Research Article

Locomotive Gear Fault Diagnosis Based on Wavelet Bispectrum of Motor Current

Mingming Zhang, Jiangtian Yang, and Zhang Zhang

School of Mechanical, Electronic and Control Engineering, Beijing Jiaotong University, Beijing 100044, China

Correspondence should be addressed to Jiangtian Yang; jtyang@bjtu.edu.cn

Received 3 February 2021; Revised 15 June 2021; Accepted 24 June 2021; Published 13 July 2021

Academic Editor: Shengwei Fei

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The motor current signature analysis (MCSA) provides a nondestructive method for gear fault detection. The motor current in the faulty gear system not only involves the frequency information related to the fault but also the electric supply frequency and gear meshing-related frequency, which not only contaminates the fault characteristics but also increases the difficulty of fault extraction. To extract the fault characteristic frequency effectively, an innovative method based on the wavelet bispectrum (WB) is proposed. Bispectrum is an effective tool for identifying the fault-related quadratic phase coupling (QPC). However, it requires a large amount of data averaging, which is not suitable for short data analysis. In this paper, the wavelet bispectrum is introduced to motor current analysis and the problem of QPC extraction under variable speed conditions is preliminarily solved. Furthermore, a fault diagnostic approach for locomotive gears using the wavelet bispectrum and wavelet bispectral entropy is suggested. The presented method was effectively applied to the locomotive online running operations, and faults of the drive gear were successfully diagnosed.

1. Introduction

Recently, much concern has been focused on developing the high-speed and the heavy-load railway technology that can satisfy the requirements of traffic [1–3]. At the same time, traffic safety has become increasingly important. Driving gears in railway locomotives are used to transmit the torque on the traction motor or on the combustion engine to the wheel set, usually operating at higher speeds. Thus, the diagnosis of gear faults has significant importance for both safety and reliability [4–9]. Vibration signal processing is widely used to detect gear faults, but its application is limited by transducer installation [10–15]. As the acceleration sensor does not have enough installation space or brings additional maintenance costs, the vehicle becomes more complicated [16]. The motor current signature analysis provides a nonintrusive way to assess the health of machinery. The continual monitoring without extra sensors and hardware makes this method especially suitable for vehicle applications [17, 18].

The tooth localized faults of gears produce mechanical impacts, causing additional mechanical torque fluctuations [19]. The motor will produce an additional torque fluctuation to balance. It leads to a slight amplitude modulation in the stator current, which creates sidebands in the stator current energy spectrum [20–22]. These changes can be used for the gear fault diagnosis. However, the unstable running speed and the time-varying load condition make the diagnosis difficult and unworkable in most cases. Amplitude modulation in the stator current often occurs intermittently. In addition, the torsional vibration reflected into the stator current is typically very subtle, and the fault-related features are usually masked by high-amplitude signals and noise [17]. The fault detection based on the current signal is a challenging task; thus, an advanced signal processing technique combining the wavelet analysis and bispectral technique is introduced. The bicoherence spectrum, a normalized version of the bispectrum, has proven to be a powerful tool to detect the phase coupling associated with the amplitude modulation of components [23, 24]. Since the classical
implementation of the bicoherence spectrum is based on the Fourier transform, no temporal information is provided. Thus, the Fourier-based bicoherence (FB) is not capable of detecting the phase coherence associated with short-time duration [25, 26]. To overcome this deficiency, the wavelet-based bicoherence was introduced by von Millegan et al. [27].

Mechanical failure will cause the distribution of signal quadratic phase coupling to change. This paper proposes wavelet bispectral entropy, which quantitatively describes the distribution of signal nonlinear components in dual frequency domains. Since the wavelet bispectral entropy is sensitive to the change of the quadratic phase coupling distribution of the current signal caused by the mechanical fault, it is used to detect the mechanical fault. In this paper, the wavelet bispectrum (WB) and wavelet bispectral entropy are introduced to analyze the stator current of locomotive traction motors, and a novel approach for gear fault diagnosis is presented. In this method, the wavelet bispectral entropy is used as the characteristic quantity to monitor the fault, and the frequency of the quadratic phase coupling is identified by the wavelet bicoherence spectrum to judge the fault location. (K_his paper proposes the following:

$$ T_{LH}(t) = T_o(t) + T_{osc}(t), $$

where $T_o$ is the static load torque and $T_{osc}$ is the dynamic torque caused by the transmission error and the stiffness of the gear contact.

