Available online at www.sciencedirect.com
ScienceDirect
Procedia Engineering 144 (2016) 234 – 241
Procedia Engineering
www.elsevier.com/locate/procedia

12th International Conference on Vibration Problems, ICOVP 2015

Bearing Fault Monitoring Using CWT Based Vibration Signature

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Abstract

This paper introduces a new approach for generating patterns of phenomena associated with vibration of bearing faults using continuous wavelet transform (CWT). These patterns may be used as signatures for identification of bearing faults. There are four types of bearing faults namely inner race fault, outer race fault, ball fault and cage fault. This work is carried out for inner race and outer race faults. The signatures obtained are found to be unique for a particular type of bearing fault and can be used for identification of bearing faults.

Peer-review under responsibility of the organizing committee of ICOVP 2015

Keywords: Vibration, Bearing; Continuous Wavelet Transform; Signature

1. Introduction

Bearings are widely used in various types of machines ranging from simple induction electric motor to complex manufacturing facilities. Bearing faults, in fact, are a common cause of machinery failures. Rotating machine is a common class of machinery in the industry. The root cause of machinery faults in rotating machinery is faulty rolling element bearing .There are many bearing fault diagnosis techniques available but still the methods that are more effective need to be researched and developed for accurate detection of the fault before machine failure. Several methods have been proposed in the literature for bearing fault detection. To inspect raw vibration signals, a wide variety of techniques have been introduced that mainly includes classical signal processing techniques and intelligent systems. However, an effective bearing fault diagnostic technique is critically needed for a wide array of industries for

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Peer-review under responsibility of the organizing committee of ICOVP 2015
doi:10.1016/j.proeng.2016.05.029

early detection of bearing defects so as to prevent machinery performance degradation and malfunction.With the emergence of new mathematical tools and AI techniques along with progress in signal processing techniques, there is ample opportunity to investigate to meet the precise requirement of bearing fault diagnosis. In this work, an experimental setup is prepared for generating vibration signals for various types of bearing faults. Then, CWT is applied to these vibration signals and a novel algorithm is developed for generating signatures of different types of bearing faults [1].

Nomenclature

τ	time translation
s	dilation (scale)
t	time

2. Experimental Setup

The experimental setup used in this experiment consists of 0.25horse power induction motor, having fixed 1440 RPM, an extended shaft is mounted on the main shaft of the motor so that the seeded fault bearings can be mounted on the shaft for taking vibration data. In this experimental setup ADXL 335 accelerometer is used to capture the vibration data from bearing housing, the faulty bearings are mounted on the shaft and they are covered by the bearing housing and accelerometer is mounted on the top of the housing. In order to collect data from the accelerometer it is coupled with ARDUINO UNO board (microcontroller) which is compatible to MATLAB 2013R where the data can be captured. The Figure 1 shows schematic diagram of the experimental setup and Figure 2 shows actual experimental setup.

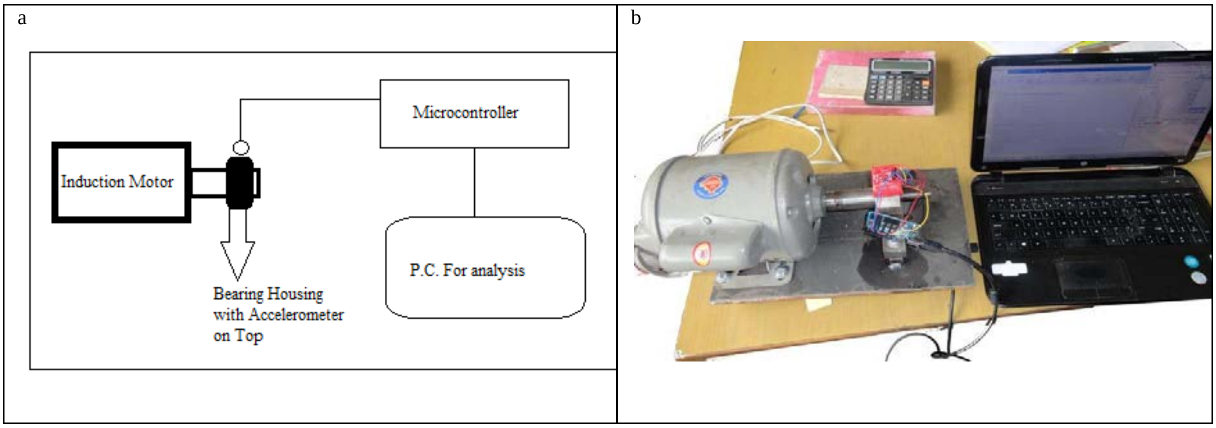

Figure. 1(a) Schematic Diagram for Experimental setup (b) Actual Experimental setup Equations

