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A sliding window feature extraction method for rotating machinery based on the lifting scheme

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Abstract

In order to diagnose and predict incipient fault of rotating machinery, a new sliding window feature extraction method based on the lifting scheme is proposed for extracting transient impacts from original signals. Firstly, a wavelet with impact characteristics is constructed by using the lifting scheme to decompose signals. Then a sliding window designed according to the revolution cycle of given rotating machinery is applied to process detail signals. By extracting modulus maxima from these windows, fault features and their locations in the original signals are revealed. An incipient impact fault caused by axis misalignment, and mass imbalance and a bush broken fault have been successfully detected by using the proposed approach.

1. Introduction

Vibration signal analysis is a general way for fault diagnosis of mechanical equipment. Any change in a system condition will result in a change in dynamic response, so vibration signals carry a great deal of information about mechanical equipment condition. Many techniques have been reported for fault diagnosis based on vibration signals, and they aim at finding some efficient fault features from the vibration signals [1–3]. However, it is still a challenge to look for effective techniques that can isolate specific features from the vibration signals.

The vibration pattern of a mechanical system is changed as the fault develops. In order to detect the presence and the type of an incipient fault and to monitor its development, proper signal processing methods should be adopted. Vibration signals picked from the system usually demonstrate non-stationary or transient property. Moreover, localized malfunctions in a rotating mechanical system produce impacts, and consequently make transient modifications in vibration signals. The features of these malfunctions are often weak at the early stage, and masked in vibration signals. To estimate the condition of a machine, techniques based on the time-domain statistical analysis are used to measure the overall root-mean-square (rms) level, crest factor, the statistical moments and so on. However, it is difficult to identify transient component in

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vibration signals by using these kinds of techniques. The Fourier transform uses sinusoid function as basis function that gives a reasonable resolution in frequency domain. It is an ideal tool for stationary signal processing. Because frequency information obtained by the Fourier transform can only be extracted for the complete duration of a signal, the spectral analysis methods based on the transform may be unable to detect the incipient faults due to the non-stationary property of the signal. The time–frequency domain analysis methods can provide frequency resolution and time resolution at the same time. The short time Fourier transform (STFT) can be taken as an alternative. Since a fixed window is used, STFT has a fixed time–frequency resolution in the time–frequency plane. The accuracy of extracting frequency is limited by the length of the window relative to the duration of the detected signal. As another alternative, the wavelet transform is an efficient tool for processing non-stationary signals, which provides flexible frequency resolution and time resolution simultaneously. A changeable window is adopted during the information, for high frequency signal, the window gets compressed and high resolution in time domain is obtained, while in a slowly changing signal situation, a wide window gives better frequency resolution. The changeable window makes it possible to work well in the time–frequency domain and to perform with good time resolution at high frequencies. So to identify the temporal instants at which transient phenomena take place, i.e. the presence of impulses in the vibration signals, can be assessed by the high-frequency part of the transformation, where the time resolution is comparable to duration of the analyzed events [4]. Moreover, WT has many basis functions to be selected, any function $\psi(t)$ satisfying the constraints, $\int_{-\infty}^{\infty}\psi(t)=0$ and $||\psi||^2=1$, can be regarded as a wavelet basis function or mother wavelet [5]. This means that a great deal of mother wavelets can be selected in wavelet analysis. These mother wavelets have their own characteristics in the frequency domain and the time domain. The results will be different as different wavelets used. So it is important to select a proper wavelet for a special problem. Much research has been done on this issue for condition monitoring and fault diagnosis in recent years [6]. The most important achievement of these engineering experiences gives us a way of selecting wavelets which depend on the fault features to be detected [7].

Abrupt changes occur in the presence of vibration signal with some malfunctions, such as friction, rub, looseness, impact, shock, and so on. They introduce singularities in vibration signal. Because these singularities carry useful information for fault diagnosis, it is valuable for us to detect them. Singularities can be identified by checking the presence of modulus maxima at specific locations in the wavelet map [8]. Some applications based on modulus maxima are found in literature. In Ref. [9], a wavelet was constructed on the basis of the derivative of Gaussian function to detect bearing defect. By modifying the intensity of modulus maxima, the bearing defect features are highlighted. In Ref. [10], a fault classification technique was developed by means of extracting modulus maxima of the detail signals as fault features. It has been shown in Ref. [4] that the amplitude and location of wavelet coefficients are important for feature selection. By truncating the maxima of special decomposition level as fault features, compression may keep these features with a good accuracy and fault features can be enhanced.

The lifting scheme is a new wavelet construction method that implements the wavelet transform in the time domain [11]. The main difference with the classical constructions is that the Fourier transform is no longer available [12]. Wavelets with some special properties can be obtained by designing a set of predictor and updater that can be chosen arbitrarily [13]. The wavelet transforms via the lifting scheme are always perfectly reconstructed no matter how the predictor and the updater are designed. Furthermore, any classical wavelet transform with finite impulse response (FIR) filters can be factored into lifting steps [12]. However, few applications on fault diagnosis are reported.