The gear fault will generate an extra periodic torque component in addition to healthy load torque. Thus, the load torque can be written as follows:

$$ T_{LF}(t) = T_{LH}(t) + T_{fp}(t). $$

In the formula, $T_{fp}$ is a periodic torque caused by a gear tooth local fault. Its Fourier series can be represented by

$$ T_{fp}(t) = \sum_{k=1}^{\infty} T_k \cos(k2\pi f_{fp}t + \phi_k), \quad k = 1, 2, 3, \ldots, $$

where $f_{fp}$ is the fundamental rotation frequency of the gears and $T_k$ and $\phi_k$ can be obtained from Fourier transform (FT). Therefore, the stator current can be written as follows:

$$ I_A(t) = I_s \sin(2\pi f_{st}t) + I_r \sin(2\pi f_{st}t + \chi_{LH}(t) + \chi_{fp}(t) + \eta_r), $$

where $f_s$ is the supply frequency and $\eta_r$, $\chi_{LH}(t)$, and $\chi_{fp}(t)$ are the phase modulation components of the normal and fault, respectively. $\chi_{fp}(t)$ can be defined as follows:

$$ \chi_{fp}(t) = \sum_{k=1}^{\infty} \chi_k \cos(k\omega_{fp}t + \alpha_k), \quad \chi_k = \frac{pT_k}{f_{fp} J_{eq}(k\omega_{fp})}, $$

where $J_{eq}$ is the traction motor side equivalent inertia and $p$ is the number of induction motor pole pairs. Formula (4) can be further simplified as follows:

$$ I_A(t) = I_{healthy}(t) + I_r \sum_{k=1}^{\infty} \frac{\chi_k}{2} \cos(2\pi(f_s - k f_{fp})t + \phi_{fk}) + I_r \sum_{k=1}^{\infty} \frac{\chi_k}{2} \cos(2\pi(f_s + k f_{fp})t + \phi_{fk}), $$

where $\phi_{fk} = \eta_r - \alpha_k \phi_{r,k} = \eta_r + \alpha_k$. Thus, the fault characteristic frequency in the stator current can be expressed as follows:

$$ f_{faulty} = |f_s \pm mf_{fp}|, \quad m = 1, 2, 3. $$

2. Motor Current Signature Analysis

Motor current signature analysis (MCSA) has become the hotspot of condition monitoring technique in the past three decades. Continual monitoring without the use of extra sensors and hardware makes this method especially suitable for industrial environment. As a completely noninvasive method, MCSA has been successfully applied to detect broken rotor bars [28], abnormal levels of air-gap eccentricity [29], and shorted turns in stator windings [30], among other mechanical problems [31–34]. However, only a few researchers [35–38] applied MCSA in the transmission system because of the fault information loss and aliasing of current signals. The purpose of this research is to analyze the modulation effects on motor current, and their phase relationship of components is used for fault diagnosis. When the localized faults occur in the gear, large extra mechanical impacts are generated in the vibration signal. This results in change in the stator current signal [39, 40]. The previous studies shown that in healthy conditions, the load torque signal consists of the static torque and the dynamic torque. Therefore, the load torque signal can be expressed as follows:

$$ T_{LH}(t) = T_o(t) + T_{osc}(t), $$

where $T_o$ is the static load torque and $T_{osc}$ is the dynamic torque caused by the transmission error and the stiffness of the gear contact.
The above analysis demonstrates that the partial failure of the locomotive gear will cause new information in the stator current, such as frequency components and phase modulated and side bands. Due to the inconstancy of traction motor speed, these frequencies also change with time. Therefore, it is necessary to use a powerful mathematical tool to extract the fault characteristic frequency by the analysis of nonstationary signal phase coupling.

