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Recent progress on decoupling diagnosis of hybrid failures in gear transmission systems using vibration sensor signal: A review

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ABSTRACT

Reliable recognition of fault type and assessment of fault severity is essential for decision making in condition-based maintenance of gear transmission systems. In engineering practice, the gear systems are often subject to hybrid faults on the same component or different components. The concurrence of multiple faults makes the fault detection, in particular, the examination of both the fault types and severities, more challenging. Recently, this research area has been recognized as an important direction. A logic solution is to decouple the hybrid faults. This paper reviews various aspects of recent research in decoupling diagnosis of hybrid faults in gear transmission systems, and discusses the techniques used for gearbox hybrid faults decoupling. The general fault detection technologies for gearboxes are also briefly summarized. A potential methodology based on the bounded component analysis (BCA) for hybrid faults decoupling is discussed. Possible future research trends of gearbox hybrid faults decoupling diagnosis are suggested.

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1. Introduction

Gear transmission systems are widely used in a variety of applications in many industries, including aerospace, mining, railway, automobile, manufacturing, agriculture and wind energy. A gearbox breakdown may result in catastrophic failures and significant economic losses [1]. For example, a bearing failure led to the damage of a thermal generator set in Japan in 1992 [2], a broken gear tooth resulted in the destruction of a helicopter in UK in 1986 [3], and a gearbox fault caused the damage of a propulsion system in the 'Zhouying 4' ship in China in 2006 [3]. According to the

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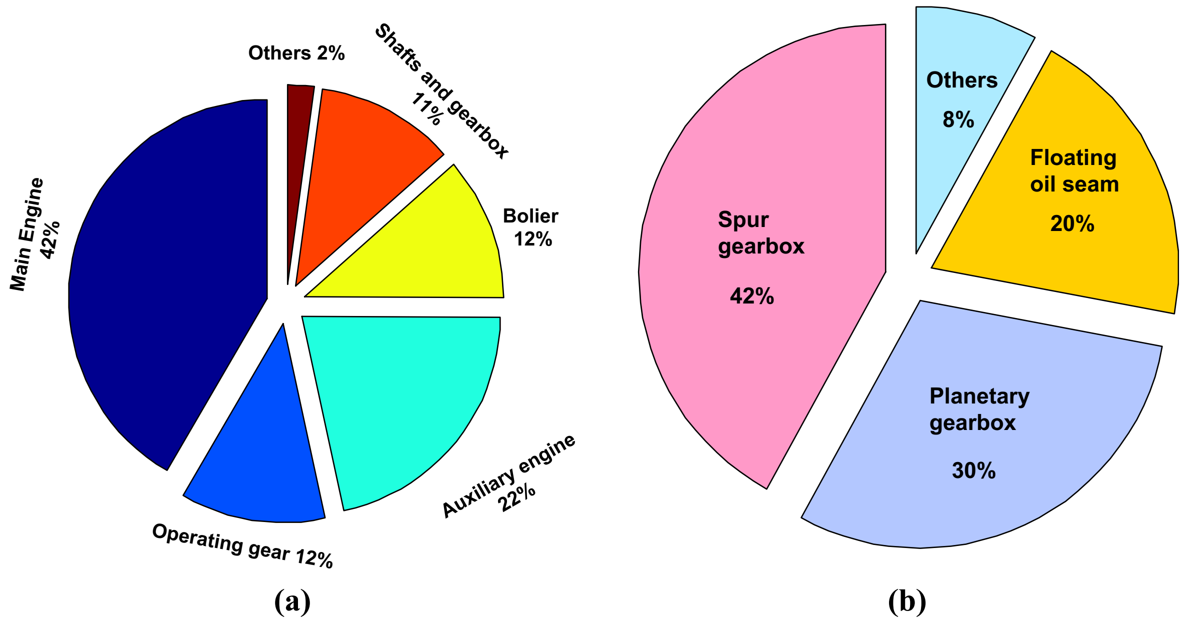

Fig. 1. (a) Settlement of claims in marine propulsions; (b) typical faults in shearer cutting parts in coal cutters.

statistics [3,4], the gearbox faults account for 80% of all the failures in the transmission machinery, and in the gearbox, the gear faults account for 60%. Moreover, according to Swedish Club Highlights [5], the most frequent failure part of a ship is the marine propulsion system (including the diesel engines), in which the gearboxes are identified as one of the most vulnerable components. In the coal mining industry, according to the latest report [6], the gear transmission components of coal cutters have the highest failure rate among other components in the machine. Fig. 1(a) shows the settlement of claims in marine propulsions [5], and Fig. 1(b) shows the fault types of the shearer cutting parts in the coal cutters [6]. The percentage of settlement of claims for the gearbox and operating gear is more than 12% in the marine propulsions (see Fig. 1(a)), and the gear and bearing failures in both the spur and planetary gearboxes account for 72% of all the faults in the shearer cutting parts (see Fig. 1(b)). In addition, in rotorcraft drive systems, the breakdown of the rotorcraft gearboxes is also a critical issue and much research has been devoted to analyzing the reliability of these gearboxes over the past 25 years [7–9]. Hence, in order to ensure safe operation of machinery, improve maintenance efficiency, save time and reduce costs, industries require the maintenance strategies be transformed from the traditional breakdown maintenance (failure and repair model) to condition-based maintenance (CBM), and toward predictive maintenance (PM) [10]. Condition monitoring and fault diagnosis (CMFD) technology provides the solid foundation for the implementation of CBM and PM [11].

2. Brief review of vibration based CMDF techniques

The fault detection is a longstanding research topic, dating back to the early stage of last century [20,21]. Over past decades, it has been widely recognized that vibration analysis can be used effectively for mechanical fault diagnosis. In the early 1940s, pioneering investigation on mechanical damage detection using vibration analysis was conducted by Collacott [12]. A milestone was reached in 1970s when the frequency analysis technologies were firstly introduced into condition monitoring of mechanical systems [13–15]. Representative work includes discrete frequency [13], cepstrum analysis [14] and signature analysis [15]. Then in the 1980–90s, some classical methodologies, including order tracking [16], time domain averaging [17], time–frequency analysis [18] (such as wavelet transform [19] and Wigner–Ville analysis [20]), and fault tree analysis [21], were developed and applied to machinery defects detection. To date, many useful techniques have been developed for gearboxes CMFD (including gears and bearings) [22–31]. Existing vibration signal analysis methodologies applied to gearbox CMFD can mainly be classified into three categories: (1) the statistical analysis, (2) the filter models, and (3) the time and/or frequency domain analysis approaches. Table 1 lists the state-of-the-art presentations of the statistical analysis approach and Table 2 provides the state-of-the-art presentations of the filter models and time/frequency approaches in the gearbox CMFD. Some researchers utilized intelligent pattern recognition techniques (namely, artificial neural network (ANN) [32], fuzzy infer-

Table 1
Representative work using the statistical analysis approach.

Category	Representative approach
Hypothesis testing	Kolmogorov–Smirnov test [38], Satterthwaite's t'-test [39], Wilcoxon rank-sum test [40]
Statistical index	Kurtosis [41], Euclidean distance [42], Mahalanobis distance [43], Kullback–Leibler distance [44], Bayesian distance [23]
Statistical learning	Principal component analysis (PCA) [45], Fisher discriminant analysis (FDA) [45], partial least squares (PLS) [46], multidimensional scaling (MDS) [47], Isomap [48], Laplacian eigenmaps (LE) [49], locally linear embedding (LLE) [50], local tangent space alignment (LTSA) [51], locality preserving projections (LPP) [52], neighborhood preserving embedding (NPE) [53], maximum variance unfolding (MVU) [54], common vector approach (CVA) [55], diffusion maps (DM) [56]
Statistical modeling	Time series model [57], Dempster–Shafer evidence theory [58], hidden Markov model (HMM) [59], proportional hazards model (PHM) [60], proportional covariate model (PCM) [61]

Table 2
Brief overview of representative examples of the filter models and time/frequency approaches.

Category	Subcategory	Representative approach
Filter model		Wavelet filter [62], Kalman Filter [63], particle filtering (PF) [64], latent component-based filter [65], morphological filter [66], Schur filter [67], independent component analysis (ICA) filter [68]
Time and/or frequency domain analysis	Time or frequency	Fast Fourier transform (FFT), Discrete Fourier transform (DFT), time synchronous averaging (TSA) [17], order tracking [16,69], resonance demodulation [70], envelope spectrum analysis [71], spectral kurtosis [72]
	Time-frequency	Wavelet transform [19], Short-time Fourier transform (STFT), empirical mode decomposition (EMD) [73], Wigner–Ville distribution (WVD) [4], Teager energy spectrum [74]

ence [33], support vector machine (SVM) [34], expert system [35], evolution intelligence [36]), and combined them with the methods presented in Tables 1 and 2 and their derivatives for fault detection and diagnosis. One example was the combination of wavelet, SVM and particle swarm optimization (PSO) [37] for rolling bearing failure detection, and the experimental analysis suggested better fault pattern recognition performance by the combination than by the standalone SVM.

