Application of a Novel Improved Adaptive CYCBD Method in Gearbox Compound Fault Diagnosis

HUER SUN, FUWANG LIANG, YUTAO LIU, KEXIN LIU, ZHIIJAN WANG, TIANYUAN ZHANG, JIYANG ZHU, AND YANG ZHAO

College of Mechanical Engineering, North University of China, Taiyuan 030051, China

Corresponding authors: Fuwang Liang (lfw163email@163.com), Huer Sun (sunhuer163email@163.com), and Yutao Liu (1139539462@qq.com)

This work was supported by Shanxi Provincial Natural Science Foundation of China under Grant 201801D121186.

ABSTRACT Recently, cyclostationary blind deconvolution (CYCBD) is often used in gearbox fault feature extraction, and it is more effective in recovering single periodic pulse. However, in the engineering application of CYCBD, the filter length ($L$) and cycle frequency ($\alpha$) need to be verified and set through a large number of experiments, and the efficiency is very low; Moreover, the effect is not good when it is used to extract composite fault features under the background of strong noise. In order to overcome the above limitations, empirical mode decomposition (EEMD) is used to preprocess the composite fault. EEMD can remove the high-frequency noise and weak correlation components in the sampled signal. The strong correlation component is reconstructed to obtain the modal function closer to the fault frequency. The chimpanzee intelligent algorithm is applied to the determination of $L$ and $\alpha$ of CYCBD by optimization to form an adaptive CYCBD. Adaptive CYCBD takes the dispersion entropy of envelope spectrum as the fitness function of chimpanzee optimization algorithm (CHOA), and finds the optimal $L$ and $\alpha$ through iteration. The optimal parameter value is applied to CYCBD, and the reconstructed modal function is deconvoluted to obtain the optimal inverse filter, so as to accurately separate the fault characteristic components. Simulation and experimental results show that this method is effective for gearbox composite fault diagnosis and extraction under strong noise background.

INDEX TERMS Cyclostationary blind deconvolution, ensemble empirical mode decomposition, the chimp optimization, dispersion entropy of envelope spectrum, fault diagnosis.

I. INTRODUCTION

With the rapid development of modern industry, gearbox has been widely used, especially in the automotive transmission system. Its stability is of great significance to improve the safety and reliability of the vehicle. As the key components of the gearbox, gears and bearings play important roles in the transmission system. Due to the complexity of the gearbox structure, when one of the parts fails, the faults interact with each other, leading to the failure of other parts. Therefore, in most cases, the faults of the gearbox is a composite fault. However, with the interference of complex operating environments and complicated transmission paths, finally, the pulse signals collected by sensors are often submerged by noise, especially when multiple faults exist at the same time, the fault location is difficult to find so that the difficulty of fault feature extraction is further increased. Therefore, it is crucial to study effective fault characterization methods.

The formation process of gearbox fault source signal is the convolution mixing process of source signal and noise. Blind deconvolution can extract fault pulse through deconvolution process. Therefore, blind deconvolution has obvious advantages in bearing fault diagnosis. Blind deconvolution theory is an effective fault diagnosis technique that includes minimum entropy deconvolution (MED) [1], maximum correlated kurtosis deconvolution (MCKD) [2], Optimal minimum entropy deconvolution adjusted (OMEDA) [3], Multipoint optimal minimum entropy deconvolution adjusted (MOMEDA) [3] and cyclostationarity blind deconvolution (CYCBD) [4]. They base on the maximization or minimization criterion of different convolutional targets by solving the inverse filter coefficients to recover the periodic or quasi-periodic pulses.
associated with the fault from the original vibration signal. Wang et al. [5] proposed the method of combing MED with EEMD to reduce the influence of noise on EEMD decomposition results, eliminate the mode mixing phenomenon of EEMD, and successfully apply it to the fault diagnosis of gearboxes. But the MED algorithm that can only extract single pulses, not periodic pulses, and often does not give satisfactory results. To improve the shortcomings of MED, McDonald proposed the maximum correlated kurtosis deconvolution (MCKD). Although MCKD can extract continuous periodic pulses, this method has poor adaptive ability, and the extraction effect will be affected by four parameters. Moreover, when the fault period is non-integer, it needs to be resampled, which may easily lead to misdiagnosis [6]. In addition, the method can only extract single faults with defined periods, not the composite fault features. To overcome the disadvantages of MED and MCKD, the MOMEDA method is proposed. The algorithm uses the time target vector to define deconvolution, and the optimal filter can be obtained without iteration, so as to determine the location of the pulse. However, in a strong noise environment, the periodic pulses extracted by this algorithm may be spurious components, and only a single pulse period can be searched at a time for a specific time interval [7]. CYCBD is a new blind deconvolution method based on the generalized Rayleigh quotient. It uses iterative eigenvalue decomposition algorithm to solve problems, and introduces second-order cyclic smoothness (ICS2) as a new criterion for inverse pleating. In the cyclic smooth case, the method considers the periodic fluctuating part of the energy flow in the random signal by introducing the cyclic frequency parameter, which makes the cyclic smooth method more realistic for methods that consider only the periodic part (e.g., MOMEDA). It is able to make up for some of the shortcomings that appear in MOMEDA. However, these key parameters need to be determined manually. If they are not determined properly, they will produce false characteristic components and easily lead to misdiagnosis. Therefore, it is necessary to improve the accuracy of diagnosis. Reference [8] proposed a new method combining cuckoo search algorithm (CSA) with CYCBD and instantaneous energy slice bispectrum (IESB) as optimization index. It can adaptively find the optimal cycle frequency and filter length parameters of CYCBD. Reference [9] proposed a new morphological difference operational entropy (MODE) index by using morphological transformation and Shannon entropy, and used grid search algorithm to accurately determine the influence parameters of CYCBD. Wang et al. [10], [11] used the equal step search strategy to adaptively select the filter length in CYCBD. However, these indexes as optimization objectives do not show deconvolution noise reduction performance. Dispersion entropy (DisEn) is an effective and fast uncertainty quantization method for nonlinear signals [12]. Compared with permutation entropy (PerEn) [13] and approximate entropy (ApEn) [14], it has better stability when dealing with high signal-to-noise ratio [15]. When there are multiple periodic pulses, the envelope spectrum analysis of the periodic signal show that the main components of the envelope spectrum are mainly concentrated in the low frequency band, resulting in the decrease of the envelope spectrum entropy. In this paper, the combination of dispersion entropy and envelope spectrum entropy have good robustness in measuring signal complexity. Considering the performance and time cost of CYCBD, chimpanzee optimization algorithm (CHOA) is adopted. Compared with other intelligent algorithms, CHOA solves the problems of slow convergence speed and easily to fall into local optimization [16]. Through the above analysis, this paper forms an adaptive CYCBD method which takes the envelope spectral dispersion entropy as the fitness function of CHOA, and finds the optimal filter length and cycle frequency through iterative method.

