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An automatic abrupt signal extraction method for fault diagnosis of aero-engines †

Qiang Pan[1], Ying Liu[1], Rui Zhou[2], Hong Wang[3], Haibing Chen[1,*] and Tian He[1]

[1]*School of Transportation Science and Engineering, Beihang University, Beijing 100191, China*
[2]*China Aero-polytechnology Establishment, Beijing 100028, China*
[3]*Beijing Key Laboratory of Long-life Technology of Precise Rotation and Transmission Mechanisms, Beijing Institute of Control Engineering, Beijing 100094, China*

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Abstract

Fault diagnosis of a mechanical device such as a complicated aero-engine system is an interesting engineering topic. Present paper aims at providing a method to automatically extract abrupt information of signals to diagnose typical faults. This proposed method is based on singular value decomposition (SVD), and it decomposes a signal via reconstruction of singular value matrix. A criterion of difference spectrum is introduced into this method to terminate the analysis procedure. To verify the proposed method, both numerical simulation and experimental work on rotor test rig and an aero-engine generator were carried out. In addition, the kurtosis of rubbing resulting from wavelet, empirical mode decomposition (EMD) and this proposed method was compared. It is shown the proposed method is advanced to wavelet and EMD in rubbing fault diagnosis of aero-engines since it can extract the most significant periodic impact feature of fault signals.

Keywords: Singular value decomposition; Difference spectrum; Abrupt information; Rubbing; Fault diagnosis

1. Introduction

Machine fault diagnosis is concerned with finding faults arising in machines to identify the faults of a mechanical system by monitoring its operating signals, from which the fault features are extracted once a fault occurs. Most of fault information, including impact, oscillation and structure failure, is carried in abrupt signals [1]. Hence how to extract abrupt information from the detected signals has become the key to diagnosing typical faults, such as operational change of structures, rotor-stator rubbing, bearing pitting and gear tooth breaking/wearing [2-5].

Since an abrupt signal usually contains important fault information, much investigation has been conducted on the signal extraction technique. By far, a number of abrupt signal processing methods, such as frequency spectrum (FS) analysis, wavelet transform (WT), empirical mode decomposition (EMD), and singular value decomposition (SVD), have been developed and led to a variety of applications in fault diagnosis field.

FS analysis is one of conventional technologies used in fault diagnosis [6]. By this method, a signal can be transformed from time domain to frequency domain by using fast Fourier transform (FFT). The frequency spectrum obtained from FFT contains multiple frequency components. If a signal carries abrupt information, a new frequency appears at a wide frequency band [7]. At a high frequency band, the variation of frequency and energy caused by abrupt information becomes quite obvious because the high frequency related information contained in normal signal is very weak. FS analysis can be used to identify strong abrupt signals. However, it is a global scheme to find the variation law from entire signals and in turn not capable of analyzing transitory signals or extracting weak abrupt information [8].

WT, which was developed from Fourier transform (FT), is used to extract information from many different kinds of data, like signals and images. Different from FT, WT can be used for multi-scale analysis of the signal through dilation and translation [9]. WT is advanced to FT to extract time-frequency features of a signal effectively [10-12] and available to abrupt signal processing [13]. However, WT still has some inevitable deficiencies [14], including interference term, border distortion and energy leakage. They may generate many small undesired spikes all over the frequency scales and make the results confusing and difficult to be interpreted. In addition, the analytical result of WT highly relies on the selection of the mother wavelet and signal decomposition level [15], and its extraction results are usually undesirable under strong noise disturbance [16, 17].

*Corresponding author. Tel.: +86 10 82316330, Fax.: +86 10 82316330
E-mail address: aw_chenhb@buaa.edu.cn
† Recommended by Editor Chongdu Cho

EMD is an adaptive signal processing method, by which any complicated signal can be decomposed into a finite small number of components. These components form a complete and nearly orthogonal basis for the original signal and described as intrinsic mode functions, which can be frequency and amplitude modulated [18]. Since the decomposition is based on the local characteristic time scale of the data, EMD is available to nonlinear and nonstationary processes [19]. In general, it can effectively extract signal features of harmonic waves since intrinsic mode functions are obtained based on the cubic spline curve fitting. But sometimes it fails to extract abrupt information because the cubic spline curves are unable to fully match the transient characteristics of signals [20].

