Improved Multivariate Hierarchical Multiscale Dispersion Entropy: A New Method for Industrial Rotating Machinery Fault Diagnosis

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ABSTRACT This paper proposes an Improved Multivariate Multiscale Dispersion Entropy (IMMDE) combined with Hierarchical Entropy (HE) for vibration signal feature extraction. The traditional coarse-grained calculation is missing the relationship between neighboring sample points in the shift operation, which may lead to missing fault information. Secondly, as the scale increases, the original sequence is gradually shortened, may lead to instability and inaccuracy in entropy estimation when dealing with short-term sequences. The improved coarse-grained calculation method overcomes its limitations to improve the stability, and using the HE method to extract deep fault frequency information from the high and low frequency components of the multivariate signal. Then, the extracted features are dimensioned using the Max-Relevance Min-Redundancy (mRMR) to create a new set of fault features to improve diagnosis efficiency. Finally, the Support Vector Machine (SVM) determines the degree and type of fault. Experiments were conducted with three examples, the results show that IMHMDE can effectively extract the feature information according to mechanical faults’ characteristics and improve the efficiency of fault diagnosis.

INDEX TERMS Improved multivariate hierarchical multiscale dispersion entropy, fault diagnosis, mRMR, rotating machinery, health condition identification.

I. INTRODUCTION

The widespread use of intelligent manufacturing has increased the number of breakdowns in mechanical equipment and increased the demand for diagnosis, necessitating early detection and repair [1]. The advancement of intelligent manufacturing technology has made it easier to obtain previously difficult-to-obtain mechanical data, and data-driven diagnostic methods have greatly improved the efficiency of fault diagnosis.

Faults in rotating machinery are primarily caused by complex internal structures and changing the external environment. Vibration analysis, Acoustic Emission (AE), temperature trend analysis, and wear debris analysis all are currently the most commonly used methods for analyzing rotating machinery faults. The vibration monitoring signals contain critical information about abnormalities in the internal structure of the machinery [2]. Vibration analysis is very effective at determining the type of rotating machinery faults and the extent of the damage. It can detect the widest range of mechanical faults, such as mechanical looseness, bearing faults, and rotor misalignment [3]. In the actual operation process, the fault pulse information is easily masked [4] by various noises and high-energy low-frequency components because of the weakness of the early fault signal of rotating machinery. There are primarily two methods to deal with such problems. The first is to enhance the effective signal by filtering out the noise, and the second is to select the
components containing useful information by signal decomposition [5]. Empirical Mode Decomposition (EMD) [6], Ensemble Empirical Mode Decomposition (EEMD) [7], Singular Value Decomposition (SVD) [8], Local Mean Decomposition (LMD) [9], [10], Variational Mode Decomposition (VMD) [11], and other decomposition methods have been proposed and widely used in rotating machinery signal analysis. These methods described above are applicable not only in test benches for bearings or gears but also in the industry for practical equipment such as wind turbines [12], tool wear [13], gas turbines [14], etc. Although such methods are useful in detecting fault signals in nonsmooth rotating machinery, the average user found it difficult to locate the fault and determine the fault state of the equipment due to a lack of knowledge of time-domain diagrams and spectra [15]. These methods described above are still inadequate in practice.

At the moment, the use of entropy to measure the complexity of time series or signals and distinguish different types of signals is a current research hotspot [16]. Entropy can quantify dynamically changing signals, to detect irregularities and instability of complex signals, while its implementation process is simpler and more practical than complex deep learning. In [17] Qi et al. used Sample Entropy (SE) to detect wind turbines in real wind farms. By comparing it to the commonly used characteristic indexes, it was discovered that the SE value has a significant vibration change in detecting the time when the turbine has problems. To effectively identify the type and degree of bearing faults, Malhotra [18] proposed the Fuzzy Entropy (FE) and Flexible Analytic Wavelet Transform (FAWT) methods. In [7], Hou extracted the vibration signal features as the input vectors for diagnosis using the Permutation Entropy (PE). Dispersion Entropy (DE) [19] is a parametric method for evaluating non-linear vibration signals, which involves mapping each element of the measurement sequence to a different class to produce different dispersion patterns. The method is noise-resistant and overcomes the loss of aligned entropy amplitude information while having a high computational speed. However, the above methods cannot estimate the long-term correlation of fault signals in complex rotating machinery structures [20]. The multiscale entropy theory methods such as Multiscale Fuzzy Entropy (MFE) [21] and Multiscale Permutation Entropy (MPE) [22] have been used. For example, in [23], Li et al. used Refined Composite Multiscale Fuzzy Entropy (RCMFE) in conjunction with the Infinite Feature Selection (IFS) algorithm to analyze rolling bearing vibration signals and accurately identify the degree and type of fault. Because multiscale analysis is primarily used to analyze low-frequency components of a signal while ignoring hidden information in high-frequency components, the Hierarchical Entropy (HE) [24] method has been applied to time series processing. The HE decomposes the vibration signal into layers and can process both high and low-frequency vibration signal components. Yan [25] et al. used Hierarchical Dispersion Entropy (HDE) combined with the improved Laplace fraction to determine the health of bearings, and the results demonstrated that the method could accurately identify different fault types of rolling bearings as well as their severity. Song [26] proposed a fruit fly search algorithm to improve the VMD combined with the HDE method for detecting faults in diesel engine injectors. The entropy methods proposed above all rely on single direction or single-channel vibration signal information to identify different types of fault signals. However, rotating machinery in industrial production typically operates in a constantly changing environment, signals collected from different directions also contain important fault information [27]. As the impulses generated by faulty components are propagated over long distances, they are inevitably weakened, resulting in the loss of fault information. Thus, the sensor signals must be collected from various directions to explore the potential information of various types of faults to improve fault detection accuracy.

