Fault detection of rolling bearing based on FFT and classification

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Abstract

The rolling bearing carries a load by placing rolling elements between two bearing rings. It is a key device in the railway vehicles for monitoring work states to ensure high reliability and better performance of rotating machine. The states of rolling bearings can be detected by the measurement of vibration signals with effective process, features extraction and analysis. The propose of this paper is to establish an efficient and robust signal processing technique and classification mechanism to detect the fault of rolling bearing. Firstly Fast Fourier Transform is used to extract features and then these parameters are input into various classification schemes for accurate fault detection. Ensemble Rapid Centroid Estimation is proposed and then compared with Artificial Neural Network, and Principal Components Analysis. The simulation analyses the approaches of fault detection and the accuracy of identification. Then the linear performance of the data is proved by least square regularized regression. Finally various schemes are compared and analyzed to obtained the most efficient method for fault detection.

Key words : Rolling bearing, ERCE, Artificial neural network, Principal components analysis, Classification, Fault detection

1. Introduction

The rolling bearing, which carries a load by placing rolling balls or rollers between two bearing rings, is the most normal device in rotating machinery. Monitoring work states of this critical device is one key factor to ensure high reliability and better performance of rotating machine in the railway vehicles. But in applications a bearing under normal loading would fail due to material fatigue along with the appearance of cracks below the surface. If this bearing continues to work the damage would spread because of the localised stresses of the defect. So most rolling bearings' lifetime can't reach their expectation and failure of bearings can cause an immediate machine breakdown. Especially in railway operation effective and efficient fault detection of rolling bearing is very critical to ensure the safety, reliability and high work quality. The states of rolling bearings can be detected by the measurement of their vibration signals.

Usually, non-stationary signals are transient in nature and the duration generally is shorter than an observation interval. Such signals can be generated due to many reasons such as the sudden breakage of a drilling bit, a flaking of the raceway of a rolling bearing, or a growing crack inside a work piece. Effective detection of non-stationary signals is necessary to avoid potential machine failures. Traditional diagnosis techniques analyse waveforms of vibration signals in the time domain

to judge working status. But usually it is a challenge to extract the feature characteristics and make an accurate evaluation. Therefore the effective mechanism of extracting appropriate statistical features is very important to detect and predict faults.

Signal process, feature extraction and state identification are three major procedures in rolling bearing fault detection. A wealth of research has been focusing on various methods in time domain and frequency domain to analyse signals. Wavelet analysis is a useful method to acquire local features of vibration signals and has been widely used in the bearing fault diagnosis. Meanwhile, other methods of signal processing may be combined to obtain better results. P.W. used Wavelet analysis and envelope detection for rolling element bearing fault diagnosis. K.C. Gryllias proposed a hybrid two stage one-against-all approach to automatically diagnose defective rolling element bearings. Jianhui Xi used wavelet packet and bi-spectrum analysis to extract features of rolling bearings. Yuan Zhang utilized Empirical Mode Decomposition (EMD), Principal Component Analysis (PCA), and the Least Square Support Vector Machine (LSSVM) to estimate safety region.

