Optimization of VMD and SVM for Gear Fault Diagnosis Based on Crested Porcupine Optimization Algorithm

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Abstract: Aiming at the difficulty of feature extraction in gearbox fault diagnosis, a new classification method based on crested porcupine optimization (CPO) algorithm, variational mode decomposition (VMD) and SVM model is proposed. Because the parameter setting of VMD method has great influence on the decomposition effect of gear vibration signal, CPO is proposed to optimize the VMD method. Decompose the vibration signal using parameter optimized VMD, and the obtained components are reconstructed by correlation analysis. Input the reconstructed signal into the support vector machine model for fault classification. Through experimental analysis, the accuracy of gear fault diagnosis by the proposed method is 95%.

Keywords: CPO; Gearbox; Fault Diagnosis; VMD; SVM

1. Introduction

Gear, as the core mechanical part of equipment, is one of the parts that are prone to failure. If the fault cannot be eliminated in time, it will affect the operation of the equipment, and it will cause safety accidents. Therefore, on-line monitoring and fault classification of gears are necessary[1-3].

Gear vibration signals are typical nonlinear signals, and common nonlinear signal processing methods mainly include EMD, EEMD, etc.[4-6]. Among them, empirical mode decomposition can effectively denoise shock vibration signals, but this method has strong modal aliasing and endpoint effects[7]. Although the ensemble empirical mode decomposition method overcomes the shortcomings of EMD in signal processing, EEMD has disadvantages such as cumbersome calculation process and the generation of false intrinsic mode components[8]. In order to solve the above problems, VMD method is proposed, which has perfect mathematical theory and completely solves the problems of modal aliasing and end effect, but the processing results of this method are greatly influenced by parameters[9-12]. Therefore, this paper uses CPO algorithm to determine the parameters of VMD. The gear vibration signal is decomposed by VMD method with optimized parameters, and the decomposed components are reconstructed by correlation analysis, and the reconstructed signals are input into the support vector machine model for fault classification. Finally, the proposed method is verified by experiments.

2. VMD

The essence of VMD decomposition is to find a set of sub modal components and limit their center frequency and bandwidth to achieve adaptive decomposition of nonlinear signals[13-15]. It decomposes the signal into several modal components, and ensures that the sum of the bandwidths of each modal component is minimized, and at the same time makes the sum of each modal component equal to the original signal. Its variational model can be expressed as:

$$\begin{cases} \min\left\{ \sum_{k}^{u_k,\omega_k} \left\| \partial_t [\delta(t) + j/(\pi t) \times u_k(t)] e^{-j\omega_k t} \right\|_2^2 \right\} \\ s.t. \sum u_k = f \end{cases} \tag{1}$$

Where, K is the number of modes, u_k is the modal component, and ω_k is the center frequency. Introducing the penalty factor a and the Large operator λ to modify the variational constraint problem to:

$$L(\{u_k,\omega_k,\lambda\}) = a\sum \left\| \partial_t [\delta(t) + j/(\pi t) \times u_k(t)] e^{-j\omega_k t} \right\|_2^2 + \left\| f(t) - \sum u_k(t) \right\|_2^2 + \left\langle \lambda(t), f(t) - \sum u_k(t) \right\rangle \tag{2}$$

1) The alternating multiplier direction method is used to optimize u_k^{n+1}, ω_k^{n+1}, and λ_k^{n+1}. To

solve the Large saddle point, the following steps are taken:

2) let $n=0$ and initialize u_k^1 , ω_k^1 and λ_k^1 .

