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Octave and Analytical Wavelet Analysis in Diagnosis and Measurement of Race Defect in Taper Roller Bearing

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***Abstract*— Rolling element bearings is an essential component in every rotating machine. In today's manufacturing organization where preventive, or predictive maintenance is one of the major expenditures in the production process, a healthy rolling element bearing play a vital role in reduction in breakdown time. Therefore it is of great importance to monitor condition of bearing and understand the behavior of defect in the bearings. Although there are various methods available for condition monitoring and fault diagnosis of the rolling element bearing it is felt that vibration analysis is most preferable technique because of its quick response and its durability.**

***Keywords*— Vibration analysis, Octave band analysis, Envelope detection, Analytical wavelet transformation, Time marginal integration.**

I. INTRODUCTION

Condition monitoring of rotary machinery is associated to the mechanical condition of the rotary machine such as vibration, bearing temperature, oil pressure, oil debris, and performance which makes it possible to decide whether the machinery is in good or bad mechanical condition. Condition monitoring makes it possible to determine the cause of the problem [1]. The use of condition monitoring allows maintenance to be planned, or other actions to be taken before the failure occurs to avoid the penalties of failure. One of the important element of condition monitoring of rotary machinery is vibration analysis. Vibration analysis is a measurement tool which is used to detect, forecast, and avert failures in rotating machinery. Employing vibration analysis on the rotating machines will improve the consistency of the machines and lead to better machine productivity and reduced down time as well as reducing mechanical failures [2].

Vibration analysis is the art of using vibration information like waveform, spectral, phase, etc. to aid in the diagnosis of machinery. When the machine cannot be taken out of service for close inspection, the efforts of diagnosing the machine condition can be difficult. In this analysis, the healths of the machine based on collected data are analyzed [3]. This allows the changes within the machine to be determined precisely and appropriate corrective action can be initiated [4]. Although there are several methods of condition monitoring, vibration analysis was chosen for several reasons. First, it is easy to implemented and reliable [5]. Second, different defects produce different vibration patterns; and can relate to a specific bearing defect. Finally vibration monitoring is relatively inexpensive [6]. Every machine in standard condition has a certain vibration signature and when fault initiates or develops in them its signature changes. The increased level of vibration and introduction of additional peaks in signal is an indication of defect [7].

Intelligent diagnosis procedure is shown in Figure 1.1, which begins with the act of data collection (obtaining signals using transducers rom machinery to be diagnosed) followed by feature extraction (extracting characteristics whose values quantitatively represent faults). As an example of extracted features, in vibration analysis, impact pulses due to defect are usually regarded as an important characteristic (feature) for bearing fault diagnosis.

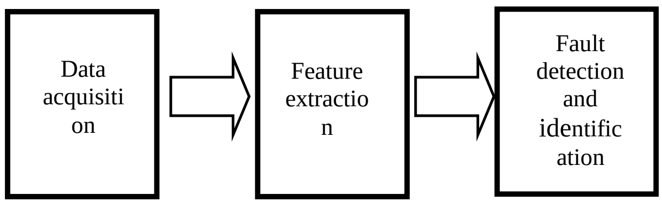

Figure 1.1: Schematic diagram of bearing fault diagnosis by vibration analysis

The variation in contact area between rolling elements and raceways due to distributed defects results in an increased vibration level [8]. Localized defects include cracks, pits and spalls in the rolling surfaces. The presence of a defect causes a significant increase in the vibration levels, which are used as the features to be sought for diagnosing different machinery faults [9]. Feature extraction techniques for diagnosing rotating machinery faults are widespread and can range from statistical to model based techniques and comprises a variety of signal processing algorithms [10].A review of feature extraction techniques are updated according to signals under time domain, frequency domain, and the combination of time and frequency domain. These categories are treated and reviewed separately as following sections.

A. Time domain Techniques

Vibration signals are initially obtained as a series of digital values representing proximity, velocity, or acceleration in the time domain. The time waveforms can be processed to achieve diagnostic objectives. Certain features such as statistical parameters can be signified using time domain vibration analysis techniques [11]. The Measurement of signal energy can be a good indicator of a bearing's health. This method has been applied with limited success for the detection of localized defects [12].In time domain techniques, vibration signal is represented in amplitude versus time plot [13].