3. Recent progress on hybrid faults decoupling

In the condition monitoring field, one challenging task is to diagnose hybrid faults that occur simultaneously in the same/different components of a machine [70,75,76]. In industrial conditions, one fault often would induce another fault. For instance, a spall in the outer race of a rolling element bearing would eventually lead to deterioration (e.g., spalling) of the rollers after a certain number of running cycles [77]. In real world, hybrid faults can be presented in defective gearboxes, and the concurrence of multiple faults on the same and/or different components of a gearbox significantly increases the difficulty in isolating the faults. The dynamic responses of different faults may present different vibration modes, but the vibration characteristics may overlap with each other in time and frequency domains. Moreover, the weak fault vibration characteristics are often masked by strong background noise. It is therefore often difficult to distinguish and identify the fault types when there are hybrid faults.

To diagnose hybrid faults for the purpose of meeting industry requirements, intelligent theories, in particular, multi-fault pattern recognition techniques, were introduced. Chen [78] combined the D–S evidential theory and ANN to diagnose compound faults in the vehicle transmission system. Pan and Ma [79] applied the Particle Swarm Optimization (PSO) optimized ANN to compound faults recognition of a gearbox. Wu and Meng [80] adopted SVM to recognize compound rub malfunctions. Li et al. [81] integrated wavelet packet transform and SVM to detect gear failures, including worn, crack and broken gear teeth, as well as their mixtures. Lei et al. [82] employed EMD and Wavelet neural network (WNN) to compound faults diagnosis of locomotive roller bearing. Zhao et al. [83] employed the K-means classifier to cluster rolling element bearing compound faults. The LSTA was used to extract useful fault features and the K-means classifier was applied for identifying different fault patterns. Li et al. [84] proposed the EMD and SVM combination to identify different bearing faults, including single and the compound faults. Up to date, intensive studies have been done and are underway in the compound faults detection using intelligent approaches. Although different compound faults patterns could be satisfactorily recognized by intelligent classifiers [85], the disadvantage of existing intelligent algorithms is the lack of '*physical meanings*', in other words, one can hardly understand how the neural networks work [77]. In addition, most intelligent classifiers use the pattern-matching metric to map the fault features to their patterns. This methodology needs a large amount of training data and the training process can be time consuming. This is because one needs use a sufficient amount of identified patterns to train and establish a model before new patterns (i.e., new fault type/severity) can be recognized. However, neither in laboratory nor in industrial practice, it is feasible to develop such a huge intelligent recognition model with all fault patterns.

One possible solution to the above mentioned problem is to decouple the hybrid faults by separating sub-signals corresponding to each single fault. For instance, in a gear pair a crack occurs in the pinion while the gearwheel has a broken tooth. The idea of decoupling the coupled faults in the gear pair is to separate the sub-signal of the crack fault and the one of the broken tooth fault. As such the hybrid faults could be transformed into single ones. To achieve this kind of compound faults decoupling, several advanced technologies were developed. The following sections will present a number of classic developments including wavelet based decoupling, EMD based decoupling, order tracking based decoupling, sparse decomposition based decoupling and independent component analysis (ICA) based decoupling.

3.1. Wavelet based decoupling approaches

The wavelet theory was firstly employed to decouple compound faults by He and his research team [86–88]. The wavelets, to be exact, the multiwavelets [25,86,87] and dual-tree complex wavelet [88–90], have been developed to decompose the vibration signals of hybrid faults into wavelet sub-signals matching various features of compound faults. Fig. 2 shows the working principle of the wavelet based faults decoupling, where the post-process approaches can be chosen from Tables 1 and 2. In Fig. 2(a), the vibration signal x collected from one channel is firstly transformed into r dimensional vector $\boldsymbol{f}$ by the preprocessor and then the input vector $\boldsymbol{f}$ is analyzed using the multiwavelets. Since the multiwavelets transform is based on several scaling functions and wavelet functions, different fault characteristics can be matched with different scaling and wavelet functions. The outputs of the multiwavelets hence carry information on different faults. It can be seen that the decoupling efficacy of the multiwavelets depends on the matching performance of the wavelet to the fault. In Fig. 2(b) the vibration signal x is firstly decomposed into several wavelet subbands by performing the dual tree wavelet packet transform. Then the fault information is examined in each wavelet sub-band signal. If the faults can be matched by the dual tree wavelet, the hybrid faults could be decoupled into different wavelet sub-band signals. Otherwise, the mode mixing of different faults may be induced, which will degrade the coupling performance on hybrid faults [91]. However, due to its rigid basis nature, the wavelet transform is essentially a partially adaptive signal processing method [92]. So the wavelet based decoupling approach may suffer from the fault mode mixing problem. Recently, a fully adaptive technique, named as empirical wavelet transform (EWT) [92], was proposed to deal with this problem. The EWT can process the fault vibration signal according to the information that the signal contains, and avoid the fault mode mixing in the faults decoupling. Consequently, bet-

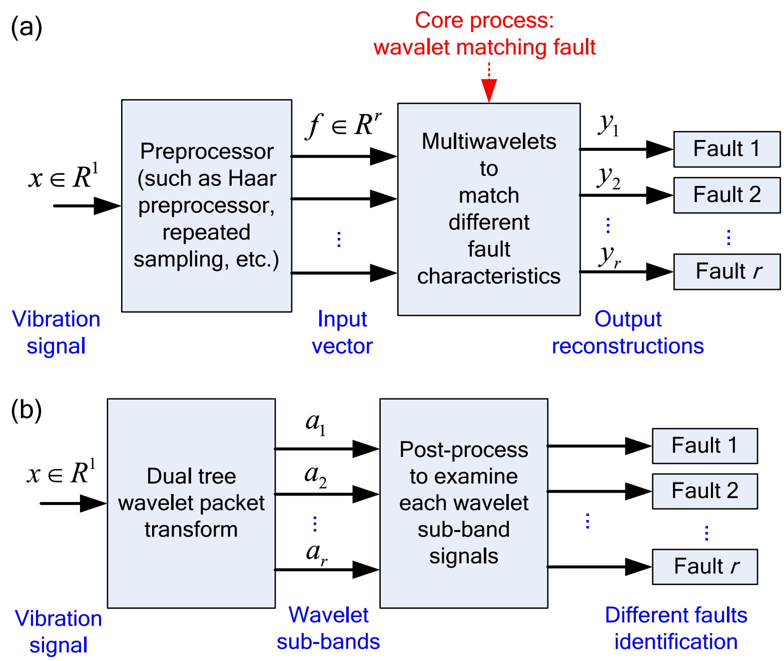

Fig. 2. Diagram block of the wavelet based fault decoupling approaches: (a) multiwavelets decoupling; (b) dual tree complex wavelet.

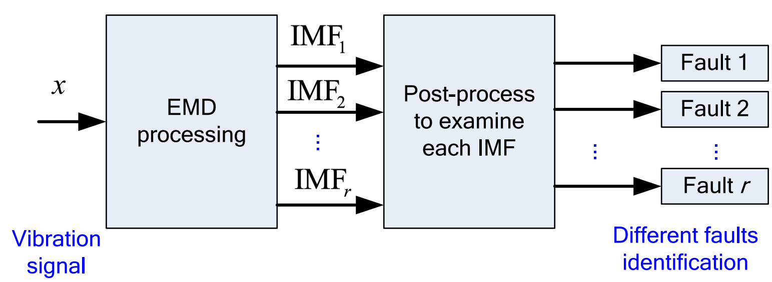

Fig. 3. Diagram block of the EMD based fault decoupling approach.

ter decoupling performance can be achieved by the EWT [91]. More examinations and validations using improved EWT approaches for the gearbox hybrid fault detection need to be performed, for instance, under the scenario of a large speed variation.

3.2. Empirical mode decomposition (EMD) based decoupling approaches

Illuminated by the decoupling manner in wavelet methods, the EMD was applied to decouple hybrid faults in gearboxes [93,94]. The EMD is able to decompose a signal into several intrinsic mode functions (IMFs) [95,96]. The IMFs reflect the time and frequency characteristics of different components contained in the signal. According to the modulation frequencies of the various fault types, the hybrid faults can be separated by the IMFs. Then by performing Hilbert demodulation on the IMFs, the hybrid faults can be detected one by one. Fig. 3 shows the working principle of the EMD based faults decoupling approach. As is well known, the EMD is sensitive to noise of the signal, and thus often suffers from the mode mixing problem, particularly when the modes are too close in frequency [97]. If mode mixing of two or more fault modes appears in one IMF, it is difficult to identify the fault type and thus to assess the fault severity. To overcome the mode mixing problem, the ensemble EMD (EEMD) was introduced by Wu and Huang [98] and then applied to decouple hybrid faults [93,94]. However, similar to the EMD, the EEMD decomposes the IMFs of a signal one by one by using a recursive algorithm. This recursive scheme may carry forward the backward errors between the IMFs, causing overestimation. In [93], a correlation measurement method was presented as the post-processing on the EEMD outputs to sift useful IMFs for hybrid faults decoupling. However, the correlation measurement cannot solve the overestimation of the EEMD in nature. To address this issue, a new method, namely the variational model decomposition (VMD) [97], was recently introduced into the EMD family. The VMD is a fully adaptive method and able to decompose the IMFs concurrently using a variational model. The errors between the extracted IMFs can be reduced so the mode overestimation issue can be resolved. Since each IMF is estimated according to its narrow-band property, the influence of harmonic frequencies and noise can be reduced to avoid the mode mixing problem. These unique features make the VMD more effective in finding the correct IMFs than the EMD based methods [97]. That means the VMD can provide better IMFs to match the fault features in hybrid faults detection. Unlike the EMD, which lacks rigorous mathematical foundations [97], the VMD is established on well-developed theories. Thus this method has greater potential for further theoretical and practical developments for decoupling hybrid faults of gearboxes.