3) Update u_k^1 , ω_k^1 , λ_k^1 using the following equation.

$$u_k^{n+1} = \frac{f(\omega) - \sum_{i \neq k} u_i(\omega) + \lambda(\omega)/2}{1 + 2a(\omega - \omega_k^n)^2} \quad (3)$$

$$\omega_k^{n+1} = \frac{\int_0^\infty \omega |u_k(\omega)|^2 d\omega}{\int_0^\infty \omega |u_k(\omega)|^2 d\omega} \quad (4)$$

$$\lambda^{n+1}(\omega) = \lambda^n(\omega) + \tau[f(\omega) - \sum_{k=1}^{k} u_k^{n+1}(\omega)] \quad (5)$$

4) Perform step 2) for many times until the following convergence condition is satisfied.

$$\sum_k \frac{\left\| u_k^{n+1} - u_k^n \right\|_2^2}{\left\| u_k^n \right\|_2^2} < \varepsilon \quad (6)$$

5) Where ε is the discrimination accuracy.

6) Obtain K modal components. When VMD is used to process the signal, the number of decomposition and the choice of penalty factor determine the final result. If the K value is too large, the original signal will be over decomposed, resulting in false components. If the K value is too small, the signal decomposition will not be thorough, causing the center frequencies of the modal components to overlap and making it impossible to decompose the main frequency signal.

3. CPO Algorithm

The most significant feature of the CPO optimization algorithm is the use of cyclic population reduction techniques to maintain population diversity while accelerating convergence speed. The mathematical model is shown below:

$$N = N_{\min} + (N' - N_{\min}) \times \left(1 - \left(\frac{t\% \frac{T_{\max}}{T}}{\frac{T_{\max}}{T}}\right)\right) \quad (7)$$

Where, t is the current value, N is the population size, T is the quantity that controls the number of cycles, $T_{\max}$ is the maximum number of cycles, and $N_{\min}$ is the minimum number of individuals generated in the population. The biggest difference between crested porcupine and other animals is their unique defense methods against predators. Therefore, the CPO algorithm simulates the unique defense strategy adopted by crested porcupine to survive in front of predators. The execution process mainly includes two stages: global exploration and local development:

$$x_i^{t+1} = x_i^t + \tau_1 \times \left| 2 \times \tau_2 \times x_{CP}^t - y_i^t \right| \quad (8)$$

The second defense strategy: crested porcupine create noise and further threaten predators. The mathematical model is as follows:

$$x_i^{t+1} = (1 - U_1) \times x_i^t + U_1 \times (y + \tau_3 \times (x_{r1}^t - x_{r2}^t)) \quad (9)$$

In equations (8) and (9), x_i^t is the position of the i-th individual at the t-th iteration, and x_i^{t+1} is the position of the i-th individual at the (t+1)-th iteration. τ_1 is a random number that follows a normal distribution. τ_2 and τ_3 are random numbers between [0,1]. x_{CP}^t is the optimal solution when the number of iterations is t , and y_i^t is the position of the predator when the number of iterations is t . U_1 is a binary vector consisting of 0 and 1, and $r1$ and $r2$ are two random integers between $[1, N]$.

2) Partial development stage. At this point, the predator is already close to the crested porcupine and will use odor and physical attacks to attack the predator. The third defense strategy: Crested porcupine will secrete a foul odor to spread in the surrounding area, preventing predators from approaching further. The mathematical model is:

$$x_i^{t+1} = (1 - U_1) \times x_i^t + U_1 \times (x_{r1}^t + S_i^t \times (x_{r2}^t - x_{r3}^t) - \tau_3 \times \delta \times \gamma_t \times S_i^t) \quad (10)$$

Fourth defense strategy: When all previous strategies fail, the crested porcupine will launch a physical attack on the predator. The mathematical model is:

$$x_i^{t+1} = x_{CP}^t + (a(1 - \tau_4) + \tau_4) \times (\delta \times x_{CP}^t - x_i^t) - \tau_5 \times \delta \times \gamma_t \times F_i^t \quad (11)$$