Based on the multiscale entropy theory [28], it is more practical to extract fault information by analyzing vibration signals from multiple channels simultaneously. Theoretical methods that have been proposed such as Multivariate Multiscale Sample Entropy (MMSE) [29] and Multivariate Multiscale Dispersion Entropy (MMDE) [30]. Because of its high computational efficiency and robust noise immunity, MMDE has been widely used in the fault diagnosis of rotating machinery. In this paper, considering the shortage of the traditional coarse-grained calculation that cannot consider all-time series simultaneously, we improve it and propose combining the Improved Multivariate Multiscale Dispersion Entropy (IMMDE) and HE. We called it Improved Multivariate Hierarchical Multiscale Dispersion Entropy (IMHMDE) and used it to analyze and study the vibration signals to improve the accuracy of fault damage identification. It allows the extraction of fault information from the vibration signals of multiple sensors simultaneously. Still, it also considers the low-frequency and high-frequency components of the signals, effectively avoiding the loss of fault information. It can extract the fault information from the vibration signals of multiple sensors simultaneously while the low and high-frequency components of the signals are considered, effectively avoiding the loss of fault information. Finally, the extracted IMHMDE features are reduced in dimensionality using [31]. The newly constructed feature set is divided into the training and testing sets before being fed into SVM for fault identification.

In summary, the main structure of this paper is as follows: Section 2 introduces the relevant theory and analysis. Section 3 explains the proposed fault diagnosis method and steps and includes a flowchart. Section 4 demonstrates the feasibility of analyzing vibration signals collected from rotating machinery components through three case studies, and Section 5 concludes with a summary of the findings and a look ahead. The specific steps of the algorithm are shown below.
II. IMPROVED MULTIVARIATE MULTISCALE DISPERSION ENTROPY

A. MULTIVARIATE DISPERSION ENTROPY (mvDE)

The paper in order to quantify the complexity of multivariate time series, DE is extended to Multivariate Dispersion Entropy (mvDE) [32], allowing it to solve more complex sequences. The specific steps of the algorithm are shown below:

1. Given a time series \( X = \{x_{k,b}\}_{k=1}^{n} \) with \( n \times L \), use the standard normal distribution density function to map the elements of the series according to the DE theorem to the \( Y = \{y_{k,b}\}_{k=1}^{n} \).

\[
y_{k,b} = \frac{1}{\sigma_b \sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\frac{(t-\mu_k)^2}{2\sigma_k^2}} dt
\]

(1)

\( \mu_k \) is the expected value, and \( \sigma_k^2 \) denotes the variance. \( Y \) is mapped to \( Z = \{z_{k,b}\}_{k=1}^{n} \) by linear methods.

\[
z_{k,b} = \text{round} \left( c y_{k,b} + 0.5 \right)
\]

(2)

\( c \) represents the class.

2. The reconstruction is carried out as follows, according to the theory of multi-dimensional embedding to reconstruct:

\[
Z_m(j) = \left[ z_{1,j}, z_{1,j+d_1}, \ldots, z_{1,j+(m_1-1)d_1}, \right.
\]

\[
| \quad z_{2,j}, z_{2,j+d_2}, \ldots, z_{2,j+(m_2-1)d_2}, \ldots, \]

\[
z_{n,j}, z_{n,j+d_n}, \ldots, z_{n,j+(m_n-1)d_n} \right] \quad (3)
\]

where \( 1 \leq j \leq L - (m - 1) d \), for simplicity, sets equal values for both the delay and the embedding dimension, \( d_n = d \), \( m_n = m ; d = (d_1, d_2, \ldots, d_n) \) for the time delay and \( m = (m_1, m_2, \ldots, m_n) \) for the embedding dimension.

3. In the reconstructed sequence matrix \( Z_m(j) \), each time series has \( mn \) elements, from which \( m \) elements are chosen at random to form the set \( \phi_{p,q}(j), p \in [1, C_m^m], q \in [1, m], C_m^m \) denoting the number of all possible combinations. Each \( \phi_{p,q}(j) \) is mapped to \( \pi_{v_0\ldots v_{m-1}} \) so when \( p = 1 \), the corresponding dispersion pattern is \( \phi_{1,1}(j) = v_0, \phi_{1,2}(j) = v_1, \ldots, \phi_{1,q}(j) = v_{q-1} \), resulting in a total of \( c_m^m \) dispersion patterns. As a result, we have \((L - (m - 1) d) C_m^m \) dispersion patterns, and the probability assigned to each pattern is calculated using equation (4):

\[
p(\pi_{v_0\ldots v_{m-1}}) = \frac{\text{Number}[j \mid L - (m - 1) d, \phi_{p,q}(j) \text{ has type } \pi_{v_0\ldots v_{m-1}}]}{L - (m - 1) d} \quad (4)
\]

4. Finally, the definition of multivariate dispersion entropy is derived from Shannon’s entropy as follows:

\[
\text{mvDE}(X, m, c, d) = - \sum_{\pi=1}^{c_m} p(\pi_{v_0\ldots v_{m-1}}) \ln p(\pi_{v_0\ldots v_{m-1}})
\]

(5)

The order of the multi-channel signal has no effect on the calculated entropy value when using multivariate dispersion entropy; however, considering the signal on one time scale may not fully reflect the time series over time, so we must introduce the concept of multiscale for its analysis.

