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Data Acquisition System and Signal Processing Technique for Bearing Fault Analysis

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Abstract

Background/Objectives: In rotating machinery bearings plays an important role to reduce rotational friction and support radial and axial loads. Abnormal vibration affects the lifetime of machinery. This abnormality may causes by bearing Fault. In order to monitor the machines health and it is needed to focus the functionality of bearing components like ball, inner race, outer race and cage component. **Methods/Statistical Analysis:** There are many methodologies available to measure and analyze the fault of bearing but they utilize expensive resource to identify the bearing system. The proposed system explains and utilizes a cost effective, less time consuming system, is used for bearing faults identification. The novel system provides real-time data acquisition and signal analysis for Fault detection. Low cost Micro Electro Mechanical System (MEMS) Accelerometer sensor is used for vibration measurement, LABJACK U3 Data acquisition system connected with Raspberry Pi-2 CPU which acquires and process with high performance of acquired data by using python application software. **Application/Improvements:** The online signal processing technique explains the abnormality of bearing time domain data's amplitude easily classify the faulty bearing. Fast Fourier Algorithm converts time domain to frequency domain which easily represents faulty components frequency with high amplitude. Short Time FFT (STFT) shows the color map with high color intensity of vibration amplitude of faulty components and its time instant. These data representation technique is utilized to easily identify fault of bearing components.

Keywords: Bearing Faults, Fast Fourier Transform, DAQ Data Acquisition System, LABJACK U3, Raspberry Pi-2, Short Time FFT

1. Introduction

Rotating machinery's heart are bearings. In machinery dynamic rotating condition, due to failure of bearings affects the operating condition of machines and it's deteriorate normal operation[1]. Therefore it is very useful to identify faults of bearings and this to be precise way to automatically find the severe of fault[2]. Because the vibration signals carry the information and signature of problem about rotating components of mechanical structure[3-5]. It gives more useful information about the operational condition of machinery component through vibration signature. The digital signal processing of vibration signal is one of the important tools to diagnose the bearings defects with different signal processing techniques, Characteristics of bearing fault can be extracted from analyzed vibration signals. This is one of the best methods for bearing Fault analysis. There are three different methods of signal processing techniques to post processing vibration signal in condition monitoring and Fault diagnostics application. These are Time-domain analysis, Frequency domain analysis and time-frequency analysis. Time-domain analysis is directly based on time vs. vibration's amplitude[6,7]. Traditional time-domain analysis calculates characteristic features from time[8], time waveform signal gives statistics features such as peak to peak, peak, Root mean square, mean, kurtosis, Skewness and kurtosis. Frequency domain analysis is based on Fourier transform, the transformed signal is in Frequency domain (Frequency vs. Amplitude of vibration signal). The main application is, it has an ability to easily identify the spectrum analysis by mean of Fast Fourier Transform (FFT))[9].

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for bearings that represent density of state vector as a set of random samples for gain analysis using extended/unscented Kalman filters was discussed by B. U. L. Jegan et al.[10]. The de-burring process of a bearing flame based on "withness simulation experiments" for improving productivity and analysis of mean work-in process fluctuation, mean lead time, error rate was examined by D. J. Shin et al.[11]. This will be very useful to identify the frequency of non-deterministic signal/ non-linear nature of signal. One of the Limitations of frequency domain analysis is inability to analyze non-stationary (dynamic condition of machinery) waveform signals generated when machinery fault occurs.

Concept of reconfigurable ALU using Signal processing applications was proposed by T. Begum et al.[12]. A Simulink model implementation of open loop and closed loop fiber optics gyroscope for the measurement of reflection rate was discussed by G. Harish Babu et al.[13]. The existing severity of the fault is discussed by Li et al. and Lotaus et al.[14,15]. The vibration based signal processing technique for fault identification is discussed by Zhu et al. and Lil et al.[16,17]. Time-domain analysis is defined based on time versus vibration's amplitude[18-20]. This Problem can be overcome by the Time Frequency analysis [Short time Frequency analysis (STFT)] the time frequency analysis is frequency-domain representation (its spectrum) changes with respect to time. Time-frequency analysis is most frequently achieved by segmenting a vibration signal into those short periods and appraising the spectrum over sliding windows. The spectrogram function calculates an FFT-based spectral estimate over each sliding window how the frequency content of the signal changes with respect to time. And Amplitude of signal represent in energy or power in two dimensionality functions of both time domain and frequency domain. This representation reveals the fault pattern and more accurate diagnostics[21].

