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Article

Fault Diagnosis Method for Rolling Bearings in High-Noise Environments Based on COA-FMD-ITEO

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Abstract: To address the challenges in extracting features from rolling bearing vibration signals in high-noise environments, a novel fault diagnosis method combining feature modal decomposition based on Cheetah Optimization Algorithm (COA-FMD) and Improved Teager Energy Operator (ITEO) is proposed. First, the Gini coefficient of square envelope spectrum (GISES) is utilized as the fitness function to adaptively optimize the key parameters of FMD through COA. Subsequently, the optimal modal components are selected from the decomposed modes by integrating the feature indicators of the envelope spectrum. Finally, the ITEO energy operator is employed to demodulate the selected modal components, using its effectiveness to enhance impact features to precisely identify the characteristic frequencies of bearing faults via the ITEO energy spectrum. Experimental findings indicate that the proposed methodology is effective in extracting fault signal characteristics in high-noise environments and accurately identifying the type of fault present.

Keywords: rolling bearing; fault diagnosis; feature mode decomposition; cheetah optimization algorithm; energy operator

1. Introduction

In the field of industrial manufacturing, evaluating the condition of rotating motors is essential for ensuring the efficient operation of critical production equipment and for maintaining the reliability and stability of industrial processes. Motor bearings, as a vital component in mechanical systems, play a crucial role in equipment performance. Therefore, effective monitoring and diagnosis of bearing condition not only enhance the accuracy of fault detection but also ensure safe equipment operation and reduce maintenance costs [1–3]. Rotating machinery is indispensable in modern manufacturing, yet it operates under demanding conditions such as high load, high speed, and elevated temperatures, making it susceptible to damage. Prolonged exposure to these harsh environments can lead to bearing failures, including cage fractures and raceway cracks, which can result in unexpected mechanical failures, costly downtime, or even catastrophic consequences [4, 5].Therefore, the timely and accurate detection of bearing faults is essential for ensuring the safe and reliable operation of rotating machinery. A significant challenge in diagnosing bearing faults is the interference caused by background noise within the recorded vibration signals. This noise, originating from complex transmission mechanisms (e.g., mechanical systems) and environmental factors (e.g., vibrations from coupled machines), obscures and distorts critical data needed for fault identification. As a result, creating efficient approaches to extract fault-related features from noisy signals has emerged as a key area of study. Installing accelerometers on the housing of rotating machinery to measure vibration signals is a common method. However, system complexity, multiple transmission paths, and background noise can hinder fault identification, as noise often masks fault characteristics, making it difficult to detect repetitive transient pulses associated with the fault.

In this scenario, various vibration signal processing methods have been developed for diagnosing bearing faults [6]. Walnut had put forward wavelet transform (WT) [7]. Ge had proposed empirical mode decomposition (EMD) [8]. Dragomiretskiy had put forward variational mode decomposition (VMD) [9]. Baker had proposed singular value decomposition (SVD) [10]. Wang ethad put forward spectral kurtosis (SK) [11]. Chaudhuri had proposed blind deconvolution (BD) [12]. Miao had put forward feature mode decomposition (FMD) [13]. The design philosophy of FMD is grounded in deconvolution theory, which involves constructing an adaptive finite impulse response (FIR) filter through iterative adjustment of filter coefficients. This process enables the processed signal to progressively approximate the desired deconvolution outcome. By employing a series of adaptive FIR filters, FMD can decompose the signal into multiple modes. FMD effectively integrates the periodic and transient characteristics of the signal, demonstrating strong robustness against noise and other interference, thereby mitigating their negative impacts.However, the input parameters for the FMD, including the number of decomposition modes and filter length, must be evaluated empirically. Incorrect settings can significantly affect its overall effectiveness.

In recent years, intelligent optimization algorithms have seen growing application in signal processing. These algorithms adaptively determine core parameters and enhance performance, particularly in FMD. The choice of preset parameters has a substantial impact on the outcomes of decomposition, thereby underscoring the importance of employing suitable optimization algorithms to identify the most effective combinations of parameters. Choosing a suitable optimization algorithm and fitness function is crucial for this process. Jia introduced a technique for fault feature extraction that employs an enhanced whale optimization algorithm (WOA) to optimize the parameters associated with FMD. The enhanced WOA integrates both Lévy flight and adaptive weighting mechanisms, employing envelope entropy as a fitness function to optimize the parameters related to modal decomposition for feature extraction [14]. The WOA algorithm requires frequent updates to position and evaluations of fitness functions during the iterative process, leading to a substantial increase in computational complexity when handling large-scale signal data. Li et al. introduced a self-adaptive parameterized FMD method that utilized a nonlinear inertial weight logarithmic descent and random adjustment of the discovery probability (DWCS) in the cuckoo search algorithm.The researchers introduced a novel method for identifying the maximum characteristic fault frequency and its harmonics, which are extracted from the envelope spectrum of bearing fault signals.They referred to this approach as the Feature Frequency Ratio (FFR). Subsequently, they employed the DWCS algorithm to adaptively identify the most effective combination of FMD parameters, guided by the maximum FFR [15].

