Rolling Bearing Fault Diagnosis Method With Enhanced Top-Hat Transform Filtering and Cyclic Spectrum Coherence

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ABSTRACT As an important component of rotating machinery, the fault information of rolling element bearing is difficult to be recognized due to the background noise and harmonic frequency contained in the tested vibration signal. In order to accurately and completely extract the fault characteristic information from the vibration signal, a fault diagnosis research method (EAVGH-CSC-EES) based on the combination of enhanced top-hat morphological filtering (EAVGH) and cyclic spectrum coherence (CSC) is proposed. First of all, in view of the problem that the existing top-hat operators cannot fully extract the signal fault characteristics, this paper selects the optimal operator from the four enhanced morphology operators to construct the EAVGH. Since the reasonable selection of structural element (SE) scale has a great influence on the filtering result of morphological operators, then this paper applies feature energy factor (FEF) to select the optimal scale of SE. Subsequently, in order to further solve the influence of the non-linear modulation frequency components in the signal, while improving the filtering performance of EAVGH. This paper uses the cyclic spectrum coherence function (CSC) to further process the filtered signal. And then the enhanced envelope spectrum (EES) of the signal is obtained. Simulation and two sets of bearing fault experiments verify the rationality and effectiveness of the EAVGH-CSC method. The comparison results with other existing methods can further prove the superiority of the method proposed in this paper.

INDEX TERMS The bearing fault diagnosis, morphological filtering, enhanced top-hat morphological operator, cyclic spectrum coherence.

I. INTRODUCTION

As an important part of rotating machinery, rolling bearings are widely used in modern machinery and equipment. Because of its long-term service in the environment of high speed and alternating load, it is easy to be damaged or even malfunction. This not only has a huge impact on the healthy operation of machinery and equipment, but also brings huge economic losses to the enterprise. When the rolling bearing has a partial failure, the part with local fault will collide with the normal part of the bearing, thus causing structural resonance. Although there is a slight slip between the rolling element and the cage. However, depending on the geometry of the bearing, the impulse will appear periodically. Usually these resonance frequencies are much higher than the fault frequency of the bearing. These resonance frequencies are generally considered to be amplitude modulated of the fault frequency [1], [2]. However, these impulse signals are usually interfered by Gaussian white noise and harmonics caused by other equipment [3]. This brings great difficulties to the fault diagnosis of the equipment. Therefore, how to effectively and accurately identify the fault impact signal of the rolling bearing from the vibration signal with strong background noise has become a key research issue [4]–[6].

Nowadays, many classic signal recognition methods (SK [7], EEMD [8] and WT [9]) have been successfully applied to the fault diagnosis of rolling bearings. However, these methods mainly focus on the de-noising of the signal and ignore the detailed information of signal fault characteristics.
Therefore, how to keep the impact characteristics of the fault signal as much as possible, but also effectively suppress the background noise and nonlinear harmonic interference is the main purpose of this paper. Different from the above fault diagnosis methods, morphological filtering (MF) directly acts on time-domain signals through structural element (SE), and it is a detection method that is simple in form and can handle nonlinear signals. MF was first applied to image processing by Matheron and Serra [10]. Nowadays, MF is widely used in mechanical fault diagnosis [11]–[20]. MF uses pre-set SE and morphological operator (MO) to perform mathematical operations with one-dimensional signals to achieve the purpose of noise reduction and feature extraction. Research shows [11], [12] that the selection of SE type has relatively little effect on the filtering results. The reasonable construction of MOs has a huge impact on the final filtering results. The basic MOs are mainly composed of dilation, erosion, opening and closing operator. The reasonable construction of these basic operators can be combined into advanced operators with different functions. Li et al. [11] successfully applied the difference between the dilation and erosion operator (MG) to the fault diagnosis of rolling bearings. Raj and Murali [12] used the MG operator to de-noise and extract features from the vibration signal of rotating machinery. Subsequently, Hu et al. [13] applied the MG operator to extract the positive and negative impulses of the fault signals. Li et al. [14] applied the difference between the closing and opening operator (DIF) to fault detection of gears. Zhang et al. [15] proved that the DIF operator can extract positive and negative impulses at the same time, and successfully detect the fault characteristics of rolling bearings. Li et al. [16] proposed a difference operator (Gco_oc) using a combination of opening-closing and closing-opening operators, and then he detected the fault of the rotating machinery by combining the diagonal slice spectrum. Although, these operators have some effect on the impulse signal extraction of rotating machinery. However, when extracting fault features, they transform the negative impulse signal into positive impulse signal and lose the integrity of vibration signals.

Considering that the morphological top-hat transform has excellent high-pass filtering characteristics, and the top-hat operator is helpful to detect the fault characteristics of the signal. In order to be able to extract the complete fault signal components, Yan et al. [17] combined the average of opening-closing and closing-opening operator (CMF) [18] and the top-hat operator (WTH) to construct a combination morphological filter-hat transform operator (CMFH). Hu and Xiang [19] combined the average of closing and opening operator (AVG) [20] and WTH to construct the average morphological filter-hat transform operator (AVGH). Although AVGH and CMFH can extract complete fault impact information, the impulse amplitude they extract is weakened due to the influence of the operator itself.

