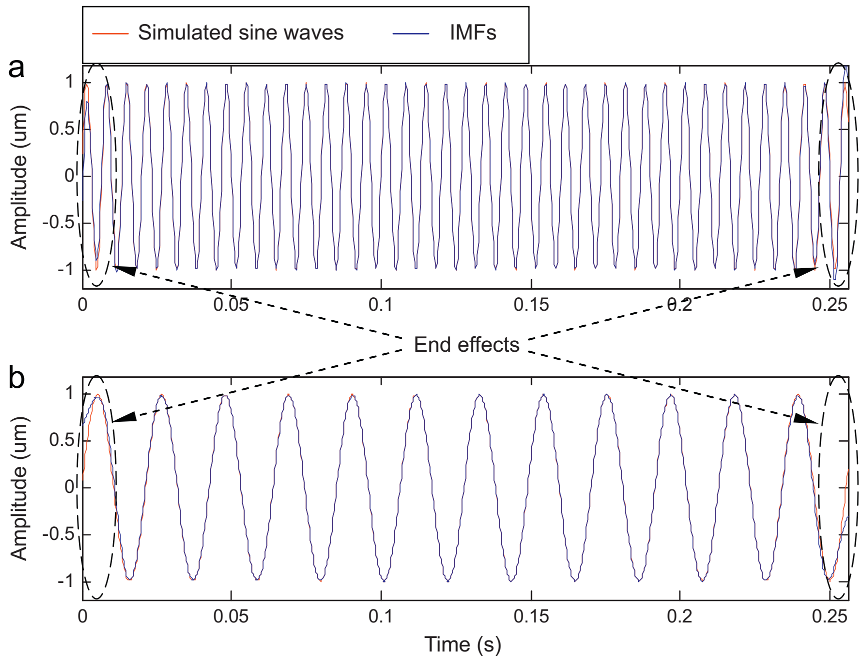

Fig. 3. (a) The simulated high-frequency sine wave and IMF c_1 and (b) the simulated low-frequency sine wave and IMF c_2.

For a clear understanding of these weaknesses of EMD, we use the simulated signal shown in Fig. 2 to illustrate the weaknesses including end effects, the IMFs being not strictly orthogonal each other and the energy being not conservative. Fig. 3 displays the two components of sine waves included in the simulated signal and the decomposed IMFs of the simulated signal by EMD. It is seen that there are distortions at the two ends of IMFs. We call this phenomenon end effects of EMD, which is caused by the EMD algorithm itself. Calculating the dot product between the two IMFs c_1 and c_2, we obtain the value of 1.5 instead of zero. This means that the two IMFs decomposed by EMD are not strictly orthogonal each other. In addition, we calculate the energy of the two IMFs and the residue. It is 514.6, 515.2 and 1161.8. We sum up the energy of these three components and get the total energy of 2191.6, which is not equal to the energy of the simulated signal 2125.8. This indicates that when a signal is decomposed by EMD, the energy is not conservative before and after decomposition.

Aiming at the drawbacks mentioned above, various theoretical analyses have been accomplished. With respect to the problem of EMD lacking a theoretical foundation, Tsakalozos et al. [24] explored the algorithm of EMD and developed a rigorous mathematical theory. Deléchelle et al. [25] constructed an analytical framework for better understanding of EMD. Feldman [26] explained the decomposition principle of EMD through theoretical analyses. Kerschen et al. [27] investigated the relationship between EMD and the slow-flow equations with the aim of understanding EMD. Rilling and Flandrin [28] considered the behavior of EMD in the simple case of a two-tone signal and then extended the results to a nonlinear model.

To eliminate the end effects included in IMFs, Yang et al. [29] proposed an enhanced method called riding wave turnover-empirical amplitude and frequency modulation demodulation. He et al. [30] introduced an extension method based on the gray prediction model to remove the end effects. Xun and Yan [31] used neural networks to extend the length of a signal at both ends before using EMD.

Regarding the sifting stop criterion, Xuan et al. [32] presented a bandwidth criterion and the simulations confirmed that the proposed criterion performed better than the criterion in the original EMD. Li and Ji [33] introduced a new stop criterion into EMD and the improved method can guarantee the orthogonality of the sifting results.

On the issue of extremum interpolation, Hawley et al. [34] modified the original EMD by replacing cubic splines with trigonometric interpolation. Roy and Doherty [35,36] applied cosine interpolation in EMD and obtained an improved decomposition. Damerval et al. [37] described a bi-dimensional EMD based on Delaunay triangulation and on piecewise cubic polynomial interpolation [38]. Qin and Zhong [39] put forward the segment power function method based on the Segment Slide Theory which is superior to the existing interpolation algorithms.

In addition, researchers further improved the original EMD method by utilizing other techniques to make it suitable for different kinds of signals. Rehman and Mandic [40] enhanced EMD to make it suitable for operation on trivariate signals. Fleureau et al. [41] proposed an extended-EMD which can decompose both mono- and multivariate signals. Rilling et al. [42] extended real-valued EMD to complex-valued EMD. Kopsinis and Laughlin [43] proposed a doubly-iterative EMD method and combined it with envelope estimation achieving an improved decomposition performance. Li et al. [44] utilized a windowed average technique to better the original EMD method. Kopsinis and McLaughlin [45] introduced the wavelet thresholding principle into EMD therefore leading to improved denoising effect. Yang et al. [46] proposed the oblique-extrema EMD method to settle the problem of neglecting slight oscillation modes in the sifting process. Liu et al. [47] proposed EMD-wavelet denoising model through the combination of EMD and wavelet.