Actually the rolling bearing vibration signals are often non-stationary and their frequency components will change with time. The traditional method, envelope-analysis, uses an analogue bandpass filter plus a rectifier and smoothing circuit. The filter extracts the resonance excited by the bearing fault from the frequency spectrum; the detector detects the envelope of the corresponding time signal. However, the computation of the Envelope Detection is subjected to strict definition the resonance frequency band and is not sufficient for non-stationary signals to make accurate detection. Beside that, envelope-analysis need general production and distribution assumptions. For this rolling bearing if those assumptions are too weak, inefficiency levels may be systematically underestimated in small samples. In addition, erroneous assumptions may cause inconsistency with a bias over the frontier. Therefore we apply Fast Fourier Transform (FFT) and classification algorithm to process and extract feature to detect and predict faults. The results show that the proposed method can correctly extract the fault characteristics for faults detection. FFT is an effective and quick method to extract features matrix in vibration signals. Combined with classification algorithms suitable features can be analysed and selected for diagnosis of abnormal operation. Generally traditional classification requires the choice of a metric in the input space, i.e., a Euclidean distance measurement must be provided. But artificial neural network (ANN) can extract statistical regularities from the input pattern sequence to build a training model for further pattern reorganization. Ensemble Rapid Centroid Estimation (ERCE) is a simplification of Particle Swarm Clustering (PSC) to do fast clustering. Principal component analysis (PCA) is an algorithm of dimension decreasing for simple classification. Baidya Nath Saha utilized PCA to perform classification for object detection. Lin Chen used PCA and SVM to classify the urinary particles. With characteristic frequencies obtained from vibration signals' spectrum FFT classification techniques can efficiently and effectively detect faults in rolling bearing. In this paper FFT is used to pre-process original data and a standard matrix with features is obtained. Then Neural Networks, ERCE and PCA are applied to detect abnormal signals. The application on experimental data shows that the extracted spectral features are informative enough to process and accurately diagnose bearing faults. Furthermore the linear performance of sampling signals is illustrated.

The main contributions of this paper contain : (1) Propose and applied ERCE for accurate fault detection based on vibration signals; (2) Compare different schemes with various features and investigated their characteristics; (3) Analyze the linear feature of sampling data; Selected the most appropriate strategy for efficient fault detection. The remainder parts of this paper are outlined as following: firstly the rolling bearing and vibration signals are illustrated. Then section 3 introduces the principle of FFT for data process. Section 4 illustrates the classification algorithms of ANN, ERCE and PCA. After that section 5 explains the experimental data. Section 6 describes the execution processes of features extract and classification. Section 7 analyses the simulation results and compares different methods. Finally the conclusions illustrate the benefits of PCA for faults detection and the future research.

2. Rolling Bearing and Vibration signal analysis

Roller bearings are usually used for high load carrying applications and the basic structure is illustrated in figure 1. Generally, bearings contain two concentric rings: an outer ring is mounted to a stationary house and an inner ring is mounted on a rotating shaft. The rolling parts are balls or rollers which transfer the load over a very small surface on the raceways. Rolling elements are bound by a cage, which prevents the contact of the rolling elements in operation, avoids poor lubrication

conditions and holds the bearing together in handling. There are a lot of reasons that can cause bearing failure, such as mechanical damage, wear damage, crack damage, lubricant deficiency, and so on. For example wear can cause a deterioration of the bearing components and inadequate lubrication can increase friction in metal-to-metal contacts. Usually cracks will appear under the surface of the bearing elements, and then, pitted and tore material can quickly accelerate the wear of a bearing, and intense vibrations can be produced because of the contacts between elements in the damaged zones.

Figure 1 Rolling Bearing Structure

Then a periodic interaction happens between rings and rolling elements. So a frequency analysis of the radial vibration signal brings the information of an amplitude modulation, which can be illustrated in Equation 1, where the carrier f_{mod} is any mechanical resonance, k is an integer and the modulating signal f_{car} is the mechanical characteristic frequency of the interaction phenomena. Faults in various parts including inner raceway, outer raceway, or rolling elements can generate specific frequency components in the machine vibration. The mechanical characteristic frequency f_{car} can be described as a function of bearing geometry and operating speed as shown in equation 2, 3, 4 and 5.

$$F_v = |f_{mod} \pm k f_{car}| \quad (1)$$

$$F_C = \frac{1}{2} F_R \left(1 - \frac{D_b \cos \beta}{D_c} \right) \quad (2)$$

$$F_O = \frac{N_B}{2} F_R \left(1 - \frac{D_b \cos \beta}{D_c} \right) \quad (3)$$

$$F_I = \frac{N_B}{2} F_R \left(1 + \frac{D_b \cos \beta}{D_c} \right) \quad (4)$$

$$F_B = \frac{D_c}{D_b} F_R \left[1 - \left(\frac{D_b \cos \beta}{D_c} \right)^2 \right] \quad (5)$$

where F_C is the cage fault frequency, F_R is the revolutions per second or relative speed difference between inner and outer race, F_O is the outer raceway fault frequency, F_I is the inner raceway fault frequency, F_B is the ball/roller fault frequency, D_b is the ball/roller diameter, D_c is the pitch diameter, N_B is the number of rolling elements, and β is the ball contact angle (zero for rollers). Although a demodulation of the vibration signal represents the knowledge of the amplitude of the modulating signals, it is still hard to distinguish the localized defects.