The paper is prepared as the following section wise. Section 2 contains the system framework, Th1eory, Section 3 explains the signal processing of Bearing's Vibration, and Mechanical system and sensors are presented. Section 4 contains the experimental setup Hardware circuit and in Section 5 explains the experimental results and validation are presented. Finally section 6 concludes the paper.

2. System Frame Work

2.1 Theoretical Calculation for Bearing Fundamental Frequencies

Bearings fundamental frequency is defined as bearing rolling components gerates when it is pass over inner race and outer race of bearing surface. These also called as fundamental fault frequencies. These frequencies are defined withthe following parameters,bearing geometry, Ball diameter, pitch diameter and relative speed between innner race and oter race.the bearing fault fequency can be calculated using below Equation:

bpfri = np/2*fs*(1+bdia/pdia*cos θ) (1)

bpfro = np/2*fs*(1-bdia /pdia*cos θ) (2)

ftfr = fs/2*(1-bdia/pdia*cos θ) (3)

bsfr = pdia /bdia*fs/2*[(1-bdia/pdia*cos θ)^2] (4)

Where,

bpfi - ball pass frequency inner race in Hz ; bpfo - ball pass frequency outer race in Hz

ftfr – fundamental train frequency in Hz ; bpfr - ball pass frequency in Hz

np – number of balls; fs – Shaft frequency in Hz; bdia - ball diameter in mm

pdia – pitch diameter in mm; θ- Contact angle.

Two different bearing has used for experiment, ans it operated as different rpm. Table 1 shows the parameters width, bore diameter, outside daimeter,and limiting speed.

Table 2 shows the defective frequency calculated from Equation (1) to (4) for bearing 6000z and 6005-2z.

Table 1. Bearing parameters

Bearings	Width in mm	Bore diameter in mm	Outside diameter in mm	Limiting speed r/ min
6000-z	12	25	47	16000
6000-z	8	10	26	40000

Table 2. Effective frequency

Bearing Types	6000z	6005-2z
Bearing defect frequency	Defect Frequency (Hz)	DefectFre-quency (Hz)
Rotational speed	1968	1040
Shaft speed Frequency	32.8	17.33
bpfi - inner race defect frequency	153.2	102.9
bpfo - outer race defect frequency	76.53	70.42
cage defect frequency	10.93	7.042
ball spin frequency	43.73	44.16
Rolling element defect frequency	87.4	89.237

2.2 Block Diagram of the Proposed Vibrational Measurement System

Bearing vibration can be measured by (MEMS) accelerometer. Output connected into LABJACK U3 Data acquisition systems analog input which converts this analog signals into digital and it is connected to low cost high performance CPU RASPBERRY PI 2. The acquired data is processed using digital signal processing technique like time domain, frequency domain and STFT. Bearing fault frequency can be identified by the FFT from its dominant peak frequency.

The Lab Jack U3 has 16 analog inputs and flexible I/O lines. It can configured as Single-ended measurements when any analog inputs connected to ground. It can also used as differential measurements when there is connection between any two inputs lines.

U3-LV has analog input resolution of 12-bits. The low-voltage single-ended analog input ranges between 0-2.4 volts or 0-3.6 volts and differential analog inputs range is ±2.4 volts (it has only pseudo bipolar).

The Raspberry Pi has in built CPU module and it has performed as mini computer. This system has following features 900 MHz quad-core ARM Cortex-A7 CPU, 1 GMB of RAM and Video Core IV GPU, it can run with the following operating system ARM GNU/Linux distributions, Snappy Ubuntu Core and Microsoft Windows 10.