In order to solve the above problems and restore the fault signal characteristics to the greatest extent. In this paper, a new enhanced top-hat transform operator (EAVGH) is proposed by combining EAVG operator [21] and BTH operator. EAVGH can not only maintain the integrity of the fault signal, but also has a better filtering effect. However, there will still be non-linear coupling interference frequency components in the vibration signal processed by EAVGH. Because the fault signal of rotating machinery has the characteristics of cyclostationary, cyclic spectrum coherence (CSC) analysis [22]–[25] is an effective tool to demodulate the fault information submerged in the vibration signal of rotating machinery. Therefore, CSC is proved to be a very effective tool to detect the fault information of rotating machinery, especially when the vibration signal has periodic modulation characteristics. In this paper, EAVGH filtering was carried out on the vibration signal, and then CSC spectrum of noise elimination signal was calculated. In order to further enhance the cycle frequency characteristics of CSC spectrum, the Enhanced Envelope spectrum (EES) was applied. Finally, a comprehensive fault diagnosis research method called EAVGH-CSC-EES was proposed. Simulation and experimental results further prove the effectiveness and superiority of method EAVGH-CSC-EES.

The rest of the article is arranged as follows: In Section 2, the mathematical morphology theory and the EAVGH operator are proposed. The CSC theory is introduced in Section 3. Section 4 describes the technical route of this article. Sections 5 and 6 introduce simulation and experimental analysis, respectively. Section 7 describes the conclusion.

II. MATHEMATICAL MORPHOLOGY

A. BASIC MORPHOLOGICAL OPERATORS

MF is mainly composed of four basic MOs: dilation, erosion, opening and closing. Suppose the signal \( f(n) \) represents a one-dimensional discrete sequence in the domain \( F = \{0, 1, 2, \ldots, N-1\} \). The SE is expressed as another one-dimensional discrete sequence in the domain \( G = \{0, 1, 2, \ldots, M-1\} \). Satisfy \( N \geq M \). The four basic MOs are defined as follows [26]:

\[
(f \oplus g)(n) = \max[f(n - m) + g(m)]
\]

(1)

\[
(f \ominus g)(n) = \min[f(n + m) - g(m)]
\]

(2)

\[
(f \circ g)(n) = (f \Theta g)(n)
\]

(3)

\[
(f \bullet g)(n) = (f \oplus g)(n)
\]

(4)

where \( \oplus \) represent the dilation operator, \( \ominus \) represent the erosion operator, \( \circ \) represent the opening operator, \( \bullet \) represent the closing operator, respectively. According to Eqs. (1)-(4), some MOs with specific properties can be constructed, the Black Top-Hat (BTH) operator and White Top-Hat (WTH) operator are defined as follows [16]:

\[
BTH(f(n)) = (f \bullet g)(n) - f(n)
\]

(5)

\[
WTH(f(n)) = f(n) - (f \circ g)(n)
\]

(6)

The Positive BTH operator (PBTH) and the Negative WTH operator (NWTH) are as follows [19]:

\[
PBTH(f(n)) = f(n) - (f \bullet g)(n)
\]

(7)

\[
NWTH(f(n)) = (f \circ g)(n) - f(n)
\]

(8)
In the actual signal processing process, BTH and PBTH have the same filtering result. At the same time, WTH and NWTH have the same filtering effect. AVG and CMF operators have the ability to extract harmonic signals, which are defined as follows:

\[
\text{AVG}(f(n)) = \frac{(f \odot g)(n) + (f \circ g)(n)}{2} \\
\text{CMF}(f(n)) = \frac{(f \cdot g \circ g)(n) + (f \circ g \cdot g)(n)}{2}
\]

Since the vibration signal of the mechanical system is often mixed with harmonic signals and background noise. In order to extract the impact signal of the faulty bearing, AVGH [19] and CMFH [17] top-hat transform operators are proposed. Their expressions are as follows:

\[
\text{AVGH}(f(n)) = f(n) - \frac{(f \cdot g)(n) + (f \circ g)(n)}{2} \\
\text{CMFH}(f(n)) = f(n) - \frac{(f \cdot g \circ g)(n) + (f \circ g \cdot g)(n)}{2}
\]

In the fault diagnosis of rolling bearings, both AVGH and CMFH can extract relatively complete fault impact information. However, the fault amplitude extracted by them has been weakened. Therefore, on the basis of the above research, a new enhanced top-hat transform operator is proposed, which can extract the fault impact information to the maximum extent.

