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ARTICLE

Research on Aircraft Engine Bearing Clearance Fault Diagnosis Method Based on MFO-VMD and GMFE

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ABSTRACT

Bearings are crucial components in aircraft power systems and mechanical structures, and their complex fault characteristics significantly impact flight safety. To improve the accuracy of aircraft bearing fault diagnosis, this paper proposes a novel diagnostic method based on optimized Variational Mode Decomposition (VMD) and Generalized Multi-Scale Fuzzy Entropy (GMFE). First, the Moth-Flame Optimization (MFO) algorithm is used to optimize the two parameters of the VMD signal decomposition method—the number of modes K and the penalty factor α—to obtain the optimal parameter combination $[K, \alpha]$. This optimized VMD method is then applied for signal decomposition and reconstruction of bearing vibration signals. Next, the GMFE entropy algorithm is employed to extract fault features from the reconstructed signals, resulting in the required set of bearing fault feature vectors. Finally, the extracted feature vector set is input into a Support Vector Machine (SVM) model for classification and diagnosis of aircraft bearing faults. Experimental results indicate that the proposed method effectively enhances the identification accuracy of bearing diagnosis and demonstrates excellent fault feature extraction capabilities.

Keywords: Aircraft; Bearing; Variational Mode Decomposition; Generalized Multi-Scale Fuzzy Entropy; Fault Diagnosis

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1. Introduction

Bearings are widely used in aircraft power systems, body structures, and control systems [1–3]. Due to their complex motion relationships that are hard to be processed by common statistical models [4–6], they are subjected to alternating loads of varying frequencies over long periods during both airborne and ground operations, making them prone to various faults, especially when compounded by severe environmental noise. This results in fault signals with pronounced nonlinear and non-stationary characteristics, further complicating fault diagnosis. Therefore, bearings play a crucial role in the operational stability and flight safety of aircraft. The aircraft bearing fault diagnosis process mainly involves steps such as signal decomposition, entropy feature extraction, and intelligent pattern recognition. Given the limitations of current methods in these steps, this paper focuses on improvement research in signal decomposition and entropy feature extraction.

Signal decomposition research is the first step in aircraft bearing fault diagnosis and directly affects the diagnostic results [7, 8]. However, traditional methods from other domains [9–11] and signal decomposition methods such as Short-Time Fourier Transform and Wavelet Transform, have certain limitations. To address these issues, Dragomiretskiy et al. [12] proposed a novel self-adaptive signal decomposition method, known as Variational Mode Decomposition (VMD), in 2014. The VMD algorithm, based on theoretical foundations, offers strong robustness and high distinctiveness of signal components, making it an ideal method for handling nonlinear, non-stationary signals. Consequently, it has been widely applied and studied in extracting fault features in various mechanical equipment bearings. However, selecting the appropriate number of modes and the penalty factor for VMD is challenging, which impacts signal decomposition accuracy. Therefore, optimizing the parameters for modes and penalty factors has become a popular research topic in VMD algorithm studies [13]. Currently, the common approach to determine the optimal parameter combination K and α for VMD is to employ heuristic algorithms. For instance, Li et al. [14] used the Grey Wolf Optimization algorithm to search for the optimal parameter combination for VMD and applied the optimized VMD algorithm to noise reduction in speech signals, achieving accurate adaptive decomposition. In 2021, Zhang et al. [15] proposed using the Whale Optimization Algorithm to optimize the two key parameters of VMD, aiming to improve the decomposition accuracy of vibration signals for rolling bearing faults. This algorithm has high computational efficiency and accuracy but can easily become trapped in local optima. Given the current challenges in determining the optimal parameter combination for VMD and the limitations of various intelligent optimization algorithms, this paper proposes a Moth-Flame Optimization-Variational Mode Decomposition (MFO-VMD) signal decomposition method to enhance decomposition accuracy and reduce reconstruction errors.