B. MULTIVARIATE MULTISCALE DISPERSION ENTROPY (MMDE)

MMDE can describe the irregularity of multivariate signals on multiple time scales, and sequences are typically down-sampled in the traditional multiscale analysis [33]. The precise procedure is as follows:

1. Given multi-channel data \( I = \{u_{k,b}\}_{k=1}^{n} \) and scale factor \( \tau \), the coarse-grained analysis \( I \) is as follows:

\[
x_{k,j}^\tau = \frac{1}{\tau} \sum_{b=(j-1)\tau+1}^{j\tau} I, 1 \leq j \leq L/\tau, 1 \leq k \leq n \quad (6)
\]

2. Coarse-grained calculation of the entropy of the multivariate time series \( \{u_{k,j}^\tau\} \) with the same parameters. This leads to the formula for MMDE:

\[
\text{MMDE}(I, m, c, d, \tau) = - \sum_{\pi=1}^{c_m^m} p(\pi_{v_0\ldots v_{m-1}}) \ln p(\pi_{v_0\ldots v_{m-1}}) \quad (7)
\]

Multivariate signal \( I \), embedding dimension \( m \), class \( c \), delay \( d \), \( p \) denotes the probability of obtaining a potential dispersion pattern for a coarse-grained sequence. The coarse-grained calculation of MMDE is shown in the Fig. 1(a). MMDE analyzes time series by extending them from a single scale to multiple scales. It is primarily calculated by averaging non-overlapping signals to produce multiple series and thus calculating multivariate entropy. This method still excludes \( \tau - 1 \) multivariate time series from the calculation and does not account for the relationships between coarse-grained time series, resulting in a lack of statistical information [33].

C. IMPROVED MULTIVARIATE MULTISCALE DISPERSION ENTROPY (IMMDE)

The traditional method for performing multiscale analysis is to compute the mean of adjacent elements using a scale factor. As the scale factor increases, the value of multiscale dispersion entropy decreases, resulting in a decrease in the number of samples in the coarse-grained sequence and instability of the entropy value. Thus, the coarse-grained calculation is improved for the analysis of multi-channel sequences, and the improved coarse-grained process is depicted in Fig. 1(b). When the time series of the k-th channel is at \( \tau = 2 \), the calculation formula using equation (8):

\[
\gamma_{k,i,j}^{(e)} = \frac{1}{\tau} \sum_{f=0}^{\tau-1} x_{k,f+i+\tau(j-1)}, \quad 1 \leq j \leq L/\tau, 1 \leq i \leq \tau, 1 \leq k \leq n \quad (8)
\]

The mvDE of all coarse-grained time series at the same scale is calculated and averaged to produce the final results. This method can improve the estimation accuracy of entropy,
which is very effective for the processing of short-term time series.

\[
\text{IMMDE}(X, m, c, d, \tau) = \frac{1}{\tau} \sum_{i=1}^{\tau} \text{mvDE}(y_{k,i,j}, m, c, d, \tau)
\]

(9)

D. SIMULATION MULTI-CHANNEL SIGNAL ANALYSIS

In this part, a three-channel white noise signal and a three-channel 1/f noise signal are selected for analysis.

IMMDE, Refined Composite Multivariate Multiscale Dispersion Entropy (RCMMDE) [32], and MMDE all have the same parameters but use different coarse-grained calculations.
computation methods, their features are extracted separately for comparison. 30 samples of sequence length 1024 were taken for each multiple synthesis signal.

Before beginning the analysis, the parameters of the three models for embedding dimension \( m \), class \( c \), time delay \( d \), and scale \( \tau \) must be set. The values \( m \) and \( c \) must adhere to the principles of \( m < L \), where \( L \) indicates the length of the signal [19]. The amplitude of the time series must be considered when setting class \( c \). If it is too small, data with different amplitudes may be combined into one class; if it is too large, data with different amplitudes will be divided too finely. This paper sets \( m = 3, \tau = 20, d = 1 \) and first discusses the influence of class \( c \) on the estimation results of different entropy value. Fig. 2 shows the results after testing, and the entropy estimation results of IMMDE and RCMMDE are more stable than MMDE under the influence of different \( c \) parameters. After the embedding dimension \( m \) is determined, the more dispersion patterns exist, the more information they contain. As \( c \) gets larger, more information is captured, but the computation time also increases, therefore, the paper sets \( c \) to 6 [19]. Additionally, the effectiveness and precision of the diagnosis are impacted by the scale selection. Too small scale features will lead to incomplete extraction of fault information, and too large scale features will result in feature redundancy and reduced computational efficiency.

For the value of the embedding dimension \( m \), the class \( c \) is set to 6, so the value can only be 2 or 3. For the parameter setting in reference [34], [35], this paper determines that the value of each parameter \( m = 3, c = 6, d = 1, \tau = 20 \).

In this section, synthetic signals are investigated to demonstrate the stability of the improved coarse-grained computation for entropy estimation during feature extraction and the effectiveness of identifying multi-channel signals with different levels of complexity. A three-channel WGN signal, a two-channel WGN signal and a one-channel 1/f noise, a one-channel WGN and a two-channel 1/f noise, a three-channel 1/f noise.

Firstly, the paper extracts the features of three methods separately, the results are shown in Fig. 3. According to the results, because the uncertainty of the WGN noise time series is higher than that of 1/f noise, the information of the WGN noise signal is primarily located on the low scale, so when using entropy calculation, the entropy value of its entire sequence is larger, and the entropy value of the signal containing more WGN noise channels is higher at the low scale. Then, as the scale increases, the entropy converges gradually, 1/f noise will have a higher signal complexity than WGN noise due to its long-range correlation, so its entropy converges slowly. When the three types of methods are compared, IMMDE and RCMMDE are found to provide more consistent entropy estimations for more complex multi-channel non-smooth signals. Also, the improved coarse-grained calculation method is more effective in differentiating different types of channel signals at low scales.