3. Wavelet Bispectrum

3.1. Fourier-Based Bispectrum. Given a signal $x(t)$, the Fourier transform is defined as follows:

$$X(f) = \int_{-\infty}^{\infty} x(t)e^{-2\pi jft}dt.$$  

(9)

The Fourier-based bispectrum is defined as follows:

$$B(f_1, f_2) = E[X(f_1)X(f_2)X^*(f_1 + f_2)],$$  

(10)

where $E[\cdot]$ is the statistical expectation operator and $*$ denotes complex conjugation.

In practical applications, Fourier-based bispectrum is usually normalized by the power spectrum as Fourier-based bicoherence (FB), i.e.,

$$BIC(f_1, f_2) = \frac{|B(f_1, f_2)|}{\sqrt{E[X(f_1)X(f_2)]^2 E[X(f_1 + f_2)]^2}}.$$  

(11)

An important feature of the FB is that its variation is always restricted between 0 and 1. Consequently, the square of FB provides a quantitative measure of quadratic phase coupling. Fourier-based bispectrum and bicoherence have been employed in detecting QPC in a wide variety of applications. It should be pointed out that, however, they are not appropriate for analyzing the short-time and intermittent duration nonlinear interactions. Thus, the wavelet-based bispectrum is applied to detect the phase relationship of nonstationary signal.

3.2. Wavelet-Based Bispectrum. The continuous wavelet transform (CWT) of signal is defined as the convolution of $x(t)$ with the scaled and normalized wavelet [41], written as follows:

$$W_f (f, t) = \frac{1}{\sqrt{|s|}} \int_{-\infty}^{\infty} x(t')\psi^*(\frac{t'-t}{s})dt',$$

(12)

where $*$ indicates the complex conjugate, $\psi(t)$ is the mother wavelet, $s$ is the scale variable, $t$ is the time shift variable, and $f$ is the equivalent Fourier frequency.

The wavelet bispectrum is introduced as follows:

$$B_{W,T}(f_1, f_2) = \int_T W_f (f_1, \tau)W_f (f_2, \tau)W_{f_3}^{*}(f_3, \tau)d\tau,$$

(13)

where $T$ is the finite time length of the signal and frequency values $f_1$, $f_2$, and $f_3$ satisfy the relationship $f_3 = f_1 + f_2$. The wavelet bispectrum is a complex quantity. It can be expressed by its magnitude and phase as follows:

$$B_{W,T}(f_1, f_2) = A(f_1, f_2)e^{i\phi(f_1, f_2)},$$

(14)

Biphase can be calculated by

$$\phi(f_1, f_2) = \phi(f_1) + \phi(f_2) - \phi(f_3),$$

(15)

where $\phi(f_1)$, $\phi(f_2)$, and $\phi(f_3)$ are obtained by CWT.

The wavelet bicoherence (WB), a normalized wavelet bispectrum, is defined as

$$b^2_{W,T}(f_1, f_2) = E\left(\frac{|B_{W,T}(f_1, f_2)|^2}{\int_T|W_f (f_1, \tau)|^2d\tau\int_T|W_f (f_3, \tau)|^2d\tau}\right),$$

(16)

where $E[\cdot]$ denotes an average operator.

WB describes the QPC among different components. The peaks in the WB indicate the phase coupling at bifrequency $(f_1, f_2)$ during the time interval $T$, and the value has the same meaning as in FB. In real systems, the phase coupling may occur intermittently and the coupling degree also changes with time. WB extends the use of the QPC detection and can extract fault feature accurately.

3.3. Comparison of Fourier-Based Bicoherence and Wavelet-Based Bicoherence. To illustrate how the bicoherence spectrum measures the phase coherence between three components, we consider a signal such that

$$x_1(t) = \cos(2\pi f_1 t) + \cos(2\pi f_2 t) + \cos(2\pi f_3 t) + e(t),$$

(17)

where $f_1 = 30$ Hz, $f_2 = 50$ Hz, and $f_3 = 80$ Hz. Then, the three sinusoidal signals satisfy the frequency relationship $f_1 + f_2 = f_3$. E(t) is zero-mean Gaussian noise with SNR 20 dB.