Entropy feature extraction is a critical step in aircraft bearing fault diagnosis technology, directly impacting the final diagnostic results. In recent years, various entropy feature extraction methods have been proposed, such as Approximate Entropy [16], Sample Entropy [17], and Fuzzy Entropy [18]. However, with the advancement of mechanical intelligence, these single-scale entropy algorithms are insufficient for the feature extraction requirements of complex mechanical fault signals. To address the limitations of single-scale entropy algorithms, Costa et al. [19] introduced Multi-Scale Fuzzy Entropy (MFE), which can more comprehensively reflect the characteristic information of mechanical fault vibration signals and provides a new approach for analyzing the complexity of time series. However, in MFE, the mean-based coarse-graining method used in multi-scale processes tends to “neutralize” the dynamic abrupt behavior of the original signal, reducing the accuracy of entropy analysis. To overcome this issue in the MFE algorithm, this paper proposes a Generalized Multi-Scale Fuzzy Entropy (GMFE) that utilizes variance-based coarse-graining instead of mean-based coarse-graining for multi-scale processing, making the entropy analysis more accurate. This enhances the accuracy of fault feature extraction and is applied to aircraft bearing fault diagnosis.

Finally, considering the complex internal structure of aircraft and the numerous excitation responses, this paper combines the established MFO-VMD signal decomposition method with the GMFE entropy analysis method to conduct diagnostic research on aircraft bearing fault signals. This diagnostic approach effectively extracts characteristic information from fault signals, achieving accurate diagnosis of aircraft bearing faults. It holds significant application value in reducing aircraft accident rates and extending the operational lifespan of aircraft.

2. Theoretical Foundations

2.1. Variational Mode Decomposition

Optimization and computational methods have been widely used in many domains[20–22]. The VMD is one of the famous algorithms and is a signal self-adaptive decomposition method solves the original signal by constructing a variational model[23–25], effectively decomposing the vibration signal into several Intrinsic Mode Functions (IMFs). This approach significantly improves upon two inherent issues of the Empirical Mode Decomposition (EMD) algorithm: endpoint effects and mode mixing. The variational model for VMD's adaptive decomposition of the original signal is as follows[15].

$$\left\{ \begin{array}{c} \min\limits_{\{u_k\},\{\omega_k\}} \left\{ \sum_k \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 \right\} \\ s.t. \sum_k u_k(t) = f \end{array} \right. \tag{1}$$

In this formula, $\{u_k\}$ represents the set of modal components while $\{\omega_k\}$ denotes the corresponding set of central frequencies. $\delta(t)$ indicates the Dirac function and k is the number of modes. f represents the original vibration signal and $\left(\delta(t) + \frac{j}{\pi t}\right) * u_k(t)$ is the spectrum of $u_k(t)$ after the Hilbert transform. $*$ denotes the convolution operation, and ∂_t indicates the gradient operation.

By introducing the Lagrange multiplier λ into Equation (1) to solve the variational model of the VMD algorithm, the constraint problem within the variational model is improved, resulting in an augmented Lagrange computational expression.

$$\begin{gathered} L(\{u_k\}\{a_k\}\lambda) = \alpha \sum_k \left\| \partial_i \left[\left(\delta(t) + \frac{j}{\pi t} \right) u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 \\ + \left\| f(t) - \sum_k u_k(t) \right\|_2^2 + \left\langle \lambda(t), f(t) - \sum_k u_k(t) \right\rangle \end{gathered} \tag{2}$$

In this formula, α represents the penalty factor, and λ denotes the Lagrange multiplier.

The specific computational steps of the VMD algorithm are as follows: 1) Initialize the relevant parameters of VMD, including $\{\hat{u_k^1}\}$, $\{\omega_k^1\}$, $\{\lambda^1\}$ and n, setting them to 0. Choose a reasonable combination of mode number and penalty factor $[K, \alpha]$. 2) Use Equation (3) to iteratively update the three parameters $\hat{u_k^1}$, ω_k^1, λ^1 in a loop.

$$\left\{ \begin{array}{l} \hat{\lambda}^{n+1}(\omega) \leftarrow \hat{\lambda}^n(\omega) + \tau \left(\hat{f}(\omega) - \sum\limits_k \hat{u_k^{n+1}}(\omega) \right) \\ \hat{u_k^{n+1}} = \frac{\hat{f}(\omega) - \sum\limits_{i \neq k} \hat{u_i}(\omega) + \frac{\hat{\lambda}(\omega)}{2}}{1 + 2\alpha(\omega - \omega_k)^2} \\ \omega_k^{n+1} = \frac{\int_0^\infty \omega |\hat{u_k}(\omega)|^2 d\omega}{\int_0^\infty |\hat{u_k}(\omega)|^2 d\omega} \end{array} \right. \tag{3}$$

