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A Fault Diagnosis Scheme of Gear Vibration Signal Based on Variational Mode Decomposition and Detrended Fluctuation Analysis

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Abstract: The vibration signal of heavy gearbox presents non-stationary and nonlinear characteristics, which increases the difficulty to extract the fault feature. When the gear has a subtle fault, it may cause a perceptible change of local fluctuation rather than the large scale fluctuation. Therefore, the feature parameters extracted from local fluctuation can effectively improve the recognition performance of the gear fault. In this paper, a novel signal processing method based on variational mode decomposition (VMD) and detrended fluctuation analysis (DFA) is proposed to identify the gear fault of heavy gearbox. Firstly, the raw vibration signal is decomposed several mode components by VMD, which is an adaptive and non-recursive signal decomposition method. Next, the sensitive mode component is selected by a maximal indicator, which is composed of kurtosis and correlation coefficient of relative higher frequency mode components corresponding to local fluctuation of raw vibration signal. Finally, the characteristics of the double-scales feature parameters of selected sensitive mode are extracted by DFA. In addition, the position of turning point of double scales is estimated by sliding windowing algorithm. The proposed method is evaluated through its application to gear fault classification using vibration signal. The results demonstrates that the recognization rate of gear faults condition have marked improvement by proposed method than the DFA of Small Time Scale (STS-DFA) method.

Keywords: Variational mode decomposition; Detrended fluctuation analysis; Heavy gearbox; Fault diagnosis

1 Introduction

Heavy gearboxes are widely used in manufacture, metallurgic, marine fields for their advantages of strong load-bearing capacity, compact structure and large transmission ratio. However, the harsh operating conditions, inevitable impact, and alternating load may cause many kinds of faults of parts in gearbox, such as shafts [1], gears and bearings [2]. The undetected failures may cause huge loss [2]. Therefore, the early fault diagnosis for gearbox is important to safer operation and higher cost reduction. The most common fault of gearbox is gear fault which usually is detected through the vibration signal. However, complicated structure of heavy gearbox, long transmission path and strong background noise usually lead to the vibration signal collected by sensor is nonlinear and non-stationary, which increases the difficulty of fault feature extraction from vibration signal. In order to solve abovementioned problems, many nonlinear and non-stationary signal analysis methods have been proposed in fault diagnosis.

One of widely used non-stationary methods is time-frequency analysis, which extracts information from the vibration signal as a function of time and frequency. It overcomes the problems encountered in frequency analysis when analyzing non-stationary events. Conventional time-frequency analysis includes Short-time Fourier transform (STFT) [3-4], Wigner-Ville distribution (WVD) [5], Wavelet Transform (WT) [6] and S-transform [7] and so on. However, the performance of STFT depends on the selection of window function, which is unsuitable for analyzing non-stationary signals. WVD suffers from cross-term interference. Although the Wavelet transform shows better performance in time-frequency analysis, it is derived from Fourier transform which can not precisely describe the following frequency with time changes. S-transform that takes the advantage of both STFT and WT is simpler in calculation than WT and easier to feature extraction [7]. Nevertheless, it is not locally adaptive as well. In order to overcome disadvantages of conventional time-frequency based method, more time-frequency analyses are developed for fault diagnosis. Huang et al. [8] proposed a recursive method termed Empirical Mode Decomposition (EMD), which adaptively decomposes the signal into a finite number of Intrinsic Mode Functions (IMFs) and a residue. However, EMD lacks the support of math theory and prone to suffer from mode mixing [5, 9]. A novel decomposition algorithm named Variational Mode Decomposition (VMD) proposed by Dragomiretsky and Zosso [10] is well adaptive to the nonlinear and non-stationary signal. VMD decomposes the signals into a series of principal mode, and each mode is constantly updated with Wiener filtering technique to minimize the constrained variational model. Therefore, central frequency of each mode will be gradually demodulated to the corresponding base band, which mitigates mode mixing [11]. By comparison analysis, it is concluded that VMD overcomes the disadvantage of lacking theoretical basis and noise sensitivity of EMD in analyzing non-stationary signals. Based on it, VMD has been widely applied into fault diagnosis [11-15]. Long et al. proposed a method combined VMD with WT [12] to reduce the strong noise in the raw signal successfully, and preserve the feature of raw signal effectively. An et al. [15] deems that the fault information in the vibration signal was concentrated within the high-frequency components and introduced variational mode decomposition and permutation entropy based method, which used VMD to extract the relative high-frequency mode components in raw vibration signal. Apart from time-frequency based approaches, a lot of feature extraction methods based on fractal theory are also developed and applied in fault diagnosis. The traditional fractal method, such as Rescaled-range analysis (R/S) and Fluctuation analysis (FA) [16], are statistical tools developed to evaluate the scaling exponent. Nevertheless, it is more suitable for stationary time series. More recently, a new random walk theory based generalized scale exponent calculation method named detrended fluctuation analysis (DFA) is introduced by Peng in 1992 [17]. DFA is extensively used to detect the long-range correlation and power law properties in non-stationary time series [18]. DFA is suitable for extraction of precise intrinsic statistical features from the time series by removing external polynomial trends of differential orders. Furthermore, it avoids the spurious detection of correlations which are artifacts of non-stationary time series [19]. Thus, it was applied into many fields, such as climate [20], heart rate dynamic [21-23], and mechanical engineering [24-32]. Chen claimed the valuable crossover properties of the scale exponents correspond to different time scales in double logarithmic chart [26]. Liu [27] claimed that DFA curves of rolling bearing’s vibration signals can be quantified by