In engineering practice, another important problem is that due to the large number of parts and complex structure, the gearbox will produce multiple faults, which can modulate and couple with each other. Coupled with complex external interference, fault feature extraction is more challenging [17], [18]. Using the above blind inverse deconvolution noise reduction method alone cannot achieve satisfactory results. Therefore, it is necessary to preprocess the fault signal. In this paper, the integrated empirical mode decomposition (EEMD) [19] is used as the preprocessing method. Compared with wavelet transform theory [20], empirical mode decomposition (EMD) [21], local average decomposition (LMD) [22], variational mode decomposition (VMD) [23], [24], singular spectrum decomposition (SSD) [25], etc., EEMD can adaptively modulate the original signal. In addition, EEMD can separate signals in the order of high frequency and low frequency. Especially when multiple faults coexist, different time scales are decomposed into different intrinsic mode functions (IMF), and the fault frequency is determined by solving the IMF of each layer. However, EEMD can not completely separate different time scales, and there is serious mode mixing [26], which increases more uncertainty in signal evaluation using envelope spectral dispersion entropy. This phenomenon can be effectively suppressed by reconstructing the IMF with the same fault to form combined IMF (CMF) with different scales. Therefore, EEMD is used to preprocess the composite fault, remove the high-frequency noise and weak correlation components of IMF, reconstruct the strong correlation components, and obtain CMF. The chimpanzee intelligent algorithm is applied to determine the $L$ and $\alpha$ of CYCBD through optimization to form an adaptive CYCBD. Adaptive CYCBD takes the dispersion entropy of envelope spectrum as the fitness function of chimp optimization algorithm (CHOA) until the dispersion entropy of envelope spectrum reaches the minimum value. CYCBD is used to further denoise the reconstructed signal, enhance the fault energy characteristics and extract the impact characteristics. The feasibility of this method is verified by the analysis of simulation signals and experimental measurement signals.
II. THEORETICAL FOUNDATION

A. THEORY OF CYCLOSTATIONARY BLIND DECONVOLUTION

The core problem of blind deconvolution product theory is to construct rules for solving the inverse filter coefficients so that the recovered signal is as close as possible to the source signal. As shown in equations (1).

\[ s = x \ast h = (s_0 \ast g) \ast h \approx s_0 \]  

where \( s_0 \) is the source signal, \( x \) is the mixed signal, \( g \) is the unknown impulse response function, which is determined by the transfer path, \( \ast \) is the inverse filter to be sought, and \( \ast \) refers to the convolution operation. The matrix expression for the signal convolution operation is:

\[
\begin{bmatrix}
  s[L-1] \\
  \vdots \\
  s[N-1]
\end{bmatrix} = 
\begin{bmatrix}
  x[L-1] & \cdots & x[0] \\
  \vdots & \ddots & \vdots \\
  x[N-1] & \cdots & x[N-L-1]
\end{bmatrix} 
\begin{bmatrix}
  h[0] \\
  \vdots \\
  h[L-1]
\end{bmatrix} 
\]

where \( N \) and \( L \) denote the lengths of \( s \) and \( h \).

In general, cyclic smooth processes are processes that exhibit a periodic behavior, which exhibits their statistical properties. If the ratio of \( n \)-order statistical moments to cumulants contains periodic components, then the stochastic process is called \( n \)-order cyclic smooth process [4]. 2-order cyclic smoothness (ICS2) is a frequency-domain indicator characterizing periodic fluctuations in signal energy, with some periodic information reflecting the occurrence of mechanical faults. The larger the indication value, the more significant the periodic behavior of the signal. Therefore, based on ICS2 index, a new method CYCBD is established.

The cyclic frequency is defined as:

\[ \alpha = \frac{k}{T_s} \]  

where \( k \) is the sample index and \( T_s \) are the cycle (in samples), which can be related to a fault occurrence rate for instance.