In this paper, a new method based on the lifting scheme is proposed for impact feature extraction of rotating machinery. By investigating the feature of impact fault in vibration signals, a biorthogonal wavelet with impact property is constructed via the lifting scheme. After doing WT for the vibration signal, a sliding window designed according to the operation cycle is applied to process the detail signal. Modulus maximum in every window is extracted as fault feature. As a result, fault features and their locations in the original signals are revealed. With the help of this method, faults with impact characteristics have been successfully detected. The rest of the paper is organized as follows. In Section 2, the background of the lifting scheme is briefly explained, and discussion of wavelet selection for feature extraction is provided. In Section 3, a feature extraction approach for transient impacts is introduced. In Section 4, an experiment is done for checking the performance of the proposed method, and two engineering application are stated. Finally, conclusions can be found in Section 5.

2. The lifting scheme

2.1. Wavelet transform using the lifting scheme

The lifting scheme was developed by Vim Sweldens in 1990s as a method to build new Biorthogonal wavelets in the time domain [11], which is used to construct second generation wavelets [11,13]. Generally, the fundamental idea behind the wavelet transform is to create a sparse approximation of a given signal using a set of functions that exploit the correlation present in the signal. The result of the transform is an approximation of a signal and a measure of a difference between the approximation and the original signal, namely the detail. The classical wavelet transform takes advantage of the Fourier transform to construct this approximation in the frequency domain. Lifting obtains the same result while operating exclusively in the time domain.

Consider a signal: $\boldsymbol{X} = \{x_k, k \in Z\}$, $k = 1,2,\ldots,L$. The approximation signal $\{s_{j+1}(k)\}$ of $\boldsymbol{X}$ at scale $j+1$ is split into two disjoint sets, namely even indexed samples $\{s_j(2k)\}$and odd indexed samples $\{s_j(2k+1)\}$. Then, a predictor is used to predict the odd indexed samples $\{s_j(2k+1)\}$ with N neighbors of the even indexed samples at scale j, N is determined by the required number of vanishing moments of the underlying wavelet function. The errors in prediction are defined as the detail signal at scale j.

$$d_j(k) = s_{j+1}(2k+1) - \sum_{m=1}^{N} p(m) s_{j+1}(2m+k-N), \quad k = 1, 2, \ldots, L/2, \tag{1}$$

where j represents the jth scale and k is a counter for detail signal, $p(m)$ is a prediction coefficient, $m = 1,\ldots,N$, the predictor is defined by

$$\boldsymbol{P} = [p(1), \ldots, p(N)]^{\mathrm{T}}.$$

To get the approximation signal on scale j, the even indexed samples $\{s_j(2k)\}$ are updated with the details $\{d_j(k)\}$

$$s_j(k) = s_{j+1}(2k) - \sum_{m=1}^{\tilde{N}} u(m) d_j(m+k-\tilde{N}/2-1), \quad k = 1, 2, \ldots, L/2, \tag{2}$$

where $u(m)$ is an update coefficient, $m = 1, \ldots, \tilde{N}$, $\tilde{N}$ is a number which represents how many neighbors of the detail signal $\{d_j(k)\}$ are used in update step. The updater is defined by

$$\boldsymbol{U} = [u(1), \ldots, u(\tilde{N})]^{\mathrm{T}}.$$

We note the underlying wavelet of the wavelet transform via the lifting scheme as $(N, \tilde{N})$. The reconstruction equation can be directly achieved from Eqs. (1) and (2) through simple operation.

2.2. Discussion

Fig. 1 shows scaling functions and wavelet functions of two different wavelets, (8, 8) and (18, 18) constructed by the lifting scheme. Wavelets constructed by the lifting scheme are biorthogonal [11]. As Fig. 1 indicated, both wavelet functions and scaling function built by the lifting scheme are compactly supported, symmetrical, and have the signature of impact (see Fig. 1). If more samples of given signal are used during lifting, both the scaling function and the wavelet function will have much more support intervals, and become smoother. At the same time, the orthogonality of the transform will be improved in the frequency domain. On the other hand, designing a biorthogonal wavelet system by enforcing vanishing moment on the underlying wavelet functions is equivalent to eliminating and preserving polynomials which predict and update steps, in other words, vanishing moment number of the wavelet function is equivalent to the order of the predictor and the updater [14]. Thus, the properties of scaling function and wavelet function depend upon the selection of the predictor and the updater. Moreover, transform with biorthogonal wavelets posses linear phase [15]. This makes the biorthogonal wavelets to have the ability to reduce phase distortion during transformation. It is helpful to detect the singularities in a signal.