3. Signal Processing Techniques

3.1 Time Domain

The signals are represented in time vs. amplitude where time in X axis Amplitude in Y axis. The significant is to identify the abnormality by noticing the vibration signals amplitude.

3.2 Frequency Domain

It's a transform of signal from time domain to frequency domain. In this, signals are represented in frequency in X axis and amplitude in Y axis. It's very useful to analysis complex signals (Non-Deterministic/Deterministic).

The conversion of a time signal to the frequency domain (and its inverse) is achieved using the Fourier Transform as defined below:

$$Sx(f) = \int_{-\infty}^{\infty} x(t)e^{-j2\pi ft}dt \tag{5}$$

$$x(t) = \int_{-\infty}^{\infty} S_x(f)e^{j2\pi ft}\,df \tag{6}$$

This function is continuous and in order to use the Fourier Transform digitally a numerical integration must be performed between fixed limits.

3.3 Short Time Fourier Transform (STFT)

A standard method used to investigate time-varying signals is the so-called Short Time Fourier Transform (STFT). This involves selecting a relatively narrow observation period, applying a time window and then computing the frequencies in that range.

For a time signal s(t) multiplied by a window function g(t), the Short Time Fourier Transform located at time 't' is given by

$$\mathrm{STFT}(\tau,\omega) = \frac{1}{\sqrt{2\pi}}\int_{-\infty}^{\infty} e^{-j\omega t}s(t)g'(t-\tau)dt \tag{7}$$

This is a useful technique if it is possible to select the observation period so that the signal can be regarded as being stationary within that period. There are a whole range of signals however where the frequency contents change so rapidly that the time period required would be unacceptably small.

This technique suffers from a further disadvantage in that the same time window is used throughout the analysis and it is this that determines the frequency resolution ($D_f = 1/T$). This fixed relationship means that there has to be a trade off between frequency resolution and time resolution. So, for good visulization the signal should be analysed with either good resolution of frequency or good resolution of time but not both at a time.

It's a short time Fourier transformation which calculates more line the normal FFT. This is achieved by having smaller real block size of data and larger FFT size. Real data is windowed and zero faded and then FFT calculated. With this procedure, we can calculate more FFT for the same time base. It's nice to be used with fast transient. Block size defines no of real data samples for the calculating FFT.

4. Experimental Setup

Figure 5 shows the bearing test kit. It consist of single phase induction motor, shaft and two bearing assembly. Rpm is controlled by external regulator.

Figure 6 shows Experimental setup of Data acquisition system with fault bearing vibration from bearing kit. LABJACK U3 DAQ connected with Raspberry pi 2 CPU via USB port. External display connected with CPU through HDMI port other accessories are interface with USB port. Raspberry pi 2 is operated by LINUX operating system and programing language is Python. Real output shows in Figure 7.

Figure 1. Deep grove ball bearing.

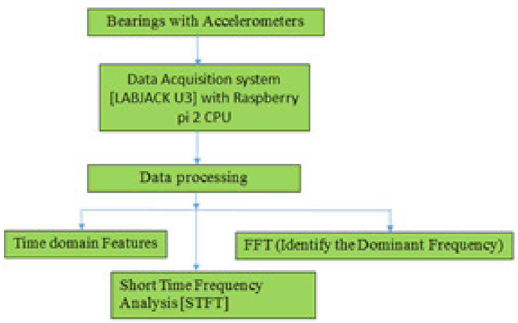

Figure 2. Block diagram of vibration measurement and signal processing technique.

Figure 3. LABJACK U3 DAQ.

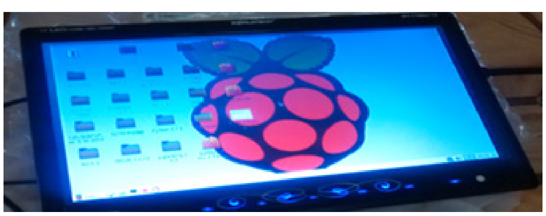

Figure 4. External display interface with Raspberry pi 2.