The general expression for Indicators of ICS2 is:

\[ ICS2 = \sum_{k=0}^{N-1} \frac{|c_s^k|^2}{|c_s^0|^2} \]  

With

\[ c_s^k = \langle |s|^2, e^{2\pi \frac{k}{T_s}} \rangle = \frac{1}{N - L + 1} \sum_{n=L-1}^{N-1} |s[n]|^2 e^{-2\pi \frac{k}{T_s} n} \]  

\[ c_s^0 = \frac{||s||^2}{N - L + 1} \]  

The matrix form of Eqs. (6) and (7) are:

\[ e_s^k = \frac{E^H |s|^2}{N - L + 1} \]  

\[ e_s^0 = \frac{\sqrt{E} H s}{N - L + 1} \]  

where

\[ |s|^2 = \left[ |s[L-1]|^2, \ldots, |s[N-1]|^2 \right]^T \]  

\[ E = [e_1 \cdots e_k \cdots e_K] \]  

\[ e_k = \left[ e^{-2\pi \frac{k}{T_s} (N - 1)} \right] \]  

Based on (6) and (7), Equation (5) can be expressed as.

\[ ICS2 = \frac{|s|^2 H E E^H |s|^2}{|s H s|^2} \]  

From this point, it can be observed that the signal containing the periodic component of \( |s|^2 \) is called \( P \left[ |s|^2 \right] \), which contains all the cycle frequencies of interest \( k \), then it can be written as:

\[ P \left[ |s|^2 \right] = \frac{1}{N - L + 1} \sum_k e_k(e_k^H |s|^2) = EE^H |s|^2 \]  

After a simple manipulation, substituting Eq. (2) and Eq. (14) into Eq. (13) returns the final outcome:

\[ ICS2 = \frac{h^H X^H W X h}{h^H R_{XX} h} \]  

where the matrix \( W \) can be expressed as:

\[ W = diag \left( \frac{P[|s|^2]}{s H s} \right) (N - L + 1) \]

\[ = \begin{bmatrix}
  \ddots & 0 \\
  0 & \sum_{n=L-1}^{N-1} \frac{|s|^2}{s H s} \end{bmatrix} (N - L + 1) \sum_{n=L-1}^{N-1} s^2 \]  

\( R_{XX}, R_{WX} \) are the weighted correlation matrix and correlation matrix respectively. Equation (15) is the generalized Rayleigh quotient. According to the properties of the generalized Rayleigh quotient, in order to maximize ICS2, it is transformed into solving the maximum eigenvalue of generalized Rayleigh quotient.

\[ R_{WX} h = R_{XX} h \lambda \]  

The maximum eigenvalue \( \lambda \) of the generalized Rayleigh quotient and the corresponding eigenvector \( h \) are obtained iteratively according to equation (17), and the eigenvector is the optimal filter of CYCBD.
B. THE CHIMP OPTIMIZATION ALGORITHM

ChOA is a new meta-heuristic algorithm that simulates the behavior of chimpanzees in hunting [16]. In the ChOA algorithm, chimps are divided into four main groups, attacker, driver, barrier, and chaser.

The hunting behavior of chimp, such as Driving and chasing the prey, can mathematically be modeled as

\[
d = |c \cdot x_{\text{prey}}(t) - m \cdot x_{\text{chimp}}(t)| \tag{18}
\]

\[
x_{\text{chimp}}(t + 1) = x_{\text{prey}}(t) - a \cdot d \tag{19}
\]

where \(t\) indicates the number of current iteration, \(a, m, \) and \(c\) are the coefficient vectors, \(x_{\text{Chimp}}\) and \(x_{\text{Prey}}\) are the position vector of the prey and the chimp, respectively, which can be calculated as follows:

\[
a = 2.f \cdot r_1 - a \tag{20}
\]

\[
c = 2.r_2 \tag{21}
\]

\[
m = \text{Chaotic}\_value \tag{22}
\]

if is reduced non-linearly from 2.5 to 0 through the iteration process (in both exploitation and exploration phases). \(r_1\) and \(r_2\) are the random vectors in \([0, 1]\). \(m\) is a chaotic vector calculated based on the various chaotic maps, which represents the effect of the sexual motivation of chimps in the hunting process.

To mathematically model the attacking behavior of chimps, it is assumed that the position of the attacker is the position of prey. Then, the positions of driver, barrier, and chaser should be updated by using the attacker’s position. So, four of the best-obtained solutions is stored and other chimps are forced to update their positions because of the best chimps’ locations. This approach is defined by the Eqs. (23), (24), (25):

\[
d_{\text{Attacker}} = |c_1 \cdot x_{\text{Attacker}} - m_1 \cdot d|,
\]

\[
d_{\text{Barrier}} = |c_2 \cdot x_{\text{Barrier}} - m_2 \cdot x|,
\]

\[
d_{\text{Chaser}} = |c_3 \cdot x_{\text{Chaser}} - m_3 \cdot x|,
\]

\[
d_{\text{Driver}} = |c_4 \cdot x_{\text{Driver}} - m_4 \cdot x| \tag{23}
\]

\[
x_1 = x_{\text{Attacker}} - a_1 (d_{\text{Attacker}}),
\]

\[
x_2 = x_{\text{Barrier}} - a_2 (d_{\text{Barrier}}),
\]

\[
x_3 = x_{\text{Chaser}} - a_3 (d_{\text{Chaser}}),
\]

\[
x_4 = x_{\text{Driver}} - a_4 (d_{\text{Driver}}). \tag{24}
\]

\[
x(t + 1) = \frac{x_1 + x_2 + x_3 + x_4}{4} \tag{25}
\]

where \(d_{\text{Attacker}}, d_{\text{Barrier}}, d_{\text{Chaser}}\) and \(d_{\text{Driver}}\) are the distance vectors; \(x_1, x_2, x_3, \) and \(x_4\) are the movement instructions given by Attacker, Barrier, Chaser and Driver, respectively.

