Fault diagnosis of motor rolling bearing based on IMF sample entropy and particle swarm optimization SVM

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Abstract. Aiming at the problem that it is difficult to effectively identify rolling bearing faults, a method for motor rolling bearing faults based on IMF sample entropy and particle swarm optimization SVM (PSO-SVM) is proposed. Firstly, the complementary collective empirical mode decomposition (CEEMD) is applied to the adaptive decomposition of bearing vibration signals to obtain a group of Intrinsic Modal Functions (IMFs). Then the sample entropy of the IMF component containing the main fault feature information was calculated to obtain the sample entropy matrix of the signal component, which was input as the feature vector into the particle swarm optimization SVM for training and testing. Through the analysis of simulation and experimental data, the method has a high identification accuracy for fault types.

1. Introduction
Fault diagnosis of motor rolling bearing is actually a process of fault type identification and fault feature information extraction is a key step to accurately identify fault type. Because of the non-linear and non-stationary characteristics of the vibration signal of the rolling bearing, it is easy to be disturbed by the hardware equipment and the surrounding environment in the process of signal acquisition [1]. Therefore, the key of fault diagnosis is to extract the sensitive characteristic information from the complex signal of rolling bearing. Empirical Mode Decomposition (EMD)[2] is a time-frequency analysis method for processing non-stable and nonlinear vibration signals, which is widely applied in the field of mechanical fault diagnosis. However, in the process of signal decomposition, EMD has some problems, such as endpoint effect, mode aliasing and so on[3-4]. Torres [5] et al, proposed a complementary ensemble empirical mode decomposition (CEEMD), which can decompose time-varying signals more accurately, effectively overcome the problems of mode aliasing and endpoint effect, and have less residual noise in signal decomposition. Sample entropy [6] is a new method to measure time complexity based on approximate entropy, and in this paper, CEEMD decomposition is combined with nonlinear theoretical sample entropy to characterize fault information by the eigenvector matrix composed of sample entropy of single signal component with strong representational significance. Particle swarm optimization is used to optimize the classification model of support vector machine (SVM), and input the above eigenvector matrix into particle swarm optimization SVM for training and testing. And compared with the recognition method using support vector machine without particle swarm optimization, and the experimental results show that the method described in this paper has higher accuracy in fault identification.
2. Basic theory

2.1 CEEMD algorithm
CEEMD method adds two groups of positive and negative white noise in pairs to the original signal, and then decomposes them by EMD. The IMFs obtained are averaged by two groups of IMF components of residual positive and negative white noise. The process of CEEMD algorithm is as follows:

1) A pair of positive and negative white noise \( n(t) \) is added to the original signal \( x(t) \):
   \[
   \begin{align*}
   x^+(t) &= x(t) + n(t) \\
   x^-(t) &= x(t) - n(t)
   \end{align*}
   \]
   (1)

2) The EMD method is used to decompose \( x^+(t) \) and \( x^-(t) \) to obtain \( \text{IMF}_{k}^{+} \) and \( \text{IMF}_{k}^{-} \).

3) Calculate the average values of \( \text{IMF}_{k}^{+} \) and \( \text{IMF}_{k}^{-} \):
   \[
   \text{IMF} = \frac{\text{IMF}_{k}^{+} + \text{IMF}_{k}^{-}}{2}
   \]
   (2)

4) The original signal can be expressed as:
   \[
   x(t) = \sum_{k=1}^{K} \text{IMF}_{k} + r(t)
   \]
   (3)

   Where \( r(t) \) is the residual amount.