**B. EAVGH**

The four basic operators of MF can be divided into two categories according to their performance: the dilation operator can extract the positive impulse signal and expand the peak of the signal. The erosion operator can expand the trough of the signal while extracting the negative impulse signal. The opening operator can suppress the peak noise (positive impulse) of the signal, and the closing operator can suppress the valley noise (negative impulse) of the signal [5]. Therefore, in order to enhance the extraction of positive and negative impulses, the dilation and closing operators are combined, and the erosion and opening operators are combined together. The four new MOs are defined as follows:

\[
F_{DC}(f(n)) = (f \odot g \cdot g)(n) \\
F_{CD}(f(n)) = (f \cdot g \odot g)(n) \\
F_{EO}(f(n)) = (f \Theta g \odot g)(n) \\
F_{OE}(f(n)) = (f \odot g \Theta g)(n)
\]

where \(F_{DC}\) and \(F_{CD}\) can extract the positive impulse signal, on the contrary, \(F_{EO}\) and \(F_{OE}\) can extract the negative impulse signal. However, \(F_{DC}, F_{CD}, F_{EO}\) and \(F_{OE}\) can only extract the one-sided spectrum of the signal. In order to be able to extract the two-sided spectrum of the signal, Guo et al. [21] proposed four enhanced morphological operators, their expressions are defined as follows:

\[
EAVG_{DC-EO}(n) = \frac{F_{DC}(f(n)) + F_{EO}(f(n))}{2}
\]

In order to prove the ability of the four enhanced morphological operators to extract harmonic signals, a set of simulated signals \(x_1 = \cos(2^\pi 30t\pi) + 1.5\cos(2^\pi 50t\pi)\) is analyzed. The sampling frequency and sampling points of the signal are 1024 Hz and 1024, respectively. The time domain diagram of signal \(x_1\) is shown in Fig. 1. The operator selects a flat SE with zero height and the scale is 5. The results of processing the signal \(x_1\) are shown in Fig. 2(a)-2(d).

**FIGURE 1. Waveform of the simulated signal.**

In Fig. 2, although the \(EAVG_{DC-EO}, EAVG_{DC-DC}, EAVG_{CD-EO}\) and \(EAVG_{CD-CD}\) can restore the harmonic signal \(x_1\), but it can be clearly seen that the \(EAVG_{CD-CD}\) is significantly better than the other three operators in restoring signals \(x_1\). Therefore, based on the above analysis, in order to further extract the impact characteristics of the fault signal from the strong interference noise, this paper proposes a new enhanced top-hat transform operator (EAVGH), and its expression is defined as follows:

\[
EAVGH(f(n)) = (f(n)) - \frac{F_{CD}(f(n)) + F_{EO}(f(n))}{2}
\]

In order to simulate the fault impact signal of the rolling bearing, another set of simulation signals \(x(t)\) is established to verify the anti-harmonic interference ability of the EAVGH operator. The expression of the signal \(x(t)\) is as follows:

\[
x(t) = x_1(t) + x_2(t)
\]

where \(x_1(t)\) is the harmonic interference signal, and its waveform is shown in Fig. 1. \(x_2(t)\) represents the simulated impact signal of the faulty bearing, and \(x_2 = 2\exp(-100t)\cdot\sin(400\pi t)\). The time domain diagrams of the signals \(x_2(t)\) and \(x(t)\) are shown in Fig. 3(a) and Fig. 3(b), respectively. It can be seen from Fig. 3(b) that the fault impact signal is distorted due to the interference of the harmonic signal \(x_1(t)\). The EAVGH operator and the other four top-hat transform operators (BTH, WTH, AVGH and CMFH) are used to process the signal \(x(t)\) at the same time. The processing results are shown from Fig. 4(a)-4(e).

As can be seen from Fig. 4, the BTH operator can only extract negative impulse signals, and the WTH operator can...
only extract positive impulse signals. Although AVGH and CMFH operators can extract positive and negative impulse signals at the same time, it can be seen from Fig. 4(c) and Fig. 4(d) that the impulse signals extracted by AVGH and CMFH operators are not effective enough. And they cannot detect the small amplitude impulse signals. It can be clearly found in Fig. 4(e) that the EAVGH top-hat operator proposed in this paper can completely extract the shock impulse signal.

In order to further quantitatively evaluate the fault feature extraction capability of EAVGH operator, the correlation coefficient [27] is introduced to evaluate the filtering performance of the above top-hat operator. The mathematical expression of the correlation coefficient is shown in Eq. (23).

\[
C_{xy} = \frac{E[(x - \bar{x})(y - \bar{y})]}{E[(x - \bar{x})^2]E[(y - \bar{y})^2]} \tag{23}
\]

where E[·] represents mathematical expectation, \(\bar{x}\) and \(\bar{y}\) represent the mean value of \(x\) and \(y\), respectively. The value of \(C_{xy}\) ranges from 0 to 1, the closer \(C_{xy}\) is to 1, and the more similar the two sets of signals are. The correlation coefficients between the results obtained by the four top-hat operators WTH, AVGH, CMFH and EAVGH in processing \(x(t)\) and the bearing fault signal \(x_2(t)\) are shown in Table 1. It can be seen from Table 1 that the EAVGH operator has obtained the maximum correlation coefficient value 0.91, which further demonstrating the ability of EAVGH operator in fault feature extraction.

