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Research on motor rotation anomaly detection based on improved VMD algorithm

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Abstract

Purpose – The electromechanical brake system is leading the latest development trend in railway braking technology. The tolerance stack-up generated during the assembly and production process catalyzes the slight geometric dimensioning and tolerancing between the motor stator and rotor inside the electromechanical cylinder. The tolerance leads to imprecise brake control, so it is necessary to diagnose the fault of the motor in the fully assembled electromechanical brake system. This paper aims to present improved variational mode decomposition (VMD) algorithm, which endeavors to elucidate and push the boundaries of mechanical synchronicity problems within the realm of the electromechanical brake system.

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Design/methodology/approach – The VMD algorithm plays a pivotal role in the preliminary phase, employing mode decomposition techniques to decompose the motor speed signals. Afterward, the error energy algorithm precision is utilized to extract abnormal features, leveraging the practical intrinsic mode functions, eliminating extraneous noise and enhancing the signal's fidelity. This refined signal then becomes the basis for fault analysis. In the analytical step, the cepstrum is employed to calculate the formant and envelope of the reconstructed signal. By scrutinizing the formant and envelope, the fault point within the electromechanical brake system is precisely identified, contributing to a sophisticated and accurate fault diagnosis.

Findings – This paper innovatively uses the VMD algorithm for the modal decomposition of electromechanical brake (EMB) motor speed signals and combines it with the error energy algorithm to achieve abnormal feature extraction. The signal is reconstructed according to the effective intrinsic mode functions (IMFS) component of removing noise, and the formant and envelope are calculated by cepstrum to locate the fault point. Experiments show that the empirical mode decomposition (EMD) algorithm can effectively decompose the original speed signal. After feature extraction, signal enhancement and fault identification, the motor mechanical fault point can be accurately located. This fault diagnosis method is an effective fault diagnosis algorithm suitable for EMB systems.

Originality/value – By using this improved VMD algorithm, the electromechanical brake system can precisely identify the rotational anomaly of the motor. This method can offer an online diagnosis analysis function during operation and contribute to an automated factory inspection strategy while parts are assembled. Compared with the conventional motor diagnosis method, this improved VMD algorithm can eliminate the need for additional acceleration sensors and save hardware costs. Moreover, the accumulation of online detection functions helps improve the reliability of train electromechanical braking systems.

Keywords Electromechanical brake system, Railway brake system, Motor fault diagnosis, Variational mode decomposition, Error energy, Feature extraction

Paper type Research paper

1. Introduction

Driven by the goal of peak carbon dioxide emissions and carbon neutrality, rail transportation equipment is developing in the direction of full electrification and intelligence. The electromechanical brake (EMB) technology has become a research hotspot in train braking technology. The safety and reliability of the train subcomponents are essential to the safe operation of the train (Dong, Chen, Wang, Jia, & Man, 2020). Unlike the conventional air brake system, the EMB system eliminates the medium, such as air, and the motor's accurate control will be directly related to the braking system's performance. High-precision control places forward strict requirements for the production and assembly of frameless motors, and the process difference will lead to poor motor consistency. In extreme conditions, faults such as increased internal friction and nonaxiality of the motors may occur. To optimize the precision of the electromechanical brake (EMB) system's control capabilities, it's imperative to conduct a comprehensive preassembly motor status diagnosis. This proactive approach is essential for mitigating variations arising from disparities in motor structures, thereby ensuring a heightened level of control consistency throughout the operational spectrum. By meticulously assessing the motor's condition before integration into the EMB system, we proactively address potential divergences, thereby bolstering the overall efficacy and uniformity of the control mechanisms. This paper proposes an improved variational mode decomposition (VMD) algorithm to identify abnormal friction interference during the no-load operation of the motor.

The empirical mode decomposition (EMD) algorithm extracts valuable signal features by iteratively decomposing the signal into multiple center frequency modes, and many scholars have applied it in various fields (Wang, Chang, Lee, & Lin, 2022). However, EMD has a mode aliasing problem; that is; the frequency spectrum of different mode functions overlaps each other, making the mode functions unable to separate. The VMD algorithm was proposed by Zosso & Dragomiretskiy (2014), and it has certain advantages in anti-mode aliasing compared with EMD. The VMD algorithm is a nonstationary signal processing method that is more sensitive to low-frequency characteristics, and the main characteristics of the speed signal at the stagnation point of motor operation are included in the low-frequency band (Alshahrani, 2005). Therefore, the VMD algorithm can better denoise and extract features of the noisy speed signal from the faulty motor and obtain the reconstructed signal by superimposing the required modal components. Jegadeeshwaran & Sugumaran (2014) proposed a fault feature signal extraction method based on VMD for fault diagnosis of hydraulic braking systems.

