Gear Fault Feature Extraction Based on MCKD-VMD

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***Abstract*—For the difficulty of gear fault extraction in locomotive transmission system, it is easy to be submerged in strong noise. A combination of MCKD-VMD (Maximum Correlated Kurtosis Deconvolution-Modulation Mode Decomposition) is proposed to extract fault features of gears. The method firstly performs correlation function fusion on the collected vibration signals, fuses the signals with higher correlations together, and effectively removes the interference signals; the MCKD method is used to enhance the signals of the fused signals to make the low-frequency signals more obvious; The MCKD enhanced signal is decomposed by VMD to obtain several modal components, and the components with larger correlation coefficients are reconstructed, and power spectrum analysis is performed to identify the fault frequency characteristics of the gear. The denoising performance of the proposed method is better than other methods by the simulation experiment of gear broken teeth. The method is compared with the MCKD-EMD method. The results show that the proposed method can not only suppress the modal aliasing problem, but also more accurate extraction of gear failure frequency and position. It has important practical significance for the early warning of locomotive early warning.**

Keywords- fault feature extraction; MCKD; VMD; gear failure; denoising performance ;

I. INTRODUCTION

As a key component of the locomotive transmission system, the gear is prone to broken teeth, wear and gear peeling during the running of the locomotive. If the fault characteristics cannot be identified in time, it will have certain serious consequences. In 2012, due to the failure of the 1000 engine gearboxes of Trent, all of Japan's airspace was grounded by five Boeing B7872s. Therefore, the fault diagnosis research of gears has important practical significance for the safe operation of locomotives.

There are aliasing and coupling phenomena between the key functional components of the locomotive transmission system, and the gear signal has characteristics such as unstable and nonlinear. Mechanical failures often occur from mild to severe. If these faults are accurately and timely identified and taken accordingly, the trend of minor fault degradation can be avoided. In order to improve the locomotive gear fault warning and safety service performance, it provides a key technical basis for ensuring the availability and reliability of data acquisition.

During the service of the locomotive, there is a lot of noise, and it is very difficult to extract the fault features of some key components in the background of strong noise. A large number of scholars have proposed various research methods for signal enhancement. McDonald et al. [1] proposed a new deconvolution method for enhanced signal impact frequency, Maximum Correlated Kurtosis Deconvolution (MCKD), which uses the maximum correlation kurtosis as the optimization target. The deconvolution of the signal is realized, and the information that is submerged becomes obvious by suppressing the influence of other noises; Tang Guiji and Wang Xiaolong [2] are difficult to extract the early faults of the rolling bearing, and combine the MCKD with the 1.5-dimensional spectrum to play the superiority of the two methods is used to extract the early weak fault information. Qi et al. [3] proposed a composite fault diagnosis method for rolling bearings based on the improved MCKD and teager energy operator hybrids. The particle swarm optimization algorithm is used to optimize the influence parameters of MCKD under different types of faults. The improved MCKD algorithm reduces the noise interference, and then uses the advantage of the teager energy operator to detect the transient impact of the signal to accurately identify the fault type.

Variational Mode Decomposition (VMD) is a new adaptive modal analysis method proposed by Dragomiretskiy K et al. [4] in 2014. Compared with Empirical Mode Decomposition (EMD) and Local Mean Decomposition (LMD), it overcomes the end effect problem and modal aliasing problem after modal decomposition. Domestic and foreign scholars have devoted a lot of energy to signal noise reduction research, but most scholars focus on the fault extraction of rolling bearings. Gear fault signals have nonlinear non-stationary modulation characteristics, and it is not easy to extract fault information; Hou Gaoyan et al. [5] proposed the method of combining LMD with multi-scale morphology to reduce the noise of the gear fault signal, and achieved good results, but the modal component after the decomposition of LMD method has aliasing phenomenon; Cui Weicheng et al. [6] proposed a local mean demodulation method based on the multi-component amplitude-modulation characteristics of the gear fault vibration

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signal, which is better than the traditional demodulation method; Tong Rui et al. [7] uses bispectral entropy as the eigenvector. The method of combining LCD decomposition method and Bayesian information criterion can effectively extract the fault characteristic frequency of the gear; Cheng Junsheng et al. [8] proposed a method of combining LMD and kurtosis spectrum. Firstly, according to the time-frequency characteristics of LMD, the signal is divided into several frequency bands. The filter frequency band is selected according to the principle of maximum kurtosis, and the fault information of the gear fault signal can be accurately obtained by performing envelope analysis on the filtered signal; Y. Shrivastava and B. Singh [9] concluded by comparing the EMD and EEMD decomposition methods that EEMD is well suited to detect flutter in turning operations in the most accurate manner; Zhao Wei [10] proposed a method combining VMD and fast spectral kurtosis. It can overcome the influence of noise to accurately identify the characteristic frequency of gear fault; LIU Yuanyuan et al. [11] compare the VMD method with EMD and LMD. VMD is equivalent to Wiener filter, which can adaptively perform modal decomposition and overcome the modal aliasing problem in EMD and LMD.