Apply the termination criterion using Equation (4) to determine whether to stop. If the stopping condition is met, the algorithm concludes, and the corresponding K IMFs are output. Otherwise, return to Step 2 to continue the computation.

$$\sum_k \left\| \hat{u_k^{n+1}} - \hat{u_k^n} \right\|_2^2 / \left\| \hat{u_k^n} \right\|_2^2 < \varepsilon \tag{4}$$

In this formula, ε represents discrimination accuracy ($\varepsilon > 0$).

2.2. Parameter Optimization for VMD Method

The choice of mode number K and penalty factor α in the VMD algorithm directly influences the decomposition effectiveness for vibration signals related to aircraft bearing faults. Therefore, this paper employs the well-known Moth-Flame Optimization (MFO) algorithm to optimize the key parameters K and α in VMD, obtaining the optimal parameter combination $[K, \alpha]$.

Seyedali Mirjalili designed the famous MFO algorithm[26], inspired by the entire movement process of moths around flames. The principles of the MFO algorithm are detailed as follows:

In the optimization process, Equation (5) represents the spatial position of the moth during movement, while Equation (6) denotes the fitness value of the algorithm. Throughout the iterative process of the MFO algorithm, moths use the fitness value of flames in the algorithm as a reference to determine whether the optimal solution corresponding to the objective function has been achieved.

$$\mathrm{M} = \begin{bmatrix} \mathrm{m_{11}} & \mathrm{m_{12}} \cdots \mathrm{m_{1d}} \\ \mathrm{m_{21}} & \mathrm{m_{22}} \cdots \mathrm{m_{2d}} \\ \vdots & \vdots \quad\quad \vdots \\ \mathrm{m_{n1}} & \mathrm{m_{n2}} \cdots \mathrm{m_{nd}} \end{bmatrix} \tag{5}$$

$$\mathrm{OM} = [\mathrm{OM_1} \;\; \mathrm{OM_2} \cdots \mathrm{OM_n}]^{\mathrm{T}} \tag{6}$$

In this formula, m represents the position coordinates of the moth, n denotes the number of moths, and d indicates the dimensionality.

1) Moth-Flame Process

In the Moth-Flame process shown in **Figure 1**, the moths utilize their biological trait of spiraling inward toward the flame center, iteratively updating their previous positions to gradually approach the center; once they reach the flame center, their movement ends, marking this position as the optimal one.

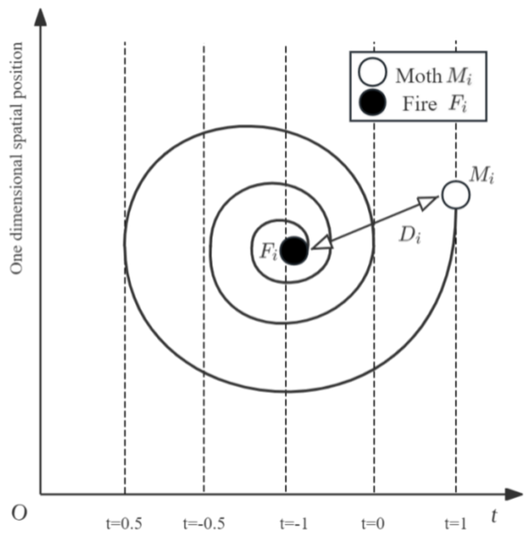

Figure 1. A graph of the curved motion of a moth around a flame.

The equation for the moth's trajectory is as follows:

$$\mathrm{M_i^{'}} = \mathrm{D_{ij}} \times \mathrm{e^{bt}} \times \cos\left(2\pi \mathrm{t}\right) + \mathrm{F_j} \tag{7}$$

2) Moth-Abandoning Flame Process

In the moth-abandoning flame process, as the moths update their positions iteratively, the fitness value of the flames is adjusted by subtracting less optimal fitness values, as represented specifically by Equation (8):

$$\mathrm{F_{num}} = \mathrm{round}(\mathrm{N} - l \times \frac{\mathrm{N}-1}{\mathrm{T}}) \tag{8}$$

where l represents the number of iterations, N denotes the maximum number of flames, and T is the final iteration count.

