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Fault diagnosis of gearbox based on improved polynomial adaptive chirp mode decomposition algorithm

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Abstract: The adaptive chirp mode decomposition (ACMD) has good time-frequency representation results in analyzing chirp signals, while there is a time-frequency ambiguity problem in the analysis of variable speed planetary gearbox vibration signals. To address this problem, a planetary gearbox fault diagnosis method based on improved polynomial adaptive chirp mode decomposition wavelet is proposed (IPACMD). Using Adaptive chirp mode decomposition, the amplitude and instantaneous frequency of multiple signal components are estimated; To avoid over-decomposition to generate spurious signal components, the similarity conditional entropy is used to optimize the adaptive chirp mode decomposition threshold ;The polynomial chirp transform (PCT) using a polynomial function instead of the linear chirp kernel in the chirp transform to improve the time-frequency aggregation of the instantaneous frequency curve of each signal component and output high-resolution time-frequency representation results. Compared with the original method, the proposed method has better time-frequency aggregation and is more effective for the analysis of variable speed planetary gearbox vibration signals. The simulation and experimental study results show that the method can effectively identify the frequency components and time-frequency characteristics of the variable-speed planetary gearbox vibration signal and realize the fault diagnosis of the planetary gearbox.

Keywords: Time-frequency analysis (TFA), Adaptive chirp mode decomposition (ACMD), Instantaneous frequency (IF), Polynomial chirplet transform (PCT), Fault pattern recognition

1 Introduction

In the fault diagnosis of variable speed planetary gearboxes, the extraction of the fault characteristic frequency of the signal and its amplitude variation is the key to fault diagnosis. As the operating conditions, load and speed parameters of the planetary gearbox change, the fault characteristic frequency and amplitude of the planetary gearbox also change with the load and speed, and the mechanical system generates a non-stationary signal of the fault characteristics over time^{[1] [2]}. Niu et al. ^[3,4] have effectively improved the machining accuracy of machine tools by investigating the effect of interference factors inside the planetary gearbox. In addition, the early fault features are weak and easily disturbed by environmental noise, and it is difficult to extract the fault feature frequencies by traditional time domain and frequency domain methods. Therefore, it is important to study the time-varying working condition planetary gearbox fault feature extraction method.

Time-frequency analysis uses a combined time-domain and frequency-domain distribution to describe the frequency components and time-varying trends of a signal. Huang E ^[5] proposed the Empirical mode decomposition (EMD) method, which uses a recursive screening algorithm to find each signal component with adaptive decomposition characteristics. Lei Y et al ^[6] applied EMD to rolling bearing fault diagnosis, but EMD is an empirical algorithm with problems such as modal confusion and endpoint effects ^[7], which affects the fault diagnosis effect. To avoid the limitations of EMD, many alternative methods are generated. Feng et al ^[8] used Ensemble Empirical mode decomposition (EEMD) to extract the features of the modulated time-varying signals. The modulated time-varying signal and successfully identified the failure of the sun gear in the planetary gear system. Liu et al ^[9] used the Local Mean Decomposition (LMD) method to decompose the multicomponent signals and successfully extracted the fault characteristics of the planetary gear system. Empirical Wavelet Transform (EWT) ^[10,11] decomposed the multicomponent time-varying signal into single frequency components and successfully accomplished the fault diagnosis of bearings. Variational mode decomposition (VMD) ^[12] was used to extract faulty bearing signal features in wind turbines. In addition, researchers used an iterative generalized synchronous compression transform, which draws the advantages of the synchronous compression transform and makes the time-frequency features more readable ^[13]. The High-Order Synchrosqueezing Transform (HSST) uses an accurate instantaneous frequency approximation to obtain a clear time-frequency signature. However, these methods still have some drawbacks in gearbox fault diagnosis; EEMD based on empirical mode decomposition suffers from modal aliasing ^[14]; LMD is less effective in dealing with narrowband signals; the processing effectiveness of EWT and VMD depends largely on the choice of parameters, which is difficult to be applied in practice; HSST is proposed on the basis of synchronous compression transform when evaluating strong time-varying modulated signals in noisy environments, a high time-frequency resolution is required, which makes the calculation process complicated and affects the practical application of engineering. To address the shortcomings of the above time-frequency analysis methods, Chen et al ^[15] proposed the variational nonlinear chirp mode decomposition (VNCMD) method, which not only extracts all signal components of the non-stationary vibration signal, but also accurately estimates the instantaneous frequency. And further proposed a more adaptive and stable method called Adaptive chirp mode decomposition (ACMD) ^[16,17]. This method can effectively extract all signal components of the non-stationary vibration signal and has good advantages in non-stationary vibration signal decomposition and instantaneous frequency estimation. However, in variable speed gearbox fault diagnosis, ACMD has the phenomenon of over-decomposition, which is difficult to handle signals with many signal components and time-varying frequencies, and the obtained results have low time-frequency aggregation, which is difficult to meet the requirements of variable speed gearbox fault diagnosis.