3. Overview of FAST FOURIER TRANSFORM (FFT)

A Fast Fourier transform (FFT) is an efficient algorithm to compute the discrete Fourier transform (DFT). A DFT decomposes a sequence of discrete data into components of different frequencies and is used in many fields. Discrete Fourier transforms are extremely useful because they reveal periodicity in input data as well as the relative strengths of any periodic components. In general, the discrete Fourier transform of a real sequence of numbers will be a sequence of complex numbers of the same length. The DFT of a vector x of length n is another vector y of length n :

$$y_{p+1} = \sum_{j=0}^{n-1} \omega^{jp} x_j + 1 \quad (6)$$

where ω is a complex unity: $\omega = e^{-2\pi i/n}$. This notation uses i for the imaginary unit, and p and j for indices which run from 0 to $n-1$. The absolute value of y at index $p+1$ measures the amount of the frequency $f = p(fs/n)$ present in the data. A series of frequencies carry all the necessary information for the subspace of interest to be identified and FFT technique forms an amplitude or power matrix for specific features in classification.

4. Classification algorithms

4.1. ANN classification

ANN is widely used in model recognition, fault diagnosis, classification and so on. ANN architecture is potentially much faster than conventional classifications methods due to its structure. ANN models have an advantage over statistical classification methods as they do not require any priori knowledge of the class statistical distribution. An artificial neural network is regarded as a mathematical model to simulate some behaviours of biological nervous systems. Neurons are connected together with weights so that they can deal with information collaboratively and store the information on these weights. In this paper, a Backpropagation (BP) neural network is used for classification. BP neural networks are trained by a supervised learning algorithm. Specifically, the process modifies the weights in the network in an iterative mode so that the resulting network fits the training data well. The entire network learning process includes two phases: the first stage is calculating from input layer to output layer. Output of all neurons can be calculated by training samples by initial structure and weight; the second stage is to modify the weights and threshold, and it starts from output layer to input layer. Weight of neurons connected to output can be adjusted according to errors of output, and also hidden layer weight can be modified. The two stages are iterative processes, which repeat until convergence. All layers adjust weight through equation 7:

$$w_i(t+1) = w_i(t) + \eta \delta_i x_j^k \quad (7)$$

η is regarded as the precision of network learning, which can be used as conditions of judgment of network finishing. δ_i is the value of error and can be defined as:

$$\delta_i = y_i(1 - y_i)(d_i - y_i) \quad (8)$$

Where y_i is the output value and d_i is the desired output.

4.2. ERCE Algorithm Overview

ERCE is a clustering algorithm to handle large-scale non-convex cluster and estimate the number of clusters with quasi-linear complexity. It is an extension of Rapid Centroid Estimation (RCE) algorithm, which is a simplification of the Particle Swarm Clustering (PSC) algorithm with less computational complexity and better stability. The process is summarized as follows: 1) Particle positions are updated only once per iteration. For each iteration, $x_i(t+1)$ is updated as follows:

$$\Delta X_i(t+1) = \omega(t) + \frac{A_i(t) + B_i(t) + C_i(t)}{K} \quad (9)$$

$$X_i(t+1) = X_i(t) + \Delta X_i(t+1) \quad (10)$$

where $A_i(t)$, $B_i(t)$, and $C_i(t)$ indicate the mean for cognitive, social, and self-organizing, respectively. K denotes the step resolution constant. 2) When all particle positions are updated the distance matrix and best positions are updated. 3) RCE introduces the minimum term which stores the best particles that minimize a user's objective function, which is defined as equation (11):