In addition to the above work, multi-channel sensor systems and wireless sensor networks have undergone rapid developments in recent years. These developments require a signal processing tool that can deal with multi-sensor signals simultaneously. The

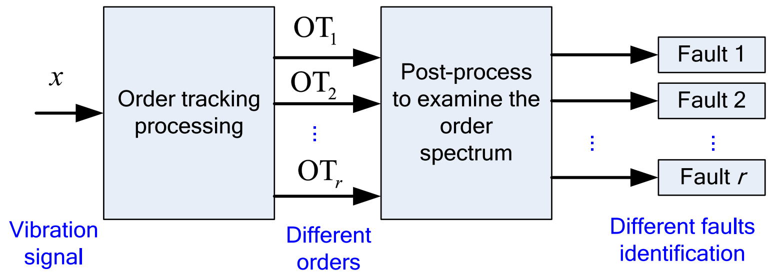

Fig. 4. Diagram block of the order tracking based fault decoupling approach.

aforementioned EMD and VMD methods can only analyse a single sensor at one computation. The multivariate EMD (MEMD) provides a solution to multi-sensor analysis [99,100]. It is interesting to notice in [99] that the MEMD can identify the true IMFs with the mode mixing depressed by the use of multi-channel sensor data and achieve much better performance in IMF extraction than the EMD. Consequently, the MEMD can be applied to correctly decouple hybrid faults into single fault modes.

3.3. Order tracking based decoupling approaches

Another possible approach is order tracking demodulation [101,102]. The order tracking technique can be mainly grouped into three categories, that is, the resampling methods [103], the Kalman filter based methods [104] and the transform based methods [69]. The most intuitive approach is the resampling methods (such as the computed order tracking), which resamples a signal in dimensionless uniform revolutions rather than in time domain so as to remove the speed variation effect of the gear shaft rotating. Xu et al. [101] and Li et al. [102] adopted the computed order tracking to decouple the compound faults in a gearbox. The Chirplet path pursuit algorithm was employed to estimate the speed reference for the resampling process of the computed order tracking. Using different order numbers, the single faults contained in the compound faults were demodulated by examining different order spectrum. Fig. 4 shows the working principle of the order tracking based faults decoupling approach. Since the order number can be an integer or a fractional number, it is feasible and applicable to track arbitrary orders, that is, the frequencies of the gear, bearing and any other components connected to the shaft [103]. Consequently, if the characteristic frequencies of the single faults in the compound faults are not the same, theoretically they can be decoupled by the computed order tracking.

On one hand, the computed order tracking adopts the interpolation techniques [103], for instance, polynomial interpolation, to resample a signal using constant rotation angle (phase) spacing. An external map of phase vs. time is established to derive the phase spacing. It should be noted that in most time the phase-time map is constructed directly in a time domain [103] by the use of a speed reference signal (such as a tachometer signal, or a shaft encoder signal, or even an estimated speed reference [101]). However, the time-based methods suffer from speed variations of the shaft due to indeterminate errors in the interpolation process and are only effective in a narrow speed range. More accurate methods for larger speed variations (for instance, up to 30%) are the phase-demodulation order tracking (PDOT) [103], which directly calculates the phase-time map using the phase demodulation to eliminate the indeterminate errors during the frequency-to-time domain transforming. Hence, the PDOT may provide better decoupling performance than the time-based order tracking in the hybrid faults detection. However, very limited work has been done and reported on the hybrid faults decoupling using the PDOT.

On the other hand, as aforementioned, the computed order tracking family is subject to slew rate limitation, such as a run up/coast down of the machines. It appears, in this case, that the Kalman filter based methods [104] is more suitable than the computed order tracking. The Vold–Kalman order tracking (VKOT) extracts the orders directly from the time domain without resampling a signal, which allows very large slew rate of the VKOT. In addition, the close and crossing orders can be decoupled by the VKOT [105] and hence the transient events of abrupt speed variations can be tackled. These features make the VKOT suitable for decoupling hybrid faults in the gearboxes.

3.4. Sparse decomposition based decoupling approaches

Sparse decomposition, a type of strongly adaptable signal processing method, is able to extract intrinsic components contained in a signal in the form of sparse representations [70]. It is possible to decouple the hybrid faults into sparse representations to characterize different single faults. Wong et al. [106] recently presented a sparse Bayesian extreme learning machine for engine hybrid faults detection. However, the sparse Bayesian was used to improve the pattern recognition ability of the intelligent classifiers. The sparse decomposition was not involved in this research. Different to [106], Zhang et al. [70] employed the resonance-based sparse decomposition (RSSD) to decompose the vibration signal of a gearbox with hybrid faults into one high resonance component and one low resonance component, which are corresponding to the gear and bearing fault oscillatory behavior respectively. Then the Teager energy operator was used as the post-processing method to detect the gear and bearing faults from the two extracted resonance components. The hybrid faults decoupling was hence achieved in this research. Based on the sparse decomposition, the morphological component analysis (MCA) was proposed to represent a signal in the sparse space using multiply dictionaries [107]. The morphological differences between individual components in the signal can be extracted using different sparse functions. The block coordinate relaxation algorithm was then used to reconstruct the morphological components from the sparse functions. One advantage of the MCA is that it can process multi-channel sensor signals. Li et al. [108] presented the MCA-FFT and Chen et al. [109,110] proposed the MCA-order tracking and MCA-Hilbert envelope to decouple hybrid failures in gearboxes. In their research, the compound faults occurred in the gears and rolling bearings were investigated. The MCA was adopted to decompose the vibration signals of the tested gearbox into one harmonic component containing the fault information of the gears, one impulse component containing the fault information of the rolling bearings and one noise component. By performing spectrum analysis using FFT, order tracking or Hilbert envelope on these morphological components, the compound faults were efficiently decoupled and identified. Fig. 5 shows the working principle of the sparse decomposition based faults decoupling approach.

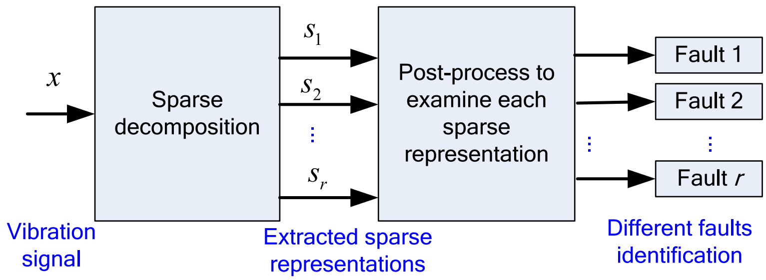

Fig. 5. Diagram block of the sparse decomposition based fault decoupling approach.

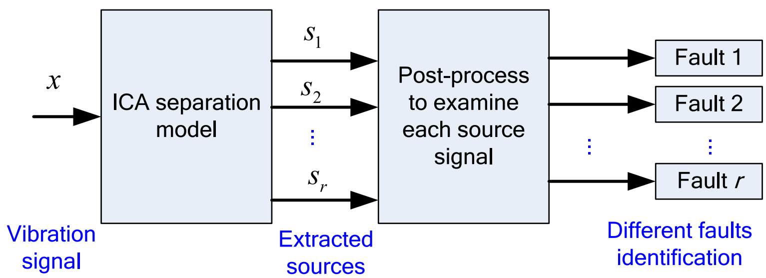

Fig. 6. Diagram block of the ICA based fault decoupling approach.

Moreover, in order to address the nonlinear aliasing of different morphological components, Li and Peng [77] and Yang et al. [111] presented the nonlinear MCA for gearbox hybrid faults decoupling. The nonlinear aliasing problem was solved by projecting the original data into the Reproducing kernel Hilbert space (RKHS), where the underlying nonlinear structure can be linearized. The experimental analysis in [77] demonstrated that the nonlinear MCA was applicable to fault detection of gearboxes in a large speed variation condition.