| Evaluation operator | Correlation coefficients |
|----------------------|--------------------------|
| WTH                  | 0.59                     |
| AVGH                 | 0.83                     |
| CMFH                 | 0.78                     |
| EAVGH                | 0.91                     |

**C. SE SCALE SELECTION**

The reasonable choice of SE scale has a great influence on the filtering result of MF. The SE is mainly composed of three parts: height, length and shape. The results [5], [16] show that the height and shape of SE have little effect on the filtering performance. Therefore, in order not to affect the calculation speed, the SE height is set to 0 and its shape is set to flat in this paper. The corresponding relationship between SE length and scale is shown in Table 2. It can be drawn from Table 2 that the length and scale of SE satisfy \(L = \lambda + 2\). The scale range of SE

| \(\lambda\) | \(L\) |
|------------|-------|
| 1          | \(0, 0, 0\) |
| 2          | \(0, 0, 0, 0\) |
| 3          | \(0, 0, 0, 0\) |
| \(n\)      | \(\ldots\) |
is usually chosen from 1 to $f_s/f_o$, $f_s$ is the sampling frequency and $f_o$ is the fault frequency of the signal.

Currently, there are many methods for selecting the optimal scale of SE (such as SNR, maximum kurtosis value, information entropy, genetic algorithm, etc.). Different from the above scale selection method, the feature energy factor (FEF) [17], [28] is proved to be a stable and accurate scale selection method. Therefore, the FEF is used to optimize the scale of SE in this paper. The expression is defined as follows:

$$\text{FEF} = \frac{E}{E^*} = \frac{\sum Y^2(i)}{\sum Y^2}$$

where $E$ represents the energy of the fault information, $E^*$ represents the total energy of the frequency spectrum, $Y(i)$ represents the amplitude corresponding to the fault frequency, $i = 1, 2, \ldots, m$ represents the order of the fault frequency. The larger the FEF, the better the filtering performance of the signal. On the contrary, the smaller the FEF, the more serious the signal is polluted by noise.

III. CYCLIC SPECTRUM COHERENCE ANALYSIS

When the rolling bearing has the local fault, its vibration signal can be described as circulatory stationary signal. The statistical characteristics of cyclically stationary signals usually show the characteristics of periodic stationary. The analysis of cyclically stationary signals is to make the vibration signals behave in a periodic manner by nonlinear transformation. Therefore, cyclic spectrum analysis is proved to be a very effective tool to detect the fault information of rotating machinery, especially when the vibration signal has periodic modulation characteristics.

The traditional spectrum analysis method adopts the auto-correlation function method, but this method has low fault diagnosis calculation efficiency. Another form of cyclic spectrum is to perform short-time Fourier transform (STFT) on the signal, and then perform Fourier transform (FFT) on the frequency time axis, which can improve the calculation efficiency of the cyclic spectrum. The specific description is as follows:

For the discrete signal $x[n], n = 0, 1, 2, \ldots, L - 1$. The STFT transformation of $x[n]$ is as follows:

$$X_{\text{STFT}}(i, f_k) = \sum_{m=0}^{N_w-1} x[n]w[n-iR]e^{-j2\pi m f_k f_s}$$

where $w[m]$ represents the window of STFT, $N_w$ represents the window length, $F_s$ is the sampling frequency, $R$ represents the block shift of STFT, and $R = F_s/2\alpha_{\text{max}}$. The discrete frequency $f_k = k\Delta f, k = 0, 1, \ldots, N_w - 1$, the frequency resolution $\Delta f$ is defined as follows:

$$\Delta f = \frac{F_s}{N_w}$$

Since the phase information plays an important role in the signal, the starting point of the reference signal is 0, the phase modified STFT of Formula (25) is described as follows [29]:

$$X_w(i, f_k) = \sum_{n=0}^{L-1} x[n]w[n-iR]e^{-j2\pi m f_k f_s}$$

where $X_w(i, f_k)$ is the complex envelope form of the signal $x[n]$ in the narrowband frequency range of $\Delta f$ and concentrated on the instantaneous sampling of $f_k$ as $iR/F_s$. Finally, the expression of the signal’s averaged cyclic
periodogram (ACP) [29] is defined as follows:

\[
S_{ACP}(\alpha, f) = \frac{1}{K\|w\|^2T} \sum_{i=0}^{K-1} X_w(i, f)X_w(i, f - \alpha)^*,
\]

\[
\|w\|^2 = \sum_{n=0}^{N_w-1} \|w[n]\|^2, \quad K = (L - N_w + B)/R,
\]

Relevant literature [29] proves that:

\[
\lim_{N_w \rightarrow \infty} \lim_{K \rightarrow \infty} S_{ACP}(\alpha, f) = S_x(\alpha, f)
\]