In order to solve the limitations of the traditional time-frequency analysis method for processing variable speed gearbox signals, an improved polynomial adaptive frequency modulation mode decomposition (IPACMD) method is proposed in this

paper. The similarity conditional entropy alternative to the residual energy to the original signal energy ratio is introduced as a new decomposition termination threshold condition to optimize the ACMD algorithm and solve the problem of signal over-decomposition; the polynomial chirplet transform (PCT) method is applied to replace the linear chirp of the traditional chirp transform by constructing a polynomial matching transform kernel function. The polynomial chirplet transform (PCT) method is applied to replace the linear chirp function of the traditional chirp transform by constructing a polynomial matching transform kernel function, which achieves higher time-frequency aggregation and improves the initial instantaneous frequency extraction accuracy. The IPACMD method is verified by simulation and experimental signals, which can effectively avoid the over-decomposition phenomenon, extract the key feature components, construct the time-frequency curve with high time-frequency aggregation and clearly represent the vibration signal fault characteristics.

2 The principle of ACMD

This paper focuses on the analysis of the gearbox vibration signal, and the gearbox signal contains multiple non-stationary vibration signal components, and the multi-component non-stationary signal is modeled as:

$$x(t) = \sum_{k=1}^K a_k(t) \cos \left[2\pi \int_0^t f_k(t) dt + \varphi_k \right] \quad (1)$$

where K is the number of signal components, $a_k(t) > 0$, $f_k(t) > 0$, φ_k denotes the initial phase of the k th signal component, and f_k denotes the instantaneous frequency of the k th signal component. According to the triangular constant transformation, the k th signal component in Eq. (1) as:

$$\begin{aligned} x_k(t) &= \alpha_k(t) \cos \left[2\pi \int_0^t \tilde{f}_k(t) dt \right] + \beta_k(t) \sin \left[2\pi \int_0^t \tilde{f}_k(t) dt \right] \\ &\begin{cases} \alpha_k(t) = a_k(t) \cos \left\{ 2\pi \int_0^t |f_k(t) - \tilde{f}_k(t)| dt + \varphi_i \right\} \\ \beta_k(t) = -a_k(t) \sin \left\{ 2\pi \int_0^t |f_k(t) - \tilde{f}_k(t)| dt + \varphi_i \right\} \end{cases} \end{aligned} \quad (2)$$

where $\tilde{f}_k$ is the target frequency function and $\alpha_k(t)$ and $\beta_k(t)$ represent the two chirp signals. ACMD uses a matching tracking algorithm to adaptively extract the components of the target signal, and the model for the k th component sought as:

$$\min_{\alpha_k(t), \beta_k(t), \tilde{f}_k(t)} \{ \|\alpha_k''(t)\|_2^2 + \|\beta_k''(t)\|_2^2 + \tau \|x(t) - x_k(t)\|_2^2 \} \quad (3)$$

where is $x(t)$ the input signal, $x_k(t)$ is the target signal component that should be extracted, $\|\cdot\|_2$ represents the l_2 norm, $(*)''$ represents the second-order derivative, and τ represents the penalty parameter.

