Complementary ensemble adaptive sparsest narrow-band decomposition method and its applications to the gear crack fault diagnosis

Yanfeng Peng¹, Junhang Chen¹✉, Ruiqiong Luo², Xiaojun Xie³, Xianyu Zhu³, Yanfei Liu⁴, Qinghua Lu⁵ and Kuanfang He⁵

Abstract
Adaptive sparsest narrow-band decomposition is the most sparse solution to search for signals in the over-complete dictionary library containing intrinsic mode functions, which transform the signal decomposition into an optimization problem, but the calculation accuracy must be improved in the case of strong noise interference. Therefore, in combination with the algorithm of the complementary ensemble empirical mode decomposition, a new method of the complementary ensemble adaptive sparsest narrow-band decomposition is obtained. In the complementary ensemble adaptive sparsest narrow-band decomposition, the white noise opposite to the paired symbol is added to the target signal to reduce the reconstruction error and realize the adaptive decomposition of the signal in the process of optimizing the filter parameters. The analysis results of the simulation and experimental data show this method is superior to complementary ensemble empirical mode decomposition and adaptive sparsest narrow-band decomposition in inhibiting the mode confusion, endpoint effect, improving the component orthogonality and accuracy, and effectively identifying the gears fault types.

Keywords
Fault diagnosis, gear, adaptive sparsest narrow-band decomposition, complementary ensemble empirical mode decomposition, local narrow-band signal

Date received: 20 November 2019; accepted: 11 February 2020
Handling Editor: Hui Ma

Introduction
With the progress of time, in the field of mechanical fault diagnosis, the analysis and processing of a vibrational signal is always a hot spot.¹,² In recent years, many fault diagnosis methods have emerged in the field of fault diagnosis, such as the sparse decomposition method and empirical mode decomposition (EMD) method, which are widely used in the analysis of mechanical vibration signals.³–⁵,¹¹

Recently, a new method was proposed by YF Peng and JS Chen, which is called the adaptive sparsest narrow-band decomposition (ASNBD) method.¹²–¹⁴

¹Hunan Provincial Key Laboratory of Health Maintenance for Mechanical Equipment, Hunan University of Science and Technology, Xiangtan, PR. China
²School of Automation, Central South University, Changsha, PR. China
³Hunan Institute of Metrology and Test, Changsha, PR. China
⁴College of Mechanical and Vehicle Engineering, Hunan University, Changsha, PR. China
⁵School of Mechatronics Engineering, Foshan University, Foshan, PR. China

Corresponding author: Junhang Chen, Hunan Provincial Key Laboratory of Health Maintenance for Mechanical Equipment, Hunan University of Science and Technology, Xiangtan 411201, PR. China.
Email: 1193815989@qq.com

Creative Commons CC BY. This article is distributed under the terms of the Creative Commons Attribution 4.0 License (https://creativecommons.org/licenses/by/4.0/) which permits any use, reproduction and distribution of the work without further permission provided the original work is attributed as specified on the SAGE and Open Access pages (https://us.sagepub.com/en-us/nam/open-access-at-sage).
The ASNBD method is based on the idea of the sparse method and adaptive and sparsest time-frequency analysis (ASTFA) method, and combined with a filter. The main idea of ASTFA is searching for the sparsest decomposition over a highly redundant dictionary, which consists of intrinsic mode functions (IMF). However, the ASTFA method is less adaptive in handling mode confusion; so for this problem, the ASNBD proposed a fast algorithm based on filter parameter optimization, which uses different approaches from those proposed by TY Hou and ZQ Shi\(^{10}\) to simplify the calculation. First, by establishing an optimal filter, one obtains the parameters of the filter by solving nonlinear problems. Then, the adjustable differential operator is used as the objective function to constrain each component to the local narrow-band signal. Finally, an inherent narrow-band component (INBC) is obtained by filtering the signal through an optimized filter. This method is called the adaptive sparse narrow-band decomposition (ASNBD) method.

When a mechanical equipment failure occurs, the vibration signal is mostly a multi-component amplitude frequency modulation signal such as a rolling bearing vibration signal. The decomposition by the ASNBD method is actually a demodulation of vibration signals, which can effectively extract the characteristics of the mechanical fault vibration signals. In addition, the rolling bearing vibration signal is a demodulated resonance. To satisfy the need for narrow-band filtering, the traditional methods must set up filter parameters, and the ASNBD method adaptively decomposes the signal into various local narrow-band signals, the sum of which provides the adaptive filter tool. Thus, the method is very suitable for the mechanical fault vibration signal analysis and processing. However, some deficiencies remain in ASNBD. When the frequency of noise is low, the decomposition ability of noise is not good. Thus, based on the optimized complementary ensemble empirical mode decomposition (CEEMD) method under EMD, the complementary ensemble (CE) method was adopted to optimize ASNBD.

