Fault Stage Feature Extraction Method Based on Antinoise Gradient Operator Morphological Filters

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Abstract. The cyclical impact signal aroused by mechanical fault contains feature information, such as fault type and fault stage. However, a transient impact component is usually modulated on the fundamental frequency and mixed with a large amount of noise. Thus, it is difficult to be extracted effectively. A feature extraction method of faults stage is presented based on morphological filter theory. An antinoise morphological gradient operator is applied to signal filtering. This operator can weaken the noise and clearly highlight the impact characteristics of different fault stages. The kurtosis of the spectrum band, including the passing frequencies of mechanical components, is used to differentiate fault stages. The applications on simulation signals and bearing test data indicate that this method can realize accurate extraction of fault characteristic frequency submerged in noise and effective distinction of different fault stages.

1. Introduction
Under harsh working conditions, the parts of mechanical equipment are worn, cracked, peeled, and damaged inevitably, leading to the degradation and failure of the whole system. Equipment breakdown causes huge economic losses and casualties\cite{1}. Proper maintenance decision can be made to avoid abnormal failure and accident caused by equipment deterioration. This goal can be achieved if the severity of fault can be assessed and the fault stage can be identified in the degradation of the mechanical system. Localized defects in rotating machine are usually due to impacts, such as periodic impact of stationary and dynamic parts and instantaneous impact of defective rotating bearings or working gears. The impulse response in the vibration signal contains information reflecting the fault severity of the system. The impulse magnitude is related to the degree of fault, and the time interval of impulse attenuation occurring reflects the characteristic frequency of the fault component\cite{2}. In actual fault signal sampling, impulse response is usually modulated in the basic frequency signal and mixed with a large amount of environmental noise during transmission. This response shows nonstationary and nonlinear characteristics, thereby limiting the direct use of traditional fault diagnosis methods. Huang Z.H decomposed the original signal into the superposition of several frequency band components through wavelet multiresolution analysis \cite{3}. They reconstructed the original signal using the band with energy concentration to acquire the signal impulse characteristics. However, the energy of the reconstructed impulse signal is seriously lost due to the wide frequency band of the impulse signal and the large frequency range of the signal energy distribution. Thus, this method cannot be directly applied to fault stage identification. In reference \cite{4}, impact time-frequency atoms are designed to extract signal impact characteristics by combining matching tracking algorithm and genetic algorithm. However, matching tracking algorithm has high computational complexity and it is
also difficult to build available atomic library. In recent years, some scholars have applied the empirical mode decomposition (EMD) method to impulse feature extraction[5]. The signal is decomposed into several intrinsic mode components (IMF) by EMD, and the impulse response is obtained through envelope demodulation in high-frequency IMF. However, the envelope of decomposed signal should have local extremum to make the EMD effective. EMD has boundary effect and position sensitivity.

Different from time-domain and frequency-domain analyses, morphological filtering is a nonlinear method based on integral geometry and random set. The result of this filtering method only depends on the signal’s geometry. Similar matching is performed to the signal by moving the morphological structure elements, thereby removing the detail signal and retaining the signal trend. This method highlights the main shape characteristics of the signal and is particularly suitable to extract the impulse characteristics of nonstationary and nonlinear signals. In addition, this method has simple calculation and easy realization[6]. In this paper, a noise-resistant morphological gradient operator is constructed based on the principle of morphology and the characteristics of mechanical system fault vibration signal. This operator can extract the impulse characteristics of the signal under strong background noise. Moreover, the kurtosis value of the characteristic frequency band in the signal filtered by antinoise morphological operator is proposed as the fault degree index to assess the fault severity of mechanical system. The performance of the proposed method is verified in terms of simulation data and vibration signals of defective rolling bearing. The result shows that this method is effective in extracting periodic impulses and can suppress the environment noises extremely well.

2. Feature Extraction of Fault Stage Based on Morphological Filter Theory

2.1. Basic Theory of Morphological Filter

Morphological filter theory was first proposed in the quantitative petrology analysis and mining value prediction of iron core deposits by a geologist, Matheron, and his student Serra at the Institute of Mining, Paris, France. Then, this theory was widely and deeply researched by scholars in various fields. Morphological filter was originally applied in image processing. Magaros and Schafer extended it to 1D time series data processing. Its basic operations are erosion and dilation and opening and closing operations[7-8].

\begin{align*}
\Theta(n) & \text{ is the input time series, and } g(n) \text{ is the structural element Assuming that } f(n) \text{ and } g(n) \text{ are discrete functions defined on } F=\{0,1,\ldots,N-1\} \text{ and } G=\{0,1,\ldots,M-1\}, \text{ respectively, where } N \geq M. \text{ The operations of erosion and dilation for time series } f(n) \text{ by structural element } g(n) \text{ are defined as follows.} \\
(f \Theta g)(n) & = \min\{f(n+m) - g(m)\}, (m = 0,1,\ldots,M-1) \\
(f \oplus g)(n) & = \max\{f(n) + g(m)\}, (m = 0,1,\ldots,M-1)
\end{align*}

where \( \Theta \) and \( \oplus \) denote the erosion and dilation operations, respectively.