In equations (10) and (11), $r3$ is a random number between $[1, N]$, γ_t is the defense factor, S_i^t is the odor diffusion factor, δ is the parameter that controls the search direction, a is the convergence speed factor, τ_4 and τ_5 are also random numbers between [0,1], and F_i^t is the inelastic collision force generated by individual physical attacks on predators. When using CPO to optimize VMD parameters, envelope entropy is used as fitness function. Its sample subset can best cover different categories or values in the dataset, representing the characteristics of the entire dataset. The details are as follows:

$$E(i) = -\sum_{i=1}^{K} p(i)\log_{10}(p(i)) \tag{12}$$

$$p(i) = \frac{a(i)}{\sum_{i=1}^{K} a(i)} \tag{13}$$

Where, K is the number of samples, $E(i)$ is the envelope entropy value, $a(i)$ is the envelope signal, and $p(i)$ is the standardization of $a(i)$. Therefore, taking the minimum envelope entropy as the optimization goal, the key parameters K and a of VMD are obtained, which solves the problems of insufficient signal decomposition and uncertain decomposition effect caused by artificially setting parameters in VMD decomposition process.

4. SVM

SVM can map linearly inseparable problems to high-dimensional space by introducing kernel functions, thereby obtaining the optimal separation plane. The mathematical model of the SVM can be expressed as follows:

$$\begin{cases} \min \dfrac{\|\omega\|^2}{2} + C\sum_{i=1}^{n} \xi_i \\ s.t \begin{cases} y_i(\omega x_i + b) \geq 1 \\ C \geq 0 \end{cases} \end{cases} \tag{14}$$

Where, b is the deviation and C is the penalty factor. Relaxation variable $\xi_i \geq 0$.

5. Fault Classification Steps

The key steps of gear fault classification based on CPO-VMD-SVM include the following steps:

Step 1: Collect signals. According to the references, the signals of gears in different running states are obtained.

Step 2: CPO algorithm is used to determine the parameters of VMD according to the minimum envelope entropy.

Step 3: The improved VMD is used to decompose the gear vibration signal and get a series of components. Use correlation analysis method to screen useful components.

Step 4: Fault classification. Input the reconstructed components into the SVM model for training and achieve fault classification.

6. Gear Fault Classification

The gear fault samples selected in this article include four working conditions: normal state, ring gear fault, planetary gear fault, and sun gear fault. Select 20 samples for each operating state, according to the ratio of training samples to testing samples of 5:5, there are 10 training samples and 10 testing samples. Firstly, CPO is used to determine the key parameters of VMD, and the improved VMD is used to process the gear vibration signal, and eight components are obtained. The obtained components are screened by correlation analysis, and the final results are shown in Table 1.

Table 1. Correlation Coefficients of Each IMF Component

IMF component	Correlation coefficient
IMF1	0.16
IMF2	0.35
IMF3	0.57
IMF4	0.41
IMF5	0.73
IMF6	0.25
IMF7	0.59
IMF8	0.32

According to Table 1, only the correlation coefficient values of IMF3, IMF5, and IMF7 are greater than 0.5. Therefore, this paper selects the above three components as samples of SVM model for fault classification. The obtained results are shown in Figure 1.

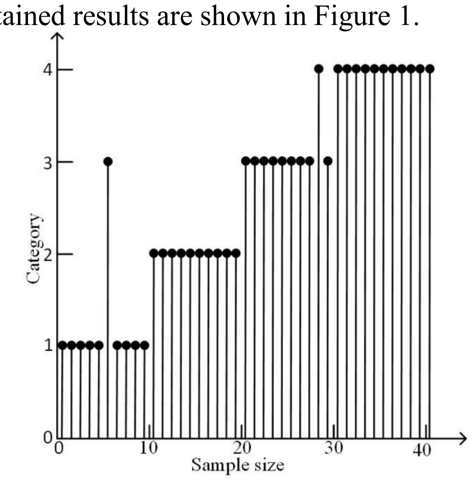

Figure 1. CPO-VMD-SVM fault Classification Results

As can be seen from Figure 1, there are 2 samples out of 40 samples to be tested with incorrect classification, and the comprehensive fault classification accuracy rate is 95%. In order to verify the advancement of this method, it is applied to fault classification together with VMD-SVM method, EMD-SVM method and EEMD-SVM method, and the fault classification results of the other three methods are shown in Figure 2-4 respectively.