SVD has also been applied effectively to extract abrupt information of raw test signals [15, 21]. SVD is the factorization of a real or complex matrix. Its effectiveness has been validated and led to many applications in signal processing and fault diagnosis in recent years [22-24]. Though SVD based technology is regarded as a good filter to suppress the nonlinearity of noise distributed in different forms [25], further investigation is still necessary, such as selection of appropriate reconstructed dimensions and the approach to reconstruct the singular value of signals.

This paper proposes an automatic method to extract abrupt information of fault signals from raw signals. The abrupt signal extraction is developed from SVD and promoted by selecting order of singular values automatically without highly relying on experience of operators. Therefore, it is easy to implement and applicable for practical engineering applications. Based on SVD, the signals are decomposed via reconstruction of singular value matrix, and then abrupt information containing fault characteristics is extracted. To verify the proposed method, both numerical analysis and experimental work were conducted. Their results were compared with wavelet and EMD methods to show advantage of the proposed method.

2. Proposed SVD based method

2.1 The reconstruction attractor trajectory matrix of time series

Assume a signal originating from the mechanical fault of a machine is in time series $x_1, x_2, x_3, \cdots, x_n$. Its reconstruction attractor trajectory is written by

$$D_m = \left[X(1), X(2), \cdots, X(t)\right], \tag{1}$$

and

$$X(t) = \left[x(t), x(t+\tau), x(t+2\tau), \cdots, x(t+(m-1)\tau\right]^T \tag{2}$$

where m is the reconstruction dimension and τ the time delay. Based on Takens' theorem, the properties of the dynamical system in the reconstructed phase space are preserved under the condition that the reconstruction dimension $m \ge 2d+1$, where d is the attractor's dimension of original dynamic system. The time delay τ is usually equal to 1. Then the reconstruction attractor trajectory is

$$D_m = \begin{pmatrix} x_1 & x_2 & \dots & x_n \\ x_2 & x_3 & \dots & x_{n+1} \\ \dots & \dots & \dots & \dots \\ x_m & x_{m+1} & \dots & x_{m+n-1} \end{pmatrix}. \tag{3}$$

2.2 SVD method

SVD is the factorization of a real or complex matrix, which leads to numerous useful applications in signal processing and statistics. Given a matrix D of order $m \times n$, it can be decomposed by

$$D = U \Lambda V^T, \tag{4}$$

where Λ is an $m \times n$ rectangular diagonal matrix with real numbers $\lambda_1 \ge \lambda_2 \ge \lambda_3 \ge \cdots \ge \lambda_p > 0$ on the diagonal:

$$\Lambda = \begin{pmatrix} \lambda_1 & & & & & & \\ & \lambda_2 & & & & & \\ & & \dots & & & & \\ & & & \lambda_p & & & \\ & & & & 0 & & \\ & & & & & \dots & \\ & & & & & & 0 \end{pmatrix} \tag{5}$$

The $m \times m$ matrix U and $n \times n$ matrix V are left-singular and right-singular matrices of D, respectively. The column vectors of U and V are standard orthogonal basis of D and expressed by $U = \{u_1, u_2, \cdots, u_m\}$ and $V = \{v_1, v_2, \cdots, v_n\}$, respectively [26].

In signal processing, reconstruction means determination of an original continuous signal from a sequence of equally spaced samples. A reconstructed signal is usually derived from the inverse operation of SVD and expressed by [27]

$$x(t) = \sum_{i=1}^{m} \lambda_i u_i v_i^T. \tag{6}$$

It is obvious the reconstruction based on various singular values results in signal components with energy of different frequency bands at different directions of a reconstruction space. Hence the selection of singular values is critical in extraction of abrupt information.