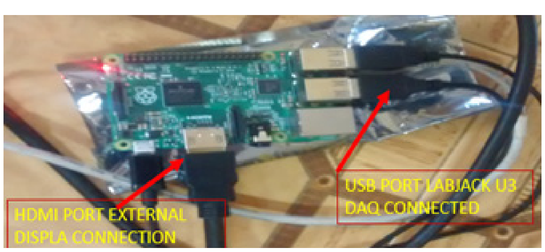

Figure 5. (a). Raspberry pi 2.

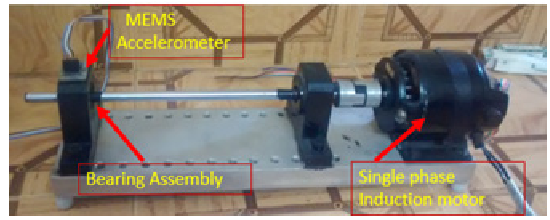

Figure 5. (b). Bearing kit.

Figure 6. Experimental setup.

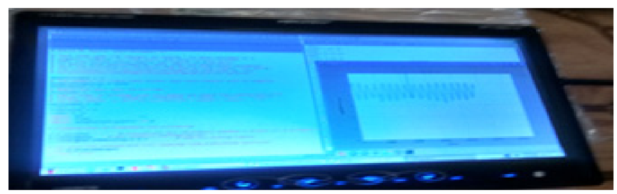

Figure 7. Experimental output display.

This experiment was conducted with four different iteration. 1. Normal bearing, 2. Ball defect bearing, 3. Inner race defectbearing and 4. Outer race defectbearing. And the experimental results shows below.

5. Experimental And Analysis Report

5.1 Normal Bearing Measurement and Analysis Results

Figure 9 and 10 shows the first iteration of bearing that is normal bearing used as reference. From time domain the peak to peak value has measured 53.87 m/s^2. The FFT graph shows the predominant frequencies from its peak amplitudes, the first peak is 17.19 Hz that is Shaft running frequency [RPM/60=1040/60=17.33] and the other peaks represents its harmonics. Also it shows the ftfr – fundamental train frequency 69.63 Hz and bpfi-ball pass frequency inner race in 104.6 Hz. STFT shows the red intensity in shaft running Frequency and its harmonics.

Figure 8. Images of defective bearings.

Figure 9. First iteration of time domain analysis of normal bearing – reference.

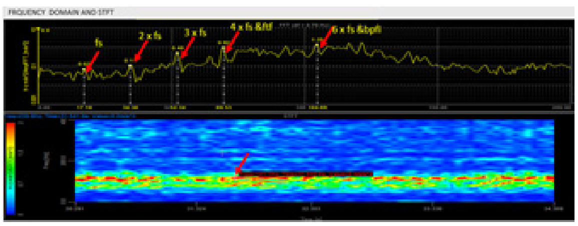

Figure 10. First iteration of frequency domain & STFT analysis of normal bearing – reference.

5.2 Ball Defect Bearing Measurement and Analysis Results

Figure 11 and 12 shows the second iteration of bearing that is ball defect bearing. From time domain the peak to peak value is 117.2 m/s^2. It is two times higher than the Normal bearing which gives basic understanding of abnormality. The FFT graph shows the predominant Frequencies and the Peak Amplitudes at 90.17 Hz Rolling element defect frequency. It is the First level of information that the running bearing having abnormality, the second peak Amplitude is 69.53 Hz which is ball pass frequency inner race and the third peak is 45.09 Hz it is Ball spinning Frequency. STFT shows the red intensity in ball spinning frequency and Ball pass outer race.

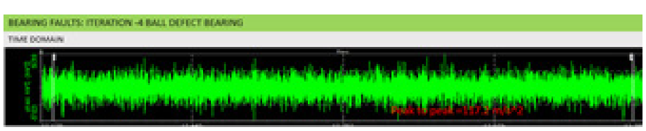

Figure 11. Second iteration of time domain analysis of ball defect bearing.