Besides the disadvantages discussed above, another outstanding shortcoming of EMD is the problem of mode mixing, which is defined as a single IMF including oscillations of dramatically disparate scales, or a component of a similar scale residing in different IMFs. It is a result of signal intermittency. As discussed by Huang et al. [8], the intermittence could not only cause serious aliasing in the time-frequency distribution, but also make physical meaning of individual IMF vague. To solve the problem of mode mixing in the original EMD, a noise-assisted data analysis method, namely, ensemble empirical mode decomposition (EEMD), was developed by Wu and Huang [48] by adding noise to the investigated signal. A brief introduction of EEMD is given in the next section.

2.3. Improved EMD methods

There are lots of improved EMD methods reported in the literature. We choose three representative methods and make a brief introduction on them in this section.

2.3.1. EEMD

To overcome the problem of mode mixing, EEMD was introduced based on the statistical properties of white noise, which showed that the EMD method is an effective self-adaptive dyadic filter bank when applied to the white noise, and the noise could help data analysis in the decomposition of EMD [49–51]. The principle of the EEMD algorithm is addressed as follows. The added white noise would populate the whole time-frequency space uniformly with the constituting components of different scales. When a signal is added to this uniformly distributed white noise background, the components in different scales of the signal are automatically projected onto proper scales of reference established by the white noise in the background. Because each of the noise-added decompositions consists of the signal and the added white noise, each individual trial may certainly produce very noisy results. But the noise in each trial is different in separate trials. Thus it can be decreased or even completely canceled out in the ensemble mean of enough trials. The ensemble mean is treated as the true solution because finally the only persistent part is the signal as more and more trials are added in the ensemble. In the EEMD method, an IMF is therefore defined as the mean of an ensemble of trials. Each trial consists of the decomposition results of the signal plus a white noise of finite amplitude [48]. Based on this principle, the steps of EEMD are given in Table 2 and Fig. 4 shows its flow chart.

In order to verify the enhanced performance of EEMD in overcoming the mode mixing problem, a simulation signal $x(t)$ is produced and shown in Fig. 5a, which is a sine wave attached by small impulses [52]. Thus, it is a combined signal and

Table 2
The EEMD algorithm.

(1)	Initialize the number of trials in the ensemble, M, the amplitude of the added white noise, and the trial number $m=1$
(2)	Perform the mth trial on the signal added with white noise
(a)	Generate a white noise series with the initialized amplitude and add it to the investigated signal $x_m(t)=x(t)+n_m(t)$, where $n_m(t)$ indicates the mth added white noise series, and $x_m(t)$ represents the noise-added signal of the mth trial
(b)	Decompose the noise-added signal $x_m(t)$ into I IMFs $c_{i,m}(i=1,2,\ldots,I)$ using the EMD method described in Section 2.1, where $c_{i,m}$ denotes the ith IMF of the mth trial, and I is the number of IMFs
(c)	If the trial number is smaller than the number required, i.e. $m<M$then go to step (a) with $m=m+1$. Repeat steps (a) and (b) again, but with a new randomly generated white noise series each time
(3)	Calculate the ensemble mean $\overline{c_i}$of the M trials for each IMF $y_i=\frac{1}{M}\sum_{m=1}^{M} c_{i,m}$, $i=1,2,\ldots,I$, $m=1,2,\ldots,M$
(4)	Report the mean y_i $(i=1,2,\ldots,I)$ of each of the I IMFs as the final IMFs

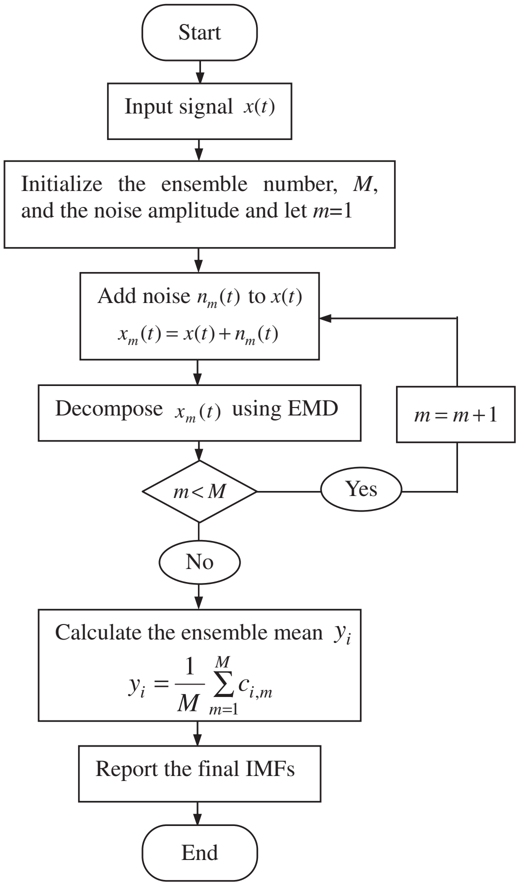

Fig. 4. Flow chart of EEMD.

contains two components. Both EMD and EEMD are utilized to process this simulation signal and the decomposed IMFs are shown in Fig. 5b and c. It is seen that the two IMFs obtained by EMD are distorted seriously. Mode mixing is occurring between IMFs c_1 and c_2. The sine wave and the impulses are decomposed into the same IMF c_1. Moreover, the sine wave is decomposed into the two IMFs. Thus, both IMFs c_1 and c_2 of EMD fail to represent the real characteristics of signal $x(t)$. However, the two components embedded in the signal are accurately decomposed into two IMFs by EEMD. IMF y_1 denotes the impulse components and IMF y_2 indicates the sine wave. Thus, the EEMD method is able to solve the problem of mode mixing and achieve an improved decomposition.