Throughout the iterative process, the number of flames is inversely related to the number of iterations. The initial positions of the flames and moths ensure that the moths' entire optimization process is effective, maintaining the algorithm's validity. For the MFO algorithm, when the fitness function meets the specified criteria, the algorithm halts and outputs the current flame position; otherwise, it continues running.

The parameter optimization process for the VMD algorithm involves initializing the two key VMD parameters K and α and calculating the fitness value. By iteratively optimizing these two parameters through the moth-flame process until the stopping condition is met, the corresponding parameter combination $[K, \alpha]$ is obtained. This optimal parameter combination is then applied to the VMD algorithm to decompose the vibration signals of aircraft bearing faults, extracting the characteristic information of bearing faults.

2.3. Generalized Multiscale Fuzzy Entropy

In conventional multiscale fuzzy entropy, the use of mean-based coarse-graining in the coarse-graining process tends to "neutralize" the dynamic abrupt changes in the original signal, thereby reducing the accuracy of entropy analysis. This paper proposes a generalized multiscale fuzzy entropy approach, in which variance-based coarse-graining replaces mean-based coarse-graining for multiscale processing, resulting in more accurate entropy analysis outcomes.

Assume $u = \{u_i, i = 1, 2, 3..., N\}$ (with embedding dimension m and similarity tolerance r) represents the original time series. The multiscale process of the time series is calculated using variance-based coarse-graining, and the expression for the calculation is:

$$\nu_j^{(\tau)} = \frac{1}{\tau} \sum_{i=(j-1)\tau+k}^{j\tau+k-1} \left(u_i - \overline{u_i}\right)^2 \tag{9}$$

In this equation, $1 \leq k \leq \tau$, $1 \leq j \leq \frac{N}{\tau}$, $\tau \geq 2$, $\overline{u_i} = \frac{1}{\tau} \sum\limits_{h=0}^{\tau-1} u_{i+h}$.

The variance-based coarse-graining process for generalized multiscale fuzzy entropy is shown **Figure 2** as follows.

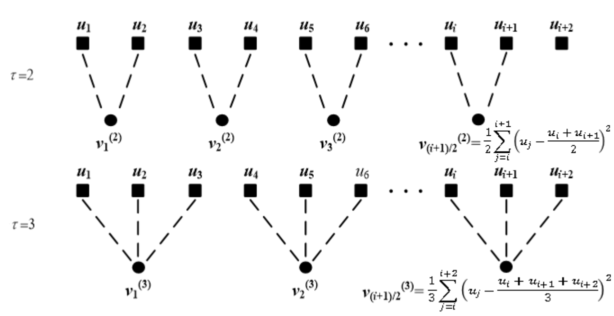

Figure 2. Generalized multiscale fuzzy entropy variance coarse-granulation process.

3. Fault Diagnosis Method for Aircraft Bearings Based on MFO-VMD and GMFE

The working principle of the aircraft bearing fault diagnosis method based on MFO-VMD and GMFE is as follows:

Due to the nonlinear and strongly coupled characteristics of vibration signals in aircraft bearing faults, this paper proposes a novel fault diagnosis method based on MFO-VMD and GMFE. The specific fault diagnosis process is as follows: First, the MFO-VMD signal decomposition method is applied to decompose the vibration signals of aircraft bearing faults, resulting in a series of IMF components. Then, based on the principle of correlation, several IMF components are summed and reconstructed. Next, the GMFE algorithm is applied to the reconstructed bearing vibration signal to extract entropy features, creating a feature vector dataset of the signal. Finally, the extracted bearing fault feature vector set is input into a Support Vector Machine (SVM) model for classification and diagnostic analysis of aircraft bearing faults due to the effectiveness of the deep learning models in many domains [27–30], thereby completing the fault diagnosis process for the aircraft bearing. Such models have better performance compared to traditional models in different domains [31–34]. For instance, Xiong et al. propose a novel end-to-end approach for Optical Character Recognition (OCR) that simultaneously denoises and classifies text, significantly enhancing OCR accuracy in noisy or degraded images by integrating these functions within a unified dual-output autoencoder framework [35]. The flowchart of this fault diagnosis method is shown in **Figure 3**.