In order to characterize the similarity between each effective mode and the original signal, the correlation coefficient is usually adopted to measure it. Jingyi (2018) proposed a signal enhancement algorithm based on correlation coefficient and VMD. Miao, Zhao, Li, Zhang, and Meng (2016) proposed a damage location method based on the energy spectrum correlation coefficient. Zhen, Li, Feng, Zhang, and Gu (2022) proposed a rolling bearing fault diagnosis method based on VMD reconstruction and degree of cyclostationarity (DCS) demodulation to solve the problem that the fault characteristics of bearings in complex environments are easily overwhelmed by noise and difficult to extract. Zimroz *et al.* (2011) studied the correlation between rolling device vibration signals and physical quantities such as speed signals and current signals, proposed a method to measure instantaneous shaft speed based on advanced vibration signal processing technology, and applied it to wind turbine gearboxes. Wangying, Mingyue, and Peng (2023) proposed a fault diagnosis method that combines VMD, margin factor (MF) and cepstrum (VMD-MF-cepstrum) to identify the rub-impact fault between the stator and rotor of an aeroengine, which can accurately identify the collision location.

The article combines variable mode decomposition with an error energy algorithm to process the slight abnormal fluctuation of the motor speed signal to achieve noise reduction and feature extraction. Firstly, the VMD decomposition is performed on the original velocity signal to calculate a series of intrinsic mode functions (IMFS) components. Then, the error energy of each IMF is calculated. Subsequently, valid IMFs are selected based on the threshold to reconstruct the signal. Finally, the cepstrum method is used to calculate the resonance peak of the enhanced reconstructed signal to obtain the envelope and locate the fault point.

2. Improved VMD algorithm

2.1 VMD algorithm

The modal decomposition method is a mathematical method that decomposes complex data sets into different data modes, which is widely used in speech recognition, image processing and signal processing. Modal decomposition can split the original data set into multiple parts, each containing a characteristic aspect of the data feature (Yu, Dejie, Junsheng, & Ge, 2003). EMD is a typical standard data processing method based on mode decomposition, which has evolved into ensemble empirical mode decomposition (EEMD), complementary ensemble empirical mode decomposition (CEEMD), complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN), VMD. Although the VMD algorithm is also a modal decomposition method, it is fundamentally different in principle from modal decomposition methods such as EMD, EEMD, CEEMD and CEEMDAN. Huang *et al.* (1998) proposed the concept of intrinsic modal components (IMF) for EMD based on satisfying the condition of a single-component signal. However, most actual signals do not meet the two conditions it requires: (i) the number of extreme points is equal to or one difference from the number of zero crossing points, (ii) the average value of the upper envelope and the lower envelope must be zero. The VMD method assumes that the signal to be analyzed comprises a series of IMF with a finite bandwidth and a specific center frequency. This paper adaptively decomposes the original motor current signal into several IMF components based on the VMD algorithm (Jiancai, Junwei, & University, 2019). The VMD decomposition process is as follows:

Perform Hilbert transform on each modal function $u_k(t)$ to calculate the analytical signal of the modal function and obtain the unilateral spectrum.

$$\left[\delta(t)+\frac{\mathrm{j}}{\pi t}\right]*u_k(t) \tag{1}$$

where the t is time, $\delta(t)$ is the impulse function, $\{u_k\}=\{u_1,\ldots,u_k\}$ is the decomposed IMF component. Multiply the above formula by $e^{-j\omega_k t}$ to adjust the center frequency of each component, through which the spectrum is modulated to the corresponding base frequency band.

$$\left[\delta(t)+\frac{j}{\pi t}\right]*u_k(t)*e^{-j\omega_k t} \tag{2}$$

$\{\omega_k\}=\{\omega_1,\ldots,\omega_k\}$ is the center frequency of the corresponding IMF component $u_k(t)$.