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two scale exponents and the exponents in a small time scale which can be utilized to identify the faulty bearing conditions. Wu et al. [29] used the sliding windowing algorithm to find the turning point of bi-logarithmic map of DFA adaptively. Sridhar et al. [30] proposed a method combined Ensemble Empirical Mode Decomposition (EEMD) with DFA for signal enhancement. Although EEMD has some improvement in solving the disadvantage of EMD, it is still sensitive to the strong background noise. Liu et al [31] employed the VMD and DFA for signal denoising. In this method, the scale exponent extracted by DFA is used to evaluate the number of mode components of VMD, which (overbinning or underbinning) impact on the efficiency of the filtering. And then VMD is employed to decompose raw signals with given mode number. The filtering signal components were constructed by VMD and DFA, which suppress the interference of the noise based on Wiener filtering principle as well as parameter optimization. In this paper, DFA is used to extract fault feature rather than evaluate the number of mode components of VMD, and then the main purpose in our work is the fault characteristics extraction, which is different from previous research. Wang and Xiao et al. [32] proposed a method that combined the scale exponent with intercept of small time scale in double logarithmic map which derive from DFA to classify the fault pattern of gears. We term this method as Small time scale DFA (STS-DFA). STS-DFA shows better performance of fault pattern recognization because the fractal features of small time scale, which represents the local fluctuation as well as high-frequency component, show better performance [32]. However, the features of different fault patterns have partly overlap because the fluctuation corresponding to the large time scale may influence the feature extraction accuracy of local fluctuation corresponding to the small time scale.

Motivated by the previous work, since the feature vector of local fluctuation corresponding to high frequency component shows better performance for gear fault classification, a novel method of VMD incorporation with DFA are mainly applied in the fault feature extraction and fault classification in gearbox vibration signal. VMD is used to extract the high-frequency mode components and eliminate the influence of fluctuation corresponding to the large time scale. The DFA is used to extract the fractal feature vector of local fluctuation of signals.

The remainder of this paper is organized as follow, the principle of VMD and DFA is described section 2. In section 3, the details of the method VMD combined DFA is described. Section 4, experiments and results of the measured signal in gear equipment system are presented by using proposed method. Finally, conclusions and future directions are given in section 5.

2 Theory descriptions

2.1 Variational mode decomposition

The VMD includes three fundamental concepts of the Wiener filter, one-dimensional Hilbert transform, frequency mixing and heterodyne demodulation. The variational mode decomposition aims to decompose the original signal $x(t)$ into a number of mode u_k which have specific sparsity properties and finite bandwidth. Each u_k component obtained by VMD has band-limited and has a corresponding central frequency. So in order to obtain precise data of bandwidth, the following section need to be finished:

By using squared L_2-norm of the gradient, the bandwidth of each mode can be estimated. Then the constrained variational mode decomposed problems is obtained as following:

$$\min_{\{u_k\},\{\omega_k\}}\left\{\sum_k \left\|\partial_t\left[\left(\delta(t)+\frac{j}{\pi t}\right)*u_k(t)\right]e^{-j\omega_k t}\right\|\right\} \tag{1}$$

where $\{u_k\}:=\{u_1\cdots u_k\}$ and $\{\omega_k\}:=\{\omega_1\cdots\omega_k\}$ respectively represent the entire mode and all the central frequencies, k express the number of mode, δ is the Dirac distribution, t time script, and $*$ denotes convolution operator.

Due the constrained problems will impact the result of VMD, there are number of method which can solve reconstruct constrained question. The parameter a quadratic penalty term α and Lagrange multipliers λ are used to deal with constrained question, so that the unconstrained expression can be obtained as follow:

$$\mathrm{L}(\{u_k\},\{\omega_k\},\lambda):=\alpha\sum_{\mathrm{k}}\left\|\partial_t\left[\left(\delta(t)+\frac{j}{\pi t}\right)*u_k(t)\right]e^{-j\omega_k t}\right\|_2^2+\left\|f(t)-\sum_k u_k(t)\right\|_2^2+\langle\lambda(t),f(t)-u_k(t)\rangle \tag{2}$$

To solve this question which acquires saddle point of the Lagrange expression, the method of alternate direction multipliers by iteratively updating can be used to acquire minimized u_k and ω_k. The specific steps will be drawn as follow:

1). Initialize $\{\hat{u}_k^1\}$, $\{\omega_k^1\}$, λ^1, $n\leftarrow 0$.