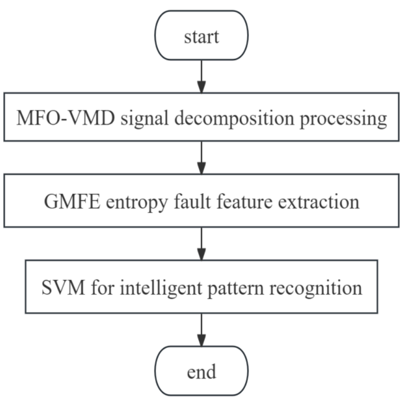

Figure 3. Calculation flow of aircraft bearing fault diagnosis based on MFO-VMD and GMFE.

4. Fault Diagnosis Study of Aircraft Bearings Based on MFO-VMD and GMFE

4.1. Data Source of Measured Vibration Signals for Aircraft Bearing Faults

This study focuses on aircraft bearing faults. Due to various constraints such as time and location when conducting aircraft bearing fault simulation experiments on production sites, the experimental data used in this research consist of previously collected vibration signals of aircraft bearing faults from the author's laboratory. These data were obtained through simulated fault experiments on Boeing 747 bearings conducted by laboratory researchers. The experiment utilized a worn-out bearing bush from Unit 1 to simulate different bearing clearance faults, including large clearance in the big head of the first and second stage connecting rods and large clearance in the small head of the first and second stage connecting rods. In addition, vibration data were collected from normally operating aircraft bearings to obtain data representing the normal state.

The time-domain vibration signal diagrams for the normal state (Normal), large clearance in the first-stage connecting rod big head (FCB), large clearance in the second-stage connecting rod big head (SCB), large clearance in the first-stage connecting rod small head (FCS), and large clearance in the second-stage connecting rod small head (SCS) are shown in **Figure 4** [36], and **Figure 5** shows the wear status of aircraft bearing bushing.

4.2. Signal Decomposition Based on the MFO-VMD Algorithm

For the vibration signals of aircraft bearings under the five different operating conditions mentioned above, the MFO algorithm is first used to calculate the optimal parameter combination $[K, \alpha]$ for the VMD signal decomposition method corresponding to each condition. Given the inherent randomness of intelligent optimization algorithms in the calculation process, the average of the results from 30 calculations is taken as the final optimal parameter combination. The corresponding optimal parameter combinations are shown in **Table 1**.