2.3.2. WPT-EMD [53]

According to the investigation done in Ref. [53], it is observed that EMD has three shortcomings including the pseudo-IMFs problem, the first IMF covering too wide a frequency range, and some signals with low-energy components being inseparable.

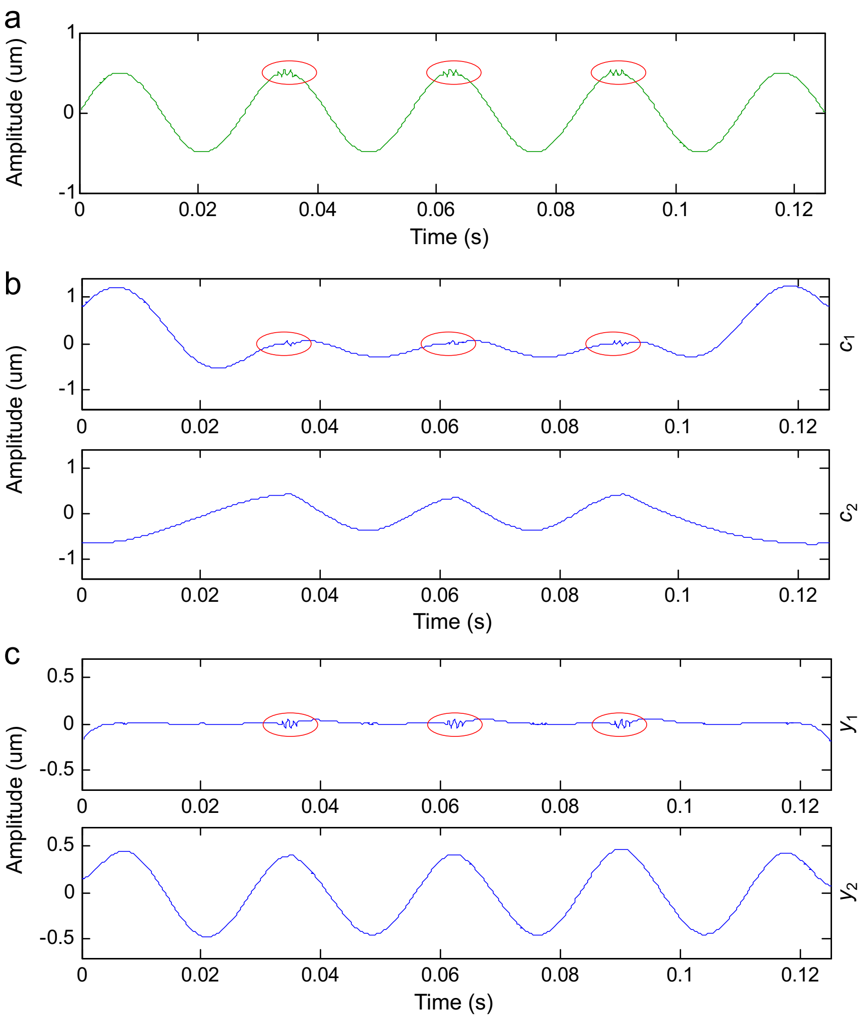

Fig. 5. (a) A simulation signal, (b) IMFs c_1 and c_2 decomposed by EMD and (c) IMFs y_1 and y_2 decomposed by EEMD.

Table 3
The WPT-EMD algorithm.

(1) Use WPT to decompose the original signal into narrow band signals
(2) Perform EMD on each of the narrow band signals
(a) Compute the correlation coefficient μ_i of the ith IMF$_i$ and the original signal. Get a thresholdλ, $\lambda = \max(\mu_i)/\eta$, where η is a 1.0 bigger ratio factor
(b) If $\mu_i \geq \lambda$then keep the ith IMF$_i$,elsethen eliminate the ith IMF$_i$ and add it to the residue signal r_n
(3) Obtain all IMFs

Aiming at these shortcomings, an improved EMD method using wavelet packet transform (WPT-EMD) was presented. In this method, WPT plus an IMF selection method was introduced into the original EMD algorithm. WPT was utilized as a preprocessor to decompose the original signal into a set of narrow band signals. Then EMD was applied to these narrow band signals and to extract IMFs. After the IMFs have been obtained, an IMF selection method was utilized to retain those vital IMFs. In comparison with the original EMD, the WPT-EMD method can overcome the three shortcomings, and therefore has better resolution both in time domain and in frequency domain. The algorithm of WPT-EMD is stated in Table 3.

2.3.3. BS-EMD [54]

To solve the problem of lacking a theoretical foundation of EMD, B-spline EMD (BS-EMD) was developed since B-spline is more mathematically amenable. In the BS-EMD, the knots of the B-splines are taken as the local extremum points of the signal and the envelope mean in the original EMD is replaced with the moving average of B-splines.

Based on the comparison results in Ref. [54], it was found that BS-EMD gave very comparable results with the original EMD, and even produced a finer decomposition than the original EMD. Considering that the algorithm of BS-EMD is much similar to that of the original EMD, the algorithm of BS-EMD is therefore not presented specifically here. A more detailed introduction of BS-EMD can be found in Ref. [54].

3. Applications of EMD in fault diagnosis of rotating machinery

Rolling element bearings, gears and rotors are the common and key components in rotating machinery. The health condition of these key components represents that of the machine itself. Hence, this section will present a review on the applications of EMD in fault diagnosis in terms of these key components, i.e. bearings, gears and rotors. Research on other diagnosis objects using EMD is introduced as well at the end of this section.

3.1. Fault diagnosis of rolling element bearings

In this section, publications regarding bearing fault diagnosis via EMD are listed and summarized following four subsections: the original EMD method, improved EMD methods, EMD combined with other techniques, and EEMD.