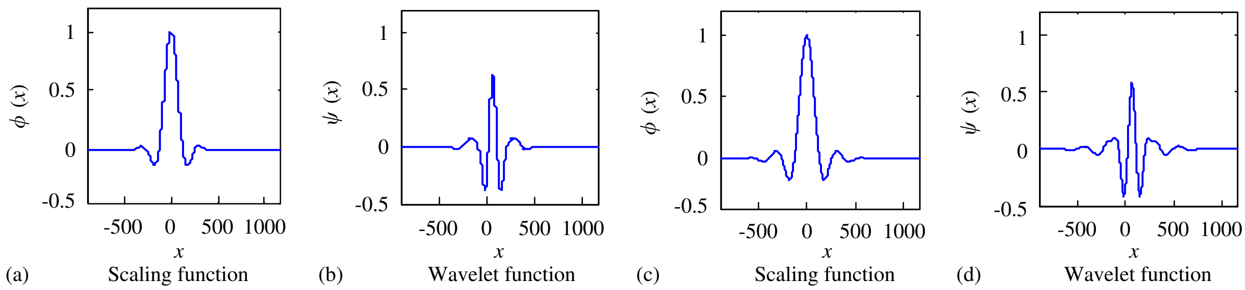

Fig. 1. Scaling functions and wavelet functions of two wavelets: (8, 8) and (18, 18), (a) and (b) for (8, 8), (c,d) for (18, 18).

As shown in Eqs. (1) and (2) above, the wavelet transform is performed using the original signal. The operation needs a proper choice of the wavelet function, that is, the selection of the predictor and the updater for lifting. Theoretically, the magnitude of the wavelet coefficients is proportional to how much the signal resembles the feature of the wavelet at particular scale and place [15]. It is important to select a proper wavelet for a special problem. In general, more compactly supported and less smooth wavelet functions are better for non-stationary signals with discontinuities, impulse and transients. Less compactly supported and much smooth wavelet functions are better for stationary, regular signals [4]. In practice, it is very often necessary to choose a proper wavelet by making a trade-off between the smoothness and compact support of the wavelet function.

Localized defects and malfunctions in rotating machinery, such as friction, rub, shock and rub-impact, produce impacts that generate impulse responses in vibration signals. Because of the damping of mechanical system, the dynamic responses of the impacts are damped oscillations at the natural frequency of the system. As we stated above, both wavelet function and scaling function for a wavelet constructed by the lifting scheme are compactly supported with an impacting shape that resembles impact fault features in vibration signal. So it is suitable for detecting and identifying transient impact signals in mechanical fault diagnosis.

3. Feature extraction method for impact fault in time domain

For rotating machinery, there exists many kinds of malfunctions that will influence the normal operation, such as coupling misalignment, rub-impact, shock, friction, etc., whose vibration signals often have different singularity properties. Singularities are always introduced into vibration signals as these malfunctions occur. They carry some important information, especially for weak or incipient faults. On the other hand, during the rotating machinery operation, these malfunctions may occur once a revolution, and contribute to the vibration signals. Therefore, vibration signals from rotating machinery are non-stationary, as well as periodical, to a great extent. It is more convenient to recognize locations of singularities by means of truncating the signal in a revolution cycle. For the purpose of developing a simple and effective way for diagnosis, we propose a sliding window feature extraction method based on the wavelet transform via the lifting scheme.

Consider a vibration signal $\boldsymbol{X} = (x_k)$, with the signal length L, the sampling frequency f_s, operation frequency of rotating machinery f. Then the sample number in a revolution cycle is f_s/f.

(1) Decomposing $\boldsymbol{X}$ with a chosen wavelet, we obtain an approximation $S = \{s_1(i)\}$ and a detail $\boldsymbol{D} = \{d_1(i)\}$ at the scale 1, where $i = 1,\ldots,L/2$. The length of both components is $L/2$.
(2) Design a sliding window to handle the detail signal $\boldsymbol{D}$.
For $\boldsymbol{D} = \{d_1(i)\}$, $i = 1,\ldots,L/2$, the window length is $w = f_s/(2f)$ that spans a revolution of the rotating machinery. The sliding window is defined by

$$\boldsymbol{wdw}(m) = \{d_1(i),\ \ i = 1 + mw, \ldots, (m+1)w\} \quad \text{for } m = 0, \ldots, L/(2w) - 1.$$

(3) Then, search modulus maxima from every window, and investigate the locations of maxima.

4. Experiment and engineering applications

4.1. Simulation experiment

The proposed method is first tested on a simulated rub-impact malfunction signal. Localized rub-impact of a rotor is a common malfunction for rotating machinery. When the rub-impact occurs, it will produce impacts. As a result of the excitation, a transient force is put on the rotor, which generates a pulse of very short duration in vibration signal. Duo to the damping of the mechanical system, the excited rotor makes a free attenuation oscillation at the natural frequency of the system. Therefore, the signature of the rub-impact response is an exponential decaying vibration, which takes place once a revolution. A simulated signal is designed that can be considered as a vibration response resulting from a localized incipient rub-impact of a rotor in a rotating machinery. Natural frequency excited is assumed to be 3000 Hz, operation frequency is assumed to be 120 Hz, and sampling frequency as 12 000 Hz. Fig. 2(a) shows the impulse responses with initial amplitude of 0.20 in several revolutions. Fig. 2(b) shows the simulated vibration signals by adding white Gaussian noise (with deviation equals to 5% of the peak amplitude of the simulated signal). The impulse response information is masked by the noise. We can hardly find any pulses in Fig. 2(b). The simulated signals are firstly decomposed by using three different wavelets: wavelet (8, 8), wavelet (18, 18) and a classical wavelet Daubechies 8 (Db8), and then post-processed with the sliding window approach stated in Section 3 above to extract the expected features. The results are illustrated in Fig. 2(c), (d) and (e), respectively.

