Intelligent Fault Detection of Ball bearing Using FFT, STFT Energy Entropy and RMS

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Abstract: According to the non-stationary characteristics of ball bearing fault vibration signals, a ball bearing fault detection method using FFT, STFT energy entropy and root mean square is put forward. In this paper, first, original rushing vibration signals are transformed into a frequency domain, then, the STFT transformation is calculated in the way that first the frequency resolution and then the time resolution has been assumed to be high. Then the theory of energy entropy mean and root mean square is proposed. The analysis results from energy entropy and root mean square of different vibration signals show that the energy and root mean square of vibration signal will change in different frequency bands when bearing fault occurs. Therefore, to diagnose ball bearing faults, we run the test rig with faulty ball bearing in various speeds and loads, and collect vibration signals in each run; then, we calculate the energy entropy mean and root mean square which are indicators of the type of faults. The analysis results from ball bearing signals with three different faults in various working conditions show that the diagnosis approach based on the utilization of, STFT and FFT for extracting the energy and root mean square of different frequency bands can identify ball bearing faults accurately and effectively. We have optimized signal decomposition levels with the use of analysis, and then, interestingly enough, we have introduced a new method to effectively diagnose different faults of rolling bearings.
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1. Introduction

The vibration signals of a ball bearing operating with faults will present non-stationary characteristics, and how to extract the fault characteristic information from the non-stationary vibration signals is the crux of the ball bearing fault diagnosis [1-3]. This is performed in traditional diagnosis techniques with the waveforms of the fault vibration signals in the time domain, and thus, construct the criterion functions to identify the working condition of roller bearings. However, because the nonlinear factors such as loads, clearance, friction, stiffness and soon have distinct influence on the vibration signals due to the complexity of the construction and working condition of ball bearings, it is very difficult to make an accurate evaluation of the working condition of roller bearings through the analysis in time domain only [4,5]. FFT analysis have had extensive use in diagnosis of faults of roller bearings, as they are both capable of extracting time and frequency local features of the signal [6-8]. Due to the limitation of the length of the FFT bases, energy leakage will occur in FFT transformations. Moreover, Fourier analysis has been the most widely used analysis method of signals for the detection of bearing faults. However, there are some crucial restrictions of the Fourier transform [6]: the signal to be analyzed must be strictly periodic or stationary; otherwise, the resulting Fourier spectrum will make little physical sense. Unfortunately, the vibration signals of rolling bearings have often non-stationary nature, and indicate non-linear processes; moreover, their frequency components can vary over time. Therefore, the Fourier transform often fails to pretty successfully diagnose the type of faults occurred in rolling bearings. On the other hand, since in time–frequency analysis methods the one-dimensional signal is mapped to a two-dimensional time–frequency plane, the information of both of time and frequency domains of a signal can be simultaneously produced. Therefore, in the later studies, the time–frequency analysis methods are widely used to detect the faults in bearings since they can determine not only the time of the impact occurring but also the frequency ranges of the impact location, and hence can determine not only the existence of faults but also the causes of faults [9].

In this paper, FFT, STFT is applied to the ball bearing fault diagnosis. First, the original acceleration vibration signals is transformed into a frequency, STFT domain, then the concept of energy entropy mean and root mean square is proposed, which defined by calculating the mean value of the vibration signal entropies and root mean square of a bearing with a fault in different various speeds a loads. By studying the energy entropy means and root mean square of different working condition signals we illustrate that it will change when different bearing fault occurs. Similarly, the original signal is decomposed by the wavelet packet, and then the energy entropy mean are extracted accordingly from the time series that are obtained after the wavelet coefficients are reconstructed. To diagnose ball bearing faults, we run the test rig with faulty ball bearing in various speeds and loads and collect vibration signals in each run, and then calculate the energy entropy mean in frequency domain and root mean square in frequency domain which indicate the fault types.

1. Experimental Procedure

Three data sets each containing twenty data files were collected from three bearings which are the same but with different faults. The first data file was collected from each test bearing when the loading was zero and the bearing was running at the highest speed (2000 rpm).The load was then increased step by step, the speed was kept at 2000rpm, and four other data files were collected. The load was then brought back to zero and speed was decreased by 1000 rpm and the next five data files were collected under five different loads similar to the first five data files. This procedure was continued until all twenty five sets of data were collected. The sampling frequency was chosen as 41.67 kHz, this sampling frequency along with the data record size of 4098 guarantees that the sampling procedure covers at least 1.6 revolutions of shaft at the lowest speed.