2.2 Sample entropy
Sample entropy is a new measure of time series complexity, similar to approximate entropy but with better accuracy. Both of them are used to measure the self-similarity and complexity of time series, but the calculation of sample entropy has little dependence on the length of data and has better consistency. The calculation process of sample entropy is as follows:

For the N point time series \( x(1), x(2), \cdots, x(N) \), Define algorithm related parameters \( m, r \), among them, \( m \) is an integer, represents the length of the comparison vector, \( r \) is a real number, represents the measurement value of "similarity" [7]. The sample entropy calculation process is as follows:

1) Reconstruct the original time series into m-dimension vector:
   \[
   H_m(i) = \{x(i), x(i+1),\ldots,x(i+m-1)\}, 1 \leq i \leq N - m + 1
   \]
   (4)

2) Define the distance between \( H_m(i) \) and \( H_m(j) \):
   \[
   d[H_m(i), H_m(j)] = \max_{k=1,m-1} |x(i+k) - x(j+k)|
   \]
   (5)

3) For the tolerance \( r \), counting the number of satisfying conditions \( d[H_m(i), H_m(j)] \leq r \) for each \( X_m(i) \), record as \( A_i \), and record the ratio of \( A_i \) to \( N - m + 1 \) as:
   \[
   B^m_i(r) = \frac{A_i}{N - m + 1}, 1 \leq i \leq N - m
   \]
   (6)

4) Calculate the average of \( B^m_i(r) \) for all values of \( i \):
   \[
   B^m_i(r) = \frac{1}{N - m} \sum_{i=1}^{N-m} B^m_i(r)
   \]
   (7)

5) Using the same method to obtain \( B^{m+1}_i(r) \), the sample entropy on the time series can be defined as:
   \[
   \text{SampEn}(m, r) = \sum_{N \to \infty} - \ln \frac{B^{m+1}_i(r)}{B^m_i(r)}
   \]
   (8)
In practical applications, when \( N \) is a finite value, the estimated value of sample entropy is:

\[
SampEnt(m, r, N) = -\ln \frac{B_{m+1}(r)}{B_m(r)}
\] (9)

In the calculation of sample entropy, \( m = 1 \) or 2, \( r = 0.1SD \sim 0.25SD \) (SD represents the standard deviation of the original time series), and \( m = 2, \ r = 0.1SD \) are selected in this experiment.

2.3 Support Vector Machine (SVM)

The core idea of SVM is to maximize the interval between categories so that the classification has higher credibility and generalization ability, while those data points close to the boundary are support vectors [8]. SVM is usually designed as a binary classifier in order to find an optimal hyperplane that can correctly segment positive and negative class samples. The optimal hyperplane \( \omega^T x + b = 0 \) can be obtained by making a nonlinear mapping. To understand the hyperplane geometrically, maximizing the geometric interval is the same as minimizing \( ||\omega|| \). Therefore, there are two cases in practical application. When the sample set is linearly separable, the optimization problem is [9]:

\[
\begin{align*}
\min & \quad \frac{1}{2} ||\omega||^2 \\
\text{s.t} & \quad y(\omega^T x + b) \geq 1, i = 1, 2, \cdots, N
\end{align*}
\] (10)

When the sample set is linearly indivisible, introducing the concept of "soft interval", that is, there can be a small number of outliers, a relaxation variable \( \xi_i > 0 \) and a penalty factor \( C \) are often added, and the penalty factor represents the tolerance for outliers and is an important parameter affecting SVM classification performance. Therefore, equation (11) becomes a convex quadratic programming problem:

\[
\begin{align*}
\min & \quad \frac{1}{2} ||\omega||^2 + C \sum_{i=1}^{N} \xi_i \\
\text{s.t} & \quad y(\omega^T x + b) \geq 1 - \xi_i, i = 1, 2, \cdots, N
\end{align*}
\] (11)

Generally, the problem of linear inseparability is solved by mapping a low-dimensional sample set to a high-dimensional one. In order to get rid of the problem of increasing the dimension of the sample set, it is supposed to find a function that makes the calculation result of the sample set in the low-dimensional space consistent with the inner product result mapped to the high-dimensional space. This is the kernel function. There are many common kernel functions, such as gaussian radial basis kernel function, neuron kernel function, polynomial kernel function, etc. By introducing kernel function \( a \) and Lagrange multiplier \( b \), equation (11) can be written as dual form:

\[
\begin{align*}
\min & \quad \frac{1}{2} \sum_{i=1}^{N} \alpha_i + C \sum_{i=1}^{N} \xi_i \\
\text{s.t} & \quad \sum_{i=1}^{N} \alpha_i y_i = 0, 0 \leq \alpha_i \leq C, i = 1, 2, \cdots, N
\end{align*}
\] (12)

Literature [10] has proved that the universality of radial basis kernel function is higher than other functions, and its expression is as follows:

\[
k(x_i, x_j) = e^{-\gamma ||x_i - x_j||^2}
\] (13)

\( g \) is the kernel parameter, representing the width of the function. It plays an important role in SVM classification performance and can be regarded as another important parameter.