C. DISPERSION ENTROPY OF ENVELOPE SPECTRUM

In order to evaluate the quality of the deconvolution components as fairly as possible during the search process, a suitable objective function is needed. In the literature [15], it has been shown that dispersion entropy gives more stable results compared to PerEn and ApEn for rotating machinery condition monitoring. When multiple periodic pulses are present, the envelope spectrum analysis of the periodic signal reveals that the main components of the envelope spectrum are mainly concentrated in the low frequency range, resulting in the decrease of the envelope spectrum entropy. Therefore, the envelope spectrum entropy can indicate the uniformity of periodic pulses. The more pulses are detected, the clearer the envelope spectrum and the smaller the entropy of the envelope spectrum [27].

Dispersion entropy (DisEn) proposed by Azami is a novel method to detect the dynamics of time series [15]. DisEn of the time series \(X = \{x_1, x_2, \ldots, x_N\}\) with the length \(N\) can be calculated in six steps as follows:

Step 1: Project the original signal into \(k\) classes, named from 1 to \(k\). The “class” here means the number of symbolization.

Step 2: Construct the embedding vector \(Z^{m,c}_j\) with embedding size \(m\) and time delay \(d\). The formula is as follows (26).

\[
Z^{m,c}_j = [z^c_1, z^c_{j+d}, \ldots, z^c_{j+(m-1)d}] \quad j = 1, 2, \ldots, N - (m - 1)d \tag{26}
\]

Step 3: Each series \(Z^{m,c}_j\) is mapped into a dispersion pattern, in which \(z^c_{j+d} = v_0, z^c_{j+2d} = v_1, z^c_{j+(m-1)d} = v_m\). The amount of all possible patterns are \(c^m\).

Step 4: For each of \(c^m\) possible dispersion patterns \(\pi_{v_0\ldots v_{m-1}}\), calculate its frequency by:

\[
p(\pi_{v_0\ldots v_{m-1}}) = \frac{\text{Number} \left\{ j \leq N - (m - 1)d, \text{type}(z^{m,c}_j) = \pi_{v_0\ldots v_{m-1}} \right\}}{N - (m - 1)d} \tag{27}
\]

where the \(\text{Number}\) represents the cardinality of the times of dispersion pattern.

Step 5: DisEn with the embedding dimension \(m\) and number of classes \(c\) are calculated according to Eq (28).

\[
\text{DisEn}(x, m, c, d) = - \sum_{\pi=1}^{c^m} p(\pi_{v_0\ldots v_{m-1}}) \cdot \ln(p(\pi_{v_0\ldots v_{m-1}})) \tag{28}
\]

Step 6: \(S_R(\omega)\) is the envelope spectrum of the original signal, so Dispersion Entropy of envelope spectrum (ESD) is defined as:

\[
\text{ESD} = \text{DisEn} (S_R (\omega), m, c, d) = - \sum_{\pi=1}^{c^m} p(\pi_{v_0\ldots v_{m-1}}) \cdot \ln(p(\pi_{v_0\ldots v_{m-1}})) \tag{29}
\]

In addition, different levels of white noise are added to the simulated signal to obtain simulated signals with different signal-to-noise ratios. Figure 2 shows the curves of ESD metric corresponding to different signal-to-noise ratios. By comparing the index values under different SNR conditions, the effectiveness of the index in evaluating the uniformity of the periodic signal is further verified. It is well known
that if the signal-to-noise ratio is higher, the characteristics of periodic influence are more obvious. As shown in the figure 2, the indicator value tends to decrease when the signal-to-noise ratio increases, which means that a smaller indicator represents a higher number of periodic shocks. This is because the regularity of the signal shocks decreases in the presence of noise interference. Therefore, the envelope spectral discrete entropy ESD metric proposed in this paper is suitable for the fair evaluation of the deconvoluted signals of CYCBD, and it can be used as an objective function in the chimpanzee parameter optimization process.

D. STEPS OF THE CHIMP OPTIMIZATION ALGORITHM

The implementation steps of the chimpanzee optimization algorithm to optimize CYCBD parameters are as follows:

- Initialize the ChOA parameters and the chimpanzee population.
- Initialize the range of CYCBD optimization parameters \( L \) and \( \alpha \).

\[
\text{while} (t < \text{maximum number of iterations})
\]
- Select a random search agent.
- End for.

\[
\text{calculate the dispersion entropy of the signal envelope spectrum after CYCBD noise reduction}
\]

\[
\text{if ESD}^t (L, \alpha) \leq \text{ESD}^{t+1}(L, \alpha)
\]
- Update \( L \) and \( \alpha \).

\[
\text{else if}
\]
- Return \( L \) and \( \alpha \).
- End if.
- Return ESD and optimal parameters \( L \) and \( \alpha \) of CYCBD.

E. ADAPTIVE CYCBD METHOD BASED ON CHIMP OPTIMIZATION FOR COMPOUND FAULT DIAGNOSIS

1. Figure 3 shows the diagnosis process of the chimpanzee optimization-based adaptive CYCBD method. In the strong noise environment, the feature informations of composite fault can be decomposed into different modal functions in the same time scale by EEMD preprocessing. Then, according to the correlation coefficients, the noise and weakly correlated components are removed and the strongly correlated components are reconstructed. And considering that the fault features are easily swamped by high-frequency noise, CYCBD is used to further extract the fault features from the reconstructed modal functions.

2. Two important parameters of CYCBD, cycle frequency and filter length, are optimized by the chimpanzee algorithm. The objective function of the optimization is chosen as the envelope spectrum dispersion entropy. In order to consider the efficiency and accuracy of the calculation, the lower limit of the search interval of the cycle frequency is set to 0.5\( \alpha \), and the search range of the filter is set to 10 to 1000.

3. The feature extraction of the reconstructed signal which uses CYCBD with optimized parameters accurately extracts the fault characteristic frequencies, which illustrates the superiority of the proposed method.