It can be clearly seen that a series of impulses are presented at regular intervals in Fig. 2(c) that the wavelet (8, 8) adopted. The positions of these impulses occurrences are just the time that we added the impact responses previously in the simulated signal. Obviously, these impulses that we extracted as the expected features are able to represent exactly the locations and the intensities of these impacts that we added previously in the simulated signal. Fig. 2(d) displays the result obtained by using the wavelet (18, 18) for the simulated signal. However, the result cannot perfectly reveal the regularities of the impacts in the simulated signal.

For the same signal, different decomposition results are achieved by using two different wavelets even if these two wavelets possess the similar signatures (see Fig. 1). In fact, the difference between these two wavelets is that they have different support intervals, i.e., less support intervals for the wavelet (8, 8), and much more intervals for the wavelet (18, 18). It is well known that wavelets with less support intervals are more compactly supported, which are better for processing non-stationary signals [4]. This is the reason why the former is more effective than the latter on extracting the impulsive features.

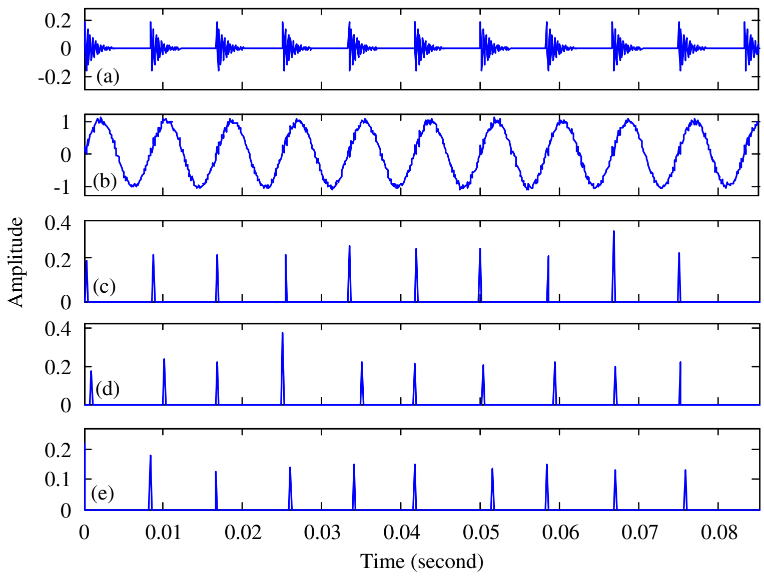

Fig. 2. Simulation signal and results obtained by proposed method: (a) impulsive responses to be added in simulated signal, (b) simulated signal, (c) result using (8, 8), (d) result using (18, 18), and (e) result using Db8.

As a matter of fact, the wavelets (N, $\tilde{N}$), where $N<8$ and $\tilde{N}<8$, also have the ability to extract the impulsive features effectively. But due to the biorthogonality of transformation, the approximation and the detail of decomposition with such a wavelet have more aliasing components that not to be expected for fault diagnosis. The wavelet (8, 8) is used as a compromise between the effectiveness of feature extraction and the orthogonality of transformation in this paper.

Fig. 2(e) displays the result by adopting the wavelet Db8 (Daubecheis 8). The positions of these extracted modulus maxima cannot correctly indicate the occurrence time when the impulsive responses take place in the original signal. The wavelet transform in theory is a series of operations to measure the similarities between the analyzed signal and the selected wavelet at different scale [5]. Higher coefficient appears when there are much more similarities between the signal and the wavelet. The wavelet function of Db8 is orthogonal, compactly supported and slow decaying [16], but it has no impact signature that the impulsive response possesses. This is the reason why the extracted features cannot accurately indicate the occurrence of the impulsive responses.

Some conclusions could be made by the above discussion. Firstly, it is important to choose a proper wavelet for feature extraction. A proper wavelet will enhance the expected features included in decomposition components, whereas an improper wavelet will dilute the informative components. Secondly, the wavelet (8, 8), which is constructed by the lifting scheme, is a better one for extracting impulsive features.

4.2. Engineering application 1

4.2.1. Problem

A machine set of a heavy-oil catalytical unit consists of gas turbine, fan, gearbox and electric motor in an oil refinery. The unit revolution speed is 5859 rev/min ($f = 97.65$ Hz in frequency). The instrument of Bently 3300 system was equipped to monitor its operating condition. Proximity transducers were mounted on each bearing bridge in vertical and horizontal directions respectively distributed on gas turbine (Bush No. 1 and 2), fan (Bush No. 3 and 4) and gear axle. A computer on-line system of surveillance and diagnosis was available for data acquisition of shaft vibration signals that came from 10 proximity transducers with sampling frequency 2000 Hz.

