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Review of local mean decomposition and its application in fault diagnosis of rotating machinery

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Abstract: Rotating machinery is widely used in the industry. They are vulnerable to many kinds of damages especially for those working under tough and time-varying operation conditions. Early detection of these damages is important, otherwise, they may lead to large economic loss even a catastrophe. Many signal processing methods have been developed for fault diagnosis of the rotating machinery. Local mean decomposition (LMD) is an adaptive mode decomposition method that can decompose a complicated signal into a series of mono-components, namely product functions (PFs). In recent years, many researchers have adopted LMD in fault detection and diagnosis of rotating machines. We give a comprehensive review of LMD in fault detection and diagnosis of rotating machines. First, the LMD is described. The advantages, disadvantages and some improved LMD methods are presented. Then, a comprehensive review on applications of LMD in fault diagnosis of the rotating machinery is given. The review is divided into four parts: fault diagnosis of gears, fault diagnosis of rotors, fault diagnosis of bearings, and other LMD applications. In each of these four parts, a review is given to applications applying the LMD, improved LMD, and LMD-based combination methods, respectively. We give a summary of this review and some future potential topics at the end.

Keywords: local mean decomposition (LMD), signal processing, gear, rotor, bearing.

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1. Introduction

Rotating machines are widely utilized in civilian, industrial and military applications. They are vulnerable to many kinds of damages especially for those working under tough and time-varying operation conditions. Early detection of these damages is important, otherwise, they may lead to large economic loss even a catastrophe [1 – 9]. Therefore, the development of effective fault diagnosis techniques is essential for safety and better maintenance decision making in applications using rotating machinery [10 – 12].

The signals collected from rotating machines are very complicated. They contain not only the frequency components from the interested rotating machine component but also interference frequencies from other neighbouring components, and environment noises. It is also common to have the phenomenon of amplitude modulation, frequency modulation and phase modulation in these signals. In addition, rotating machines often work under time-varying speed and load conditions, which causes the signals collected from them non-stationary [13 – 16]. If a fault occurs in a rotating machine, the fault signature is hard to be identified due to the above-mentioned interferences.

Many signal processing methods have been developed for the rotating machinery based on the theory of basis function expansion, such as fast Fourier transform, short-time Fourier transform, and wavelet transform (WT) [17 – 22]. Fourier series expansion lays a foundation for fast Fourier transform and short-time Fourier transform. Wavelet basis expansion is the core of the wavelet transform. These basis function expansion based methods have many merits, such as simplicity, uniqueness and symmetry, but they also suffer from inflexibility and lack degree of freedom [23]. Prior knowledge or analysis on signals is required to identify a proper basis function and the expansion coefficients. These types of methods do not work very well for non-stationary complicated signals collected from the rotating machinery.

Adaptive mode decomposition methods are effective in dealing with non-stationary signals. It does not require much prior knowledge about the signals to use these methods. They can capture the local properties of a signal such

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as fault symptoms very effectively. Lei et al. [24] gave a very detailed review on empirical mode decomposition (EMD) and its applications in fault diagnosis of rotating machinery. Feng et al. [25] reviewed almost all the adaptive mode decomposition methods, such as EMD, local mean decomposition (LMD), intrinsic time-scale decomposition, local characteristic scale decomposition, Hilbert vibration decomposition, empirical wavelet transform, variational mode decomposition, nonlinear mode decomposition, and adaptive local iterative filtering. LMD was briefly reviewed in [25,26], but it is not thorough especially in the area of fault diagnosis of rotating machines. Only about 10 papers related to LMD were covered in [25] and four papers related to LMD were covered in [26]. Here, we will give a comprehensive review on the LMD and its applications of LMD in fault detection and diagnosis of rotating machinery machines and their components. Some examples are illustrated for better understanding.

With LMD, a complicated signal can be decomposed into many mono-components, namely product functions (PFs). The PF is a product of a frequency modulated signal and an envelope signal. The main idea of LMD is to progressively smooth a signal by using moving averages. Through LMD, the instantaneous frequency (IF) of each PF can be obtained. It does not need the Hilbert transform (HT) as EMD does. The IF is a key parameter to describe the physical nature of each mono-component (i.e., PF).

The application of LMD has been quite wide, e.g., in biology [27], medicine treatments [28] and engineering [29]. We will give a comprehensive review of the LMD-based methods focusing on its applications in gears, rotors, bearings and others. For each category, a review will be given on the applications by using LMD, improved LMD methods, and LMD-based combination methods, respectively.

There are three reasons for such a review. First, LMD is a powerful adaptive mode decomposition method, which has been widely used in the fault diagnosis of the rotating machinery. In addition, many improvements have been made on the LMD method for better decomposition performance. However, a comprehensive review of LMD does not exist. Therefore, it is necessary to give a comprehensive review of LMD and its applications in fault diagnosis of rotating machinery in this paper. The literature review will facilitate other researchers especially new researchers to properly use or further improve the LMD based fault diagnosis methods. Second, a thorough literature review is conducted for gears, bearings, rotors and other rotating machinery, respectively. For each of them, the references are divided into three categories to facilitate the readers: applications using LMD, applications using improved LMD methods, and applications using LMD-based combination methods. For the researchers who work on the condition monitoring of the rotating machinery, they can easily find the research state-of-art in using the LMD and its variants. Our work will help them and save their time to find proper methods for their specific applications. Third, although many improvements have been made on LMD, there are still some issues which should be studied in-depth. The authors have been improving the LMD for many years. The insights and experiences shared in this paper will benefit other researchers to further improve the LMD method.

2. LMD

2.1 Description of LMD

The LMD is proposed to estimate the IF and instantaneous amplitude (IA) of a signal [4]. LMD can decompose a multi-component signal into a series of PFs and a residue. Each PF is a mono-component which is, in essence, the product of an envelope signal and a frequency modulated signal. Based on the definition of the PF, a two-lever circulation algorithm is used to complete the decomposition. First, a rigorous calculation of the PF is completed through the inner cycle. Second, the decomposition of the signal based on the iterations is performed in the outer cycle. Given any signal $x(t)$, eight steps are required to implement the LMD method.

Step 1 Find out all local extrema n_i of the original signal $x(t)$. Calculate the local mean value m_i and local envelope estimate a_i of two successive extrema n_i and n_{i+1} by using (1) and (2), respectively.

$$m_i = \frac{n_{i+1} + n_i}{2} \tag{1}$$

$$a_i = \frac{|n_{i+1} - n_i|}{2} \tag{2}$$

Step 2 Connect all the local mean values m_i and local envelope estimate a_i by using straight lines.

Step 3 Construct the local mean function $m_{11}(t)$ and the amplitude function $a_{11}(t)$ by smoothing the local mean and envelope estimate via the moving averaging method.