Assume that the signal is discretized into N points, i.e., $t=t_0:t_{(N-1)}$. The objective function matrix can be obtained by bringing Eq.2 into Eq.4:

$$\min_{s_k, M_k} \{ \|\Omega s_k\|_2^2 + \tau \|x - M_k s_k\|_2^2 \} \quad (4)$$

where $\Omega = \begin{pmatrix} \mathbf{H} & \\ & \mathbf{H} \end{pmatrix}$. $\mathbf{H}$ is a second-order difference matrix, $s_k = [\alpha_k^T, \beta_k^T]^T$, $x = [x(t_0):x(t_{N-1})]^T$, $M_k = [c_k, d_k]$, and c_k and d_k satisfy the condition that:

$$\begin{aligned} c_k &= \text{diag}[\cos(\varphi_k(t_0)), \dots, \cos(\varphi_k(t_{N-1}))] \\ d_k &= \text{diag}[\sin(\varphi_k(t_0)), \dots, \sin(\varphi_k(t_{N-1}))] \end{aligned} \quad (5)$$

where $\varphi_k = 2\pi \int_0^t \tilde{f}_k(t) dt$. In order to solve Eq. (5) minimally and optimally, the target signal s_k and the frequency function $\tilde{f}_k(t)$ are updated alternately by means of iterations. Then, after the m th iteration, the target signal is represented as :

$$s_k^m = \left(\frac{1}{\tau} \Omega^T \Omega + (M_k^m)^T M_k^m \right)^{-1} (M_k^m)^T x \quad (6)$$

the signal components sought as:

$$x_k^m = M_k^m s_k^m \quad (7)$$

the transformation of frequency can be obtained as:

$$\Delta \tilde{f}_k^m(t) = -\frac{1}{2\pi} \frac{d}{dt} \left[\tan^{-1} \frac{\beta_k(t)}{\alpha_k(t)} \right] \quad (8)$$

then the required instantaneous frequency as:

$$f_k^{m+1} = f_k^m + \left(\frac{1}{\sigma} \Omega^T \Omega + I \right)^{-1} \Delta \tilde{f}_k^m(t) \quad (9)$$

where I is the unit matrix and σ is the weighting factor. The individual signal components of $x(t)$ can be obtained after several iterations.

3 Improved polynomial adaptive chirp mode decomposition

3.1 Polynomial chirp wavelet transform

According to the non-stationary vibration signal model established in the previous section, polynomial matching kernel parameters are constructed [18], and when the kernel parameters and the signal model are in better agreement, then high time-frequency aggregation can be obtained. The time-varying speed gearbox signal has the characteristics of nonlinear frequency modulation, and the polynomial frequency modulation wavelet transform kernel parameter signal model can be constructed as:

$$z(t) = A \exp \left(j 2\pi \sum_{i=1}^{n+1} \frac{1}{i} a_{i-1} t^i \right) \quad (10)$$

where a_n is the polynomial coefficient and n is the number of polynomials, the instantaneous frequency is:

$$IF(t) = \sum_{i=1}^{n+1} a_{i-1} t^i \quad (11)$$

construct the polynomial transformation kernel function $m_p(t)$ as:

$$m_p(t) = \sum_{i=2}^{n+1} c_{i-1} t^i \quad (12)$$

where c_n is the polynomial coefficient, then the polynomial chirp wavelet transform is:

$$\begin{aligned} PCT(t_0, \omega; \alpha_1, \dots, \alpha_n, \sigma) &= \int_{-\infty}^{+\infty} \bar{z}(t) \omega_\sigma(t - t_0) \exp(-j\omega t) dt \\ \bar{z} &= z(t) \Phi^R(t; \alpha_1, \dots, \alpha_n) \Phi^S(t; t_0, \alpha_1, \dots, \alpha_n) \\ \Phi^R(t; \alpha_1, \dots, \alpha_n) &= \exp\left(-j \sum_{k=2}^{n+1} \frac{1}{k} \alpha_{k-1} t^k\right) \\ \Phi^S(t; t_0, \alpha_1, \dots, \alpha_n) &= \exp\left[j \left(\sum_{k=2}^{n+1} \frac{1}{k} \alpha_{k-1} t^k\right) t\right] \end{aligned} \quad (13)$$

where t_0 and t represent the window of the time span of the sliding analysis centered on the time span of the analysis and the window of the constant centered on t_0 . $\omega_\sigma(t)$ is a Gaussian window function:

$$\omega_\sigma(t) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left[-\frac{1}{2} \left(\frac{t}{\sigma}\right)^2\right] \quad (14)$$

the PCT algorithm is able to concentrate energy along each signal instantaneous frequency and has good interference immunity, we use the PCT algorithm to provide the initial instantaneous frequency for the ACMD algorithm.

3.2 Similarity conditional entropy termination criterion

The iteration stopping threshold in the ACMD algorithm is based on stopping when the ratio of the residual signal energy to the original signal falls below ε :

$$\frac{\|x_k^m - x_k^{m-1}\|_2^2}{\|x_k^{m-1}\|_2^2} < \varepsilon \quad (15)$$

However, this criterion fails in some cases of low signal amplitude energy, where the energy ratio of the decomposed signal to the original signal is as high as 0.1361 ($\varepsilon \leq 0.1$), as shown in Figure 1. At this time, ACMD has completed the decomposition of the signal to extract the signal frequency and amplitude information, which, according to the original stopping criterion, cannot properly stop the ACMD decomposition, leading to over-decomposition. In order to avoid this situation, this paper introduces the similarity conditional entropy to replace the original stopping criterion of the remaining signal energy ratio. The similarity conditional entropy can effectively measure the interdependence between two variables and identify the degree of correlation.

Fig.1 Comparison of original signal and decomposed signal at low amplitude energy

The mutual correlation information of two discrete random variables X and Y can be defined as:

$$CI(X, Y) = H(Y) - H(Y|X) \quad (16)$$

where $H(Y)$ is the similar conditional entropy of variable Y and $H(Y|X)$ is the uncertainty of variable Y conditional on variable X .

$$H(Y) = -\sum_{i=1}^n p(y_i) \log p(y_i)$$

$$H(Y|X) = -\sum_{x \in X} \sum_{y \in Y} p(x, y) \log p(y|x) \quad (17)$$

When X is known, the weaker the correlation between X and Y , the larger $H(Y|X)$ is. Therefore, $CI(X, Y)$ is small when the correlation between X and Y is weak. Whether the residual signal contains important information of the original vibration signal should be the stopping criterion for ACMD decomposition.

The original gearbox signal is preprocessed using ACMD, and the preprocessing result is denoted as x_i , which contains much less noise than the original signal. Assuming that k signal components $x_i (i = 1, \dots, k)$ are obtained, the residual signal is represented as:

$$r_i = x_i - \sum_{i=1}^k x_i \quad (18)$$

The mutual information between the residual signals r_i and x_i is $CI(r_i, x_i)$. Set 0.02 as the stopping threshold of decomposition, when $CI(r_i, x_i)$ is lower than 0.02, the residual signal is considered to contain little useful information of the gearbox signal. By the similarity conditional entropy termination criterion, the ACMD decomposition can stop the decomposition in time to avoid the overdecomposition phenomenon.