For the simulation, 6000 samples were generated and these samples were divided into 30 blocks; therefore, each block has 200 samples. The phases of components $f_1$ and $f_2$ were chosen from a set of random numbers which are uniformly distributed over $(-\pi, \pi)$, but the phase of the third component $f_3$ was given as the sum of phases of the components $f_1$ and $f_2$, i.e., $\phi_3 = \phi_1 + \phi_2$. The waveform and power spectrum of signal $x_1(t)$ are shown in Figure 1. By inspecting the power spectrum, the origin of the $f_3$ component cannot
be determined. It is because the power spectrum is independent of the phases of waves. In an effort to understand the origin of the $f_3$ component, the bicoherence spectrum is calculated and shown in Figure 2.

In Figure 1, the presence of the peak at frequency pair (30 Hz, 50 Hz) indicates that these two components are indeed interacting to generate the 80-Hz component. Since the magnitude of its peak is equal to 1.0, it is concluded that all of the energy in the 80-Hz component is due to the interaction of the 30-Hz and 50-Hz components. The Fourier-based bicoherence can describe the phase coupling between waves, but it requires a large quantity of data in long term.

In order to demonstrate the ability of wavelet-based bicoherence in detecting the short-term phase coupling, another computer-generated signal $x_{11}(t)$ is considered [42]. The signal is exactly the same as the test signal $x_1(t)$, except the phase. We also generated 30 blocks of the signal, and each block contains 200 points. In each block, $f_1$ and $f_2$ were assigned random phases distributed uniformly on $[-\pi, \pi]$. In all, except block numbers 13–16, the phase of $f_3$ was also selected randomly and independently. Thus, in all blocks, except 13–16, there was no phase coupling. However, in blocks 13–16, the phase of $f_3$ was set equal to the sum of the phases of $f_1$ and $f_2$ to simulate the quadratic phase coupling among the three signals. Therefore, $x_{11}(t)$ is a signal where quadratic phase coupling is absent, except over a relatively short-time interval (blocks 13–16).

The Fourier-based and wavelet-based bicoherence is used to analyze the signal $x_{11}(t)$, and the results are shown in Figures 3 and 4. There is no distinct peak in Figure 3. It implies that the quadratic phase coupling in blocks 13–16 was not detected. The Fourier-based bicoherence cannot discriminate the QPC occurred in a relatively short time. One can find two large peaks at frequency pairs (30 Hz, 50 Hz) and (50 Hz, 30 Hz) in Figure 4, and the maximum value is 0.6596. This illustrates that the 80-Hz component is the result of frequency coupling of 30-Hz and 50-Hz components. The intermittent QPC can be detected by the wavelet-based bicoherence.

3.4. Wavelet Bispectrum Entropy. Entropy, as a complexity measure, has been widely applied for time series analysis in numerous disciplines, ranging from logic and physics to biology and engineering. Zhou [43] proposed bispectral entropy, which quantitatively describes the distribution of non-Gaussian signals in dual frequency domains, analyzes vibration signals, and diagnoses gear faults. This paper proposes wavelet bispectral entropy on the basis of bispectral entropy. The calculation steps of wavelet bispectral entropy are as follows:

1. Perform wavelet bispectrum transformation on the wavelet signal $\{x(t)\}$ to obtain the wavelet bispectrum $WB(\omega_1, \omega_2)$.

2. Due to the symmetry of the bispectrum, removing redundant information can divide the dual frequency domain of the wavelet bispectrum into a triangular domain: $\omega_2 \geq 0$, $\omega_1 \geq \omega_2$, $\omega_1 + \omega_2 \leq \pi$, and finally obtain $WB'(\omega_1, \omega_2)$.