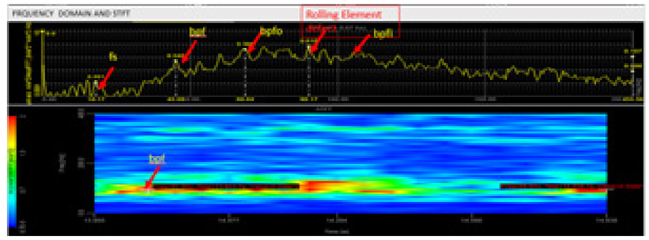

Figure 12. Second iteration of frequency domain & stft analysis of ball defect bearing.

5.3 Inner Race Defect Bearing Measurement and Analysis Results

Figure 13 and 15 shows the third iteration of bearing that is Inner race defect bearing. From time domain the peak to peak value is 87.36 m/s^2. It is 1.5 times higher than the Normal bearing which gives basic understanding of abnormality. The FFT graph shows the predominant Frequencies and the Peak Amplitudes at 87.50 m/s^2. Rolling element defect frequency It is the First level of information that the running bearing having abnormality, the second peak Amplitude is 104.2 Hz which is ball pass frequency inner. Also it affects outer race which reflects the third higher peaks from ball pass frequency outer race in 70 Hz. STFT shows the red intensity in ball pass frequency inner race and shaft running Frequency and its harmonics.

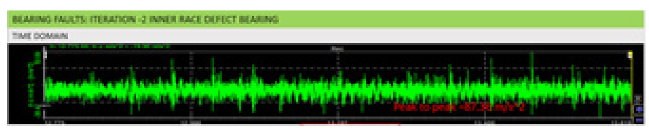

Figure 13. Third iteration of time domain analysis of inner race fault bearing.

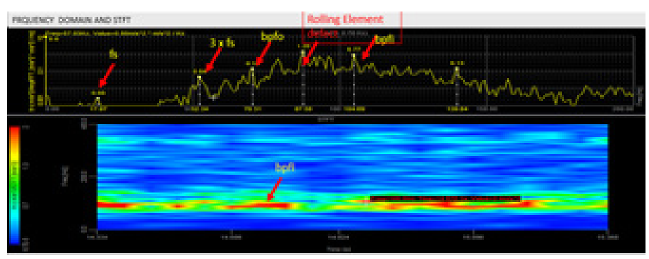

Figure 14. Third iteration of frequency domain and STFT analysis of inner race bearing fault.

5.4 Outer Race Defect Bearing Measurement and Analysis Results

Figure 15 and 16 shows the third iteration of bearing that is Outer race defect bearing. From time domain the peak to peak value is 55.37 m/s^2. It is slightly higher than the Normal bearing which gives basic information about abnormality. The FFT graph shows the predominant Frequencies and the Peak Amplitudes at 103.2 ball pass frequency inner race and second peak from 87.8 Hz Rolling element defect frequency It is the First level of information that the running bearing having abnormality, the second peak Amplitude is 69.53 Hz which is ball pass frequency inner race. STFT shows the red intensity in ball pass frequency outer race and shaft running Frequency and its harmonics.

Figure 15. Third iteration of time domain analysis of outer race bearing fault.

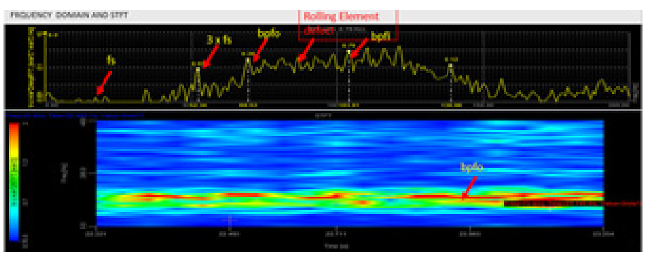

Figure 16. Third iteration of frequency and STFT domain analysis of outer race bearing fault.

6. Conclusion

This research work provides a simplest measurement setup which is cost-effective for small/medium scale industries and easiest signal processing technique to analyze the bearing fault vibration. By predicting such error in most industries may enhance their productivity by a 20-30%.

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