III. PERFORMANCE EVALUATION BY SIMULATED SIGNALS

When the gears and bearings have local failures, they will vibrate once per revolution. Therefore, the pitting, cracking of the gears, or the vibration fault signal of the inner and outer rings of the bearing often show the characteristics of periodic vibration.

Equation 30 simulates the fault signal of a rolling bearing, where \( M \) is the number of vibrations in the periodic vibration signal; \( B_m \) is the amplitude of the \( m \) vibration; \( \beta \) is the decay rate of the vibration. The fault characteristic frequency \( f_c \) satisfies \( f_c = 1/T_p \). \( f_n \) is the intrinsic frequency; \( u(t - mT_p) \) is the unit step function; \( n(t) \) is the Gaussian white noise. In this paper, the sampling frequency is 10000Hz and the two intrinsic frequencies are 400 Hz and 160 Hz respectively. Setting \( y_1 = 1 \), \( T_1 = 0.025 \), \( y_2 = 0.8 \), \( T_2 = 0.05 \). In Fig. 4,(a) and (b) are two fault sources of (d), which are 20Hz and 40Hz respectively, and (c) is Gaussian noise.
of 3.8dm.

\[
 s(t) = \sum_{m=0}^{M} B_m \exp[-\beta(t - mT_p)] \\
 \times \cos[2\pi f_{re} \times (t - mT_p)]u(t - mT_p) \\
 y(t) = s(t) + n(t) 
\]  

(30)

Firstly, the EEMD is used to decompose the analog signal, and the EEMD is decomposed into eight layer intrinsic mode functions. Correlation coefficients are shown as Table 1. Excluding the last three smaller correlation components, the first five components are shown in Fig.5. From Figure 5a, it can be seen that IMF1 has a amount of modal
TABLE 1. The correlation coefficient.

| IMF | IMF1 | IMF2 | IMF3 | IMF4 | IMF5 | IMF6 | IMF7 | IMF8 |
|-----|------|------|------|------|------|------|------|------|
| correlation coefficient | 0.541 | 0.406 | 0.313 | 0.23 | 0.16 | 0.1  | 0.075 | 0.064 |

components noise and weaker fault characteristics. It can be seen from Figure 5b, the sidebands on both sides of IMF2 of the intrinsic frequency 400Hz are also weak, and the fault characteristic components are not obvious. There is interference from noise in IMF1 and IMF2, the same intrinsic frequency is decomposed into different layers, and the modal mixing phenomenon is also serious. Although the amplitude of the sidebands has improved, IMF3 is still not obvious compared to IMF1 and IMF2. The 40 Hz frequency appearing in IMF4 is the frequency of analog signal 1, and the 20 Hz appearing in IMF5 is the frequency of analog signal 2. It can be seen from the spectrum that the fault information of analog signal 1 is decomposed into IMF1, IMF2 and IMF4, and the fault information of analog signal 2 is decomposed into IMF3 and IMF5. To eliminate the mode mixing, the decomposition results are reconstructed as shown in Figure 6.

To further eliminate the influence of noise on the EEMD decomposition results, CMF1 and CMF2 were optimized by the chimp optimization algorithm, respectively. The two periodic vibrations of the simulated signal are 1/40 and 1/20 respectively, and the corresponding frequencies are 40 Hz and 20 Hz. Therefore, the lower limit of the cyclic frequency interval is 30 and 15 respectively, and the upper limit of its interval is 200. The search interval of the CYCBD filter length is set to [10, 1500]. Using the method proposed...
in this paper, the optimal filter length of CMF1 is $L_1 = 862$, $T_1 = 40$; the optimal filter length of CMF2 is $L_2 = 920$, $T_2 = 20$. Noise reduction is performed on the CMF1 and CMF2 signals by using CYCBD with optimal parameters respectively, and the results are shown in Fig. 7.

From the envelope spectrum, it can be seen that at 40 Hz, 80 Hz, 100 Hz, 120 Hz, 160 Hz, and 200 Hz, there are significant peaks in the envelope spectrum, which correspond to the fault frequency and its doubling frequency, triple frequency, quadruple frequency and quintuple frequency respectively, and the spectral lines are obvious. Figure 7(b) shows the results for CMF 2. A clear periodic pulse can be observed. The peaks appear at 20 Hz, 40 Hz, 60 Hz, 80 Hz, and 100 Hz frequencies of the envelope spectrum, which are twice, three, four, and five times the fault frequency, respectively. Obviously, the results obtained by the optimized CYCBD are significantly better than those obtained by the EEMD. Therefore, the proposed optimization method using the envelope spectral dispersion entropy as the deconvolution iterative objective function can enhance the fault characteristics and improve the diagnostic performance.

IV. EXPERIMENTAL ANALYSES
A. CASE 1
In order to verify the reliability of this method, the measured data are selected for analysis, and the layout of the test bench is shown in Fig 8. As shown in Fig. 9, the fault of the rolling bearing with model NJ405 is the spalling of the inner ring, the fault of the rolling bearing with model NJ210 is the crack of the outer ring, and the faults are all artificially set. As for the test bed parameter settings, the sampling rate of the acceleration sensor is set at 10kHz, the sensitivity is set at 0.01V /ms-2, and the speed of the test bed is set at 500r/min. According to the bearing fault calculation theory, the fault characteristic frequency of NJ405 is 147Hz, and that of NJ210 is 231Hz.