3. Calculate the probability of wavelet bispectral amplitude in dual frequency domains:

$$P_{WB}(\omega_1, \omega_2) = \frac{|WB'(\omega_1, \omega_2)|}{\sum_{\omega_1=0}^{\pi} \sum_{\omega_2=0}^{\pi} |WB'(\omega_1, \omega_2)|}$$

4. Wavelet bispectral entropy can be expressed as follows:

$$H_{WB} = -\sum_{\omega_1=0}^{\pi} \sum_{\omega_2=0}^{\pi} P_{WB}(\omega_1, \omega_2) \ln P_{WB}(\omega_1, \omega_2).$$

The wavelet bispectral entropy reflects the uniformity of the wavelet bispectrum amplitude in the dual frequency domain. If the wavelet bispectrum amplitude is uniformly distributed, the wavelet bispectral entropy is large;
Figure 2: The Fourier-based bicoherence of signal $x_1(t)$: (a) mesh; (b) contour.

Figure 3: The Fourier-based bicoherence of signal $x_{11}(t)$: (a) mesh and (b) contour.

Figure 4: The wavelet-based bicoherence of signal $x_{11}(t)$: (a) mesh; (b) contour.
otherwise, the wavelet bispectral entropy is small. The amplitude of the wavelet bispectrum represents the intermittent quadratic phase coupling degree of the signal. Calculating the entropy of the wavelet bispectrum amplitude can quantitatively describe the wavelet bispectrum amplitude distribution in the dual frequency domain. Early faults cause the quadratic phase coupling in the motor current to be weak and randomly distributed, and the wavelet bispectral entropy value is large. As the faults expand, the quadratic phase coupling between certain frequency components increases and the corresponding wavelet bispectral amplitude increases. Due to the nonuniform distribution, the wavelet bispectral entropy decreases. The experiment proves that the wavelet bispectral entropy is very sensitive to the change of the quadratic phase coupling distribution of the motor current signal caused by the mechanical fault, and it can be used to detect the occurrence of the mechanical fault.

4. Experimental Validation

In order to simulate the drive of locomotive shaft, a test bench is set up as shown in Figure 5. The test machine is driven and controlled by an AC-DC-AC converter, where 220V single-phase AC is converted into three-phase power. The specifications of the induction motor are listed in Table 1.

The motor is connected to an experimental gearbox with the number of teeth at input $N_1 = 28$ and at the output $N_2 = 85$. After the gear box decelerates, the axle is driven to rotate. The wheel drives the track wheel to rotate, and the gear box accelerates to drive the DC generator acting as a load. The resistance box absorbs energy in the form of electric current and releases it in the form of heat. The current signal was sampled under the condition of gear wheel worn. Set sampling frequency to 2000 Hz and the number of sampling points to 28000. During the experiment, the induction motor was operated under speed-varying conditions. The motor supply frequency went from 19.8 Hz to 26.1 Hz, and the corresponding speed changed form 1265 r/min to 1670 r/min. The pinion rotation frequency changed in the range of 21.1 Hz to 27.8 Hz, and gear wheel rotation frequency increased in the range of 6.95 Hz to 9.2 Hz. Figure 6 shows the waveform and power spectrum of the motor current signal, and the time-frequency distribution is shown in Figure 7. It can be found that the motor supply frequency increased with time linearly.

Applying the wavelet-based bicoherence to the first 100 sampling points of the sampled signal, the result is shown in Figure 8. There are some weaker peaks in the wavelet bispectrum of the stator current signal of the gear under normal operating conditions. The motor current signal has phase coupling, and the power supply frequency of 19.8 Hz is modulated by $2f_s$ (6.2 Hz) frequency. This is the fundamental characteristic of the motor current signal. Among them, synchronous speed $n_1 = 1500$ r/min, actual speed $n = 1265$ r/min, and slip rate $s = 0.16$:

$$s = \frac{n_1 - n}{n_1}$$

(20)

Large gears and small gears are replaced with tooth surface wear, tooth root cracks, and broken teeth. Under the same variable speed conditions, stator current signals are

| Parameters       | Value     |
|------------------|-----------|
| Rated voltage    | 220 V     |
| Rated current    | 3.3 A     |
| Motor power      | 1.5 kW    |
| Number of phases | 3 poles   |
| Number of poles  | 2         |
| Supply frequency | 50 Hz     |
| Rated speed      | 2865 r/min|

Figure 5: The test bench.
collected, wavelet bispectral analysis is performed, and wavelet bispectral entropy is calculated. The results are shown in Table 2. When gears have various faults, the wavelet bispectral entropy is reduced, which corresponds to the enhancement of the quadratic phase coupling between certain frequency components. Wavelet bispectral entropy can be used as a feature to monitor gear faults, and further analysis is needed to determine the location of the fault.