2). Minimization with regard to u_k, ω_k, λ by updating.

$$\hat{u}_k^{n+1}(\omega)=\frac{\hat{f}(\omega)-\sum_{i\neq k}\hat{u}_i(\omega)+\left(\hat{\lambda}(\omega)/2\right)}{1+2\alpha(\omega-\omega_k)^2} \tag{3}$$

$$\omega_k^{n+1}=\frac{\int_0^\infty \omega|\hat{u}_k(\omega)|^2 d\omega}{\int_0^\infty|\hat{u}_k(\omega)|^2 d\omega} \tag{4}$$

$$\lambda^{n+1}=\lambda^n+\tau\left(f-\sum_k u_k^{n+1}\right) \tag{5}$$

3). Repeat iteratively update the procedure of the formulas (3)-(5) until values of three expression converges, which is aimed to satisfy the condition of $\sum_k\left\|\hat{u}_k^{n+1}-\hat{u}_k^n\right\|_2^2/\|\hat{u}_k^n\|_2^2<e$, where e is a given value.

2.2 Detrended fluctuation analysis

The detrended fluctuation analysis proposed by Peng et al. in 1992. It is suitable for nonlinear and non-stationary signal as well as eliminating spurious detection of long-range dependence in non-stationary. DFA is showed as follow by consisted of the three main steps:

1). Suppose $x(t)$ is time series of the length N, compute $x(t)$ with $\bar{x}$ by integration to obtain $M(n)$;

$$M(n)=\sum_{N=1}^{n}(x(t)-\bar{x})\qquad n=1,2,\cdots,N \tag{6}$$

where $\bar{x}$ is the average time series $x(t)$.

2). In order to acquire corresponding fluctuation function, the time series $x(t)$ is divided into number of $N_S \equiv (\frac{x(t)}{s})$ segments of equal length s. The length of the series can't be divide the length s into an integer, the series $x(t)$ is extended for opposite direction until the whole length of the series come to $2N$. Thereby, the $2N_S$ segments and each sub-time series corresponding least squares m order fits can be obtained:

$$M_k(n)=\sum_{j=0}^{m} \vartheta_j t^j \qquad (k=1,2,3,\cdots,2N_s) \tag{7}$$

where $M_k(n)$ is the trend of the k-th sub-time series, which is the fitting polynomial in this sub-time series. Linear, quadratic, cubic, or high-order polynomials can be used in the fitting procedure (usually called DFA1, DFA2, DFA3, etc.). ϑ_j is the coefficient of j-th order.

3). For each sub-time series, compute the fluctuation function:

$$F(s)=\sqrt{\frac{1}{2N_S}\sum_{k=1}^{2N_S}(M(n)\text{-}M_k(n))^2} \tag{8}$$

where

$$F(s,k)^2=\frac{1}{s}\sum_{i=1}^{s}\{M[(k\text{-}1)\,s+1]\text{-}M_k(n)\}^2 \qquad \text{if } k=1,2,\cdots,N_S \tag{9}$$

$$F(s,k)^2=\frac{1}{s}\sum_{i=1}^{s}\{M[N\text{-}(k\text{-}N_S)\,s+i]\text{-}\mathrm{M_k(n)}\}^2 \qquad \text{if } k=N_S+1,\cdots,2N_S \tag{10}$$

where $M_k(n)$ is linear regression of the segments length s. $F(s)$ is the fluctuation trend function.

4). By repeating the procedure 1 to 2 for each segments length s, if the time series is long-range power-law correlated which can be indicated as:

$$F(s)\sim s^{\alpha} \tag{11}$$

$$F(s)=As^{\alpha} \tag{12}$$

where α is named as the general Scale exponent. It can be calculated by taking logarithm of both sides of (12),

$$log(F(s)) = log\,A + \alpha\, log\, s \tag{13}$$

and the scale exponent α and the intercept $log\,A$ are used as feature vector for time series.

The scale exponent α is a parameter of autocorrelation attributes of the time series which characterizes long-range power-law correlation properties. Theoretically, the value of scale exponent α is described as five stages, which also represent difference correlation of time series. When scale exponent α equal to 0.5, 1, and 1.5, it reflects to the characteristics of the time series which is uncorrelated signal or white noise, 1/f noise, and Brownian motion, respectively.

When $0<\alpha<0.5$ the time series in this scale interval presents an anti-persistent long memory characteristics (negative correlations). When $0.5 < \alpha < 1$, it shows sustained long memory characteristic in this scale interval (positive correlations).