B. Frequency domain techniques

In this technique data is presented in terms of frequency and its magnitude. Frequency domain techniques are used when information of frequency in signal is important to identify cause of periodicity [14]. This technique is quite useful for analyzing stationary signals whose frequency components do not change over time. In other words, this technique is very accurate if the rpm of the shaft does not change over time or does not change at least during each updated duration of time analysis [11].

C. Time- Frequency domain techniques

Instead of distinct observation of the time from the frequency characteristics of a signal, it is prefer to use a joint time frequency technique. Time-frequency (TF) analysis results are presented in a spectrogram or scalogram, which shows the energy distribution of a signal in the time-frequency domain. A spectrogram/ scalogram are an intensity graph contains time in abscissa and frequency in ordinate. Intensity of color explains the power of the signal at the corresponding time and frequency. In this transform, sine wave basis functions are modified which are more concentrated in time but less concentrated in frequency. It uses an arbitrary but fixed-length window function "w" for analysis, over which the actual non-stationary signal is assumed to be approximately stationary. TF analysis decomposes such a non-stationary signal into a two dimensional time-frequency representation S(t, f) of the signal x(t) using that sliding window at different times. The Short-time Fourier transform (STFT) is defined as [15]:

$$s_x^{(w)}(\tau, f) = \int_{-\infty}^{+\infty} [x(t).w^*(t-\tau)].e^{-i2\pi ft}dt$$

Where x(t) is the signal itself, w(t) is the window function, and "*" stands for its complex conjugate. For every τ and f, a new STFT coefficient is computed to obtain a true time- frequency representation of the signal. Limitation of STFT is that it is only suitable for non-stationary signals [16]. Once a window has been chosen for STFT, the time-frequency resolution is fixed over the entire time-frequency plane since the same window is used at all frequencies. There is always a tradeoff between time resolution and frequency resolution in STFT. To overcome the boundaries of the standard STFT, Wavelet Transform (WT) was introduced in the field of signal processing. WT in its continuous form delivers a flexible time-frequency window, which narrows when detecting high frequency phenomena and widens when examining low frequency behavior. Thus time resolution becomes arbitrarily good at high frequencies, although the frequency resolution becomes arbitrarily good at low frequencies. Therefore WT is highly preferable tool to fulfill both time and frequency resolution requirements more accurately. The wavelet transform can be imagine as an extension of the classic Fourier transform while excepting that instead of working on single scale, it works on a multiscale basis. The wavelet transform can be categorized as continuous or discrete. The main advantage of the continuous wavelet transformation (CWT) is its ability to deliver information simultaneously in time and scale with adaptive windows[17]. Using CWT, Calculating wavelet coefficients at every feasible scale is a large quantity of work, and produces a disagreeable lot of data[18].To overcome such a problem an analytical wavelet transformation based on the Morlet wavelet was introduced by Lin [19].

II. UNDERLYING THEORY

A. Earlier fault diagnosis of rolling element based on octave band analysis

The most common methods of analyzing vibration data to diagnose bearing damage are by observing changes in the decibel level and the power spectrum. With increasing bearing damage it has been observed that the decibel level increases. A refinement of straight decibel level measurement is to observe changes in different octave, or one-third octave frequency bands.

Sound-level measurements provide a predictable way to measure sound but do not contain frequency information, making it challenging to compare different soundsor vibration. Octave analysis filters the signal and measures the energy at the output to deliver useful frequency information. When more detailed information about a compound sound is desirable, the frequency range of 20Hz to 20kHz can be divided into bands. This is performed electronically within a sound level meter. These bands commonly have a bandwidth of one octave or one third octave. In octave band, sound levels are stated in decibels (dB), and logarithmic frequency scale. The measurements are made over an interval of frequency which is called the bandwidth and is specified by an upper and lower frequency limit, *fi*+1 and *fi*, respectively, called cut-off frequencies.

In acoustics the frequency bandwidths are usually specified in terms of octaves and one-third-octaves. However, in special cases also the different fractional-octaves can be used. An octave is defined as an interval of frequency such that the upper frequency limit is twice the lower limit, that is *fi*+1 = 2*fi*. The general relationship between the upper and the lower cut-off frequencies is given by *fi*+1 = 2*n* *fi*, where *n* is the number of octaves, either a fraction or integer. The mid frequency *fc* of *n*-

octave band is the geometric mean of the frequency band given by $f_{ci} = f_{i+1} * f_i$ .The octave band sound pressure level in decibels represents a measure of the mean squared pressure of the sounds within the particular frequency band. For the one third octave there are three times as many data points, which provide a finer filtering process of the sound.