Figure 9 shows the wavelet bispectrum of the first 100 sampling points of the motor current signal under the condition of the gear root crack. There are two distinct peaks exhibited by the bicoherence and are located at bifrequency...
pairs (21.1, 19.8) Hz and (19.8, 21.1) Hz, indicating the occurrence of phase coupling. The motor supply frequency is 19.8 Hz, and 21.1 Hz is the third harmonic of gear wheel rotation frequency. These peaks suggest the existence of a significant fault on the gear wheel. Figure 10 illustrates the results of the last 100 sampling points of current signal analyzed by wavelet bicoherence. One can find the two peaks at bifrequency (26.0, 27.8) Hz and (26.0, 27.8) Hz. It is noteworthy that 26.0 Hz is the motor supply frequency at that time, and the third harmonic of gear wheel rotation frequency is 27.8 Hz.

The above analysis shows that the gear wheel fault causes quadratic phase coupling of the motor current signal. The associated frequency and phase couplings were changing with time. The wavelet bicoherence can extract quadratic phase coupling under variable speed conditions. It is thus a promising tool for fault detection.

5. Industrial Experiment

Based on the simulation signal analysis and experiments, the proposed method was applied to the locomotive running test and its reliability was further verified in the industrial field, by adopting Shenyang Railway Bureau freight train type HXN3. HXN3 AC Diesel Locomotive is equipped with six YJ116A induction traction motors with a shaft power of 663 kW, and the rated current is 219 A. The gearbox transmission ratio is 16:85. The HXN3 type locomotive is mainly used for freight on busy main railways with the maximum speed of 120 km/h. In the test, the locomotive running speed was 77 km/h, and the corresponding rotational speed of the motors was 2076 r/min. The power supply frequency was 67.4 Hz. The rotation frequency of the pinion was 34.6 Hz, while the rotation frequency of the gear wheel was 6.5 Hz.

One phase current of the locomotive traction motor was sampled at a frequency of 2000 Hz. The waveforms and power spectrum are shown in Figure 11. From Figures 11(a) and 11(b), one can observe that there are many components in the motor current. Due to the modulation effect, the sideband structure around the fundamental component (i.e., supply frequency of 67.4 Hz) can be found. That is the significant characteristic of the motor current spectrum. Figure 12 shows the time-frequency distribution of the locomotive motor current. Form the figure, one can find that the supply frequency does not mean an absolute fix and correspondingly the locomotive speed was changing slightly.

Applying the bicoherence to the current signal, the mesh and contour obtained are shown in Figure 13. There are small peaks exhibited by the bicoherence, and the maximum value is 0.14. It is evident that the bicoherence is beginning to indicate a minimal amount of QPC; however, the location of the peaks is arbitrary. As mentioned above, the Fourier-based bicoherence is only suitable for the signal sampled in a steady speed of the machine. This disadvantage restricts the machinery signal processing by bicoherence analysis. As a result, it is impossible to determine if these peaks are due to gear fault or a result of any other nonfault source. Figure 14 illustrates the results of the current signal analyzed by the wavelet bicoherence. There are some significant peaks

| Condition | Normal | Wear | Crack | Broken |
|-----------|--------|------|-------|--------|
| Gear      | 8.0993 | 8.0890 | 8.0874 | 8.0678 |
| Decrement ($10^{-4}$) | — | 103 | 119 | 315 |
| Pinion    | 8.0993 | 8.0690 | 8.0585 | 8.0518 |
| Decrement ($10^{-4}$) | — | 303 | 408 | 475 |

Figure 9: The wavelet bicoherence of motor current fault signal (the first 100 sampling points): (a) mesh and (b) contour.