2.1. Accelerometer

An accelerometer is a device that measures proper acceleration ("g-force"). Proper acceleration is not the same as coordinate acceleration (rate of change of velocity). Accelerometers have multiple applications in industry and science. Highly sensitive accelerometers are components of inertial navigation systems for aircraft and missiles.. Figure 3 shows ADXL 335 accelerometer which is used in the experiment.

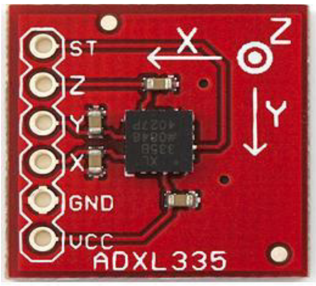

Figure. 2 ADXL 335 Accelerometer

2.2. *Arduino Board*

Arduino is an open-source computer hardware and software company, project and user community that designs and manufactures kits for building digital devices and interactive objects that can sense and control the physical world.An Arduino board consists of an Atmel 8-bit AVR microcontroller with complementary components. Figure 4 shows ARDUINO UNO board used in the experiment.

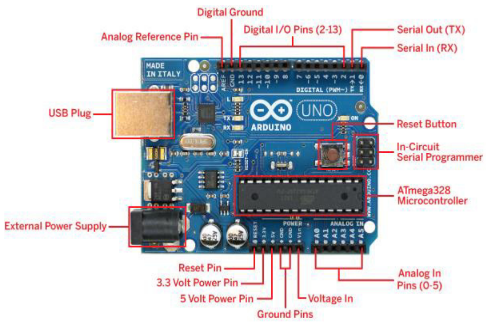

Figure. 3 Arduino Board

2.3. *Bearings*

Thirty seven unassembled bearings of bearing no. 6204 are arranged and on those bearings various types of faults are seeded by the EDM machine and some are dipped in the acid solution for creating the rusting effect on the races, ball and cage. Indentation is made in inner and outer race of the bearing for simulating the bearing inner and outer race defect due to overloading. In ball and cage corrosion, pitting is main cause for their failure so similar type of faults is seeded in cage and ball. Then these unassembled bearings are riveted and converted into the full assembled bearing, ready for the experimental.

3. Application of CWT for feature extraction from bearing faults

Three types of signal processing techniques are available for analyzing any signal / waveform namely time domain, frequency domain and time-frequency domain. Based on their comparison, as given in table 1.1, it is found appropriate to apply wavelet transform to analyze the vibration waveform of various types of bearing faults.

Table 1.1: Comparison of wavelet with RMS, Fourier, and STFT of a signal

Technique	**Domain**	**Characteristics**
RMS	Time	Good time resolution. Poor frequency resolution.
Fourier	Frequency	Poor time resolution. Good frequency resolution.
STFT	Time Frequency (windowed)	Areas of time and frequency resolved together but fixed resolution.
Wavelet	Time Frequency	Areas of low frequency resolved well in the frequency domain but have poor time resolution. Areas of high frequency have good time resolution but poor frequency resolution.

From the above, it reveals that wavelet based techniques are most effective for extraction of features. The continuous wavelet transform has been applied to healthy bearing along with bearings with inner race, outer races, cage and ball faults and CWT plots are obtained, which they can do online.