Based on the above analysis, this paper proposes a MCKD-VMD method for gear fault feature extraction. This method can not only enhance the periodic impact frequency of the signal, but also effectively overcome the noise interference. Firstly, there are redundant noise signals and interference components of other frequency components for the vibration signals collected by the sensors. The signals are fused by the cross-correlation function algorithm; The signal impact frequency is enhanced by the superiority of MCKD's own filtering, the impact period frequency is more obvious; The signal is adaptively decomposed into several components by VMD, then the signal is denoised, and the fault features are extracted by the power spectrum. The practicality of the method in the extraction of gear fault signal information is verified by an experimental example.

II. MCKD-VMD METHOD BASIC PRINCIPLE

A. Data Fusion Based on Cross-correlation Function

The cross-correlation function represents the degree of correlation between the two signals: assuming that there are two sets of discrete signals (x(n) and y(n)), the cross-correlation function of x(n) , y(n) can be expressed as:

$$R_{xy}(m) = \frac{1}{N-m}\sum_{n=1}^{N-m} x(n)y(n+m), (m = 0,1,2,\dots,k) \quad (1)$$

where: N - the number of data;

B. Basic Principles of MCKD

MCKD makes full use of the periodic characteristics of impact faults, which can effectively suppress the influence of noise and other interference components. The essence is to find an FIR filter f (L) (L is the length of the filter) to maximize the correlation kurtosis of the original impact sequence, in order to restore its characteristics, to achieve the purpose of enhancing the signal [13] . The main performance parameters in the MCKD algorithm are period T, filter order L and displacement number M.

By selecting an optimal filter f(l), the correlation kurtosis $K_{C,M}(T)$ is maximized, and its objective function is:

$$\mathrm{MCKD_M(T)} = \max_{f}\left[\mathrm{K_{C,M}(T)}\right] = \max_{f}\frac{\sum_{k=1}^{N}\left(\prod_{m=0}^{M} y_{k-mT}\right)^2}{\left(\sum_{n=1}^{N} y_k^2\right)^{M+1}} \quad (2)$$

where: T - the period of the impact signal;

M - the number of displacements;

f - filter vector, $f = [f_1, f_2, \dots, f_L]^T$;

L - the length of the filter;

To solve the objective function, we can think of equation (2) as:

$$\frac{d}{df_l}\mathrm{K_{C,M}(T)} = \frac{d}{df_l}\frac{\sum_{k=1}^{N}\left(\prod_{m=0}^{M} y_{k-mT}\right)^2}{\left(\sum_{k=1}^{N} y_k^2\right)^{M+1}} = 0 \quad (3)$$

The matrix representation of the filter f(l) coefficients:

$$f = \frac{\|y\|^2}{(M+1)\|\beta\|^2}\left(X_0 X_0^T\right)^{-1} A \quad (4)$$

where: $f = [f_1, f_2, \dots, f_L]^T$;

$$A = \sum_{m=0}^{M} X_{mT}\,\alpha_m;$$

$$X_0 = \begin{bmatrix} x_1 & x_2 & \cdots & x_N \\ 0 & x_1 & \cdots & x_{N-1} \\ \cdots & \cdots & \cdots & \cdots \\ 0 & 0 & \cdots & x_{N-L+1} \end{bmatrix}_{L\times N};$$

$$\beta = \begin{bmatrix} y_1 & y_{1-T} & \cdots & y_{1-MT} \\ y_2 & y_{2-T} & \cdots & y_{2-MT} \\ \cdots & \cdots & \cdots & \cdots \\ y_N & y_{N-T} & \cdots & y_{N-MT} \end{bmatrix}_{N\times 1};$$

$$X_{mT} = \begin{bmatrix} x_{1-mT} & x_{2-mT} & \cdots & x_{N-mT} \\ 0 & x_{1-mT} & \cdots & x_{N-mT-1} \\ \cdots & \cdots & \cdots & \cdots \\ 0 & 0 & \cdots & x_{N-mT-L+1} \end{bmatrix}_{L\times N};$$

$$\alpha_m = \begin{bmatrix} y_{1-mT}^{-1}\left(y_1 y_{1-T}\cdots y_{1-MT}\right)^2 \\ y_{2-mT}^{-1}\left(y_2 y_{2-T}\cdots y_{2-MT}\right)^2 \\ \cdots \\ y_{N-mT}^{-1}\left(y_N y_{N-T}\cdots y_{N-MT}\right)^2 \end{bmatrix}_{N\times 1};$$

The process of finding the filter f(l) parameter in an iterative manner is shown in Fig. 1:

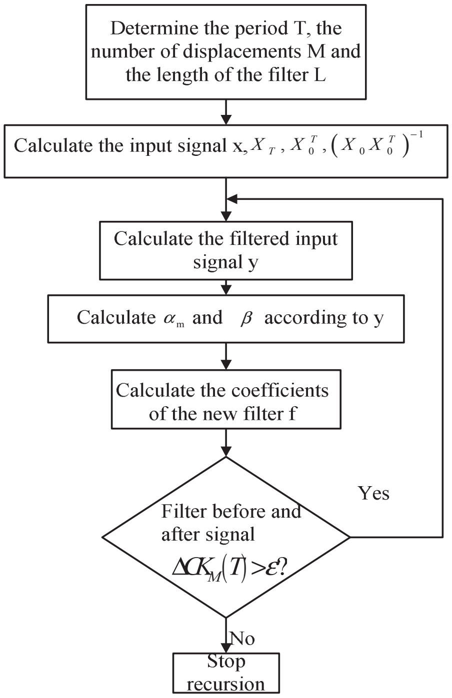


Figure 1. Filter f(l) parameter solution iterative process diagram

C. *Basic Principles of VMD*

VMD is an algorithm for constructing variational problems and solving variational problems. By constraining the variational variation model by means of signal Hilbert transform, Wiener filtering, etc., finding the optimal solution of the model can decompose the signal into a specified number based on the center frequency and the finite bandwidth filtered signal - the Us component. It is a completely non-recursive signal decomposition method.