2.4 Particle swarm optimization optimization model parameters

Penalty factor \( C \) and kernel function parameter \( g \) are the main factors that affect SVM recognition
performance. This paper uses particle swarm optimization algorithm to optimize these two parameters to improve SVM recognition accuracy. The main steps of the optimization process are as follows:

1) Algorithm initialization: set the algorithm's local search ability, global search ability, maximum number of iterations, population size, maximum and minimum values of penalty factors and kernel function parameters, and initialize the particle position and speed.

2) Calculate the cross validation accuracy of the population as the adaptive value.

3) Find and update the historical optimal values of individual particles and global particles.

4) Renew the velocity and position of particles in the population.

5) Determine the iteration stop condition, if the iteration stop condition is satisfied, output the optimal value, otherwise return to step 2).

The iteration stop condition is set. When the maximum number of iterations or the change value of the global optimal value meets the minimum limit, the iteration is stopped and the optimal parameter is obtained.

3. Fault diagnosis of motor rolling bearing based on IMF sample entropy and particle swarm optimization SVM

The process of rolling bearing fault diagnosis based on IMF sample entropy and particle swarm optimization SVM is shown in figure 1. It mainly includes data collection, feature extraction, classifier parameter optimization, sample data training and testing, and fault identification and analysis.

The specific steps are as follows:

1) Vibration signals in four different states of rolling bearing are collected respectively: normal state, inner ring fault, outer ring fault and rolling body fault. N samples were taken at a certain sampling frequency to obtain 4N groups of original sample signals. Due to limited space, the waveforms of the inner ring fault signal are shown in figure 2.

2) The CEEMD algorithm is used to decompose all the original vibration signals in four different states to obtain several IMF components. Sample entropy is used to quantify each component $T = \{\text{SampEn}_1, \text{SampEn}_2, \ldots, \text{SampEn}_N\}$, and the sample entropy eigenvector matrix is obtained.

3) Optimize the parameters of SVM classifier with particle swarm optimization algorithm, and input the eigenvector matrix obtained from 2) into the classifier for training and testing, so as to realize the fault diagnosis of rolling bearing.

4. Experimental analysis

In order to verify the effectiveness of the proposed fault diagnosis method for rolling bearings based on IMF sample entropy and particle swarm optimization SVM, the rolling bearing data from Case Western Reserve University bearing data center website were analyzed and processed. The type of rolling bearing used in the experiment is 6205-2RS JEM SKF deep groove ball bearing with input shaft speed $n = 1750\text{r/min}$ and sampling frequency $12\text{kHz}$. The validity of the proposed method in the paper is verified by the data of four bearing states: normal condition, inner ring fault, outer ring fault and rolling body fault. Fifty sets of sample data were collected for each state. The first 20 samples for...
each state were taken as training set, and the remaining 30 samples were taken as test set. Set classification label, normal condition 1, inner ring fault 2, outer ring fault 3, rolling body fault 4. The training samples and test samples are shown in table 1.

| Bearing state    | Training set | Test set | Classified labels |
|------------------|--------------|----------|-------------------|
| Normal condition | 20           | 30       | 1                 |
| Inner ring fault | 20           | 30       | 2                 |
| Outer ring fault | 20           | 30       | 3                 |
| Rolling body fault | 20       | 30       | 4                 |

(1) Firstly, CEEMD decomposition was carried out on the training sample data to obtain several IMF components. The first five IMF components with more fault information were selected to calculate the sample entropy. Then, five sample entropy values were calculated from each sample as the eigenvector of the sample, and the sample entropy eigenvector matrix was constructed.