Figure 10 is the measured original data, with a length of 10,000 sampling points selected. (b) is the frequency spectrum of the original signal, from which the fault frequency and other effective information cannot be extracted. Firstly, use EEMD to decompose the sampled signal. Figure 11 shows the EEMD decomposition result, (b) is the component spectrum. The correlation coefficient is shown in Table 2.
It can be seen from the figure 11(b) that IMF1 and IMF2 contain a lot of noise and the fault features are submerged, and IMF3, IMF4, IMF6 have the same fault features. Although the spectral lines of these components are rather confusing, it can be judged from the peak values of 147Hz, 588Hz, 735Hz and 882Hz that this is the fault frequency of the inner ring of the NJ405. It can be clearly seen from IMF5 that 231Hz is the fault frequency of NJ210. By reconstructing the components with the same fault frequency, the result is shown in Figure 12. CMF1 represents the fault reconstruction of NJ405, and CMF2 represents the fault reconstruction of NJ210, as shown in (a). (b) corresponds to the frequency spectrum of CMF1 and CMF2 respectively. It can be seen CMF1 from (b) that only the inner ring fault frequency and its fourth harmonic generation are obvious, but there are many interference frequencies near the fourth harmonic generation, and there is no second and third harmonic generation of fault frequency, so it is easy to be misdiagnosed. In CMF2, only the fault frequency of the outer ring is present, and no frequency multiplication occurs.

Therefore, it is necessary to adopt the adaptive CYCBD method. Firstly, set the CMF1 cycle frequency search range [73.5, 300] and filter length [10; 1200]. The cyclic frequency search range of CMF2 is [115.5, 500], and the filter length is [10; 1200]. The envelope spectrum dispersion entropy is used as the objective function of the chimp optimization algorithm. The search results are as follows: \([L, \alpha] = [147, 458]\) of CMF1; \([L, \alpha] = [231, 36]\) of CMF2. Using these parameters,
the optimization results of CYCBD are shown in Figure 13: the fault frequency extracted by CMF1 corresponds to 1 time, 2 times and 3 times of the fault frequency of the outer ring of the NJ405 bearing. The fault frequencies extracted by CMF 2 correspond to the fault frequencies of the outer ring of the NJ210 bearing. In this paper, the effectiveness of the method is fully verified.

B. CASE 2
In this paper, experimental data of rolling bearings in single-gear transmissions of new energy vehicles are used to verify the generality of the proposed fault diagnosis method. The main components of the test experiment bench include the test transmission, servo motor, acceleration sensor, and data acquisition device. As shown in Figure 14 the AC servo-electric is connected to the input and output of the transmission through a splined bushing. The transmission torque is loaded by the servo motor in a manner. The motor power is 2.4 KW, the speed range is 0-3000 r/min, and the maximum torque is 7.7 N.m. In order to verify the effectiveness of the proposed method, this paper diagnoses the compound fault of bearing and gear. The bearing and gear fault are defective, as shown in Figure 15. The vibration signal is acquired by using NI Compact DAQ 9234. The acceleration sensor model is PCB35233, and its sensitivity is 100m v/g. The sampling frequency is 12.8 KHz, and the input shaft speed is 1800 r/min. After calculation, the failure frequency of bearing is 183.5 Hz, and the failure frequency of gear is 540Hz.

Figure 16 shows the vibration signals collected by the accelerometer sensor mounted on the gearbox. It’s obvious from Figure 16 (b) that the peaks are relatively high at 183.5 Hz and 367 HZ, which correspond to failure frequency of outer ring of bearing and its double frequency respectively. There is no obvious peak at 540Hz, which indicates that the gear fault frequency is submerged by noise, and the gear
fault characteristic frequency cannot be determined in the spectrum.

A fault signal is decomposed by EEMD, and the results are shown in Figure 17. The correlation coefficients are shown in Table 3. It can be seen from the figure 17(b) that IMF1 contains a large amount of high-frequency noise and the fault features are drowned out. IMF2, IMF3, IMF4 have serious modal mixing phenomenon, and the same fault feature is decomposed into different components. Although spectral lines of these components are confusing, the frequencies of the three components can be judged according to the peaks of 367HZ, 367HZ, and 183.5HZ, corresponding to the outer ring fault frequency and its two times respectively. It is obvious from IMF5 that the gear has a fault frequency of 540HZ.

The decomposition structure is reconstructed in order to eliminate the modal mixing phenomenon and enhance the fault features. First, the high-frequency noise component of IMF1 is removed, and then the components containing the same fault features are summed. In other words, IMF2, IMF3 and IMF4 are summed and reconstructed as CMF1, and IMF5 is kept as CMF2. IMF6 to IMF8, which do not contain the fault feature information, are removed. The reconstructed result is shown in Fig. 18, and the envelope processing is shown in Fig. 18(b). From Fig. 18(b), it can be found that the spectral lines are confusing, and there are many interference frequencies around the fault characteristic frequency, which is easy to cause misdiagnosis. layers, which do not contain the fault feature information, are removed. The reconstructed
The correlation coefficients of IMFs.

| IMF   | IMF1 | IMF2 | IMF3 | IMF4 | IMF5 | IMF6 | IMF7 | IMF8 |
|-------|------|------|------|------|------|------|------|------|
| Coefficient | 0.889 | 0.523 | 0.113 | 0.0409 | 0.0312 | 0.0107 | 0.0093 | 0.0026 |

The reconstructed signal is processed according to the method in this paper, and the results are shown in Figure 19. According to a priori analog signal, in order to improve the extraction efficiency and accuracy, the initial length of the filter is set to 10, the end length is 1200, and the initial values of the search loop frequency are 91.7 and 270, respectively. The end values are set to 300 and 1000 respectively. The dispersion entropy of envelope spectrum is used as the iterative objective function to optimize the chimp algorithm, which improves the performance of CYCBD parameter adapt-
In order to fully illustrate the advantages of the method in this paper, the reconstructed signal is processed by MCKD, and the results are compared with the results of MCKD.