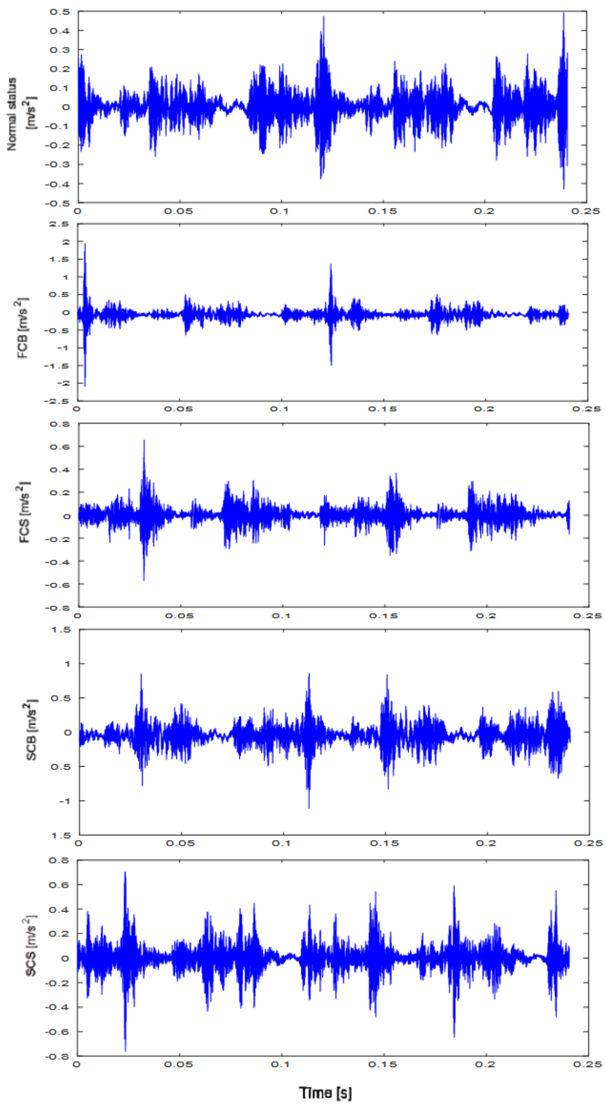

Figure 4. Time domain waveform diagram corresponding to five different bearing clearance states.

The optimal parameter combinations obtained from the above calculations are then input into the VMD algorithm to decompose the vibration signals of aircraft bearings under the five different operating conditions. Using the principle of correlation, the decomposed IMF components are summed and reconstructed. To further validate the effectiveness of the proposed MFO-VMD signal decomposition algorithm, we take the condition of large clearance in the secondary connecting rod small head bearing as an example. Using three signal decomposition methods—LMD, GA-VMD, and MFO-VMD—the vibration signals of aircraft bearings under the five different operating conditions are separately decomposed and reconstructed. The reconstructed signals are then analyzed using envelope spectrum analysis. The reconstructed envelope spectrum diagrams corresponding to the three adaptive signal decomposition methods are shown in **Figures 6–8**.

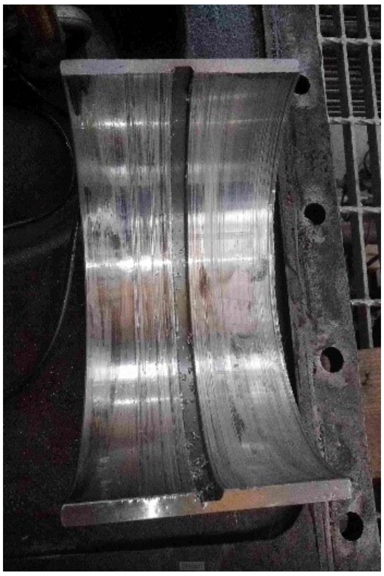

Figure 5. Wear status of aircraft bearing bushing.

Table 1. Optimal parameter combination $[K_0,\alpha_0]$.

Condition of Operation	$[K_0,\alpha_0]$
Normal	[4,2012]
FCB	[5,1545]
FCS	[5,2368]
SCB	[4,1289]
SCS	[4,1574]

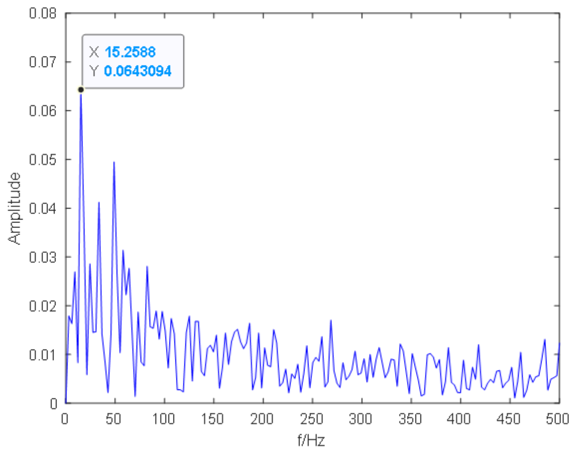

Figure 6. Envelope spectrum after signal decomposition and reconstruction by LMD method.

By comparing **Figures 6–8**, it can be concluded that the envelope spectra reconstructed using the LMD, GA-VMD, and MFO-VMD signal decomposition methods all display a peak at twice the frequency, which aligns with the actual characteristic frequency of the aircraft bearing fault. However, compared to LMD and GA-VMD, the MFO-VMD envelope spectrum exhibits the highest peak and the most significant noise suppression effect. This outcome effectively validates the computational superiority of the MFO-VMD signal decomposition method developed in this paper, demonstrating its improved capability in extracting fault characteristics from aircraft bearing vibration signals.