(1) Construction variation

Suppose that the signal x(t) is decomposed into K components by the VMD algorithm, and the variational problem is constructed by seeking the bandwidth of the Us modal component by the following steps:

Step 1: In order to obtain the analytical signal of each Us component, perform a Hilbert transform to obtain a unilateral spectrum solution formula:

$$\left(\delta(t)+\frac{j}{\pi t}\right)y_k(t) \tag{5}$$

Step 2: Mix the modal analysis signal obtained above to estimate the center frequency $e^{-j\omega_k t}$, and adjust the spectrum of each Us component to the baseband by the transfer frequency method, as shown in equation (6):

$$\left[\left(\delta(t)+\frac{j}{\pi t}\right)y_k(t)\right]e^{-j\omega_k t} \tag{6}$$

Step 3: According to the L^2 norm of the demodulated signal, estimate the bandwidth of each Us component, and obtain the objective function model of the constrained variational problem as equation (7):

$$\begin{cases}\min\limits_{[y_k],[\omega_k]}\left(\left\|\frac{\partial\left[\left(\delta(t)+\frac{j}{\pi t}\right)*y_k(t)\right]}{\partial t}e^{-j\omega_k t}\right\|^2\right)\\ \sum_{k=1}^{K} y_k(t)=y(t)\end{cases} \tag{7}$$

where: $\{y_k\}=\{y_1,y_2,y_3,\dots,y_k\}$ - K components that are decomposed into;

$\{\omega_k\}=\{\omega_1,\omega_2,\omega_3,\dots,\omega_k\}$ - the center frequency of the Kth Us component;

$\delta(t)$ - pulse function;

(2) Solving the variation

Transform the constrained optimization problem into an unconstrained optimization problem whose extended Lagrange expression is:

$$L[\{y_k\},\{\omega_k\},\lambda(t)]=\alpha\sum_{k=1}^{K}\left\|\frac{\partial\left[\left(\delta(t)+\frac{j}{\pi t}\right)*y_k(t)\right]}{\partial t}e^{-j\omega_k t}\right\|_2^2+\left\|y(t)-\sum_{k=1}^{K}y_k(t)\right\|_2^2+\left\langle\lambda(t),y(t)-\sum_{k=1}^{K}y_k(t)\right\rangle \tag{8}$$

Using the Alternate Direction Method of Multipliers (ADMM), the extended Lagrange is obtained by alternately updating y_k^{n+1}, ω_k^{n+1}, λ^{n+1} the saddle point of the daily expression [14] , $y_k^{n+1}(t)$ is expressed as:

$$\hat{Y}_k^{n+1}(\omega)=\frac{\hat{Y}(\omega)-\sum_{i\neq k}\hat{Y}_k(\omega)+\frac{\hat{\lambda}(\omega)}{2}}{1+2\alpha(\omega-\omega_k)^2} \tag{9}$$

where: $\hat{Y}(\omega)$ - Fourier transform of $y(t)$;

$\hat{Y}_i(\omega)$ - Fourier transform of $y_i(t)$;

$\lambda(t)$ - Fourier transform of $\lambda(t)$;

The time domain signal of each modal component can be obtained by Fourier transforming the filtered signal.

Equation (10) is the center of gravity of the current modal power spectrum after updating:

$$\omega_k^{n+1}=\frac{\int_0^{\infty}\omega|\hat{u}_k(\omega)|^2d\omega}{\int_0^{\infty}|\hat{u}_k(\omega)|^2d\omega} \tag{10}$$

where: $y_k^{n+1}(t)$ - the modal function at the n+1th cycle;

$\omega_k^{n+1}(t)$ - the center of gravity of the power spectrum of the updated modal function;

$\lambda^{n+1}(t)$ - the multiplication operator at the n+1th cycle;

Fig. 2 shows the process of implementing the VMD algorithm:

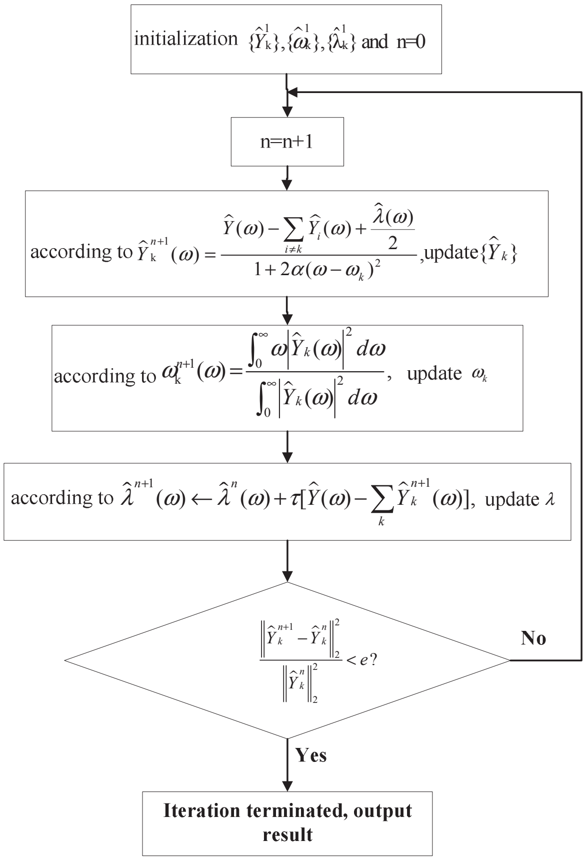


Figure 2. VMD decomposition algorithm flow chart

D. Based on MCKD-VMD gear fault diagnosis method

The gear fault signal has weak, non-linear and non-stationary characteristics. The VMD method directly decomposes the fault signal, which cannot accurately identify the fault frequency, and the hidden information cannot be completely extracted. The MCKD method is a new convolution technique for enhancing the periodic impact component of the signal based on the minimum entropy deconvolution, which can make the low-frequency submerged components of the signal become obvious.

In this paper, the fault signal collected is firstly subjected to cross-correlation function fusion calculation, so that the signals with high correlation can be retained and merged together, and the redundant noise signal is removed. Then the MCKD signal is enhanced, and the enhanced signal VMD is decomposed into a series. The Us modal component is calculated by the correlation coefficient between the component and the original signal, and the component with larger correlation coefficient is reconstructed. Through the power spectrum analysis, the obtained fault frequency is compared with the theoretically calculated fault frequency, and the gear fault feature is extracted. The steps are:

Step 1: The collected vibration signals are fused together by a correlation function fusion algorithm to effectively utilize useful data and delete redundant data;

Step 2: Performing MCKD on the fused signal to enhance the signal impact component;

Step 3: Performing VMD decomposition on the enhanced signal to obtain a series of modal components;

Step 4: By calculating the correlation coefficient of each modal component and the original signal, the component with the larger correlation coefficient is reconstructed to obtain a new signal. Finding a power spectrum of the reconstructed signal;

Step 5: Accurately analyze the gear fault characteristics by power spectrum analysis.

The algorithm flow chart is shown in Fig. 3:

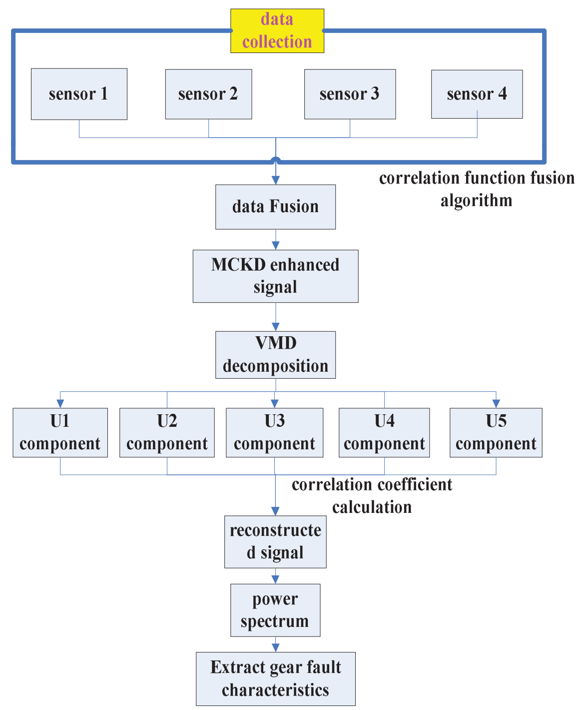


Figure 3. MCKD-VMD gear fault extraction flow chart

III. EXPERIMENTAL VERIFICATION

In order to verify the effectiveness and practicability of the proposed method in gear fault feature extraction, it is introduced into the gearbox gear fault diagnosis experimental platform. Taking the fixed-axis gearbox gear on the American DDS power transmission fault diagnosis comprehensive experimental platform shown in Fig. 4 as the research object, the test bench from left to right is the motor, planetary gearbox, fixed-axis gearbox and magnetic powder brake. The transmission diagram of the fixed-shaft gearbox is shown in Fig. 5. The number of gears and transmissions of the transmission gears are shown in TABLE Ⅰ. The relevant frequencies of the transmission system are shown in TABLE Ⅱ. The acceleration sensors are used (SN178383). The experiment simulates the fault with the gear box gear broken tooth. The fault gear is located at the third gear meshing position of the pinion of the intermediate shaft, and the sampling frequency is 25600 Hz.

