Bearing Fault Diagnosis based on Vibration Signature Analysis using Discrete Wavelet Transform

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Abstract: A **rolling element bearing defect is very common in rotating machine. It is an important part of, and widely used in plant machinery. Incipient fault diagnosis of rolling element bearing is essential because failure of machine due to bearing defect leads to serious consequence in terms of downtime and production loss. The production efficiency and plant safety can be improvise by continuous monitoring the condition of bearing .Vibration signal analysis plays important role in condition based monitoring because vibration signal carries dynamic information of machine, which enable it to detect different fault of machine. Many traditional features and analysis techniques are used in fault diagnosis such as time series analysis, frequency domain analysis and time frequency domain along with raw vibration signal. The use of discrte wavelet transforms (DWT) with Time synchronous averaging (TSA) is proposed in this work for fault diagnosis. The proposed work compares fault diagnosis capabilities of DWT using raw vibration signal and time synchronous signal of the machine vibration.**

Keyword : DWT, TSA , Bearing defect

I.INTRODUCTION

When the machine is operated under the normal condition the vibration is small and constant but when fault is developed, the dynamic process of machine changes, which alters the vibration pattern. The faulty vibration signal and normal vibration can be compare and analyse to determine the sign of failure. In practice, such comparisons are not effective with unprocessed (raw) data due to large variation in time series data, in such cases features extraction technique provides considerably good result as compare to the data itself. Extracted features are more stable and well behaved also provide a reduced data set. The features are categorized into five different groups based on their pre-processing needs as depicted in figure 2. Some of the recent work on bearing fault diagnosis by feature extraction techniques, reported as follows. McInery et.al (2003) describes the fault diagnosis technique of rolling element bearing with the help of industrial module by envelope analysis and kurtosis feature [1], Bhende A.R. et.al (2011) feature like kurtosis, crest factor, shape factor and impulse factor are used to compare the signal using time and frequency domain analysis techniques[2]. Devaney M. J. et.al (2004) proposed a technique using root mean square (RMS) as fault feature along with wavelet packet decomposition of raw vibration signal, also suggested a radial basis function neural network model for fault diagnosis [3].Garcia-Prada J.C. et.al (2007) proposed a incipient fault diagnosis technique based on multi layer perception neural network modelling, using the detail coefficient of DWT as input to the neural network[4]. A RMS feature extraction related to the bearing damage using wavelet transform for the different aging cycle of the machine is proposed by Seker. S et,al (2003) [5]. Wang H. et al (2009) developed a method based on the kurtosis wave and information divergence for rolling element bearing fault diagnosis, also compare the proposed method with the traditional envelop spectra [6].

The section.2 of the paper gives a detail of bearing fault. Section.3 mentioned the DWT. Section.4 provides an overview of TSA method and section.5 discuss the proposed method. At the end Results and conclusion are in Section. 6

II. BEARING FAULT

There are number of mechanism that leads to failure in bearing, such as mechanical damage, cracks, lubricant deficiency corrosion. Nick and dents in the roller track stress on the contacts, loss of dimension related problem gradually distort the bearing. Fault associated with lubricant and friction increase the metal to metal contact causes enlarge plastic deformation by tearing locally fractioned welded contact. Insufficient lubricant causes the adhesive wearing progress. Poor lubrication increases the bearing temperature which speed up the deterioration processes. High humidity environment cause the surface oxidation and produces rust particles [1]

The bearing characteristics frequency of defect depends on the geometry of the bearing and on the type of bearing defect due to the different frequencies with which these components rotate relative to neighbouring component. The characteristics fault frequency for outer race inner race and rolling element defects are defined by following equation.

Outer race characteristic:

$$f_{\mathrm{OD}} = \frac{n}{2} f_{rm} \left(1 - \frac{\mathrm{BD}}{\mathrm{PD}} \cos\phi\right). \qquad \text{..........(1)}$$

Inner race characteristic:

$$f_{ID} = \frac{n}{2} f_{rm} \left(1 + \frac{BD}{PD}\cos\phi\right)$$ ....(2)

Roller element defect characteristic:

$$f_{BD} = \frac{PD}{2BD} f_{rm} \left(1 - \left(\frac{BD}{PD}\right)^2 \cos^2\phi\right)$$ ....(3)

Where *fm* is shaft frequency *n* is number of balls, φ is contact angle, BD is ball diameter, *PD* is pitch diameter

Figure 1 component of rolling element bearing (Source [1])

III.DISCRETE WAVELET TRANSFORM

A Fourier analysis consists in breaking up a signal in to a sigh waves with different frequencies. Similarly a wavelet analysis is the breaking-up of a signal into shifted and scaled version of function called mother wavelet, where DWT is discrete in terms of sampling scaling and shifting parameters not in signal, quick way of obtaining a DWT is to use filter bank of low pass and high pass filter which is followed by down sampling to compute approximate and detail coefficient where approximate is low pass filtered and detail is high pass filter which is derived from mother wavelet, same process is continue with the approximate low frequency coefficient to increase the level of decomposition by breaking it up in approximate and detail part. The shape and the frequency response of these filter depends on the type and order of mother wavelet used in analysis [7][8][9].