It was found that vibrations on Bush No. 3 of fan and its neighbor Bush No. 2 of gas turbine are greater than the other detection points when the unit was working. To investigate the reason, we take a set of vibration signals of Bush No. 3 with the length of 256 for analysis as displayed in Fig. 3(a).

4.2.2. Analysis

The wavelet (8, 8) is adopted for analysis. Modulus maxima of detail signal are extracted by using the proposed method, the result is shown in Fig. 3(b), x and y, are used to denote these peaks, namely Peak x, and Peak y.

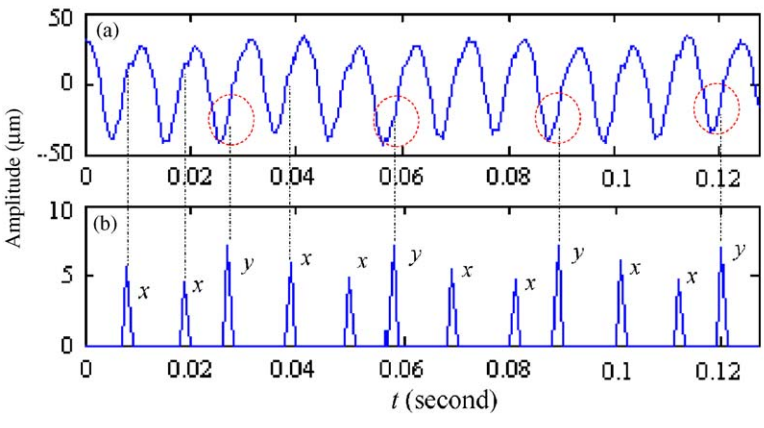

Fig. 3. Vibration signal of Bush No. 3 on fan (a) and the extracted features (b).

It can be seen that the extracted modulus maxima have a distinct regularity in ranking sequence and magnitude. In Fig. 3(b), every two peaks of x and one Peak y occur alternately and periodically. The interval between every two peaks of x is about 10 ms, which is equal to the time of a revolution of the unit. Compared with the original signal, Fig. 3(a), it is clear that Peak x is nicely associated with a little convexity in the original signal. When Peak y appears, the corresponding waveform in the original signal exists as an abrupt change marked with dash-line circle in Fig. 3(a) that occurs every three operation cycles.

We examine the neighboring detection point, Bush No. 2 of gas turbine, with the same approach above. A signal with the length of 256 is taken as displayed in Fig. 4(a). Fig. 4(b) shows the result. It is clearly noted that (1) every two peaks of x and one Peak y are visible alternately, (2) the interval of every two peaks of x is about 10 ms and (3) Peak x is associated with a little convexity in the original signal, while Peak y corresponds to an abrupt change that appears once every three revolutions in the original signal.

Apparently, the extracted features in Figs. 4(b) and 3(b) have the same regularities except for the difference in amplitude. We noticed that a stronger impulse signal Peak y exists and excites intermittently in the original signal. It occurs every three revolutions, in other words, the occurrence frequency of Peak y is equal to 1/3 of the operation frequency. The harmonic component, 1/3 of the operation frequency, is a symptom of early impact-rub fault in rotating machinery [17]. Therefore, it is sure that a slight impact between rotor and axial-bush arose when the unit was running.

In order to investigate what caused the fault during working of the unit, we process the signals again with FFT technique. FFT spectrums of these two signals are shown in Figs. 5 and 6, separately. In Fig. 5, there are three dominant peaks. However, the frequency $f/3$ cannot be viewed on FFT spectrum. The corresponding frequencies of these three peaks are $f_1 = 23.4$ Hz, $f_2 = 97.7$ Hz, and $f_3 = 195.3$ Hz. Intuitively, f_2 is the operation frequency ($f_2 = f$), and f_3 is two times the operation frequency ($f_3 = 2f$). Furthermore, frequency

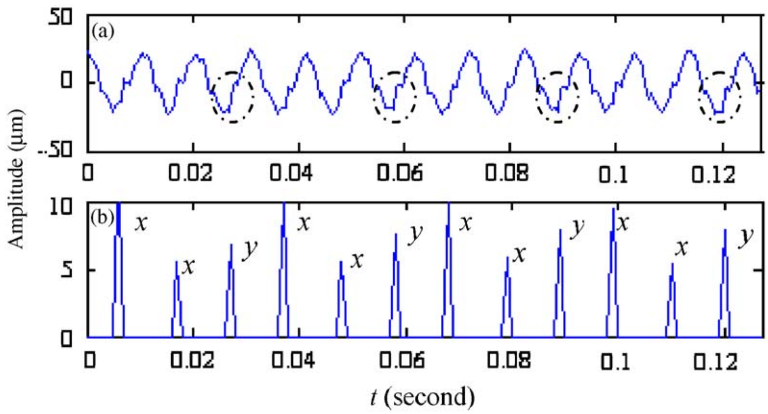

Fig. 4. Vibration signal of Bush No. 2 of the gas turbine (a) and the extracted features (b).