Figure 4. American DDS power transmission fault diagnosis comprehensive experimental platform

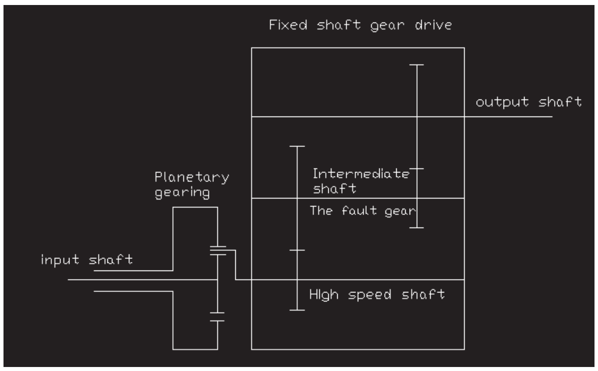


Figure 5. Schematic diagram of the gearbox drive

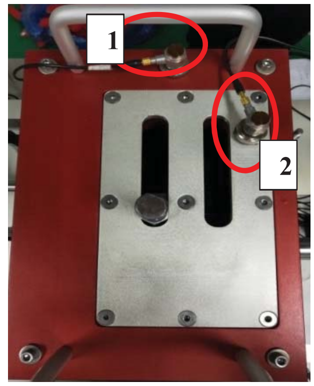
TABLE I. NUMBER OF GEARS OF THE GEARBOX OF EACH GEARBOX AND GEAR RATIO OF EACH STAGE

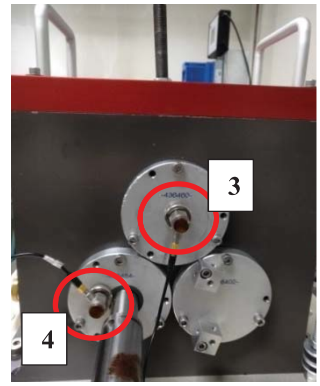
Transmission system	**The number of teeth**		**Transmission ratio**
Primary drive (planetary gear)	*The number of sun gear teeth*	*The number of teeth of the ring gear*	4.5714
	28	100	
Secondary drive (fixed shaft gear)	*The number of teeth of high speed shaft gear*	*The number of teeth of the intermediate shaft large gear*	3.4483
	29	100	
Three-stage transmission (fixed shaft gear)	*The number of teeth of the intermediate shaft pinion*	*The number of teeth of the output shaft gear*	2.5
	36	90	

TABLE II. RELEVANT FREQUENCIES OF THE TRANSMISSION SYSTEM

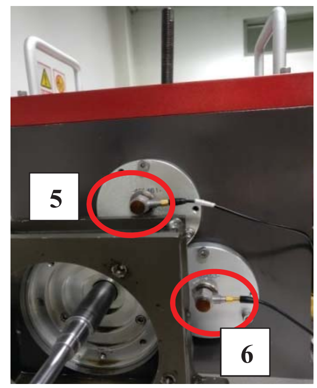
Input shaft frequency	40Hz
Intermediate shaft frequency shift	2.5375Hz
First stage meshing frequency	1120Hz
Third stage meshing Frequency	91.35Hz
Second stage meshing frequency	253.75Hz
High speed shaft frequency	8.7501Hz
Output shaft frequency	1.015Hz

Fig. 6 shows the position of the sensor measuring point when the gear fault signal is collected.





(a) Upper cover point position (b) Right box measuring point position



(c) Left box measuring point position

Figure 6. Sensor measuring point position

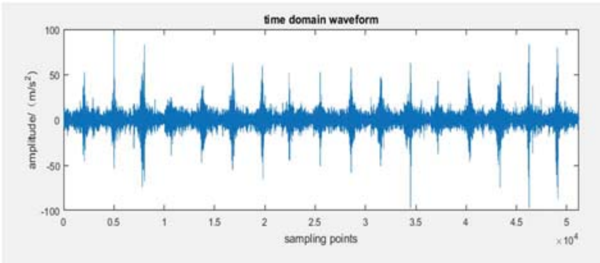
As shown in Fig. 6, this gear fault diagnosis experiment uses 6 sensors to arrange the measuring points. The length of each sampling time is 2s, and 6 sets of vibration data are obtained for each sampling. A total of 10 times are taken: $[x_{11}(t),\ldots,x_{16}(t)]$, $[x_{21}(t),\ldots,x_{26}(t)]$, total 6×10 group data. Calculating the weights of the six measurement points, as shown in TABLE 3:

TABLE III. LOCATION OF THE MEASURING POINT AND THE CORRESPONDING WEIGHT OF THE COLLECTED DATA

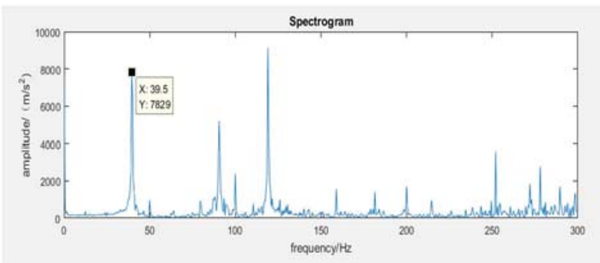
Measuring point position	$\boldsymbol{p_i}$
1	0.09
2	0.16
3	0.27
4	0.11
5	0.25
6	0.12

According to the weight proportion of each data shown in TABLE Ⅲ, data fusion based on cross-correlation function is used for data fusion.

