A Fault Feature Extraction Method of Motor Bearing Using Improved LCD

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ABSTRACT Local characteristic-scale decomposition (LCD) is an adaptive decomposition method for non-stationary and nonlinear time-varying signals. In this paper, kernel mapping is used to replace random mapping in LCD, and a fault feature extraction method based on kernel local characteristic-scale decomposition-Hilbert envelope spectrum (KLCD-Hilbert) is proposed. This method first performs wavelet noise reduction on the bearing fault signal, and then uses the KLCD method to adaptively decompose the motor bearing vibration signal into several intrinsic scale components (ISC), the kernel function determines the number of ISCs. Finally, create the Hilbert envelope spectrum of each state vibration signal in turn, and input the extracted characteristic data into the structure of the extreme learning machine (ELM) to realize the fault identification of the motor bearing. The experimental results show that the KLCD-Hilbert envelope spectrum can better reflect the fault characteristics of the motor bearing than the time domain or frequency domain amplitude in the process of identifying the state of the motor bearing. Moreover, the KLCD method has a higher recognition rate than the local mean decomposition (LMD) and empirical mode decomposition (EMD) methods.

INDEX TERMS Kernel local characteristic-scale decomposition, fault, feature extraction, intrinsic scale components.

I. INTRODUCTION
In mechanical and electrical equipment, the motor bearing is the most basic component, and its operation state can directly affect the performance of the entire mechanical equipment. The working space and use environment of mechanical equipment are highly complicated and degenerate. When in a harsh working environment and a high-frequency working state, the running state of motor bearings will change indefinitely with time. In the mechanical equipment of the same model in the frame, the service life of motor bearings has different degrees of difference, and there is a big difference. Due to this characteristic of bearings, in actual use, there will be situations where the bearings have greatly exceeded the life and are still in good working, and there may be various faults when the bearings are far from the life time. Therefore, if the bearings are inspected and repaired on time, there will be two cases: dismantling the bearings before their expected life and disposal will result in waste; if the bearings fail to reach the end of their life, they will be repaired and then dismantled until the scheduled maintenance. Down the scrap, the machine’s working accuracy decreases after the bearing faults and before it is removed, or a serious fault occurred before the time, resulting in a major accident of the entire machine [1].

Diagnosis of the current bottleneck fault is the problem of feature extraction, which can directly relate to the reliability and accuracy of fault identification [2]. In order to solve the key problem of feature extraction, many methods have been proposed, such as power spectrum analysis, time domain analysis, demodulation analysis, adaptive noise reduction, etc. The fault identification is more efficient with these methods, but there are also some limitations [3]–[5]. Based on the limitations of these methods, NASA Nor- den E. Huang proposed empirical mode decomposition (EMD) [6]–[9] in 1998, which is an adaptive signal processing method that can adaptively decompose complex multi-component signals into the sum of several stable component signals [10], and then perform Hilbert transform on each component to obtain the instantaneous frequency and instantaneous amplitude. The obtained Hilbert spectrum can accurately reflect the distribution law of energy in the signal...
on various scales in space [11]–[13]. This method has obvious advantages when dealing with non-stationary signals [14]. It is widely used in fault identification research. Hu et al. proposed to maximize the kurtosis value as the basis for selecting the demodulation signal sequence. STFT’s vibration signal demodulation algorithm [15]. Yi et al. proposed an envelope demodulation analysis method using analytical functions composed of real and imaginary parts of harmonic wavelet and harmonic wavelet combination [16]. Song et al. have verified the envelope demodulation analysis method based on Hilbert transform and proved its effectiveness. However, the method is still in the development stage [5], and there are under-envelope [17], over-envelope and frequency confusion. It is still under study. Intrinsic time-scale decomposition (ITD) is a new adaptive time-frequency analysis method [18], which can decompose a non-stationary signal into the sum of several inherent rotation components, which has obvious advantages compared with EMD, but this method does not explain the physical meaning of the inherent rotation component. Chen [19] proposed a local characteristic-scale decomposition (LCD) algorithm based on the physical meaning of the ITD method and its inherent rotation component. This method can adaptively decompose any complex signal into several instantaneous frequencies with physical meaning. The sum of intrinsic scale components (ISC) is very suitable for processing multi-component AM-FM signals. LCD is a newly proposed method [20], [21]. Compared with EMD and local mean decomposition (LMD), the LCD method has better time-frequency localization characteristics, and can more effectively extract the localized information of the original signal to obtain the essential characteristics of the signal. The effect is more superior, with faster calculation speed.

