Damage Analysis of Rolling Bearings Based on Model Correlation Dimension

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Abstract. Vibration signals of the rolling bearing are non-stationary, EMD is occupied to decompose the signals; then ARMA model, which has higher accuracy, is established based on the signal principal components from the EEMD; then correlation dimension of the Auto-regressive (AR) parameters, taken from the ARMA model, serve as the feature vectors to be input to LSSVM for discriminating the actual conditions of rolling bearings. The results demonstrate that: the fault-patterns could be obtained accurately with the presented method, and it is an effective analysis method.

1. Introduction
Rolling bearings are mostly popular as rotor supports. A rolling bearing with damage could cause breakdown of machinery, or even serious consequences. In order to guarantee the reliable run of the rolling bearing, damage state analysis of rolling bearings has been a hot problem in the engineering research. Feature extraction is the key for damage analysis [1,2], which is based on pattern recognition. ARMA model can describe the objective laws accurately of vibration signal, especially the characteristic parameters of auto-regressive from ARMA model are the most sensitive to the change of the working condition. Therefore, it is very effective for the auto-regressive parameters, as feature vectors, to analyze the state. The quality of classifier is crucial for damage analysis. Least squares support vector machine (LSSVM), proposed by Suykens and Vandewalle, is the improvement of SVM and it has been proved to be an excellent classifier. For the above reasons, the method based on the correlation dimension of ARMA model and LSSVM is presented.

2. Model Correlation Dimension

2.1. Parametric Model
The vibration signals of rolling bearings are usually non-stationary, which will weaken feature extraction of the damage analysis greatly. Targeting the non-stationary of signals, ensemble empirical mode decomposition (EEMD) is proposed and applied to feature extraction of rolling bearings. With EEMD, each signal will be decomposed into a number of intrinsic mode functions (IMFs). Then ARMA (p, q) models are established based on the main IMFs.
The general equation of ARMA model in coordinate format as follows:


\[ s_i + \sum_{k=4}^{p} \phi_k s(t-k) = a_i - \sum_{k=1}^{q} \theta_k a(t-k) \]  

(1)

Where \( t \) is the length of data sequence. As an independent distributed sequence, the variance of \( a_i \) is \( \sigma^2 \). \( p,q \) is the order number of auto-regressive(AR) model and moving-average (MA) model. \( \phi_1, \phi_2, ..., \phi_p \) and \( \theta_1, \theta_2, ..., \theta_q \) are the coefficients of AR parameters and MA parameters separately.

2.2. Model Correlation Dimension

Correlation dimension has been widely used as a powerful tool. The most commonly used algorithm for calculating correlation dimension of the attractor from time series is the Grassberger-Procaccia (G-P) algorithm [3]. The specific correlation dimension is calculated by the method of state space reconstruction. The correlation dimension is sensitive to the attractor of the rotating machinery system, that is, the correlation dimension changes with the change of the rotating machinery system. Therefore, the correlation dimension can be taken as the dynamic response characteristic of the system, and the change of correlation dimension can reflect the fault pattern of the bearing.

Given the vibration signal of the rolling bearing, which is to be analyzed and processed, is \( x_1, x_2, ..., x_i, ..., x_N \), where the AR parameters of ARMA model for the sequence \( x_i \) are taken as \( \{\phi_N\} \). Firstly, the first vector \( Z_1(m, \tau) = \{x_i, x_{i+\tau}, x_{i+2\tau}, ..., x_{i+(m-1)\tau}\} \) in the m-dimensional space is supported by the data sequence. \( \tau = k \Delta t \) is the time delay, \( \Delta t \) is the sampling interval of data, \( k \) is any integer, \( m \) is the embedded dimension, that is the dimension of reconstructed space.

Then, construct the second vector in the m-dimensional space: \( Z_2(m, \tau) = \{x_{i+k}, x_{i+2k}, ..., x_{i+(m-1)k}\} \)

And so on, a set of vectors would be constructed: \( Z_1(m, \tau), Z_2(m, \tau), ..., Z_i(m, \tau), ..., Z_M(m, \tau) \) where \( M = N - k(m - 1) \) is the number of vectors reconstructed. The distance between the vector \( Z_i \) and the vector \( Z_j \) is defined as \( r_{ij} = |Z_i - Z_j| \). Given a any integer \( r \), the correlation dimension of the reconstructed phase space is:

\[ D_\chi = \lim_{r \to 0} \frac{\ln C_r / \ln r}{\ln r} \]  

(2)

Among them: \( C_r = \frac{1}{N(N-1)} \sum_{i,j=1}^{N-m+1} \sum_{j=1}^{N-m+1} H(r - |Z_i - Z_j|) \)

\( i \neq j \), \( r \) is the m-dimensional supersphere radius, \( H \) is the Heaviside function, i.e

\[ H(r - |Z_i - Z_j|) = \begin{cases} 1 & (r - |Z_i - Z_j|) \geq 0 \\ 0 & (r - |Z_i - Z_j|) < 0 \end{cases} \]  

(3)

Draw the scale line \( \ln r - \ln C_r \), then the slope of the line is the correlation dimension of the corresponding time series. When the correlation dimension reaches saturation value, the appropriate correlation dimension is obtained.
3. Steps of Damage Analysis

Damage Analysis process of the rolling bearing is as follows:

1) Sampling: obtain corresponding signals of the rolling bearing;
2) Modeling: decompose the sampled signals with EEMD, then ARMA model is established from the principal IMF component signals obtained through decomposition, and the corresponding associated dimensions are calculated by extracting AR parameters. The searching scheme of ARMA model is shown in Fig.1. Initial values of ARMA (p, q) model parameters p=1, q=1. If the model is not applicable, let p=p+1 or q=q+1 continue to fit the ARMA (p, q) model until the applicable model order is found. During the fitting process, the model order is determined by using the F test method (the significance level of F test is set as 0.05), and the rise and fall of the model order is determined by the relative changes of sum of residual squares.

