Rolling bearing fault diagnosis based on MEEMD sample entropy and SSA-SVM

Xuguang Li¹a*, Liyou FU²b

¹ Department of Business Studies, Shanghai DianJi University, Shanghai 201306, China
² Department of Business Studies, Shanghai DianJi University, Shanghai 201306, China

a*1151320530@qq.com, bfuly@sdju.edu.cn

Abstract. The penalty parameter (c) and kernel parameter (g) contained in Support Vector Machine (SVM) cannot be adaptively selected according to actual samples, which results in low classification accuracy and slow convergence speed. A novel sparrow search algorithm was used to optimize the parameters of SVM classifier. Firstly, an improved ensemble empirical mode decomposition (MEEMD) method was used to decompose non-stationary and nonlinear vibration signals, and the eigenmode function (IMF) was obtained by removing abnormal signals from the original signals through permutation entropy, and the sample entropy was extracted. Finally, a fault diagnosis model based on SSA-SVM is constructed, and the high recognition rate and effectiveness of this method are proved by simulation and experimental data analysis.

1.Introduction

The operation and maintenance of modern industry is very dependent on rotating parts such as bearings, which can easily cause personnel accidents and property losses under complex working conditions. Therefore, it is necessary to monitor and diagnose the fault of rolling bearing. Wavelet analysis is the main method to deal with bearing vibration mode at present[1], EMD, EEMD decomposition method, etc. Complementary set empirical Mode decomposition (CEEMD), which introduces gaussian white noise with opposite sign in the original signal to cancel the residual auxiliary noise in EEMD, improves the mode aliasing problem[2]. Compared with EEMD, the reconstruction error is reduced, but the amount of calculation is increased, and the white noise amplitude needs to be selected, which is not conducive to the adaptability of the algorithm. Zheng Jinde et al. [3] proposed to take sample entropy as threshold value to improve set empirical Mode decomposition (MEEMD), which has certain advantages to remedy the above shortcomings.

At the same time, the kernel learning SVM with good performance of sparsity and robustness has higher recognition accuracy than decision tree and multi-layer neural network in the scale of small and medium-sized data samples[4]. SVM solves the classification problems of sequence nonlinearity and sample space dimension disaster[5]. But its classification effect depends largely on the choice of parameters. It is difficult to select the penalty coefficient C to distinguish the best mapping of over-fit and under-fit and the kernel parameter G of the kernel function through adaptive selection, resulting in large classification errors. Chinese and foreign scholars introduced swarm intelligence algorithm to carry out SVM parameters[6-7]. While improving classification accuracy, it should not be ignored,
such as Zhang Yue et al. [8] adopted Genetic Algorithm (GA) to optimize SVM parameters, but its optimization speed was slow. Hai Tao et al. [9] used Particle Swarm Optimization (PSO) to optimize SVM parameters, but it was still difficult to avoid falling into local optimal solutions. Xue, Jianka et al. [10] proposed a novel bionic swarm intelligence algorithm—Sparrow Search Algorithm (SSA) in 2020 to optimize the above problems to a certain extent.

In this paper, A MEEMD-SSA-SVM diagnosis model was jointly established based on MEEMD, which decomposed IMF components with rich fault information and combined with sample entropy with good statistical stability and sent into SSA iteratively optimized SVM for training and classification.

2. Fault feature extraction

2.1 Decomposition principle of MEEMD

MEEMD introduced the concept of permutation entropy in signal analysis, which has the function of detecting the randomness of time series, and its size can reflect the randomness of signal series[11]. The basic principle of MEEMD is to evaluate the complexity of decomposed signals by calculating permutation entropy, which ranges from 0 to 1. The larger the permutation entropy is, the greater the signal complexity will be. Signals with excessive complexity will be regarded as abnormal signals and the abnormal signals will be removed from the original signals. Finally, the remaining signals are decomposed by EMD, that is, the decomposition results of MEEMD are obtained.

The time-domain waveform of impact signal generated when the bearing inner ring fails is shown in figure 1, and the signal is decomposed by MEEMD, as shown in figure 2. Finally, 8 IMF components and 1 residual component are obtained. The decomposition is complete and the number of components is small, which effectively inhibits the generation of pseudo-components. The first three components clearly show the regular impact characteristics of bearing inner ring faults, which ameliorated the mode confusion problem to some extent. On the whole, MEEMD method has a good effect and the decomposed components are reasonable.