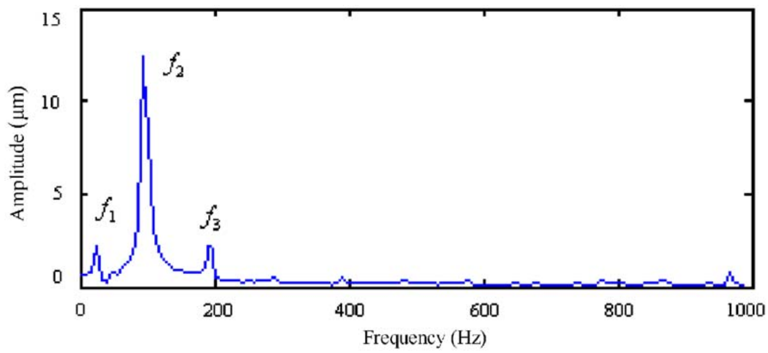

Fig. 5. FFT spectrum of vibration signal of Bush No. 3.

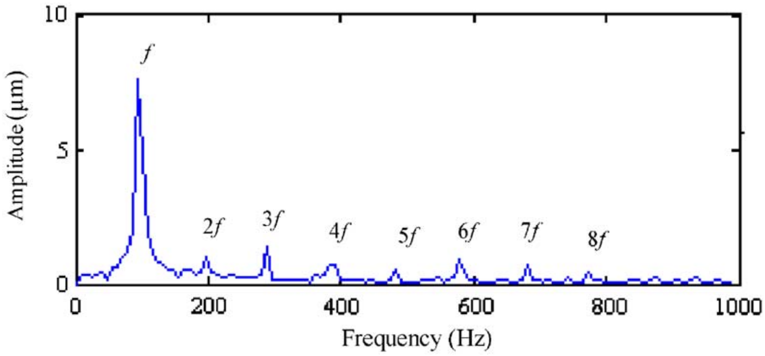

Fig. 6. FFT spectrum of vibration signal of Bush No. 2.

$f_1 = 23.4\,\text{Hz}$ seems to be a fractional harmonics of the operation frequency, which equals to 1/4 of the unit operation frequency ($f_1 = f/4$). But it is verified by further investigation that frequency f_1 is the revolution frequency of the low speed axle of gearbox.

As investigated above, the component of operation frequency $f_2 = f$ and its harmonics $f_3 = 2f$ exist at the same time in Fig. 5. These indicate axis misalignment between the rotor shaft of fan and the gas turbine shaft [18].

In Fig. 6, besides component of the operation frequency, there exist some other harmonics components of the operation frequency, 2–8f, on the spectrum. But they are smaller in magnitude. This is the feature of rotor imbalance in the frequency domain [18].

Studying the structure of the system, it is found that a disc coupling was designed to connect the rotor shaft of the fan and the shaft of the gas turbine. They were not properly mounted in alignment when the system was assembled. To compensate axial misalignment, the disc coupling had to make a relative motion when the unit was running. As a result, weak vibrations are produced, and little convexities appeared in the vibration signal. On the other hand, because of the relative motion caused by axial misalignment and rotor imbalance, gap between rotor and axial-bush was varied when the unit was running. Eventually two parts touched each other, and localized friction occurred. Therefore, an elastic restoring force acted on the rotor from the axial-bush, and an impact took place. This is the reason why Peak y is increased. All these indicate that the fault was brought about by axial misalignment and rotor imbalance that produced components of the operation frequency and doubled operation frequency in vibration signal. Because of axial misalignment and rotor imbalance, impact-rub fault took place. The fault introduced the fractional harmonic components of the operation frequency, 1/3 of the operation frequency, and caused non-stationary vibration. On this condition, greater vibrations were generated on Bush No. 3 of the fan and its neighbor Bush No. 2 of the gas turbine when the unit was running.

4.2.3. Comparison

In order to illuminate the validity of the wavelet (8, 8) for feature extraction, the vibration signal of Bush No. 3 is processed again by using the wavelets, (18, 18) and Db8, respectively. Fig. 7 shows the results, where Fig. 7(a) for the original signal, Fig. 7(b) for the result of the wavelet (18, 18) and Fig. 7(c) for the result of Db8. It is obvious that the results of both wavelets cannot perfectly reveal the relationship between the extracted features and the original signal, this is helpless for further analysis.

4.3. Engineering application 2

The revolution speed of gearbox output axle of an oxygen generator in a steel mill is 14485 rev/min (241.42 Hz). One day, it was reported that vibrations of gearbox were extensively increased with high frequency noise while the unit was working. The gearbox was supported by four plain bearings. For the purpose of monitoring and diagnosis, accelerometers were used to pick up vibration signals from axle bushes