2.3 Selection of order of singular values

The fault signal detected from a machine usually consists of three components: Impact, harmonic background signal and noise [28]. Thus, it is key to separate these three components

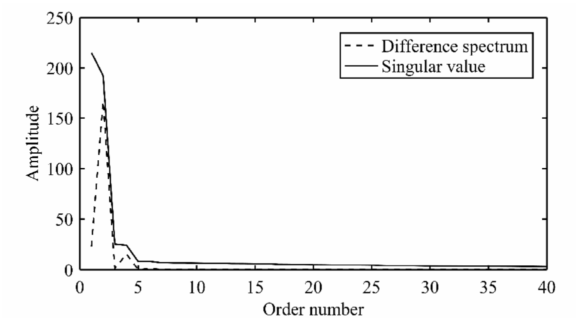


Fig. 1. The singular values detected from a machine and their difference spectrum.

from the signal and enhance their fault information. However, separation of such components is not easy because sometimes the frequency of a fault signal is very close to frequency of impact signal or noise [29, 30]. The SVD based method is an optional solution to identify the types of signal components because the decomposed singular values of matrix D_m vary with different category of components.

It has been indicated that the harmonic signal contributes to high singular values at first several orders and the impact signal affects the values at orders of middle phase [25]. Unlike these two types of signals, noise is associated with small singular values, which are almost not changed at different orders. Fig. 1 shows an example of the singular values detected from a machine and their difference spectrum. It is seen the values are changed obviously at different phases. Clearly, the reconstructed singular values at different orders carry various quantity of energy at different frequency bands. It means the selection of orders of singular values is of great importance in signal decomposition and extraction. Large number of singular values usually leads to mixture of noise or abrupt information with normal signals originating from the source. While, small size of singular values may lose useful information of signals. Thus, it is necessary to choose a suitable number of singular values at proper position in abrupt information extraction.

If the singular values are capable of dividing into a number of sections based on the category of their signal components, it is probable to conduct singular value reconstructions, respectively, and decompose the different components of the signals. As a result, each resulting component would not be disturbed by other decomposed components and in turn accurate abrupt information is observed. One option to implement it is arranging the singular values of reconstruction attractor trajectory matrix in a descending order and taking the difference between each two neighboring singular values over a threshold as a criterion to identify various energy sections. When it happens, these two neighboring singular values are reconstructed and the signal decomposition is implemented. As mentioned above, SVD is based on the mechanism that signals at different frequency bands carry various quantity of energy. To denote the percentage of the energy contained in an abrupt signal among entire signals, a parameter k, defined by the amplitude ratio of abrupt signal to sinusoidal signal, is

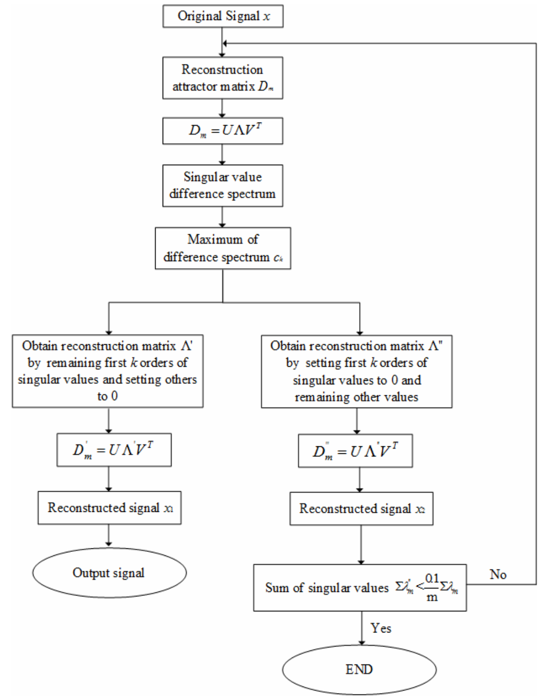


Fig. 2. The flowchart of abrupt information extraction process based on the proposed SVDS.

introduced in this paper.

2.4 Abrupt information extraction based on difference spectrum of singular values

To extract the abrupt information effectively, a difference spectrum of singular values is introduced to select the appropriate order of singular values. Arranging the singular values in a descending order and their difference spectrum is defined by

$$c_n = \lambda_n - \lambda_{n+1} \text{ , } n = 1, 2, \cdots, q-1, \tag{7}$$

where the series $c_1, c_2, \cdots, c_{q-1}$ represent the difference between each neighboring singular values. Obviously, the maximum c_k means the difference of neighboring singular values between λ_k and λ_{k+1} is the largest, i.e., the singular value changes most abruptly at λ_k. Categorizing the singular values from λ_1 to λ_k into one frequency band of signals, the expected components can be extracted accurately after reconstructing these singular values. Then the rest of signals are reconstructed to extract new components belonging to second frequency band of signals. Such process can be repeated to extract the abrupt information at different frequency bands until a given termination condition is triggered.