The Gaussian smoothing index is obtained by performing the norm gradient square root operation on the demodulated signal to estimate the bandwidth of each component (Zhao & Zhao, 2005). The expression of the constrained variation model is as follows:

$$\min_{\{u_k\},\{\omega_k\}}\left\{\sum_k\left\|\delta_t\left[\left(\delta(t)+\frac{j}{\pi t}\right)*u_k(t)\right]*e^{-j\omega_k t}\right\|_2^2\right\},\cdots,s.t.\sum_k u_k=f \tag{3}$$

By introducing quadratic penalty factor α and Lagrange multiplier $\lambda(t)$, VMD algorithm transforms constrained variation problem into unconstrained variation problem (Manataki, Vafidis, & Sarris, 2014). α ensures the reconstruction accuracy of the signal, and $\lambda(t)$ ensures the strictness of the constraints.The extended Lagrangian expression as Equation (4).

$$\arg\min_{\{u_k\},\{\omega_k\}}\left\{\alpha*\sum_k\left\|\delta_t\left[\left(\delta(t)+\frac{j}{\pi t}\right)*u_k(t)\right]*e^{-j\omega_k t}\right\|_2^2+\left\|f(t)-\sum_i u_k(t)\right\|_2^2+\left\langle\lambda(t),f(t)-\sum_i u_k(t)\right\rangle\right\} \tag{4}$$

Based on alternating direction multiplier method (ADMM) and Plancherel theorem, the L2 norm problem is isometric converted to its Fourier transform.

$$\widehat{u}_k^{n+1}(\omega)=\left[\widehat{f}(\omega)-\sum_{i\neq k}\widehat{u}_i(\omega)+\widehat{\lambda}(\omega)\Big/2\Big)\right]\Big/\left[1+2\alpha(\omega-\omega_k)^2\right] \tag{5}$$

where $(\omega-\omega_k)^2$ is the remainder of the Wiener filter. In the same way, the minimum value of the center frequency ω_k is calculated as Equation (6).

$$\omega_{\mathrm{k}}^{\mathrm{n+1}}=\int\omega\left|\widehat{u}_k(\omega)\right|^2 d\omega\Big/\left(\int_0^\infty\left|\widehat{u}_k(\omega)\right|^2 d\omega\right) \tag{6}$$

The convergence condition of the above algorithm is $\sum_k\left\|u_k^{n+1}-u_k^n\right\|_2^2/\left\|u_k^n\right\|_2^2<\varepsilon$. The difficulty of VMD algorithm lies in effective IMF selection (Varun, Bilas, & Pachori, 2012). In this paper, error energy is used as the judgment basis for selecting effective modal components to solve this problem.

2.2 Error energy algorithm

The probability density function represents the likelihood of the output value of a random variable, which is another expression of a random variable. The most intuitive way to describe the similarity of two signals in signal processing is to calculate the error energy between them (Altunay, Telatar, & Erogul, 2010). The smaller the error energy, the higher the similarity between the two signals. If the error energy is 0, the corresponding two signals are the same (Andrieux, Abda, & Barangar, 2005).

If there are two signals $S_1(n)$ and $S_2(n)$, the error signal is:

$$v(n) = S_1(n) - \mathrm{A}S_2(n) \tag{7}$$

A is the scaling coefficient of the signal, and the index that directly characterizes the similarity of the two signals is the energy of the error signal in Equation (8).

$$E_v = \sum v^2(n) = \sum [S_1(n) - AS_2(n)]^2 = E_1 - 2A\sum S_1(n)S_2(n) + \mathrm{A}^2E_2 \tag{8}$$

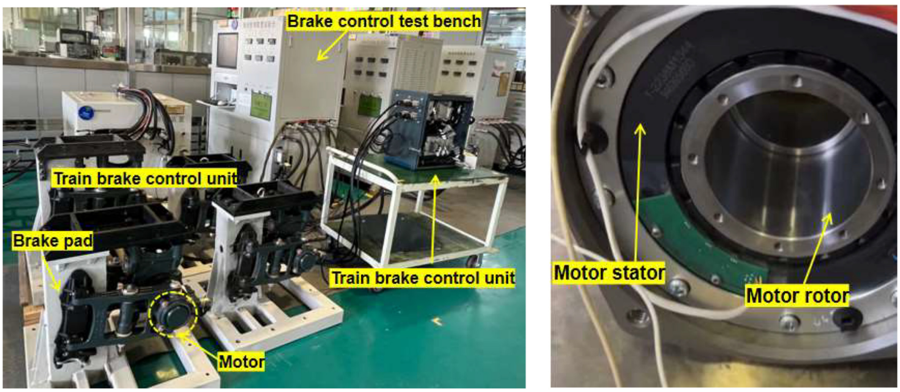
where E_v represents the error energy, E_1 is the energy of the signal $S_1(n)$, and E_2 is the energy of the signal $S_2(n)$.When $\mathrm{A} = \sum S_1(n)S_2(n)/E_2$, E_v is minimum. If the correlation function of two signals is defined as $C = \sum S_1(n)S_2(n)$, then the corresponding error energy is $E_v = E_1 - C^2/E_2$.