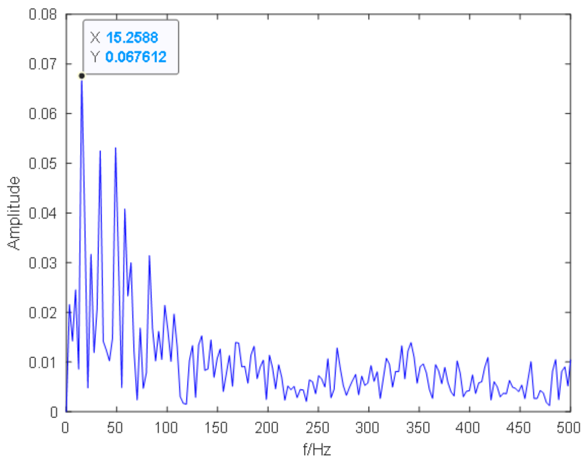

Figure 7. The envelope spectrum after signal decomposition and reconstruction by GA-VMD method.

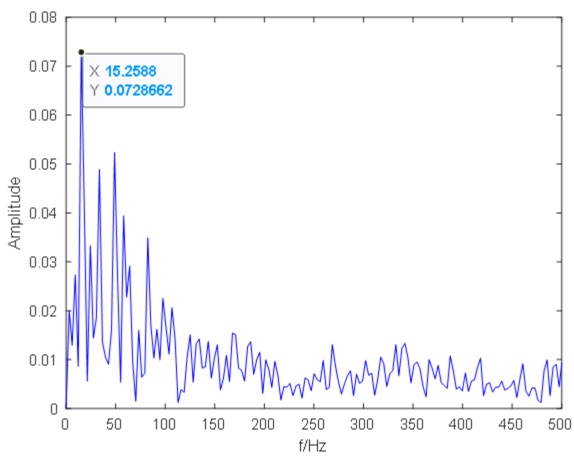

Figure 8. The envelope spectrum after signal decomposition and reconstruction by MFO-VMD method.

4.3. Fault Feature Extraction Analysis Based on Generalized Multiscale Fuzzy Entropy (GMFE)

After decomposing and reconstructing the vibration signals of aircraft bearings under the five different operating conditions, the constructed GMFE is used to perform entropy feature extraction analysis on the reconstructed signals, generating a fault feature vector set for the aircraft bearings. According to reference [37], the GMFE parameters are set as embedding dimension m = 2 and threshold r = 0.25.

To further validate the superiority of GMFE, MFE and GMFE feature extraction analyses are performed on the vibration signals of aircraft bearings under the five different conditions, with the results shown in **Figures 9** and **10**. Analysis of **Figures 9** and **10** indicates that, when using multiscale fuzzy entropy (MFE) to calculate the entropy curves of the vibration signals, the entropy value increases with the scale factor when it is greater than 2, but the curves exhibit multiple overlaps and intersections, resulting in poor feature extraction performance.

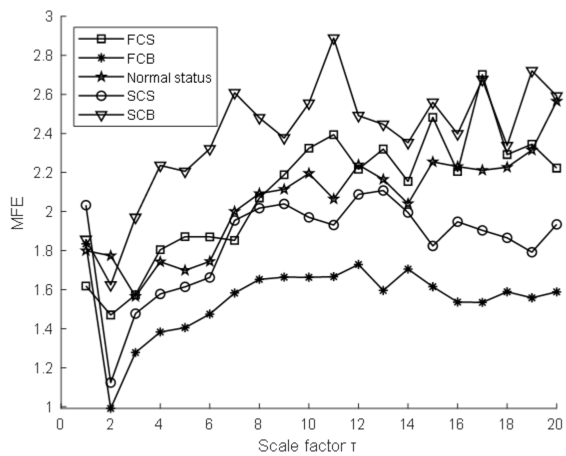

Figure 9. MFE entropy curves of bearing under different working conditions.