Fig. 7 is a time-domain waveform diagram and a frequency spectrum diagram of a gear broken-tooth vibration signal based on cross-correlation function fusion. It can be analyzed from the figure that the fault characteristics are not recognized by the noise influence of the gearbox operation and the equipment accuracy factor, and there are some high frequency impact components. It contains 39.5Hz high frequency components for high speed shaft frequency conversion.

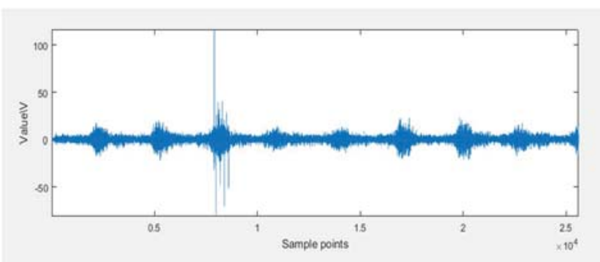


(a) Time domain waveform

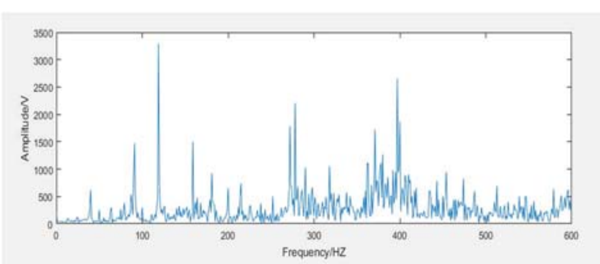


(b) Spectrogram

Figure 7. Time domain waveform and spectrum of the fusion fault signal



(a) Time domain waveform



(b) Spectrogram

Figure 8. Time domain waveform and spectrogram after MCKD processing

The fusion fault signal is enhanced by the MCKD signal, and the time domain waveform and the spectrum diagram shown in Fig. 8. It can be seen that the time domain waveform diagram of the fault signal has obvious impact components, and the low frequency component in the spectrum diagram is enhanced and becomes obvious. However, the fault characteristics of the gear are still not recognized.

The kurtosis criterion is a numerical statistic that reflects the distribution characteristics of a random variable.

$$k = \frac{E(x-\mu)^4}{\sigma^4} \tag{11}$$

where: μ - mean value of the signal

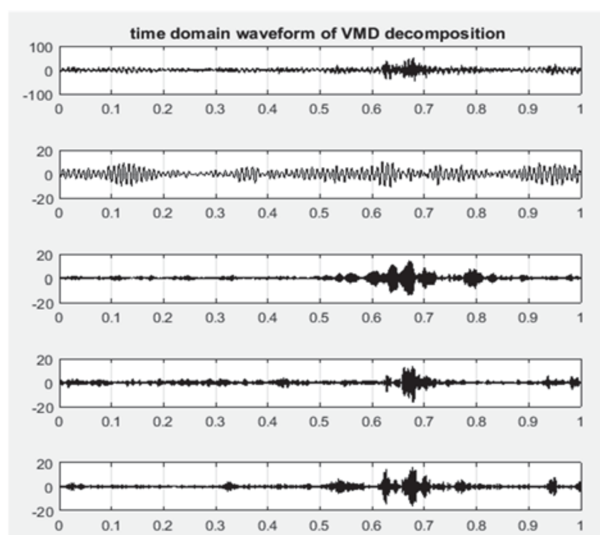
σ - the standard deviation of the signal

E(x) - the expected value of the variable x

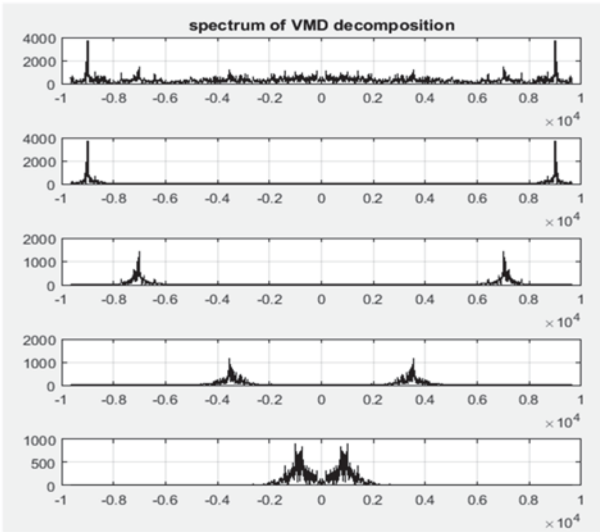
The kurtosis criterion is sensitive to the weak fault signal of the gear. When the gear is running under normal conditions, the vibration signal obeys the normal distribution. When the gear has a broken tooth fault, the vibration signal does not obey the normal distribution due to the mechanical shock caused by the broken tooth and a series of vibrations, and the value of the kurtosis coefficient becomes large.

The kurtosis value of the fusion fault signal is 11.25, and the kurtosis value after the MCKD signal enhancement is 19.6. The larger the kurtosis value, the more impact components are contained in the signal, so the signal processed by MCKD contains more fault information, indicating that MCKD can effectively enhance the impact component of the gear broken fault signal.