2.1- Test Bearings

An impact impulse is generated every time a ball hits a defect in the raceway or every time a defect in a ball hits the raceway. Each such impulse excites a short transient vibration in the bearings at its natural frequencies. Each time this defect is rolled over an impact is produced the energy of this impact depends on the severity of the defect Many failure modes of a rolling element bearing produce such a discontinuity in the path of the rolling elements, Moreover the majority of rolling element bearing failure cases begin with a defect on one of the raceways. In this research defects on inner raceway (IRD), outer raceway (ORD), balls (BLD) and abrasive in cage (ABR), poor lubrication (PRL) defect were introduced in the form of scratches. These scratches provide the aforementioned discontinuity in the path of rolling elements. Therefore a rolling element bearing with a nick or a fatigue spall or even a brindled bearing affects the time domain signal very similar to a bearing which has a scratch on one of its components.

2.2- Fast Fourier transform (FFT)

A Fast Fourier transform (FFT) is an efficient algorithm to compute the discrete Fourier transform (DFT) and its inverse. There are many distinct FFT algorithms involving a wide range of mathematics, from simple complex-number arithmetic to group theory and number theory. An overview of the available techniques and some of their general features has been presented in this article.

A sequence of values is decomposed into different frequency components through using a DFT. Though this operation is effective in many fields (see discrete Fourier transform for properties and applications of the transform), it is often too time-consuming to be practically computable from the definition. On the other hand, an FFT is able of quickly computing the same result; that is, the computation of a DFT of N points with the use of the definition takes O (N^2) arithmetical operations, while an FFT computes the same result with only O (N log N) operations. The computation speed in these two methods is substantially different, particularly for long data sets with N of the order of thousands or millions; thus, the computation time in such cases can be practically reduced by several orders of magnitude, and also, the improvement is approximately proportional to N/log (N). This huge improvement has made many DFT-based algorithms practical; FFTs are of great importance to a wide variety of applications, from digital signal processing and solving partial differential equations to algorithms for quick multiplication of large integers [10,11].

3. Short-Time Fourier Transform

The Short-Time Fourier Transform (STFT) (or short-term Fourier transform) is a powerful tool for the purpose of signal processing which characterize a specifically useful class of time-frequency distributions which can indicate complex amplitudes versus time and frequency for any signal. The following formula gives the definition of the STFT transformation:

$$sf(b.w) = \int_{-\infty}^{+\infty} f(t)g(t-b)e^{-iwt}dt \quad (1)$$

As it can be seen in E. (1), STFT is a time-frequency transformation; that is, it represents all the information of time, frequency and domain of the signal simultaneously. STFT is an indication of energy conservation law which states that:

$$\int_{-\infty}^{+\infty} |g(t)|^2 dt = 1 \quad (2)$$

With the use of Parsoval equation 2, the following relation can be obtained:

$$\int_{-\infty}^{+\infty} |f(t)|^2 dt = \frac{1}{2p}\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} |sf(b.w)|^2 dbdw \quad (3)$$

Using the short-time Fourier transformation, the signal can be revised as the following equation:

$$f(t) = \frac{1}{2p}\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} sf(b.w)g(t-b)e^{iwt}dbdw \quad (4)$$

The weakness of STFT it is impossible to have high resolution in both time and frequency domains.

The Discrete Fourier Transform (DFT) is an invertible transform and an important tool widely used in signal processing and analysis. DFT can be computed with the use of stable efficient algorithms known as Fast Fourier Transform (FFT) algorithms. Its applicability is for cases with discrete time and frequency variables. Let x_n and X_k respectively represent the discrete time signal and the discrete frequency transform function. The DFT is given by

$$X_k = \sum_{n=0}^{N-1} x_n e^{-j2p\,kn/N},\ k = 1,\ 2, \ldots, N \quad (5)$$

Where

$$x_n = \frac{1}{N}\sum_{k=0}^{N-1} X_k e^{j2pkn/N} \qquad (6)$$

Root Mean Squared (RMS) AND Energy entropy

The RMS value of a signal is directly related to the energy or destructive ability of the signal. Energy and root mean square of a signal are obtained in equation (7) and (8)