Moreover, the process of identifying the most relevant modes from the various components obtained through modal decomposition has posed a significant challenge. Zhong proposed a methodology for selecting the center frequency by utilizing grid division frequencies and their harmonics, employing the maximum signal-to-noise ratio as a criterion. The mode associated with the selected center frequency exhibited the highest signal energy while simultaneously demonstrating the lowest noise energy [16]. Zhou had utilized the variance contribution rate to identify the effective mode components from those obtained through modal decomposition [17]. Wu had proposed using the Spearman correlation coefficient and energy values to select the feature IMF [18]. The aforementioned indicators exhibit insufficient robustness to noise and demonstrate a high degree of dependence on the type and characteristics of the signal.

When a bearing malfunctions, its fault vibration signal typically exhibits a modulated form, making demodulation analysis essential for diagnosing bearing faults. Common demodulation techniques had included the Hilbert Transform (HT) [19]. However, HT's demodulation results had often exhibited non-instantaneous response characteristics, thereby increasing demodulation errors. Subsequently, the Teager Energy Operator (TEO) [20]. and the Analytic Energy Operator (AEO) [21]. had been proposed as alternatives. AEO's energy spectrum had accurately identified characteristic fault frequencies, aiding in fault diagnosis. However, TEO and AEO's high sensitivity to noise had led to suboptimal SNR performance in the demodulated signals.

To enhance the accuracy of fault diagnosis in motor rolling bearings, it is essential to employ advanced signal processing techniques and noise reduction methods. These methods will reliably extract fault features, thereby ensuring optimal motor operation and maintenance efficiency.

In feature mode decomposition, the selection of parameters often depends on experience and lacks adaptability, resulting in suboptimal decomposition outcomes. Furthermore, in pattern recognition that encompasses critical fault information, there is a deficiency of effective comprehensive indicators, complicating the accurate extraction of the most valuable components from the decomposed modes. Simultaneously, traditional energy operators encounter challenges with insufficient accuracy when analyzing modulation and impact component signals, which adversely affects the identification of fault characteristic frequencies and the thorough investigation of fault causes.

Based on the discussions outlined, this paper introduces a novel fault diagnosis approach referred to as COA-FMD-ITEO. This approach uniquely integrates feature modal decomposition with an advanced Improved Teager Energy Operator, utilizing the Cheetah Optimization Algorithm. The primary innovations and original contributions of this research are summarized as follows:

1) Introduce the envelope spectrum Gini coefficient to guide the Cheetah Optimization Algorithm in achieving adaptive optimization of key parameters for empirical mode decomposition.This data-driven optimization framework

not only effectively reduces the need for manual parameter adjustment, but also significantly improves the accuracy of signal decomposition.

2) By integrating the kurtosis and peak factor of the envelope spectrum, a comprehensive index of the envelope spectrum is proposed to precisely identify the optimal mode that contains critical fault information.

3) A novel energy operator based on central finite difference sequences has been proposed to replace the traditional forward difference method. This operator can be effectively applied to modulation analysis, significantly enhancing the impact components in rolling bearing fault signals. Subsequently, by constructing the ITEO energy spectrum, precise identification of bearing characteristic frequencies is achieved, providing theoretical support for further analysis of the causes of faults.

The remaining sections of this paper are structured as follows: Section 2 presents the foundational details of Feature Mode Decomposition (FMD). The Cheetah Optimization Algorithm (COA) is employed to optimize the FMD model parameters, and the ITEO. Section 3 details the proposed method. Section 4 presents computational experiments conducted on public datasets. Section 5 concludes the paper.

2. Preliminaries

2.1. Feature Mode Decomposition (FMD)

FMD can effectively reveal the impacts of bearing faults that are obscured by significant background noise. The primary procedures are outlined below:

Step 1: Commence the initialization process by inputting the original vibration signal x and configuring the parameters for Frequency Modulation Decomposition (FMD). This includes specifying the number of modal decompositions n, the filter length L, and the number of frequency segments K.

Step 2: Initialize the FIR filter bank using K Hann windows, and set the initial iteration counter $i = 1$.

Step 3: Signal filtering: Filter the original signal. The signal is filtered using an initialized filter bank to obtain the decomposed modal components $u_k{}^i(k = 1,2,\cdots,K)$, where $u_k{}^i = x * f_k{}^i$, and $*$ denotes the convolution operation.

Step 4: The optimization of filter parameters is performed using the original signal x, the decomposed modal components $u_k{}^i$, and the estimated fault cycle $T_k{}^i$. The estimation of $T_k{}^i$ is derived from the local maximum value $R_k{}^i$ of the autocorrelation function associated with $u_k{}^i$ at zero crossing. After one iteration, i is incremented by 1.

Step 5: The goal is to check whether the current iteration count i has attained the predefined maximum value. If not, go back to step 3. Otherwise, move on to step 6.

Step 6: Conduct a correlation analysis to develop a correlation matrix denoted as $CC_{(K\times K)}$. This process involves calculating the correlation coefficients for each pair of modal components. Identify the two modal components that exhibit the highest correlation coefficient, and subsequently compute their correlation kurtosis using the previously determined fault period $T_k{}^i$. Following this, select the modal component that demonstrates a greater correlation kurtosis to serve as the decomposed modal component. At this stage, reduce the number of filters by adjusting K to $K-1$.