$$f(x, y) = \sum_{i=1}^{n_c} \sum_{\forall y_i \in C_i} D(X_i, Y_i) \quad (11)$$

where C_i denotes the clustered set i with the centroid represented by x_i . $D(.,.)$ denotes the specified distance function. At the same time several strategies such as Swarm, Particle Reset and Substitution strategies and white noise update scheme are combined for optimization. ERCE is an extension of RCE and improves the performance from several aspects: 1) Further

simplify RCE's update rules and reduces its overall memory-usage and computational complexity with discarding the calculations for cognitive and social terms; 2) Employ an efficient hybrid ensemble aggregation technique to handle non-convex clusters and estimate the number of clusters in larger datasets; 3) Increase the diversity of particles during swarm mode, by using "charged particles" idea.

4.3. Principle of PCA

PCA is a vector space transformation and often used to transform a multi-variables space into a subspace which preserves maximum variance of the original space in minimum number of dimensions. The measured process variables are usually correlated to each other. PCA can be defined as a linear transformation of the original correlated data into a new set of uncorrelated data. In normal condition, the PCA is established with a collected data matrix $X \in R^{n \times m}$, where n is the number of samples and m is the number of variables. This matrix must be standardized to eliminate the effects of different units of variables. So the standard database X is firstly normalized. Then construct the covariance matrix:

$$R = \frac{1}{n-1} X^T X \quad (12)$$

And then perform the singular value decomposition (SVD) decomposition on R :

$$R = U D_\lambda U^T \quad (13)$$

Where $U_{m \times m}$ is a unitary matrix, and $D = \text{diag}(\lambda_{i=1,2,\dots,n})$ is a diagonal matrix. In equation 13, $U = [u_1, u_2, \dots, u_m]$ is a standard base of R_m and the database $\tilde{X}$ is described based upon U . The variances of X in the every direction from the new coordinate satisfy $\lambda_1 > \lambda_2 > \dots \lambda_n$. The transformation matrix $p \in R^{m \times k}$ is generated by choosing k eigenvectors or columns of U related to k eigenvalues. Elements of T , called as scores, are calculated by Columns of matrix P : $T = X \times P$. Scores are the values of the original measured variables that have been transformed into the reduced dimension space.

5. Experimental Data

Bearing vibration signals represent the most important information for the early detection of bearing fault because transient impulses are generated at a repetition rotation. In our experiment bearing fault diagnosis was conducted with experimental data in the normal and fault rolling bearing. The rolling bearing experimental data was obtained by State Key Lab of Rail Traffic Control and Safety, Beijing Jiaotong University and the experimental apparatus are shown in figure 2(a). The cylindrical roller bearing is NU205M with the size of 25mm $\times$ 52mm $\times$ 15mm and is shown in figure 2. The speeds are 597 rpm, 890 rpm and 1190 rpm respectively. The fault of the outer race is in the middle of the race, the depth is nearly 0.5 mm and the width is 1-2 mm as shown in figure 2(b); The sampling frequency of outer race vibration signals in the experiment is 25kHz and each experiment contains continuous 32 sections with 1024 points in every section. The first data file was collected from fault and normal test bearing, which was running at the speed of 597 rpm. Then the speed changed to 890 rpm and 1190 rpm respectively. Correction factor is 50.3 Mv/EU. Part of the data are shown in figure 3 and 4.

Vibration accelerating signals of rolling bearing in different speeds show some features inside. But it is difficult to distinguish the impact caused by the crack directly and it is not easy to build a model by the original signals. Therefore pre-processed data is necessary and envitable for further analysis and evaluation.

6. Procedure of fault detection

6.1. Structure of Process

For fault detection these vibration signals are decomposed with FFT to acquire a standard feature matrix. Then ANN, ERCE and PCA methods are applied to detect faults. The structure is demonstrated in figure 5.