The morphological opening and closing operations for series \( f(n) \) by structural element \( g(n) \) are defined as follows.

\begin{align*}
(f \circ g)(n) & = [f \Theta g] \oplus g(n) \\
(f \bullet g)(n) & = [f \oplus g \Theta g](n)
\end{align*}

where \( \circ \) and \( \bullet \) denote the open and closing operations, respectively.

Each of the four basic operations of morphological filter can extract signal characteristics individually, but different operations have different effects. Figure 1 shows the results of erosion, dilation, opening, and closing operations on signals with the same structural elements.
As shown in the above diagrams, the erosion operation sharpens and reduces the signal peak, widens the signal trough, and shrinks it to the inside. The dilation operation widens the signal peak, sharpens, and reduces the signal trough, and the signal expands to the outside. The opening operation eliminates the signal peak and remains the trough. The closing operation eliminates the signal trough and remains the peak. In practical applications, the four basic operations of morphological filtering are usually combined to achieve better filtering effect. Hao RJ constructed filters by combining the morphological open-close and close-open operations in different orders to achieve positive and negative noise filtering of the signal[9]. Literature[10] constructed a morphological open-close average filter to extract signal with positive and negative impact characteristics.

2.2. Noise-resistant Morphological Gradient Operator

Gradient operator is used for edge detection in image processing. A large gradient value of a point indicates that the light changes rapidly at that point and it may be the edge point[11]. In 1D signal processing, the gradient operator can be used to detect the transient information added to the stationary signal and highlight the impact characteristics. Literature[12] constructed the following morphological gradient operators by using erosion and dilation operations.

\[
MG_{DE} = (f \ominus g)(n) - (f \Theta g)(n)
\]  

Dilation and erosion morphological gradient operators can extract impact characteristics extremely well. However, they are sensitive to noise and are unsuitable for signals mixed with intensive background noise. Opening and closing operations have strong ability to suppress noise, but the signal filtered by opening and closing gradient operators has statistical bias. A noise-resistant erosion–dilation morphological gradient operator is created by combining the strong noise suppression by morphological opening and closing operations and the effective impact extraction by gradient operator.

\[
G_{mg} = (f \circ g \ominus g)(n) - (f \Theta g)(n)
\]
2.3. Fault Stage Feature Extraction Based on Antinoise Morphological Gradient Operator
The vibration signal of mechanical fault is usually accompanied with periodic transient impact response. The magnitude of impact indicates the fault stage. The larger the impact magnitude is, the more serious the mechanical damage. The frequency of the impact appearance is related to the defect’s location and movement cycle. In the signal sampling process, cyclical transient impact response is modulated by signal’s fundamental frequency and mixed with strong environmental noise. This response shows nonlinear and nonstationary characteristics and cannot be used to fault identification directly. In order to extract the signal’s periodic impact feature for fault stage identification, a method of signal process by using the anti-noise morphological gradient operator is proposed. Filtered by the antinoise morphological gradient operation, the impact signal demodulated, and sensitive noise suppressed at the same time. Moreover, a fault stage identification method based on the kurtosis index of spectral characteristic frequency band is suggested. During mechanical failure, the contact area and contact pressure of two match components at the defect change, leading to amplitude–frequency modulation of the signal. This condition results in many frequency peaks and harmonic components in the low-frequency band of the signal[13]. The worse the mechanical fault is, the richer the frequency peak component in the low-frequency band. The frequency band between the maximum and minimum of possible fault frequency is set as the characteristic frequency band. The kurtosis value of characteristic frequency band in the signal spectrum filtered by noise-resistant gradient operator is calculated as the index of fault stage identification.

Kurtosis is a statistic index that reflects the degree of deviation from its normal distribution of a variable. It can be used to describe the intensity of sudden change in a signal and to characterize the peak degree of signal waveform[14]. The calculation formula of kurtosis is expressed as Eq.5.

\[
k = \frac{1}{N} \sum_{i=1}^{N} \left( \frac{x_i - \bar{x}}{\sigma_i} \right)^4
\]

where \( N \) is the signal length, \( x_i \) is the signal value, \( \bar{x} \) is the signal’s mean, and \( \sigma_i \) is the signal standard deviation.