![Figure 1. Inner ring fault vibration signal.](image)

2.2 The sample entropy

Sample entropy is a measure of time series complexity proposed by Richman et al. [12]. The lower the sample entropy is, the lower the complexity of time series is. The larger the value, the higher the complexity of time series. Sample entropy is an improvement on approximate entropy. Compared with approximate entropy algorithm, sample entropy has the advantages of strong anti-noise interference, high accuracy and good consistency. It does not depend on the length of data and can be used as the fault feature of fan gearbox.
3. Support Vector Machine optimized based on SSA algorithm

3.1. Support Vector Machines

Support Vector Machines are machine learning methods developed by Professor Vapnik for dichotomizing supervised learning[13]. The essence of SVM is to maximize the distance between different samples in the data set from the nearest interface and the hyperplane by dividing the unique optimal classification hyperplane, as shown in figure 3. H1 and H2 are parallel to the H hyperplane.

The radial basis kernel function (RBF) has the characteristics of simple calculation process and strong anti-interference. Therefore, this paper adopts SSA to its kernel function parameter g and combines it with penalty parameter c, which has significant influence on classifier fitting accuracy and learning ability, to establish a joint optimization model.

In this paper, the radial basis kernel function mathematical model formula is:

\[ k(x_m, x_n) = \exp\left(-\frac{||x_m - x_n||^2}{2g^2}\right) \]  

(1)

Type: \( g \) is the radius of the kernel function, \( x_m \) is the center of the kernel, \( x_n \) is the feature vector of the input sample.

3.2. Sparrow search algorithm

SSA algorithm is a new swarm intelligence optimization algorithm based on the close cooperation among finders, entrants and watchmen in nature, which enables sparrows to quickly find food, compete for resources and make anti-predation behaviors.

Discoverers benefit from superior visual range to guide the hunt. Its location update mathematical
model is described as follows:

\[
X_{j,k}^{t+1} = \begin{cases} 
X_{j,k}^t \exp \left( -\frac{1}{\alpha_{\text{max}}} \right) & R_c < R_{ST} \\
X_{j,k}^t + Q \alpha & R_c \geq R_{ST}
\end{cases}
\]  

(2)

Type: \( t \) is the current iteration number; \( T_{\text{max}} \) is the maximum number of iterations; \( X_{j,k}^{t+1} \) is the position of the \( J \)TH sparrow in the \( t+1 \) iteration of the \( K \) dimension; \( \alpha \) is a random number between \((0,1]\); \( Q \) is a random number subject to a normal distribution; \( R_c \), \( R_{ST} \) are warning value and safety value respectively; \( L \) is the matrix whose size is \( 1 \times k \) and the mean of the elements is 1.

Entrants continue to follow the discoverers and hunt down the food they find, increasing the population's fitness. Its location update is described as:

\[
X_{j,k}^{t+1} = \begin{cases} 
Q \exp \left( -\frac{X_{\text{worst},j}^{t+1} - X_j^t}{\beta} \right), & i > \frac{B}{2} \\
X_{j,k}^t + \lambda \left( X_{\text{best},j}^{t+1} - X_j^t \right) A \cdot L, & \text{Other}
\end{cases}
\]  

(3)

Type: \( X_{\text{worst},j}^{t+1} \) is the discoverer's worst global position in the \( t \) iteration; \( X_j^{t+1} \) is the finder's best position; \( A \) is the matrix with size \( 1 \times d \) and elements randomly assigned to 1 or -1:

\[ A = \text{rand}(1 \times d) \cdot 2 - 1. \]

The vigilante is a random conversion from the group that has joined and leads the group in danger into anti-predator behavior, withdrawing and abandoning the current food. Its location update is described as:

\[
X_{j,k}^{t+1} = \begin{cases} 
X_{j,k}^t + \omega \frac{X_{j,k}^t - X_{\text{worst},j}^{t+1}}{(f_j - f_{\text{best}}) + \beta}, & f_j = f_{\text{best}} \\
X_{j,k}^t + \gamma \frac{X_{j,k}^t - X_{\text{best},k}^{t+1}}{f_j - f_{\text{best}}}, & f_j \neq f_{\text{best}}
\end{cases}
\]  

(4)

Type: \( X_{\text{best},k}^{t+1} \) is the optimal global position information of early warning sparrow in \( t \) iteration; \( \gamma \) is the step size, obeys the standard normal distribution; \( \omega \) is a random number whose range is \([-1, 1]\); \( f_j \), \( f_{\text{best}} \) and \( f_{\text{worst}} \) are the fitness, global difference fitness and global optimal fitness of sparrows respectively.