Therefore, kernel local characteristic-scale decomposition (KLCD) algorithm not only has a good effect in the decomposition of motor bearing signals, but also greatly reduces the amount of calculation, which can be used for fault diagnosis. In view of the characteristics of bearing fault vibration signals that are multi-component AM and FM signals and their complex working environment, the collected signals are first de-noised, then the KLCD method is used to decompose the noise-reduced signal to highlight the bearing fault information, and the envelope spectrum analysis is performed to obtain the effective fault characteristic frequency. Finally, the extracted fault information can be pattern recognized in the extreme learning machine (ELM) to achieve the fault identification of the motor bearing.

II. KLCD AND HILBERT ENVELOPE SPECTRUM
A. KLCD DECOMPOSITION
LCD is based on the local characteristic time scale of the signal. It defines the intrinsic scale component of the physical meaning of the instantaneous frequency [22]. Based on this, it takes any two adjacent extreme points as a span, and performs segmentation on the signal. The linear transformation realizes the adaptive decomposition of the signal, thereby obtaining the ISC component with the physical meaning of the instantaneous frequency and the instantaneous amplitude, and then obtaining the complete time-frequency distribution of the original signal.

The LCD method can decompose any complex signal into several ISC components. The specific steps are as follows:

Step 1: For the entire data signal, find all the maximum point \( (\tau_k, X_k) \) and minimum point \( (\tau_{k+1}, X_{k+1}) \) and set the parameter \( a \). Use equation (1) to obtain each baseline control point \( L_k \), and then perform cubic spline interpolation on all \( L_k \) to obtain Limit signal line \( L_1 \).

\[
L_{k+1} = a \left[ X_k + \left( \frac{\tau_{k+1} - \tau_k}{\tau_{k+2} - \tau_k} \right) \right] + (1-a) X_{k+1} \tag{1}
\]

Step 2: Separate \( L_1 \) from the original signal to get \( P_1 \). If \( P_1 \) meets the conditions of the intrinsic scale component, then \( P_1 \) is the first ISC component of \( x(t) \). The ideal ISC component should satisfy \( L_{k+1} = 0 \), but it is difficult to achieve in the actual calculation process. You can set the fluctuation amount \( \Delta \), and the iteration ends at \( |L_{k+1}| \leq \Delta \).

Step 3: If \( P_1 \) does not meet the conditions that the ISC has, repeat steps 1 and 2 as the original signal, and cycle \( k \) times until the ISC component \( P_k \) that meets the conditions is obtained, and \( P_k \) is the first component \( ISC_1 \).

Step 4: After separating \( ISC_1 \) from \( x(t) \), a new signal \( r_1 \) is obtained, and the steps 1 to 3 are repeated as the original model to obtain the second component \( ISC_2 \) of \( x(t) \). Repeat the cycle \( n \) times to obtain \( n \) components of the signal \( x(t) \) that satisfy the condition, until \( r_n \) is a monotonic function. In this way, \( x(t) \) can be decomposed into the sum of \( n \) ISC components and a monotonic function \( r_n \), that is,

\[
x(t) = \sum_{p=1}^{n} ISC_p(t) + r_n(t) \tag{2}
\]

By the linear kernel function,

\[
K(x_i, x) = x_i \cdot x \tag{3}
\]

Since there are false and fault-insensitive components in all ISCs obtained by LCD, in order to determine how many ISCs are the input data, the kernel function is used to map the input space to the feature space through nonlinear transformation, and then a linear learning method is designed to remove The linear transformation is transformed into the inner product operation, and then the kernel function is used to replace the inner product operation to obtain the optimal result.

B. HILBERT ENVELOPE ANALYSIS
During the Hilbert transformation, the vibration signal is caused to have a phase shift of 90°, so as to form an analytical signal with the original signal.

