Rolling bearing fault diagnosis method based on VMD and LSSVM

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Abstract. The vibration signal of rolling bearing is complex, it is difficult to extract fault features and diagnose accurately. In this paper, a rolling bearing fault diagnosis method based on variational mode decomposition and GWO-LSSVM is proposed. The variational mode decomposition algorithm is used to decompose the bearing vibration signal, and the fuzzy entropy of each component signal is calculated. GWO is used to optimize the parameters of LSSVM. The least square support vector machine is used to identify the bearing fault.

1. Introduction

As an important component of rotating machinery, bearing is prone to failure, and its failure will directly affect the performance of the whole machine in terms of accuracy, service life, safety, and reliability. When the mechanical bearing failure, the production process is affected. Aside from causing economic loss, such failure may bring safety risk to the operators or even catastrophic consequence. Therefore, real-time monitoring and fault diagnosis of bearing is of great significance to ensure the reliable and safe operation of mechanical equipment and to avoid major accidents.

Variational mode decomposition (VMD) is a non-recursive and adaptive signal decomposition method which can effectively suppress mode mixing and has good robustness in the presence of noises [1]. VMD has been used to decompose the bearing vibration signal [2-3]. Least squares support vector machine (LSSVM) was proposed by Suykens and Vandewalle [4]. It is an extension of support vector machine (SVM). Apart from inheriting the advantages of SVM in solving nonlinear and high dimensional problems with small sample size, this method further simplifies the computational complexity and improves the computing speed. Grey wolf optimization (GWO) algorithm is a swarm intelligence algorithm proposed by Mirjalili et al [5]. It simulates the predation behavior of wolves. It has been proved that the algorithm has obvious advantages in precision and stability. GWO algorithm has been widely used in parameter optimization of neural network, support vector machine, extreme learning machine and so on [6-8]. In order to obtain the best performance of LSSVM, GWO is used to optimize the parameters of LSSVM.

2. Variational mode decomposition

VMD is a completely non recursive signal mode decomposition method. The main idea of this method is to decompose the signal into discrete components by iteratively searching for the optimal solution of the variational model. The frequency center and bandwidth of each component are updated iteratively in the frequency domain, and the effective decomposition of the signal in the frequency domain is realized adaptively [9].
In VMD, it is assumed that the original signal is composed of several IMFs, and each IMF is defined as an AM-FM signal whose expression is

\[ u_k(t) = A_k(t)\cos(\phi_k(t)) \]  

(1)

where \( A_k(t) \) is instantaneous amplitude of \( u_k(t) \), and \( \omega_k(t) \) is instantaneous frequency of \( u_k(t) \),

\[ \omega_k(t) = \frac{d\phi_k(t)}{dt}. \]

The procedure for constructing a variational model is as follows.

1. For each mode, the analytical signal of each IMF is obtained through the Hilbert transform, and its single side spectrum can be obtained:

\[ [(\delta(t) + \frac{j}{\pi t})^* u_k(t)] \]

(2)

2. For each mode, the estimated center frequency of each IMF is adjusted by adding an exponential term, and the spectrum of each IMF is modulated into the corresponding baseband:

\[ [(\delta(t) + \frac{j}{\pi t})^* u_k(t)]e^{-j\omega_k t} \]

(3)

3. The bandwidth of the demodulated signal is estimated through Gaussian smoothing, and the bandwidth of each modal signal can be obtained.

4. In the frequency domain, the center frequency and bandwidth of each mode are continuously updated using Eqs (1) and (2), thus obtaining many band-limiting IMFs. Assumed that the original signal \( f(t) \) is decomposed into \( K \) IMF components, the expression of the corresponding constrained variational model is

\[ \min_{\{u_k\},\{\omega_k\}} \left\{ \sum_{k=1}^{K} \left| \hat{c}_k [(\delta(t) + \frac{j}{\pi t})^* u_k(t)]e^{-j\omega_k t} \right|^2 \right\} \]

s.t. \( \sum_{k} u_k = f \)

(4)

where \( \{u_k\} = \{u_1,\ldots,u_k\} \) is \( K \) IMF components obtained through VMD decomposition, \( \{\omega_k\} = \{\omega_1,\ldots,\omega_k\} \) is center frequency of each IMF component, \( \hat{c}_k \) is partial derivative of the time \( t \) for the function, \( \delta(t) \) is unit pulse function, \( j \) is imaginary unit, \( \| \cdot \|_2 \) is 2-norm, \( * \) is convolution.

The penalty factor and Lagrange multiplication algorithm are introduced to solve the equation (4), and the optimal solution is obtained.

Feature extraction is a key step in fault diagnosis. In this paper, the combination of variational mode decomposition and fuzzy entropy method is used to extract fault features from bearing vibration signals. According to the method of reference [10], the fuzzy entropy of bearing vibration data is calculated.

3. Least squares support vector machine and its parameter optimization

3.1. Least squares support vector machine

Least squares support vector machine (LSSVM) is an expansion of standard SVM. The most significant difference between LSSVM and the standard SVM lies in the loss function. LSSVM uses the quadratic term of error as the loss function, and replaces the inequality constraint of standard support vector machine with equality constraint. The complex process of solving convex quadratic
programming problem is transformed into the process of solving a set of linear equations. These improvements reduce the computational complexity and speed up the calculation.