From the viewpoint of energy, no useful abrupt information would be extracted from the signals if the energy contained in components of those signals is much smaller than the energy of initial signals. Thus, the termination condition is established by the criterion that the decomposition ends when the sum of

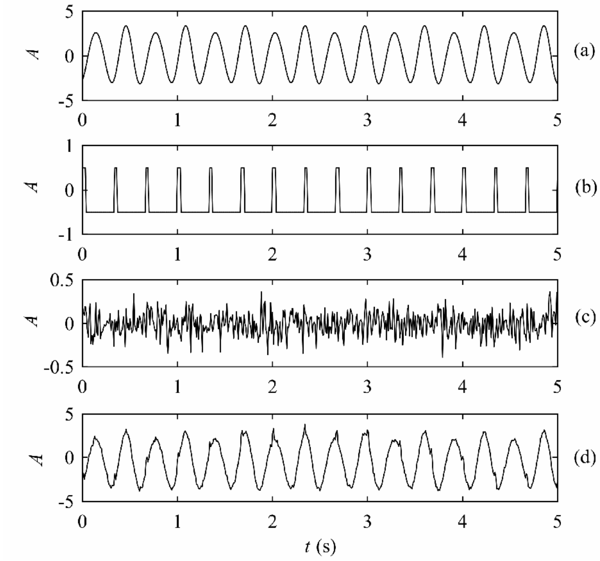


Fig. 3. The component signal and their composite signal: (a) The trigonometric function x_1; (b) the pulse sequence; (c) the white Gaussian noise; (d) composite signal.

singular values of residual signal components begins to be smaller than one-tenth of the average of singular values deriving from the trajectory matrix of initial signals. This criterion is built on the basis of numerous experimental results, aiming at the target that the decomposition times are enough to extract weak abrupt information without too many redundancy calculations. The abrupt information extraction of fault signals is based on a proposed singular value difference spectrum (SVDS) method. Fig. 2 addresses the detailed extraction process by a flowchart.

3. Numerical simulation

Given a signal

$$x(t) = x_1 + x_2 + x_3 \tag{8}$$

where x_1 is a typical harmonic signal, which may be defined by a function of trigonometric sines and cosines, for example

$$x_1 = 3\sin(20t+5) + 0.4\cos(30t+5) \tag{9}$$

The variable x_2 represents the component containing abrupt information of signals and expressed by a pulse sequence with amplitude 0.5 and frequency 6π Hz. And x_3 is white Gaussian noise whose average is 0 and variance is 0.5. Under such conditions, the parameter k is equal to 1/6. Figs. 3(a)-(c) show the signals x_1, x_2, x_3, respectively, and Fig. 3(d) shows the composite signal superposed by these three signals.

It is found in Fig. 3 that the amplitudes of either abrupt signal or noise are smaller than sinusoidal signal; thus the amplitude of their composite signal is not significantly high. It is seen that the amplitudes of noise and abrupt signal are not quite different, so does their energy. It means the pulse signal is usually mixed with noise and not easy to be separated. However, the singular values at each order have different contribution to different types of signal components. Such feature is utilized by the proposed SVDS method to decompose the signals. And a MATLAB program based on the proposed method is compiled. Given the order of reconstruction matrix 40 and k equals to 1, the signal is decomposed and its result is plotted in Fig. 4. The kurtosis of original signal and its components are also calculated and listed in Table 1.

Table 1. The kurtosis of original signal and its components.