Table 2: Wavelet bispectral entropy under four working conditions of large and small gears.
emerging at various bifrequencies. Two significant peaks at determined bifrequency (19.5, 67.4) Hz and (67.4, 19.5) Hz are found in Figure 14.

It is noteworthy that 67.4 Hz is close to the power supply frequency, and 19.5 Hz is the third harmonic of the gear wheel rotational frequency. It shows the interaction between power supply frequency and gear wheel (see formula (9) where $m = 3$). Then, we concluded that there was a fault on the gear wheel. In the subsequent operation of the locomotive, the current signal of the traction motor of the drive shaft was continuously detected, and it was found that the wavelet bispectral entropy value has been decreasing indicating that the phase coupling in the current signal is strengthening and the fault is developing. So, it was decided to shut down for maintenance. When the locomotive returned to the depot, we examined the traction system and disassembled the running gear. The running gear is damaged, and some teeth are broken. Figure 15 is a photo of damaged gear. The diagnostic conclusion was thus verified.

Using the motor current signal wavelet bispectrum analysis, the fault feature of locomotive gear can be extracted effectively.

Motor current signature analysis provides a promising approach to locomotive gear fault detection with no extra sensors. This paper focuses on gear fault diagnosis by detecting the presence or magnitude change of gear fault frequency in current signal. Since the speed of the traction motor is unstable in running online, the wavelet bispectrum was introduced to analyze the phase relationship of fault-related frequencies. Some factors irrelevant to gear faults are omitted in the proposed fault feature extracting method, such as parametric variations in the traction motor, power supply frequency and gear wheel. (see formula (9) where $m = 3$). Then, we concluded that there was a fault on the gear wheel. In the subsequent operation of the locomotive, the current signal of the traction motor of the drive shaft was continuously detected, and it was found that the wavelet bispectral entropy value has been decreasing indicating that the phase coupling in the current signal is strengthening and the fault is developing. So, it was decided to shut down for maintenance. When the locomotive returned to the depot, we examined the traction system and disassembled the running gear. The running gear is damaged, and some teeth are broken. Figure 15 is a photo of damaged gear. The diagnostic conclusion was thus verified.

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Figure 13: The Fourier bicoherence of the locomotive motor current signal: (a) mesh; (b) contour.

Figure 14: The wavelet bicoherence of the locomotive motor current signal: (a) mesh; (b) contour.

Figure 15: The badly worn gear wheel.
supply quality, and catenary dynamic parameters, because these frequencies are quite different from gear fault frequencies. Local defects of gear are identified by comparing the current signature of gear fault frequencies in the fault case against that in the baseline case. This helps us to improve the robustness of the proposed approach.

6. Conclusion

The wavelet bispectrum has been used to analyze the stator current signal and diagnose the locomotive gear failures. The effectiveness of the proposed method is verified, and the conclusions are summarized as follows.

When the gear fails, the mechanical torque will change and cause the phase modulation of the stator current of the drive motor, resulting in the side band of the stator current spectrum. Since the motor rotational speed changes, frequency and phase couplings transiently occur. The side band caused by the gear failure is very faint and appears intermittently, completely submerged in high-amplitude harmonic frequency components and noise. The wavelet bispectrum provides a powerful tool for the intermittent phase couplings analysis. The wavelet bispectral entropy can describe the uniformity of the wavelet bispectrum amplitude distribution, which is used as a characteristic quantity to monitor the occurrence of faults. The combination of wavelet bispectrum and wavelet bispectral entropy is used for current analysis of the locomotive traction motor, which can accurately extract the characteristics of locomotive gear faults. The motor current signature analysis does not need extra sensors and hardware; therefore, it is especially suitable for vehicle working continual monitoring. Combined with the wavelet bispectrum, a novel locomotive gear fault diagnostic method is developed. The proposed method is effectively applied to the online running tests of locomotive, and the faults of driving gear are diagnosed successfully.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

This research was supported by the National Natural Science Foundation of China (No. 51975040).

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