The CE method is derived from CEEMD, which is an improvement of the EMD method. It adds positive and negative pairs of white noise to the original EMD method and performs set averaging, which avoids the scale mixing problem and significantly reduces the phenomenon of mode aliasing. However, the introduction of the CE method into the ASNBD method can effectively counter the low-frequency noise to optimize ASNBD method. The accuracy of the new CE-ASNBD was improved compared to the original ASNBD method. In the field of mechanical failure, the measurement results of gear signal during high-speed operation are often interfered by weak noise signal. CE-ASNBD diagnosis can effectively remove fine noise interference and accurately decompose effective fault components.

### ASNBD method

**Definition of the intrinsic narrow-band component**

A signal that can be interpreted as \( A(t) \cos(\omega t + \varphi(t)) \) can be called a narrow-band signal.\(^{11,12}\) We know from the last formula that \( \varphi(t) \) is slow-varying, \( A(t) \) is band-limited and the maximal frequency of \( A(t) \) is much smaller than \( \omega \). The local narrow-band signal can be defined by the formula. The definition of a local narrow-band signal can be considered a local narrow-band signal if the signal in the adjacent interval of any point is approximate to a narrow-band signal.

The components that satisfy the definition of a narrow-band signal are called intrinsic narrow-band components (INBCs).

**Definition of the singular local linear operator**

Linear operator \( T \) is a local linear operator if there exists a neighbour \( B_r \) of \( t \in R \) such that

\[
T(S)(t) = T(S|_{B_r})(t)
\]

where \( S|_{B_r} = S(t) \) when \( t \in B(t) \) and 0 otherwise. \( T \) is called a singular local linear operator when it is a singular operator. The singular local linear operator \( T \) proposed by Peng and Hwang is used in this article

\[
T = \left( \frac{1}{\omega^2} \frac{d^2}{dt^2} + 1 \right)^2
\]

### ASNBD method

In the ASNBD method, the signal is decomposed by searching for the optimal sparse decomposition.\(^{12}\) The iterative process of ASNBD is as follows:

1. Set \( r_0(n) = x(n) \) and \( i = 1 \).
2. Solve the nonlinear unconstrained optimization problem \( P2 \)

\[
P2: \quad \text{Minimize} \quad ||T(INBC_i(n))||_2^2 + \lambda ||D(r_{i-1}(n) - INBC_i(n))||_2^2
\]

where \( T \) is the differential operator defined in the equation. Minimizing \( ||T(INBC_i(n))||_2^2 \) indicates that \( INBC_i(n) \) is constrained to be a local narrow-band signal with respect to the operator. \( D(r_{i-1}(n) - INBC_i(n)) \) is the first-order differentiation of \( r_{i-1}(n) - INBC_i(n) \). Because \( r_{i-1}(n) - INBC_i(n) \) is the decomposed residue, \( D(r_{i-1}(n) - INBC_i(n)) \) is used to regulate the residue. \( \lambda \) is the weight of \( ||T(INBC_i(n))||_2^2 \) and \( ||D(r_{i-1}(n) - INBC_i(n))||_2^2 \), which is similar to \( \lambda \) in Peng and Hwang.\(^{15}\) Generally, satisfactory results can be obtained when \( \lambda \) is set to 1. In optimization problem \( P2 \), all data sets of \( INBC_i(n) \) must be optimized.
Therefore, $N$ parameters must be optimized in each iteration if $x(n)$ is $N \times 1$-dimension data, which may cause massive calculation.

3. Set $r_i(n) = r_{i-1}(n) - INBC_i(n)$.
4. If $||r_i(n)||_2 < \varepsilon$, stop. Otherwise, set $i = i + 1$ and go to step 2.

### CE-ASNBD

#### CE

The CE method comes from the CEEMD algorithm, which adds auxiliary white noise to the original signal in the form of positive and negative pairs.\(^{15-17}\) Compared with the CEEMD method, after the addition of a single white noise, a new subtle noise which is not completely decomposed by a single white noise will appear in the decomposed result, and the subtle noise caused by the addition of new white noise can be eliminated as far as possible after the addition of a pair and the overall average. The process is as follows.