4. MEEMD-SSA-SVM combined model fault diagnosis process

The decomposition steps of MEEMD-SSA-SVM bearing fault diagnosis model based on sample entropy feature extraction are as follows

1) The bearing vibration signal extracted in Section 5.1 is decomposed by MEEMD algorithm. The logarithm of white noise is 50, the standard deviation of the original signal is 1.5 times as the white noise amplitude, the permutation entropy threshold is set as 0.6;

2) The first 6 order IMF components rich in high frequency information of impact faults are selected to extract their sample entropy to form training set and test set;

3) Set the maximum number of iterations of SSA algorithm, the ratio of different functional sparrows, the optimization range of two important parameters \( c \) and \( g \), and the population size;

4) The fitness of each sparrow was calculated and sorted to determine its specific species; The position of sparrow population was updated according to formula \((2 - 4)\). The fitness value of the new position of individual sparrows was calculated, and the optimal fitness value was selected after the update to continue the update iteration;

5) Check whether the maximum number of iterations is met. If not, jump to \((4)\) continue the
operation. If the conditions are met, use SVM matching the best parameters to classify test samples and obtain diagnostic results. See figure 4 for the detailed process;

![Flow chart of MEEMD-SSA-SVM model.](image)

**Figure 4. Flow chart of MEEMD-SSA-SVM model.**

### 5. Case analysis of rolling bearing fault diagnosis

#### 5.1. Experimental sample source and feature extraction

Experimental data came from the fault data set of SKF6205-2RS, a deep groove ball bearing at the driver end with a sampling frequency of 12kHz, provided by Case Western Reserve University. The fault diameter was set as 0.1778mm. The approximate spindle speed is 1797 r/min. Six bearing vibration states are selected as normal state, inner ring fault, rolling body fault, outer ring fault 3:00(directly in the load zone) direction, 6:00(orthogonal to the load zone) direction, 12:00(orthogonal to the load zone) direction. 25 groups of samples were taken from each state, with a total of 100 groups. Five samples from each group were randomly selected to form the training set and 20 samples to form the test set (with four significant digits reserved).

#### 5.2. Comparison of optimization convergence performance of algorithm parameters

The feature vectors were fed into PSO-SVM and GA-SVM and SSA-SVM for comparative analysis. The maximum number of iterations is set to 100, and the diagnostic accuracy of fault diagnosis output is taken as the fitness. The accuracy optimization iteration performance curves of the three methods are shown in figure 5. When the optimal fitness is stable, the SVM optimized by SSA algorithm completes optimal classification after the minimum number of iterations. The classification accuracy of GA method is low. Although it has strong robustness, its encoding and decoding methods are complex and time-consuming, and the convergence speed is slow and the global search ability is not strong. It can be seen that the SSA algorithm can obtain the best SVM parameter combination more quickly and accurately than the current mature PSO and GA algorithms.
Figure 5. Three classification models were used to optimize performance curves.

5.3. Comparison of fault diagnosis effects of different models

Finally, 150 groups of test samples were used to test the working state of bearings by using the trained SVM parameters c and g as the optimal parameters of the classifier. The classification results and performance test results of the three models are shown in table 1. It can be seen that the parameter combination will change with different classes of intelligent optimization algorithms. Among them, the recognition rate of SSA-SVM test is 93.33%, and the diagnosis effect is the best. Compared with the two GA-SVM and PSO-SVM diagnostic models, the recognition rate is increased by 5.0% and 5.83% respectively, and the optimization time is the fastest.

| Algorithm Model | PSO-SVM | GA-SVM | SSA-SVM |
|-----------------|---------|--------|---------|
| Penalty parameter c | 83.7087 | 10.4713 | 0.8237 |
| Nuclear parameter g | 0.0100 | 0.1268 | 7.4339 |
| Accuracy rate/% | 87.50 | 88.33 | 93.33 |
| Iteration time/s | 3.7241 | 4.617546 | 3.1485 |

6. Conclusions

Based on the results and discussions presented above, the conclusions are obtained as below:

1. It can be seen from figure 6, figure 7, and figure 8 that the prediction errors of PSO-SVM are mainly concentrated in the three kinds of outer ring damage with relatively serious mode aliasing, but the classification of the other kinds of faults is good. In GA-SVM classification effect, due to the interference of three approximate outer ring feature vectors, other faults are affected to varying degrees, resulting in low overall classification accuracy. The classification effect of SSA-SVM has a relatively excellent effect in suppressing the mode aliasing of three kinds of outer ring damage and similar feature vectors, and it has a slight impact on the classification of other faults, with outstanding comprehensive classification ability.

2. The comprehensive results show that compared with GA-SVM and PSO-SVM classification models, SSA-SVM classification model has high diagnostic accuracy, is not easy to fall into local extremum, has fast convergence speed, and has strong searching ability. Combined with MEEMD algorithm and sample entropy, the method can effectively identify multiple types of bearing faults and their locations during the operation of rotating equipment to a certain extent, providing reference for its health maintenance.
Figure 6. GA-SVM classification model.  

Figure 7. PSO-SVM classification model.  

Figure 8. SSA-SVM classification model.  

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