B. Characterization of bearing defect based on envelope detection

As the rotating inner race, with a defect, passes through the load zone; that is, as a rolling element strikes to the defect which moves into and out of the load zone, modulated impulses will occur periodically with each shaft rotation. Therefore, the envelope of the impulses can be described as a function of load distribution [20]. The characteristic signals from a faulty bearing are masked after the measurement system, noise, distortions and disturbances. The purpose of the algorithm is to recover and enhance those signals by removing the undesired effects. Achieving this with minimum computational power, effort and complexity, without additional preprocessing applications such as filtering or envelope detection, and as a low cost system is surely the desired goal. Figure 2.1 present the steps involve in envelope detection.

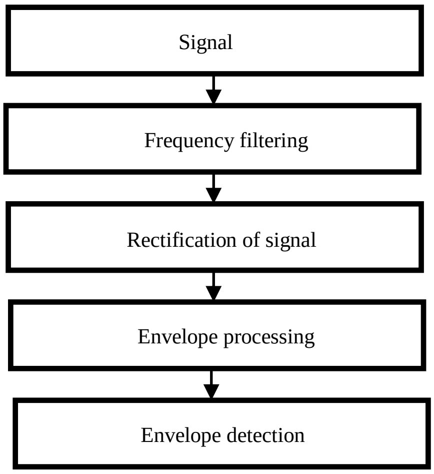

Figure 2.1: Steps involve in envelope detection of signal

Vibration signals raised on degraded bearings contain repetitive shocks, which excite high frequency resonances. A direct frequency analysis does not always give access to interesting information when the energy content of the signal, in consequence of these resonances, is located in these high frequencies. However, these repetition frequencies can be easily highlighted in the envelope signal. Classically, the signal is first band pass-filtered around the frequency range where a significant broadband increase has been detected [21]. From the filtered signal, which must contains only the repetitive impulses; one performs envelope detection or amplitude demodulation, which gives the outline of the signal.

C. Vibration signal processing based on analytical wavelet transform (AWT)

The analytical wavelet transform (AWT), can be supposed as a hybrid of the wavelet transform and Fourier transform The AWT characterizes a signal by its frequency and amplitude as in the Fourier transform. However, the AWT is a function of time, dissimilar the Fourier transform. The AWT is an ideal tool for the analysis of transient events in the vibration and acoustic signals.AWT is a distinctive family of complex-valued wavelet transforms to analyze the modulated oscillations. The complex-valued wavelet transform has appeared as a significant non-stationary signal processing tool. Continuous complex wavelets have been used for the classification of modulated oscillatory signals and its discontinuities.AWT can recover the properties of the signal, without stating a parametric model for its structure, on the basis of contaminated observation. For contaminated signals the direct construction of the analytic signal via the Hilbert transform leads to ineffective outcomes as the amplitude and phase will then reflect the aggregate properties of the multi-component signal. It is essential to separate the signal of interest while simultaneously translating it analytic. The AWT is a technique for constructing a family of diversities of a time series which are together localized and analytic. Mathematically, the AWT of a signal $a_x(t)$ is $W_s a_x(t)$, can be defined as:

$$W_s a_x(t) = \int_{-\infty}^{+\infty} a_x(u)\,\psi_s^*(u-t)\,dt$$

$$W_s a_x(t) = \int_{-\infty}^{+\infty} \left(\frac{1}{S}\right) a_x(u)\, g\left(\frac{u-t}{S}\right) e^{-j\eta\left(\frac{u-t}{S}\right)} dt$$

Where S is the scale $\psi_s^* = g\left(\frac{u}{S}\right) e^{j\eta\left(\frac{u}{S}\right)}$ is the wavelet function of scale S, $j = -1$ and η is a parameter that relates the scale with the frequency.

For efficient analysis of the AWT spectrum and clear visualization of AWT scalogram, the time marginal integral (TMI) play a vital role in AWT transformation. The TMI returns the outcome of integrating the scalogram along the frequency axis, or the integral of each row of scalogram. The TMI spectrum is correspondent to the smoothed instantaneous power of the signal. The instantaneous power exposes that how the power of the signal changes over time. The Equation below defines the time marginal integration:

$$TMI = \int_{-\infty}^{+\infty} SP(t,\omega)\,d\omega$$

Where, $SP(t,\omega)$ is the spectrogram of the signal in time-frequency plane.