3. Motor fault diagnosis based on improved VMD algorithm

3.1 Introduction to the motor control system

Train EMB technology is the cutting-edge technology in braking research in the rail transit industry (Chi & Meng-Ling, 2019). Unlike the traditional air braking and hydraulic braking, the EMB system drives the transmission actuator through the motor, which drives the brake disc to clamp the brake disc to achieve train braking. The actual EMB control system and permanent magnet synchronous motor are shown in Figure 1.

The permanent magnet synchronous motor is the power source of the EMB system. The driver inverts the 110V direct current (DC) power into three-phase electricity to power the motor. The application and relief of braking force are closely related to the motor's electrical



Train EMB test platform
(a)

Servo motor
(b)

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Figure 1.
EMB control system physical diagram

signal input. As the input electrical signal strengthens, the motor output torque increases, and vice versa. In order to ensure accurate motor control, it is necessary to ensure that the motor and transmission mechanism have good mechanical consistency (Guigon, Baraduc, & Desmurget, 2010). The fluctuation of the feedback signal under constant motor speed and idling (i.e. no braking force) is monitored in real time to reflect this characteristic (Liu, Hu, & Cui, 2005). Theoretically, if the mechanical consistency is good, the feedback signal changes of the motor during idling motion will be relatively smooth. Insufficient mechanical consistency of the motor often leads to unstable fluctuations in signals such as current or speed when the motor is idling, because greater torque is required to overcome the additional unbalanced mechanical resistance (Kuroda *et al.*, 2001).

3.2 Feedback signal collection of motor

A pole-pair reluctance rotary transformer is installed at the tail of the motor inside the brake cylinder as a signal acquisition device. The selected magnetoresistive rotary transformer has the advantages of large phase displacement, good reliability, simple structure and low cost, which can meet the requirements of train products for reliable operation, vibration resistance, and adaptability to harsh environments. The rotor of the rotary transformer connects to the motor's rotor. Multiple sets of excitation electrical signals are generated when the motor rotates, and the positive excitation, negative excitation, positive cosine, negative cosine, positive sine and negative sine feedback signals are output to the motor driver through the six feedback lines output by the rotary transformer. These electrical signals change with the rotation angle of the motor rotor. After receiving these electrical signals, the motor driver converts them into control physical quantities such as rotation speed and position angle through a conversion circuit. The rotary transformer used in the experiment is shown in Plate 1.

The motor power can constantly supply voltage DC 110V, which will invert into a three-term alternating current through the driver for motor motion. The working voltage of the driver is constant voltage DC 24V. During the entire motor operation, the driver device collects real-time signals such as current, voltage, speed and position feedback. The sampling frequency is 100HZ, and the sampling interval is 1000us. In order to better capture the abnormal fluctuations of electrical signals, the motor speed is set to a slow constant speed of 5 rpm. Figure 2 shows the local enlarged waveform of the feedback speed signal for a no-load motor collected under regular operation and fault conditions. It can be seen that the motor has small fluctuations under normal conditions, and the speed fluctuation amplitude becomes more significant at the fault position, which is caused by the mechanical stagnation of the internal structure.

Source(s): Authors' own work

Plate 1.
Rotary transformer for experiments

3.3 Validation of motor fault diagnosis by improved VMD algorithm

The original data prepared for the experiment is shown in Figure 3, which is a time series data set of approximately 1 minute. It can be seen from the experimental data set that the speed feedback fluctuates irregularly around 5 rpm, and there are five apparent large-scale abnormal fluctuations. The abnormal rotation of the rotor inside the motor causes this. This experiment aims to identify the fault points with large abnormal signal fluctuations through the improved VMD method. The difficulty in diagnosing this abnormal fluctuation signal lies in the fusion of fault and typical signal characteristics. In addition to large signal fluctuations, the fault point also contains standard fluctuation signals and noise signals, which will cause interference in the identification. If recognition is performed directly based on the original timing signal, these interferences will affect accuracy. Therefore, filtering, noise reduction and feature enhancement of the original signal are the keys to improving fault diagnosis efficiency.