Although the sparse decomposition shows its high efficacy in hybrid faults decoupling, its performance is unfortunately influenced by the diversity and adaptability of the dictionaries [111,112]. How to establish adaptive self-learning dictionaries is an important research topic. In addition, the morphology reconstruction algorithm in the MCA methods is also an interesting research topic.

3.5. Independent component analysis (ICA) based decoupling approaches

Another popular technique for hybrid faults decoupling is ICA based methods [113]. ICA can be used to extract featured components (i.e., the components containing characteristic information of each single fault in the hybrid faults) of signals collected from multi-channel sensors. Hence, hybrid faults could be decoupled into single ones in the form of featured components. In the ICA decomposition, ideally, the vibrations caused by different faults are assumed to be independent to each other, e.g., the independence between the harmonic characterized waveforms of gear faults and the impulse characterized waveforms of rolling bearing faults, so the ICA could capture the featured components of the single faults in the hybrid failures in the form of independent components. ICA's decoupling capability was demonstrated in [114–116] where the vibration signal of hybrid failures in gear and bearing was decoupled into desired independent components. Each independent component represented a single fault vibration. Then intensive methods in Tables 1 and 2 could be readily applied for single fault detection. Fig. 6 shows the working principle of the ICA based faults decoupling approach.

The key issue in the ICA based decoupling processing is that each single fault contained in the hybrid faults should be extracted by one source. However, the mutual independent assumption of the ICA significantly limits its decoupling efficiency. This is because in real world the vibration sources in a multi-shaft running system are often coupled with each other and thus the mutual independent assumption may not be valid. Recent advancements indicated that the dependent component analysis (DCA) [117] can relax this mutual independent requirement and hence has more application potential than the ICA. The following section will discuss the applications and challenges of the DCA and other available techniques for gearbox hybrid faults decoupling.

4. A challenging issue in hybrid faults decoupling

Although literature review indicates that, in the past few decades, significant progress has been made on decoupling diagnosis of hybrid faults in gearbox, little work has been reported on the correlation of faults vibration sources. Since, at any instance of time, components work together to complete the function of a mechanism, inevitably, close connections and coupled effects between the components would influence their dynamic responses and performance. The vibration signals excited by different components and/or faulty parts would be, to some degree, dependent/correlated. This dependence/correlation may significantly influence the fault diagnosis result, leading to misdiagnosis or omission [118]. For instance, in a multi-stage gear system, when two different gears failed because of localized cracks with the same fault frequency characteristic, they will generate similar/closely correlated vibration waveforms. One fault may be easily omitted when the spectrum analysis is used to identify the fault frequency and its harmonics in the failure shooting procedure. Unfortunately, this issue in the compound faults decoupling diagnosis has not been well studied although the correlation is often present in real hybrid faults vibration signals. The correlation of the fault vibration sources in the hybrid faults would greatly increase the fault detection difficulty. Hence, it is necessary to improve the above mentioned five methodologies to make them suitable for dealing with the correlation of the fault vibration sources.

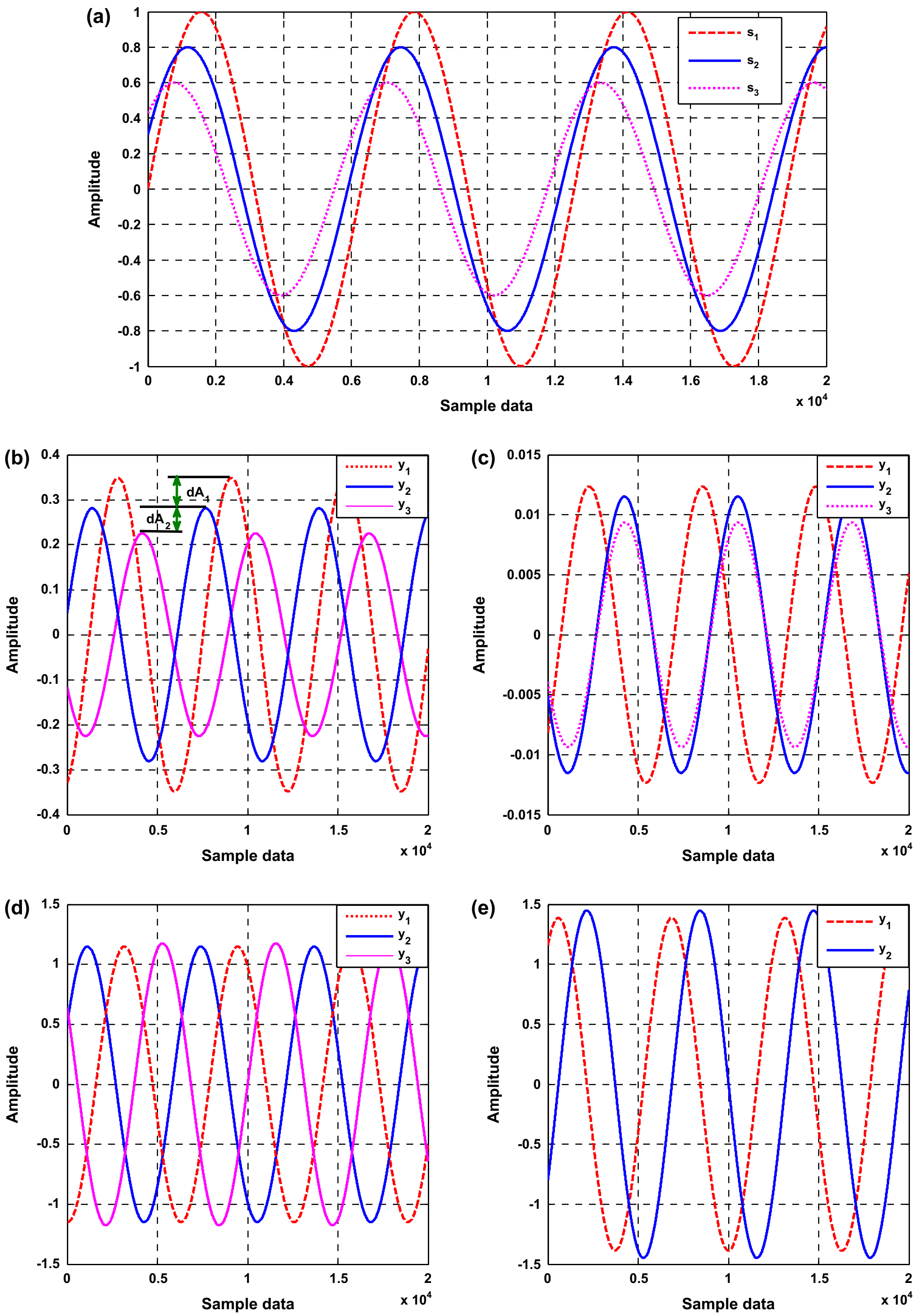

Fig. 7. The waveforms of the sources **S** and the recovered sources **Y** from **X** with 50 dB noise: (a) the original sources **S**; (b) the C-BCA; (c) E-BCA; (d) JADE; (e) FastICA. Note that the FastICA failed to identify three sources.

A potential solution in the ICA based methods is the use of DCA algorithms. The DCA algorithms take into account the dependent characteristics between source signals. One of the DCA algorithms, a recently proposed bounded component analysis (BCA) [119–125], is able to separate not only the independent sources but dependent/correlated sources. The BCA framework was firstly established by Cruces [119] and then extended to a more geometric framework by Erdogan [120]. Unlike the ICA, which assumes the statistical independence, the BCA takes the geometrical properties of the sources to recover them from the unknown mixtures. An influential study conducted by Pham [126] showed that the order statistics of the geometrical properties of the sources could be use-