Step 7: Conduct the termination assessment by evaluating whether the current filter number K corresponds to the specified decomposition modal number n. If a match is identified, conclude the iterative process and acquire the final n modal components.

The overall workflow of the algorithm is depicted in Figure 1.

The three input parameters of the Feature Modal Decomposition (FMD)—filter length L, number of decomposition modes n, and frequency division number K—significantly impact the decomposition effectiveness. Specifically, an improper setting of the number of decomposition modes n can result in over-decomposition or mode mixing, while an unsuitable filter length L can diminish the filter's performance. Additionally, an incorrect frequency division number K will directly affect the quality of demodulation. Thus, optimizing these three parameters of FMD is essential for improving its capability to extract fault features in the presence of significant background noise.

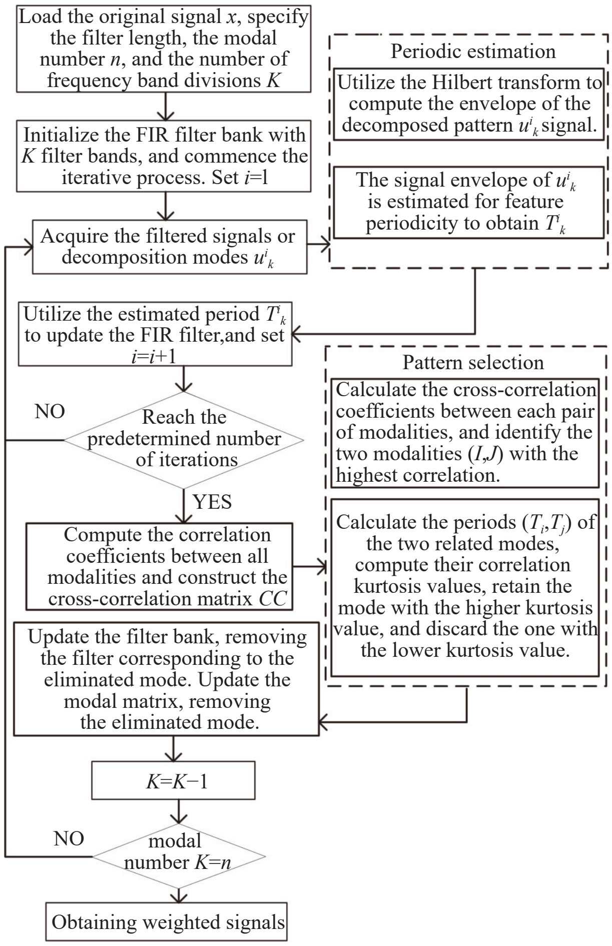

Figure 1. Flowchart of the FMD algorithm.

2.2. The Cheetah Optimization Algorithm (COA) Optimizes the FMD Model Parameters

Given the significant impact of FMD's three input parameters (filter length L, number of decomposition modes n, and frequency division number K) on decomposition performance and the potential issues from improper settings, this paper proposes using the Cheetah Optimization Algorithm (COA) to optimize FMD model parameters. This aims to enhance FMD's capability in extracting fault features under strong background noise.

Inspired by cheetah hunting strategies, Akbari et al. introduced a nature-inspired Cheetah Optimization (CO) algorithm in 2022 [22]. The CO algorithm aims to find the optimal solution to the target problem by emulating the hunting behaviors of cheetahs. The specific hunting strategies are as follows:

2.2.1. Search

Searches can be categorized into static and dynamic modes. Static searches focus on locating prey within the cheetah's territory, while dynamic searches gather information about prey in surrounding areas. Static search is effective for densely distributed and actively foraging prey, whereas dynamic search is better suited for sparsely scattered and mobile prey. The mathematical modeling of the search strategy in the Cheetah Optimization Algorithm is as follows:

$$X_{i,j}^{t+1} = X_{i,j}^{t} + \hat{r}_{i,j} \cdot \varphi_{i,j}^{t} \tag{1}$$

where $X_{i,j}^{t}$ represents the current hunting position, $X_{i,j}^{t+1}$ represents the next hunting position, t denotes the hunting time, T is the maximum hunting time, i represents the specific cheetah number (where $i = 1, 2, \cdots, n$), j represents the dimension of the optimization problem (where $j = 1, 2, \cdots, D$), $\hat{r}_{i,j}$ is a random number following a standard normal distribution ($\hat{r}_{i,j} \sim N(0,1)$), representing the situation where cheetahs may quickly escape and change direction when encountering hunters or enemies, and $\varphi_{i,j}^{t}$ represents the search step length, where $\varphi_{i,j}^{t} = 0.001 \cdot \dfrac{t}{T} > 0$.

2.2.2. Sit-and-wait Strategy

To minimize the risk of being detected by the prey, cheetahs approach the animal through stealthy actions. The mathematical modeling of the cheetah optimization algorithm during the search strategy is as follows:

$$X_{i,j}^{i+1} = X_{i,j}^{i} \tag{2}$$

The sit-and-wait strategy in the Cheetah Optimization (CO) algorithm requires that the positions of all cheetahs should not be adjusted simultaneously to enhance the success rate of hunting. This strategy helps the CO algorithm avoid premature convergence.