IV.TIME SYNCHRONOUS AVERAGING

In five different group of signal processing techniques thirteen different traditional features like rms, kurtosis, crest factor, FM0, NA4 etc are used in vibration signal analysis and fault detection, these signal processing are;1)raw signal analysis, 2)Time synchronous averaging (TSA), 3)Residual (RES) signal analysis 4) Differential (DIF) signal analysis 5) Band-pass mesh signal (BPM) analysis.[10]

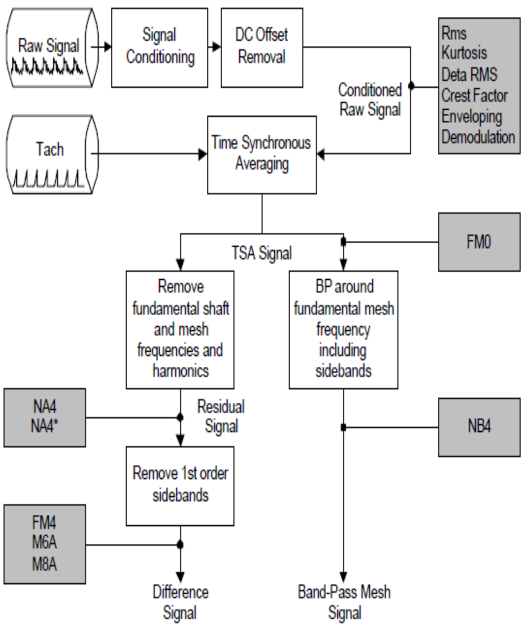

Figure.2: Feature extraction and Vibration signal processing techniques (source [11])

a time synchronous averaging (TSA) is a signal processing technique in which vibration signal coming out of sensor, is segmented based on the synchronous (Trigger) signal. It is used to extract repetitive signals from additive noise. In TSA approach a raw data is divided up into block of equal length segment, related to the synchronous signal and averaged together [10]. An accurate knowledge of the repetitive frequency of the desired signal or a signal that is synchronous with the desired signal (such as shaft running frequency) is the basic need of the process.
Sufficient synchronous averaging of the vibration signal cancel out the random noise from it, the remainder is an improved estimate of the desired signal, called TSA signal. Before segmentation of the signal, number of data points in the series is increased by means of interpolation. This will provide a closer approximation when the signal is segmented and averaged.

A tachometer signal can be used as a synchronous (trigger) signal for rotating machinery. Each segment will start based on the leading edge of a tachometer pulse and end on the corresponding data point that precedes the next tach pulse. Because of slight speed changes over the sample and inaccuracies in the tach pulse, the number of points in each segment might vary slightly can be include chop off and during synchronised segmentation are averaged out at the end.

V. DISCUSSION

Present section proposed a simplified procedure to compare the diagnostic capability of the raw and unprocessed data analysis method with TSA data signal based on DWT. Large impact of the harmonic fault frequency and vibration from the other macro part of the rotating machine crushes the fault frequency in the spectrum of the vibration dada. The power spectrum of the raw data and TSA signal data under inner race defect is shown in the figure.3 and figure.

4. It is observed from the power spectrum of the TSA data that sufficient average of the time series data, synchronous to the trigger, averages the random noise and the non synchronous component of the signal. It brings out the fault frequency and minimizes the complexity of data. The fault frequency is highlighted in the Power spectrum of the TSA data which is buried in the power spectrum of the RAW data.

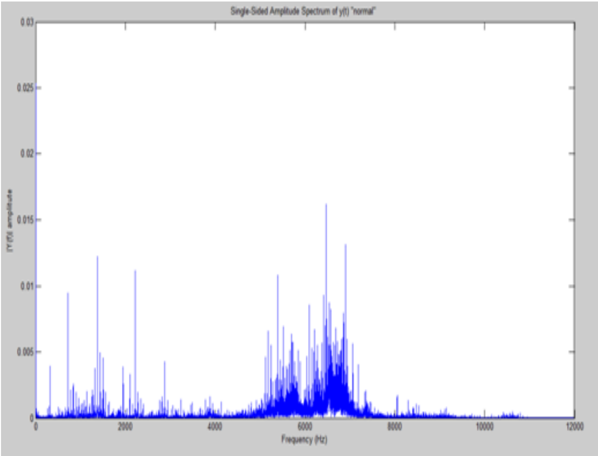

Figure.3: Power spectrum of the raw data signal (IR defect)