Suppose a given training sample set is \( \{(x_i, y_i) \mid i = 1, 2, \ldots, n\} \), \( x_i \) is a \( d \)-dimensional input vector, \( x_i \in \mathbb{R}^d \), \( y_i \) is a 1-dimensional output vector, \( y_i \in \mathbb{R} \). Thus, the LSSVM classification problem is transformed into an optimization problem. The corresponding target optimization function is:

\[
\min_{w, \xi, \nu} \frac{1}{2} w^T w + \frac{1}{2} \sum_{i=1}^{n} \nu_i^2 \\
\text{S.T. } y_i[w^T \varphi(x_i) + b] = 1 - \xi_i
\]

\( w \) is weight vector, \( \xi_i \) is error, \( \nu \) is regularization parameter, \( b \) is offset quantity, and \( \varphi(x) \) is nonlinear mapping function from the input space to the signature space. A Lagrangian operator is introduced to solve the above constraint optimization problem. Finally, the LSSVM decision function is expressed as follows:

\[
y(x) = \sum_{i=1}^{N} \lambda_i K(x_i, x) + b
\]

\( \lambda \) is the Lagrange coefficient, \( K(x_i, x) \) is the kernel function. The kernel function used in this paper is radial basis function:

\[
K(x_i, x) = \exp \left( -\frac{\|x - x_i\|^2}{2\sigma^2} \right)
\]

### 3.2. Grey Wolf optimization algorithm and its optimization LSSVM

In GWO algorithm, gray wolves are divided into \( \alpha \) wolf, \( \beta \) wolf, \( \delta \) wolf and \( \omega \) wolf according to their social rank. \( \alpha \) wolf plays a leading role. Its responsibility is to make decisions. \( \beta \) wolf assists \( \alpha \) wolf in making decisions. \( \delta \) wolf carries out the orders of \( \alpha \) wolf and \( \beta \) wolf, and dominates \( \omega \) wolf. The predation process of gray wolf mainly includes encircling, hunting and attacking prey.

The mathematical modeling includes the following equations:

\[ D = CX_f(t) - X(t) \]  
\[ X(t + 1) = X_f(t) - AD \]  
\[ A = 2ar_1 - a \]  
\[ C = 2r_2 \]  
\[ D_\alpha = |C_1X_\alpha - X| \]  
\[ D_\beta = |C_2X_\beta - X| \]  
\[ D_\delta = |C_3X_\delta - X| \]  
\[ X(t + 1) = (X_1 + X_2 + X_3) / 3 \]

\( D \) is the distance between the current wolf individual and the guide wolf, \( t \) is the number of iterations, \( a \) is the convergence factor, \( r_1, r_2 \) are random numbers, and \( r_1, r_2 \in [0, 1] \).

In LSSVM algorithm, its regularization parameters and kernel parameters need to be set. In order to obtain the best LSSVM parameter values, GWO was used to optimize the values of regularization parameters and kernel parameters. In the process of GWO optimizing LSSVM, the parameter \([\gamma, \sigma]\) of LSSVM is mapped to the position of gray wolf, and the fitness function is the diagnostic error rate of LSSVM.
The steps of optimizing LSSVM parameters by GWO are as follows:

Step 1 Sets the parameters of the initialization algorithm, including the size of the population and the dimension of the individual.

Step 2 Initialize population, and the position of gray wolf represents the value of parameter $[\gamma, \sigma]$ of LSSVM.

Step 3 The fitness value of each individual was calculated. The fitness values of all individuals are arranged in ascending order, and the positions corresponding to the first three fitness values are updated to the positions of $\alpha$ wolf, $\beta$ wolf and $\delta$ wolf, the position of $\omega$ wolf is updated according to equation (15), the values of factor $A$ is updated according to equation (10), the values of factor $C$ is updated according to equation (11).

Step 4 If the maximum number of iterations is reached, stop the algorithm and output the optimal solution, that is, the position of alpha wolf, otherwise, return to step 3.

4. Rolling bearing fault diagnosis process

In this paper, empirical wavelet transform, permutation entropy and least squares support vector machine are applied to rolling bearing fault diagnosis. The diagnosis process is shown in Figure 1.

5. Experiment

The experimental data is the bearing data set of CWRU. The rolling bearing model is 6205-2RS JEM SKF, the power of driving motor is 24KW, the motor load is 2 HP, and the sampling frequency is 12000 Hz. The experimental data include rolling element fault, inner ring fault, outer ring fault and normal bearing vibration data. There are 200 data samples in this experiment, which are composed of four types of fault samples, each of which has 50 samples. 80% of each type of sample is used as training sample and 20% of each type of sample is used as test sample. Each sample consists of 2048 sampling data points. The diagnosis process is shown in Figure 2.
Figure 2. Time domain waveforms of various bearing faults.

Experimental parameter setting: the population size of GWO algorithm is 20, and the maximum number of iterations is 200. The value of component number k of VMD is 6 and the penalty factor $\alpha$ is 122. After GWO optimization of LSSVM parameters, the best values of LSSVM parameters are obtained: $\gamma=82.7$ and $\sigma=1.1$. In order to verify the effectiveness of the proposed method, the proposed method is compared with LSSVM and GA-LSSVM. The results are shown in Table 1. As can be seen from Table 1, the fault diagnosis accuracy of the proposed method is the highest, which shows that the method is effective.

| Method      | Accuracy (%) |
|-------------|--------------|
| LSSVM       | 85           |
| GA-LSSVM    | 95           |
| GWO-LSSVM   | 97.5         |

6. Conclusion
This paper presents a method of bearing fault diagnosis based on VMD and GWO-LSSVM. The complex vibration signal of rolling bearing is decomposed by VMD, and the fuzzy entropy of the component signal is taken as the fault feature, which is the key to improve the accuracy of fault diagnosis. The accuracy of fault diagnosis can be effectively improved by using LSSVM optimized by GWO. The experimental results show that the proposed method is better than LSSVM and GA-LSSVM.

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