Three-channel noise signals with a length of 1024 are tested 30 times in order further to demonstrate the stability of the improved multiscale calculation method. The coefficient of variation is obtained by dividing the standard deviation of the sequence by the average value. Fig. 4 shows the final results, the improved coarse-grained calculation method used in this research has a lower coefficient of variation than both MMDE and RCMMDE at different scales. The difference is obvious when processing the three-channel 1/f signal with the highest complexity.
FIGURE 5. Example of $k = 3$ hierarchical decomposition.

FIGURE 4. Comparison of the coefficients of variation of the four multi-channel signals.

### III. FAULT SIGNAL CLASSIFICATION METHOD

#### A. IMPROVED MULTIVARIATE HIERARCHICAL MULTISCALE DISPERSION ENTROPY (IMHMDE)

This paper combines HE with IMMDE to analyze the characteristics of vibration signals.

1. Assume a time series $X = \{u_{k,b}\}_{k=1,2,\ldots,n}$. First, define the average operator of this time series by specifying its high-frequency $Q_0(x)$ and low-frequency $Q_1(x)$.

$$
\begin{align*}
Q_0(x) & = \frac{u_{k,b} + u_{k,b+1}}{2}, b \in [1, L - 1]
Q_1(x) & = \frac{u_{k,b} - u_{k,b+1}}{2}, b \in [1, L - 1]
\end{align*}
$$

2. When $j = 0$ or $j = 1$, the operator matrix $Q_j(x)$ obtained by decomposing the components of the first level is defined as follows:

$$
Q_j(x) = \begin{bmatrix}
\frac{1}{2} \left(-\frac{1}{2}\right)^j & 0 & \cdots & 0 & 0 \\
0 & \frac{1}{2} \left(-\frac{1}{2}\right)^j & \cdots & 0 & 0 \\
0 & 0 & \frac{1}{2} \left(-\frac{1}{2}\right)^j & \cdots & 0 \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
0 & 0 & 0 & \cdots & \frac{1}{2} \left(-\frac{1}{2}\right)^j
\end{bmatrix}_{2^{n-1} \times 2^n}
$$

3. The hierarchical component of the $i$-th channel can be obtained by decomposing the multi-channel time series.

$$
X_i,k,e = Q_{v_{k+1}} \cdot Q_{v_{k+1}}^{-1} \cdots Q_{v_{k+1}}^{-1} \cdot X_i
$$

$k$ is the number of layers and $e$ is the number of nodes. $e$ and vector $v_q = [v_1, v_2, \ldots, v_k]$ are related as

$$
e = \sum_{q=1}^{k} 2^{k-q} v_q
$$

The decomposition process when $k = 3$ is shown in Fig. 5.

4. Repeat the preceding steps to perform hierarchical decomposition of the multi-channel time series. The multivariate hierarchical component of each node is obtained, and its IMMDE value is calculated, allowing the IMHMDE calculation formula to be obtained.

$$
\text{IMHMDE} (X, k, e, m, c, d, \tau) = \text{IMMDE} (X_i,k,e, m, c, d, \tau)
$$

In comparison to IMMDE, IMHMDE has an additional parameter $k$ that represents the number of layers. Because a too large $k$ will increase computation time and affect accuracy.
and $k$ is too small to extract the high-frequency and low-frequency information in the signal, $k = 3$ is chosen to balance computation time and information richness [36], [37]. Because IMHMDE considers layering, the scale will add too much redundant information, so this paper sets its scale to 8 [24], [35], resulting in 64 features.

In this section, the paper proves the superiority of IMHMDE method, four types of multi-channel signals in Section II are used for verification. The t-SNE visualizes high-dimensional data and preserves high-dimensional clustering information by mapping high-dimensional data to a two-dimensional feature space [38]. Fig. 7 shows the clustering results of IMHMDE, IMMDE, RCMMD, MMDE.

IMHMDE can completely separate the four classes of signals compared to the other three multi-entropy methods, and the clustering results are more compact compared to the other methods.

![Flow chart of IMHMDE calculation.](image)

**FIGURE 6. Flow chart of IMHMDE calculation.**

In addition, the real vibration signal is easily contaminated by background noise. As real vibration signals are susceptible to noise, the two-channel signal generated in the Eq. (15) is used to verify the anti-noise performance of the algorithm. The sampling frequency of each channel is set to 512 Hz and the length is 40 s. The signals are extracted using IMHMDE, IMMDE, RCMMD, MMDE and clustered using the t-sne method. The parameters of the four types of methods are the same as those mentioned above.

Therefore, Signal Noise Ratios (SNR) of $-4$, $-2$, $2$ and $4$ dB are added to the signal. Fig. 8 shows the t-SNE clustering results for four methods respectively. The clustering results of the proposed method are more resistant to noise than IMMDE, RCMMD and MMDE. It is known that IMHMDE is also effective in identifying when the vibration signal contains different levels of noise.

\[
\begin{align*}
    s &= 10^8 \sin(2^pi \cdot 80^t + pi/3) \\
    s1 &= 8^8 \sin(3^pi \cdot 50^t + pi/4)
\end{align*}
\]

**B. MAX-RELEVANCE AND MIN-REDUNDANCY(mRMR) FEATURE SELECTION**
The features extracted by IMHMDE contain unnecessary redundant information, too many features can reduce diagnostic accuracy and increase computational time costs, so the most relevant features need to be selected for the dataset. The mRMR method proposed by Peng [31] can effectively reduce the dimensionality of features to improve efficiency. The following is its definition:

The degree of similarity between variables is frequently measured using mutual information methods. The following formula can be used to calculate the degree of similarity between two random variables, $x$, and $y$.

\[
I (X; Y) = \sum_{x \in X} \sum_{y \in Y} P (x, y) \log \frac{P (x|y)}{P (x) P (y)}
\]

$p(x), p(y)$ denotes their probabilities respectively and $p(x, y)$ is the joint probability density. The criterion for maximum correlation is as follows:

\[
\max_{i} D (s, c), D = \frac{1}{S} \sum_{i=S} I (x_i, c)
\]

$x_i$ represents features, $c$ represents the class. The feature space dimension is represented by $S$, the mutual information between features and classes is represented by $I (x_i, c)$, and the $m$ features with the highest mutual information are chosen. Similarly, to reduce feature redundancy, we introduced the minimum redundancy criterion:

\[
\min R(S), R = \frac{1}{|S|^2} \sum_{x_i, x_j \in S} I (x_i; x_j)
\]

Min-redundancy eliminates features that are more dependent on one another and chooses features that are the most dissimilar to one another. The method is created by combining and optimizing these two criteria.

**C. IMHMDE-mRMR-SVM**
Support vector machine (SVM) has good robustness to multiple fault types of time series in the field of industrial signal. The diagnosis process is shown in Fig. 9:

1. Use multiple accelerometers installed in different directions to collect multi-channel vibration signals of rotating machinery and obtain fault signal data of different components.
2. Randomly sample multi-channel signals, select test and training samples, and use IMHMDE to extract features from samples and form feature data sets.
3. Use the mRMR method to select the most relevant fault features and eliminate redundant features. Then the feature set is divided into a training set and a test set.
4. Construct the SVM model, pre-train the model with the training feature set, and then input the test set into the model using the trained model to verify the fault classification performance of the proposed method.

**IV. EXPERIMENTAL VALIDATION**
This section validates the fault diagnosis performance of the proposed method using rotating machinery vibration signals.
Bearing data from Case Western Reserve University (CWRU) [39] and Xi’an Jiaotong University [40], gearbox data from Southeast University [41]. These data sets contain rotating machinery components with a high fault probability, bearings, gears, and different damage types and compound faults, which can be used to test the validity of the method described in this paper. All methods in this paper were run by Matlab 2016a software, with the main hardware environment consisting of an AMD Ryzen 7 4800H CPU and 16GB RAM.

A. CASE 1

1) SINGLE WORKING CONDITION RESULT ANALYSIS

Fig. 10 depicts CWRU rolling bearing fault test stand, which includes an electric motor, a torque transducer, a dynamometer, and control electronics, with specific

FIGURE 7. T-SNE dimension reduction performance of different methods.

FIGURE 8. Comparison of anti-noise capabilities of different methods.
parameters and fault frequency information shown in Tables 1 and 2. The test bench set motor horsepower is 3hp, the motor speed is 1730r/min, bearing inner ring, outer ring, and ball fault damage diameters include 0.1778mm, 0.3556mm, and 0.5334mm, vibration signal sampling frequency is 12khz, sensor-collected acceleration signals include fan base acceleration and drive acceleration, where the fan end model number is SKF6203, and the drive end model number is SKF6203.

The signals include nine types of fault signals and one type of normal bearing signals as test samples for verification. In each class, the synchronous vibration signal of the fan and the drive end is used as the multi-channel data. The time series length of each sample is 1024, and 100 samples are selected for each type of signal to divide the test and training set. The specific information is given in Table 3, in which the outer ring fault is the vibration data collected by the sensor installed in the direction of six o’clock.

Firstly, the bearing fault signals of the above test data are used for research to verify the accuracy of the proposed method results. Fig. 11 depicts the waveforms of the various
rolling bearing fault and normal signals. For feature extraction, the following multivariate methods are used: IMHMDE, IMMDE, RCMMDE, MMDE, MMSE, and MMFE. To reduce redundant information in the features, the extracted features are ranked in importance using mRMR. The identification accuracy of the faults is tested using different scales to determine the best scale features.

Here, the paper selects 50 samples randomly from the feature set as the training set and 50 samples as the testing set. The diagnosis is carried out under a different number of features. Fig. 12 shows the results of the IMHMDE feature selection. The reconstructed feature set is then fed into SVM to compare the results of various fault identification methods. As the number of sensitive features increases, Fig. 13 depicts the average accuracy curve after 15 trials for the different methods. From the results, the MMSE has poor diagnostic results. The results of fault identification tend to stabilise when the number of IMHMDE features equals 4. Other methods require stabilisation at higher scales, and the smaller the scale the lower the time cost required.

In order to verify how good the accuracy of IMHMDE is when performing bearing vibration signals, the number of IMHMDE features is set to 4, and tests are conducted on multi-channel fault signals. Fig. 14 depicts the confusion matrix of IMHMDE fault diagnosis. The results show that IMHMDE is 100% accurate and all test samples are correctly classified, effectively identifying the extent and type of fault.

Due to the random nature of the test results, the scale is set to 4 for 25 trials and the results are shown in Fig. 15. The specific diagnostic results are recorded in Table 4. It can be found that the average accuracy of IMHMDE reaches about 99.68%, and the accuracy of each fault identification is better than that of other methods. Receiver Operator Characteristic (ROC), Area Under the Curve (AUC) can evaluate the model.