The cyclic spectrum coherence (CSC) function is defined as follows:

\[
\gamma(\alpha, f) = \frac{S(\alpha, f)}{\sqrt{S(0, f)S(0, f - \alpha)}}
\]

Eq. (30) represents the cross-correlation of the complex envelope signal \(X_w(i, f)\) at frequency \(f\) and frequency \(f - \alpha\), the spectral components of different frequencies are simultaneously detected, the amplitude of the fault frequency of the rolling bearing at the cycle frequency \(\alpha\) is enhanced. Finally, in order to obtain the diagnosis result, the Enhanced Envelope Spectrum (EES) [30] of CSC is defined as follows:

\[
S_{EES}(\alpha) = \int_{f_l}^{f_u} |\gamma(\alpha, f)|df
\]

IV. THE TECHNICAL ROUTE OF EAVGH-CSC-EES

The technical route of the EAVGH-CSC-EES method proposed in this paper is shown in Fig. 5. Specific steps are as follows:

**Step 1**: The vibration signal of the rolling element bearing is collected.

**Step 2**: The FEF values of experimental signal at different MF scales are calculated, and the optimal scale is selected.

**Step 3**: EAVGH filters the signal at the optimal scale.

**Step 4**: The cyclic spectral coherence of the de-noising signal is calculated.

**Step 5**: The EES is applied to extract the characteristic information of the fault bearing.

V. SIMULATION

A. SIMULATION VERIFICATION OF EAVGH-CSC-EES

In actual working conditions, the fault characteristic signal of rolling bearing will not only be interfered by harmonics, but also be affected by background noise and random interference signals. In order to verify the effectiveness of the algorithm proposed in this paper, a set of bearing fault simulation signal model is established:

\[
y(t) = y_1(t) + y_2(t) + y_3(t) + y_4(t) + \delta(t)
\]

\[
y_1(t) = \sum_{i=1}^{I} A_i x_i(t - iT_A - \tau_i)
\]

\[
y_2(t) = \sum_{n=1}^{N} B_n s_n(t - nT_B)
\]

\[
y_3(t) = \sum_{m=1}^{M} C_m \sin(2\pi f_m + \varphi_m)
\]

\[
y_4(t) = \sum_{p=1}^{P} C_p \cos(2\pi f_p + \varphi_p)
\]

The fault model of the bearing is composed of five parts: the fault signal \(y_1(t)\), the random impulse interference signal \(y_2(t)\), the harmonic interference signal \(y_3(t)\) and \(y_4(t)\), and the white Gaussian noise signal \(\delta(t)\). In the model, \(A\) is the amplitude of the fault signal, \(T\) represents the time interval between the two shock signals, and \(\tau\) a random variable that is usually used to simulate random sliding of the roller. \(B\) is a variable and it is the amplitude of the random impulse signal. \(C\) is the amplitude of the harmonic interference signal, \(f\) represents the frequency of the harmonic signal, and \(\varphi\) is the phase angle. \(s(t)\) represents the impulse response function of the mechanical system and can be described as follows:

\[
s(t) = e^{-at} \sin(2\pi f_o t + \varphi)
\]

where \(a\) is the decay factor, \(f_o\) is the resonance frequency. A simulated signal is established based on Eq. (32). The numerical parameters in the model are shown in Table 3. The white Gaussian noise signal \(\delta(t)\) is \(-10\) dB. The sampling frequency is 1024Hz, the signal length is 10240. The components of the simulated signal are shown in Fig. 6. The time domain diagram and frequency domain diagram of the simulated signal \(y(t)\) are shown in Fig. 7(a) and Fig. 7(b), respectively. In Fig. 7(b), the interference frequencies of 20Hz, 30Hz, 40Hz and 50Hz are very obvious, while the bearing fault characteristic frequency of 16Hz cannot be identified.

EAVGH and four top-hat morphological operators (WTH, BTH, AVGH, and CMFH) were also selected to process the
TABLE 3. The bearing fault model parameters.

| Parameter | Value | Parameter | Value |
|-----------|-------|-----------|-------|
| $A$       | 4     | $r$       | 0     |
| $f_c$     | 200   | $C_0$     | 1.1, 1.2 |
| $f_0$     | 1     | $f_s$     | 30, 40 |
| $N$       | 10    | $C_2$     | 1, 1.2 |
| $T_s$     | 1/16  | $f_p$     | 20, 50 |
| $\varphi$| 0     |           |       |

FIGURE 6. The components of the simulation signal $y(t)$: (a) fault pulse signal $y_1(t)$, (b) random interference signal $y_2(t)$, harmonic interference signal $y_3(t)$ and harmonic interference signal $y_4(t)$.

signal $y(t)$. Firstly, the SEs of these operators are selected. The FEFs of above operators changing with the scale are shown in Fig. 8. It can be seen from Fig. 8 that the optimal scale of each top-hat operator appears between 0-10. When the scale is 5, the EAVGH operator obtains the global maxFEF 0.097. It is larger than other top-hat operators. When the scale is 4, the maxFEF of the CMFH is 0.081. The FEF index of these top-hat operators is better than the envelope spectrum. The filtering results after processing signal $y(t)$ under their optimal scale are shown in Fig. 9(a)-9(f), respectively.