First, the intensity of auxiliary white noise is set. The standard deviation function $std(s)$ is used to calculate the standard deviation of the original signal $s$ by MATLAB so that the original signal can be divided by the standard deviation function to obtain a new function $st$. Then, the random function $randn$ is introduced

\[
\begin{align*}
temp &= randn(1,1) \ast Nstd \\
X_1 &= S + \text{temp} \\
X_2 &= S - \text{temp}
\end{align*}
\]

To make $S_1 = X_1 \ast st$ and $S_2 = X_2 \ast st$, a group of signals with opposite auxiliary white noise is obtained. By controlling the size of $Nst$, the intensity of auxiliary white noise can be set. The selective size of the $Nst$ is set according to the needs, generally around 0.1.

Then, white noise of a fixed intensity is added to the original signal, and the EMD decomposition is performed to obtain an IMF component. Then, $N$ groups of different white noises are added to decompose the corresponding times, and the obtained component is generally average

\[
IMF = \frac{1}{N} \sum_{i=1}^{N} E_i(x + \varepsilon o_i)
\]

In the formula, $IMF$ is the first-order component, $N$ is the number of times that different white noises are added, $E_i$ is the ith component generated by the EMD decomposition, $\varepsilon$ is the ratio of added noise and $o_i$ is the added white noise. This method solves the problem of mode aliasing in EMD and can eliminate the residual auxiliary noise in the reconstructed signal well. Moreover, the noise implementation time can be low, and the computational efficiency can be improved.

#### CE-ASNBD

The ASNBD method has many advantages in signal processing, but it also has disadvantages. For low-frequency noises, the decomposition effect is relatively poor. Therefore, this article was inspired by the CEEMD method after the ensemble empirical mode decomposition (EEMD) optimization, and the ASNBD was optimized by the CE method to improve the accuracy. The iterative process of the algorithm is as follows:

1. In the original signal, add $N$ groups of fixed intensity symbols opposite to white noise $N$ and obtain a series of signals as follows

\[
\begin{align*}
R_1(t) &= r_{1,1}(t), r_{1,2}(t), r_{1,3}(t), \ldots, r_{1,N}(t), r_{2,N}(t) \\
r_{1,1}(t) &= f(t) + nt_1 \\
r_{2,1}(t) &= f(t) - nt_1 \\
&\vdots \\
r_{1,N}(t) &= f(t) + nt_N \\
r_{2,N}(t) &= f(t) - nt_N
\end{align*}
\]

2. Decompose the signal into solving optimization problem $P3$

\[
P3 : \text{Minimize} \quad ||T(INBC_i(n))||_2^2 + \lambda \quad ||D(R_i(n) - INBC_i(n))||_2^2
\]

$INBC_i(n)$ is defined as the local narrow-band signal, that is, $INBC_i(n)$ satisfies the condition of over-complete dictionary library $D_i$ as shown in equation (6). $D(R_i(n) - INBC_i(n))$ is the first-order differentiation of $R_i(n) - INBC_i(n)$. Substitute some of these signals and obtain $2N$ INBC components: $INBC_{1}, INBC_{2}, INBC_{3}, \ldots, INBC_{2N-1}, INBC_{2N}$. The integral average method is applied to the obtained INBC components

\[
INBC_{1,1} = \frac{1}{2N} \sum_{i=1}^{2N} INBC_i
\]

where $INBC_{1,1}$ is the first-order INBC component, and $N$ is the number of different added noises. Next, the residuals of the first-order INBC component are calculated and subtracted.
3. Calculate the residual of the first-order INBC component

\[ R_{i+1}(n) = R_i(n) - \text{INBC}_i(n) \]  

(8)

4. If \( ||R_{i+1}(n)||_2 < \varepsilon \), stop. Otherwise, set \( i = i + 1 \) and go to step 2.

The flowchart of CE-ASNBD is shown in Figure 1. In step 2, all data points in the original signal must be optimized. To reduce the large amount of calculation of data points, the calculation and optimization of data points can be transformed into the calculation and optimization of parameter vectors \( \eta \) of filter \( \chi(k|\eta) \) designed in this article. The method to solve the optimization problem \( P4 \) is as follows:

1. Calculate the fast Fourier transformation (FFT) of \( r_i(n) \), which is denoted by \( \tilde{r}_i(k) \).

2. Design a filter \( \chi(k|\eta) \) (\( \eta = [\omega_c, \omega_b, \omega_e] \)) as follows (see also Figure 2)

\[
\chi(k|\eta) = \begin{cases} 
\sin \omega [k - \omega_c + \omega_b + \pi/(2\omega)], & \omega_c - \omega_b - \pi/(2\omega) \leq k < \omega_c - \omega_b \\
1, & \omega_c - \omega_b \leq k \leq \omega_c + \omega_b \\
\cos \omega (k - \omega_c - \omega_b), & \omega_c + \omega_b < k \leq \omega_c + \omega_b + \pi/(2\omega) \\
0, & \text{else} 
\end{cases}
\]  

(9)

3. Solve the following nonlinear unconstrained optimization problem \( P4 \)

\[
P4: \quad \text{Minimize} \quad ||T \{ \text{iff} \{ X(k)|\lambda \tilde{r}_i(k) \} \} ||_2^2 + \lambda ||D(R_i(n) - \text{iff} \{ X(k)|\lambda \tilde{r}_i(k) \} ||_2^2
\]

(10)

4. Obtain the optimal parameter \( r_i(k) \) through the filter; then

\[
\text{INBC}_i(t) = \text{iff} \{ X(k)|\lambda \tilde{r}_i(k) \}
\]

(11)

Like the CEEMD method, the CE-ASNBD method adds auxiliary white noise to the original signal in the form of positive and negative pairs using the zero mean value of the added white noise and uses multiple cycles to calculate the mean value to make the noise in the signal cancel each other. Compared with the original ASNBD method, CE-ASNBD improves the accuracy.
of the signal even for low-frequency noises. The flow-chart of A is shown in Figure 1.

Simulation comparative analysis

To verify the advantages and disadvantages of the CE-ASNBD, ASNBD and CEEMD methods, simulation signals were used for the preliminary verification. Without loss of generality, we use a mixed signal to verify the three methods. The expression of the simulation signal is as follows

\[
\begin{aligned}
    x_1(t) &= (1 + 0.7 \cos(12\pi t) \cdot \cos(100\pi t + \sin(15\pi t^2))) \\
    x_2(t) &= \cos(40\pi t) \cdot e^{-3t} \\
    y(t) &= x_1(t) + x_2(t) + n(t)
\end{aligned}
\]

(12)

\(y(t)\) is a mixture of \(x_1(t)\), \(x_2(t)\) and \(n(t)\). \(x_1(t)\) is composed of an amplitude-modulation–frequency-modulation (AM–FM) signal. \(x_2(t)\) is a mixture of the exponential signal and the cosine signal, and \(n(t)\) is an intermittent noise with a signal-to-noise ratio of 1.8167 dB.

The time-domain waveforms of \(y(t)\), signal \(x_1(t)\), signal \(x_2(t)\) and intermittent noise \(n(t)\) are shown in Figure 2(a)–(d), respectively. \(y(t)\) is decomposed using CE-ASNBD, ASNBD and CEEMD, respectively. The CE-ASNBD decomposition results are shown in Figure 3(a)–(c). The ASNBD decomposition results are shown in Figure 4(a)–(c). The CEEMD decomposition results are shown in Figure 5(a)–(c).

The INBC components decomposed by CE-ASNBD are highly consistent with the original value, and the INBC components decomposed by ASNBD have a small error compared with the real value, while the

![Figure 3. CE-ASNBD decomposition results: (a) \(INBC_1\) component, (b) \(INBC_2\) component and (c) residue.](image)

![Figure 4. ASNBD decomposition results: (a) \(INBC_1\) component, (b) \(INBC_2\) component and (c) residue.](image)

![Figure 5. CEEMD decomposition results: (a) \(IMF_1\) component, (b) \(IMF_2\) component and (c) residue.](image)

| Method          | \(R_1\)    | \(R_2\)    | \(E_1\)    | \(E_2\)    | \(IO\)  |
|-----------------|------------|------------|------------|------------|--------|
| CE-ASNBD        | 0.9726     | 0.9665     | 0.0542     | 0.0675     | 0.0270 |
| ASNBD           | 0.9706     | 0.9396     | 0.0579     | 0.1181     | 0.0701 |
| CEEMD           | 0.5507     | 0.6500     | 1.1278     | 0.7565     | -0.0734|

CE-ASNBD: complementary ensemble adaptive sparest narrow-band decomposition; ASNBD: adaptive sparest narrow-band decomposition; CEEMD: complementary ensemble empirical mode decomposition.
IMF components decomposed by CEEMD have significant mixed modes compared with the real value and a huge error.