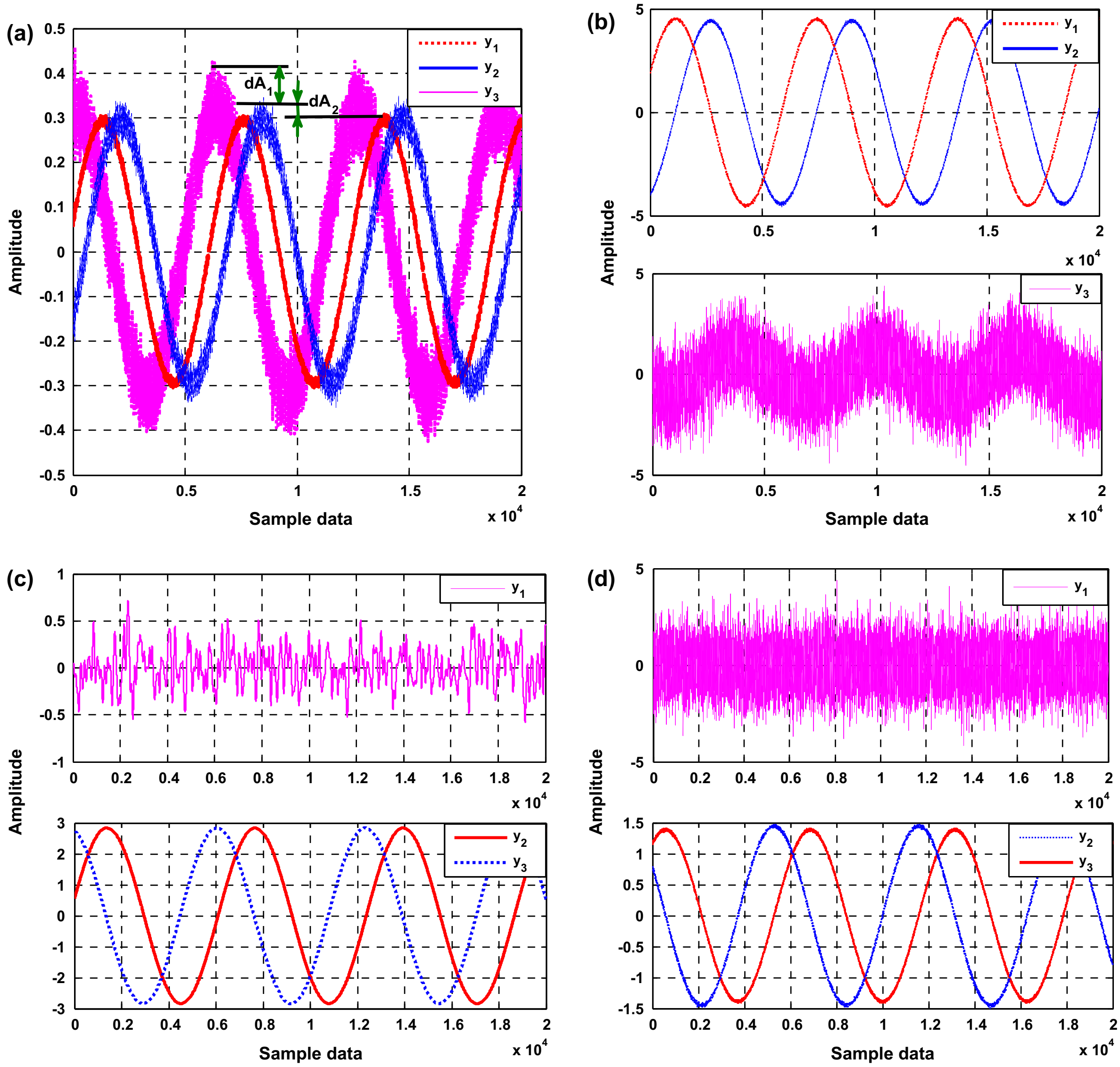

Fig. 8. The recovered sources **Y** from **X** with 0 dB noise: (a) C-BCA; (b) E-BCA; (c) JADE; (d) FastICA.

ful for bounded sources separation in the ICA framework. In the light of this, the BCA shows that using the geometrical properties the assumption of mutual independence required by the ICA approach is no longer necessary for the separation of both independent and dependent sources from their mixtures [119]. This feature is extremely important for vibration analysis because in practice the gearbox vibration signals do not always meet the mutual independence requirement of the ICA [118]. Additionally, in most practical applications mechanical vibration signals/sources are bounded, for instance, the amplitude modulation frequency modulation (AMFM) characteristics of gear meshing vibration [8]. Hence, the BCA is more suitable than the ICA in hybrid faults decoupling. Cruces [119] showed that the ICA failed to recover true sources in a communications scenario where a correlation coefficient was imposed to the original sources. In [119], they proposed a criterion to minimize the perimeter of the estimated component in order to efficiently identify correlated sources. Further, they explained how the ICA framework (algorithms like the ThinICA, joint approximate diagonalization of eigen-matrices (JADE) or FastICA) failed in recovery of dependent sources. Moreover, in [122] Cruces compared the performance of the BCA and JADE in an over-determined noisy mixture case for correlated sources. The results demonstrated that the BCA had a high separation performance than the JADE method over a wide range of correlation coefficient values of the sources. The same conclusions were drawn by Erdogan in [120], where the analysis results showed that when the correlation of sources was gradually increasing, the separation performance degraded gracefully for the ICA algorithms. Moreover, Erdogan introduced a new BCA algorithm based on two novel geometric objects, namely Principal Hyper-Ellipsoid and Bounding Hyper-Rectangle [120]. By maximizing them, the new BCA produced promising separation results even with a very high correlation of sources. All these mentioned work has corroborated the advantages of the BCA framework against ICA framework in the recovery of both independent and dependent sources. The strict constrain of mutual independence assumption of the ICA has been relaxed into a weaker hypothesis, i.e. the domain separability in the BCA [121]. The ICA can be regarded as a special case of the BCA for bounded signal. As a result, the BCA is flexible and available for wider applications than the ICA. It is suitable to employ

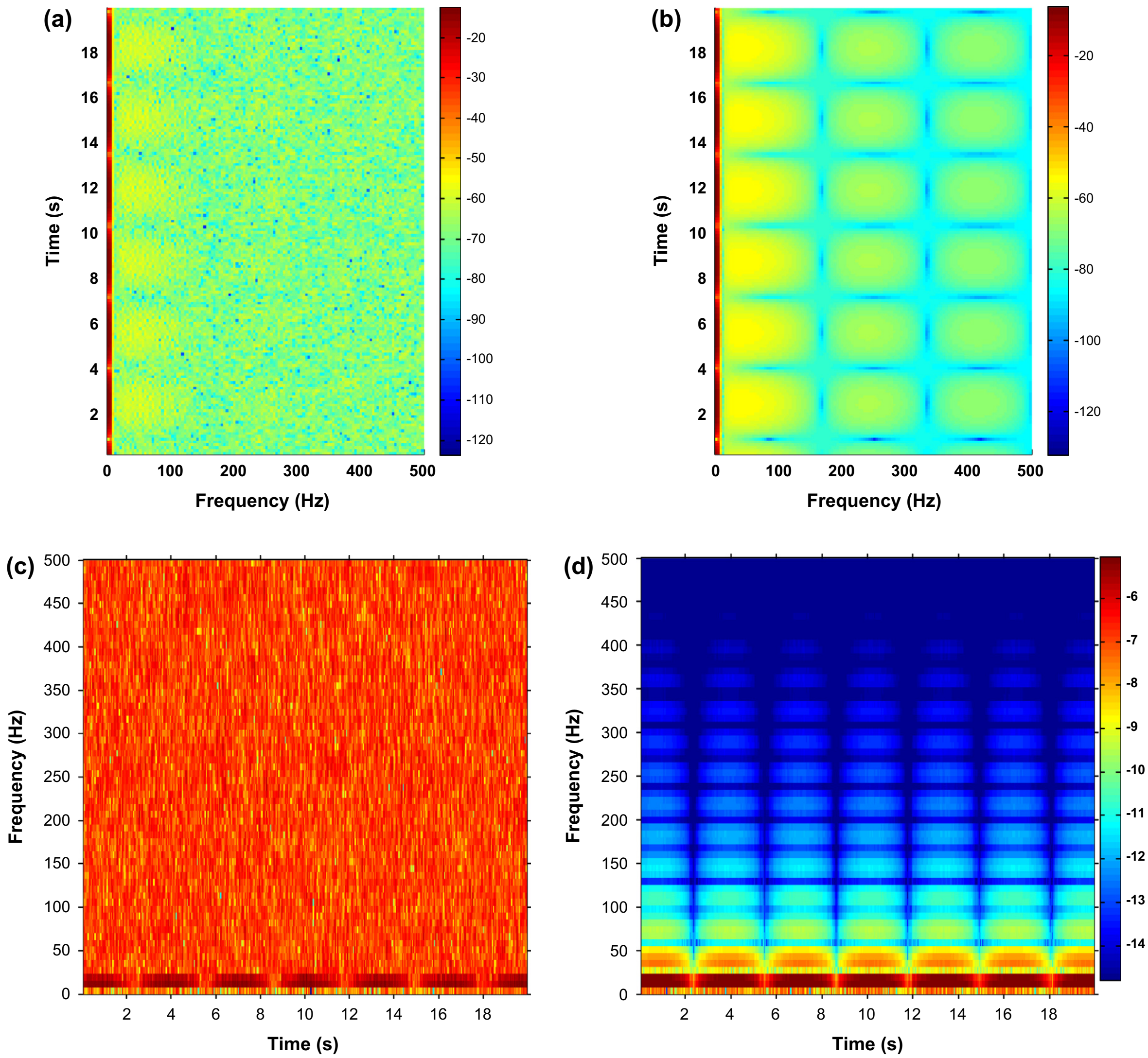

Fig. 9. The time-frequency presentations of (a) an original mixture, x_1, and (b) a re-constructed mixture by VKOT; the spectrograms of orders of (c) an original mixture, x_1, and (d) a re-constructed mixture by VKOT.

the BCA to decouple hybrid faults in the gearbox with consideration of dependence/correlation of the faults vibration.