$$E = \sqrt{\sum_{i=1}^{n} |x(i)|^2} \qquad (7)$$

$$X_{rms} = \sqrt{\frac{1}{N}\sum [x(n)]^2} \qquad (8)$$

Where x (i) the amount of vibration signals have sampling point i and n total number of samples used to are. If the vibrations signal to the original components of the analysis, we formed m components separately and we will calculate the energy of each component to the set the energy distribution reached. Because each component Posts Contents are different frequency, energy distribution consisting of a space frequency can be

$$E = \{E_1, E_2, \ldots E_m\} \qquad (9)$$

Energy and entropy as defined in [20]:

$$H_{EN} = -\sum_{i=1}^{m} P_i \log pi \qquad (10)$$

Where $P_i = \frac{E_i}{E}$ is the percent of the energy of ith in the whole signal energy $E = \sum_{i=1}^{m} E_i$.

4. Results and discussion

4.1- FFT Energy Root Square and Energy Entropy

In this stage, the original signal was transformed into the frequency domain; then, three dominant frequency band widths were observed. These three ranges are shown in Tables (1). Thus the values of energy root mean squares (RMS) in each of these ranges were calculated according to Eq. (8); moreover, the sum of RMS in all three ranges was obtained. Thereafter, the ratios of the energies of each of these ranges to the total energy were calculated; furthermore, with the use of Eq. (10), the entropy energies for each of three types of faults were obtained. Here, from the values shown in the table, it can be simply inferred that both of these criteria; i.e., entropy energy and RMS, can be utilized for the purpose of fault diagnosis.

Also in this section, the original acceleration vibration (Fig.1), frequency spectrum (Fig.2-4) of signal for three type faults at 2000 rpm speed and 1000N load are shown. The FFT energy Root mean squares and energy entropy for three different faults at 2000 rpm speed and 1000N load are shown in table 1 and 2.

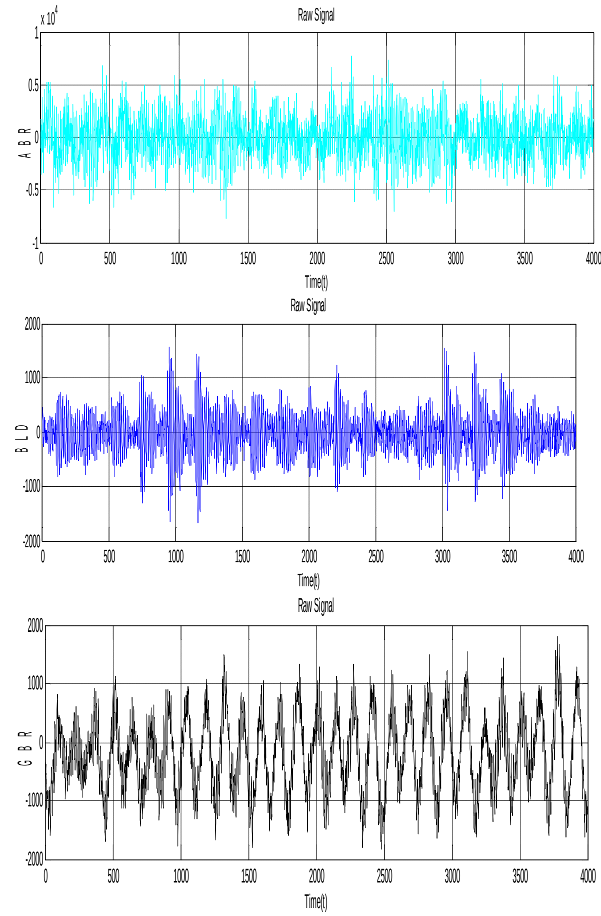

Fig.1. Original acceleration vibration of the signal for three different faults

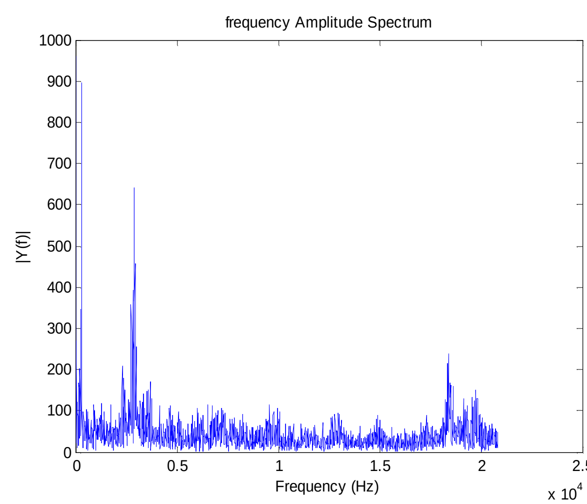

Fig. 2. Amplitude spectrum of the signal for ABR faults at 2000 rpm speed and 1000N load.