3.1. *Continuous Wavelet Transform*

The continuous wavelet transform is a time-frequency representation of signals. It is convolution of a signal *x* (t) with a set of functions which are generated by translations and dilations of a main function i.e. mother wavelet. Mathematically, the CWT is given by:

$$\psi_{s,\tau}(t)=\frac{1}{\sqrt{s}}\psi\left(\frac{t-\tau}{s}\right) \tag{1}$$

$$CWT_{\psi}x(s,\tau)=W_x(s,\tau)=\int_{-\infty}^{\infty}x(t)\psi^{*}_{s,\tau}(t)dt \tag{2}$$

Here, τ is the time translation and *s* is the dilation (scale) of the wavelet and both are real numbers[2-3].
Following are the five easy steps used to compute the CWT coefficients for a signal:

- Choosing a wavelet, and matching it to the section at the start of the signal.
- Calculating CWT coefficients, which measures how similar the wavelet and the section of the signal are.
- Shifting the wavelet to the right by translation $\boldsymbol{\tau}$, and repeating the steps 1 and 2 above. Calculating values of CWT coefficients for all translations.
- Scaling the wavelet, and repeating steps 1to 3 above.
- Repeating step 4 for all scales.

The CWT coefficients computed as above, form a matrix at the different scale and translation values; the higher value of coefficients suggest a high correlation (similarity) between the portion of the signal and that version of the wavelet[4-6]. The colors in the plot show the relative values of the CWT coefficients. The light areas means higher values of the CWT coefficients and therefore, signal is very similar to the wavelet. Whereas, dark area means lower values of the CWT coefficients and it shows that the corresponding time and scale versions of the wavelet are dissimilar to the signal.

3.2. CWT plots of Bearing Fault :

The CWT plots for waveforms of healthy bearing, faulty inner race and outer raceshave been obtained using MATLAB and are shown from Figures 4.a to Figure 6.c.

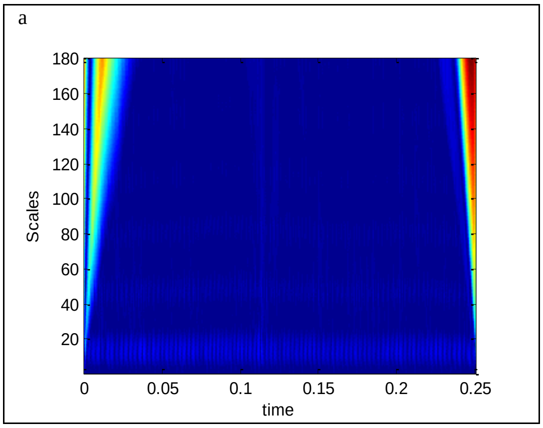

Figure. 4 (a) Healthy Bearing's CWT plot

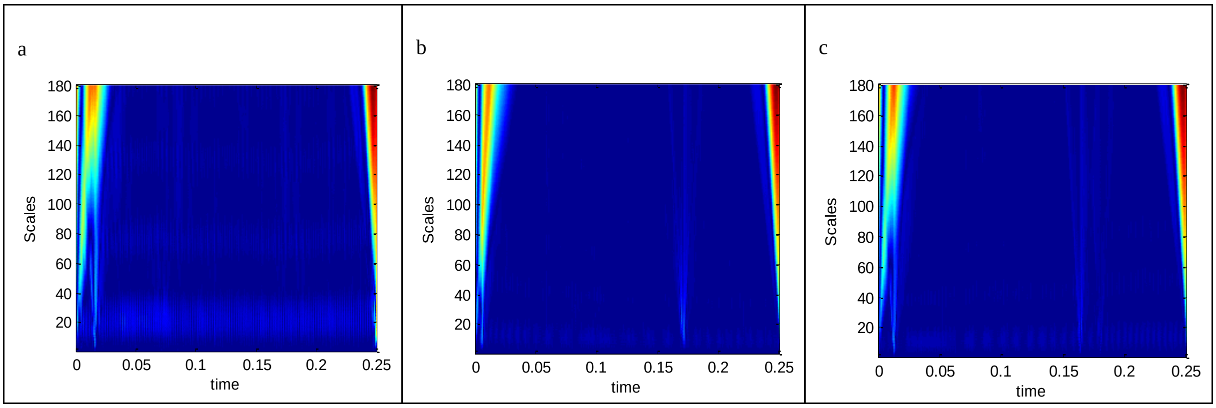

Figure. 5 Signal containing Inner Race Defects with different index of fault and its CWT plot.