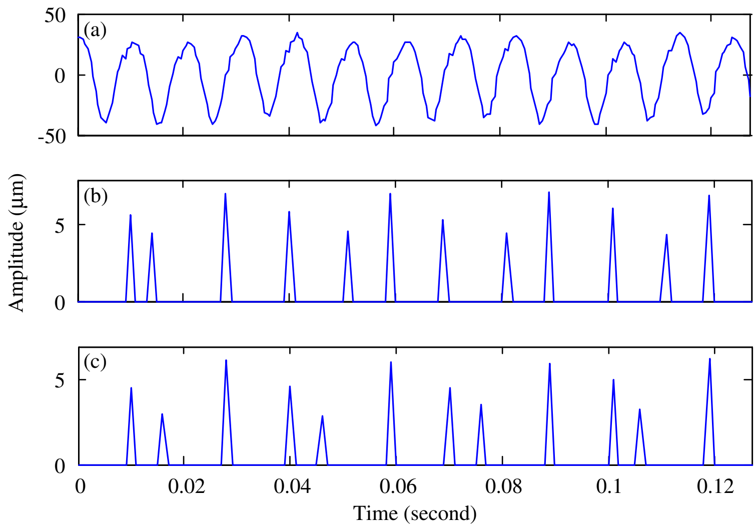

Fig. 7. Features extracted by classical wavelets for the same signal of Bush No. 1 of fan.

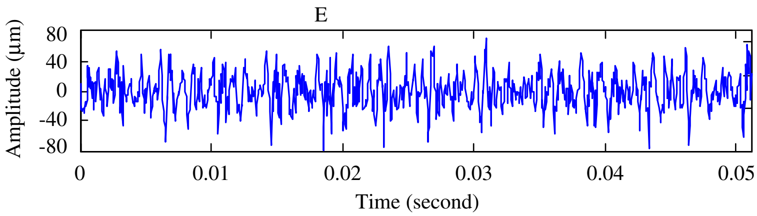

Fig. 8. Vibration signal acquired from Axle-bush No. 3.

of the gearbox at a sampling frequency of 20 000 Hz. It was found that vibration of Bearing No. 3 was the most significant among these four bearings, and the temperature measured on the axle bush of Bearing No. 3 was the highest, which exceeded 50 °C. Fig. 8 displays the vibration signal acquired from Axle-bush No. 3.

Fig. 9 displays the extracted modulus maxima by means of the proposed method with the wavelet (8, 8). It can be clearly observed that these modulus maxima arrayed regularly in equal interval, i.e., the time interval of any two adjacent impulses was approximately identical. These extracted features are difficultly identified directly in the vibration signal. Because a sliding window with the width of the revolution cycle of the output axle was applied, Fig. 9 demonstrates a fact that there existed an impact source that produce impulsive vibration every revolution periodically in the unit as the gearbox is working.

The energy distribution of wavelet packets at scale 3 is displayed in Fig. 10. The vibration signal was discomposed into eight frequency bands, and we achieved eight wavelet packets Nos. 1–8. The bandwidth of a wavelet packet is 1250 Hz. The energy vector is defined by [19]

$$E(m) = \sum_i [c_{j,m}(i)]^2,$$

where $m = 1,\ldots,8$, j is considered as the scale number, and i is the index of wavelet packet coefficients. Fig. 10 indicates that high-frequency vibration was more powerful in the vibration signal, and the signal energy was distributed over the whole analyzed frequency band with different magnitude.

On the basis of the investigation above, we come to a conclusion that Axle-brush No. 3 was damaged. Because of the presence of cracks on the bush, impacts were produced when the axle was running. For this excitation, transient impulse was generated in the vibration signal, and synchronously an impulsive response was excited with the natural frequency of the unit. This resulted in an increase in the vibration energy at high frequency band. The conclusion was proved to be correct in later repair work. By checking the axle bush after shutting down the unit, it was discovered that this bush was broken.

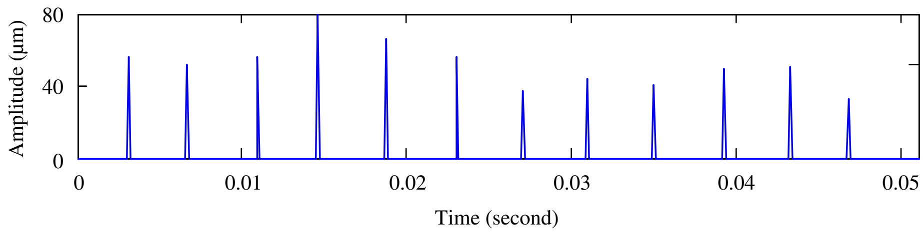

Fig. 9. Features extracted by wavelet (8, 8).

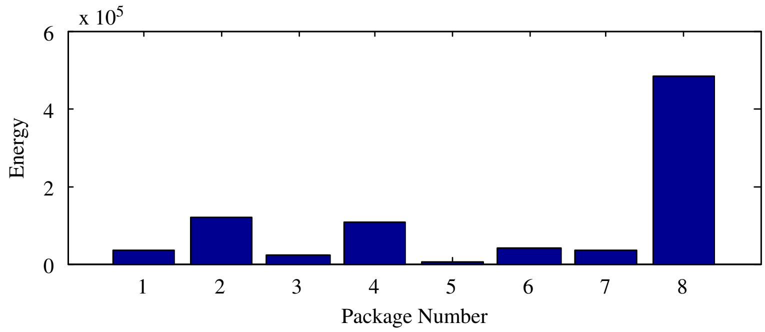

Fig. 10. Energy distribution of wavelet packets on scale 3.