MCKD processes the reconstructed components, and the results are shown in Figure 20. It can be observed that only a limited number of pulses can be extracted by MCKD, which is the result of its principle. Figure 20 (b) shows the envelope analysis of the results of MCKD. Since the number of points corresponding to the CMF1 and CMF2 period is not equal to an integer, the MCKD performs the resampling process. This causes the frequency in the envelope spectrum to deviate from the fault frequency. Moreover, the spectrum lines in the envelope spectrum are confusing, which can easily cause misdiagnosis. Therefore, the proposed method in this paper is superior to MCKD.

V. CONCLUSION
In order to solve the transmission compound fault diagnosis problem, a CHOA-based parameter adaptive CYCBD feature extraction method is studied. CHOA is introduced to determine the optimal parameters for CYCBD. The algorithm has its unique advantages and it updates the position of a single search agent by involving all search agents. The results of the current work can be summarized as follows: (a) The extraction effect of CYCBD is influenced by the cycle frequency and filter length, and these two parameters have different effects on the results. The two optimal parameters are determined simultaneously the chimpanzee algorithm, thus making CYCBD adaptive. (b) The envelope spectral dispersion entropy can accurately indicate the variation of the signal, and more shock faults can be extracted by using the envelope spectral dispersion entropy as the objective function of the optimization algorithm. (c) Using the combination of CYCBD and EEIMD, the noise reduction of the decomposed signal by using CYCBD method can further enhance the energy of the shock model to realize the diagnosis of compound faults, and also provide new ideas for extracting weak shock faults in compound faults.

REFERENCES

[1] H. Endo and R. Randall, “Enhancement of autoregressive model based gear tooth fault detection technique by the use of minimum entropy deconvolution filter,” Mech. Syst. Signal Process., vol. 21, no. 2, pp. 906–919, Feb. 2007.
[2] D. He, X. Wang, S. Li, J. Lin, and M. Zhao, “Identification of multiple faults in rotating machinery based on minimum entropy deconvolution combined with spectral kurtosis,” Mech. Syst. Signal Process., vol. 81, pp. 235–249, Dec. 2016.
[3] G. L. McDonald and Q. Zhao, “Multipoint optimal minimum entropy deconvolution and convolution fix: Application to vibration fault detection,” Mech. Syst. Signal Process., vol. 82, pp. 461–477, Jan. 2017.
[4] M. Buzzoni, J. Antoni, and G. D’Elia, “Blind deconvolution based on cyclostationarity maximization and its application to fault identification,” J. Sound Vib., vol. 432, pp. 569–601, Oct. 2018.
[5] Z. Wang, Z. Han, and Q. Liu, “Weak fault diagnosis for rolling element bearing based on MED-EEMD,” Trans. Chin. Soc. Agricult. Eng., vol. 30, no. 23, pp. 70–78, 2014.
[6] F. Jia, Y. Lei, H. Shan, and J. Lin, “Early fault diagnosis of bearings using an improved spectral kurtosis by maximum correlated kurtosis deconvolution,” Sensors, vol. 15, no. 11, pp. 29563–29577, Nov. 2015.
[7] Z. Wang, W. Du, J. Wang, J. Zhou, X. Han, Z. Zhang, and L. Huang, “Research andapplication of improved adaptive MOMEDA fault diagnosis method,” Measurement, vol. 140, pp. 63–75, Jul. 2019.
[8] Q. Zhang, H. Pan, Q. Fan, F. Xu, and Y. Wu, “Research on fault extraction method of CYCBD based on seagull optimization algorithm,” Shock Vibrat., vol. 2021, pp. 1–11, Jul. 2021.
[9] X. Wang, G. Tang, and Y. He, “Application of RSSD-OCYCBD strategy in enhanced fault detection of rolling bearing,” Complexity, vol. 2020, pp. 1–24, Feb. 2020.
[10] Z. Wang, J. Zhou, W. Du, Y. Lei, and J. Wang, “Bearing fault diagnosis method based on adaptive maximum cyclostationarity blind deconvolution,” Mech. Syst. Signal Process., vol. 162, Jan. 2022, Art. no. 108018.
[11] Z. Wang, W. Zhao, W. Du, N. Li, and J. Wang, “Data-driven fault diagnosis method based on the conversion of erosion operation signals into images and convolutional neural network,” Proc. Saf. Environ. Protection, vol. 149, pp. 591–601, May 2021.
[12] M. Rostaghi and H. Azami, “Dispersion entropy: A measure for time-series analysis,” IEEE Signal Process. Lett., vol. 23, no. 5, pp. 610–614, May 2016.
[13] F. Xu, P. W. T. Tse, Y. J. Fang, and J. Liang, “A fault diagnosis method combined with compound multiscale permutation entropy and particle swarm optimization—support vector machine for roller bearings diagnosis,” Proc. Inst. Mech. Eng., J. J. Eng. Tribol., vol. 233, no. 4, pp. 615–627, Apr. 2019.
Committee.

Shanxi Vibration Engineering Society and Shanxi Tribology Professional Mechanical Engineering Society. He is also the Executive Director of the 8th and 9th Committee (Director) of Tribology Branch, Chinese

[14] J. Ma, Z. Li, C. Li, L. Zhan, and G.-Z. Zhang, “Rolling bearing fault diagnosis based on refined composite multi-scale approximate entropy and optimized probabilistic neural network,” *Entropy*, vol. 23, no. 2, p. 259, Feb. 2021.

[15] M. Rostaghi, M. R. Ashory, and H. Azami, “Application of dispersion entropy to status characterization of rotary machines,” *J. Sound Vibrat.*, vol. 438, pp. 291–308, Jan. 2019.