FIGURE 7. The time domain spectrum and FFT spectrum of the simulated signal $y(t)$.

FIGURE 8. The FEF-scale graphs of different top-hat operators.

It can be found from Fig. 9(a) and Fig. 9(b) that both BTH and WTH can identify the bearing fault frequency of 16Hz, but they are seriously affected by background noise interference. The frequency interference of 30Hz, 40Hz and 50Hz is obvious. In Fig. 9(c), A VGH can detect the bearing fault frequencies of 16Hz, 32Hz, 48Hz, 64Hz and 80Hz, but the magnitude of the fault frequency is relatively weak. In contrast, both CMFH and EAVGH can detect obvious rolling bearing fault frequencies. However, the comparison shows that the filtering performance of the EAVGH is better than that of the CMFH. The above comparison results show that the feature extraction ability of the EAVGH top-hat operator is better than other top-hat operators.

It can be seen from the above analysis results that the signal $y(t)$ is still not well filtered by using MF alone. Therefore, the EAVGH-CSC-EES method proposed in this paper is used to process the signal $y(t)$. In EAVGH-CSC-EES method, the window length $N_w$ is $2^6$, cyclic frequency resolution is 0.1Hz, the maximum cycle frequency $\alpha_{max}$ is 100Hz, $w[n]$ is selected as the Hanning window, the result of the processing is shown in Fig. 10. In Fig. 10(a), the obvious cyclic energy lines with a period of 16 Hz appear in the cyclic spectrum coherence.
image. The fault frequency of rolling bearings (16 Hz, 32 Hz, 48 Hz, 64 Hz and 80 Hz) can be clearly seen in Fig. 10(b). The result of processing the signal $y(t)$ directly using the CSC-EES method is shown in Fig. 11. In Fig. 11(a), the cyclic energy spectrum of the fault feature is not very clear. From the EES processing results in Fig. 11(b), the fault frequency information of the rolling bearing is seriously disturbed. The comparison result shows that the filtering effect of EAVGH-CSC-EES method is better than that of CSC-EES method.

B. THE ROBUSTNESS AND SENSITIVITY ANALYSIS OF EAVGH-CSC-EES

In Eq. (32) in Section 5.1, when the SNR of the fault model is $-10$ dB, we discussed the ability of the EAVGH-CSC-EES method to extract bearing fault features. The comparison
results with the EAVGH and CSC-EES methods further prove that the EAVGH-CSC-EES method has superior fault detection capabilities. In this section, we discuss the robustness of the EAVGH-CSC-EES method and its sensitivity to weak fault feature extraction.

For the FEF index (the frequency range is 0-100Hz, and the fault characteristic number \( f \) is 5.) of Eq. (24), it can not only be used as an evaluation factor for selecting MOs, but also can measure the feature extraction ability of the algorithm. When the SNR of the Gaussian noise signal \( \delta(t) \) changes from -14dB to -5dB, the FEF-SNR curve obtained by the EAVGH-CSC-EES and the CSC-EES method processing the signal is shown in Fig. 12. From Fig. 12, with the increase of SNR, the FEF values obtained by the two methods increase. But the fault feature extraction ability of the method proposed in this paper is better than that of the CSC-EES method. When the SNR increases from -10dB to -14dB, the EAVGH-CSC-EES method can still detect system fault information. In order to further verify the sensitivity of the EAVGH-CSC-EES method under strong background noise. When the SNR of \( \delta(t) \) is -14dB, its time-domain spectrum and envelope spectrum are shown in Fig. 13(a) and 13(b), respectively. In Fig. 13(b), the bearing fault frequency of 16 Hz and its harmonic frequencies have been completely submerged. The method proposed in this paper and the CSC-EES method are used to process the signal in Fig. 13(a). The processed results are shown in Fig. 14 and Fig. 15, respectively. Although the fault signal is severely affected by noise, the fault frequencies of 16 Hz, 32 Hz and 48 Hz can still be clearly identified in Fig. 14(b). Comparing with Fig. 15(b), it can be found that the bearing fault amplitude detected by the CSC-EES method is relatively weak for the signal that has not been filtered by EAVGH.

Based on the above analysis, the EAVGH-CSC-EES method proposed in this paper not only has strong anti-interference ability, but also has high sensitivity to periodic shock signals. It is suitable for detecting early failures of rotating machinery.