Signal	Kurtosis
Original signal	1.61
First decomposition	1.51
Second decomposition	1.63
Third decomposition	5.95
Fourth decomposition	6.77
Fifth decomposition	6.31

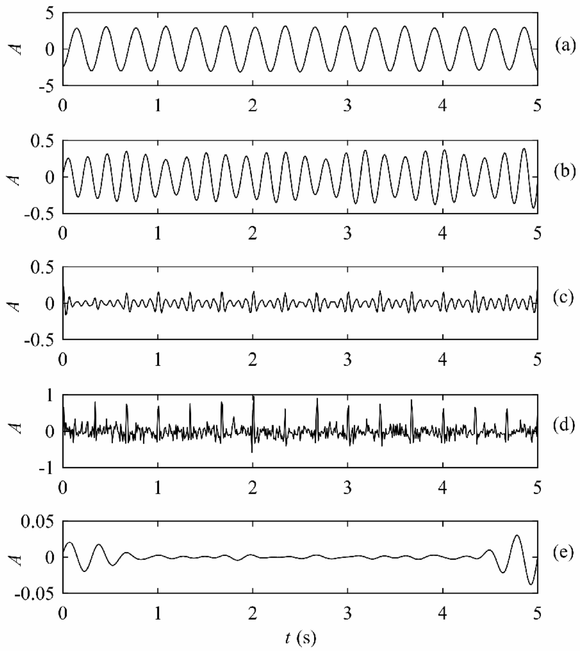


Fig. 4. The decomposition results based on SVDS method: (a) First decomposition; (b) second decomposition; (c) third decomposition; (d) fourth decomposition; (e) fifth decomposition.

The results show that the first and second decomposition results can be, respectively, fitted by two harmonic signals, $3\sin(20t+5)$ and $0.4\cos(30t+5)$. Table 1 shows that the kurtosis of the component after the fourth decomposition is the largest and it is more than four-times of the kurtosis of the original signal. It presents strong impact characteristic of the signal, indicating the abrupt information has been successfully extracted. Compared with simulated impact signal, it can extract the impact period and amplitude of the abrupt signal as

Table 2. The kurtosis of abrupt signals obtained by SVDS, WT and EMD methods.

Method	Kurtosis
Proposed SVDS	6.77
WT	5.16
EMD	4.09

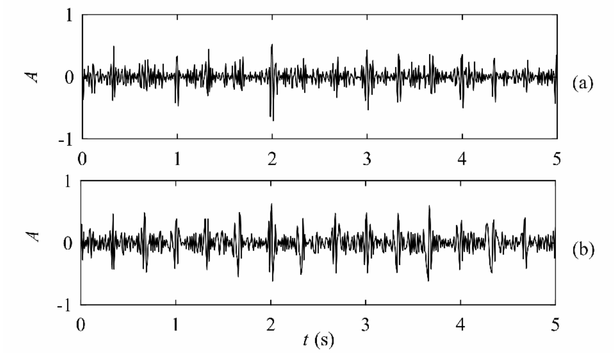
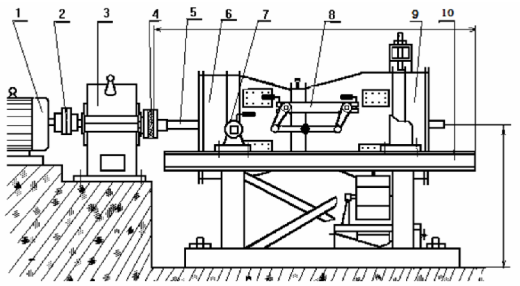


Fig. 5. The extraction results obtained from: (a) WT; (b) EMD.



1. DC motor; 2. Coupling; 3. Speed increaser; 4. Soft coupling; 5. Shaft; 6. Engine; 7. Front pedestal; 8. Transmission and locking device; 9. Rear pedestal; 10. Bench

Fig. 6. Experimental setup of the rubbing generator of an aero-engine.

well, i.e., the relative energy of the abrupt signal. The waveform of signal in the fifth decomposition shows the energy contained in residual signals is small enough to stop the next decomposition, verifying the proposed termination condition works well.

To highlight the advantage of the proposed method, the same signals were also extracted by two general methods, WT and EMD. In wavelet decomposition, the wavelet is db5. Their resulting waveforms are, respectively, shown in Figs. 5(a) and (b). The final kurtosis of abrupt signals obtained by these three methods is listed in Table 2. The kurtosis obtained from these three methods is large enough to present strong impact features, and the one derived from the proposed SVDS method is the largest.