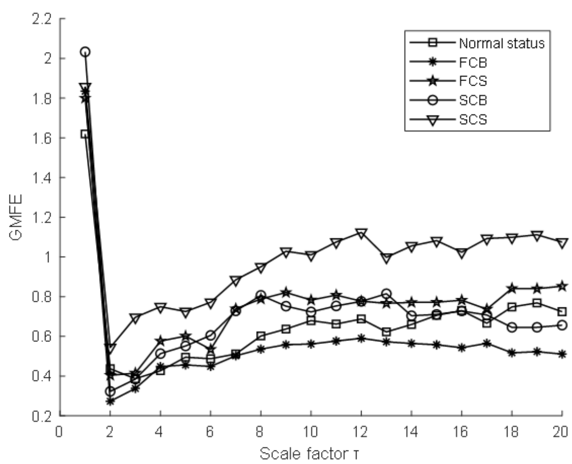

Figure 10. GMFE entropy curves of bearing under different working conditions.

In contrast, the GMFE for the aircraft bearing vibration signals initially increases and then decreases as the scale factor increases, with better separability in the entropy curves. This provides a clearer extraction of fault features for the five different operating conditions of the aircraft bearings. The comparative results further demonstrate that the GMFE algorithm developed in this paper provides superior entropy feature extraction effectiveness.

4.4. Intelligent Pattern Recognition Results for Aircraft Bearings

To verify the effectiveness and superiority of the aircraft bearing fault diagnosis method based on MFO-VMD and GMFE developed in this paper, a comparative analysis was conducted with several classic fault diagnosis methods for aircraft bearings. First, the MFO-VMD method was used to decompose and reconstruct the bearing vibration signals. Then, the GMFE entropy algorithm was applied to extract fault features from the reconstructed signals. Finally, the extracted fault feature vector set was input into a SVM for recognition and diagnostic analysis.

For this process, 210 feature vector sets were extracted for each of the five different operating conditions of the aircraft bearings. A random selection of 140 feature vector sets was used as the training set for the SVM algorithm, while the remaining 70 sets were used as the test set, thus facilitating the fault recognition and diagnostic analysis [38, 39]. The fault diagnosis results for aircraft bearings are shown in **Table 2**. Analysis of **Table 2** indicates that the aircraft bearing fault diagnosis method based on MFO-VMD and GMFE constructed in this paper achieves a recognition accuracy of 99.4%, an improvement of nearly 9% over the LMD-MSE fault diagnosis method. The experimental result demonstrates the effectiveness of the proposed approach, suggesting its potential application in other domains in the future [40–42].

Table 2. Fault diagnosis results of aircraft bearings.

Condition of Operation	LMD-MSE	(GA-VMD)-MFE	(GWO-VMD)-GMFE	(MFO-VMD)-GMFE
Normal	90%	94.3%	98.6%	100%
FCB	92.9%	94.3%	98.6%	98.6%
FCS	92.9%	92.9%	97.1%	100%
SCB	90%	94.3%	97.1%	100%
SCS	88.6%	92.9%	94.3%	98.6%
Overall recognition accuracy	90.9%	93.7%	97.1%	99.4%

5. Conclusion

In response to the nonlinear, unstable, and feature-coupled characteristics of aircraft bearing vibration signals, this paper proposes a new fault diagnosis method for aircraft bearings based on MFO-VMD and GMFE. The main findings of this study are as follows: 1) The proposed MFO-VMD signal decomposition method, designed to address the strong local nonstationary characteristics of aircraft bearing vibration signals, reduces the error in signal decomposition and reconstruction. Experimental results indicate that, compared with the LMD and DE-VMD signal decomposition methods, the MFO-VMD method significantly improves the decomposition accuracy of vibration signals associated with aircraft bearing faults. 2) A GMFE is proposed, which replaces mean-based coarse-graining with variance-based coarse-graining for multiscale processing. This approach enhances the accuracy of entropy analysis, thereby improving the precision of fault feature extraction. 3) The extracted fault feature vectors were input into a SVM for recognition and diagnostic analysis. Experimental results demonstrate that the fault diagnosis method based on MFO-VMD and GMFE constructed in this study achieves a recognition accuracy of 99.4%, an improvement of nearly 9% compared to the LMD-MSE fault diagnosis method.

Author Contributions

T.Z. is responsible for the conceptualization and design of the hybrid model framework, as well as its testing. G.Z. is responsible for data preprocessing, feature engineering, and drafting the manuscript. Y.C. leads the experimental analysis and result interpretation, as well as drafting the manuscript.

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Data Availability Statement

Not applicable.

Conflicts of Interest

The authors declare no conflict of interest.

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