The motor speed signal collected in the experiment is processed through VMD combined with the error energy algorithm: filtering, selecting effective modes, eliminating background noise and reconstructing the leakage signal. During the VMD decomposition process, the preset value determines the number of IMF submodes. Suppose this value is less than the number of valuable components in the signal to be decomposed. In that case, it will cause insufficient decomposition and lead to modal aliasing, an under-decomposition phenomenon. Suppose the preset value exceeds the number of valuable components in the signal to be decomposed. In that case, some useless false components will be generated, which is an over-decomposition of the signal. Therefore, the determination of the value is significant for VMD. The penalty coefficient determines the bandwidth of the IMF component. The smaller the

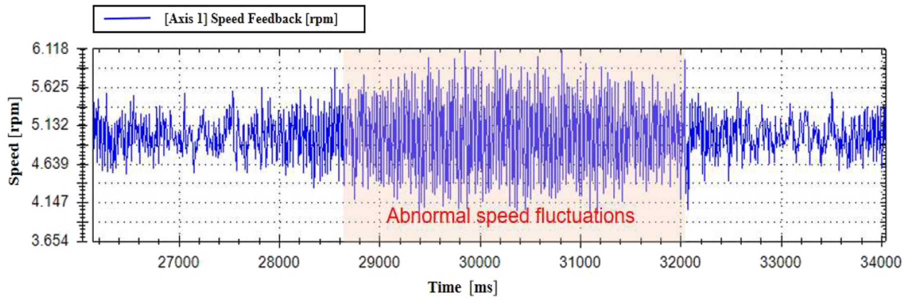

Figure 2.
Motor speed signal under normal and fault conditions

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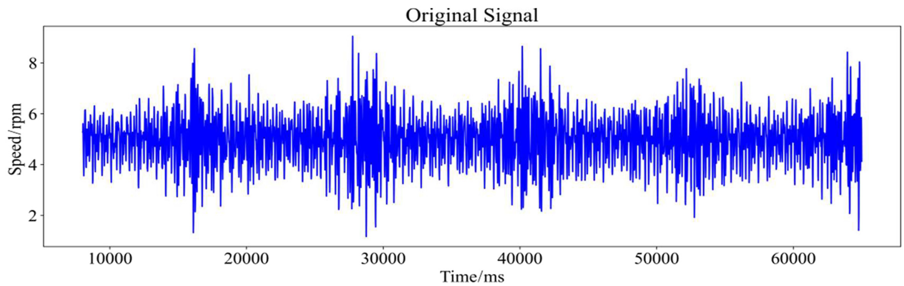

Figure 3.
The original signal of the motor speed

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penalty coefficient, the greater the bandwidth of each IMF component. If the value of α is too large, it will cause the loss of frequency band information, so it is necessary to determine the best parameter combination [K, α].

Many scholars use the central frequency observation method for VMD decomposition and determine the K value by observing the central frequency under different K values. However, this method is accidental and can only determine the number of modes K and cannot determine the penalty parameter a. The whale optimization algorithm (WOA) is an intelligent optimization search method in which the global exploration and local development processes in the optimization phase can be run and controlled separately. The optimization process does not require manual setting of complex control parameters, which improves the efficiency of the algorithm and reduces the difficulty of application. The WOA algorithm has a novel structure and few control parameters, and shows good optimization performance in solving many numerical optimization and engineering problems. Since the motor speed signal fluctuates complexly, choosing the WOA algorithm can effectively avoid local optimal phenomena. This paper optimizes VMD parameters based on the WOA (Kashani, Camp, Armanfar, & Slowik, 2020) using the minimum value of envelope entropy as the fitness function. Envelope entropy represents the sparse characteristics of the original signal. When there is more noise and less feature information in the IMF, the envelope entropy value is more significant; otherwise, the envelope entropy value is more diminutive. Finally, a suitable set of VMD parameters [K, α] = [5, 2000] are adopted as VMD decomposition parameters.

In order to verify whether the selection of parameters K is reasonable, this paper attempts to decompose the original signal into more IMF components. It selects the parameter combination [K, α] = [5, 2000] to decompose the original signal for comparison and verification. All 10 modal components of the improved VMD decomposition are shown in Figure 4. All the IMF decomposition results show that the first five IMF components contain the most helpful information in the original signal. In contrast, the signal feature distribution in the IMF6-IMF10 sequence is relatively sparse, which further verifies the effectiveness of the whale optimization algorithm for parameter optimization.