2.2.3. Attack Strategy

The cheetah's hunting approach relies on its velocity and nimbleness. Upon starting an attack, the cheetah monitors the current location of its target and modifies its trajectory to align more closely with the prey's ultimate position.Simultaneously, each cheetah optimizes its path based on the prey's movements and the positions of alpha or neighboring cheetahs. The mathematical modeling of the offensive strategy in the Cheetah Optimization Algorithm is as follows:

$$X_{i,j}^{t+1} = X_{B,j}^{t} + r_{i,j} \cdot \beta_{i,j}^{t} \tag{3}$$

where $X_{B,j}^{t}$ represents the current best position in the cheetah population, $r_{i,j}$ is the turning factor, and $\beta_{i,j}^{t}$ is the interaction factor.

The Gini index (GI) is an effective sparsity indicator that, compared to traditional sparsity measures, exhibits stable gradient characteristics and robustness against random pulse noise. Through assessing the sparsity of the squared envelope spectrum, it is possible to effectively extract bearing fault features.

The square envelope spectrum (S_{SE}) of signal x can be mathematically formulated as:

$$S_{SE} = abs(T_{FF}(|x + j \cdot \text{Hilbert}(x)|^2)) \tag{4}$$

where T_{FF} represents the Fast Fourier Transform; $Hilbert$ denotes the Hilbert Transform; $abs()$ represents the absolute value operation.

The Gini index of squared envelope spectrum sparsity (GISES) is defined as a measure that can effectively reveal fault characteristics in the squared envelope spectrum without requiring prior fault data. It also possesses higher resistance to random noise and interference.

The GISES (S_{GISE}) of signal x is defined as:

$$S_{GISE}(x) = 1 - 2\sum_{n=1}^{N} \frac{S_{SE}(x)_{(n)}}{\|S_{SE}(x)\|_1} \left(\frac{N - n + 0.5}{N}\right) \tag{5}$$

where $S_{SE}(x)_{(n)}$ represents the n-th spectral line amplitude after sorting the vector $S_{SE}(x)$ in ascending order. $\|S_{SE}(x)\|_1$ denotes the l_1 norm of vector $S_{SE}(x)$. N is the number of spectral lines in $S_{SE}(x)$.

The kurtosis of the envelope spectrum characterizes the shape of the signal's envelope and serves as an effective indicator of the stationarity of impact signals. The envelope spectrum peak factor is a dimensionless index for evaluating the signal's impact characteristics.

Based on the above analysis and combining the advantages of both indicators, a composite indicator of envelope spectral characteristics is constructed. The kurtosis of the envelope spectrum E_{sk} and envelope spectrum peak factor E_c are defined as:

$$\begin{cases} E_{sk} = \dfrac{\sum_{m=1}^{M} |S_E(m)|^4}{(\sum_{m=1}^{M} |S_E(m)|^2)^2} \\ E_c = \dfrac{\max(X(z))}{\sqrt{\sum_z X(z)^2/Z}} \end{cases} \tag{6}$$

where $S_E(i)$ is the envelope spectrum of the signal. m is the number of sampling points of the envelope spectrum. $X(z)$ is the amplitude sequence of the original signal envelope spectrum, where $z = 1, 2, \cdots, Z$.

The composite metric of envelope spectral characteristics is defined as:

$$E_{k,i} = E_{sk,i} \times E_{c,i} \tag{7}$$

where $E_{sk,i}$ and $E_{c,i}$ are the kurtosis and peak factor of the i-th mode, respectively.

To accurately extract periodic fault impact signals, this paper proposes an adaptive optimization approach for FMD parameters using the Cheetah Optimization Algorithm (COA). Traditional FMD parameter optimization involves selecting the filter length L and decomposition modal number n. In this study, we optimize three parameters:

filter length L, decomposition modal number n, and frequency segmentation number K. Specifically, B_{cost} and B_{pos} represent the best fitness and corresponding position after initialization. X_{best} and I_{best} denote the updated best posi tion and fitness of the cheetah, while $maxI_t$ is the maximum number of iterations. The specific steps are as follows:

Step 1: Set the range of FMD parameters: Carefully determine the appropriate values for the modal number of decomposition n, the frequency band division number K, and the filter length L. These parameters are critical to the performance of the FMD algorithm.

Step 2: Initialize CO parameters: In this paper, the population size is set to 10, and the number of iterations is established at 30. The dimensionality of the optimization problem is defined as D = 3. These parameter configurations are derived from preliminary analysis and experimental design, aiming to achieve a balance between thorough exploration of the solution space and computational efficiency.

Step 3: Calculation of the fitness function: In this study, the Gini index of the spectrum sparsity of the squared envelope is used as the fitness function, with the maximum Gini index of each modal component serving as a discrimination criterion.

Step 4: When determining the optimal parameters of FMD, the corresponding best position X_{best} is identified as the optimal parameter combination when the fitness I_{best} reaches its optimal value.

The specific process of FMD parameter optimization using the COA is illustrated in Figure 2.