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**TABLE 1.** Rolling bearing information.

| Inner Diameter | Outer Diameter | Thickness | Roller Diameter |
|----------------|----------------|-----------|-----------------|
| 25mm           | 52mm           | 15mm      | 7.94mm          |

**TABLE 3.** Fault frequencies of various types (multiples of rotational frequency Hertz).

| Inner Ring Fault | Outer Ring Fault | Cage Fault | Ball Fault |
|------------------|------------------|------------|-----------|
| 5.4152           | 3.5848           | 0.3982     | 4.7135    |

---

**FIGURE 11.** Original bearing fault vibration signal waveform diagram; red represents fan end, and blue represents drive end.
TABLE 3. Bearing fault information.

| Label | Fault Type | Defect Size(mm) | Abbreviation | Training Sample | Testing Sample |
|-------|------------|-----------------|--------------|-----------------|----------------|
| 1     | Inner Race Fault 1 | 0.1778 | IR1 | 50 | 50 |
| 2     | Inner Race Fault 2 | 0.3556 | IR2 | 50 | 50 |
| 3     | Inner Race Fault 3 | 0.5334 | IR3 | 50 | 50 |
| 4     | Outer Race Fault 1 | 0.1778 | OR1 | 50 | 50 |
| 5     | Outer Race Fault 2 | 0.3556 | OR2 | 50 | 50 |
| 6     | Outer Race Fault 3 | 0.5334 | OR3 | 50 | 50 |
| 7     | Ball Fault 1 | 0.1778 | BE1 | 50 | 50 |
| 8     | Ball Fault 2 | 0.3556 | BE2 | 50 | 50 |
| 9     | Ball Fault 3 | 0.5334 | BE3 | 50 | 50 |
| 10    | Normal | 0 | Nor | 50 | 50 |

Fig. 16 depicts the Auc-Roc curve of IMHMDE. It can be found that the improved method can correctly classify the fault types. Table 5 records the values of different indicators of various methods after 15 runs, including F1-score, Matthews correlation coefficient (MA), False Positive Rate (FPR), True Positive Rate (TPR) and so on. The proposed method is optimal for all indicators.

Meanwhile, as with multivariate signals, the same number of training and test sets were selected to validate the univariate method. The single channel signals are verified using Improved Hierarchical Multiscale Dispersion Entropy (IHMDE), Hierarchical Multiscale Dispersion Entropy (HMDE), Improved Multiscale Dispersion Entropy (IMDE), Multiscale Dispersion Entropy (MDE) with the same set of parameters multivariate method, and the results are shown in Table 6. Comparing the experimental results, the single channel signal also achieves good fault diagnosis results. IHMDE, HMDE, IMDE is more effective than MMDE, which shows that the improved coarse-grained calculation and hierarchical entropy method can improve the fault diagnosis accuracy truly.

2) ANALYSIS OF RESULTS UNDER VARIABLE WORK CONDITIONS

Considering that the mechanical rolling bearings usually work in a changing environment, to test the signal processing ability of this method under varying working conditions, the
The vibration signals of three bearing fault types are also chosen: outer ring fault, inner ring fault, and ball fault. Table 7 shows the specifics of the signal. Here, 400 test samples and 400 training samples are randomly selected to verify the bearing signals in these ten states.

Fig. 17 depicts the fault features selected for the variable operating conditions. The number of features is set to 1 to 20 for 15 trials respectively, and the average diagnostic rate results are shown in Fig. 18. It can be found that the accuracy of the different methods starts to stabilize at a scale of 13, indicating that increasing the number of features will not have a significant impact on the results of fault diagnosis. For further analysis, the scales of different entropy are set to 13 in this case. Fig. 19 shows the confusion matrix of IMHMDE with a scale of 13, and only two samples are misclassified in its classification results.

Here, 25 trials are conducted for six multivariate entropy models to verify the stability of IMHMDE, and the results are shown in Fig. 20, and detailed information on the diagnostic results of the six methods is recorded in Table 8. The results show that the final average accuracy of IMHMDE is stable at 97.8%, and the IMHMDE, RCMMDE, MMDE, MMFE, and MMSE are 96.83%, 95.64%, 92.10%, 92.65%, and 80.08 %, respectively. By comparison, IMHMDE can also effectively extract fault information to identify fault types under more complex changing conditions, and the results are improved compared with other methods. Table 9 and Fig. 21 show the vibration signal data of different hp and different diameter damage are used to analyze the results.

The vibration signals of three bearing fault types are also chosen: outer ring fault, inner ring fault, and ball fault. Table 7 shows the specifics of the signal. Here, 400 test samples and 400 training samples are randomly selected to verify the bearing signals in these ten states.

FIGURE 16. IMHMDE Roc curve.

TABLE 5. Performance of different indicators.

| methods  | Precision | Recall | FPR   | MA      | F1-Score |
|----------|-----------|--------|-------|---------|----------|
| IMHMDE   | 0.9990    | 0.9990 | 0.0001| 0.9989  | 0.9990   |
| IMMDME   | 0.9896    | 0.9890 | 0.0012| 0.9880  | 0.9890   |
| RCMMDE   | 0.9877    | 0.9680 | 0.0016| 0.9851  | 0.9862   |
| MMDE     | 0.9264    | 0.9230 | 0.0086| 0.9135  | 0.9230   |
| MMFE     | 0.9768    | 0.9760 | 0.0027| 0.9736  | 0.9760   |
| MMSE     | 0.7468    | 0.7370 | 0.0292| 0.7105  | 0.7358   |

TABLE 6. Performance of different univariate methods.