Step 4 Subtract the local mean function $m_{11}(t)$ from the original signal $x(t)$ to obtain a residue signal $h_{11}(t)$.

$$h_{11}(t) = x(t) - m_{11}(t) \tag{3}$$

Then, a frequency modulated signal $s_{11}(t)$ can be obtained as

$$s_{11}(t) = \frac{h_{11}(t)}{a_{11}(t)}. \tag{4}$$

Step 5 Repeat Steps 1 – 3 to get the envelope estimate $a_{12}(t)$ of $s_{11}(t)$. If the envelope function $a_{12}(t) = 1$, stop the procedure and take $s_{12}(t)$ as the first purely frequency modulated (FM) signal. Otherwise, let $s_{11}(t)$ be the original signal and repeat Steps 1 – 4 n times until the envelope function $a_{1(n+1)}(t)$ of $s_{1n}(t)$ satisfies $a_{1(n+1)}(t) = 1$. The first iterative process can be expressed as follows:

$$\begin{cases} h_{11}(t) = x(t) - m_{11}(t) \\ h_{12}(t) = s_{11}(t) - m_{12}(t) \\ \qquad \vdots \\ h_{1n}(t) = s_{1(n-1)}(t) - m_{1n}(t) \end{cases} \tag{5}$$

where

$$\begin{cases} s_{11}(t) = \dfrac{h_{11}(t)}{a_{11}(t)} \\ s_{12}(t) = \dfrac{h_{12}(t)}{a_{12}(t)} \\ \qquad \vdots \\ s_{1n}(t) = \dfrac{h_{1n}(t)}{a_{1n}(t)} \end{cases}. \tag{6}$$

Step 6 Calculate the corresponding instantaneous amplitude of the product function as

$$a_1(t) = a_{11}(t)a_{12}(t)\dots a_{1n}(t) = \prod_{q=1}^{n} a_{1q}(t). \tag{7}$$

Step 7 Construct the first product function $\mathrm{PF}_1(t)$ using

$$\mathrm{PF}_1(t) = a_1(t)s_{1n}(t). \tag{8}$$

In theory, $\mathrm{PF}_1(t)$ contains the most oscillation information of the signal $x(t)$. The IA of $\mathrm{PF}_1(t)$ is $a_1(t)$ and the IF can be calculated as follows:

$$f_1(t) = \frac{1}{2\pi}\frac{\mathrm{d}[\arccos(s_{1n}(t))]}{\mathrm{d}t}. \tag{9}$$

Step 8 Compute the residue signal $u_1(t)$. Regard $u_1(t)$ as a new signal and repeat the above procedure k times until $u_k(t)$ does not contain oscillation. The second iterative process can be expressed as follows:

$$\begin{cases} u_1(t) = x(t) - \mathrm{PF}_1(t) \\ \qquad \vdots \\ u_k(t) = u_{k-1}(t) - \mathrm{PF}_k(t) \end{cases}. \tag{10}$$

Correspondingly, the original signal can also be reconstructed using

$$x(t) = \sum_{p=1}^{k} \mathrm{PF}_k(t) + u_k(t) \tag{11}$$

where $u_k(t)$ is the residue signal and k is the number of PFs.

A flowchart of the LMD method is presented in Fig. 1 for better understanding.

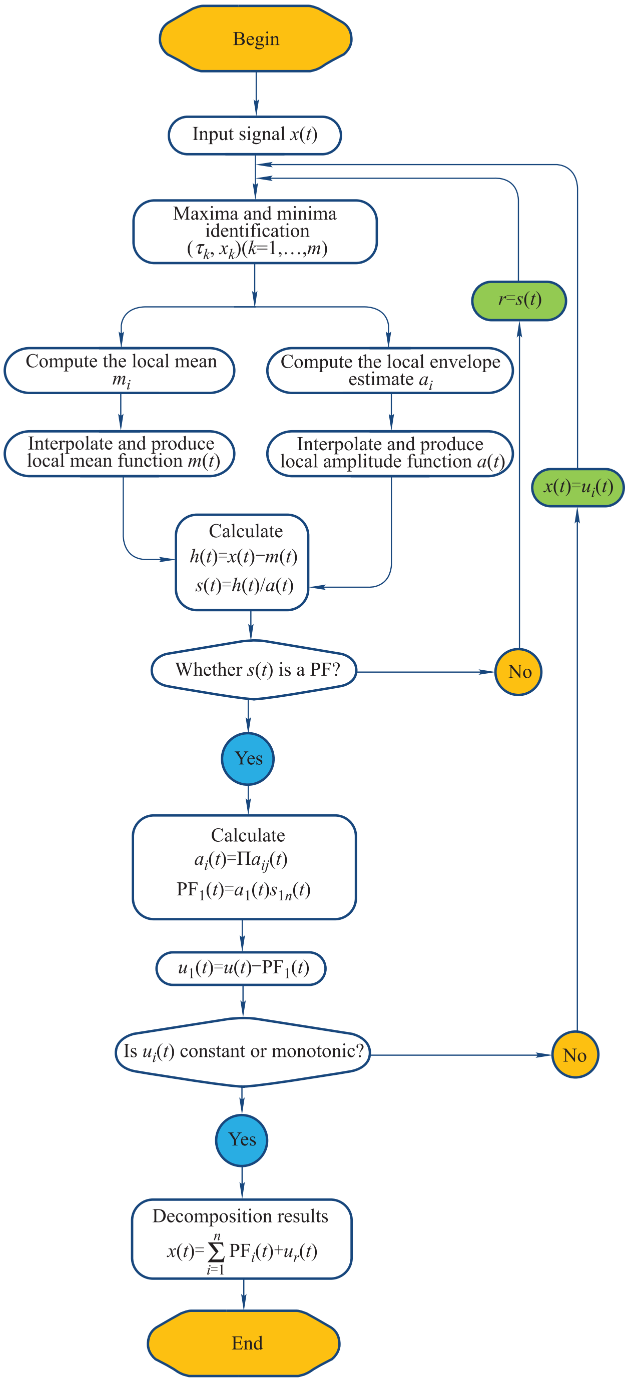


Fig. 1 Flowchart of LMD

Next, we use a synthetic signal $x(t)$ as expressed in (12) to illustrate the performance of the LMD method. The time duration of the signal is 1 s with sampling frequency 1 000 Hz.

$$\begin{cases} x = x_1(t) + x_2(t) \\ x_1(t) = (1 + 0.5\cos(2\pi f_{\mathrm{AM}_1} t))\cdot \\ \qquad \cos(2\pi f_{\mathrm{PM}_1} t)) + 1.5\cos(20\pi t) \\ x_2(t) = (1.5 + 0.5\cos(2\pi f_{\mathrm{AM}_2} t))\cos(60\pi t) \end{cases} \tag{12}$$

The simulation signal consists of two mono-component signals $x_1(t)$ and $x_2(t)$.

$x_1(t)$ is an amplitude modulated (AM)-FM signal with modulation frequencies $f_{\mathrm{AM}_1} = 7$ Hz and $f_{\mathrm{FM}_1} = 100$ Hz. $x_2(t)$ is an AM signal with a modulation frequency $f_{\mathrm{AM}_2} = 0.5$ Hz. Fig. 2 shows the time domain waveforms of $x(t)$, $x_1(t)$ and $x_2(t)$, respectively.