[16] M. Khishe and M. R. Mosavi, “Chimp optimization algorithm,” *Expert Syst. Appl.*, vol. 149, Jul. 2020, Art. no. 113338.

[17] L. S. Dhamande and M. B. Chaudhari, “Compound gear-bearing fault feature extraction using statistical features based on time-frequency method,” *Measurement*, vol. 125, pp. 63–77, Sep. 2018.

[18] N. Li, W. Huang, W. Guo, G. Gao, and Z. Zhu, “Multiple enhanced sparse decomposition for gearbox compound fault diagnosis,” *IEEE Trans. Instrum. Meas.*, vol. 69, no. 3, pp. 770–781, Mar. 2020.

[19] Y. Jiang, C. Tang, X. Zhang, W. Jiao, G. Li, and T. Huang, “A novel rolling bearing defect detection method based on bispectrum analysis and cloud model-improved EEMD,” *IEEE Access*, vol. 8, pp. 24323–24333, 2020.

[20] J. Chen, J. Rostami, P. W. Tse, and X. Wan, “The design of a novel mother wavelet that is tailor-made for continuous wavelet transform in extracting defect-related features from reflected guided wave signals,” *Measurement*, vol. 110, pp. 176–191, Nov. 2017.

[21] J. Wang, J. Li, H. Wang, and L. Guo, “Composite fault diagnosis of gearbox based on empirical mode decomposition and improved variational mode decomposition,” *J. Low Freq. Noise, Vibrat. Act. Control*, vol. 40, no. 1, pp. 332–346, Mar. 2021.

[22] Y. Xu, K. Zhang, C. Ma, S. Li, and H. Zhang, “Optimized LMD method and its applications in rolling bearing fault diagnosis,” *Meas. Sci. Technol.*, vol. 30, no. 12, Dec. 2019, Art. no. 125017.

[23] J. Ding, D. Xiao, and X. Li, “Gear fault diagnosis based on genetic mutation particle swarm optimization VMD and probabilistic neural network algorithm,” *IEEE Access*, vol. 8, pp. 18456–18474, 2020.

[24] Z. Wang, N. Yang, N. Li, W. Du, and J. Wang, “A new fault diagnosis method based on adaptive spectrum mode extraction,” *Struct. Health Monitor.*, Jan. 2021, Art. no. 147592172098694.

[25] Z. Wang, H. He, J. Wang, and W. Du, “Application research of a novel enhanced SSD method in composite fault diagnosis of wind power gearbox,” *IEEE Access*, vol. 7, pp. 154986–155001, 2019.

[26] J. Gu and Y. Peng, “An improved complementary ensemble empirical mode decomposition method and its application in rolling bearing fault diagnosis,” *Digit. Signal Process.*, vol. 113, Jun. 2021, Art. no. 103050.

[27] Z. Wang, J. Zhou, J. Wang, W. Du, J. Wang, X. Han, and G. He, “A novel fault diagnosis method of gearbox based on maximum kurtosis spectral entropy deconvolution,” *IEEE Access*, vol. 7, pp. 29520–29532, Feb. 2019.

**HUER SUN** received the Ph.D. degree from Taiyuan University of Technology, Taiyuan, China. He is currently an Associate Professor with the North University of China. He is mainly engaged in the research of mechanical equipment condition and intelligent diagnosis, tribological science and engineering, intelligent robotics, and new energy vehicle transmission system testing technology. He is a Senior Member of Chinese Mechanical Engineering Society, and a member of the 8th and 9th Committee (Director) of Tribology Branch, Chinese Mechanical Engineering Society. He is also the Executive Director of Shanxi Vibration Engineering Society and Shanxi Tribology Professional Committee.

**FUWANG LIANG** received the bachelor’s degree from Taiyuan University of Technology, Taiyuan, China, in 2018. He is currently pursuing the master’s degree with the School of Mechanical Engineering, North University of China, Taiyuan. His research interests include mechanical fault diagnosis and signal processing.

**YUTAO LIU** received the bachelor’s degree in engineering from the College of Information, Shanxi Agricultural University. He is currently pursuing the master’s degree in engineering with the North University of China. His research interests include mechanical fault diagnosis and signal processing.

**KEKIN LIU** received the bachelor’s degree from Taiyuan University of Technology, Taiyuan, China, in 2018. She is currently pursuing the master’s degree with the School of Mechanical Engineering, North University of China, Taiyuan. Her research interests include mechanical fault diagnosis and signal processing.

**ZHIJIAN WANG** received the Ph.D. degree from Taiyuan University of Technology, Taiyuan, China. He is currently a Professor with the North University of China. He has published more than a dozen articles in these areas. He is a member of Chinese Society of Vibration Engineering.

**TIANYUAN ZHANG** received the bachelor's degree from Shenyang Institute of Technology, Fushun, China, in 2020. He is currently pursuing the master’s degree with the School of Mechanical Engineering, North University of China, Taiyuan, China. His research interests include mechanical fault diagnosis and signal processing.

**JIYANG ZHU** received the bachelor’s degree from the North University of China, Taiyuan, China, in 2019, where he is currently pursuing the master’s degree with the School of Mechanical Engineering. His research interests include mechanical fault diagnosis and signal processing.

**YANG ZHAO** received the bachelor’s degree from Shanxi Datong University, Datong, China, in 2019. He is currently pursuing the master’s degree with the School of Mechanical Engineering, North University of China, Taiyuan, China. His research interests include mechanical fault diagnosis and signal processing.

---

**HUER SUN**

**FUWANG LIANG**

**YUTAO LIU**

**KEKIN LIU**

**ZHIJIAN WANG**

**TIANYUAN ZHANG**

**JIYANG ZHU**

**YANG ZHAO**