| Methods | Parameter | Max  | Min  | SD  | Ave  |
|---------|-----------|------|------|-----|------|
| IHMDE   | k,λ,λ = 3, m = 6 | 100% | 97.20% | 0.068 | 98.84% |
| MMDE    | k,λ,λ = 3, m = 6 | 100% | 97.60% | 0.010 | 98.72% |
| IMDE    | λ,λ = 3, c = 6 | 99.2% | 96.00% | 0.009 | 97.28% |
| MDE     | λ = 3, m = 6 | 93.6% | 89.60% | 0.020 | 91.10% |

TABLE 7. Different work condition information.

| Label | Fault(inches) | Fault Type | Training Sample | Testing Sample | Work Condition |
|-------|---------------|------------|-----------------|----------------|----------------|
| 1     | 0.007          | Inner      | 40              | 40             | Condition 1: 0hp,1797 rpm speed |
| 2     | 0.014          | Inner      | 40              | 40             | Condition 2: 2hp,1750 rpm speed |
| 3     | 0.021          | Inner      | 40              | 40             | Condition 3: 3hp,1772 rpm speed |
| 4     | 0.007          | Outer      | 40              | 40             | Condition 4: 3hp,1730 rpm speed |
| 5     | 0.014          | Ball1      | 40              | 40             | Condition 5: 1hp,1797 rpm speed |
| 6     | 0.021          | Ball2      | 40              | 40             | Condition 6: 2hp,1750 rpm speed |
| 7     | 0.007          | Ball3      | 40              | 40             | Condition 7: 3hp,1772 rpm speed |
| 8     | 0.014          | Normal     | 40              | 40             | Condition 8: 1hp,1797 rpm speed |
| 9     | 0.021          | Normal     | 40              | 40             | Condition 9: 2hp,1750 rpm speed |
| 10    |               | Normal     | 40              | 40             | Condition 10: 3hp,1772 rpm speed |
By comparison, it can be found that the result of IMHMDE is the best.

Similarly, we conduct some contrast experiments to detect the advantages of the multivariate approach compared to univariate approaches. Without loss of generality, 15 trials are performed for each approach. From Table 9, it can be found that some of the univariate signals are diagnosed better than the multivariate method under variable working conditions, while the results of IMHMDE are similar to those of the univariate method, which indicates that the method is better at feature extraction.

**B. CASE 2**

The bearing compound fault data of Xi’an Jiaotong University is selected to verify the fault diagnosis results. The test device is shown in Fig. 22. The platform comprises an AC motor, motor speed controller, shaft, supporting bearing, hydraulic loading system, and tested bearings. The test bearing type is LDK UER204 rolling bearing, the sampling
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The frequency is 25.6 kHz/min, and the number of balls is 8. When the environment is 35h/12kN, the fault types include the outer ring fault, cage fault, the inner ring, and outer ring compound fault. Similarly, the inner ring fault under 37.5Hz/11kN and the compound fault under 40Hz/10kN are selected. As far as the type of failure is concerned, the failed parts of the test bearing cover the outer ring, inner ring, cage and rolling element, and the types of failure are outer ring wear, outer ring cracking, inner ring wear, cage fracture, etc.
For compound failures, the data is collected when different parts of the bearing fail at the same time.

Fig. 23 and Table 11 depict the waveforms and selected data set information for the faulty vibration signals, and Fig. 24 depicts the selected features. Then, 15 trials are carried out with the scale features set to 2 to 20. The average diagnostic results of various entropy models at different scales are shown in Table 12. It can be found that the average accuracy of IMHMDE at various scales is significantly higher than that of other methods. At a scale equal to 4, IMHMDE achieves an accuracy of around 96%, and the final result is stable at about 99% with the increase of the scale. Since IMHMDE contains more fault information when extracting features, it can effectively locate different faults when identifying such more complex fault types.

The Confusion matrix results of fault diagnosis are shown in Fig. 25. It can be found that only one sample was misclassified. The feature scale of IMHMDE is then set to 17 and

**TABLE 13.** Performance of different indicators.

| Methods | Precision | Recall | FPR   | MSE | F1-Score |
|---------|-----------|--------|-------|-----|----------|
| IMHMDE  | 0.9921    | 0.9917 | 0.0017| 0.9901| 0.9917   |
| IMMDDE  | 0.9714    | 0.9667 | 0.0067| 0.9614| 0.9657   |
| RCMMDDE | 0.9712    | 0.9667 | 0.0067| 0.9614| 0.9657   |
| MMDE    | 0.9423    | 0.9250 | 0.0150| 0.9146| 0.9199   |
| MMSE    | 0.9463    | 0.9375 | 0.0125| 0.9281| 0.9376   |
| MMSE    | 0.4600    | 0.4750 | 0.1050| 0.3605| 0.4559   |

**TABLE 14.** Performance of different univariate methods.

| Methods | Parameter Setting | Max     | Min     | SD   | Ave   |
|---------|-------------------|---------|---------|------|-------|
| IMHMDE  | $\lambda=3,\delta=1,\alpha=3,\epsilon=6$ | 99.33%  | 99.33%  | 0.006| 99.25%|
| HMDE    | $\lambda=3,\delta=1,\alpha=3,\epsilon=6$ | 99.33%  | 99.33%  | 0.006| 99.17%|
| IMDE    | $\lambda=1,\delta=3,\alpha=3,\epsilon=6$ | 99.17%  | 92.50%  | 0.019| 96.57%|
| MDE     | $\lambda=1,\delta=3,\alpha=3,\epsilon=6$ | 95%     | 90.83%  | 0.021| 93.80%|