4. Experimental validation

Fig. 6 shows the experimental setup of the rubbing generator of an aero-engine. The test signal originating from the generator is shown in Fig. 7. The rotation speed of the rotor is 2340 r/min and rotation frequency is 39 Hz. The sampling frequency is 5000 Hz. The clearance between the rotor and stator case is adjustable to control the generation and level of the rubbing. The clearance adjustment is implemented by misaligning the axes of the rotor and stator.

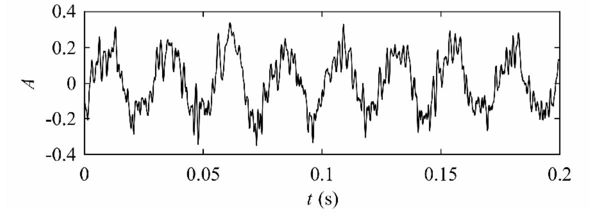


Fig. 7. Test signals originated from the rubbing generator of an aero-engine.

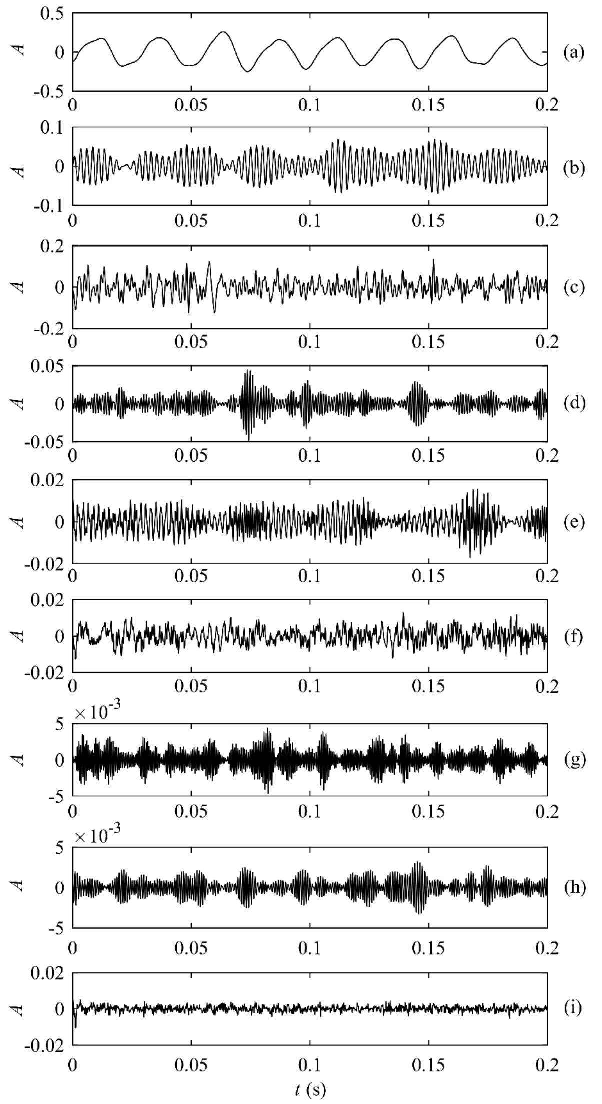


Fig. 8. Decomposition results: (a)-(i) Signals extracted from first to ninth decomposition respectively.

To validate the proposed method, a slight rubbing test was carried out. Based on the proposed method, the rubbing sig-

Table 3. The kurtosis of original signal and its components.