3.1.1. The original EMD method in bearing fault diagnosis

The original EMD method, proposed by Huang et al. [8], has been widely used to detect and diagnose faults of rolling element bearings. This section will review the literature in which EMD was individually employed in bearing fault diagnosis without any additional methods. Xu et al. [55] adopted EMD to analyze the vibration signals of accelerated life tests of bearings and investigated the evolving trend of a bearing life cycle. Cheng et al. [56] proposed the energy operator demodulation approach based on EMD for bearing fault diagnosis. Fan and Zuo [1] utilized the amplitude acceleration energy of IMFs to represent fault characteristics of both bearings and gears. Yan and Gao [57] effectively detected the deterioration of a test bearing through instantaneous frequencies identified by EMD. Li et al. [58] utilized the marginal spectrum based on EMD to identify different patterns of bearing faults. Li [59] calculated the instantaneous energy of IMFs for detecting damage on bearing inner race and outer race. Chiementin et al. [60] compared EMD and discrete wavelet transform, and found that both of them were effective on early detection of impulse defects on bearings. Mei et al. [61] calculated fractal dimensions of IMFs to indicate bearing health conditions. Tsao et al. [62] executed the envelope analysis on the selected IMFs which contain bearing fault information, and experimental results demonstrated the efficiency of their method in bearing fault detection.

3.1.2. Improved EMD methods in bearing fault diagnosis

Several improved EMD methods have been proposed aiming to enhance the performance of EMD in bearing fault diagnosis. Du and Yang [63,64] improved the local mean calculation of EMD and therefore obtained a better result of bearing fault diagnosis. Dong et al. [65] enhanced the efficiency of the sifting process of EMD and detected the inner race fault of bearings. Terrien et al. [66] presented an algorithm for IMF automatic selection and the detection results of bearing vibration signals verified its advantage. Yan and Gao [67] proposed two criteria, the energy measure and the correlation measure, for determining the most representative IMF of EMD to locate bearing defects.

3.1.3. EMD combined with other techniques in bearing fault diagnosis

Many researchers have applied EMD combining with other techniques to bearing fault diagnosis in recent years and achieved better diagnosis results compared with the use of EMD alone. Miao et al. [68] introduced a joint method based on EMD and independent component analysis for fault signature detection of bearing outer and inner races. Yu et al. [69] applied EMD and Hilbert transform to the envelope signals of bearings and produced the local Hilbert marginal spectrum to diagnose bearing faults. Li and Zheng [70] proposed a signal analysis approach based on EMD and Teager Kaiser energy operator for bearing fault detection. Rai and Mohanty [71] introduced Fourier transform of IMFs into the Hilbert–Huang transform for discovering rolling element bearing defects. Li et al. [72] applied Wigner–Ville distribution based on EMD to bearing fault diagnosis and therefore prevented the presence of cross terms. Chen et al. [73] utilized EMD and Hilbert transform to generate the local marginal spectrum from which the outer and inner race faults in a bearing were diagnosed. Aiming at the problem of bearing diagnosis under the run-up or run-down process, Li et al. [74] developed a method based on EMD, order tracking and energy operator and evaluated its effectiveness. Peng et al. [53] applied wavelet packet transform to ameliorate the deficiencies of EMD and formed an improved method for bearing fault detection. Tang et al. [75] eliminated mode mixing using morphological filter and blind source separation, and verified the method by detecting bearing outer race faults. Yang et al. [76] calculated the characteristic amplitude ratios of IMFs as the input indicators of support vector machines to fulfill bearing fault recognition. Cheng et al. [77] constructed an autoregressive model for each IMF, and obtained autoregressive parameters to diagnose bearing faults. Yang et al. [78] calculated the energy entropy of EMD as the input features of artificial neural networks for identifying bearing fault patterns. Cheng et al. [79] used EMD and singular value decomposition to extract features and support vector machines to classify fault patterns of bearings and gears. Lei et al. [80–82] employed EMD to preprocess bearing vibration signals and artificial intelligent techniques, i.e.

neural networks and genetic algorithms, to recognize bearing fault types and damage levels based on the features extracted from the preprocessed signals.

3.1.4. EEMD in bearing fault diagnosis

EEMD, as one of the most representative improved EMD methods, has been used to diagnose bearing faults at a fast pace, which is addressed particularly in this paragraph. An et al. [83] applied EEMD and Hilbert transform to highlight the weak fault features and detected the bearing pedestal looseness fault. Ali et al. [84] presented an approach based on EEMD and envelope spectrum and reliably diagnosed bearing local defects. Zvokelj et al. [85] combined EEMD and principal component analysis (PCA) to detect bearing local defects. This method used a linear PCA technique assuming a linear variable interrelationship. To overcome this disadvantage, Zvokelj et al. [86] developed an improved version using nonlinear kernel PCA and used it for fault detection of large-size and low-speed bearings. Zhang et al. [87] investigated parameter selection issues of EEMD and proposed a modified EEMD method in diagnosing bearing faults. Lu and Wang [88] introduced a method based on EEMD and redundant second generation wavelets to improve the accuracy of bearing fault diagnosis. Lei et al. [89] combined the merits of EEMD and wavelet neural networks and developed an automatic fault identification method of locomotive bearings. Guo and Tse [90] applied EEMD to bearing fault diagnosis and further discussed the influence of parameter selection in EEMD on the decomposition results.

3.2. Fault diagnosis of gears

Since EMD is suitable for processing non-stationary signals, it has been used not only for bearings but also for gears. Many publications are on the use of EMD for gear fault diagnosis. This section is to review such papers. Similar to Section 3.1, this section contains the following four aspects for gear fault diagnosis: the original EMD method, improved EMD methods, EMD combined with other techniques, and EEMD.