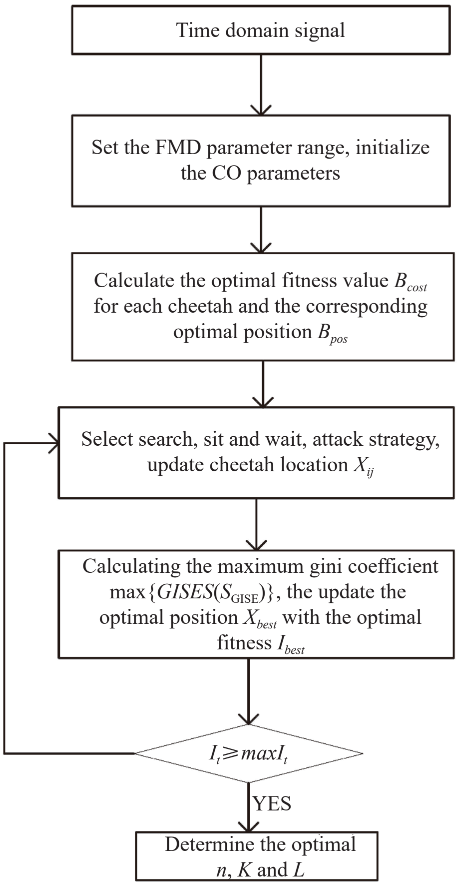

Figure 2. Flowchart of the FMD algorithm.

2.3. Improved Teager Energy Operator

The traditional method generally employs the Hilbert transform to demodulate and analyze the signal, subsequently plotting the envelope spectrum. In this paper, The Improved Teager Energy Operator (ITEO) has been introduced as a method for demodulating vibration signals and producing the corresponding energy spectrum.

The Analytical Energy Operator (AEO) develops an enhanced demodulation model by integrating the characteristics of analytical signals derived from the Hilbert transform with the time-frequency analysis capabilities of the energy operator. In contrast to traditional Hilbert Transform (HT) methods, the AEO fundamentally eliminates the need for the Bedrosian theorem, which is used to separate the frequency bands of signal envelopes and frequency modulation components. Through the construction of combinations involving higher-order derivatives in the form of analytical signals, AEO is able to directly extract the instantaneous energy features of a signal in the time domain.

This approach effectively addresses the frequency oscillation issues commonly encountered due to endpoint effects in HT-based methods. However, the AEO method does have limitations; the estimation of instantaneous frequency is susceptible to cumulative errors from differential operations at points of abrupt signal changes, resulting in significant fluctuations at the endpoints.

Based on the definition of an analytic energy operator, the following calculation is performed for any continuous signal $x(t)$ (with respect to time t):

$$\Theta[x(t)] = \dot{x}(t)\tilde{x}(t) - x(t)\tilde{\dot{x}}(t) \tag{8}$$

where $\tilde{x}(t)$ represents the Hilbert transform of the signal $x(t)$, and $\dot{x}(t)$ represents the first-order derivative of the signal $x(t)$.

Its discrete form can be expressed as:

$$\Theta[x(n)] = \dot{x}(n)h[x(n)] - x(n)h[\dot{x}(n)] \tag{9}$$

where $h[\cdot]$ represents the Hilbert transform of the signal $x(n)$.

As a result, to enhance the smoothness of the original discrete signal and improve the precision of the demodulation procedure, the central finite difference sequence is utilized in place of the forward difference within the symmetrical difference analytic energy operator. This can be represented as follows:

$$\dot{x}(n) = \frac{x_{n+1} - x_{n-1}}{2} \tag{10}$$

By inserting Equation (10) into Equation (9),we derive the discrete representation of the ITEO energy operator, as documented in [23]. This can be mathematically expressed as follows:

$$\Theta[x_n] = \frac{[x_{n+1} - x_{n-1}] \cdot h[x_n]}{2} - \frac{h[x_{n+1} - x_{n-1}] \cdot x_n}{2} \tag{11}$$

The Improved Teager Energy Operator effectively reduces noise, enhances weak transient impact components in the original vibration signal, while maintaining the symmetry and original amplitude of the signal. This enhanced signal facilitates more accurate feature extraction, significantly improving demodulation performance.

3. Diagnosis of Rolling Bearing Faults

In modern industrial applications, rolling bearings serve as critical components of mechanical systems, and their operational reliability significantly influences the stability and performance of these systems. Particularly in motors, the condition of rolling bearings is pivotal to ensuring the motor's reliable operation. However, under actual operating conditions, intense noise interference frequently obscures fault feature information within vibration signals, complicating fault diagnosis considerably.

Within the realm of fault diagnosis for motor rolling bearings, it is essential to effectively extract fault characteristics by employing advanced signal processing techniques and noise reduction methodologies.This approach enhances diagnostic accuracy and ensures optimal operation and maintenance efficiency of the motor, making it a key issue that urgently needs to be addressed.

This paper determines the theoretical fault characteristic frequencies through the use of bearing geometric parameters, such as the inner diameter, outer diameter, number of rolling elements, and contact angle. Additionally, it identifies significant peaks in the energy spectrum that correspond to these theoretical fault frequencies. If a significant concentration of energy is observed at a specific frequency, the corresponding fault type is diagnosed.