Signal	Kurtosis
Original signal	2.01
First decomposition	1.65
Second decomposition	2.27
Third decomposition	3.05
Fourth decomposition	4.57
Fifth decomposition	2.88
Sixth decomposition	2.61
Seventh decomposition	2.86
Eighth decomposition	3.03
Ninth decomposition	3.08

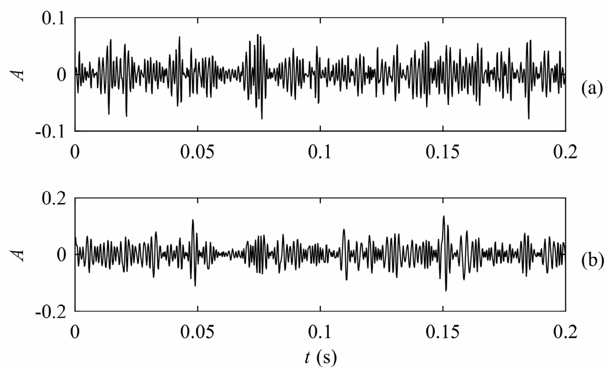


Fig. 9. Extraction of rubbing signals based on: (a) WT; (b) EMD.

nals were analyzed via the MATLAB program with reconstruction matrix order 40, and the decomposition results are shown in Fig. 8. The calculated kurtosis is listed in Table 3.

It is shown in Fig. 8 that harmonic signals, abrupt signals and noise are extracted in sequence based on SVDS method. In the fourth extraction, the periodic impact feature of signals is clearly observed, as shown in Fig. 8(d). Moreover, the kurtosis in this step of decomposition is the largest and its impact feature is very significant. It validates that the proposed method is effective to decompose signal and extract abrupt information in practical applications.

The same rubbing signals were decomposed by using WT and EMD methods, and their extraction results are plotted in Figs. 9(a) and (b), respectively. The comparison among them reveals that the extracted signals based on the proposed method and wavelet possess a significant periodic impact feature and their amplitudes and impact time are almost the same, while the extracted signals resulting from EMD method are not satisfying. The kurtosis is calculated and summarized in Table 4. It is found the kurtosis of SVDS is the largest and that of WT is the smallest.

The extracted signals were demodulated and their envelope spectrum is plotted in Figs. 10(a)-(c), respectively. The envelope spectrums obtained from WT and EMD methods mix multiple components with impact signals; thus the rubbing

Table 4. The kurtosis of rubbing signals obtained from an aero-engine generator by different methods.

Method	Kurtosis
Proposed SVDS	4.57
WT	3.46
EMD	3.76

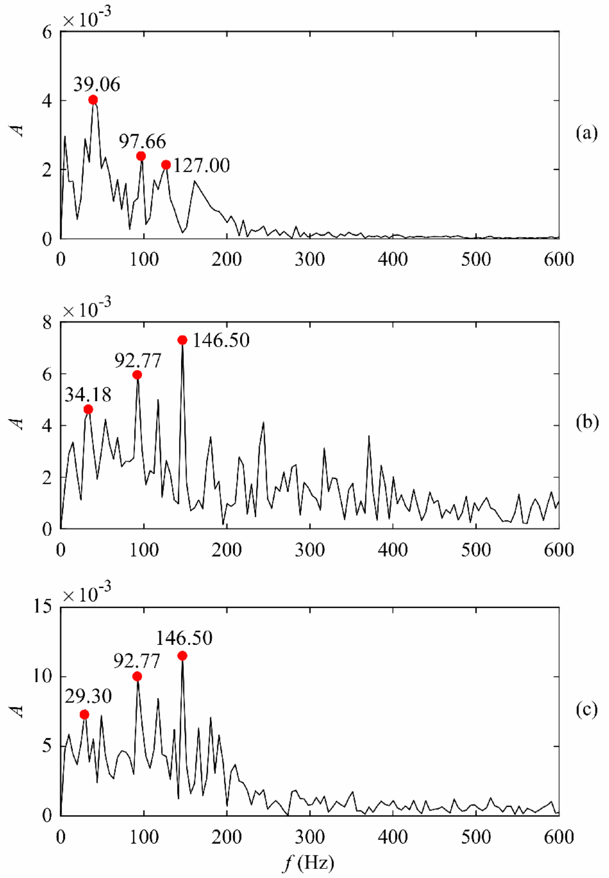


Fig. 10. The envelop demodulation spectrum of extracted signals based on (a) proposed SVDS method; (b) WT method; (c) EMD method.

feature is not observed obviously. The envelope spectrums obtained from the proposed method also contain some mixed components. However, its primary frequencies appear at the peak value nearby 39.06, 97.66 and 127.00 Hz and present a multiplication frequency relation. Moreover, the rubbing in tests is local rub-impact, which happens once in one cycle. Hence, the demodulated impact frequency must be the same with rotation frequency. The demodulated frequency derived from the proposed SVDS method is 39.06 Hz, which accurately reflects the primary frequency and impact feature of vibrations. Though the impact frequencies obtained from WT and EMD methods present periodic impact feature, the two frequencies 34.18 and 29.30 Hz derivate from the rotation frequency. It definitely verifies the proposed method is more effective than other two methods.