3.2.1. The original EMD method in gear fault diagnosis

This section attempts to summarize the papers related to the use of EMD only in gear fault diagnosis. Li and Zhang [91] produced the marginal spectrum of gear vibration signals using EMD and implemented fault diagnosis of gear wear. Cheng et al. [92] developed the frequency family separation method with EMD for gear fault diagnosis. Loutridis [93,94] presented a method based on EMD for monitoring the evolution of gear faults and established an empirical law which related the energy content of IMFs to crack magnitudes. Parey and Tandon [95,96] used EMD to process vibration signals of gears and calculated kurtosis value from the selected IMFs for early fault detection. Wang et al. [97] extracted the instantaneous energy density of IMFs and established the prediction curve of gear failure. Li et al. [98] utilized EMD to decompose adaptively angle-domain stationary signals to detect gear faults under varying speeds. Ibrahim and Albarbar [99] compared EMD and Wigner–Ville distribution and observed that the EMD method was more suitable for gear fault diagnosis. Wang and Heyns [100] re-sampled an IMF of EMD to approximate order tracking without requiring knowledge of rotational speeds. Their results illustrated the usefulness of the proposed method. Shao et al. [101] developed a virtual instrument system based on EMD for gear damage detection and diagnosis. Yang et al. [102] compared the maximal overlap discrete wavelet packet transform and EMD in gear fault diagnosis and found that the former performed better than the latter.

3.2.2. Improved EMD methods in gear fault diagnosis

To achieve more accurate results of EMD in gear fault diagnosis, various enhanced versions of EMD have been produced in gear fault diagnosis. He et al. [103] developed a midpoint-based EMD method and its application to gear fault diagnosis indicated that the method is valuable in discovering gear fault signatures. Liu et al. [104] applied B-spline EMD for local fault diagnosis of the gear and observed that the method was more effective than continuous wavelet transform. Cheng et al. [105] used support vector machines to predict a signal limiting the end effects of EMD and with this approach, gear tooth breakage was detected. For the problem of EMD lacking strict orthogonality, Qin et al. [106] presented an orthogonal EMD and applied it to gear fault diagnosis. Cheng et al. [107] developed the energy difference tracking method as a stopping criterion in the sifting process of EMD and verified the method by diagnosing a gear fault with broken teeth. Parey and Pachori [108] applied variable cosine windows to overcome the end effects of EMD and computed the statistical parameters of IMFs to detect gear faults. Wang et al. [109] modified the monotone piecewise Hermite interpolation method to improve local mean approximation of EMD for gear fault detection. Ricci and Pennacchi [110] introduced a merit index that allowed the automatic selection of IMFs for gear fault diagnosis and demonstrated it based on the diagnosis result of a spiral bevel gear.

3.2.3. EMD combined with other techniques in gear fault diagnosis

The combination of EMD with other signal processing techniques or artificial intelligent techniques is an effective strategy to better EMD in gear diagnosis. In this aspect, researchers have carried out the following investigations. Li [111] used EMD to analyze vibration signals for incipient fault diagnosis of gearboxes after preprocessing the signals using a wavelet-based filter. Li et al. [112] presented the Teager–Huang transform which combined EMD and Teager Kaiser energy operator in gear fault diagnosis and noticed that the method had better resolution than Hilbert–Huang transform.

Zamanian and Ohadi [113] introduced a feature extraction method integrating EMD and the Gaussian correlation of wavelet coefficients to discover wear and chip features of gearboxes. Li and He [114] incorporated a threshold-based denoising technique into EMD to increase the signal-to-noise ratio of signals and then developed a feature for gear fault detection. Cheng et al. [115] combined EMD, autoregressive model and support vector machines, and achieved an experimental success rate of 100% in identifying health conditions of gears. Lei et al. [116] used EMD as a preprocessor to extract fault features from gear signals, and neural networks and the *K* nearest neighbor algorithms to identify different modes and degrees of gear faults. Shen et al. [117] realized the mode identification of gear faults by utilizing the merits of EMD in processing non-stationary signals and multi-class support vector machines in pattern recognition.

3.2.4. EEMD in gear fault diagnosis

Several researchers have utilized EEMD to detect and diagnose gear faults in the past few years. Ai and Li [118] applied EEMD to fault diagnosis of gear crack and demonstrated the effectiveness by experiments. Guan et al. [119] combined EEMD with order tracking techniques and developed a diagnostic feature for fault detection of a two-stage helical gearbox. Lei et al. [120,121] employed EEMD to improve bispectral analysis in gear fault diagnosis and produced enhanced results than the original bispectral analysis. Lin and Chen [122] applied EEMD to multiple fault diagnosis of gearboxes and effectively extracted the multiple fault information. Zhou et al. [123] utilized EEMD for online monitoring and diagnosis of gear wear states. Zhao et al. [124] implemented fault diagnosis of worm gears by using EEMD to analyze servo motor current signals.

3.3. Fault diagnosis of rotors

Generally, displacement signals are collected and used in detecting and diagnosing rotor faults, such as rub-impact, fatigue crack, misalignment, unbalance, etc. The composition of the displacement signals is relatively simple. Therefore, EMD and its improved methods perform well in diagnosing rotor faults. Consequently, considerable papers addressing such research have been published, which will be summarized in this section. The section consists of four parts: the original EMD method, improved EMD methods, EMD combined with other techniques, and EEMD.

