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Application of VMD feature fusion in fault diagnosis of rolling bearings

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Abstract: In response to the complex nature of bearing faults and the difficulty of a single feature accurately reflecting the overall fault information, this paper proposes a VMD feature fusion method for rolling bearing fault diagnosis. Firstly, use VMD to decompose the bearing vibration signal; Secondly, calculate energy entropy, singular value entropy, permutation entropy, and sample entropy to form a fusion feature vector; Finally, the least squares support vector machine (LS-SVM) is used as a classifier to identify bearing fault types. Through experiments, this method can effectively achieve bearing fault diagnosis.

Keywords: VMD; Feature fusion; Fault diagnosis.

1. Introduction

Rolling bearings are widely used and easily damaged important components in mechanical equipment, and their operating status directly affects the entire mechanical system [1]. Accurately detecting bearing faults and implementing necessary maintenance measures based on their types is of great significance for ensuring enterprise safety production and reducing economic losses [2].

The essence of Variational Mode Decomposition (VMD) [3] is to establish a non-recursive method for variational models, effectively overcoming problems such as modal aliasing. This method has good robustness to noise and is less limited by signal sampling frequency, making it superior to methods such as EMD and EEMD.

2. Variational Mode Decomposition

2.1. VMD principle

The VMD method decomposes the fault signal $f(x)$ into K intrinsic mode functions $u_k(t)$, which can be expressed as

$$u_k(t) = A_k(t)\cos(\phi_k(t))$$

In the formula, $A_k(t)$ ≥ 0 is the instantaneous amplitude of $u_k(t)$; $\omega_k(t)$ is the instantaneous frequency of $u_k(t)$; $\Phi_k(t)$ is a non-decreasing phase function. The detailed steps of VMD method are as follows:

Initialize the values of $\{u_k^1\},\{\omega_k^1\}$, λ^1 and to 0.

Let $n = n+1$, execute the entire loop.

Let $k = 0, k = k+1$, and when $k < K$, execute inner loop 1, updating u_k to:

$$u_k^{n+1} = \arg\min_{u_k} L\left(\{u_{i<k}^{n+1}\},\{u_{i\geq k}^{n}\},\{\omega_i^n\},\lambda^n\right)$$

When $k = 0, k = k+1$,and $k < K$ execute inner loop 2, update ω_k is:

$$\omega_k^{n+1} = \arg\min_{\omega_k} L\left(\{u_i^{n+1}\},\{\omega_{i<k}^{n+1}\},\{\omega_{i\geq k}^{n}\},\lambda^n\right)$$

Update λ For:

$$\hat{\lambda}^{n+1}(\omega) \leftarrow \hat{\lambda}^n(\omega) + \tau\left(\hat{f}(\omega) - \sum_k \hat{u}_k^{n+1}(\omega)\right)$$

Repeat steps 2) to 5) until the iteration stop condition ($\sum_k \left\|\hat{u}_k^{n+1} - \hat{u}_k^n\right\|_2^2 \Big/ \left\|\hat{u}_k^n\right\|_2^2 < \varepsilon$ ($\varepsilon > 0$)) is met, the loop stops, and K intrinsic mode components are output.

2.2. Number of Modal Decompositions K

The VMD method requires determining the number of decompositions K and penalty factors α, Determine K by calculating the correlation coefficient. When K =6, the two component coefficients are similar, and K =5 is chosen as the number of decompositions. The calculation results are shown in Table 1.

Table 1. Correlation coefficients between different components and the same fault signal under different K values

K	Correlation coefficient between IMF component and original signal ρ					
	ρ_1	ρ_2	ρ_3	ρ_4	ρ_5	ρ_6
$K=2$	0.6467	0.5386	—	—	—	—
$K=3$	0.6451	0.5239	0.3405	—	—	—
$K=4$	0.3342	0.6589	0.5117	0.4114	—	—
$K=5$	0.3325	0.6466	0.5126	0.4025	0.1763	—
$K=6$	0.6534	0.5075	0.3321	0.3237	0.1788	0.1025

3. LS-SVM principle

LSSVM converts the training of SVM into solving a system of linear equations, and the specific steps are as follows:

$$f(x) = w^T \varphi(x) + b$$

The optimization problem of LS-SVM can be changed to:

$$\begin{cases} \min\ J(w,e) = \frac{1}{2} w^T w + \frac{1}{2} \gamma \sum_{i=1}^{N} e_i^2 \\ \text{s.t. } y_i = w^T \varphi(x_i) + b + e_i,\ i = 1,2,\cdots N \end{cases}$$