VI. EXPERIMENT

A. CASE 1 THE ROLLING BEARING OUTER RACE FAULT EXPERIMENT

In order to further verify the effectiveness of the proposed method, the bearing fault test benches for wind turbines were built, as shown in Fig. 16. The test bench consists of an electric motor, planetary gearbox, coupling and generator. The fault signal of the bearing is collected by the acceleration sensor. The shape of the bearing and the wear failure of the outer ring of the bearing are shown in Fig. 17(a) and Fig. 17(b), respectively. The geometric parameters of the tested bearing are shown in Table 4. During the experiment, the speed of the motor was 1590rpm, the theoretical fault frequency of bearing outer ring \( f_{BPFO} \) is 95.4Hz, the sampling frequency of the test equipment is 16384Hz, and the signal length is 16384.

The time-domain diagram of the experimental signal obtained by the sensor, the FFT spectrum and its envelope spectrum are shown in Figs. 18(a)-18(c), respectively. Although the impulse signal can be found in Fig. 18(a), the fault frequency component of the bearing can hardly

![FIGURE 12. FEF-SNR curve obtained by CSC-EES and the proposed method.](image_url)

![FIGURE 13. The time domain spectrum and envelope spectrum when the SNR is -14dB.](image_url)

![FIGURE 14. When the SNR is -14dB, the signal processing result of the method proposed in this paper: (a) CSC spectrum, (b) EES spectrum.](image_url)
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FIGURE 15. When the SNR is $-14\text{dB}$, the signal processing result of the CSC-EES: (a) CSC spectrum, (b) EES spectrum.

FIGURE 16. The bearing fault test benches for wind turbines.

FIGURE 17. (a) experimental bearing, (b) outer race fault.

TABLE 4. Structural parameters of the bearing.

| parameter       | value     | parameter       | value     |
|-----------------|-----------|-----------------|-----------|
| Bearing Type    | 6332      | Ball diameter   | 50.8mm    |
| Outer diameter  | 340mm     | Ball number     | 9         |
| Inside diameter | 160mm     | Contact angle   | 0°        |
| Thickness       | 68mm      | Pitch diameter  | 250mm     |

be detected from the frequency spectrum of Fig. 18(b) and Fig. 18(c).

The EAVGH is performed on the experimental signal, and the obtained FEF and scale relationship curve is shown in Fig. 19. From Fig. 19, the optimal scale obtained is 2. The time-domain spectrum and envelope spectrum obtained at the optimal scale are shown in Fig. 20(a) and Fig. 20(b), respectively. In Fig. 20(b), the bearing fault frequencies $f_{BPFO}$, $4f_{BPFO}$ and $6f_{BPFO}$ can be identified, and the remaining fault frequency components are contaminated.

The EAVGH-CSC-EES method is used to process the experimental signal. The window length $N_w$ is $2^7$, cyclic frequency resolution is 1Hz, the maximum cycle frequency $\alpha_{\text{max}}$ is 800Hz, $w[n]$ is selected as the Hanning window, the results of the processing are shown in Fig. 21(a) and Fig. 21(b), respectively. In Fig. 21(a), the obvious cyclic energy lines with a period of $f_{BPFO}$ appear in the cyclic spectrum coherence image. In Fig. 21(b), the cyclic frequency of the bearing fault frequency ($f_{BPFO}$, $2f_{BPFO}$, ... , $8f_{BPFO}$) can be clearly presented.

The results obtained by using CSC-EES method to process the experimental signals are shown in
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Fig. 20. The experimental signal is processed by the EAVGH method: (a) Filtered result, (b) Envelope.

Fig. 21. The experimental signal processing result of the algorithm proposed in this paper: (a) CSC spectrum, (b) EES spectrum.

Fig. 22. The experimental signal processing result of the CSC-EES: (a) CSC spectrum, (b) EES spectrum.

Fig. 23. The experimental signal processing result of the SK: (a) the fast kurtogram, (b) Envelope.

FIGURE 20. The experimental signal is processed by the EAVGH method: (a) Filtered result, (b) Envelope.

FIGURE 21. The experimental signal processing result of the algorithm proposed in this paper: (a) CSC spectrum, (b) EES spectrum.

The experimental signal processed by the EAVGH method can identify the bearing outer ring fault ($f_{BPFO}$, $2f_{BPFO}$, and $6f_{BPFO}$), the fault amplitude is weak and the interference frequency component is more complicated. In EEMD method, ratio of the standard deviation of the added noise is 0.04 and ensemble number is 100. The main 4th order IMF components are listed in Fig. 24(a). From the envelope spectrum processing result in Fig. 24(b), the fault frequency component of the bearing is still seriously affected by the background interference. It is confirmed that EEMD is affected by the mode mixing problem. The comparison results show the advantages of the algorithm proposed in this paper.
B. Case 2 The Rolling Bearing Inner Race Fault Experiment

In order to verify the effectiveness of the proposed algorithm, a set of the condition based maintenance fault database [31] of bearing inner ring fault data is applied. The fault form of the bearing is shown in Fig. 25. In this data set, the input rotation frequency of the shaft is 25Hz, and the data sampling frequency is 48828Hz. The theoretical inner ring fault frequency \( f_{BPFI} \) is 118.9Hz. The geometric parameters of the bearing are shown in Table 5. Fig. 26 shows the time-domain graph and its spectrum of the test data. Although the periodic shock signal can be seen in Fig. 26(a), the fault frequency of the bearing \( f_{BPFI} \) in Fig. 26(b) is seriously disturbed.