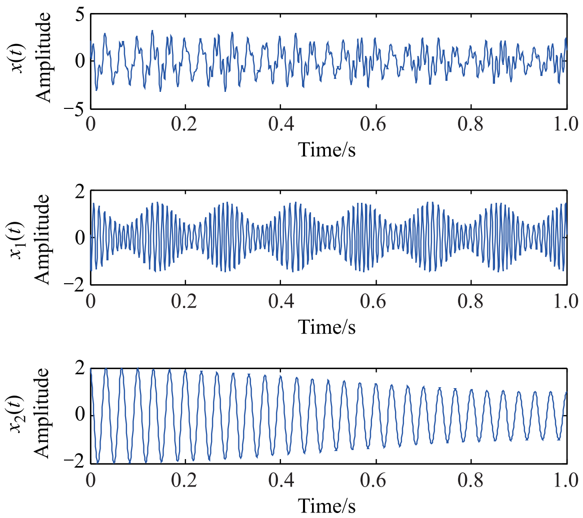


Fig. 2 Time domain waveforms of $x(t)$, $x_1(t)$ and $x_2(t)$

We then apply the LMD to decompose the simulation signal $x(t)$. The decomposition results are presented in Fig. 3. Two PFs and a residue signal $u_r(t)$ are generated. $\mathrm{PF}_1(t)$ is an AM-FM component corresponding to $x_1(t)$ and PF_2 is an AM component corresponding to $x_2(t)$. $\mathrm{PF}_1(t)$ and $\mathrm{PF}_2(t)$ match well with $x_1(t)$ and $x_2(t)$, respectively. The residue signal $u_r(t)$ contains two unexpected peaks, which demonstrates that the demodulation is not perfect. We will give more explanation about the shortcomings of LMD in Section 2.2.

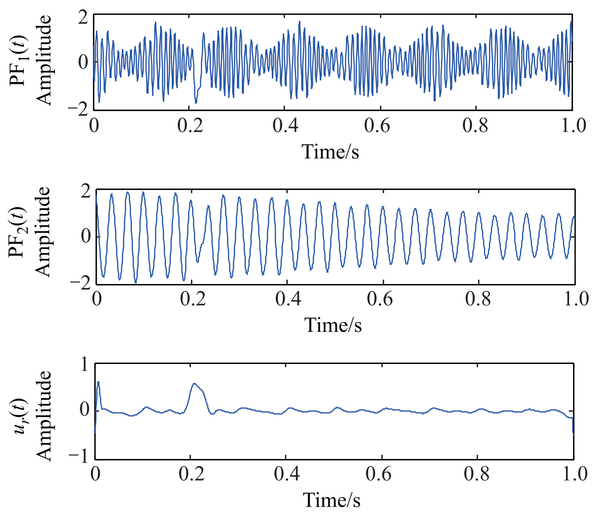


Fig. 3 Demodulation of $x_1(t)$ using LMD

2.2 Drawbacks of LMD

LMD shows good ability in demodulating amplitude and frequency modulated signals. However, it is not perfect. It has shortcomings, e.g., end effects and mode mixing. For better understanding, the decomposition results in Fig. 3 are utilized to illustrate the end effect and mode mixing problems. Fig. 4 shows $\mathrm{PF}_1(t)$ and its corresponding real AM-FM signal $x_1(t)$. We can observe distortions in the two ends of $\mathrm{PF}_1(t)$. This phenomenon is called the end effect of LMD. In addition, we can see another distortion at around 0.2 s. This is called mode mixing of LMD. These phenomena are also common in EMD [24]. Fig. 5(a) gives the time-frequency distribution (TFD) of $\mathrm{PF}_1(t)$ and $\mathrm{PF}_2(t)$ generated by LMD and Fig. 5(b) presents the TFD of the real signal $x(t)$. The time-frequency of $\mathrm{PF}_2(t)$ has a fine time-frequency resolution and its instantaneous frequency is almost a constant at 30 Hz. However, the time-frequency of $\mathrm{PF}_1(t)$ occurs severe frequency distortion especially at around 0.2 s due to the mode mixing between $\mathrm{PF}_1(t)$ and $\mathrm{PF}_2(t)$.

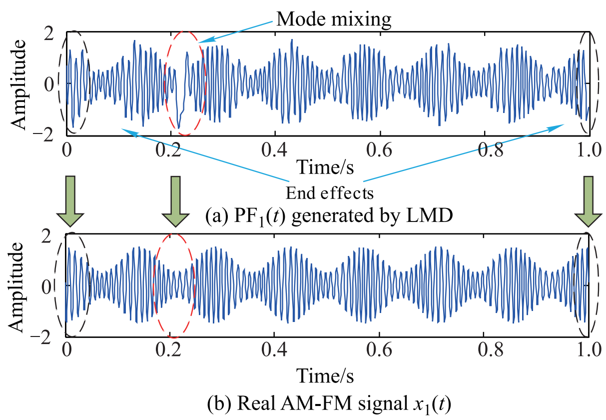


Fig. 4 Illustration of mode mixing and end effects

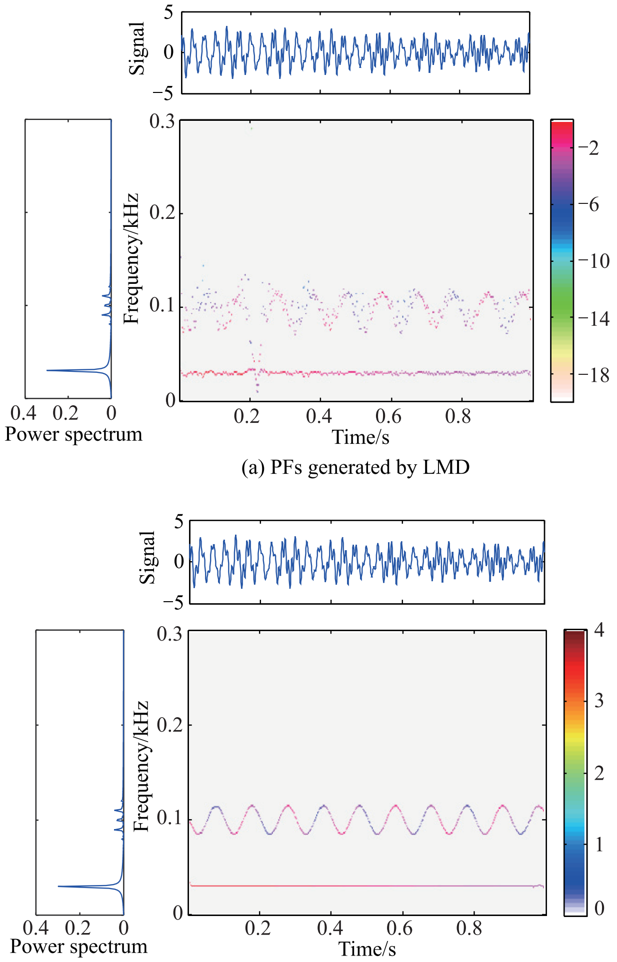
To quantitatively measure the decomposition performance of LMD, root means square error (RMSE), orthogonal index (OI) [30,31] and energy loss are taken as measure indicators. The definition of RMSE and OI are expressed in (13) and (14), respectively.