The vibration signal \( x(t) \) is recorded as \( H \left[ x(t) \right] \) after being transformed by Hilbert:

\[
H[x(t)] = \frac{1}{\pi} \int_{-\infty}^{\infty} \frac{x(t)}{t-\tau} d\tau = x(t) \frac{1}{\pi t} \tag{4}
\]
Among them, the analysis signal \( z(t) \) of \( x(t) \) can be expressed as:

\[
  z(t) = x(t) + jH \left[ x(t) \right] = a(t)e^{j\psi(t)} \tag{5}
\]

The magnitude \( a(t) \) after Hilbert transformation is:

\[
  \left\{ \begin{array}{l}
  a(t) = \sqrt{x^2(t) + H^2\left[ x(t) \right]} \\
  \psi(t) = \tan^{-1}\left[ \frac{H\left[ x(t) \right]}{x(t)} \right]
  \end{array} \right. \tag{6}
\]

It can be known from the above steps that the instantaneous frequency and instantaneous amplitude of each ISC component obtained by the KLCD have practical physical meaning, that is, each ISC component satisfies the condition of Hilbert transform.

The Hilbert transform of the ISC component in Eq. (2) can be obtained:

\[
  H\left[ ISC_p(t) \right] = \frac{1}{\pi} \int_{-\infty}^{\infty} ISC_p(t') \frac{dt'}{t-t'} \tag{7}
\]

On this basis, the envelope signal is calculated for each ISC to obtain:

\[
  B_p(t) = \sqrt{H\left[ ISC_p(t) \right]^2 + ISC_p^2(t)} \tag{8}
\]

Envelope spectrum can be obtained by performing spectral analysis on the signal of Eq. (8).

### III. FAULT IDENTIFICATION BASED ON ELM

#### A. ALGORITHM OF ELM

The extreme learning machine is a generalized single hidden layer feed forward neural network machine learning algorithm [23]. The connection weights and hidden layer thresholds between the input layer and the hidden layer are randomly generated, and there is no need to adjust during the training process, so it can avoid the cumbersome iterative adjustment of neural network parameters [24].

Suppose there are \( N \) arbitrary samples \((X_i, t_i)\), where \( X_i = (x_{i1}, x_{i2}, \ldots, x_{in})^T \in \mathbb{R}^n \), \( t_i = (t_{i1}, t_{i2}, \ldots, t_{in})^T \in \mathbb{R}^m \), \( n \) is the dimension of the input layer, and \( m \) is the dimension of the output layer. For a single hidden layer feed forward neural network with \( L \) hidden layer nodes, the output can be expressed as:

\[
  \sum_{j=1}^{L} \beta_j g(W_j \cdot X_i + b_j) = o_i \tag{9}
\]

In the formula, \( i = 1, 2, \ldots, N \), \( W_j = (w_{j1}, w_{j2}, \ldots, w_{jn})^T \) are the input weights, \( \beta_j = (\beta_{j1}, \beta_{j2}, \ldots, \beta_{jm})^T \) is the output weights, \( b_j \) is the bias of the \( j \) hidden layer unit, and \( g(x) \) is the activation function.

In order to make the classification result \( o_i \) consistent with the real result \( t_i \), it can be expressed as:

\[
  \sum_{i=1}^{N} \| o_i - t_i \| = 0 \tag{10}
\]

There are \( \tilde{W}_j, \tilde{b}_j, \tilde{\beta}_j \), such that,

\[
  \sum_{j=1}^{L} \beta_j g(W_j \cdot X_i + b_j) = t, \quad i = 1, 2, \ldots, N \tag{11}
\]

The matrix is expressed as:

\[
  H\beta = T \tag{12}
\]

In the formula, represents the output of the hidden layer neuron, represents the weight of the output, and represents the expected output.

\[
  H(W_L, b_L, X_L) = \begin{bmatrix}
  g(W_L \cdot X_1 + b_L) \\
  \cdots \\
  g(W_L \cdot X_N + b_L)
  \end{bmatrix}_{N \times L}
\]

among them,

\[
  \beta = \begin{bmatrix}
  \beta_1^T \\
  \vdots \\
  \beta_L^T
  \end{bmatrix}_{L \times M}, \\
  T = \begin{bmatrix}
  T_1^T \\
  \vdots \\
  T_L^T
  \end{bmatrix}_{N \times M}
\]