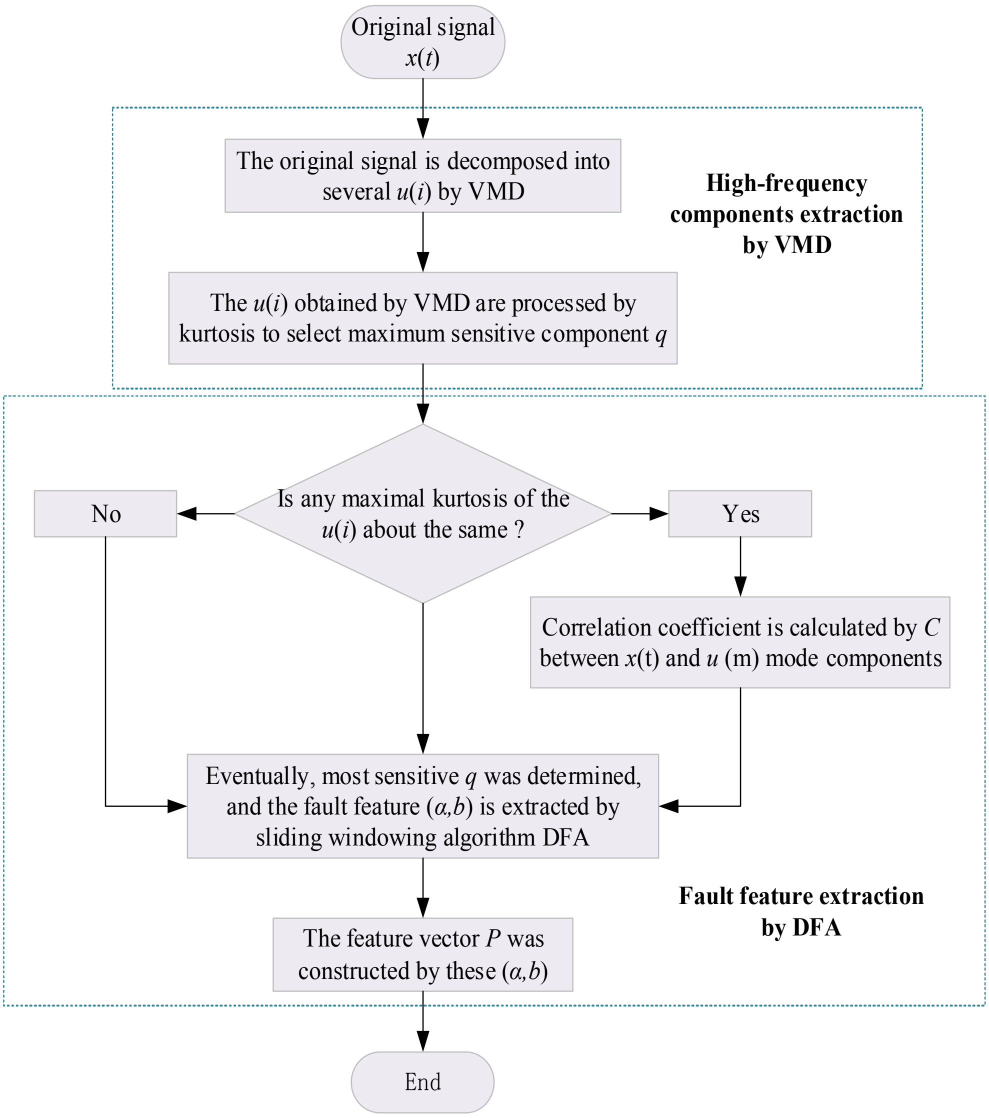

Figure1.The flowchart of fault diagnosis of VMD-DFA method

3. The proposed fault diagnosis method of gearbox based on VMD-DFA

In proposed method, VMD is exploited alone with the DFA. VMD is used to extract high-frequency mode components corresponding to local fluctuation and eliminate the influence of fluctuation corresponding to the large time scale. DFA is used to extract the feature vector of local fluctuation of selected high-frequency components. The flowchart of the researched fault diagnosis method of VMD-DFA is plotted in Figure 1. The specific procedures are described as follows:

1. The raw vibration signal $x(t)$ was collected by the sensor, which was decomposed by VMD into N mode components $u(i)=\{u(1), u(2),\cdots, u(N)\}$, $i=\{1, 2, \cdots, N\}$.
2. The index of the most sensitive component q is selected by (14) in $u(i)$.

$$q = \arg_i \max \left\{ \frac{E(u(i)-\mu_i)^4}{\sigma_i^4} \right\} \tag{14}$$

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where μ_i and σ_i are corresponding to mean and standard deviation of i-th mode component of VMD, respectively. The $\frac{E(u(i)-\mu_i)^4}{\sigma_i^4}$ is actually the kurtosis of $u(i)$.

3. If the maximal kurtosis of some component mode are about the same, the index of the most sensitive component q is selected by (15) and (16):

$$C_i = \left\{ \frac{\sum_{i=1}^{m}(x(t)\text{-}\bar{x})\ (u(m)\text{-}\bar{u})}{\left[\ \sum_{i=1}^{m}(x(t)\text{-}\bar{x})^{\ 2}\sum_{i=1}^{m}(u(m)\text{-}\bar{u})^{\ 2}\right]^{1/2}} \right\} \tag{15}$$

$$q = \arg_i \ \max\{C_1, C_2 \cdots C_m\} \tag{16}$$

where $x(t)$ represent the original signal and $u(m)$ is mode component whose maximal kurtosis is about the same; m is the length of time series. C_i indicates cross-correlation coefficient of the i-th maximal kurtosis component.

4. The sensitive component q is analyzed and acquire bi-logarithmic map by DFA. Then the sliding windowing algorithm is used to capture turning point of the bi-logarithmic map. The position corresponding to the smallest value of Δd is the position of turning point.

$$\Delta d = \arg_i \max\{\ |\sigma_i - \sigma_j|\ \} \tag{17}$$

where σ_i and σ_j are corresponding to the variance of distance of points of the two time scales to their corresponding fitting line.