The error energy algorithm calculates the error energy table, and then the effective mode is selected to reconstruct the speed signal. Table 1 shows the error energy distribution of each

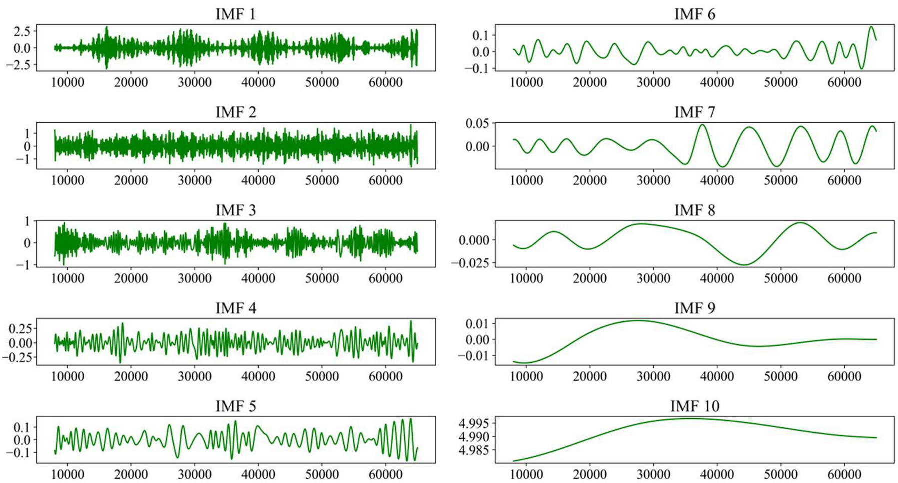

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Figure 4. VMD decomposition process of motor speed signal when K = 10

mode and the original signal. In general, if the error energy value of each mode is much smaller than the threshold, then these modes contain more practical information and are called effective modes (Shi, 2020). All error energies are averaged to calculate the threshold = 17.556, and the effective IMF is selected according to this threshold; only the IMF1 is the effective mode. The reconstructed signal after eigenvalues scaling is shown in Figure 5. The reconstructed signal has less noise and is similar to the original signal. By comparing Figures 3 and 5, the difference is that the reconstructed new sequence has more minor amplitude fluctuations than the original signal at non-fault positions, which can reduce the interference of feature recognition at the fault moment.

The correlation coefficient can reflect the degree of correlation between two signals (Mason, Brookes, & Rumsey, 2005). According to the literature, the correlation coefficient is divided into several types: no correlation, low correlation, significant correlation and high correlation (Yang, Liu, & Zhang, 2017). The correlation division between the two signals is shown in Table 2 (Hongwei, Dongdong, Lingling, Bingkun, & Daifeng, 2019). In the experiment, the cross-correlation between the original signal and the reconstructed signal is

Table 1.
Error energies of different IFM (intrinsic mode function) modal

Mode	IMF 1	IMF 2	IMF 3	IMF 4	IMF 5
Error Energy/rpm	2.387	17.698	18.439	17.847	19.209
Mode	IMF 6	IMF 7	IMF 8	IMF 9	IMF 10
Error Energy/rpm	18.786	19.698	20.439	20.847	20.209

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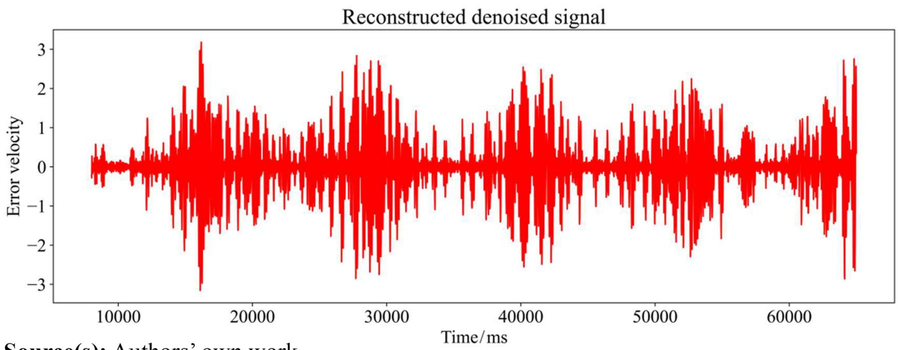

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Figure 5.
Reconstructed denoised signal

Table 2.
Correlation degree division table

Correlation coefficient (γ)	Degree of correlation
$\|\gamma\| \le 0.3$	No correlation
$0.3 < \|\gamma\| \le 0.5$	Low correlation
$0.5 < \|\gamma\| \le 0.8$	Significant correlation
$0.8 < \|\gamma\|$	High correlation

Source(s): From the literature "Gas Pipeline Leak Detection Based on Improved VMD Algorithm" (Hongwei *et al.*, 2019) calculated, and the correlation coefficient is 0.871, which is a high correlation and verifies the effectiveness of the feature extraction of the improved algorithm.