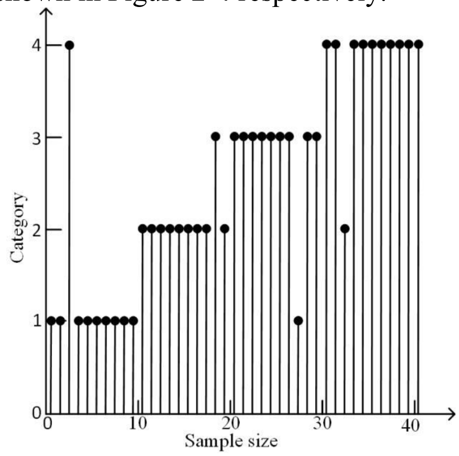

Figure 2. Fault Classification Results Based on VMD-SVM

In Figure 2, 4 samples out of 40 samples to be tested are wrongly classified, and the comprehensive fault classification accuracy rate is 90%.

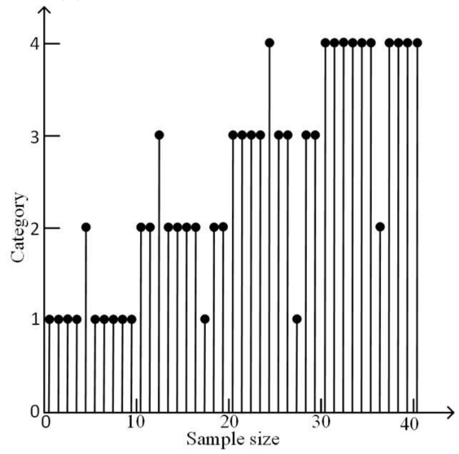

Figure 3. Fault Classification Results Based on EMD-SVM

As can be seen from Figure 3, there are 6 samples out of 40 samples to be tested, and the comprehensive fault classification accuracy rate is 85%.

As can be seen from Figure 4, 3 samples out of 40 samples to be tested are classified incorrectly, and the comprehensive fault classification accuracy rate is 92.5%.

To sum up, the comprehensive accuracy of gear fault classification based on CPO-VMD-SVM proposed in this paper is 95%, which is obviously higher than VMD-SVM, EMD-SVM method and EEMD-SVM. The experimental results verify the advanced nature of this method.

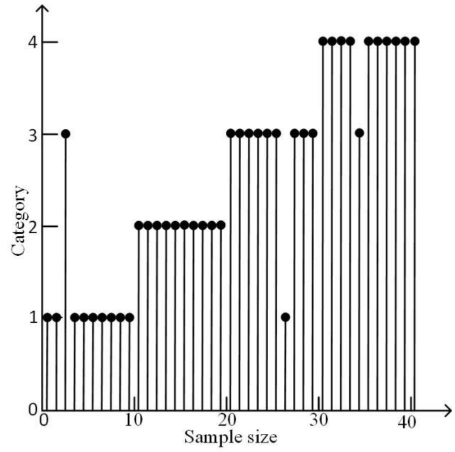

Figure 4. Fault Classification Results Based on EEMD-SVM

7. Conclusion

Aiming at the difficulty and low accuracy of gear fault diagnosis, a new fault classification method based on CPO-VMD-SVM is proposed. The parameters of VMD are determined by CPO, the gear vibration signal is processed by improved VMD, and a series of components obtained are screened by correlation analysis method, and finally input into SVM model for classification. The final experimental analysis results show that the comprehensive gear classification accuracy of the proposed method is 95%, and it has high fault diagnosis accuracy.

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