To more intuitively compare the effects of the three methods, this article uses two methods to verify the practicability of the CE-ASNBD, ASNBD and CEEMD methods.
First, the Hilbert transform was used to calculate the instantaneous amplitude and frequency (IA and IF) of CE-ASNBD, ASNBD and CEEMD for comparison, and the INBC and IMF components generated by each method in Figures 3–5 were transformed and calculated. For convenience, the instantaneous amplitude is named IA, and the instantaneous frequency is named IF. The results are shown in Figure 6, where the true value is the black curve, CE-ASNBD is the blue curve, ASNBD is the red curve and CEEMD is the

**Table 3.** GR435 gear data working data sheet.

| Data name | Degree of tooth surface crack (ratio of root crack width to root width) | Motor speed (n/min) | Sampling frequency |
|-----------|--------------------------------------------------------------------------------|---------------------|--------------------|
| GR435     | 10%                                                                           | 1200                | 2048               |

![Figure 9. Schematic diagram of the gear testbed system.](image9)

![Figure 10. Record GR435: (a) raw time signal and (b) envelope spectrum of the raw signal.](image10)

![Figure 11. CE-ASNBD decomposition result of the gear fault signal.](image11)
green curve. In the IA and IF diagrams, CEEMD has obvious fluctuations and errors compared with the real value, while CE-ASNBD has the smallest error among the three methods.

The second comparison is in terms of the energy parameters $E_i$, correlation coefficients $r_i$ and orthogonal coefficients $O_i$ of the three decomposition methods.\textsuperscript{18,19} Table 1 shows that the CE-ASNBD method has better correlation coefficient, orthogonal coefficient and energy parameters than the ASNBD method and CEEMD method.

The results of the two comparisons can prove that the CE-ASNBD method has better decomposition effect than the original two methods, but there are obvious modal confusion and other problems in the CEEMD decomposition process. Although there is no obvious modal confusion problem in the ASNBD method, it is less accurate than the optimized CE-ASNBD method.

To further verify the noise resistance of the CE-ASNBD method, this article adds three white Gaussian noises with different signal-to-noise ratios of $-3$, $0$, and $3$. The original ASNBD method is compared with the CE-ASNBD method.

The results of CE-ASNBD and ASNBD in the first signal are shown in Figure 7, and the results of the second signal are shown in Figure 8. The results are compared in terms of the energy parameters and correlation coefficient, as shown in Table 2. Table 2 shows that the

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure12.png}
\caption{Four envelope spectra of CE-ASNBD: $INBC_1$, $INBC_2$, $INBC_3$ and $INBC_4$.}
\end{figure}

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure13.png}
\caption{ASNBD decomposition result of the gear fault signal.}
\end{figure}

ASNBD method is obviously inferior to the CE-ASNBD method for each index in the comparison of Gaussian white noise with three signal-to-noise ratios. Thus, the CE-ASNBD method is indeed better than ASNBD method at least for the ($-3$, $0$, $3$) Gaussian white noise.
Experimental data analysis

To further verify the practical feasibility of the CE-ASNBD method, a gear vibration signal fault detection was performed. As a commonly used method for mechanical failure detection, an envelope spectrum analysis can verify the feasibility of the CE-ASNBD method. The CEEMD method and ASNBD method were also used for fault detection of gear signals.

The experimental data of a gear are offered by Hunan University. The experiment system and its schematic are shown in Figure 9. The literature review shows that in the fault diagnosis, the mechanical fault data can be divided into three types: diagnosable (Y), undiagnosable (N) and potentially diagnosable (p). By processing the data,20,21 the undiagnosable data can be converted into diagnosable data to prove the advantages of the method. Thus, we used GR435 in the database for the proof. The sampling frequency of GR435 is 1024, its rotational speed is 1200 n/min and the degree of gear failure is 10% (ratio of root crack width to root width). The failure frequency of the data can be calculated. According to the formula of gear failure frequency, the gear failure frequency $f_0$ is about 20 Hz.22,23

The specific data are shown in Table 3.