3.3.1. The original EMD method in rotor fault diagnosis

This section describes the applications of EMD in rotor fault diagnosis. Yang and Tavner [125] used EMD to purify shaft signals and then constructed a transient shaft orbit plot to diagnose rotor-to-stator rub and fluid excitation faults of rotor systems. Wang et al. [126] made a comparison between EMD and local mean decomposition in diagnosing a rotor rub-impact fault. Gai [127] applied EMD to refine rotor startup signals, plotted Bode diagrams based on IMFs, and then obtained fault characteristics. Chan and Tse [128] presented a data compression algorithm based on EMD and the algorithm was verified by detecting rotor misalignment and unbalance faults. Patel and Darpe [129] used EMD to discover features from vibration responses at the presence of rotor rub and fatigue crack faults. Wu and Qu [130] accomplished sub-harmonic fault diagnosis such as rotating stall and pipe excitation with EMD. Lee and Choi [131] obtained better results in diagnosing rub and looseness using EMD compared with short time Fourier transform and wavelet analysis. Han et al. [132] used EMD to explore time-frequency characteristics of rub-impact motions of a dual-disc rotor system. Lei et al. [133] extracted fault indicators from each IMF for identifying damage degrees of rotors. Lin et al. [134] investigated the characteristics of IMFs to identify shaft health conditions. Yang and Suh [135] used EMD to analyze the dynamic responses of a rotor-journal bearing system to better understand the behaviors of the system. Lin and Chu [136] applied EMD to acoustic emission signals for extracting features of natural fatigue cracks on rotors. Guo and Peng [137] utilized EMD-based Hilbert-Huang transform to explore the nonlinear responses of a rotor with growing crack at the startup process.

3.3.2. Improved EMD methods in rotor fault diagnosis

The enhanced EMD methods for rotor fault diagnosis are summarized in this section. Wu and Qu [138] introduced a slope-based method to restrain the end effects of EMD and used the method successfully for detecting the radial rub between the rotor and stator. Yang et al. [139] investigated bivariate EMD for diagnosing a rotor unbalance fault and noticed that their method was more powerful than the original EMD. Qi et al. [140] developed a method based on cosine window to overcome the end effects and applied the improved EMD method to rub fault diagnosis of a rotor system. Wu et al. [141] chose information-rich IMFs to construct the marginal Hilbert spectra and then defined a fault index to identify looseness faults in a rotor system. Gao et al. [142] overcame the mode mixing problem of EMD by combining neighboring IMFs to a mode function, which accurately reflected rotor rub-impact faults.

3.3.3. EMD combined with other techniques in rotor fault diagnosis

In rotor fault diagnosis, combining EMD with other techniques is another means to achieve better results than the original EMD alone besides the improved EMD methods addressed above. These results will be summarized in this section. Peng et al. [143] adopted wavelet packet transform to modify EMD and the diagnosis results of rotor rub-impact faults proved that the modified method clearly revealed the fault characteristics. Dong et al. [144] combined EMD and Laplace wavelet for identifying rotor cracks. Zhao et al. [145] employed multivariate EMD and full spectrum for monitoring rub faults of a rotor system. Bin et al. [146] combined EMD and wavelet packet decomposition for feature extraction and used neural networks for classifying ten types of rotor faults consisting of imbalance, crack, misalignment etc. Li et al. [147] calculated the maximal singular values of IMFs as the input features of support vector machines to identify rotor rub-impact faults.

3.3.4. EEMD in rotor fault diagnosis

In addition to applying EMD and its improved methods for rotor fault diagnosis as reviewed earlier, many papers have focused on rotor diagnosis using EEMD although EEMD was introduced quite lately. Wu et al. [148] combined EEMD and autoregressive model to identify looseness faults of rotor systems. Lei et al. [52,149] proposed EEMD-based methods to detect early rub-impact faults of rotors and the comparison with EMD demonstrated their superiority in extracting fault characteristic information. Wu and Chung [150] proposed a hybrid EEMD and EMD approach to process the complicated vibration signals for diagnosing the shaft misalignment fault of rotating machinery.

3.4. Other applications

In addition to its application to fault diagnosis of bearings, gears and rotors, EMD has also been extended to other diagnosis objects due to its strong capability in processing non-stationary and nonlinear signals. This section is intended to summarize the results of such investigations.

3.4.1. The original EMD method in other diagnosis objects

Yadav and Kalra [151] combined representative IMFs to obtain a cumulative mode function and extracted indicators from its envelope spectrum for detecting faults of an internal combustion engine. Chen et al. [152,153] processed structure vibration signals using EMD and then produced feature vectors for estimating damage status of composite aircraft wingbox. Jose et al. [154] extracted fault features from original startup current signals with EMD for fault diagnosis of induction machines. Kalvoda and Hwang [155] utilized EMD to analyze accelerometer signals in detecting cutter tool wear under several cutting conditions. Rezaei and Taheri [156] presented an EMD-based energy index for damage detection of beam-type components. Braun and Feldman [157] thoroughly investigated and compared major properties of EMD and Hilbert vibration decomposition (HVD) by using a simulated acoustic signal and a simulated rotor blade vibration signal, and observed that both EMD and HVD successfully separated different frequency quasi-harmonic signals and a single slow aperiodic component while the latter had a better frequency resolution. Lin et al. [158] applied EMD to an impact-echo test for internal crack detection of concrete specimens. Kalvoda and Hwang [159] used EMD to analyze dynamic force and acceleration signals of the cutting process of machine tools. Bassiuny and Li [160] employed EMD to extract the crucial characteristics from feed-motor current signals for monitoring the conditions of an end mill. Antonino-Daviu et al. [161] used EMD to discover characteristics from stator startup current signals and detected the eccentricity fault in induction electrical machines. Zhang et al. [162] applied EMD to characterizing structural damage and compared it with Fourier transform.