3.3 Improved polynomial adaptive chirp mode decomposition

In the application of variable speed gearbox fault diagnosis, the fault characteristic frequency of vibration signal changes with the speed, the vibration shock is not periodic, and the traditional time domain and frequency domain methods are difficult to reflect its non-stationary and time-varying characteristics. For gearbox vibration signals, this paper proposes an improved polynomial adaptive chirp mode decomposition method with the following procedure.

(1) The signal is STFT transformed to obtain ridge 1, and the initial transform kernel parameters are obtained by fitting a polynomial to ridge 1 using the least squares

method.

(2) The signal is polynomially wavelet chirp transformed according to the initial transform kernel parameters to obtain ridge 2, and a polynomial fit to ridge 2 is performed by the least squares method to obtain parameter 2 replacing parameter 1.

(3) Determine whether the transformation kernel parameter 2 is optimal, if it is optimal, end the process and output the instantaneous frequency result, if it is not optimal, set parameter 2 as the initial transformation kernel parameter and repeat step (2).

(4) After the initial instantaneous frequency is obtained, the target signal function s_k and signal components x_k^m are iteratively updated according to equations (6) and (7).

(5) The instantaneous frequency increment $\Delta \tilde{f}_k^m(t)$ and the instantaneous frequency f_k^{m+1} are calculated according to equations (8) and (9).

(6) When the similarity condition entropy stop condition is satisfied, i.e., even the residual signal basically does not contain fault characteristic information, the iteration stops and the signal component and instantaneous frequency are output; otherwise, return to step (4) to continue the cyclic process, and the decomposition process is shown in Fig.2.

Fig.2 Flow chart of IPACMD

4. Simulation signal analysis

4.1 Polynomial chirp wavelet transform

The IPACMD for non-stationary signals is investigated in this paper, and the simulated signals are composed of two non-stationary signals that are very close in the time-frequency plane.

$$\begin{aligned} x_1(t) &= (1 + 0.3 \sin 3\pi t) \times \cos[2\pi(130t + 150t^2) + \sin 20\pi t] \\ x_2(t) &= (1 + 0.3 \cos 3\pi t) \times \cos[2\pi(80t + 150t^2) + \sin 20\pi t] \\ x(t) &= x_1 + x_2 \end{aligned} \quad (19)$$

the instantaneous frequencies of the two signal modes are : $IF_1 = 130 + 300t + 10 \cos 20\pi t$, $IF_2 = 80 + 300t + 10 \cos 20\pi t$, the signal waveform is shown in Fig.3

Using the traditional time-frequency analysis method for initial instantaneous frequency prediction of the signals, the extracted time-frequency result ridges cannot reveal the correct instantaneous frequencies due to the interference between the two signal frequencies that are relatively close and affected by noise, as shown in Figure 4. By comparing the time-frequency results obtained by ACMD and IPACMD, it can be observed that ACMD has serious energy diffusion and loss in the interference region of the two signal components, as shown in Fig. 5, which cannot clearly represent the time-frequency structure of the signal. On the contrary, the time-frequency image obtained by IPACMD has good time-frequency aggregation, as shown in Figure 6, which can effectively resolve the two close signal components and clearly reveal the time-varying instantaneous amplitude and instantaneous frequency. The time-domain waveform corresponding to each item is shown in Figure 3, and the time-domain waveform and envelope spectrum of the original simulation signal are shown in Figure 4.

The results show that IPACMD can further optimize the instantaneous frequency and extract the signal components with closer frequencies, and well balance the signal energy of these two close components, so as to accurately estimate the instantaneous frequency and reconstruct the signal components. It has a good effect on the extraction of signal components.

Fig.3 Time domain waveform of the simulated signal Fig.4 Time-frequency results of STFT

Fig.5 Time-frequency results of ACMD

Fig.6 Time-frequency results of IPACMD

4.2 Analysis of fault simulation signal of variable speed planetary gearbox

When the variable speed planetary gearbox has a local wear fault of the sun wheel, the vibration signal has a steady state chirp signal with the engagement frequency as the carrier frequency and the gear rotation frequency and its multiplier as the modulation frequency, and there is also a periodic shock amplitude modulation signal.