$$\mathrm{RMSE} = \sqrt{E(s(t) - c(t))^2} \tag{13}$$

where $s(t)$ and $c(t)$ stand for the original signal component and the decomposed signal corresponding to $s(t)$, respectively.

$$\mathrm{OI} = \frac{\sum\limits_{i=1}^{N_{\mathrm{PF}}} \sum\limits_{j=1}^{j<i} \left| \sum\limits_{k=1}^{N} \mathrm{PF}_{ik} \times \mathrm{PF}_{jk} \right|}{\sum\limits_{k=1}^{N} (x_k - u_k)^2} \tag{14}$$

where N_{PF} is the number of PFs, N denotes the length of a PF, x_k represents the original signal, u_k stands for the residue after the LMD decomposition, $\mathrm{PF}_{ik}(t)$ and $\mathrm{PF}_{jk}(t)$ are the ith and jth PF at sifting step k, respectively.



(b) Real signal $x(t)$

Fig. 5 Time-frequency spectrum

Table 1 gives the test results by using the above-mentioned measure indicators. Note that the values of the three parameters should be the smaller the better (they should be zero if the decomposition is perfect). From Table 1, we observe that the RMSE values of $\mathrm{PF}_1(t)$ and $\mathrm{PF}_2(t)$ are 0.172 7 and 0.140 5, respectively. It indicates that there is some degree of distortion occurring in $\mathrm{PF}_1(t)$ and $\mathrm{PF}_2(t)$. The OI values of $\mathrm{PF}_1(t)$ and $\mathrm{PF}_2(t)$ are not zero, which means that the two PFs are not orthogonal with each other. The total energy loss is 191.8 (the energy of the original signal is 1 747.7 and the energy of the decomposed signals is 1 555.9), which implies that the energy will decrease after the LMD decomposition.

Table 1 Performance evaluation of LMD method by using three indicators

RMSE		OI	Energy loss
PF1	PF2		
0.172 7	0.140 5	0.064 3	LMD method

It should be noted that the sifting stopping criterion of LMD in Step 5 is hard to be determined in practice. Therefore, a variation δ is usually given in advance such as $1-\delta \leqslant a_{1(n+1)}(t) \leqslant 1+\delta$ and $-1 \leqslant s_{1n}(t) \leqslant 1$. In the example illustrations of this paper, we set the variation $\delta = 10^{-5}$.

2.3 Improved LMD methods

Since LMD has the drawbacks as mentioned above, many studies have been done to improve the performance of LMD.

Liu et al. [32,33] developed a soft sifting stopping criterion that enables LMD to achieve a self-adaptive stop for each sifting process. The proposed soft sifting stopping criterion is effective for improving the decomposition accuracy of LMD. Guo et al. [34] developed a novel signal waveform extension method to eliminate the end effects of LMD. Liu et al. [35] proposed the integral extension LMD (IELMD) to suppress the end effects of LMD. Zhao et al. [36] combined support vector regression (SVR) with LMD to achieve endpoint continuation of the decomposed signals, which reduces the end effects of LMD.

Li et al. [37] developed an improved LMD method called differential rational spline-based LMD to alleviate the mode mixing of LMD. Yang et al. [38] presented the ensemble LMD (ELMD) to reduce the mode mixing of LMD. Deng [39] used cubic spline interpolation in LMD to obtain the local mean function and envelope estimation function for better extremum interpolation. Wang et al. [40] adopted the cubic B-spline interpolation to generate the envelope estimation function and demonstrated its effectiveness by using experimental signals. Zhang and Liu [41] applied the Hermite interpolation to replace the moving average process in LMD and validated its advantage in bearing fault diagnosis.

We can see many methods have been developed to improve the performance of LMD. We will not be able to give details on all the methods. We select two prospective methods, namely ELMD method and spline-based LMD to illustrate their advantages compared with the original LMD.

2.3.1 ELMD

As we know, LMD can decompose a signal into many PFs. The IFs of each PF are significant in fault diagnosis of rotating machines. Unfortunately, the mode mixing leads to the IFs loss of physical meaning, which causes the bad performance of LMD in real applications. Targeting at addressing this shortcoming, Yang et al. [38] obtained the filter bank structure of the white noise by numerical experiments and then developed the ELMD. ELMD has been widely used in many applications [38,42–44]. ELMD can reduce the mode mixing to be some extent and enhance the decomposition accuracy of the LMD method.

The filter bank structure of the white noise is represented by a high-pass filter and a series of band-pass filters in the frequency domain. When a signal is added by the white noise and then decomposed by LMD, all scales of the signal would be automatically decomposed into the corresponding frequency bands of the filter bank determined by the white noise. Consequently, the phenomenon of mode-mixing can be avoided to some extent [11]. Detailed steps of implementing the ELMD are summarized and a flowchart of ELMD is given in Fig. 6 for better understanding.

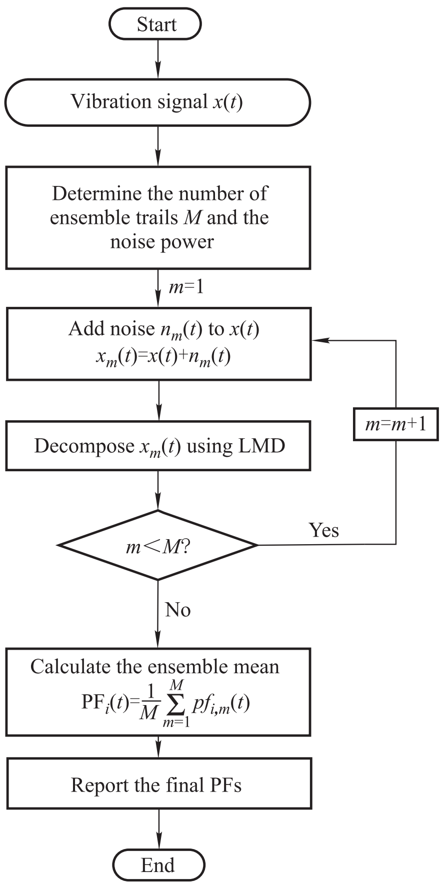


Fig. 6 Flowchart of the ELMD method

Step 1 Determine the power of the added noises and the number of ensembles M.

Step 2 Add the mth trial of the white noise $n_m(t)$ to the original signal to generate the mth new noise-added signal $x_m(t)$, $x_m(t) = x(t) + n_m(t)$.

Step 3 Decompose the noise-added signal $x_m(t)$ by using LMD to obtain I_{PFs} where I is the number of PFs.

Step 4 Repeat the above Step 2 and Step 3 M times to generate M sets of PFs.