In order to be able to train a single hidden layer neural network and obtain \( W_j, \tilde{b}_j, \tilde{\beta}_j \), such that,

\[
  \| H(W_j, \tilde{b}_j)\beta_j - T \| = \min_{W,B,\beta} \| H(W_j, b_j)\beta_j - T \|, \\
  j = 1, 2, \ldots, L \tag{14}
\]

When the input weight \( W_i \) and hidden layer bias \( b_i \) of the single hidden layer feed forward neural network are randomly determined, the solution process of the single hidden layer neural network can be obtained by the least square equation,

\[
  \| H\tilde{\beta} - T \| = \min \| H\beta - T \| \tag{15}
\]

Solve the above formula,

\[
  \tilde{\beta} = H^+ T \tag{16}
\]

#### B. FAULT IDENTIFICATION PROCESS

The fault identification process of motor bearing based on the KLCD-Hilbert envelope spectrum proposed in this paper is as follows.

Step 1: Wavelet analysis is used to eliminate the noise in the vibration signal, and then the signal after noise reduction is adaptively decomposed into several ISC components of different scales by the LCD method: \( ISC_1, ISC_2, \ldots, ISC_n \). Each component contains fault information in different frequency bands and scales of the original signal, and then use the kernel function to find the optimal number of ISC components.

Step 2: Determine the first three ISC components containing the main fault information by the kernel function, and then analyze the spectrogram to determine the feature vector through the Hilbert envelope spectrum.

Step 3: Input the extracted feature vector into the fault identification model of the extreme learning machine.
The flow of the fault identification method of motor bearings based on KLCD-Hilbert envelope spectrum is shown in Fig. 1.

![FIGURE 1. The flowchart of KLCD-Hilbert envelope spectrum fault identification.](image)

**IV. EXPERIMENTAL RESULTS AND ANALYSIS**

**A. EXPERIMENTAL DATA**

By using experimental data provided by Case Western Reserve University Bearing Data Center [25]. The type of the deep groove ball bearing at the motor drive end is SKF6205. The vibration signal is collected by a 16-channel data recorder. The power and speed are measured by a torque sensor and a decoder. And 48kHz, the motor speed is approximately 1772 r/min.

The data of 12kHz sampling frequency at the driving end of the motor bearing was selected for experiments. The data were collected in 11 states: normal state of motor bearing, rolling element fault, inner ring fault and outer ring fault. Among them, data1, data2, and data3 represent the fault status of motor bearing rolling elements, data 4, data 5, and data 6 represent the fault status of different performance degradation of the motor bearing inner ring, data 7, data 8, and data 9 represent the fault status of different performance degradation of the motor bearing outer ring, data 10 and data 11 indicate normal status. The load of each state is 1hp, hp is imperial horsepower, 1hp = 0.75kW, 1024 points are taken for each time domain sample, and 1 group of 1hp samples in 11 states is 100 groups.

**B. CONSTRUCTION OF FEATURE DATA SETS**

In the process of collecting data, noise is unavoidable, so it is necessary to denoise the signal first. This paper uses wavelet denoising method to reduce the time domain of data1 as shown in Fig. 2. Through the kernel function LCD, select the first 3 ISC and 1 residual component, as shown in Fig. 3.

![FIGURE 2. Time domain diagram of rolling element fault signal after noise reduction.](image)

**C. MOTOR BEARING STATUS RECOGNITION**

In order to prove the advantages of the characteristic data of Hilbert envelope spectrum, this paper conducts state recognition experiments on the time domain signal and frequency domain amplitude spectrum of motor bearing under the structure of extreme learning machine. The abscissa is the number of samples, and the ordinate is the fault category label. The expected output and the actual output are the samples with the correct diagnosis, and vice versa, the samples with the wrong diagnosis. The Hilbert envelope spectrum characteristic data after the decomposition of the previous KLCD is used for fault identification by ELM. 825 of the data samples are selected as training samples, and the remaining 275 are used as test samples. The diagnostic test results are shown in Fig. 7. It can be seen from the figure that there are a total of 275 sets of test samples, of which 249 sets are correctly diagnosed, so the correct diagnosis rate is calculated: $C_1 = \frac{269}{275} = 97.82\%$. Fig. 5 shows the diagnosis result of the time-domain signal feature input to the extreme learning machine, the diagnosis accuracy rate is 81.09%, Fig. 6 is the diagnosis result of the frequency domain amplitude spectrum feature input to the extreme learning machine, the diagnosis accuracy rate is 81.09%.
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FIGURE 5. Recognition result of time-domain signal characteristics.