The reconstructed new signal is evenly distributed on both sides of the X-axis. It can be seen that the mechanical failure causes the signal to continuously fluctuate violently. In order to highlight the fault characteristics, this article strengthens the reconstructed signal so that all signal features are distributed above the X-axis, as shown in Figure 6. It can be seen that the abnormal signal fluctuations appear more intense.

In order to explore the changing rules of signal amplitude, the cepstrum method is adopted to estimate the formant (Yi-Cheng, Yu-Ying, Yan-Hu, & Xiao-Juan, 2015), thereby calculating the formant amplitude, formant position and envelope, as shown in Figure 7. The envelope can well reflect the amplitude fluctuation of the enhanced signal. The intervals between the resonance peaks are 12150ms, 11630ms, 12000ms and 11010ms, respectively, showing a periodic pattern of approximately 12s. The motor speed is 5rpm, and the 12s cycle means the motor rotates precisely once. This condition proves that every time the motor rotates to a specific position, there will be jamming, resulting in severe speed fluctuations. Finally, a fault discrimination threshold $\phi = 0.0075$ is set. When the envelope signal exceeds 0.0075, it indicates that the motor has a mechanical jamming fault. In addition, another fault warning threshold $\eta = 0.0050$ is under-considered as well. When the envelope signal exceeds 0.0050, it indicates that the motor is at risk of mechanical interference failure. If the envelope value is less than 0.005, it means that there is no abnormal friction resistance inside the motor, and the

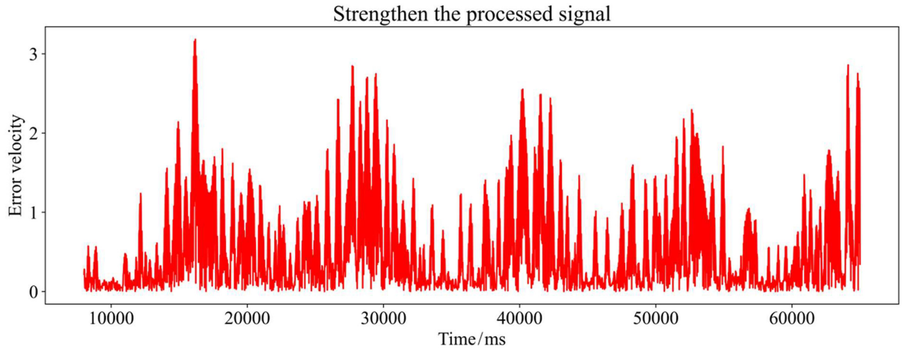

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Figure 6. Strengthen the error velocity signal

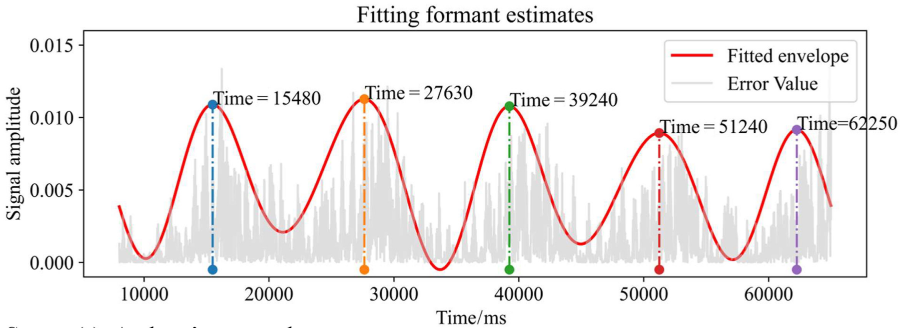

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Figure 7. Locate the fault point of the enhanced signal based on the cepstrum method

mechanical structure has good consistency. The diagnostic process of threshold discrimination is shown in Figure 8.