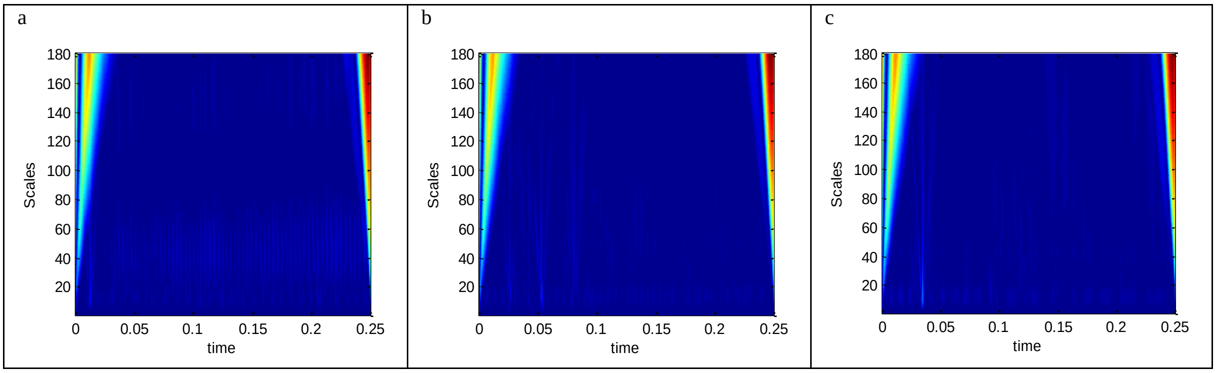

Figure. 6 Signal containing Outer race defect with different index of fault and its CWT plot.

4. Generation of Bearing fault Signature

The proposed algorithm for generation of signatures of various bearing faults is presented through block diagram in Figure 7. Initially, CWT coefficient matrix of Bearing faults signal is obtained and subtracted from CWT coefficient matrix of pure bearing waveform. This results in a matrix named as 'Difference Coefficient Matrix' (DCM), which dominantly contains the features of bearing faults data. On careful investigation of DCM, it revealed that the scale-wise (i.e. row-wise) values of coefficients of DCM follow a typical pattern for a specific type of bearing faults. The elements of each row of DCM are added and the resultant matrix is named as the 'Unique Feature Matrix' (UFM).It is also observed that the UFM possesses unique features for a bearing faults type and it can therefore be used to generate a unique pattern/ signature[7-10].

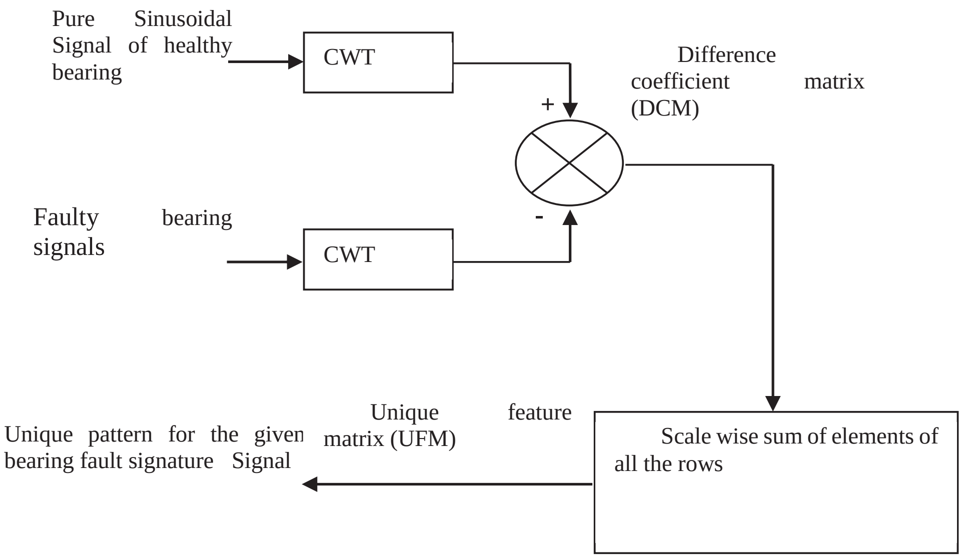

Figure. 7 Algorithm for generation of fault Signature

The algorithm for generating Bearing faults signature may be summarized in following five steps:

Step 1: Generating data of pure as well as one of the Bearing faults waveform (both of matrix size 1x1800).