Step 5 Compute the ensemble mean of the M trails for each PF as $\mathrm{PF}_i(t) = \dfrac{1}{M}\sum\limits_{m=1}^{M} pf_{i,m}(t)$, where $\mathrm{PF}_{i,m}(t)$ represents the ith $(i = 1, 2, 3, \ldots, I)$ PF of the mth $(m = 1, 2, 3, \ldots, M)$ trial.

Step 6 Take the obtained mean of $I_{\mathrm{PF}_i(t)}$ $(i = 1, 2, 3, \ldots, I)$ as the final decomposition results.

To illustrate the advantages of ELMD, a synthetic signal $x(t)$ is used to compare the performance between LMD and ELMD. The synthetic signal $x(t)$ consists of three signals $x_1(t)$, $x_2(t)$ and $x_3(t)$. $x_1(t)$ represents a high-frequency cosine signal with discontinuity. $x_2(t)$, $x_3(t)$ denote two cosine signals with different frequencies.

$$\begin{cases} x(t) = x_1(t) + x_2(t) + x_3(t) \\ x_1(t) = 0.1 \times \cos(2\pi \times 0.16t) \times u(t - 300) \\ x_2(t) = 0.2 \times \cos(2\pi \times 0.05t) \\ x_3(t) = \cos(2\pi \times 0.005t) \end{cases} \tag{15}$$

where $u(t)$ is a step signal.

Fig. 7 gives the time domain signals of $x(t)$, $x_1(t)$, $x_2(t)$ and $x_3(t)$, respectively. LMD and ELMD are utilized to decompose $x(t)$, respectively. The decomposition results are illustrated in Fig. 8 and Fig. 9, respectively. In the plots, the $\mathrm{PF}_1(t)$, $\mathrm{PF}_2(t)$ and $\mathrm{PF}_3(t)$ correspond to $x_1(t)$, $x_2(t)$ and $x_3(t)$, respectively.

It can be seen from Fig. 8 that the PFs generated by the LMD are anamorphic with severe mode mixing. By contrast, the PFs generated by the ELMD match well with the original signals with slight scale-mixing as shown in Fig. 9. The comparison illustrates that ELMD can alleviate the mode mixing and obtain more accurate decomposition results. This is because the added noises help LMD improve its filtering property [44].

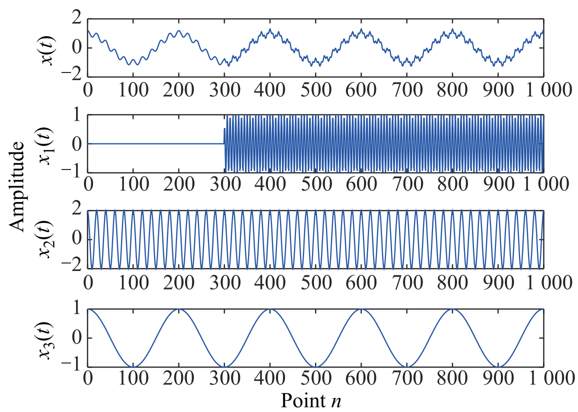


Fig. 7 Time domain of waveforms of $x(t)$, $x_1(t)$, $x_2(t)$ and $x_3(t)$

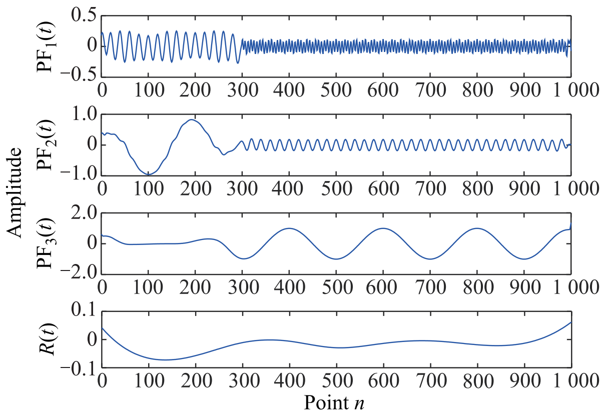


Fig. 8 Decomposition of $x(t)$ using LMD

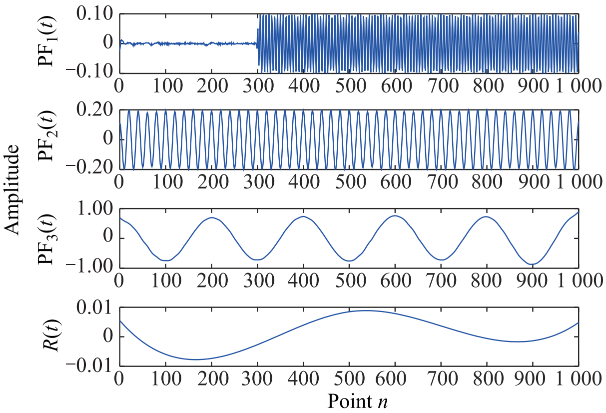


Fig. 9 Decomposition of $x(t)$ using ELMD

2.3.2 Spline-based local mean decomposition

LMD uses extrema to generate the local mean and envelope, then applies the moving average to smooth the local mean function and envelope estimation function. To decrease errors induced in the smoothing process, spline-based LMD is developed to generate the local mean function and envelope estimation function [39]. The upper envelope and the lower envelope are obtained by connecting the local maxima and local minima using cubic spline curves, respectively. The local mean is defined as the mean of the upper envelope and the lower envelope.

In the spline-based LMD, the upper and lower envelope functions at the ith section of the arbitrary adjacent extreme points are represented by $env_i^{\max}(t)$ and $env_i^{\min}(t)$, respectively. The spline-based LMD obtains the local mean function and the local envelope function using (16) and (17), respectively.

$$m_i(t) = \frac{env_i^{\max}(t) + env_i^{\min}(t)}{2} \tag{16}$$

$$a_i(t) = \frac{env_i^{\max}(t) - env_i^{\min}(t)}{2} \tag{17}$$

where $m_i(t)$ and $a_i(t)$ are the local mean function and local envelope function for the ith section of the arbitrary adjacent extreme points, respectively.

Compared with LMD, spline-based LMD can generate more accurate decomposition results with less computational time [39]. Inspired by the spline-based LMD, other interpolation methods such as B-spline [40], rational spline interpolation [45], cubic Hermite interpolation [46], rational Hermite interpolation [47], cubic trigonometric Hermite interpolation [48] and monotonic piecewise cubic Hermite interpolation [49], are also used in LMD for better decomposition performance.

3. Applications of LMD in fault diagnosis of rotating machinery

The applications of LMD in fault diagnosis of rotating machines and components such as gears, rotors, and bearings are mainly reviewed. Some common applications in other fields are also reviewed.

3.1 Fault diagnosis of gears

The section is divided into three categories as follows: applications using LMD, applications using improved LMD methods, and applications using LMD-based combination methods.