5. Illustration of the BCA decoupling performance

This section discusses in further detail the BCA framework for decoupling and diagnosis of hybrid faults in the gearbox. In this section, the BCA based hybrid fault decoupling approach is illustrated using two numerical simulations: (1) a simple simulation on a synthesized signal (from 3 sinusoid signals with the same frequency); and (2) a simulated gearbox hybrid fault signal [127]. The decoupling performance of the BCA is compared with existing ICA based decoupling methods.

5.1. Simulation on correlated sources

Literature review suggests promising potentials of using the BCA for correlated source separation; however, the dependence/correlation of fault vibration sources has seldom been considered in the field of mechanical hybrid fault detection. Hence, in this numerical simulation, without loss of the generality, a simple example is presented to illustrate the BCA separation performance on the following three highly dependent sources:

$$\begin{cases} s_1 = 1 * \sin(t + 0) \\ s_2 = 0.8 * \sin(t + \pi/8) \\ s_3 = 0.6 * \sin(t + \pi/4) \end{cases} \tag{1}$$

where three sinusoid signals s_1, s_2 and s_3 have the same frequency but different amplitudes and phases. A randomly generated mixing matrix $\mathbf{A}$ was used to mix the sources, and has the following form

$$\mathbf{A}_{8\times3} = \begin{bmatrix} 0.46 & 0.81 & 0.49 & 0.09 & 1.28 & -0.17 & -0.67 & 0.28 \\ 0.06 & 0.31 & -1.73 & 1.10 & -1.36 & 0.01 & 0.19 & 1.17 \\ 1.39 & -0.11 & 0.35 & -0.59 & -0.47 & -0.55 & 1.62 & -1.75 \end{bmatrix}^{\mathrm{T}} \tag{2}$$

In order to simulate the noise scenario in Eq. (1), the MATLAB function, agwn$(\cdot)$, was employed to generate the additional white Gaussian noise $\mathbf{N}$ to the mixtures, $\mathbf{X}$. Thus the observation model can be expressed as

$$\mathbf{X} = \mathbf{AS} + \mathbf{N} \tag{3}$$

where $\mathbf{A} = \mathbf{A}_{8\times3}$ and $\mathbf{S} = [s_1, s_2, s_3]^{\mathrm{T}}$. The goal of the BCA is to recover the original sources $\mathbf{S}$ from $\mathbf{X}$ by obtaining the estimated signals $\mathbf{Y} = [y_1, y_2, y_3]^{\mathrm{T}}$ ($\mathbf{Y} \approx \mathbf{S}$). Fig. 7(a) shows the waveforms of the original sources and Fig. 7(b) presents those of the recovered sources $\mathbf{Y}$ from

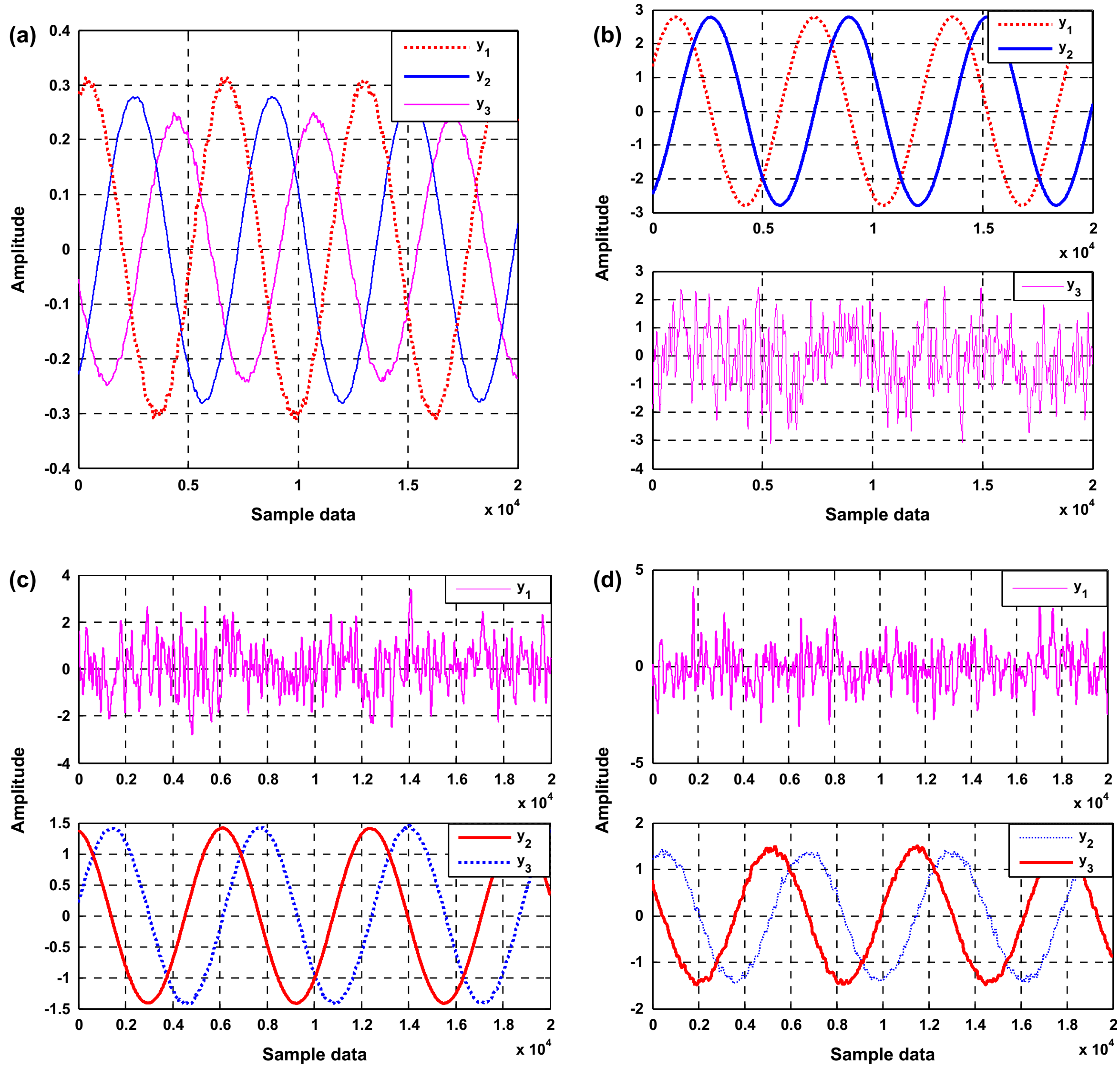

Fig. 10. The recovered sources **Y** from **X** with 0 dB noise after order tracking processing: (a) C-BCA; (b) E-BCA; (c) JADE; (d) FastICA.

X with 50 dB noise **N** using the Cruces's BCA in [119] (C-BCA). It is interesting to note that **S** was correctly recovered by **Y** in Fig. 7(b) even though noise was introduced into the mixture. The amplitude and phase variances were clearly depicted by the C-BCA method. The performance of the C-BCA was compared with that of the Erdogan's BCA (E-BCA) [120], JADE and FastICA in Fig. 7(c–e). As shown in these figures, the FastICA only separated two sources (i.e., $\mathbf{Y} = [y_1, y_2]^T$) from the original ones, while the E-BCA and JADE was able to recover all the three sources (i.e., $\mathbf{Y} = [y_1, y_2, y_3]^T$). Comparing Fig. 7 (b) with (c) and (d), it can be observed that the E-BCA correctly identified the amplitude variances but not exactly all the three phase variances, and the JADE correctly identified the phase variances but failed to recover the amplitude variances. Hence, in this comparative study, the two BCA approaches performed better than the two ICA methods, and the C-BCA appeared to yield the best performance among all the approaches.

Then, the noise level was increased from 50 dB to 0 dB to evaluate the separation performance of these methods. Fig. 8 shows the recoveries of the C-BCA, E-BCA, JADE, and FastICA with 0 dB noise **N**.

As shown in Fig. 8(a), the C-BCA gives correctly estimated sinusoid sources, although the signals appear to be noisy. Fig. 8(a) also shows the amplitude and phase variances obtained via the C-BCA. In Fig. 8(b), it is interesting to see that the E-BCA effectively separated two sources while the third estimation, y_3, was not as good as expected. The recovered y_3 appears to be heavily contaminated by the noise although a sinusoid behavior can be observed. As a result, the performance of the E-BCA was worse than that of the C-BCA in this simulation. It is not surprising that both the JADE and FastICA failed to recover the first source y_1 (see Fig. 8(c) and (d)); however, these two approaches yielded high quality estimates of the other sources y_2 and y_3. Similar to the E-BCA, the JADE and FastICA performed worse than the C-BCA. From the analysis results, it can be concluded that the noise degraded the performance of all the above methods, including the C-BCA (see the severe distortion of the waveforms in Fig. 8(a)).