5. The left of turning point is termed the small time scale, and the right is the large time scale. The characteristic parameters of double time scale (α , b) can be extracted by (13), respectively, and these (α , b) are used to construct feature vector P.

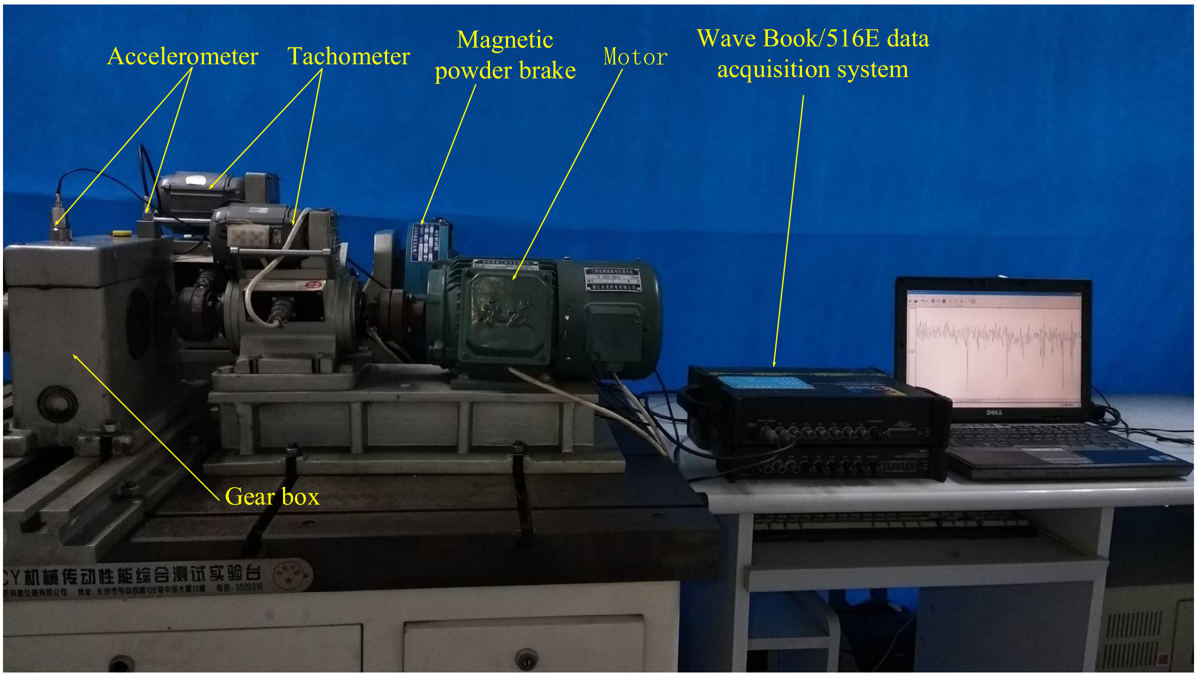

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Figure 2. The experimental facility of the gearbox fault detection

4. Experiment

In order to verify feasibility and effectiveness of the proposed method in fault diagnosis, the vibration signals collected by the experimental facility system were used. The experimental facility system shown in Figure 2. The experimental setup is composed of a single stage gearbox with a pair of spur gears, an electric machine, a magnetic powder brake with necessary load, and an I/O Tech Wave Book/516E 16-bit 1 MHz data acquisition system with Ethernet interface. The 20-teeth pinion which is setup on input shaft of a 0.55KW DC motor meshed with an 80-teeth gear, which is loaded by magnetic power brake. The vibration signal generated by operating gearbox was picked up by PCB piezoelectric vibration accelerometer, which is mounted on vertical direction of the input bearing block. The motor's rotational speed randomly changes in the range of 300r/min-1217r/min. The dataset includes four fault patterns: normal, scratched, toothless, and circular pitch error and each pattern has 100 samples. The vibrations signal was acquired with sample frequency of 4000 Hz, and sample time of 0.5 second. The vibration acceleration signals of the four states were demonstrated in Figure 3.