III. EXPERIMENT AND RESULT

A customized test rig was used to perform experiments. Shaft in the test rig was supported by two self-aligned taper roller bearings (Manufacturer: NBC, Bearing number: 30205) as shown in Figure 3.1. The shaft was driven by an alternating current motor of 0.50 HP capacity (Manufacturer: Crompton). The rpm of motor was kept at 2050 by a belt pulley arrangement. One of the end of the shaft has provision for mounting the disk to load the shaft. In the present research work load of 2 kg was used throughout for all the observations. A uni-axial (ICP®) accelerometer (Manufacturer: PCB Piezoelectronics, Model No.: 353B34) was placed above the bearing casing perpendicular to the axis of rotation of the shaft. A data acquisition system (Manufacturer: National Instruments Corporation, Model: SCXI-1000 with SCXI-1530 module having BNC input) is used to acquire the vibration signal obtained from the accelerometer. A program was developed in Labview environment to acquire and display the signal along with its FFT. Sampling rate was set at 70000 samples per second. There was provision to record/store the signal in the hard disk of computer for further processing and analysis. To measure seeded groove defect width vibration data is processed in Labview 7.1 environment.

Figure 3.1: Photograph of test rig used in the present research work

The defect of width 0.5 mm is introduced in four different inner races of said bearing. These defects were produced on the outer periphery of inner race in the form of groove defect with electric discharge machining (EDM) process. The reason behind choosing EDM besides using conventional machining is that bearing material is too hard to cut the groove with later process. The inner race defect of 0.5 mm shown in figure 3.2

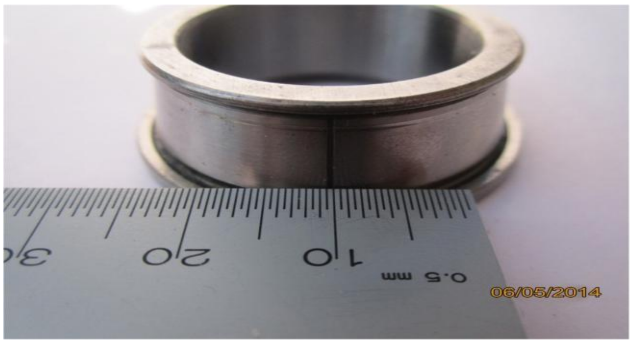

Figure 3.2: Photograph of inner race of taper roller bearing having groove defect width of 0.5 mm generated by EDM process

Octave band analysis of burst portion and without burst portion of same signal was performed for early diagnosis of fault in the bearing and presented in Figure 3.3. It can be analyzed from the graph that burst portion of signal contain higher band power (blue bars) in comparison of without burst signal (red bars). This type of behavior shows presence of fault in the bearing.

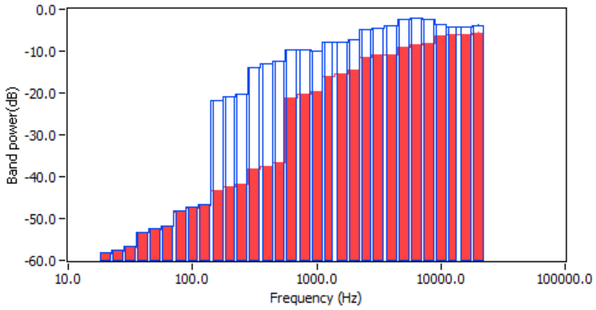

Figure 3.3: Octave band graph of healthy bearing and bearing having inner race defect

For characterizing the fault in taper rolling bearing, envelope detection technique is applied. The envelope spectrum of defective inner race (defect size 0.5 mm) is shown in Figure 3.4. Similar results were obtained for other defect sizes using envelope detection. From the envelope detection it is clear that fault occurs in inner race of tested bearing, as peaks are obtained at 337Hz, 674 Hz and 1011Hz. Which are multiple of theoretical inner race defect frequency (337 Hz).

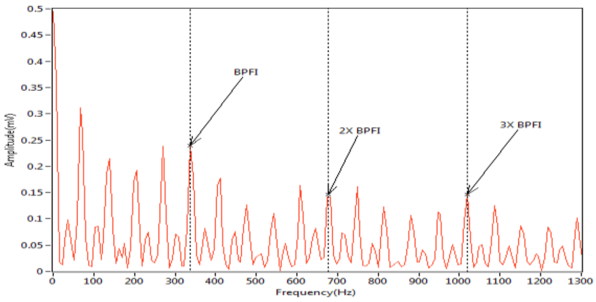

Figure 3.4: Power spectrum of envelope detection of bearing having inner race defect

Defect width of inner race is measured using analytical wavelet transformation and for ease of estimation of burst duration TMI of AWT was applied in Labview 7.1.
For defect width of 0.50 mm, one of the bursts in raw signal is enlarged and is shown in Figure 3.5, Scalogram of AWT is shown in Figure 3.6 and TMI of AWT scalogram is shown in Figure 3.7.