Subsequently, this article proposes a parameter optimization method for feature modal decomposition (FMD) and the energy operator, which accurately extracts fault features in high-noise environments, Consequently, this approach facilitates effective and accurate fault diagnosis. The procedure is depicted in Figure 3. and the comprehensive steps are delineated in the following section.

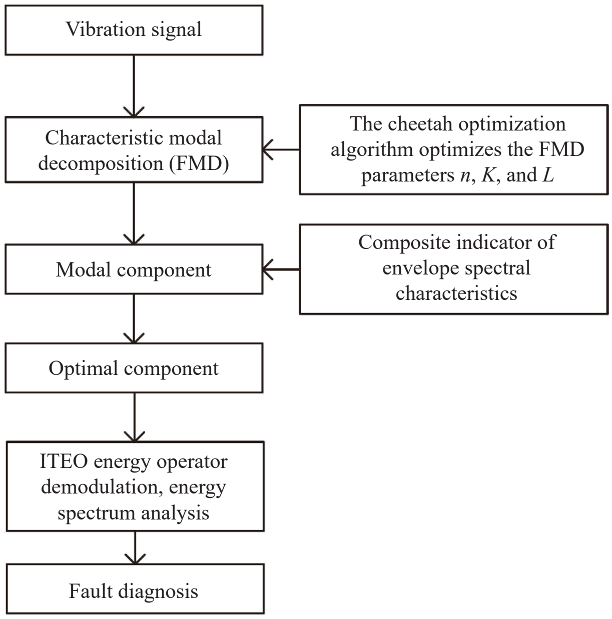

Figure 3. Flowchart for fault diagnosis.

3.1. Parameter Optimization Phase

The Cheetah Optimization Algorithm (COA) is utilized to optimize three critical parameters associated with feature modal decomposition (FMD): the quantity of modal components n and the number of divisions within the frequency bands K. and the filter length L. During the optimization process, the Squared Envelope Spectrum Gini Coefficient (GISES) serves as the fitness function. Through iterative optimization, the goal is to maximize the GISES value, thereby identifying the optimal configuration of the FMD parameters.

3.2. Feature Modal Decomposition Phase

The vibration signal of the rolling bearing is examined through FMD with optimized parameters. FMD leverages deconvolution theory, iteratively updating the filter to approximate the deconvolution target function. This process allows the signal to be decomposed into multiple intrinsic mode functions (IMFs), each capturing distinct frequency characteristics. These IMFs serve as the foundation for the subsequent extraction of fault characteristics.

3.3. Modal Selection Phase

A criterion for selecting modal parameters is proposed, known as the Envelope Spectrum Feature Synthesis Index, which incorporates kurtosis and peak factor. The modal component with the highest comprehensive evaluation index is selected as the optimal modal component.

3.4. Fault Diagnosis Phase

Through the application of demodulation analysis, the optimal mode of the vibration signal of the bearing is evaluated by means of ITEO method, the fault characteristics embedded within the signal can be significantly amplified, thereby enhancing their detectability. Furthermore, through the application of energy spectrum analysis, the spectral characteristics of the ITEO-demodulated signal can be thoroughly examined.

This method offers a novel, efficient and highly practical approach for the diagnosis of rolling bearing failures in environments with strong noise. By optimizing FMD parameters, scientifically decomposing signals, meticulously selecting modes, and conducting robust demodulation analysis, this approach markedly improves the precision and dependability of fault detection.

4. Experimental Analysis

In order to validate the effectiveness of this approach, fault data of rolling bearings from Case Western Reserve University was chosen as the experimental foundation. The rolling bearing model used is 6205RS-JEM SKF, with relevant parameters shown in Table 1. The bearing fault type is an outer race fault, with a sampling frequency of 12 kHz, a rotation speed of 1797 r/min, and 12,000 sampling points were selected for analysis. According to Equation (12), the calculated characteristic frequency of the outer race bearing fault is 107.3 Hz.

Table 1 Rolling Bearing Structure Parameters

Parameter	Value
Rolling Element Diameter (d/mm)	7.94
Pitch Circle Diameter (D/mm)	39.04
Number of Rolling Elements (n)	9
Contact Angle ($\beta/°$)	0

The equation for determining the characteristic frequency of bearing faults is presented as:

$$f_o = \frac{rn}{120}(1 - \frac{d}{D}\cos\beta) \tag{12}$$

In modern industrial production and mechanical operation, noise is an inevitable phenomenon that not only affects the working environment but also interferes with the monitoring and fault diagnosis of mechanical equipment. To more accurately simulate the noise effects under actual working conditions, we artificially introduced −8 dB Gaussian white noise to the original fault signal. Figure 4. illustrates the time-domain representation of the signal after adding noise. Figure 5. illustrates the envelope spectrum of outer ring noise added signal.