First, GR435 was processed and analysed. The original signal diagram and envelope spectrum are shown in Figure 9. According to the envelope spectrum and calculation in Figure 10, only the double-fault frequency $2f_0$ is visible, so it cannot be used as the basis for the fault diagnosis.24–26 Therefore, we used the CE-ASNB, ASNBD and CEEMD methods to decompose the original signal, and the results are shown in Figures 11–16. In Figure 11, the frequency $f_0$, frequency doubling $2 \times f_0$ and frequency tripling $3 \times f_0$ clearly appear. Therefore, after the decomposition by the

---

**Figure 14.** Four envelope spectra of ASNBD: INBC$_1$, INBC$_2$, INBC$_3$ and INBC$_4$.

**Figure 15.** CEEMD decomposition result of the gear fault signal.
CE-ASNBD method, the failure frequencies of each frequency doubling are intuitively shown. 27–29

According to the results in Figures 11–16, CE-ASNBD is superior to ASNBD in processing the non-stationary signal generated by the gear fault and can identify the gear surface crack fault that cannot be classified by the original envelope spectrum analysis method or CEEMD method.

The component diagram decomposed by the ASNBD method cannot clearly show the presence of a triple frequency, so its accuracy in the fault diagnosis of this gear signal is lower than that of the CE-ASNBD method, whereas the component diagram of the CEEMD method in this gear signal can only show a part of the fault frequency. These results indicate that the CE-ASNBD method can diagnose data that cannot be diagnosed with the original envelope spectrum or the CEEMD method.

Conclusion

Based on the ASNBD method, this article proposes the CE-ASNBD method. The CE-ASNBD method is better than the original ASNBD method in low-frequency noise resistance and adaptability. Compared with the CEEMD method, it avoids the calculation of extremum and alleviates the problems of modal mixing and end effect in CEEMD. Compared with ASNBD, the decomposition accuracy is improved by adding white noise and set average. The simulation results show that CE-ASNBD is better than ASNBD and CEEMD in terms of element accuracy, noise resistance, instantaneous amplitude and frequency accuracy. CE-ASNBD is also used to analyse the experimental signal of the gear with a tooth surface fault. The results show that CE-ASNBD is effective in mechanical gear fault diagnosis. However, among the three methods, CE-ASNBD takes the longest time to compute, followed by ASNBD, and CEEMD is the fastest. Therefore, the future research direction is to ensure the computational accuracy, improve the computational efficiency and reduce the computational time of CE-ASNBD, and we will study a rapid optimization algorithm of CE-ASNBD.

Data availability

Previously reported .mat data were used to support this study and are available at DOI: 10.1016/j.mechmachtheory.2007.05.007. These prior studies (and data sets) are cited at relevant places within the text as references.

Declaration of conflicting interests

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

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship and/or publication of this article: This work was supported by the National Key Research and Development Programme of China (2018YFF0212904 and 2018YFB1308000), National Natural Science Foundation of China (51805161), Hunan Provincial Key Research and Development Programme (2018JJ3187 and 2017JJ1015), and Changsha Science and Technology Programme (KQ1905019).
References

1. He K and Li XJ. A quantitative estimation technique for welding quality using local mean decomposition and support vector machine. J Intell Manuf 2016; 27: 525–533.

2. Li YB, Xu MQ, Liang XH, et al. Application of band-width EMD and adaptive multi-scale morphology analysis for incipient fault diagnosis of rolling bearings. IEEE T Ind Electron 2017; 64: 6506–6517.

3. Zheng JD, Pan HY and Cheng JS. Rolling bearing fault detection and diagnosis based on composite multiscale fuzzy entropy and ensemble support vector machines. Mech Syst Signal Pr 2017; 85: 746–759.

4. Zheng JD, Jiang ZW and Pan HY. Sigmoid-based refined composite multiscale fuzzy entropy and t-SNE based fault diagnosis approach for rolling bearing. Measurement 2018; 129: 332–342.

5. Peng Y, Chen J, Liu Y, et al. Roller bearing fault diagnosis based on adaptive sparsest narrow-band decomposition and MMC-FCH. Shock Vib 2019; 2019: 7585401.

6. Peng Y, Li Z, He K, et al. Broadband mode decomposition and its application to the quality evaluation of welding inverter power source signals. IEEE T Ind Electron. Epub ahead of print 28 November 2019. DOI: 10.1109/TIE.2019.2955429.

7. Qi H, Shi Y, Tian Y, et al. A new fault diagnosis and fault-tolerant control method for mechanical and aeronautical systems with neural estimators. Adv Mech Eng 2019; 11: 1687814019891659.