(2) The SVM model was trained with the sample data of the training set, and the SVM model was optimized with the particle swarm optimization algorithm. The local search capability of the algorithm was defined as 1.5, the global search capability was defined as 1.6, the maximum number of evolution was set as 300, the population size was set as 30, and the speed constraint factor was set as 0.9. Through particle swarm optimization, the optimal SVM parameters $C$ and $g$ were obtained as 1.6832 and 0.1028 respectively. After the training, the SVM diagnostic model was obtained.

(3) The test set is extracted according to the method of extracting the features of the training set samples, and the feature vector of the test sample is constructed. The feature vectors constructed with test samples were input into the trained SVM model, and the classification effect was obtained as shown in figure 3. From the figure, it can be seen more intuitively the number of error samples. The SVM classifier misclassified the sample size as 6, among which 4 inner ring fault samples were misclassified as rolling body fault, 1 outer ring fault samples were misclassified as inner ring fault, and 1 rolling body fault samples were misclassified as inner ring fault.

![Figure 3. PSO-SVM classification results](image)

To illustrate the effectiveness of the proposed method in this paper, the SVM model without optimization of particle swarm optimization was used to classify and identify the sample data. The classification effect is shown in figure 4. It can be seen that compared with the method proposed in this paper, this method has more misclassification samples. The classification result comparison are shown in table 2. It can be seen from the comparison of methods in the table that the method proposed in this paper is optimal in prediction accuracy and classification time.

| Method     | Prediction accuracy | Classification time |
|------------|---------------------|---------------------|
| SVM        | 85.8333% (103/120)  | 98.32s              |
| PSO-SVM    | 95.0000% (114/120)  | 26.3s               |
Figure 4. SVM classification results

5. Conclusion
This paper presents a fault diagnosis method for rolling bearings based on IMF sample entropy and particle swarm optimization SVM. Complementary ensemble empirical mode decomposition (CEEMD) is used to decompose bearing vibration signals and a set of intrinsic mode functions (IMF) is obtained. The sample entropy of the main IMF component was calculated to obtain the sample entropy matrix of the signal component, which was input as the eigenvector into the particle swarm optimization SVM for training and testing. Compared with the recognition method of support vector machine without particle swarm optimization, the experimental results show that the proposed method in this paper has higher classification accuracy in bearing fault recognition.

References
[1] Rehman N, Mandic D P. (2010) Multivariate empirical mode decomposition. J. Proceedings of the Royal Society A, 466(2117):1291-1302.
[2] Cheng J S, Yu D J, Yang Y. (2006) Rolling bearing fault diagnosis method based on EMD and SVM. J. Aviation Dynamics Daily, 21(3):575-580.
[3] Xiang D, Ge S. (2014) Fault feature extraction method based on EMD sample entropy-LLTSA. J. Aviation Dynamics Daily, 29(7):1535-1542.
[4] Lou J W, Hu C B, Zhao J L. (2014) EEMD Sample Entropy in SVM Recognition of Bearing Faults. J. Mechanical Drive, 38(3):41-44.
[5] Torres M E, Colominas M A, Schlotthauer G, et al. (2011) A complete ensemble empirical mode decomposition with adaptive noise. In: IEEE International Conference on Acoustics Speech and Signal Processing, Prague. pp. 4144-4147.
[6] Richman J S, Moorman J R. (2000) Physiological time-series analysis using approximate entropy and sample entropy. J. Aip Heart & Circulatory Physiology, 278(6):2039-2049.
[7] Shang D, Xu M, Shang P. (2017) Generalized sample entropy analysis for traffic signals based on similarity measure. J. Physica A Statistical Mechanics & Its Applications, 474:1-7.
[8] Fu D P, Zhai Y, Yu Q M. (2017) Research on Rolling Bearing Fault Diagnosis Based on EMD and Support Vector Machine. J. Machine Tool and Hydraulic, 45(11):184-187.
[9] Bian B B. (2017) Rolling bearing fault diagnosis method based on LCD noise reduction and LS-SVM. J. Combination machine tools and automatic processing technology, 1(2):119-122.
[10] Song G M, Wang H J, Liu H, et al. (2010) Analog circuit fault diagnosis based on lifting wavelet transform and SVM. J. Journal of Electronic Measurement and Instrument, 24(1):17-22.