3.4.2. Improved EMD methods in other diagnosis objects

Li et al. [163] proposed a ranged angle-EMD method and with this method, clearance-related faults of a diesel engine were identified. Bao et al. [164] modified the EMD method by estimating the local mean of a signal via windowed average and used the modified method to extract modulated cavitation noise from ship-radiated noise. Lin [165] utilized EEMD for fault diagnosis of the reciprocating compressor on an offshore platform aiming at the non-stationary characteristics of compressor signals.

3.4.3. EMD combined with other techniques in other diagnosis objects

Li et al. [166] combined EMD and continuous wavelet transform to analyze the structure response signals and detect the exact location and severity of structural damage. Yang [167] used EMD to decompose the ‘monocomponent’ functions extracted from signals with an adaptive band-pass filter for diagnosing engine valve faults. Guo et al. [168] combined EMD and median filter to process friction signals. Bassiuny et al. [169] utilized EMD to extract feature vectors and the learning vector quantization networks to monitor a sheet metal stamping process. Chen et al. [170] combined EMD and zoom fast Fourier transform to detect broken rotor bars of induction motors. Wang and Heyns [171] integrated the merits of EMD, computed order tracking and Vold–Kalman filtering for inter-turn short circuit fault diagnosis of an alternator. Shen et al. [172] extracted energy features from dominant IMFs as input vectors of support vector machines to diagnose diesel engine faults. Li and Liang [173] combined EMD and correlated reconstruction to extract the weak signature of metallic debris in lubricating oil lines for providing clearer machine health information. Wu and Liao [174] adopted EMD for feature extraction and neural networks for fault classification in a diagnosis system of an automotive air-conditioner blower. Sun et al. [175] calculated energy features of IMFs as the inputs of BP neural networks for structural damage identification. Zhou and Zhao [176] put forward a method based on complexity features of EMD and least square support vector machines for diagnosing centrifugal pump faults.

4. Discussions

In previous sections, we have summarized reported studies on using EMD in fault diagnosis of rotating machinery. Actually, the literature on this subject is huge and diverse. A review on all of the literature is impossible and omission of some papers would be inevitable. It is believed that the applications of EMD to fault diagnosis of rotating machinery have

Table 4
Summary of the use of EMD for fault diagnosis.

Objects	References	Methodologies
Bearings	Xu et al. [55], Cheng et al. [56], Fan and Zuo [1], Yan and Gao [57], Li et al. [58,59], Chiementin et al. [60], Mei et al. [61], Tsao et al. [62]	**The original EMD method alone**
	Du and Yang [63,64] Dong et al. [65] Terrien et al. [66] Yan and Gao [67]	**Improved EMD methods:** • Modifying the local mean calculation • Enhancing the sifting process efficiency • Selecting the most representative IMF
	Miao et al. [68] Yu et al. [69] Li and Zheng [70,72,74] Rai and Mohanty [71] Chen et al. [73] Peng et al. [53] Tang et al. [75] Yang et al. [76,78] Cheng et al. [77,79] Lei et al. [80–82]	**Combinations of EMD with:** • Independent component analysis • Teager Kaiser energy operator • Wigner–Ville distribution • Order tracking • Wavelets • Autoregressive model • Singular value decomposition • Artificial neural networks • Genetic algorithms • Support vector machines
	An et al. [83], Ai et al. [84], Zvokelj et al. [85,86], Zhang et al. [87], Lu and Wang [88], Lei et al. [89], Guo and Tse [90]	**EEMD**
Gears	Fan and Zuo [1], Li and Zhang [91], Cheng et al. [92], Loutridis [93,94], Parey and Tandon [95,96], Wang et al. [97], Li et al. [98], Ibrahim and Albarbar [99], Wang and Heyns [100], Shao et al. [101], Yang et al. [102]	**The original EMD method alone**
	He et al. [103] Liu et al. [104] Cheng et al. [105,107] Qin et al. [106] Parey and Pachori [108] Wang et al. [109] Ricci and Pennacchi [110] Cheng et al. [79,115] Li [111] Li et al. [112] Zamanian and Ohadi [113] Li and He [114] Lei et al. [116] Shen et al. [117]	**Improved EMD methods:** • Midpoint-based EMD • B-spline EMD • Orthogonal EMD • Enhancing stopping criteria • Restraining the end effects • Selecting the optimal IMF **Combinations of EMD with:** • Wavelets • Teager Kaiser energy operator • Autoregressive model • Singular value decomposition • Support vector machines • Artificial neural networks • *K* nearest neighbor algorithms
	Ai and Li [118], Guan et al. [119], Lei et al. [120,121], Lin and Chen [122], Zhou et al. [123], Zhao et al. [124]	**EEMD**
Rotors	Yang and Tavner [125], Wang et al. [126], Gai [127], Chan and Tse [128], Patel and Darpe [129], Wu and Qu [130], Lee and Choi [131], Han et al. [132], Lei et al. [133], Lin et al. [134], Yang and Suh [135], Lin and Chu [136], Guo and Peng [137]	**The original EMD method alone**
	Wu and Qu [138] Yang et al. [139] Qi et al. [140] Wu et al. [141] Gao et al. [142] Peng et al. [143] Dong et al. [144] Zhao et al. [145] Bin et al. [146] Li et al. [147]	**Improved EMD methods:** • Bivariate EMD • Restraining the end effects • Selecting the optimal IMF • Overcoming the mixing problem **Combinations of EMD with:** • Wavelets • Full spectrum • Support vector machines • Artificial neural networks
	Wu et al. [148], Lei et al. [52,149], Wu and Chung [150]	**EEMD**
Others	Yadav and Kalra [151], Chen et al. [152,153], Jose et al. [154], Kalvoda and Hwang [155,159], Rezaei and Taheri [156], Braun and Feldman [157], Lin et al. [158], Bassiuny and Li [160], Antonino-Daviu et al. [161], Zhang et al. [162]	**The original EMD method alone**
	Li et al. [163] Bao et al. [164] Lin [165]	**Improved EMD methods:** • Ranged angle-EMD • Modifying the local mean calculation • EEMD