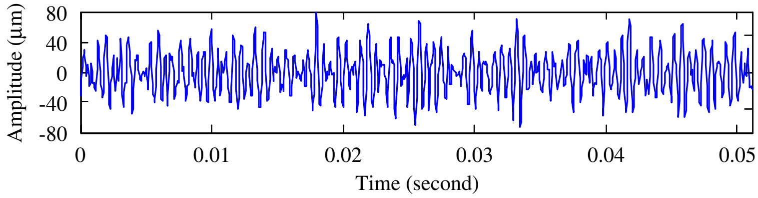

Fig. 11. Vibration signal gathered from Axle-brush No. 3 after repair.

Rebooting the unit after replacing the broken bush with a good component, vibrations were greatly decreased, and high frequency noise was also weakened. Fig. 11 shows a set of vibration signal gathered from Axle brush No. 3 after repair.

We applied the same method to process this signal. The extracted modulus maxima and energy distribution of wavelet packets at scale 3 are displayed in Figs. 12 and 13. Obviously, in Fig. 12, when the unit is running under the normal condition, extracted modulus maxima ranked irregularly with smaller amplitudes. In Fig. 13, the energy of the signal were mainly concentrated on the low frequency band less than 5000 Hz, but on the high frequency band greater than 5000 Hz, there existed much little energy.

With the purpose of comparison, the wavelets, (18, 18) and DB8, were also used to process the faulty signal. The extracted features are shown in Figs. 14 and 15. It can be seen that the time interval of any two adjacent impulses was no longer equal consistently in both figures. Evidently, the faulty signal processed with the wavelet (8, 8) can give us more perfect information for condition monitoring and fault diagnosis, than the other two wavelets.

5. Conclusion

It is important to select a proper wavelet for a special problem. The scaling function and wavelet function constructed by means of the lifting scheme have impact features in shapes that resemble the impact features in vibration signals. In addition, the property of linear phase makes wavelets to have the ability to reduce phase distortion during transformation. All these are useful to detect transient component in vibration signals.

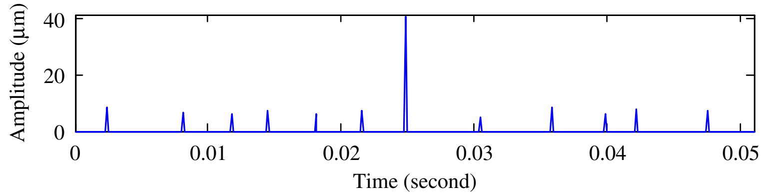

Fig. 12. Modulus maxima extracted from the vibration signal after repair.

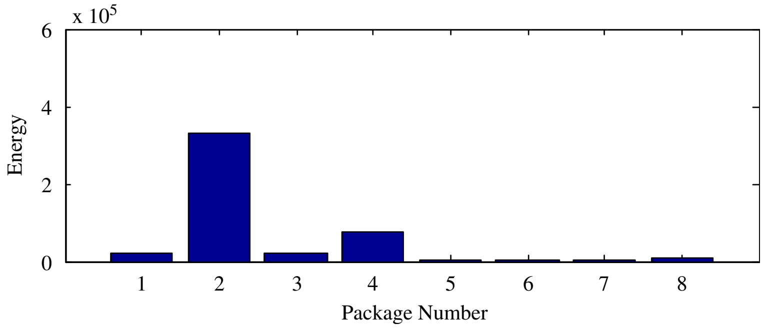

Fig. 13. Energy distribution of wavelet packets on scale 3 of the vibration signal after repair.

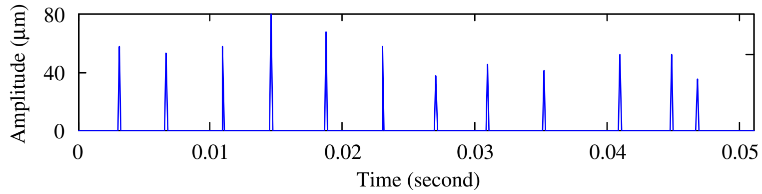

Fig. 14. Features extracted by using wavelet (18, 18).

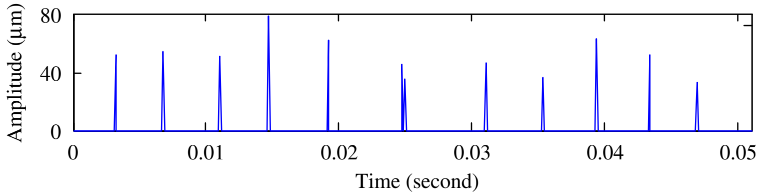

Fig. 15. Features extracted by using wavelet DB8.

Compared with other wavelets, the wavelet (8, 8) can provide a better performance for extracting impulsive feature.

A new method using the lifting scheme is presented to extract fault features from vibration signals of rotating machinery. By building a wavelet with impact characteristic, vibration signal is decomposed. Then a sliding window that spans a revolution of rotating machinery is adopted to process the detail signal, and fault features are obtained through extracting modulus maxima from these windows. The method has been used for practical applications successfully.

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