According to the characteristics of the vibration signal, the simulation signal is constructed as:

$$x(t) = \left[1 - \cos \left(2\pi \int f_{sr}(t) dt \right) \right] \left[1 + A \cos \left(2\pi \int f_s(t) dt + \phi \right) \right] \times \cos[2\pi \int f_m(t) dt + B \sin(2\pi \int f_s(t) dt + \varphi) + \theta] + n(t) \quad (20)$$

ere $f_{sr}(t)$ is the rotation frequency, $f_m(t)$ is the engagement frequency, the local wear fault characteristic frequency is $f_s(t)$, A and B are the modulation coefficients, and ϕ , φ and θ are the phases. Let $A = 0.6$, $B = 0.05$, $\phi = \varphi = \theta = 0$, and $n(t)$ be the white noise with a signal-to-noise ratio of 0.5 dB.

The configuration of the number of teeth of the planetary gearbox is shown in Table 1, and according to the data in the table, we can get $f_{sr}(t) = -12t^2 + 12t + 15$,

$$f_m(t) = \left(\frac{50}{3}\right) f_{sr}(t), \quad f_s(t) = \left(\frac{10}{3}\right) f_{sr}(t).$$

The simulated signal waveform, spectrum and time-frequency spectrum of Eq. (21) are shown in Figs. 7, 8 and 9. From Fig. 8, it can be seen that the speed variation leads to the blurring phenomenon of frequencies in the spectrum plot and the confusion of the engagement frequency and its side frequencies. As shown in Figure 9, the time-frequency spectrum obtained by STFT is not able to represent these signal components clearly due to the interference of noise and poor resolution.

Therefore, using the IPACMD to process the simulated signal, as shown in Fig. 10(b), the proposed method can clearly identify the fault feature components, and the time-frequency image obtained by the IPACMD method correctly reveals the instantaneous frequencies and energies that shift with time compared to the time-frequency ridges obtained by the ACMD algorithm (as shown in Fig. 10(a)). According to the characteristic frequencies given in the simulated signals, the three and their combined frequencies of sun wheel wear fault characteristic frequency, gear meshing frequency and sun wheel absolute rotation frequency are successfully separated and extracted in

the time-frequency map obtained by the proposed method, as shown by the logo in the figure. The ability of the method to handle the time-varying features of the variable speed gearbox fault signal under strong noise conditions is demonstrated.

Therefore, IPACMD results can be applied to the separation and analysis of variable speed gearbox fault signal feature extraction. The simulation results show that the method can effectively extract the time-varying features of the non-stationary vibration signal under strong noise conditions.

Table 1 Planetary gearbox parameters

Parameters	Gearbox first stage	Gearbox second stage
Ring gear teeth	100	100
Planetary wheel teeth Number	40 (3)	36 (4)
Solar tooth number	20	28

Fig.7 Time domain waveform of a simulated signal

Fig.8 Frequency domain waveform of a simulated signal

Fig.9 Time-frequency results of STFT processing of variable speed planetary gearbox fault simulation signals

(a) Time-frequency diagram of ACMD processing

(b) Time-frequency diagram of IPACMD processing

Fig.10 Comparison results between the improved method and the original algorithm

4. Experimental Signal Analysis of Planetary Gearbox Sun Wheel Failure

In this section, IPACMD is used to analyze the experimental signals of localized faults in the sun wheel of the planetary gearbox. Figure 11 shows the planetary gear train test bench, and the gearbox parameters are shown in Table 2. The experimental procedure was performed by testing the vibration signal through the acceleration sensor on the top of the gearbox case with a sampling frequency of 20 kHz, and the signal acquisition was performed during the growth of the motor speed from 12 Hz to 20 Hz. In order to simulate gear failure, spalling damage was machined on a certain gear of the 1st stage sun wheel.