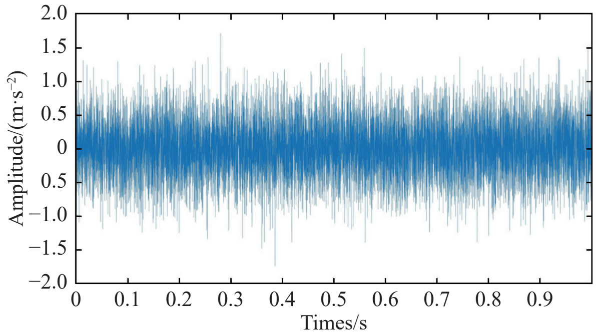

Figure 4. Time-domain diagram of outer ring noisy signal.

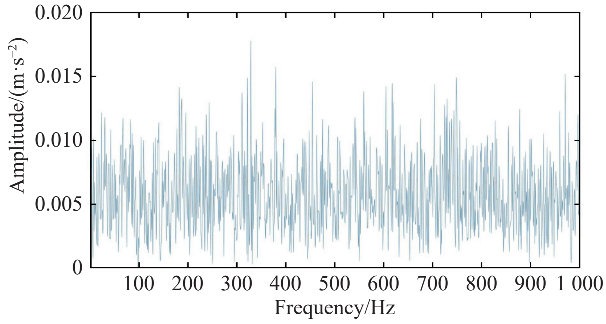

Figure 5. Envelope spectrum of outer ring noisy signal.

A method that combines the Cheetah Optimization Algorithm (COA), Feature Modal Decomposition (FMD), and Improved Energy Operator (ITEO)— referred to as COA-FMD-ITEO— is employed to decompose, extract features, and identify the state of bearing fault vibration signals. This approach aims to effectively extract subtle fault features and diagnose faults.

4.1. Optimization of FMD Parameters

Optimize the modal number n, the number of frequency bands K, and the filter length$L$ by first setting the range of parameters. $n \in [2,5]$. The number of frequency bands $K \in [n_{best}+1, 15]$. The filter length $L \in [5,80]$. Here, n_{best} is the optimal modal number. Use the Cheetah Optimization Algorithm (CO) to optimize the three key parameters of FMD, with the squared envelope spectral Gini coefficient (GISES) as the fitness function, and maximize the GISES value through iterative optimization. The optimal parameter combination is finally determined: $n = 3, K = 12, L = 79$.

4.2. FMD Decomposition Results

The FMD decomposition of the fault signal was conducted using the final optimized parameter combinations. From this decomposition, three intrinsic mode functions (IMFs) were obtained. To evaluate these IMFs comprehensively, the cragginess and peak factor of the envelope spectra for each component were calculated, with the results summarized in Table 2. It is evident that IMF1 exhibits the highest integrated index value, confirming its status as the optimal component for further analysis.

Table 2 Correlation Values of IMF Calculations

	IMF1	IMF2	IMF3
Envelope Entropy	4706.1	4691.1	4673
Envelope Peak Factor	72.6	72.5	72.5
Comprehensive Index	341662	340104	338792

4.3. ITEO energy spectrum

Subsequently, to enhance the detection of fault features, the ITEO energy operator was employed for demodulation analysis on the selected optimal component (IMF1). The resulting energy spectrum, illustrated in Figure 6. reveals distinct frequency components associated with the bearing fault.

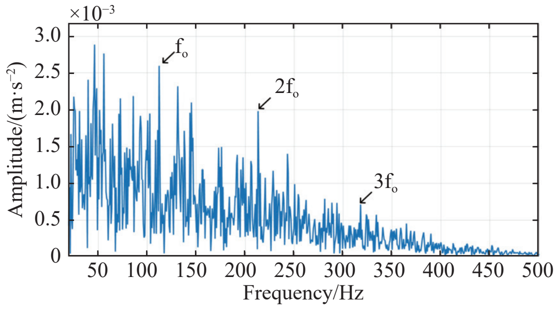

Figure 6. IMF1 energy spectrum.

In the process of analyzing the bearing vibration signal using the FMD-ITEO method, the parameters for the FMD were empirically set to $K = 83$, $n = 4$, and $L = 12$. Modal decomposition of the vibration signal was then performed using these parameters. Subsequently, the performance of each mode was evaluated through the comprehensive envelope spectrum index to identify the optimal mode. Finally, a demodulation analysis was conducted in conjunction with the ITEO algorithm, and the resulting energy spectrum is presented in Figure 7.

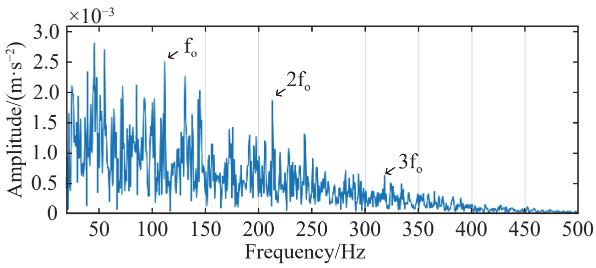

Figure 7. FMD-ITEO energy spectrum.

In the process of analyzing bearing vibration signals using the EMD-ITEO method, the vibration signals are initially decomposed into intrinsic mode functions (IMFs) using empirical mode decomposition (EMD). Subsequently, the comprehensive envelope spectrum index is employed to assess the performance of each IMF, thereby identifying the optimal mode. Based on this selection, the ITEO algorithm is further utilized to perform demodulation analysis, and the resulting energy spectrum is illustrated in Figure 8.