Bearing the above conclusion in mind, the VKOT was applied in this review to alleviate the noise effects, and at the same time, extracts the signal components of interest. Unlike the computed order tracking technology [103], the VKOT decomposes orders (super-/sub-harmonics of the fundamental frequency) directly in the time domain without resampling. Hence, the smearing of the dominating frequency components due to frequency transforma-

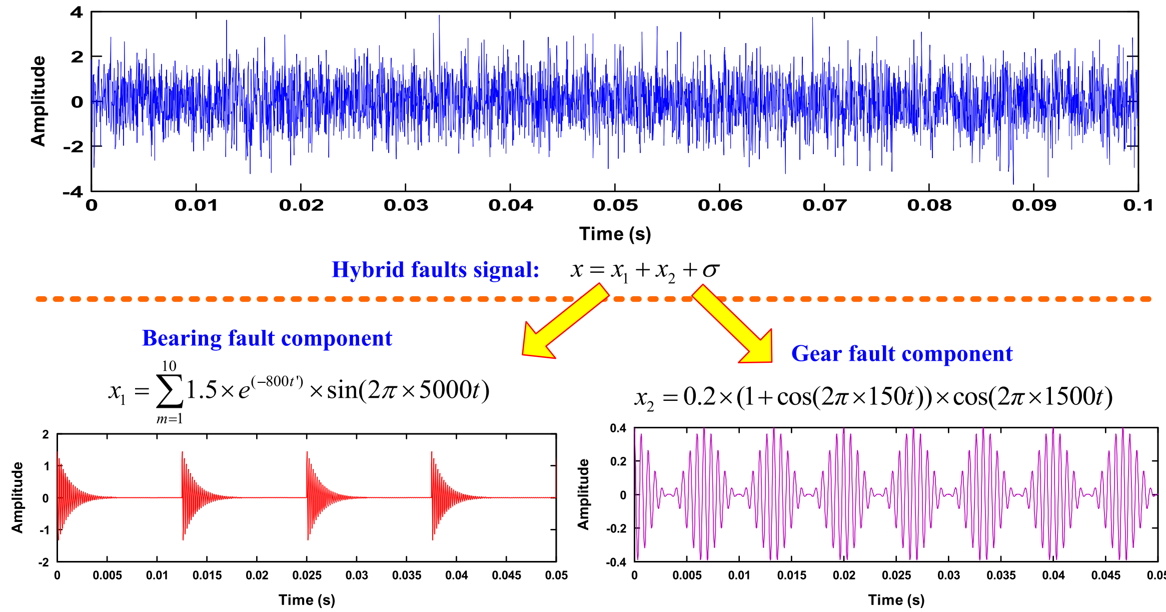

Fig. 11. The waveforms of the hybrid faults signal x, bearing fault component x_1, and gear fault component x_2.

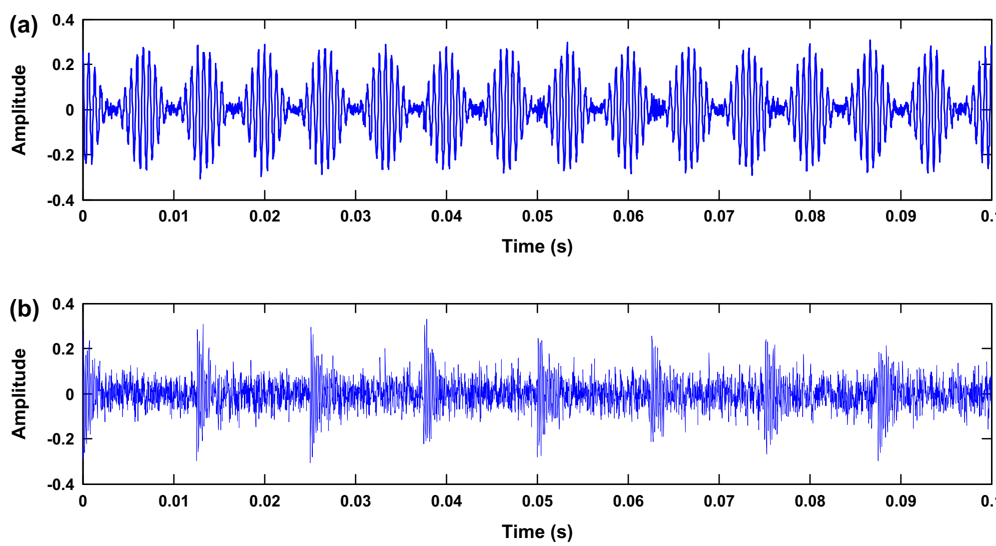

Fig. 12. The waveforms of the decoupled sources by the C-BCA: (a) the gear fault source and (b) the bearing fault source.

tion could be redressed, and the noise effects could also be addressed [104].

Figs. 9 and 10 show the order tracking results. Fig. 9 presents the time–frequency presentations and order spectrograms of the original mixture and its reconstruction after order tracking. It is evident that the original mixture was corrupted by heavy noise, especially in Fig. 9(c) where a high noise level can be observed. In Fig. 9(c), only the basic order concentrating around 16 Hz (i.e. about 100 times of the fundamental frequency, 0.16 Hz) could be well discovered. This is probably a consequence of the influence of the randomly mixing process of the original sources, as well as the heavy noise. On the contrary, the image was tidied out dramatically by VKOT processing in Fig. 9(b). The white Gaussian noise was depressed and the dominating frequency components were sorted out. One can note in Fig. 9(d) that except for the 100th order (16 Hz) component, other orders appeared regularly along the frequency axis and their amplitude intensities distributed along a sinusoid waveform. It may indicate that the additional noise was efficiently removed and the intrinsic components of the original signal preserved. Then the performance of the C-BCA, E-BCA, JADE and FastICA in dependent sources separation was investigated. Fig. 10 shows the source separation results. It can be observed in Fig. 10(a) that the C-BCA generated satisfactory recovery sinusoid sources. The amplitude and phase variances were captured precisely in Fig. 10(a) and the estimated results were as good as in Fig. 7(b) where a 50 dB noise level was introduced. The performance of the order tracking based C-BCA was greatly improved in Fig. 10(a) in comparison to the results shown in Fig. 8(a). The noise in Fig. 8(a) was eliminated. However, in Fig. 10(b–d) it can be observed that only two high quality sources y_2 and y_3 were recovered by the E-BCA, JADE and FastICA methods, while the first sinusoid source y_1 was still misidentified.

Nevertheless, the above analysis results demonstrate that the BCA methods have a strong ability of separating dependent/corre-

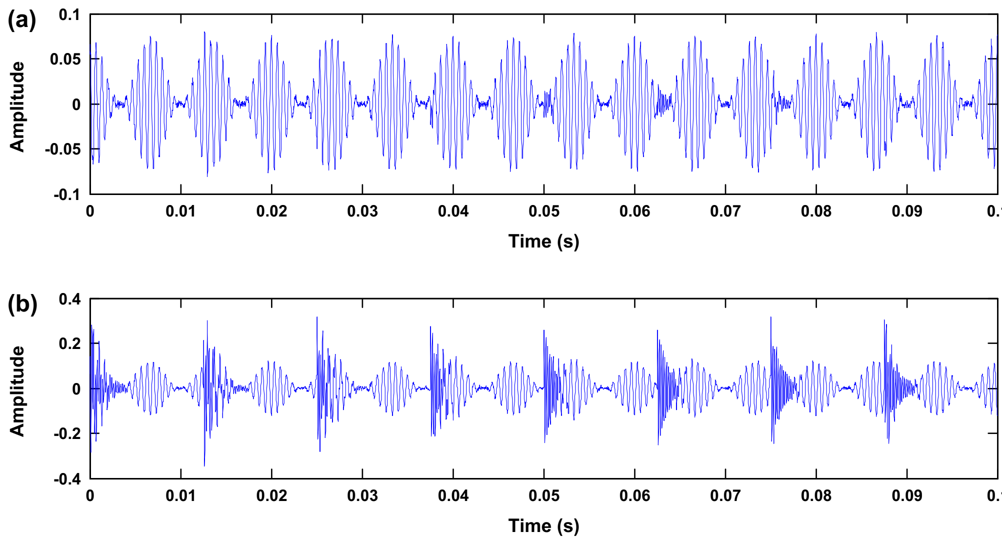

Fig. 13. The waveforms of the decoupled sources by the E-BCA: (a) the gear fault source and (b) the bearing fault source.