Step 2: Obtaining CWT coefficient matrix (matrix size 180x1800) for both of them.

Step 3: Calculating DCM(matrix size 180x1800) by subtracting CWT coefficient matrix of bearing faults waveform from CWT coefficient matrix of pure waveform.

Step 4: Evaluating UFM by adding all the elements of a row of DCM (matrix size 180x1).

Step 5: Plotting the row wise values of UFM with respect to its scale as signature.

5. Results and Discussion

After setting up the experimental setup, CWT is applied on the raw vibration data acquired from the faulty bearings and signatures are found out for various types of faults. The CWT and signatures for various faults are shown below:

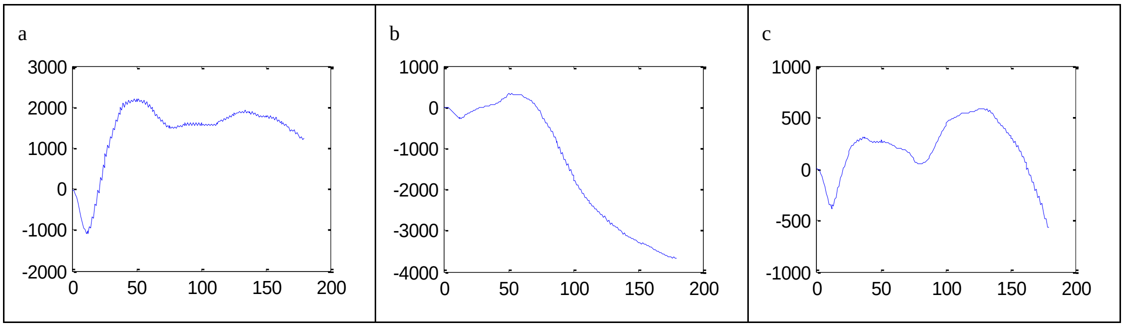

Figure. 8 (a) Inner race rusty (b) Indentation in inner race (c) Indentation of high Index

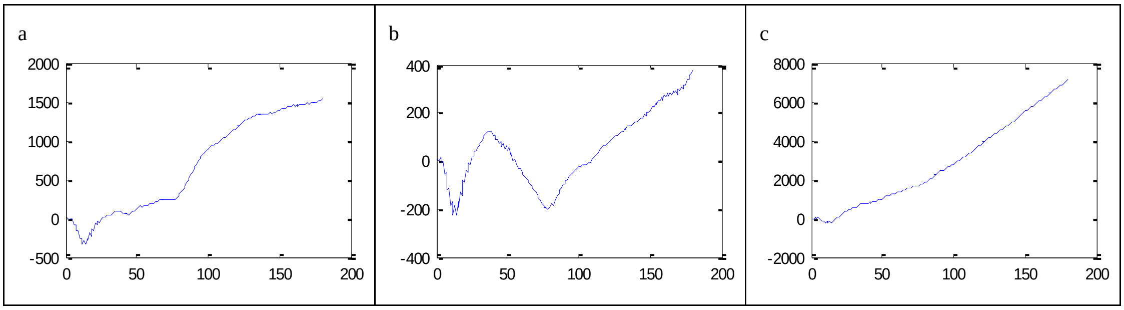

Figure. 9(a) Outer race rusty (b) Indentation in outer race (c) Indentation of high Index

Hence, by seeing the signatures formed by CWT one can classify the different type of a bearing fault. CWT proved to be an effective tool for identifying the faults in bearing and after training such data in Artificial Neural Network this fault diagnosis technique can be made online and fully intelligent [11-12].

6. Conclusion

CWT analysis is an effective tool for analyzing bearing fault data because in this one gets all the three details i.e. time detail; frequency detail; and amplitude detail. CWT signatures are the unique feature which is shown in this paper and these can be used to classify the bearing faults visibly. We can conclude this that cwt signatures can be used as fault classification tool in ball bearing fault diagnosis.

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