From the Lagrange function and KKT condition, it can be seen that:

$$\begin{bmatrix} 0 & 1_N^T \\ 1N & \Omega + \gamma^{-1} I \end{bmatrix} \begin{bmatrix} b \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ y \end{bmatrix}$$

Where $1_N = [1, 1, \cdots, 1]$, $y = [y_1, y_2, \cdots, y_N]$, $\alpha = [\alpha_1, \alpha_2, \cdots, \alpha_N]$ are Lagrange multiplier, and I is a $n \times n$ matrix of order:

$$\Omega_{ij} = \varphi(x_i)^T \varphi(x_j),\ i、j = 1,2,\cdots N.$$

According to the Mercer condition,

$$K(x_i, x_j) = \varphi(x_i)^T \varphi(x_j)$$

Therefore, the optimal decision function is:

$$f(x) = \sum_{i=1}^{N} \alpha_i K(x_i, x) + b$$

4. Experimental verification

The method was validated using standard rolling bearing fault data from Case University, Western Reserve, USA. Perform VMD decomposition on rolling bearing signals under different states, and calculate their kurtosis values. Select the IMF component with higher kurtosis values as the fault feature sensitive component. The results are shown in Table 2.

Table 2. IMF component kurtosis values under different operating conditions

working condition	IMF component				
	IMF1	IMF2	IMF3	IMF4	IMF5
normal	3.2811	2.3121	1.6557	3.1221	3.0812
Inner ring	3.1225	5.1466	6.6875	2.9567	5.0866
Outer ring	3.7756	4.0598	4.0569	1.7589	1.8687
Rolling element	2.5587	4.5781	8.5413	1.2569	10.5268

The high kurtosis value indicates that the vibration impact of the IMF component is more obvious. Three sensitive IMF components under different working conditions are selected to calculate four entropy values, as shown in Table 3.

Table 3. Characteristic parameters of dynamic bearing vibration signals under different working conditions

working condition	characteristic parameter					
	HEN	HS	HF	PE1	PE2	PE3
normal	0.0486	0.0596	0.4786	1.4523	3.7456	3.5236
Inner ring fault	0.9620	0.3885	1.0678	2.8056	4.6986	4.2567
Outer ring fault	0.9896	0.4756	1.3658	3.0756	2.8697	4.5697
Rolling element fault	1.0869	0.6855	1.3857	2.7569	4.3689	3.8559

Select 30 sets of rolling bearing signals under different states for fault diagnosis. Select 20 sets of signal feature vectors from each state as training samples for LS-SVM, and the remaining 10 sets as test samples. The recognition results are shown in Table 4.

Table 4. Rolling Bearing Fault Diagnosis Results Based on VMD Feature Fusion

working condition	LS-SVM recognition results	Recognition Rate	Overall recognition rate
normal	1 1 1 1 1 1 1 1 1 1	100%	100%
Inner ring fault	2 2 2 2 2 2 2 2 2 2	100%	
Outer ring fault	3 3 3 3 3 3 3 3 3 3	100%	
Rolling element fault	4 4 4 4 4 4 4 4 4 4	100%	

To demonstrate the effectiveness of the VMD method, a rolling bearing fault diagnosis method based on EEMD feature fusion was adopted. The results are shown in Table 5.

Table 5. Rolling Bearing Fault Diagnosis Results Based on EEMD Feature Fusion

working condition	LS-SVM recognition results	Recognition Rate	Overall recognition rate
normal	1 1 1 1 1 1 1 1 1 1	100%	85%
Inner ring fault	2 4 4 2 2 2 4 2 2 2	70%	
Outer ring fault	3 3 3 4 3 3 3 4 3 3	80%	
Rolling element fault	4 4 4 4 4 4 4 4 4 2	90%	

5. Conclusion

The VMD feature fusion method proposed in this article can effectively diagnose rolling bearing fault signals under different working conditions, and the diagnostic accuracy is better than the EEMD method. The kurtosis value can reflect the impact of vibration signals. By calculating kurtosis, sensitive IMF components can be screened, and corresponding entropy values can be calculated, which are input into LSSVM to identify fault types. Provide certain ideas for fault diagnosis of rolling bearings.

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