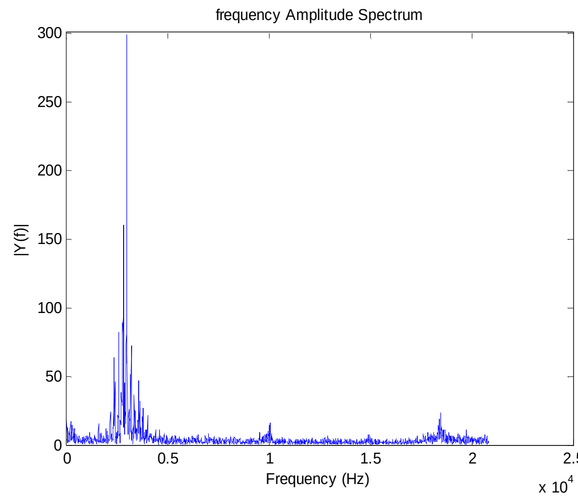

Fig. 3. Amplitude spectrum of the signal for BLD faults at 2000 rpm speed and 1000N load.

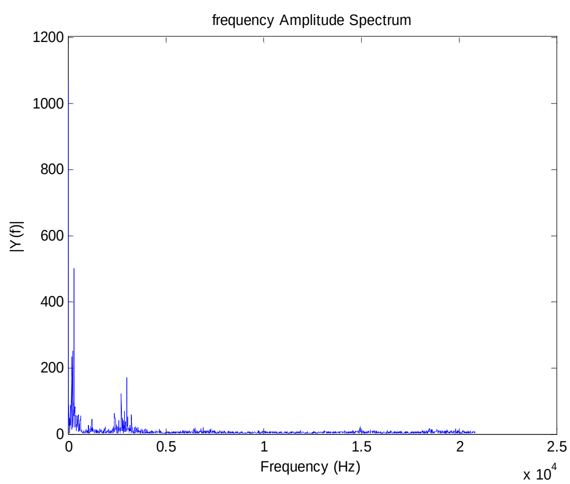

Fig. 4. Amplitude spectrum of the signal for GBR faults at 2000 rpm speed and 1000N load.

Table 1. The FFT energy root mean square for three different faults at 2000 rpm speed and 1000N load.

frequency-band (HZ)	ABR	BLD	GBR
10_325	26.1151	1.0483	17.3036
2760_3035	28.7072	9.9035	6.4114
18330_18560	12.9435	1.1062	0.7805

Table 2. The FFT energy entropy for three different faults at 2000 rpm speed and 1000N load

ABR	BLD	GBR
0.9761	0.9998	0.5149

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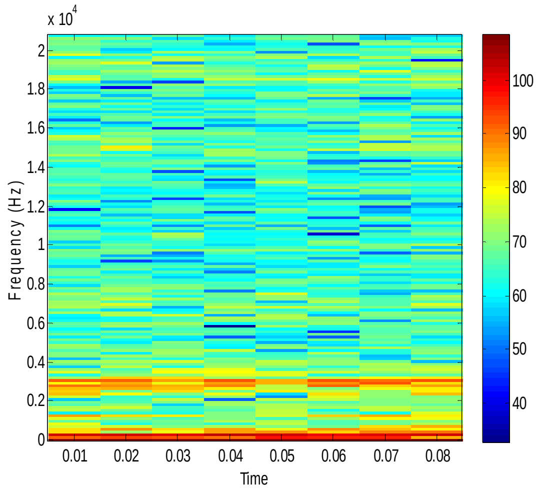
4.2- STFT Energy Root Mean Square and Energy Entropy

In this stage, we have used two approaches to choose the window. In the first approach, time resolution has been increased; thus, frequency resolution would have been decreased. Furthermore, the second approach has been considered to be the opposite of the first approach.