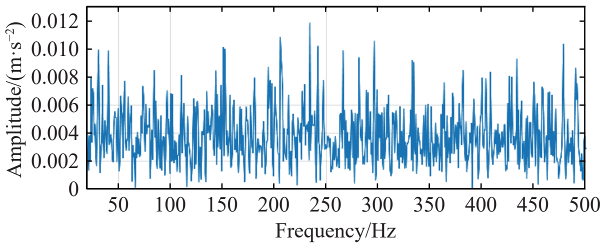

Figure 8. EMD-ITEO envelope spectrum.

For comparison, the PSO algorithm was employed to optimize the parameters a and K in the VMD algorithm, using the envelope spectral peak factor as the criterion for adaptation evaluation. Following this, VMD was applied to decompose the signal. The peak envelope spectral factor of the resulting IMF components was then assessed to determine the IMF component with the highest peak envelope spectral factor, which is regarded as the optimal IMF component.Lastly, Hilbert demodulation was applied to the optimal IMF component to produce the envelope spectrum, which is illustrated in Figure 9.

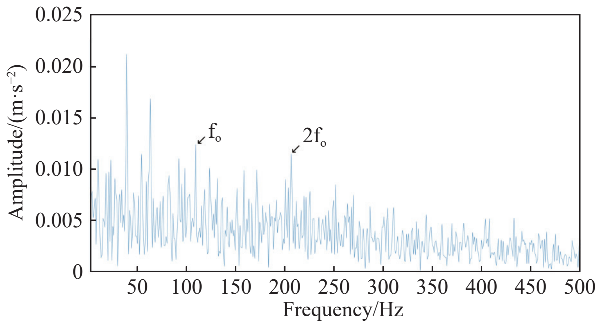

Figure 9. PSO-VMD envelope spectrum.

In order to assess the effectiveness of the method presented in this paper, we utilize the impulse index defined in Equation (13) to compare and analyze the sensitive mode components extracted by the four methods. The impulse index denotes the ratio between the peak value and the average amplitude of the signal. A larger impulse index suggests more significant transient impact characteristics in the signal.The pulse indices of the sensitive modal components obtained from the four methods are presented in Table 3.

$$I_p = \frac{\max|x(n)|}{\frac{1}{N}\sum_{n=1}^{N}|x(n)|} \tag{13}$$

where N represent the number of sampling points of a discrete signal. $x(n)$ denotes a discrete-time sequence. $\max|x(n)|$ indicates the maximum absolute value of the discrete signal. $\frac{1}{N}\sum_{n=1}^{N}|x(n)|$ represents the arithmetic mean of the absolute values of the discrete signal.

Table 3 The optimal component pulse indicators for the four methods

Method	Pulse Index
Proposed method	0.803
EMD-ITEO	0.023
FMD-ITEO	0.777
PSO-VMD	0.216

Through a comparative analysis of Figure 6, 7, 8 and 9. the methodology presented in this study successfully extracted three characteristic frequencies $(f_o, 2f_o, 3f_o)$. In contrast, the FMD-ITEO method also identified three characteristic frequencies, while the PSO-VMD method was limited to two characteristic frequencies $(f_o, 2f_o)$, and the EMD-ITEO method was unable to detect any characteristic frequencies.

Furthermore, the impulse index associated with the proposed method was the highest among the evaluated techniques, suggesting its effectiveness in identifying the impact characteristics of early faults. This indicates an enhanced ability for feature extraction, which, in turn, contributes to improved accuracy in fault diagnosis. The proposed method not only effectively preserves high-frequency characteristic information but also accentuates the peaks of the characteristic frequencies. A higher peak at the characteristic frequency results in a more pronounced contrast with background noise, thereby facilitating the identification and diagnosis of fault features.

5. Conclusion

In response to the challenge of isolating distinctive signals from rolling bearing vibrations amidst substantial noise interference, this study introduces a fault diagnosis methodology that integrates feature modal decomposition using the Cheetah Optimization Algorithm (COA-FMD) with the Improved Teager Energy Operator (ITEO). Experimental validation has yielded the following conclusions:

1) Using the Generalized Index of Signal Envelope Sparsity (GISES) as the fitness function and optimizing FMD parameters through the hunting optimization algorithm enables optimal signal decomposition. Combined with the envelope feature comprehensive index for optimal mode selection and the ITEO energy operator for demodulation

analysis, fault characteristic frequencies can be accurately identified.

2) Compared to other signal processing methods, the proposed approach extracts multiple frequency components of fault characteristic frequencies more comprehensively. Furthermore, the sensitive components obtained exhibit not only a higher impulse index but also a lower amplitude in the presence of background noise. As a result, this method demonstrates superior feature extraction performance in high-noise environments, facilitating the accurate identification of fault types.

Author Contributions: **Chenlong Mao** was instrumental in developing the core algorithm, which integrates essential parameters of the adaptive optimization feature modal decomposition through the Cheetah Optimization Algorithm. These parameters include the number of modes, the number of frequency bands, and the lengths of the filters. **Chuanbo Wen** played a vital role in establishing the research framework and providing theoretical guidance. Both authors contributed to the writing and revision of the manuscript.

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