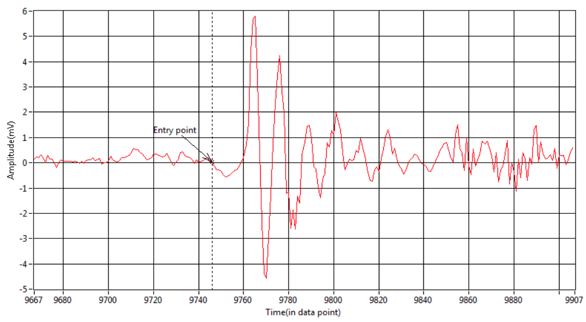

Figure 3.5: An enlarged burst in raw vibration signal for bearing having inner race defect of width 0.50 mm

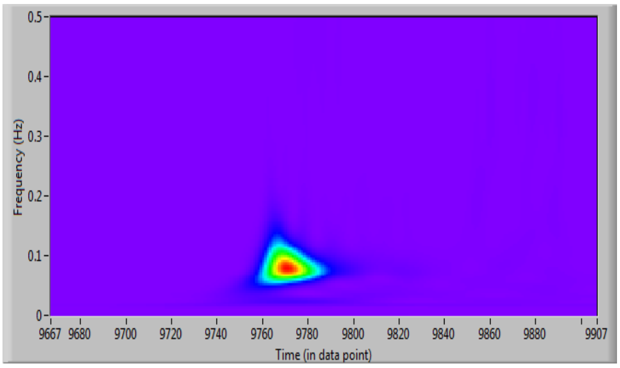

Figure 3.6: AWT of vibration signal showing burst duration for bearing having inner race defect of width 0.50 mm

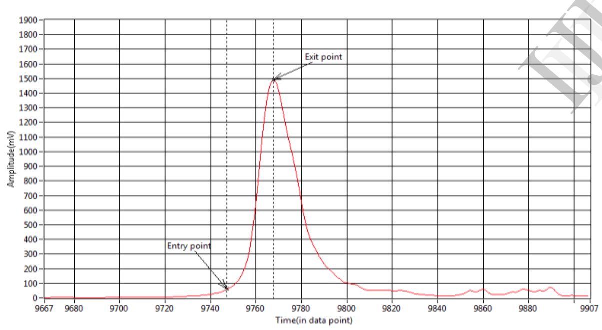

Figure 3.7: TMI of AWT scalogram of vibration signal for bearing having inner race defect of width 0.50 mm

In the present case burst duration is estimated as 18 data point. The estimated burst duration further will be used in estimating the defect width of inner race.

The size of defect present on bearing race can be calculated with the help of vibration burst duration(Δt) which is already estimated above for inner race defect width of size 0.5 mm using AWT. The inner race defect width L_{id} is [22].

Table 3.1: Inner race groove defect width measurement using TMI of AWT scalogram

Actual defect width in (mm)	**Data point (measured)**	**Burst duration (in sec) Data point/sampling rate**	**Defect width measured by present technique in(mm)**	**%age Error**
0.5	18	0.000257	0.5167	3.36

IV. CONCLUSIONS

On the basis of experimental results and observations, the following points are concluded:

1. Higher decibel level as obtained during octave band analysis indicating presence of defect. For healthy bearing, maximum value of octave is obtained as -7dB.
For inner race defect the values comes to -3 dB.
2. Envelope detection is effective in identifying fault at different races of the bearing. For the inner race defect the frequency comes to be 337 Hz. This is very close to the theoretical frequencies.
3. Analytical wavelet transformation is helpful in locating the exit point of the roller from the groove defect.
4. TMI of AWT scalogram is useful in measurement of burst duration/ defect size. Due to blunt resolution of scalogram it is necessary to adopt TMI of AWT scalogram for clear visualization of burst duration.
5. Defect size measured by the technique is very close to the actual size of defect. Error in measurement is 3.36% for inner race.

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