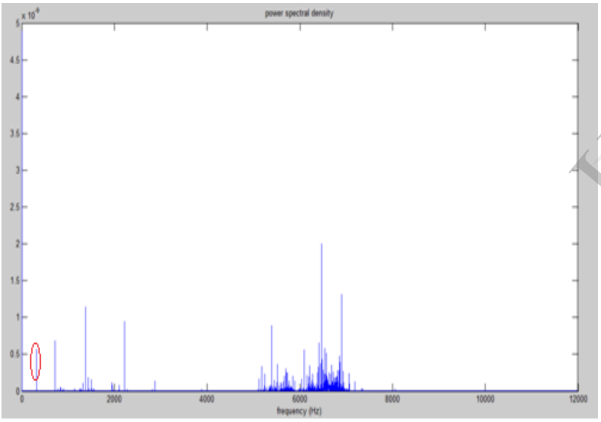

Figure.4: Power spectrum of the TSA data signal (IR defect)

Vibration data used here is collected from the case Western Reserve bearing data centre. Sampling frequency is 12khz and shaft rotating frequency is 29.95 hz or 1797 RPM. Fault frequency under the inner race, outer race and bearing defect condition is theatrically calculated as 162 Hz, 107 Hz and 141 Hz with the help of the equations (1), (2), (3) respectively. Fault frequency of 162 Hz of inner race condition is buried in the high frequency random noise in the spectrum of raw data but can be easily detectable and highlighted in power spectrum of TSA signal.

Proposed method uses the DWT method for comparative analysis of the raw signal and TSA data. In discrete wavelet transform the number of decomposition level and selection of suitable mother wavelet selection is very important, a generalised idea about the number of decomposition level for DWT is mentioned in [11], in which it is recommended to decompose the signal in such a way that, last detail frequency sub set should contain the shaft rotating frequency 29.95 Hz in it. Selection of mother wavelet is based on the variance method proposed by [12]. In which wavelet producing highest average variance of the detail coefficient is selected as suitable mother wavelet for the DWT method, on the basis of this 'sym 8' is selected as mother wavelet and eight decomposition level are used to decomposed the TSA signal using DWT. Features which can used as symptom parameter to detect the variation in vibration pattern along with TSA and raw data are Combat, energy, FMo and kurtosis, RMS, amplitude peak, frequency peak for fault diagnosis. Kurtosis is the inertial feature provide superior figure of merit amongst all other, for both the category [13]. A DWT is used to decompose the raw vibration signal and time synchronous average (TSA) of the same, in to low pass approximate and high pass detail coefficient as discussed in section(II) , under normal and faulty condition. The Kurtosis trained of detail coefficient of the both DWT of raw vibration signal and TSA are tabulated in table 1 and table 2 and the for three different fault type of rolling element bearing, Inner race, Outer race and ball bearing defect.

Table.1 Kurtosis trained raw data signal

Kurtosis	**D1**	**D2**	**D3**	**D4**	**D5**	**D6**	**D7**	**D8**
Normal	3.117	2.536	2.733	3.790	3.420	3.574	3.551	3.067
BRF	4.567	4.774	3.452	3.711	3.491	3.056	4.462	56.01
IR	8.142	6.716	4.520	3.269	3.813	2.552	2.845	36.28
OR	10.337	11.44	4.438	3.572	3.644	3.024	35.55	113.11

Table.2 Kurtosis trained TSA data signal

Kurt osis	D1	D2	D3	D4	D5	D6	D7	D8
Nor mal	2.6 59	2.1 03	3.4 10	3.1 62	3.0 26	2.9 02	3.55 04	3.17 6
BRF	4.5 33	4.6 01	3.5 74	2.9 70	3.4 78	3.2 44	13.2 86	69.8 58
IR	6.1 49	4.9 91	3.8 17	3.0 99	3.4 80	2.6 30	62.1 59	64.0 97
OR	4.1 93	4.4 49	3.3 00	3.9 09	3.6 07	2.9 86	150. 87	35.5 19

VI. RESULT AND CONCLUSION

Kurtosis trends associated to all detail sub-bands are listed in Table 1 and 2. According to these outcomes, it is observe (from the table.1) that detail D1 of raw data showing large variation as compare to the detail D1 of the TSA signal listed in table 2. Above variation is due to harmonics of the fault frequency, noise and other high frequency component. Such variation is redounded, misleads the fault analysis because the fault frequency variation is not expected in the frequency range of D1 detail (3000-6000 Hz).A large variation in the Detail D6 and D7 can be observe as the deviation due to the fault frequency of different fault type, listed in table.1 and table.2.The time synchronous average of the vibration signal leads to the effective outcomes as compare to the raw data processing. The kurtosis extracted from the DWT detail sub band of the TSA signal, can be reliably used as discrimination feature for the fault diagnosis. It produces the excellent classification result.

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