The VMD decomposition is performed on the vibration signal enhanced by the MCKD signal, and Fig. 9 shows the VMD decomposition result and the corresponding spectrum diagram. Calculating the correlation coefficient values of the five modal components and the original gear broken tooth fault signal, as shown in Fig. 10. It can be seen from the figure that the U1, U3 and U4 components obtained by the decomposition are highly correlated with the original signal, the three modal components are selected for signal reconstruction, and the reconstructed components are subjected to power spectrum calculation, and the power spectrum is shown in Fig. 11.



(a) VMD decomposes the time domain waveform of U1-U5



(b) VMD decomposes the spectrum of U1-U5

Figure 9. VMD decomposition time domain waveform diagram and corresponding spectrum diagram

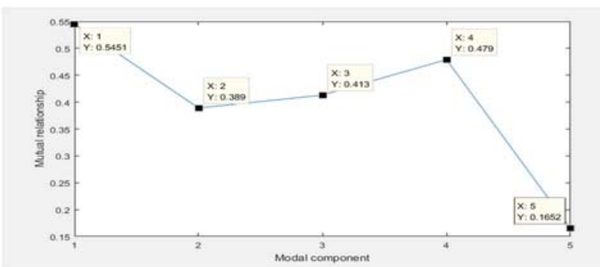


Figure 10. VMD decomposition results and correlation coefficient values of the original signal

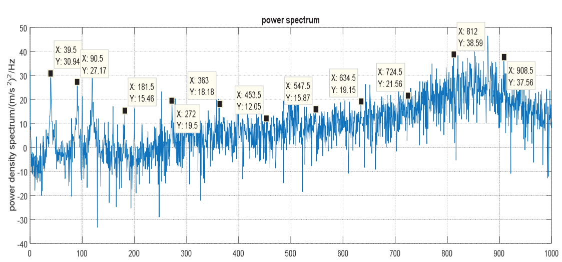
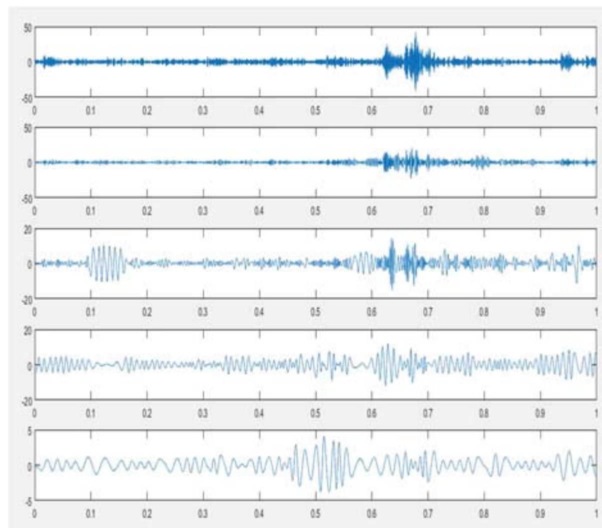


Figure 11. Power spectrum of VMD decomposition reconstructed signal

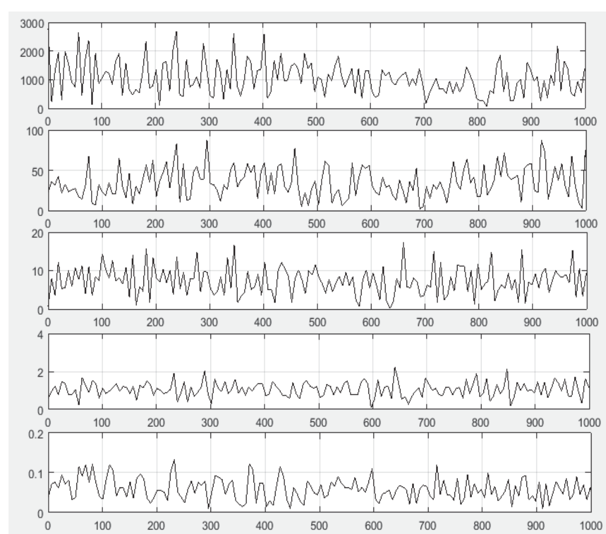
It can be analyzed from Fig. 11 that the shock signal is 39.5 Hz, the frequency is the input shaft frequency, and the theoretical value is 40 Hz. Since the input shaft is connected to the motor, there is a large interference noise when the motor works. This noise frequency is inevitable; Contains shock signal 90.5Hz, the frequency is the third-stage meshing frequency of the gearbox, its theoretical value is 91.35Hz, and its double frequency 181.5Hz, triple frequency 272Hz, quadruple frequency 363Hz and five times frequency 453.5Hz, etc., because the gear broken tooth fault set by the test bench is the pinion of the intermediate shaft, the position of the fault pinion is the third gear gear meshing position. In summary, the gear fault and position analyzed by the power spectrum of the reconstructed signal are consistent with the gear fault and position results set by the actual gearbox fault diagnosis test bench. It can be concluded that the fault characteristics of the gear can be accurately identified based on the MCKD-VMD method.

IV. RESULTS ANALYSIS

The EMD decomposition is performed on the signal enhanced by the MCKD signal, and the EMD decomposition result and the corresponding spectrogram are shown in Fig 12. Calculate the correlation coefficient values of the five IMFs components and the original gear breaking fault signal, as shown in Fig. 13. It can be seen from the figure that the IMF1, IMF2 and IMF3 components obtained by the decomposition are highly correlated with the original signal, the three IMFs components are selected for signal reconstruction, and the reconstructed components are subjected to power spectrum calculation, and the obtained power spectrum is obtained. As shown in Fig. 14.