3.1.1 Applications using LMD

Chen et al. [50] utilized LMD to analyze vibration signals of gearboxes and successfully identified their fault frequencies. Chen et al. [51] adopted LMD to generate the time-frequency representation (TFR) of gearbox vibration signals for fault diagnosis. Wang et al. [52] applied the instantaneous time-frequency spectrum (ITFS) based LMD to detect the damages on a low-speed helical gearbox. Cheng et al. [53] compared LMD with EMD and demonstrated that LMD had better feature extraction ability for amplitude and frequency modulated signals. Li [54] conducted an envelope spectrum analysis of selected PFs and experimentally demonstrated its effectiveness in fault diagnosis of gear wear. Pan et al. [55] applied envelope spectrum based LMD to identify localized gear damages.

3.1.2 Applications using improved LMD methods

Some improved LMD methods have been developed to obtain more accurate decomposition results for gear fault diagnosis. Zhou et al. [56] applied the cubic interpolation instead of moving average in LMD to improve the decomposition efficiency, and a mean generating function model was used to restrain the end effect. Their method was demonstrated to be effective in gear localized fault detection. Li et al. [47] developed an optimized LMD (OLMD) method based on a bandwidth selection criterion to select the suitable PF in the sifting process. Experimental results validated the effectiveness of OLMD in gear fault diagnosis. Wei et al. [57] presented a Hermite-based LMD method and proved its effectiveness in gear fault signature extraction. To alleviate the end effects of LMD, Guo et al. [34] introduced a waveform extension method to improve the decomposition accuracy of LMD and demonstrated effectiveness of their method in diagnosing gear wear faults. Liu et al. [33] developed a self-adaptive stopping criterion and demonstrated the effectiveness of their proposed method in gear fault diagnosis. Li et al. [37] proposed a differential rational spline-based LMD (DRS-LMD) method to alleviate the mode mixing and generate more accurate decomposition results. This method outperforms LMD in early fault detection of gears.

3.1.3 Applications using LMD-based combination methods

The combination of LMD with other signal processing methods or artificial intelligent techniques has been adopted by many researchers in gear fault diagnosis. Cheng et al. [58] combined order tracking with LMD to identify gear fault frequencies in the run-up and run-down operation conditions. Zheng et al. [59] combined LMD and generalized morphological fractal dimensions (GMFDs) to extract gear fault features and then applied kernel fuzzy c-means (KFCM) to fulfill gear fault diagnosis. Liu et al. [60] proposed a hybrid fault diagnosis method by using the second generation wavelet transform (SGWT) and LMD. The SGWT was applied to remove background noises and then LMD was employed to detect localized damage on a gear. Han et al. [61] incorporated LMD with sample entropy (SE) and time-frequency peak filtering (TFPF) in gear fault diagnosis and demonstrated that their method has better fault detection ability than the combination of wavelet and TFPF. Guo et al. [62] presented a gear fault diagnosis method by the combination of synchrosqueezing transform and LMD and demonstrated that the proposed combination method could improve the time-frequency representation of LMD. Wang et al. [63] applied LMD to obtain gear fault signatures after removing the strong noises by using the minimum entropy deconvolution (MED). Li et al. [64] applied LMD as a preprocessor to extract fault signatures from gear vibration signals, then back propagation (BP) neural network was utilized to identify different gear health conditions. Wan et al. [65] presented a fault diagnosis framework based on LMD and least squares support vector machine (LSSVM) to classify different gear fault types. Chen et al. [66] incorporated fuzzy entropy into LMD to extract gear fault features and then applied an adaptive neuro-fuzzy inference system (ANFIS) to identify gear fault types. Wei et al. [67] conducted fault pattern identification of gears by combining LMD, permutation entropy (PE) and extreme learning machine (ELM). Liu et al. [68] combined LMD and multi-class reproducing wavelet support vector machines (RWSVM) to classify health conditions of gears.

For convenience, a summary of the combination methods is given in Table 2 and Table 3. Table 2 summarizes the signal processing methods that are combined with LMD for gear fault diagnosis. Table 3 summarizes the classifiers that are combined with LMD for fault classification.

Table 2 Signal processing methods combined with LMD for gear fault diagnosis

Combination method	Reference
LMD + Morlet wavelets	[69]
Order tracking + LMD	[58]
LMD + Chirp-Z transform (CZT)	[70]
SGWD + LMD	[60]
LMD + SE + TFPF	[61]
LMD + Cyclostationary demodulation	[71]
LMD + Synchrosqueezing transform + TFR	[62]
MED+ LMD + Cyclic autocorrelation function demodulation	[63]
LMD + Kurtosis	[72]

Table 3 Classifiers combined with LMD for gear fault classification

Classifier	Feature extraction method
BP	LMD + Energy characteristic [64]
LSSVM	LMD + Energy characteristic [65]
KFCM	LMD + GMFDs + Mutual information entropy value [59]
ANFIS model	LMD + Fuzzy entropy [66]
ELM	LMD + PE [67]
RWSVM	LMD + Statistic features [68]

3.2 Fault diagnosis of gears

This section describes the applications of LMD in rotor fault diagnosis.

3.2.1 Applications using LMD

Wang et al. [73] applied LMD in fault diagnosis of a mill rubbing rotor and demonstrated its effectiveness for early fault detection. Ren et al. [74] utilized LMD to diagnose a rotor crack fault and demonstrated that LMD had better performance than EMD in terms of mitigating end effects. Xiang et al. [75] demonstrated the effectiveness of LMD in the diagnosis of turbine rotors with imbalance, oil whirl and rubbing faults, respectively.

3.2.2 Applications using improved LMD methods

Yang et al. [38] achieved fault diagnosis of a rotor system by using ELMD. A method of boundary process and a strategy for determining the step size of the moving average were presented to improve the LMD in [76]. The improved LMD method performed well in the detection of rub-impact faults of a rotor system and was demonstrated to be more powerful than LMD. Hu et al. [77] demonstrated that spline-based LMD outperformed LMD in fault detection of a rotor system. Deng et al. [39] incorporated the cubic B-spline interpolation into LMD to improve the decomposition efficiency, which was effective in detecting rotor misalignment faults.

3.2.3 Applications using LMD-based combination methods

Zhang et al. [78] combined LMD and pattern spectrum to extract the fault characteristics of a rotor system. Deng et al. [79] calculated the Teager energy kurtosis (TEK) of each PF derived from LMD and then utilized the obtained features to diagnose a rotor-bearing rig with rub-impact rotor faults. Xiang et al. [80] employed LMD and Wigner-Ville distribution to obtain the time-frequency representation and verified the effectiveness of their method in detecting rotor imbalance faults. Zhang et al. [81] combined wavelet packet decomposition, LMD and self-adaptive Wigner-Ville distribution to separate the aliasing modes while maintaining the natures and features of the original PF component, which was experimentally demonstrated to be effective in fault diagnosis of rotor systems.

Table 4 summarizes the reported studies of LMD-based combination methods for rotor fault diagnosis.