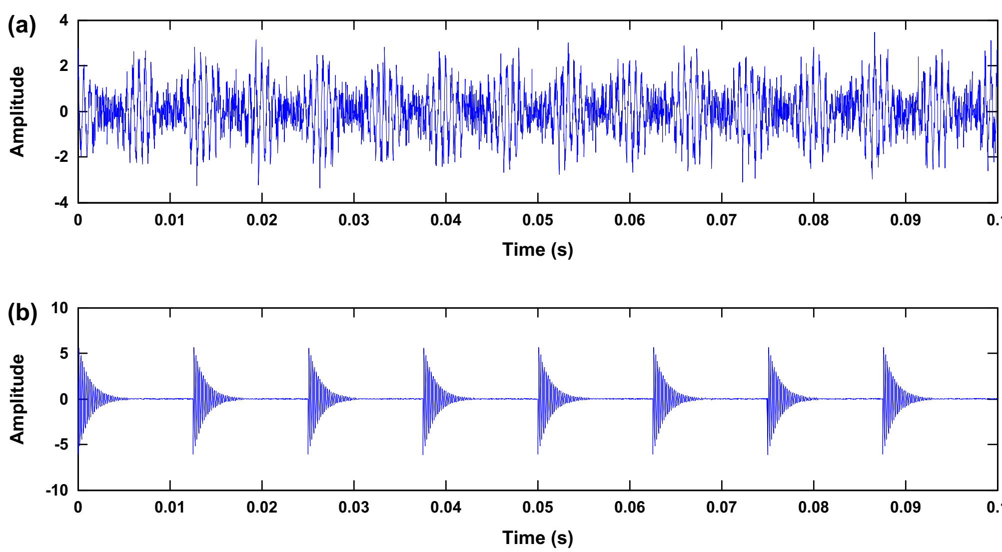

Fig. 14. The waveforms of the decoupled sources by the JADE: (a) the gear fault source and (b) the bearing fault source.

lated sources in noiseless conditions of the BSS and in heavy noise conditions. If proper de-noising processing is applied to the mixtures, the C-BCA can produce excellent performance in separating dependent sources. However, the ICA based methods do not appear to work with dependent sources.

5.2. Simulation on gearbox hybrid faults

Here we consider a simulated vibration signal x [127], which contains a bearing fault component x_1 and a gear fault component x_2. Fig. 11 shows the details of the simulated signal.

$$\begin{aligned} x &= x_1 + x_2 + \sigma \\ &= \sum_{m=1}^{10} 1.5 \times e^{(-800t')} \times \sin(2\pi \times 5000t) \\ &\quad + 0.2 \times (1 + \cos(2\pi \times 150t)) \times \cos(2\pi \times 1500t) + \sigma, \end{aligned} \tag{4}$$

where $t' = t - mt_b$, with $t_b = 0.0125$ s and $m = 1, 2, \ldots, 10$, and σ is the additive Gaussian white noise. It can be seen that the impulsive interval of the bearing fault is t_b (see the waveform of x_1), i.e. the fault frequency is $1/t_b = 80$ Hz, and the gear meshing and fault frequencies are respectively 1500 Hz and 150 Hz (see the waveform of x_2). Since the fault waveform types and the characteristic frequencies are different, the identification of the two fault components can be regarded as an independent source separation problem.

Three sensors were used to record the hybrid faults signal at the sampling frequency of 30 kHz. The fault decoupling was then carried out using the C-BCA, E-BCA, JADE and FastICA. Figs. 12–15 provide the fault decoupling results.

It can be seen from Fig. 12 that the gear fault component x_2 was correctly recovered by the C-BCA (see Fig. 12(a)) while the bearing fault recovery was blurred by noise (see Fig. 12(b)). A comparison between the recovered bearing fault component in Fig. 12(b) and the original one x_1 in Fig. 11 shows that the impulsive interval t_b was correctly preserved in the recovered signal. Similar results can be seen in Fig. 13. The waveforms of the fault sources recovered by the E-BCA indicate that the gear fault component x_2 was correctly identified, while the recovered source for the bearing

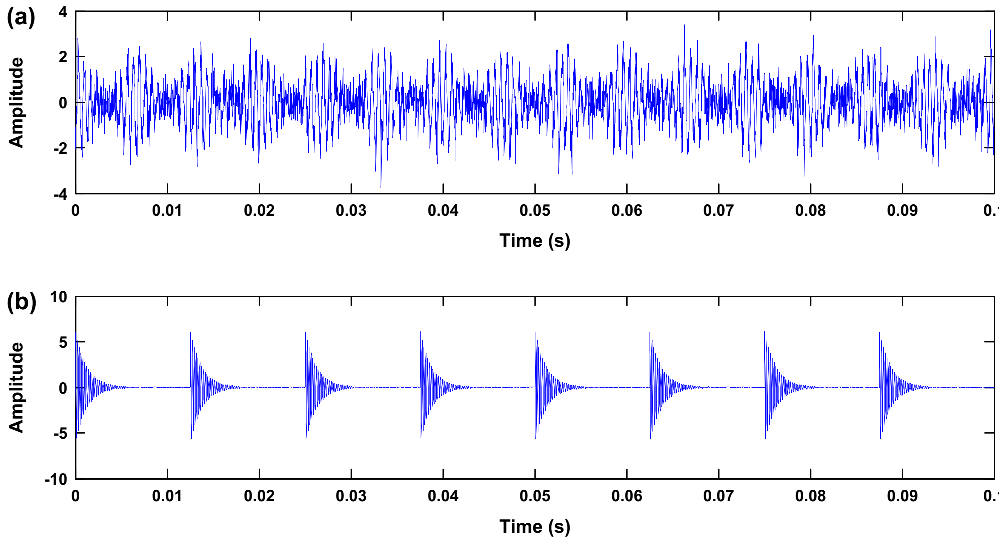

Fig. 15. The waveforms of the decoupled sources by the FastICA: (a) the gear fault source and (b) the bearing fault source.

fault component x_1 exhibits mode mixing. It can be observed in Fig. 14 that the JADE correctly identified the bearing fault component x_1 and recovered its waveform. However, it failed to recover the waveform of the gear fault component x_2. Similar results were found in Fig. 14, where the waveform of the gear fault source recovered by the FastICA appears to be severely distorted although the periodicity of the gear fault (t_g = 1/150 s = 0.0067 s) seems to be correctly preserved.

Overall, the four methods were able to precisely identify one fault source from the original hybrid faults measurements. Moreover, important features (i.e., t_b and t_g) of the misidentified fault source were extracted to provide useful information for the fault detection. Hence, the four methods presented somewhat comparable performance in the fault decoupling in this simulation. It should be emphasized that the JADE and FastICA are popular and highly effective algorithms in independent source separation. The analysis results suggest that the BCA was also capable of separating independent vibration sources.

The above two simulations exemplify the advantage of the BCA against the ICA, in that the BCA is capable of dealing with both independent and dependent vibration sources. In a real transmission mechanism, the vibration sources, especially for those associated with multiple shafts, are often closely correlated. The hybrid faults decoupling needs to address the separation of both independent and dependent vibration sources. Hence, it is more desirable to develop the BCA based decoupling methods for gearbox hybrid faults detection. We are currently working on a BCA based technique for decoupling and diagnosing hybrid faults in wind turbine gearboxes and the outcomes will be reported in due course.

6. Concluding remarks

Detection and diagnosis of hybrid faults is an important and challenging research topic in mechanical CMFD and has attracted increasing attention in recent years. This review summarizes recent progress on developed methods for decoupling and diagnosing hybrid faults in gear transmission systems, and discusses five categories of methodologies, namely (1) wavelet, (2) EMD, (3) order tracking, (4) sparse decomposition and (5) ICA based decoupling methods.

The challenge of having dependent characteristics of different faults or dependence/correlation in the hybrid faults is discussed. This may be overcome using the BCA technique. The performance of the existing hybrid faults decoupling techniques can likely be improved in this aspect. In what follows, we summarize future research directions in decoupling diagnosis of hybrid faults in gear transmission systems.

(a) Enhancement of wavelet based decoupling methods to improve the matching efficacy of the wavelet-to-fault by considering the dependence/correlation in the hybrid faults. The EWT [91] and its improvement methods can be considered for this purpose.
(b) Enhancement of empirical mode decomposition (EMD) to solve the mode mixing problem in hybrid faults decoupling, especially to address the dependence/correlation in the hybrid faults. The MEMD [99,100] and VMD [97] would be the research emphasis owing to their good performance in reducing mode mixing.
(c) Development of new order tracking techniques by taking the phase demodulation into account to enhance its accuracy in identifying dependence/correlation in the hybrid faults. The PDOT [103] is a promising technique in the new generation of order tracking owning to its high accuracy. Improvement on its slew rate limitation seems to be an interesting research direction, which is expected to provide high efficacy for gearbox hybrid fault decoupling.
(d) New insight into the diversity and adaptability of the dictionaries for the sparse decomposition. Especially, an interesting topic is to develop adaptive self-learning dictionaries for the MCA methods to address the dependence/correlation issue in the hybrid faults decoupling.
(e) Development of new DCA based methods for hybrid faults decoupling, for instance, simultaneous BCA algorithms for stable-state operation of the gear systems and convolutive BCA algorithms for variant speed operation. Other DCA methods, such as the algorithm presented in [117], are worth investigating.
(f) Suitable noise cancellations are crucial to be incorporated into the aforementioned decoupling methods. Special emphasis should be focused on the hybrid fault detection under a large speed variation scenario.

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