**FIGURE 27.** DDS experimental station of southeast university [40].

**TABLE 15.** Gear fault information.

| Label | Fault Type | Training Sample | Testing Sample | Condition   |
|-------|------------|-----------------|----------------|-------------|
| 1     | Chipped    | 40              | 40             | 20Hz-0V     |
| 2     | Health     | 40              | 40             | Gear fault  |
| 3     | Miss       | 40              | 40             | Gear fault  |
| 4     | Root       | 40              | 40             | Gear fault  |
| 5     | Surface    | 40              | 40             | Gear fault  |

**FIGURE 28.** Multichannel signals - chipped: (a) - (d) Signals from 1 # - 4 # sensors.
TABLE 16. Average accuracy of various fault diagnosis methods at different scales.

| Different Method | Standard Deviation | \( \tau = 2 \) | \( \tau = 3 \) | \( \tau = 4 \) | \( \tau = 5 \) | \( \tau = 6 \) | \( \tau = 7 \) | \( \tau = 8 \) | \( \tau = 9 \) | \( \tau = 10 \) |
|------------------|-------------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|
| IMHMDE           | 0.0038            | 80.43        | 90.73        | 92.63        | 92.07        | 93.00        | 93.33        | 93.93        | 93.77        | 93.87        |
| IMMDE            | 0.0039            | 74.37        | 81.47        | 87.50        | 88.20        | 90.47        | 89.53        | 90.03        | 89.77        | 89.80        |
| RCMMDM           | 0.0042            | 72.47        | 80.63        | 87.40        | 87.60        | 89.70        | 89.80        | 89.57        | 88.90        | 88.63        |
| MMDE             | 0.0063            | 67.75        | 70.38        | 72.75        | 74.19        | 78.38        | 80.94        | 81.69        | 83.00        | 82.31        |
| MFME             | 0.0074            | 65.81        | 68.75        | 72.00        | 74.56        | 75.19        | 78.50        | 80.63        | 82.31        | 84.88        |
| MMSE             | 0.0037            | 80.23        | 80.55        | 84.05        | 85.45        | 85.36        | 83.82        | 84.00        | 84.18        | 86.00        |

FIGURE 29. \( \tau = 15 \) IMHMDE confusion matrix.

TABLE 17. Performance of different indicators.

| Methods   | Precision | Recall | FPR  | MA | F1-Score |
|-----------|-----------|--------|------|----|----------|
| IMHMDE    | 0.9632    | 0.9629 | 0.0095 | 0.9533 | 0.9622   |
| IMMDE     | 0.9140    | 0.9125 | 0.0208 | 0.8923 | 0.9127   |
| RCMMDM    | 0.9056    | 0.9000 | 0.0226 | 0.8799 | 0.9011   |
| MMDE      | 0.8572    | 0.8580 | 0.0321 | 0.8255 | 0.8571   |
| MFME      | 0.9229    | 0.9185 | 0.0187 | 0.9019 | 0.9195   |
| MMSE      | 0.8937    | 0.8915 | 0.0236 | 0.8689 | 0.8910   |

FIGURE 30. IMHMDE Roc curve.

TABLE 18. Performance of univariate methods.

| Methods | Parameter Setting | \( \tau = 15 \) | Max | Min | SD | Ave |
|---------|-------------------|----------------|-----|-----|----|-----|
| IMHMDE  | \( k = 3, d = 1 \), \( m = 3, c = 6 \) | 97% | 96% | 0.005 | 96.4% |
| IMMDE   | \( k = 3, d = 1 \), \( m = 3, c = 6 \) | 98% | 95% | 0.014 | 96.2% |
| IMDE    | \( k = 3, d = 1 \), \( m = 3, c = 6 \) | 96% | 84% | 0.042 | 90.0% |
| MDE     | \( k = 3, d = 1 \), \( m = 3, c = 6 \) | 87.2% | 75% | 0.065 | 83.85% |

Case 1 and case 2 fully prove the excellent performance of this method in various fault diagnoses of bearings in different environments. Similarly, the components of rotating machinery that often fail include gears, the gearbox contains more components, and the environment is more complex. Therefore, the vibration signal data of the gearbox are used to verify the method.

The primary test environment is shown in Fig. 27. In this paper, the signal of the four sensors under the condition of 20Hz-0V is analyzed. The fault type is shown in Table 15, and the waveform of the vibration signal collected by the sensor is shown in Fig. 28.

The IMHMDE is used to extract high-dimensional fault features from the original signal of the gearbox. In order to verify the identification performance of this method for the gear fault of a gearbox, the corresponding number of features is selected. 20 features are selected in Fig. 29. Samples are selected to input into the SVM classifier for recognition. Table 16 records the results after 15 trials. It is found that the average accuracy and scale are positively correlated. It can...
be seen from the results that the optimal number of features suitable for different methods is not the same. The method proposed in this paper has higher accuracy than other models, and the recognition accuracy at a lower scale is also higher than that of other models, so the efficiency of fault diagnosis will also be improved. method proposed in this paper is significantly better than the other models.

V. CONCLUSION

In this paper, a new method IMHMDE is proposed to quantify the complexity of multi-channel vibration signals and to analyse rotating machinery signals by combining mRMR and SVM. In this method, hierarchical and improved multiscale analysis of the signals is performed. Compared to traditional methods, the extracted features are more stable and can extract fault feature information in greater depth and solve some of the problems associated with traditional multiscale calculations. The method contains more abundant fault information, considering the relationship between multiple sensors in the original time series and the sequence information under different time scales.

In addition, the advantages of IMHMDE are examined using rotating machinery and simulation data, and a comparison is made between different multi-entropy models and unit entropy models. The results show that IMHMDE outperforms other methods in detecting dynamic sequence changes and effectively improves the fault identification accuracy.

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