Table 4 LMD-based combination methods for rotor fault diagnosis

Combination method	Reference
LMD + Pattern spectrum	[78]
LMD + TEK	[79]
LMD + Self-adaptive Wigner-Ville distribution	[81]
LMD + Multi-Class RWSVM	[68]
LMD + AR + Neural network	[82]

3.3 Fault diagnosis of bearings

This section describes the applications of LMD in bearing fault diagnosis.

3.3.1 Applications using LMD

Liu et al. [83] performed envelope analysis on selected PFs obtained from LMD and demonstrated its effectiveness in wind turbine bearing fault diagnosis. Li et al. [84] applied LMD and envelope spectrum analysis on bearing vibration signals for fault detection. Wang et al. [85] utilized LMD to extract fault signatures of rolling bearings with outer race faults and experimentally demonstrated its effectiveness.

3.3.2 Applications using improved LMD methods

Wang et al. [86] developed the so-called complete ELMD with adaptive noise (CELMDAN) to eliminate residual noise and generate the same number of PFs at different trials. Their diagnosis results indicated that CELMDAN could extract more fault characteristic information of rolling bearings with less interference than ELMD. Deng et al. [39] used cubic spline interpolation to obtain the local mean function and envelope estimation function to improve calculation efficiency of LMD, which was effective in diagnosing a rotor-bearing system with rub-impact faults. Chen et al. [46] improved the calculation efficiency of LMD using monotone piecewise cubic Hermite interpolation (MPCHI) instead of cubic spline interpolation (CSI) to construct the envelope estimation function. This method is successful in fault diagnosis of reciprocating compressor bearings. Liu et al. [87] proposed a method called integral extension LMD (IELMD) to alleviate the end effects of LMD and demonstrated its effectiveness in analyzing ball bearing faults. Zhao et al. [88] put forward an improved LMD algorithm based on extracting the extrema of envelope curve to reduce the influence of high-frequency noise, and experimental results showed that it was effective and reliable in bearing fault diagnosis.

3.3.3 Applications using LMD-based combination methods

Xie et al. [89] combined LMD and Wigner-Ville spectrum entropy (WVSE) for rolling bearing fault diagnosis, and demonstrated that their method had good performance in fault pattern recognition. Yu et al. [90] incorporated multilayer hybrid denoising into LMD for signal denoising and demonstrated its effectiveness in weak fault feature extraction of rolling bearings. Yang et al. [91] proposed a fault diagnosis method based on the variable predictive model based class discriminate (VPMCD), order tracking and LMD, and then applied it in feature extraction of rolling bearings. Deng et al. [92] combined LMD and Fourier transform to obtain spectra features for bearing fault diagnosis. Hunglinh et al. [93] calculated the characteristic amplitude ratios of PFs as input indicators of support vector machine (SVM) to classify fault patterns of roller bearings. Liu et al. [94] introduced a feature extraction method by integrating LMD and the multi-scale entropy to discover effective features for fault diagnosis of bearings. Han et al. [95] combined LMD, sample entropy and energy ratio to extract features considered as inputs of the SVM for pattern identification. Tian et al. [96] combined LMD and singular value decomposition (SVD) to extract features from rolling bearing signals, and then utilized ELM to diagnose bearing faults. Zhao et al. [97] used Hermite LMD (HLMD) and multiscale fuzzy entropy (MFE) to extract effective features for bearing fault diagnosis. Cai et al. [98] combined LMD and Wigner higher moment spectrum (WHMS) to diagnose bearing faults and demonstrated that their method was more powerful than the Wigner-Ville spectrum analysis. Shi et al. [99] presented a novel feature extraction method based on LMD and PE. The features were used in the optimized K-means clustering algorithm to classify bearing fault types. Xu et al. [100] combined LMD and morphological filtering to extract bearing fault features and then used LSSVM to classify various bearing fault types. Gao et al. [101] combined LMD, multiscale permutation entropy (MPE) and hidden Markov model (HMM) for bearing fault diagnosis. In [39,102,103], LMD was employed to preprocess bearing vibration signals and generated effective features that were considered as inputs of SVM to classify bearing fault types.

For readers' convenience, Table 5 and Table 6 list the signal processing methods and classifiers, respectively, that are combined with LMD for bearing fault diagnosis.

Table 5 Signal processing methods combined with LMD for bearing fault diagnosis

Combination method	Reference
LMD + WVD + WVSE	[89]
LMD + Fourier transform	[92]
LMD + Correlation analysis + WHMS	[98]
LMD + HT + Teager energy operator (TEO) + Fourier transform	[104]
LMD + Ensemble empirical mode decomposition (EEMD) + Time-frequency analysis	[105]
LMD + Wavelet threshold denoising method + Kurtosis	[106]
LMD + SVD + Time frequency map + marginal spectrum	[107]

Table 6 Classifiers combined with LMD for bearing fault diagnosis

Classifier	Feature extraction method
VPMCD	LMD + Computed order tracking (COT) [91]
SVM	LMD + Fault characteristic amplitude ratios [93,108], LMD + Mutiscale sample entropy (MSE) [94], LMD + SE + energy ratio [95], HLMD + Adaptive mutiscale fuzzy entropy (AMFE) [102], HLMD + MFE [97]; LMD+ MPE + Laplacian score [103]; LMD + Morphological filtering [100], LMD + Autoregressive model [109], LMD + PCA [110], LMD + Energy entropy [111], LMD + Kernel principal component analysis [112]
ELM	LMD + SVD [96]
K-means clustering	LMD + PE [99]
HMM	LMD + Multiscale permutation entropy (MPE) [101]
MDTW	LMD + PE [113]
BP	LMD + Energy characteristics [114], LMD + Power spectrum [115]
FCM	ELMD + SVD [116]
Mahalanobis distance	LMD + Kullback-leibler divergence [117]
Neural network	ELMD + Energy characteristic [118]

3.4 Other LMD applications

Besides the applications of LMD in fault diagnosis of gears, rotors and bearings, there are many applications of LMD in other fields which will be reviewed in this section.

3.4.1 Applications using LMD

Smith [27] invented LMD and applied it to analyze a set of scalp electroencephalogram visual perception data. Lin et al. [119] employed LMD to examine the signals captured from an offshore platform for fault diagnosis.

3.4.2 Applications using improved LMD methods

Si et al. [48] proposed an improved LMD method based on the cubic trigonometric Hermite interpolation (CTHI) with shape parameters, and experiments demonstrate its effectiveness in identifying different cutting categories of a shearer. Zhao et al. [36] developed an improved LMD method to restrain the end effects of LMD and applied it to classify faults of a hoister. Zhao et al. [120] employed rational Hermite interpolation to generate the envelope-line and demonstrated the advantages of the improved LMD in fault diagnosis of reciprocating compressors. Zhao et al. [49] proposed a compound interpolation envelope LMD by using a novel envelope construction method called monotonic piecewise cubic Hermite interpolation. The effectiveness of their method is validated in the diagnosis of reciprocating compressor oversized bearing clearance fault.