3) Damage analysis: LSSVM is trained by taking the characteristics sample data of associated dimensions from bearing AR model, and the regression function model is obtained by solving, and the fault recognition is conducted on the test sample by using the trained network. The process is shown in Fig. 2

![System modeling scheme](image1)

![Process of fault identification](image2)

4. Experimental Study

In order to demonstrate the proposed method, an example on damage analysis of rolling bearing is tested in this paper. The vibration signal of rolling bearings is from Case Western Reserve Lab (CWRU) [4]. The test stand is shown in Fig 3. In this experiment, single point defects are introduced to the bearings using electro discharge machining. The outer raceway faults at the driving end and fan end are arranged at 3:00 direction, 6:00 direction and 12:00 direction respectively. The original signals are collected using an accelerometer mounted at the drive end of the motor. Vibration signals are collected by a data recorder at the sampling rate of 12 KHz. The type of test bearings is the deep groove ball bearing 6205-SKF. Select 20 data sets from both the normal and the fault-seeded bearings (diameter: 0.007 inches, motor load: 0) respectively, and the intercept length is 0.25s. The compiler of signal processing is performed with Matlab 7.04. Firstly, EEMD is carried out for the signals under various state of the bearing, then the main IMF component of the signals are analyzed by correlation. The first three high-frequency IMF components, containing the main fault characteristic information, are selected to establish the ARMA model and the corresponding AR parameters are extracted to calculate the correlation dimension.
FIG. 4 is the correlation dimension of AR parameters from the 1MF1 component ARMA model of vibration signals in different states. The correlation dimension of the outer raceway damage bearing is higher than the other three states significantly from FIG. 4. The correlation dimensions of 1MF2 component and 1MF3 component are shown in FIG. 5 and FIG. 6 respectively. It can be seen from FIG. 5 and FIG. 6 that different embedded dimensions can get different associated dimensions. FIG. 4, FIG. 5 and FIG. 6 illustrate that the correlation dimensions of the different 1MF components of ARMA model can be used as feature indicators to analysis the bearing state.

After processing the vibration signals of rolling bearing in four states, 20 sets of feature vectors corresponding to four states can be obtained. Select 10 sets from the characteristic vector data randomly of the four states, and the remaining data are taken as the testing data. When the embedding dimension m is 7, various damage states are distinguished clearly. Therefore, 40 sets, from the AR parameters correlation dimensions of the first three 1MF components in the four states (m=7) respectively, are input into LSSVM classifier for training in this paper. In the testing process, 4 binary classifiers are established, denoted as LSSVM 1, LSSVM2, LSSVM3 and LSSVM4 respectively corresponding to the normal state, outer ring damage, inner ring damage and rolling body damage. When the LSSVM1 classifier is training, 10 sets corresponding to the normal state are considered as one type, which is expressed as +1, and the remaining 30 sets are labeled as -1; then the classifier corresponding to the normal state of optimization coefficient is established according to the basic principle of LSSVM. Use the same approach to train LSSVM2, LSSVM3, and LSSVM4. Table 1 lists the classification function values of all test samples for 4 LSSVM classifiers. It can be seen that the classifier has identified all testing samples correctly of rolling bearing.
Table 1. Fault identification based on LSSVM

| state         | normal | outer raceway damage | inner raceway damage | rolling damage |
|---------------|--------|----------------------|----------------------|-----------------|
| testing sets  | 1 (9)  | 10                   | 10                   | 10              |
| LSSVM1        | 0.9537 (+1) | (-1)                  | (-1)                  | (-1)              |
| LSSVM2        | -0.6235 (-1) | (+1)                  | (-1)                  | (-1)              |
| LSSVM3        | -0.3462 (-1) | (-1)                  | (+1)                  | (-1)              |
| LSSVM4        | -0.8735 (-1) | (-1)                  | (-1)                  | (+1)              |
| recognition rate | 100%   | 100%                 | 100%                 | 100%             |

5. Conclusion
The damage analysis method based on model correlation dimension is proposed according to the characteristics of non-stationary fault signal of rolling bearing. In this method, EEMD is used to carry out the smooth transformation of signal sequence, and ARMA model is used to build the accurate model for the decomposed dynamic data, and the associated dimension of the model's auto-regressive parameters are used as feature vector to be input to LSSVM for training and identification. The experimental results show that the recognition effect is ideal.

References
[1] Fatao Hou, Jin Chen, Guangming Dong. Weak fault feature extraction of rolling bearings based on globally optimized sparse coding and approximate SVD. J. Sci. Mechanical Systems and Signal Processing. 111 (2018) 234-250.
[2] Tingkai Gong, Xiaohui Yuan, Xiaohui Lei, et al. Fault detection for rolling element bearing based on repeated single-scale morphology and simplified sensitive factor algorithm. J. Sci. Measurement. 127 (2018) 348-355.
[3] W. J. WANG, J. CHEN, Estimation and Application of Correlation Dimension of Experimental Time Series, J. Sci. Journal of Vibration and Control. 7 (2001) 1035-1047.
[4] Information on http://www.eecs.cwru.edu/laboratory/bearing/download.htm