All the steps are described as following: 1) Set roll bearing in normal and outrace fault state and collect acceleration vibration signals in determined segments. 2) Select 128 sampling points from input signals in per section. Then use Blackman Harris window to minimize spectral leaks and process every section of data into FFT as shown in figure 6. 3) Calculate the power of DFT. We take only the half side of the FFT transform according to symmetry of the Nyquist sampling. 4) Discard

Figure 2 Experimental apparatus and Cylindrical rolling bearing

Figure 3 abnormal Signals

Figure 4 normal signals

Figure 5 Structure of fault detection in roll bearing

all zero vectors and acquire a result matrix, which is set to a standard Neural Network or ERCE input format (e.g. rows as features, columns as observations). 5) Apply different classification methods.

Method 1: a) Use standard deviation to obtain major features and process these in ANN; b) Input two dimensional statistical status data and targets to train ANN; c) Classify the test and analyse the accuracy.

Method 2: a) Calculate $\log_{10}$ frequency magnitude scales linearly to input RPM according to equation (14):

$$y(t) = \frac{\log_{10}(fft(x(t)))}{RPM} \quad (14)$$

b) Extract all features in scaled matrix and process them in Neural Network for two clusters (one is normal and the other is abnormal) for training;

c) Test new data in Neural Network pattern to detect faults from vibration signals.

Method 3: a) Scale the FFT result matrix to input RPM as equation (14); b) Process the statical feature vectors into RCE and return the search history of the algorithm; c) Use the history data and CA-tree compression to get the representative cluster centroids for merge in ERCE; d) Feed the clustering results to detect the fault points and acquire the accuracy of classification.

Method 4: a) Obtain the power matrix of FFT and scale results according to input RPM; b) Build a PCA model based on pre-processed data and get the eigenvalues; c) Choose the calculated score for classification.

6.2. Pre-analysis of data

Firstly we choose the input values which are transformed by FFT as shown in figure 6.

Sampling frequency of 25 kHz in the FFT is used to return 128 point DFT and the Vertical axis in figure 6 shows part of the frequency range. A simple explanation about the Matlab code is in the following:

```

x = data(i-w\ _size+1:i , col\ _index );
m = length(x); l;o
% x is the signal of interest , w\ _size is the window size

n = pow2(nextpow2(m));
% calculate how many points we need for our fft

w = blackmanharris(m);
% Blackmanharris window is used to minimize spectral leaks , producing 'sharper' fft

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```

y = fft(x.*w,n); % do fft
f = (0:n-1)*(fs/n); % Frequency range
power = y.*conj(y)/n; % Power of the DFT

f_{nyq}=f(1:floor(n/2));
% Take only the left side of the fft transform, according to the nyquist sampling.
p_{nyq} = power(1:floor(n/2));
% Only use the positive frequency.

```

Figure 6 Pre-process of Original signals

Feature matrixes, which contain 64 frequency features and observed values, are formed at different operating speeds and working conditions. Then we analyse the estimation of the mean and an estimation of the standard deviation to DFT power. The power spectral density describes how the power of a time series is distributed with frequency. Mathematically, it is denoted as the Fourier transform of the autocorrelation sequence of the time series. The standard deviation is a measure of how far the signal fluctuates from the mean. The variance represents the power of this fluctuation. Differences in standard deviations show the high significance in the data for further analysis. From the standard deviation we can obtain two important frequencies 2150 Hz and 4700 Hz of the 12 and 25 features as special features for analysis and comparison due to the high standard deviation, which is illustrated in figure 7 at various speeds.

6.3. Classification and fault detection

6.3.1. Using ANN with two major features With two major features acquired from pre-analysis we build up a BP neural network for fault detection with 2 input-layer neurons, one hidden-layer neurons and two output-layer neurons to represent the normal and abnormal states as shown in figure 8. The transfer function of each neuron is set to the sigmoid function.

Figure 7 Power Probability

Figure 8 Neural network structure

In order to make the BP neural network classify reliably, the BP neural network has to be trained properly with 1536 training samples, which contains normal and abnormal data half in half. (1) Input samples to the neural network to match the targets: normal and abnormal as 1 and 0. (2) Compute the error of the network by given corresponding output data. Then, propagate the error backward to the input layer. These steps will be repeated until the network error is small.