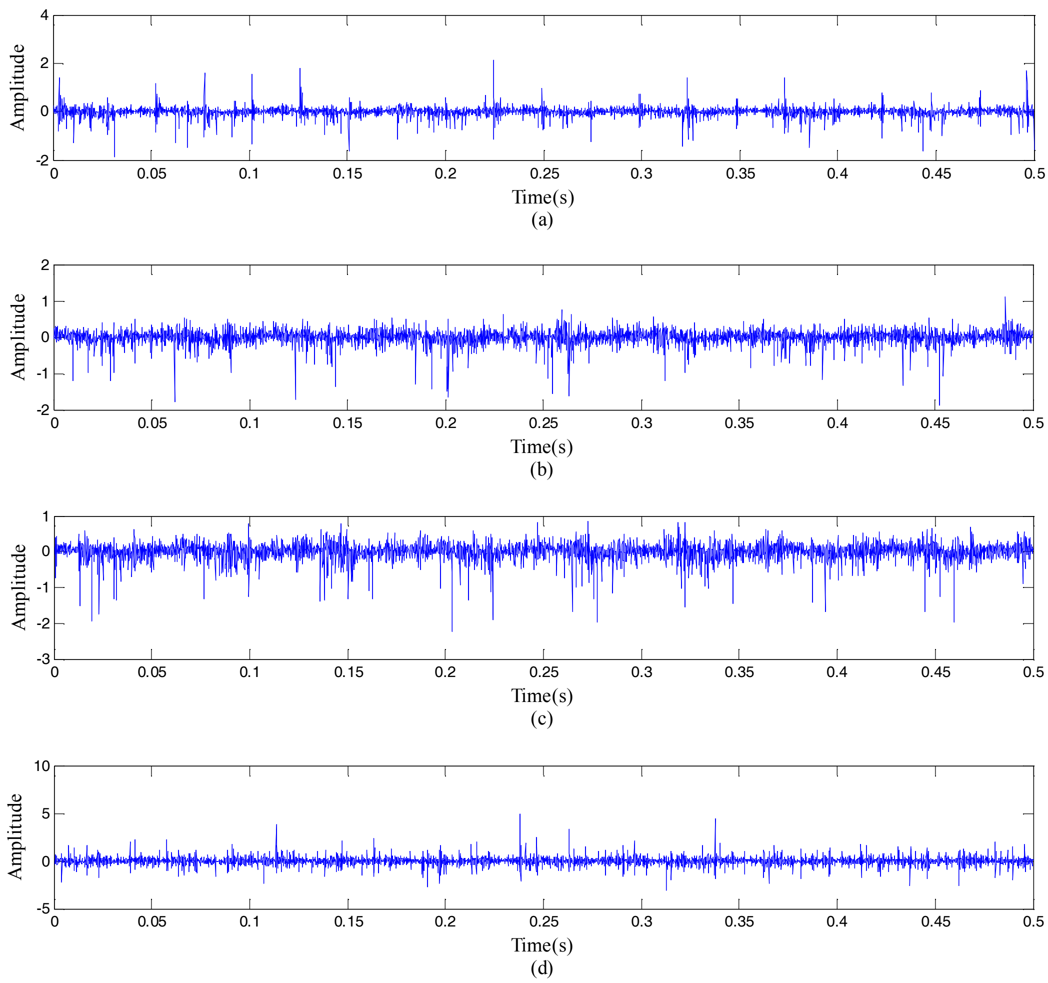

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Figure 3. Time-domain waveform of the gear vibration signals: (a) toothless, (b) scratched, (c) normal, and (d) circular pitch error.

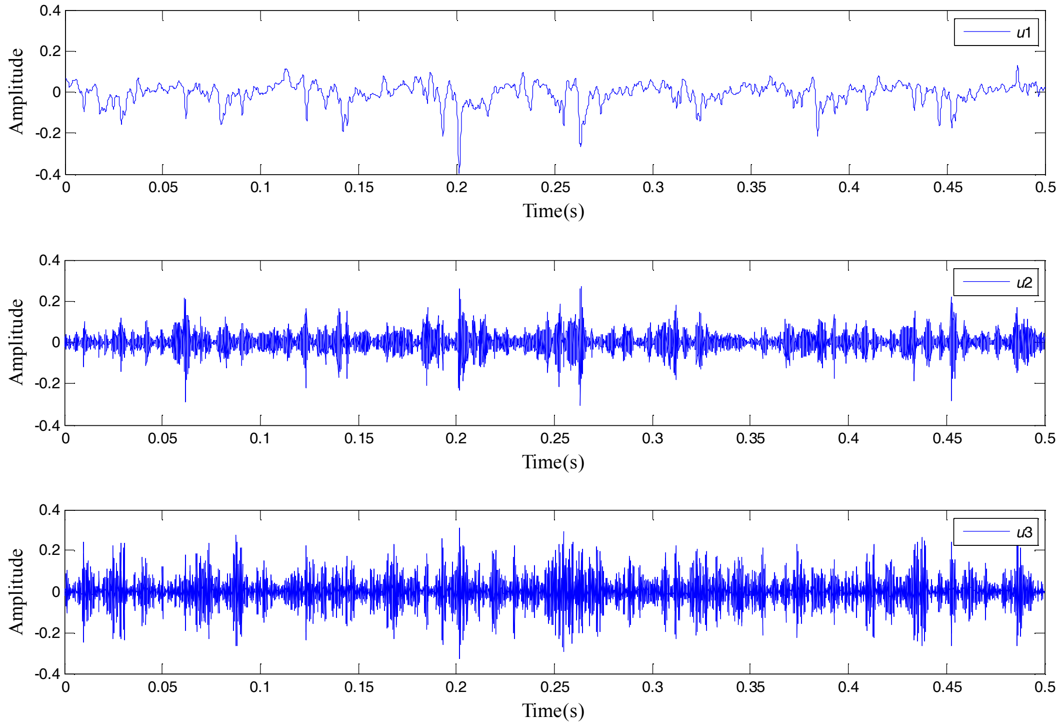
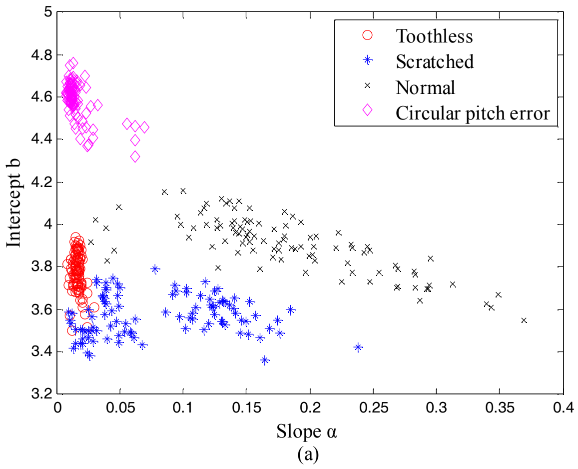