5. Conclusions

This paper proposes a new signal decomposition method based on SVD method, in which the singular value difference spectrum is introduced to extract abrupt information of detected fault signals. It is self-adaptive with an established termination condition capable of separating and ending signal processing automatically. To better understand the proposed method, the extraction procedure of this method is described in detail.

To verify the effectiveness of the proposed method, both numerical simulation and experimental work were conducted. The simulation result indicates the difference spectrum is quite helpful in selecting singular values of reconstructed signals in signal decomposition and separate category of multiple components in the viewpoint of energy. In addition, rubbing tests on a rubbing generator of an aero-engine were performed. The results show the extraction of abrupt information from fault signals is satisfying.

To shed light on the advantage of the proposed SVDS method, the same fault signals were also analyzed by WT and EMD method. Comparison among these three methods indicates that the extracted signal resulting from the proposed method possesses more significant periodic impact feature and more accurate primary frequency with fewer disturbed components than WT and EMD methods in rubbing fault diagnosis. It is advanced due to its ability to automatically extract the abrupt information of faults from raw signals without highly relying on experience of operators.

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Qiang Pan received his B.S. degree in Department of Jet Propulsion from Beijing University of Aeronautics & Astronautics in China in 2001 and completed his Ph.D. degree in Department of Mechanical Engineering at Inha University, South Korea, in 2009. Presently he is a lecturer in School of Transportation Science and Engineering at Beihang University. His research interests include material and structure analysis of aircraft and aero-engines, aircraft airworthiness and fault diagnosis.
Email: panqiang@buaa.edu.cn

Ying Liu received her B.S. degree in School of Transportation Science and Engineering at Beihang University in 2016. Now she is a graduate student in School of Transportation Science and Engineering, Beihang University. Her research interests include fault diagnosis of aircraft, neural network algorithm and signal processing. Email: xiaoyingzi@buaa.edu.cn

Rui Zhou received his B.S. degree in Department of Aircraft Design Engineering from Nanchang Hangkong University in 2016 and M.S. degree in School of Transportation Science and Engineering at Beihang University in 2019. Now he is an engineer in Aeropolytechnology Establishment of China. His research interests include fault diagnosis, acoustic emission and signal processing. Email: zhourui1022@buaa.edu.cn

Hong Wang received her B.S. degree in Thermal and Power Engineering from Hohai University, China, in 2004 and Ph.D. degree in Department of Vehicle Operation Engineering from Beihang University, China, in 2012. She is a Senior Engineer at Beijing Key Laboratory of Long-life Technology of Precise Rotation and Transmission Mechanisms, Beijing Institute of Control Engineering. Her research interests include fault diagnosis, dynamic analysis and vibration control of mechanical systems. Email: hongwang1981@163.com

Haibing Chen received his B.S. and M.S. degrees in Aerospace Engineering from Beijing University of Aeronautics & Astronautics in China in 2001 and 2003, respectively and his Ph.D. degree in School of Aerospace Science and Engineering at Beihang University in China in 2009. Presently he is a lecturer in School of Transportation Science and Engineering at Beihang University. His research interests include nonlinear flight dynamics and control, airworthiness and signal processing. Email: aw_chenhb@buaa.edu.cn

Tian He received his B.S. and M.S. degrees in Mechanical Engineering from Shijiazhuang Tiedao University, China, in 2001 and 2004, respectively, and his Ph.D. in Aerospace Propulsion Theory and Engineering from Beihang University, China, in 2008. He is an Associate Professor in School of Transportation Science and Engineering, Beihang University. His research interests include fault diagnosis, acoustic emission, vibration control and vibration signal processing. Email: hetian@buaa.edu.cn