Afterwards we input 1000 collected values to the trained network and judge their working state. Table 1 shows that when we use these two special features in ANN and get the accuracy of classification is around 80%.

6.3.2. Using ANN with all features Then we calculate $\log_{10}$ frequency magnitude scales linearly to input RPM and use all 64 frequency features acquired by FFT to classify in ANN again. Using 1536 values to train the neural network model and choose 1000 signals to verify the result and these points are divided into different groups, which are associated with the working states of inputting data. The value 1 represents the abnormal state and value 0 represents the normal state as shown in figure 9. Figure 10 shows the validation and the test is almost identical. Because more features are used in classification,

consequently the accuracy increases to 98% as shown in Table 1 .

Figure 9 Fault detection results

Figure 10 ANN Training record

6.3.3. Fault detection with ERCE We use ERCE with all 64 frequency features to detect abnormal data. On each iteration, every RCE particle makes a decisive movement to the centre of mass in each cluster based on optimization strategies. Fuzzy Ensemble Aggregation with CA-tree compression is used in ERCE to get representative cluster centroids. CA-tree compression threshold is set to 0.01, substitution probability is 0.03, and maximum number of iterations is 100. Finally the accuracy of fault detection is around 96% as shown in Table 1.

6.3.4. PCA From the pre-processed data, we use samples of 64 frequency features and compute the feature matrix U for PCA analysis. The eigenvalues U_i and corresponding eigenvectors V of covariance matrix C from training samples X are obtained, and further decreasingly ordered. Although more components can be chosen the first component represents the high portion of data and it is effective for classification as shown in Figure 11. It is obvious to see the scores of sampling signals are easily divided into two groups by the threshold and the accuracy is 95.12%.

7. Experimental Results analysis

The vibration signals are tested by different methods to analyse the accuracy in diagnosing. We use confusion matrix to compare the results as shown in table 1. The results show the accuracy of applying all features is obviously higher than the two features in ANN. When using all features ANN and ERCE have almost the same accuracy. When using one feature in PCA the accuracy is similar to the previous methods with all features.

The main reason for this result is that the vibration signals actually show the linear performance after FFT transformation. The least square regularized regression (LSRR) can be applied for the linear identification. Considering the computational and convergence behaviour ,LSRR is a powerful mathematical model to estimate the relation between the input and output. A linear combination is the form $f = X_{i1}\beta_1 + X_{i1}\beta_1 + \dots$. The model may represent a straight line, a parabola or any

Figure 11 PCA Classification

Table 1 Confusion matrix results of three methods

Parameters	ANN1	ANN2	ERCE	PCA
Features	2	64	64	1
Sensitivity	81.4%	96%	99.2%	
Specificity	81.5%	99.5%	93.7%	
Accuracy	81.4%	97.7%	96.3%	95.12%

other linear combination of functions. Therefore it is the reason that PCA is effective and efficient to detect faults in the outer race vibration signals. In the simulation we compute the linear regression and get the matrix of β . The derivatives $\partial f / \partial \beta_j$ depend only on the values of the independent variable, so the model is linear in the parameters. Also current residual plots in centroid frequency in figure 12 show that the fitting exhibits the desired homoscedasticity.

Figure 12 Homoscedasticity of residual pots

8. Conclusions

In the research, FFT is used to transform the time domain to frequency domain for features extraction and then apply ANN, ERCE and PCA are applied to recognize the faults. For these kinds of vibration signals in roll bearing, FFT is the most important step to pre-process data for feature extraction and it is necessary to perform linear analysis before fault detection.

The simulation results prove the classification is accurate to detect faults and the later three different methods acquired the similar results. But PCA is preferred of one feature due to the linearity of pre-processed signals, which are proved by linear analysis with LSRR. The PCA method has simple calculation process, few limitations and does not need complicated training. Therefore it is the most efficient method to be implemented for fast and accurate detection of this type of vibration signals. In the future research, multi-states and dimensions signals will be considered and detected by appropriate schemes.

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