Figure 4. The calculation result using VMD for gear fault signal, $u1$, $u2$ and $u3$ are three decomposed mode components of the gear fault signal, respectively.

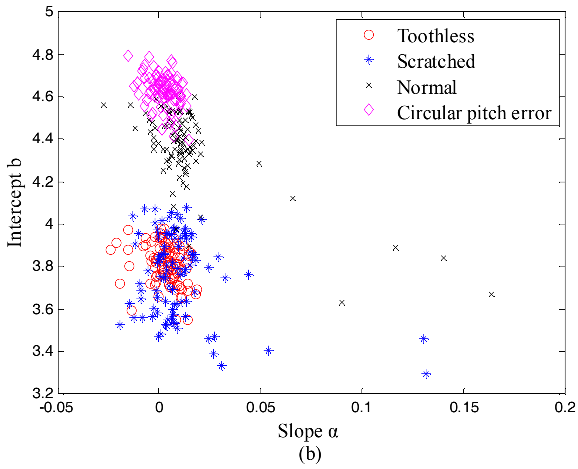
An instance of vibration acceleration signal (Figure 3(b)) for a gear scratched pattern is decomposed into three components by VMD, and is shown in Figure 4. The three mode components are applied to processing all signals in [10], therefore, three mode components is distributed across the different frequency bands in this paper. The fault information in vibration signal for gear is concentrated within the high-frequency components which correspond to the local fluctuation [15]. Therefore, the sensitive mode component is selected within $u2$ and $u3$ by (14)-(16). With DFA algorithm, the feature parameter (α , b) of double time scale were effectively extracted for gear fault diagnosis.

In our research, the detrended order is one and range of window sizes is from 8 to 512 sample points. The dataset includes four fault pattern: toothless, scratched, normal, and circular pitch error and each pattern have 100 sample which were calculated by VMD-DFA to obtain the characteristic values (α_{ij} , b_{ij}) where i is gear fault pattern and j is the number of fault pattern. The mapping of feature vector (α_{ij} , b_{ij}), $\{i$=1, 2, 3, 4; j=1, 2, ⋯, 100$\}$ for four gear states were shown in Figure 5. The Figure 5(a), 5(b) is results in small time scale and large time scale by VMD-DFA respectively, and Figure 5(c) is the results by STS-DFA.

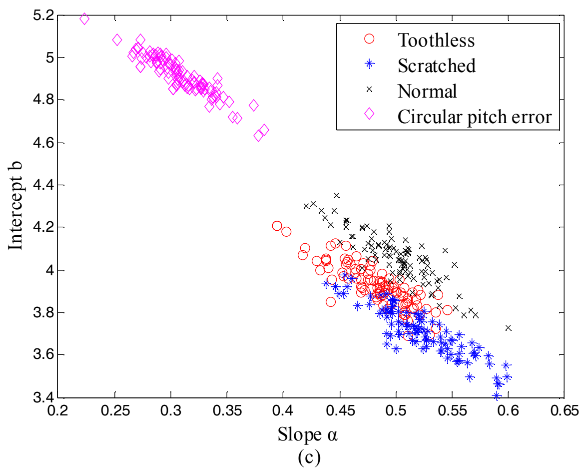
Figure 5(a) shows that the four states (toothless, scratched, normal, and circular pitch error) are fundamentally distinguished by proposed method in small time scale, except that toothless and scratched have subtle overlap. Figure 5(b) shows that the state of the circular pitch error has a large overlap with normal, and the scratched and toothless are overlapped completely. The results prove that the feature parameters from small time scale have better performance than the lager time scale for detection of four fault states. In addition, the scale exponent slope α of four states of gears trend to zero, which indicates a strong anti-persistent long memory characteristics in this time series interval. In Figure 5(c), the small time scale parameters extracted by STS-DFA, the normal, toothless and scratched have varying degrees overlap, especially toothless and scratched. So the proposed method has better distinguished performance than STS-DFA for the gear four faults.



(a) Mapping of results for small time scale by VMD-DFA



(b) Mapping of results for large time scale by VMD-DFA



(c) Mapping of results for small time scale by STS-DFA

Figure 5. (a) Mapping of results for small time scale by VMD-DFA. (b) Mapping of results for large time scale by VMD-DFA. (c) Mapping of results for small time scale by STS-DFA.