FIGURE 6. Recognition result of frequency domain amplitude spectrum characteristics.

FIGURE 7. Recognition result of Hilbert envelope spectrum characteristics.

is 88.73%. The experimental results obtained by summarizing the three feature data are shown in Table 1.

| Input data          | Training accuracy % | Test accuracy % | Elapsed time / s |
|---------------------|---------------------|-----------------|------------------|
| Time-domain signal  | 100                 | 81.09           | 2476             |
| Frequency domain    | 100                 | 88.73           | 2845             |
| Hilbert envelope spectrum | 100             | 97.82           | 3546             |

It can be seen from the experimental results in Table 1 that the training accuracy of ELM reaches 100%, indicating that the fault recognition method can effectively recognize the state of the training data, but the test accuracy of different features has large differences. The accuracy rate of is the lowest, which proves that this feature cannot better represent the characteristics of the test data. It is not ideal as the input data of ELM, and the test accuracy of the frequency domain amplitude spectrum feature is lower than that of the Hilbert envelope spectrum feature. Therefore, the Hilbert envelope spectrum feature proposed in this paper is more sensitive to faults and can better represent the fault features of motor bearings.

In order to further prove the effectiveness of the KLCD-Hilbert envelope spectrum feature extraction method proposed in this paper, this paper also compares the pattern recognition results of EMD and LMD feature extraction data input into ELM. The results are shown in Table 2. Fig. 8 is the diagnosis result of data decomposed by EMD into ELM, the diagnosis accuracy rate is 84.36%, and Fig. 9 is the diagnosis result of data input after LMD into ELM, the diagnosis

| Decomposition method | Recognition accuracy % | Elapsed time / s |
|----------------------|-------------------------|------------------|
| KLCD                 | 98.73                   | 3278             |
| EMD                  | 84.36                   | 2354             |
| LMD                  | 82.18                   | 7465             |

It can be seen from the experimental results in Table 1 that the training accuracy of ELM reaches 100%, indicating that the fault recognition method can effectively recognize the
In this paper, the following conclusions can be drawn. According to the methods and experimental results presented, the shorter the time required, the higher the recognition rate is. Fig. 10 shows the diagnosis result of KLCD. The accuracy rate can reach 98.73%. Compared with the previous two methods, the feature data extracted by KLCD-Hilbert envelope spectrum input into ELM has the highest diagnostic accuracy. Therefore, this paper adopts the fault identification structure of KLCD-Hilbert envelope spectrum and extreme learning machine. It can be seen from Table 2 that the recognition accuracy after KLCD and ELM pattern recognition can reach 98.73%, which is more accurate than the recognition of EMD and LMD. The higher the rate, the shorter the time required.

V. CONCLUSION

According to the methods and experimental results presented in this paper, the following conclusions can be drawn.

1) The KLCD algorithm proposed in this paper is a new adaptive non-stationary signal processing method based on the kernel function, extreme points and local feature scale parameters. This method improves the original ITD algorithm by defining the ISC component with the physical meaning of the instantaneous frequency and at the same time introducing the cubic spline curve into the algorithm.

2) The ISC is obtained by KLCD of the signal after wavelet denoising, and then the Hilbert envelope spectrum feature is extracted as the fault information of the motor bearing, which is input into the ELM for state recognition to realize the fault identification of the motor bearing. Good decomposition characteristics can be obtained.

3) The results show that KLCD is better than EMD and LMD. It has a higher recognition rate and less time than EMD and LMD in terms of the time required for complete decomposition and the accuracy of fault identification. The recognition accuracy is higher than other methods 14.37% and 16.55% respectively. Compared with the time domain and frequency domain features, Hilbert envelope spectrum characteristics can obtain the fault information of the motor bearing more effectively. It further shows that the research method in this paper has achieved good results in the fault identification of motor bearings, and it also provides a strong basis for subsequent research.

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