(a) EMD decomposes the time domain waveform of IMF1-IMF5



(b) EMD decomposes the spectrum of IMF1-IMF5

Figure 12. EMD decomposition

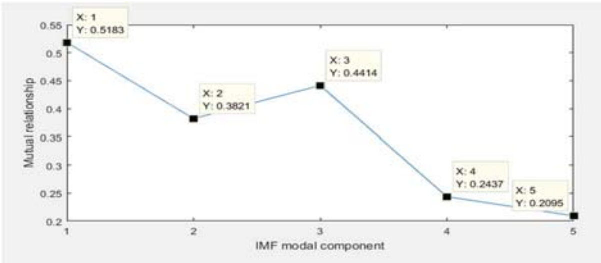


Figure 13. EMD decomposition results and correlation coefficient value of the original signal

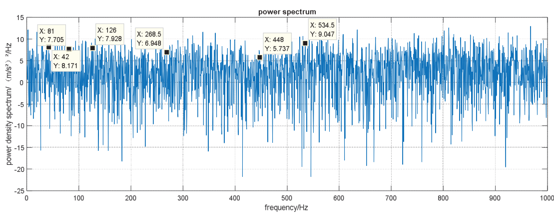


Figure 14. Power spectrum of EMD decomposition reconstructed signal

It can be analyzed from Fig. 14 that the shock signal is 42 Hz, the frequency is the input shaft frequency, and the theoretical value is 40 Hz. Since the input shaft is connected to the motor, there is a large interference noise when the motor works. This noise frequency is not available. Avoided; 81Hz, 126Hz are the double frequency and triple frequency of the input shaft frequency, the theoretical value is 80Hz, 120Hz; The impact signals are 268.5 Hz, 448 Hz and 534.5 Hz, respectively, three times, five times and six times the frequency of the third stage meshing frequency of the gear, and the theoretical values are 270 Hz, 450 Hz and 540 Hz. Because of the background of strong noise and limitations of EMD decomposition, the third-order meshing frequency of 90Hz is submerged, and its individual high-frequency components are reflected.

In order to analyze the effect of the signal enhanced by MCKD signal after decomposition by two decomposition methods, the mean square error (RMSE) and peak signal-to-noise ratio (PSNR) are selected as the evaluation index [15] , as shown in TABLE Ⅳ:

RMSE: Reflect the difference in amplitude between the fault signals before and after the various methods:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}[\hat{f}(t_i)-f(t_i)]^2}{n}} \quad \cdots\cdots \quad (12)$$

where: $\hat{f}(t_i)$ – pre-processing fault data

$f(t_i)$ - post-processing fault data

The larger the value, the worse the signal quality, and the smaller the value, the better the signal quality.

PSNR: The ratio of the maximum possible power of the signal to the destructive noise power that affects its representation accuracy, defined as follows:

$$\mathrm{PSNR} = 10 \cdot \log_{10}\left(\frac{\mathrm{MAX}^2}{\mathrm{MSE}}\right) = 20 \cdot \log_{10}\left(\frac{\mathrm{MAX}}{\sqrt{\mathrm{MSE}}}\right) \quad (13)$$

where: MAX - Maximum peak value of the signal;

MSE - mean square error of i, j, $\mathrm{MSE} = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - K(i,j)]^2$;

As analyzed by equation (13), the smaller the MSE, the larger the PSNR and the better the signal quality.

TABLE IV. METHODS AND CORRESPONDING EVALUATION INDEX VALUES

Evaluation index	**Fusion signal**	**MCKD enhanced signal**	**MCKD-VMD processed signal**	**MCKD-EMD processed signal**
RMSE	0.00917	0.00592	0.00193	0.00208
PSNR	14.72	20.49	25.68	22.35

It is analyzed from TABLE Ⅳ that the two signal indicators that are enhanced by MCKD are significantly higher than the original fusion signal. The signal is more likely to highlight the fault frequency after EMD and VMD decomposition, and the decomposition effect of VMD is obviously better than the EMD decomposition effect.

V. CONCLUSION

In view of the problem that the gear failure is easily submerged by noise and difficult to be recognized during the operation of the locomotive transmission system, this paper combines the MCKD-VMD method to analyze the fault characteristics of the actual acquired signal. The initial fault of the gear is not easy to be identified, especially in the process of strong interference noise. MCKD can realize the deconvolution of the signal according to the superiority of the algorithm itself, effectively suppressing the interference noise, and thus making the impact component of the signal more obvious. Through two evaluation indicators, it can be analyzed that MCKD not only has the characteristics of enhanced signals, but also plays an important role in the extraction of gear fault information; The gear fault frequency is usually superposed by various component components, it is necessary to find a decomposition method that can separate these frequency components. The VMD decomposition method and the reconstruction of its components can accurately identify the fault frequency and position. Experimental results show, compared with EMD, VMD can overcome the influence of noise, effectively suppress the modal aliasing and end effect in the EMD decomposition process, making the fault effect more obvious, and effectively extracting the fault information that is submerged in the noise. It provides a key technical foundation for the safe operation of locomotives.

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