8. Peng Y, Liu Y, Cheng J, et al. Remaining useful life prediction of rolling bearing using adaptive sparsest narrow-band decomposition and locality preserving projections. Adv Mech Eng 2019; 11: 1687814019889771.

9. He K, Zhang Z and Xiao S. Feature extraction of ac square wave saw arc characteristics using improved Hilbert–Huang transformation and energy entropy. Measurement 2013; 46: 1385–1392.

10. Hou TY and Shi ZQ. Data-driven time-frequency analysis. Appl Comput Harmon A 2012; 35: 284–308.

11. Yeh JR, Shieh JS and Huang NE. Complementary ensemble empirical mode decomposition: a novel noise enhanced data analysis method. Adv Adapt Data Anal 2010; 2: 135–156.

12. Peng YF, Cheng JS, Yang Y, et al. Adaptive sparsest narrow-band decomposition method and its applications to rotor fault diagnosis. Measurement 2016; 91: 451–459.

13. Lu Y, Xie R and Liang SY. CEEMD-assisted kernel support vector machines for bearing diagnosis. Int J Adv Manuf Tech 2020; 106: 3063–3070.

14. Peng YF, Cheng JS, Yang Y, et al. Adaptive sparsest narrow-band decomposition method and its applications to rolling element bearing fault diagnosis. Mech Syst Signal Pr 2017; 85: 947–962.

15. Peng SL and Hwang WL. Adaptive signal decomposition based on local narrow band signals. IEEE T Signal Process 2008; 56: 2659–2676.

16. Zhao LY, Yu W and Yan RQ. Gearbox fault diagnosis using complementary ensemble empirical mode decomposition and permutation entropy. Shock Vib 2016; 2016: 3891429.

17. Imadouche Y, Kedadouche M, Alkama R, et al. A frequency-weighted energy operator and complementary ensemble empirical mode decomposition for bearing fault detection. Mech Syst Signal Pr 2016; 82: 103–116.

18. Cohen L. Time-frequency analysis: theory and applications (Bai Juxian, trans.). J Acoust Soc Am 1995; 134: 4002–4002.

19. Liu C, Zhang LH, Ren TQ, et al. Detection of rail fastener conditions using time-frequency entropy based on orthogonal empirical mode decomposition. Appl Mech Mater 2013; 333–335: 1708–1712.

20. Yu DJ, Luo JS and Shi ML. Signal separation and instantaneous frequency estimation based on multi-scale chirplet sparse signal decomposition. J MeasInstrum 2010; 1: 17–21.

21. Smith WA and Randall RB. Rolling element bearing diagnostics using the Case Western Reserve University data: a bench mark study. Mech Syst Signal Pr 2015; 64: 100–131.

22. Wu JT, Yang Y, Yang XK, et al. Fault feature analysis of cracked gear based on LOD and analytical-FE method. Mech Syst Signal Pr 2018; 98: 951–967.

23. Han DY, Zhao N and Shim PM. Gear fault feature extraction and diagnosis method under different load excitation based on EMD, PSO-SVM and fractal box dimension. J Mech Sci Technol 2019; 33: 487–494.

24. Huang W, Li S, Fu X, et al. Transient extraction based on minimax concave regularized sparse representation for gear fault diagnosis. Measurement 2020; 151: 107273.

25. Cheng J, Yang Y, Li X, et al. An early fault diagnosis method of gear based on improved symplectic geometry mode decomposition. Measurement 2020; 151: 107140.

26. Sharma V and Parey A. Extraction of weak fault transients using variational mode decomposition for fault diagnosis of gearbox under varying speed. Eng Fail Anal 2020; 107: 104204.

27. Li W, Liu C, Hu Y, et al. Diagnosis for timing gears noise of a diesel generating set. In: Wahab MA (ed.) Proceedings of the 13th international conference on damage assessment of structures. Singapore: Springer, 2020, pp.582–593.

28. Cheng Z, Gao M, Liang X, et al. Incipient fault detection for the planetary gearbox in rotorcraft based on a statistical metric of the analog tachometer signal. Measurement 2020; 151: 107069.

29. Kim Y, Park J, Na K, et al. Phase-based time domain averaging (PTDA) for fault detection of a gearbox in an industrial robot using vibration signals. Mech Syst Signal Pr 2020; 138: 106544.