4. Conclusion and outlook

Using the improved VMD algorithm, taking advantage of signal activity characteristics is an innovative strategy for motor mechanical fault diagnosis for EMB systems in railway brake fields. It introduces the error energy algorithm to decompose and screen the signal modal components effectively. This solution can realize the signal's decomposition and reconstruction to identify the motor's abnormal speed characteristics effectively. In order to verify the effectiveness of signal decomposition and reconstruction, the correlation between the reconstructed signal and the original signal is calculated, which proves that the reconstructed signal with considerable noise removed still contains most of the abnormal features of the original signal. Finally, the resonance peak and envelope of the enhanced reconstructed signal were calculated to identify the fault point accurately, and the diagnosis results were verified by combining them with the rotation period of the motor. The method proposed in this article is simple and efficient and can be practically applied to motor abnormality diagnosis in train electromechanical brake systems.

Fault diagnosis of motor with speed feedback signal is also the innovation of this paper. In the industrial field, most motor fault diagnosis is done by diagnosing motor current signals or installing an acceleration sensor on the motor to collect vibration signals for diagnosis. When the motor rotates, the speed and vibration signals will fluctuate abnormally due to the jamming of the internal mechanical structure of the motor. The characteristics of mechanical jamming will be reflected in these two physical quantities. When the motor rotates, the motor speed signal and vibration signal will fluctuate abnormally when the internal mechanical structure jams. The characteristics of mechanical jamming will be reflected in these two physical quantities. Compared with the diagnosis method based on vibration signals, fault diagnosis of the motor directly through the speed signal avoids installing additional acceleration sensor equipment. Under this condition, the developer can significantly save space in the brake cylinder, and it is a motor diagnosis method that is very suitable for EMB systems.

The motor fault diagnosis method proposed in this article is easy to implement, does not require complex mathematical modeling of the entire motor control system, and does not require large data sets for model training. The diagnosis speed is fast and can meet the demand for real-time diagnosis of motor faults. The signal processed by the improved VMD algorithm in this article only needs to use threshold discrimination to achieve fault warning

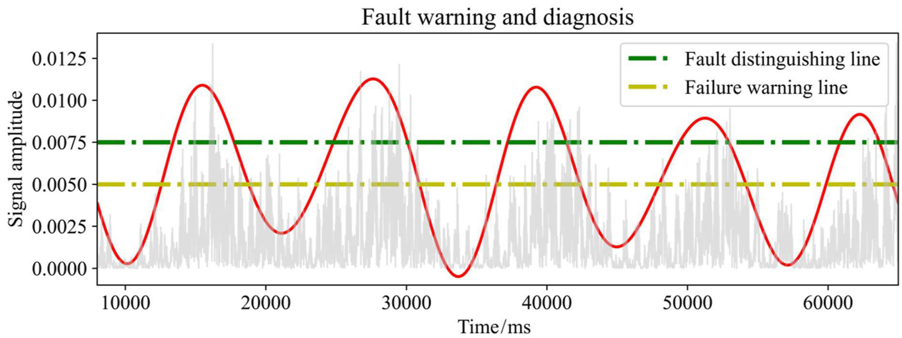

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Figure 8.
Fault diagnosis process by threshold discrimination method

and identification, which greatly simplifies the complicated fault diagnosis problem. This method is used to detect mass-produced factory motors. By embedding the entire diagnostic program into the driver, automatic diagnosis of the motor can be realized, which will reduce the extra work of manual troubleshooting of mechanical faults. In addition, during the actual operation of the vehicle equipped with the EMB system, the driver program can also be called regularly to detect the internal structure of the motor to avoid changes in the internal structure caused by mechanical strain or long-term fatigue work that affect the braking application. The research of this automatic diagnosis method is of great value to the mass production and operation security of the EMB system, which is significant to improve the reliability of the EMB system and promote the broad application of EMB technology.

For the future, there is still much work worthy of further research. The diagnostic method proposed in this article has a prerequisite: the no-load operating conditions of the motor must be met during diagnosis. Because once the motor is blocked, its motion state will be changed and the motor speed signal will rapidly attenuate. At this time, it is meaningless to rely solely on the motor speed signal for abnormality identification. During the operation of the motor, other signals are also collected, such as current signals. If the internal structure of the motor is abnormal at constant speed, the motor will require greater torque to overcome excess friction, which will cause the current to increase. Therefore, the current signal also contains valuable fault information and is another physical quantity that can be used to diagnose motor faults. In the next stage, our team will explore the relationship between current and friction and further study the automatic motor fault diagnosis algorithm based on current signals or multiple signals, such as current and speed, so that it can diagnose the motor in more usage scenarios.

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