The periodic impact response in the signal varies when the mechanical system deteriorates into different fault stages, result that the magnitude of the low-frequency band in the spectrum increases with the severity of fault. Therefore, the kurtosis of characteristic frequency band of the filtered signal is calculated by using Eq.5 to distinguish the different damage levels of fault.

The process of fault stage identification using morphological filtering of noise-resistant morphological gradient operator is as follows:
- Filter the mechanical fault signal with the antinoise morphological gradient operator to eliminate intense background noise interference. This step highlights the impact characteristics of signals in different fault stages.
- Convert the signal to frequency domain through fast Fourier transformation (FFT) for analysis and processing.
- Calculate all possible fault frequencies in accordance with the characteristics of mechanical elements and their movement frequency. Identify fault types in terms of the signal frequency spectrum.
- Calculate the kurtosis value of characteristic frequency band of the signal and identify the fault stage. The smaller the kurtosis value is, the more serious the fault.

3. Simulation verification
Many mechanical fault signals have damped vibration. But the attenuation characteristics are usually submerged due to noise interference. This paper uses the composition of damped vibration signal and random noise to simulate the actual sampled fault signal. The simulation signal is generated as Eq.6.

\[
Y = Ae^{-\frac{2\pi \omega_0 t}{\sqrt{1-\sigma^2}}} \sin(2\pi \omega_0 t) + A_i N(0,1)
\]
where $A$ is the amplitude of damped vibration signal, $\zeta$ is the relative damping coefficient, $\omega_d$ is the vibration frequency, and $A_2$ is the noise amplitude. The values of each parameter are shown in Table 1.

| Parameter | $A$ | $\zeta$ | $\omega_d$ | $A_2$ |
|-----------|-----|---------|------------|-------|
| Value     | 2   | 0.1     | 20         | 3     |

Set the sampling frequency to 2000 Hz and sampling time to 1 s. The simulated waveform shown in Figure 2 is obtained by superimposing the sampled signals twice. The signal’s attenuation characteristics are submerged in noise, and many high-frequency components are found in its spectrum.

Filter the simulated signal by using the antinoise morphological gradient operator with triangular structure element of length 15. The waveform shown in Figure 3(a) is obtained. Convert the waveform to frequency domain by FFT. It can be seen that the signal’s high-frequency noise is filtered, and the characteristic frequency emerges prominently.

4. Example Verification
The rolling bearing experimental data of Case Western Reserve University were used to identify different failure stages by artificially making material flaking defects of different sizes and depths on the inner race, outer race, and rolling element. When the rolling bearing runs at the same speed and under the same load, typical fault bearing vibration data at different damage stages were sampled. Outer race fault signals with rotational speed of 1772 rpm and fault frequency of 105.9 Hz of slight
and severe damage degree were selected for analysis. Their time-domain waveforms and spectrum are shown in Figures 4 and 5, respectively.

![Signal time-domain waveform](image1)

![Signal spectrum](image2)

Figure 4. Original signal and its spectrum of slight fault

![Signal time-domain waveform](image3)

![Signal spectrum](image4)

Figure 5. Original signal and its spectrum of severe fault

The slight and severe faults signals are filtered with noise-resistant morphological gradient operator and converted to frequency domain through FFT. The result is shown in Figures 6 and 7. As shown in the time-domain waveform, the high-frequency noise is effectively moved after morphological filtering, prominently showing the signal impact characteristics. The fault frequency submerged in noise is accurately extracted, and the spectrum components differ greatly in different fault stages. Under the running speed of 1772 rpm, the bearing inner ring fault frequency is calculated as 159.9 Hz, outer ring fault frequency is 105.9 Hz, the holder’s fault frequency is 11.7 Hz, and rolling element fault frequency is 139.2 Hz. Thus, the characteristic frequency bands are selected as 10–160 Hz between the maximum and minimum fault frequencies. The kurtosis values of slight fault characteristic band and severe fault characteristic band are 31.76 and 18.86, respectively. These values can distinguish the different stages of fault development considerably.
Figure 6. Morphological filtering result of slight fault signal

Figure 7. Morphological filtering result of severe fault signal

5. Conclusion

A morphological filtering method based on antinoise morphological gradient operator is proposed to extract mechanical impact characteristics of different fault stages. This method can remove intense noise interference while retaining the impact characteristics in different fault stages. The kurtosis value of characteristic frequency band in the filtered signal spectrum is used to quantify the fault severity and identify fault stages. The simulation signal analysis shows that the antinoise morphological gradient operator can adequately suppress the strong environment noise interference and highlight the mechanical fault frequency. Vibration signal analysis of bearings with slight and severe damage shows that the noise-resistant morphological gradient operator can accurately extract the fault frequency. The signal’s characteristic frequency band kurtosis value can significantly distinguish different stages of fault development.

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