Table 4 (*continued*)

Li et al. [166], Yang [167], Guo et al. [168], Bassiuny et al. [169], Chen et al. [170], Wang and Heyns [171], Shen et al. [172], Li and Liang [173], Wu and Liao [174], Sun et al. [175], Zhou and Zhao [176]	**Combinations of EMD with:** • Wavelets • Median filters or adaptive filters • Order tracking • Learning vector quantization networks • Support vector machines • Artificial neural networks

also been published in other languages as well. However, non-English publications are not considered in this review due to the limitation of language proficiency. In this section, the literature described in Section 3 is synthesized in a table following the diagnosis objects, i.e. rolling element bearings, gears and rotors. The table is supposed to provide a more direct view of reported studies to readers who concern with the use of EMD in fault diagnosis. From the description in Section 3 and Table 4, we provide the following observations.

(1) Most papers put emphasis on the key components, namely, bearings, gears and rotors as they are commonly used and play a critical role in rotating machinery. By using EMD to process vibration signals collected from machinery and discover fault characteristics, health condition monitoring and fault diagnosis of the machine could be accomplished with the assistance of expertise of diagnosticians. EMD has been proved effective to detect faults of major components on rotating machinery under research environments.
(2) Making comparisons on applications of EMD for different diagnosis objects, i.e. rolling element bearings, gears and rotors, it is found that EMD performs better in extracting fault characteristics of rotors than both bearings and gears. It can be explained that in fault diagnosis of rotors, displacement signals are used and their composition is relatively simple. However, accelerometer signals are generally adopted in fault diagnosis of bearings and gears, and they are noisy and complicated. As a result, using EMD, fault characteristics of bearing and gears cannot be extracted as clearly as those of rotors, while it is possible to exactly discover such characteristics of bearing and gears with wavelets. Wavelets being non-adaptive, however, have the shortcoming that their analysis results depend on the choice of the wavelet base function. This may lead to a subjective and a priori assumption on the characteristics of the signal. As a result, only the signal characteristics that correlate well with the shape of the wavelet base function have a chance to produce high value coefficients. Any other characteristics will be masked or completely ignored. In a word, for EMD and wavelets, it is hard to say that one can exceed the other always.
(3) The original EMD, however, had several outstanding problems because of lacking theoretical foundation. These problems include mode mixing, end effects, interpolation problems, stopping criterion, and best IMF selection, etc. Such drawbacks would result in meaningless or undesired IMFs generated by EMD, which could reduce the accuracy of fault diagnosis and even mislead diagnosis decision making. To overcome the shortcomings of EMD, various improved EMD methods like EEMD have been developed and they offer great improvement over the original EMD in fault diagnosis of rotating machinery.
(4) At the early introduction of EMD, researchers utilized EMD in fault diagnosis individually and without combining with other methods. But currently, the combination of EMD with other techniques has attracted more attentions from researchers. For example, EMD has been combined with other signal processing techniques or artificial intelligent methods for feature extraction and fault identification. The application results show that better performance has been achieved by the combination strategy.
(5) Although excellent performance of both EMD and its improved methods in fault diagnosis has been demonstrated in many papers, there are still some unsettled problems at present. Taking EEMD as example, EEMD loses the self-adaptive merit compared with EMD although it can reduce the mode mixing problem. That is to say, how to adaptively select the amplitude of the added noise and determine the number of ensemble in EEMD is still an open issue, as they directly affect the decomposition effectiveness.

5. Prospects of EMD in fault diagnosis

(1) As discussed in the previous section, researchers have widely used EMD to detect and diagnose faults of bearings, gears and rotors in rotating machinery. However, one thing that we must keep in mind is that investigation on fault mechanism and dynamic response characteristics of rotating machinery is of primary importance. Therefore, EMD could be applied to fault diagnosis properly instead of blindly only if we thoroughly understand both the fault mechanism and the advantages of EMD in diagnosing such kind of fault.
(2) It is evident that the applications of EMD in fault diagnosis of rotating machinery have demonstrated the merits of EMD and the weaknesses as well. However, most of the demonstrations are based on simulated signals or lab experimental signals under research environments. How the existing methods based on EMD perform for real-world signals is also an interesting question. Considering many open problems associated with EMD, the efforts to further explore EMD methods should be encouraged to develop robust and practical fault diagnosis methods.

(3) The core of the algorithms of EMD and its improved methods is based on an iterative process including the operations of interpolation and sifting etc. Correspondingly, these algorithms are time-consuming. Thus, to develop fast online fault diagnosis algorithms based on EMD may require more attentions in future research.

6. Concluding remarks

In this paper, we have attempted to provide a review of applying EMD to fault diagnosis of rotating machinery. In the review, all reported applications of EMD in fault diagnosis are divided into a few main aspects based on the key components of rotating machinery, namely, rolling element bearings, gears and rotors. For each component, the review is accomplished following diagnosis methodologies including the original EMD method, improved EMD methods, EMD combined with other techniques, etc. Research on other diagnosis objects is surveyed as well. In addition, open problems of EMD in fault diagnosis of rotating machinery are pointed out and possible future trends are discussed. We hope that this review has synthesized individual pieces of information on the use of EMD in rotating machinery fault diagnosis and would give comprehensive references for researchers in this field.

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