3.4.3 Applications using LMD-based combination methods

Tang et al. [121] combined LMD and Lempel-Ziv complexity (LZC) to extract fault features of reciprocating compressor gas valves and verified the effectiveness of their method. Sun et al. [122] used the LMD and envelope spectrum entropy to extract fault features of a pipeline system and then classified various health conditions using SVM. Li et al. [123] combined cascaded bistable stochastic resonance (CBSR) with LMD to diagnose the reciprocating compressors. Jiang et al. [124] combined LMD with the improved adaptive multi-scale morphology analysis (IAMMA) to detect the damages on hydraulic pumps. Tian et al. [125] applied SVD to extract features from PFs, then used these features as inputs of SVM for fault identification of hydraulic pumps. Sun et al. [42] proposed a time-delay estimation algorithm based on ELMD and high-order ambiguity function (HAF) to locate natural gas pipeline leaks. Zhao et al. [97] combined LMD and MFE to extract fault features of reciprocating compressors and then achieved fault pattern identification. Wang et al. [126] introduced a novel intelligent method by combining LMD, PCA and SVM to detect leakage in natural gas pipelines. Huang et al. [127] calculated the time segmentation energy entropy (TSEE) of PFs and used them as inputs of the support vector data description (SVDD) to classify various fault types of high voltage circuit breakers. Sun et al. [128] adopted ELMD and sparse representation for fault classification of natural gas pipelines. Si et al. [129] proposed an intelligent method based on LMD, Laplacian score (LS) and fuzzy C-means (FCM) to recognize different cutting categories and working conditions of a shearer.

For convenience, Table 7 summarizes the signal processing methods that are combined with LMD for other applications. Table 8 summarizes the classifiers that are combined with LMD for other applications.

Table 7 Signal processing methods combined with LMD for other applications

Classifier	Application	Feature extraction method
FCM	High voltage circuit breakers	LMD+TSEE + SVDD [127]
	Shearer cutting	LMD + Time-frequency analysis + LS [129]
	Wind turbine	ELMD + Singular values [130]
ELM	Pipeline	LMD + Information entropy [131]
LR	Hydraulic pump	LMD + PCA [132]
SVM	Natural gas pipeline	LMD + Wavelet packet decomposition + Envelope spectrum entropy [122]
	Diesel engine	LMD + Fault characteristics [133]
	Analog circuit	LMD + Correlation analysis [134]
	Shearer cutting	LMD+ MFE [48]
	Hydraulic pump	LMD + SVD [125] LMD + Approximate entropy [135]
	Reciprocating compressor	LMD+MSE [136]
Sparse representation classifiers	Natural gas pipeline	ELMD + Kullback-Leibler divergence [128]
RWSVM	Natural gas pipeline	LMD + PCA [126]
BP	Reciprocating compressor gas valve	LMD + Lempel-Ziv complexity [121] LMD + Autoregressive-generalized autoregressive conditional heteroscedasticity model [137]
	Subway auxiliary inverter	LMD + Approximate entropy [138]
Classifier	Applications	Feature extraction method

Table 8 Other applications using LMD-based combination methods

Technique	Application	Reference
CBSR + LMD	Reciprocating compressor	[123]
LMD + IAMMA	Hydraulic pump	[124]
ELMD + Kullback-Leibler divergence + HAF	Natural gas pipeline	[42]
LMD+ Independent component analysis (ICA)	Biomedical source separation	[28]
LMD+Time-frequency entropy	DC traction power supply system	[139]
LMD+Detrended fluctuation analysis (DFA)	Ionospheric scintillation	[140]
WT+ LMD	Hydro turbine	[141]

4. Summary

There are many successful applications of the LMD in fault diagnosis of gears, bearings and rotors. A summary is given as follows.

(i) The applications of LMD and its variants are mainly performed for key components of the rotating machinery such as gears, rotors and bearings. This is because these components are critical components of a machine and the failure of these components will cause serious consequence on the whole machine.

(ii) LMD has shortcomings such as end effects, mode mixing, and difficulties to determine the sliding step size and the iteration stop criterion. Many improvements have been done by now. For example, ELMD is proposed for addressing mode mixing, spline-LMD is developed for sliding step selection, and an integral extension LMD is designed for solving end effects.

(iii) Some side effects may occur in the improved LMD methods, which should get users' special attention in applying these methods. For example, the rational spline function is used in RS-LMD to estimate the local mean function and envelope estimate function (moving average is used in the original LMD). This improvement can avoid the phase difference of PFs and step size selection, which makes the decomposition result more accurate and gives higher computation efficiency. However, RS-LMD has its new problems. For example, the selection of the tension parameter becomes more difficult. An unsuitable tension parameter may make the decomposition result of RS-LMD worse than that of the spline-based LMD method.

(iv) LMD-based combination methods perform well in detecting machine faults especially weak faults. In the beginning, LMD is not designed for fault diagnosis. Later, researchers introduce LMD for fault diagnosis by observing the time domain and frequency domain plots of each PF component. However, it is hard to find some mechanical faults, especially weak faults, by conducting time-frequency analysis on PF components. Some researchers start to combine LMD with other methods such as signal processing methods or machine learning methods. The LMD-based combination methods can not only diagnose more types of faults but also give more accurate results. However, the determination of many model parameters is hard and very often expert experiences are needed.

5. Prospects

LMD, proposed in 2005 by Smith, has been widely used in the fault diagnosis of the rotating machinery and many improvements have been made on LMD. However, there are still some issues we can work on to address.

(i) It is necessary to develop a multivariate LMD. As we know, multiple channels of data are often acquainted together. The dependence of these signals should be studied and the improved LMD should be able to deal with data from multiple channels, simultaneously.

(ii) Repeatability tests and tests on multiple machines are required to develop robust fault diagnosis methods. Many methods are tested to be effective on one set of data or one experimental test rig. Repeatability tests and tests on multiple machines are required for these methods to be used in real applications.

(iii) The efficiency should be further improved. Many methods are developed to improve the fault diagnosis performance at a cost of decreasing computational efficiency. It is important to improve the computational efficiency of LMD-based methods to satisfy online health monitoring requirements.

(iv) The sifting stop criterion of LMD has a strong effect on the orthogonality between PFs and their corresponding instantaneous frequencies. However, it is difficult to satisfy the theoretical condition $\lim\limits_{n\to\infty} a_{1n}(t) = 1$ in real applications. Further study about the sifting stop criterion is still required.

(v) Some outliers or wild points may be generated in the sifting process (for example, the interpolation during envelope estimations may generate outliers), which may lead to extremely bad decomposition results. This problem is often ignored by researchers. In our opinion, further studies should be conducted to avoid these outliers in the sifting process.

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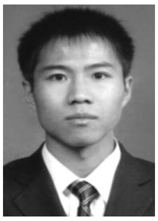

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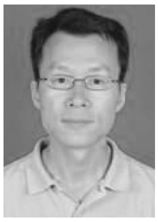

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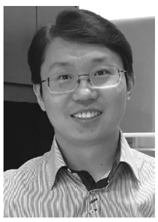

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