Since the characteristic frequency changes with time, it is difficult to determine the fault characteristics from the waveform and frequency peaks. As shown in Figure 15, the STFT, due to the fixed window function, although the trend of frequency is well represented at 0.5-1s, there is obvious mixing and interference between frequencies at 0-0.5s, where the frequencies are closer, and the obtained time-frequency images are not able to clearly represent these signal components.

IPACMD can effectively deal with the closer frequency components and can effectively avoid the mutual influence between adjacent components, as shown in Figure 16(b). IPACMD separates the time-varying frequency components and obtains the results with high time-frequency accuracy. While the ACMD algorithm obtains time-frequency ridges (as shown in Fig. 16(a)), although it has better components for signal components in the 0.5-1s part, due to the reason of insufficient accuracy of instantaneous frequency extraction, there is obvious mixing between frequency components in the part with small frequency interval of 0-0.5s, and the frequency components of the signal cannot be accurately identified.

Therefore, IPACMD solves the problem of frequency component crossover and interference, and combines the PCT method with similarity conditional entropy to solve the problem of insufficient accuracy and over-decomposition of initial instantaneous frequency acquisition. It can effectively analyze the complex time-frequency structure of the planetary gearbox under time-varying speed, as shown by the logo in Fig. 16(b). Among them, the main frequency is the difference between the meshing frequency and the solar path fault characteristic frequency $f_m - f_s$, whose energy is significantly

enhanced in 0~1s. In addition, the sum of the engagement frequency and the fault characteristic frequency $f_m + f_s$, the engagement frequency f_m , the difference between the engagement frequency and the solar wheel rotation frequency $f_m - f_{sr}$, and the associated combined frequencies are also present. These features prove the existence of a localized fault in the sun wheel, which is consistent with the experimental reality.

In summary, IPACMD method can more clearly and accurately represent the vibration signal components of gearboxes at time-varying speeds than the ACMD algorithm, and the experimental data test results show that the method can effectively extract the fault characteristics of variable speed gearboxes

Table 2 Planetary gearbox parameters

Parameters	Gearbox first stage	Gearbox second stage
Ring gear teeth	100	100
Planetary wheel teeth Number	40 (4)	36 (4)
Solar tooth number	20	28

Fig.11 Planetary gear transmission system test bench

Fig.12 Time domain of a experimental signal

Fig.13 Frequency domain of a experimental signal

Fig.14 Measured rotational speed of the driving motor

Fig.15 Time-frequency results of STFT processing

(a) Time-frequency diagram of ACMD processing

(b) Time-frequency diagram of IPACMD processing

Fig.16 Comparison results between the improved method and the original algorithm

5 Conclusions and Prospects

5.1 Conclusions

The results of simulation and experimental analysis show that IPACMD for gearbox fault feature extraction has good time-frequency aggregation. The main conclusions obtained are as follows.

IPACMD time-frequency analysis method is proposed, and the similarity conditional entropy is used to optimize the adaptive chirp mode decomposition threshold, which solves the problem of over-decomposition of the original method for variable speed gearbox signals. IPACMD method uses the PCT method for initial instantaneous frequency estimation. Compared with the traditional time-frequency detection method, PCT can effectively solve the problem of interference between the vibration signal components of gearboxes when analyzing the signal components of time-varying frequencies.

According to the simulation and experimental analysis results, IPACMD can effectively extract the time-varying fault characteristics and generate high-resolution time-frequency representation results, clearly represent the fault-related characteristic components in the vibration signal, and effectively identify the local faults in planetary gearboxes.

5.2 Prospects

The method proposed in this paper can distinguish different types of health

conditions, but it is still unable to identify specific fault types. Therefore, the deep learning algorithm will be combined to achieve qualitative analysis of signals in the future.

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Code availability: The algorithm involved in this paper is still being studied by the research group, so it is not publicly disclosed.

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