In the first approach, a matrix with the dimensions 417*8 has been obtained whose frequency and time axes have been divided into 417 and 8 parts, respectively. The column windows can be clearly seen form Fig. (5) Which are, indeed, the time windows. Moreover, as it has been illustrated in Fig.(6), in the second approach, a matrix with the dimensions 417*8 has been obtained whose frequency and time axes have been divided into 10 and 398 parts, respectively.

Thereafter, at the next stage, the corresponding values of RMS for one of the column windows of Fig. (5), including the frequency range of [2000-3000], and also for one of the row windows of Fig. (6), containing the range of frequencies of [100-1200], have been calculated with the use of Eq.(8). Then, these calculated values have been divided by the value of RMS of the total signal. Moreover, the entropy energy has been calculated for the row window of Fig. (6), and the obtained results have be tabulated in Tables (3, 4, and 5), respectively. It should be pointed out that we have chosen these frequency ranges in view of their higher values of amplitudes.

(a)



(b)

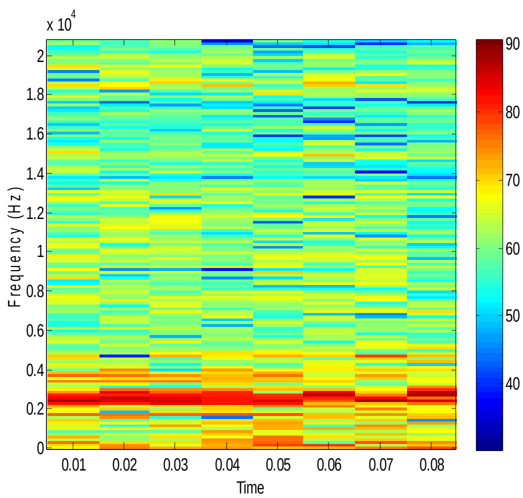
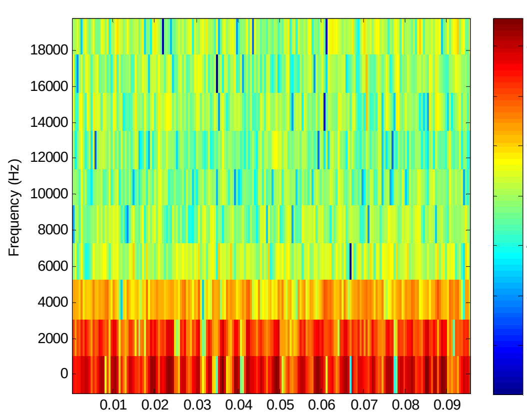


Fig. 5. STFT of the signal for two different faults at 2000 rpm speed and 1000N load (frequency resolutions are increased): (a) GBR, (b) BLD.

(c)



(d)

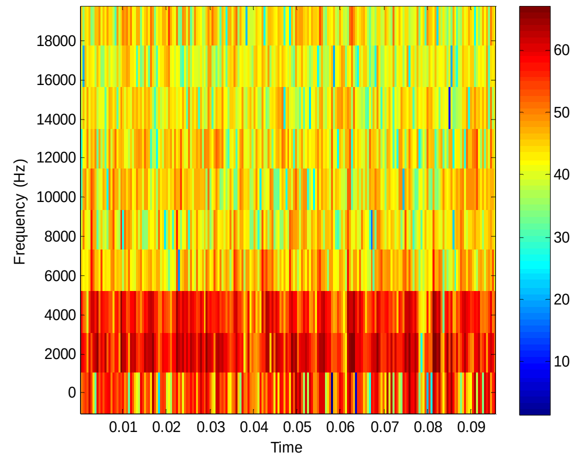


Fig. 6. STFT of the signal for two different faults at 2000 rpm speed and 1000N load (time resolutions are increased): (a) GBR, (b) BLD.

Table 3. The STFT energy root mean square for row window for three different faults at 2000 rpm speed and 1000N load

ABR	BLD	GBR
0.0139	0.0552	0.0023

Table 4. The STFT energy root mean square for column window for three different faults at 2000 rpm speed and 1000N load.

ABR	BLD	GBR
0.015	0.0022	0.0001

Table 5. The STFT energy entropy for three different faults and 1000N load.at 2000 rpm speed

ABR	BLD	GBR
0.3569	0.3390	0.1420

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