In order to verify the advantage of VMD-DFA, 320 training data (each state has 80 samples) were used for training purposes and 80 training data (each state has 20 samples) were used for testing analysis. We build the probability distribution model of feature vector (α_{ij}, b_{ij}) by Gaussian mixture model, and identify the fault pattern of testing data by Bayesian maximum likelihood

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classifier. The Gaussian mixture model (GMM) and Bayesian maximum likelihood classifier can be described as follow respectively:

$$p(x) = \sum_{k=1}^{M} \beta_k p_k(x) = \sum_{k=1}^{M} \beta_k N(x;\mu_k,\Sigma_k) \tag{18}$$

where M is the number of mixtures, β_k is the constraint mixture weight values that $\sum \beta_k = 1$, and $x = (\alpha, b)$. $N(x;\mu_k,\Sigma_k)$ represents Gaussian probability function of the k-th normal distribution. μ_k is mean and $\sum_k$ is covariance matrix.

Under the Gaussian mixture model $p(x)$, highest likelihood can be expressed as follow:

$$\hat{d} = \arg\max \ p(Y|d_i) \ , \tag{19}$$

where Y is the feature vector (α, b) of testing sample, $p(Y|d_i)$ is the probability of Y with known i-th gear fault condition described by i-th GMM.

Table 1. Classification results based on VMD-DFA and STS-DFA method.

Method	Normal	Scratched	Toothless	CPE	TRR
VMD-DFA	(79/80)	(78/80)	(78/80)	(80/80)	(315/320)
(Resb)	98.75%	97.5%	97.5%	100%	98.43%
VMD-DFA	(20/20)	(20/20)	(18/20)	(20/20)	(78/80)
(Inde)	100%	100%	90%	100%	97.5%
VMD-DFA	(80/80)	(78/80)	(78/80)	(80/80)	(316/320)
(Jack)	100%	97.5%	97.5%	100%	98.75%
S-DFA	(77/80)	(71/80)	(68/80)	(80/80)	(296/320)
(Resb)	96.25%	88.75%	85%	100%	92.5%
S-DFA	(19/20)	(14/20)	(15/20)	(20/20)	(68/80)
(Inde)	95%	70%	75%	100%	85%
S-DFA	(77/80)	(71/80)	(64/80)	(80/80)	(292/320)
(Jack)	96.25%	88.75%	80%	100%	91.25%

CPE: 'circular pitch error', TRR: 'total recognition rate', VMD: 'variational mode decomposition', DFA: 'detrended fluctuation analysis', STC: 'small time scale'. Rseb: 'Re-substitution test'. Inde: 'Independent dataset'. Jack: 'Jackknife test'.

To evaluate validity of the proposed algorithm, this algorithm and STS-DFA were compared by Re-substitution test, Jackknife test, and Independent dataset, respectively. The Re-substitution test method reflects the algorithm's self-compatibility, and Jackknife test is a cross-test method reflects promotion ability of the algorithm. The Independent test is to verify the actual application. The results of experiment were listed in table 1. From table 1, we can learn about that the recognition rate of three test-algorithm of VMD-DFA method is as high as 95% or more. Total recognition rate of the proposed method improved 6% than STS-DFA with Re-substitution test, which shows higher self-compatibility. In the independent dataset test, the results verify that VMD-DFA is more accuracy and the overall recognition rate increased by 12.5%. In the last jackknife test, overall recognition rate of VMD-DFA improved 7.5% comparing with STS-DFA, which better revealed the vibration characteristically of the original signal. From three test-method data results, it is not difficult to draw a conclusion that the proposed method is better than STS-DFA, which has a higher rate of identification for the fault signal.

5. Conclusion

Due to the characteristics of nonlinear and non-stationary of the heavy-large gearbox vibration signal, a novel fault diagnosis method VMD-DFA for gearbox is proposed in this paper. The main research work is summarized as follows:

(1) VMD is used to extract the high-frequency mode components, which eliminates the influence of fluctuation corresponding to the large time scale and obtains mainly fault information of the vibration signal. DFA is used to extract the fractal feature vector of local fluctuation of signals.

(2) The measured gear signals derived from the gear experiment system were used to verify the effectiveness of the proposed method. By using the Gaussian mixture model (GMM) with Bayesian maximum likelihood classifier, three test-methods were employed to comparative analysis so as to verify the effectiveness of the proposed method. The experiment results demonstrate that the proposed method has obvious advantages in extraction of gearbox fault characteristics comparing with STS-DFA.

(3) However, the parameters of VMD, such as the number of mode u, bandwidth control parameter σ, which have a certain effect on extracting the feature fault frequency as well as reducing the influence of noise. Thus, the future research should be focused on the optimization of relative parameter of VMD.

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Author Contributions

In this paper, X.H. conceived the idea, organized the paper and analyzed the data; H.S. contributed to algorithm design and data handling. Y.C. and authors revised the paper for intellectual content.

Competing Interests

The authors declare that there is no conflict of interests regarding the publication of this article.

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