The EAVGH-CSC-EES method in this paper is used to process the experimental signal in Fig. 26(a), and the processing result is shown in Fig. 27. From Fig. 27(a), the cyclic frequency lines of the fault frequency are clearly visible. And the modulation spectrum lines of the rotation frequency and fault frequency can also be clearly seen. In Fig. 27(b), the bearing fault frequency \( (f_{BPFI}, 2f_{BPFI}, 3f_{BPFI}, 4f_{BPFI} \text{ and } 5f_{BPFI}) \) and the rotation frequency \( (f_r) \) are clearly visible. The EAVGH-CSC-EES method not only has good filtering effect but also has strong fault feature extraction ability.

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**TABLE 5.** Structural parameters of the bearing.

| Pitch diameter | Roller diameter | Ball number | Contact angle |
|---------------|-----------------|-------------|---------------|
| 1.245         | 0.235           | 8           | 0°            |

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For comparison, three methods (CSC-EES, SK and EEMD) are applied to process the experimental signal.
in Fig. 26(a). The processing results of the experimental signal are shown in Figs. 28-30. Comparing Fig. 27(a) and Fig. 28(a), the cyclic spectrum coherent image of the CSC-EES method contains a lot of background noise interference frequency components. In Fig. 28(b) and Fig. 29(b), although both the CSC-EES method and the SK method can identify the fault characteristics of the bearing, the filtering performance of these two methods is poor. The EEMD method effectively decomposes the experimental signal into multiple IMF components. From Fig 30(b), although EEMD has better noise cancellation performance, it can only identify the third-order bearing fault frequency ($f_{BPFI}$, $2f_{BPFI}$ and $3f_{BPFI}$). The EEMD’s fault feature extraction ability is weak.

In order to quantitatively evaluate the fault feature extraction capability of the above methods, the FEF index of Eq. (24) is used for evaluation. The larger the FEF, the stronger the fault feature extraction capability of this method. In Eq. (24), the frequency range is 0-600Hz, and the fault characteristic number $i$ is 5. The comparison results of EAVGH-CSC-EES, CSC-EES, SK and EEMD methods are shown in Table 6. It can be seen from Table 6 that the EAVGH-CSC-EES obtains the maximum FEF value of 49.41. The above analysis results can further show that EAVGH-CSC-EES has better fault feature extraction capability.

| Method          | FEF (%) |
|-----------------|---------|
| EAVGH-CSC-EES   | 49.41   |
| CSC-EES         | 15.64   |
| SK              | 7.95    |
| EEMD            | 23.78   |
VII. CONCLUSION
In order to extract accurate and complete fault characteristic information of the rolling element bearing from strong background noise and harmonic interference, this paper proposes a comprehensive fault diagnosis method based on the combination of enhanced top-hat morphological filtering (EAVGH) and cyclic spectrum coherence (CSC). This paper first constructs the EAVGH operator. This operator can enhance the extraction of the positive and negative impulses of the fault signal. In the verification of the correlation coefficient between the simulated signal processed by the WTH, AVGH, CMFH and EAVGH operators and the fault signal, the EAVGH operator obtained the largest correlation coefficient value. When comparing the fault feature extraction capabilities of EAVGH, CSC and EAVGH-CSC, the EAVGH-CSC method inherits the advantages of the two algorithms and obtains the best results. Finally, the results of simulation and experiment comparison with other methods further prove the superiority of the algorithm proposed in this paper.

DISCUSSION
This paper proposes a rolling bearing fault diagnosis research method based on enhanced top-hat filtering and cyclic spectrum coherence, and the effectiveness and superiority of the algorithm proposed are verified through simulation and experiment. However, the algorithm still needs improvement.

We can try to optimize the algorithm proposed from two aspects: (1) In this paper, when performing enhanced top-hat filtering, FEF factor is used to select the optimal morphological scale. Although FEF factor has high calculation accuracy, its calculation efficiency is slow. Therefore, in the future, we can try to construct new indicators to select the optimal scale of MF, and finally achieve the purpose of improving computing efficiency. (2) Another way to improve the calculation efficiency can try to use the fast spectral correlation method to extract the fault characteristics of the vibration signal. If the computational efficiency of the algorithm proposed is improved, it will be more suitable for fault diagnosis of rotating machinery.

In the future research on fault diagnosis of rotating machinery, the following four aspects can be further studied: (1) Try to use the proposed approach to diagnose the considered faults. (2) Study the multi-fault cases combining at least two faults simultaneously. (3) The proposed method is used to diagnose gear faults. (4) Try to apply the proposed method to diagnose the acoustic signal.

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