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Bearing Faults Detection and Diagnosis Based on Wavelet Packet Transform Analysis

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ABSTRACT
In the modern industrial environment there is increasing demand for automatic condition monitoring. With reliable condition monitoring faults could be identified in their early stages and further damage to the system could be prevented. Automatic bearing fault diagnosis may be loomed as a pattern recognition problem, which allows for a significant reduction in maintenance costs of rotating machines, as well as the early detection of disastrous faults. An important concern that has been investigated in this paper is the presence of noise, which disturbs the vibration signals, and impacts of this on bearing defects. The paper proposed a new strategy describes a scheme for bearing localized defect detection based on wavelet packet transform to reduce noise effect in bearing fault diagnosis systems. Wavelet packet transform provides a high resolution time frequency distribution from which periodic structural ringing due to repetitive force impulses, generated upon the passing of each rolling element on the defect, are detected. Experiments indicate that the proposed strategies can be significantly reducing the presence of noise by capturing the vibration signals in the bearing housing with either healthy or one of the faulty bearing and decomposed each signal using wavelet packet transform up to six level.
Keywords: Bearing fault, vibration analysis, condition monitoring, diagnosis and wavelet packet transform.

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I. INTRODUCTION

In domestic and industrial applications, bearing is one of the most important elements as critical mechanical components in rotating machinery, failure of bearing causes of breakdown in rotating element. The sturdiness and reliability of the bearing is essential for the health of a machine. Due to above reasons, various measurement methods have been developed by Tandon and Choudhary (1999) with the objective of detection and identification of faults in bearings. Defects in bearing may arise during the manufacturing process as well as during operation time of the bearing under heavy load or uneven conditions. For improving the quality inspection of bearings, it is important to identify the defects during condition monitoring have been presented by Davis (1998) and Collacott (1977). Kim and Lowe (1983) broadly classified them as vibration and acoustic measurements, temperature measurements and wear-debris analysis. Considerable research has been carried out for the development of various algorithms to detect the bearing fault and diagnosis. Tandon and Choudhary (1999) also presented a comprehensive appraisal of the different vibration and acoustic methods for the condition monitoring of roller bearings, such as vibration measurements in the time and frequency domains, the shock-pulse method, sound pressure and the sound-intensity method. Ho and Randall (2000) explained that when a fault occurs on one surface of a bearing hits another surface, a force impulse is generated that excites responses in the bearing and the machine. Morel (2002) has investigated that 40% of the total machine faults are due to bearing fault in case of rotary machinery. The impulse response is usually measured by an acceleration, velocity or displacement sensor and the analysis of the vibration signal with amplitude modulation is usually based on the high-frequency resonance technique called envelope analysis.

The prevention of potential damage to machinery is necessary for safe and reliable operation of process plants. Failure prevention can be achieved by sound specification, selection and design audit routines. When a failure occurs, then finding the absolute root cause of that failure is the main prerequisite to the prevention of future failure events. The extensive research has been carried out in the area of machine health condition monitoring (MHCM) and the work is still going on. During the twentieth century Machine Health Condition Monitoring has evolved from breakdown maintenance to the developing stages of diagnosis of machinery and its components. The future of MHCM is the design of smart machinery with the built-in diagnostic capabilities. The machine health condition monitoring is based on a systematic engineering approach of data acquisition, signal processing, fault pattern recognition and classification of fault's features. In many domestic and industrial applications, rolling element bearings are regarded as critical components with the strong influence on fundamental functionality of rotating machinery. For this reason, various measurement methods have been developed with the aim of detection and identification of faults in bearings, among these methods, vibration analysis has been established as the most common and reliable technique in order to detect the anomalous behavior**.** Most of the industrial rotating machinery work continuously for several hours.

The objective of the research is to early detecting of defects on bearings of rotating machinery, as it is the critical components where dynamic loads and forces are applied during operation. The interaction of defects in the bearings produces impulses of vibration cause for the natural frequencies excitement of the bearing elements, which can be analyzed by Fast Fourier Transform (FFT) for predicting the condition of bearings described by Tandon and Choudhary (1999). The Fourier Transform (FT) represents a signal by a family of complex exponents with infinite time duration. Therefore, FT is useful in identifying harmonic signals. Vibration analysis has been the most employed methodology for detecting bearing defects have been presented by He, Jiang and Feng (2009). This paper focused on the wavelet decomposition of the time signal as an alternative of the Fourier Transform. This technique provides better analysis for non stationary signals as permitting analysis of frequency bands to sort out the desired frequencies and rejecting other as considering noises. The Root Mean Square (RMS) value of a vibration signal is a time analysis feature, which is the measure of the power content in the vibration. This feature can track the overall noise level, but can not provide any information on which component is failing. This paper also compared the RMS values of the frequency bands of our interest with the RMS values of the healthy bearing considering it as a baseline. The paper has considered the various vibration signatures such as sound, temperature and vibration amplitude. But the sound and temperature were not shown their significant variation during experiments.

This paper is organized as follows. In section 2, a brief detail of Theoretical Background has been discussed. Section 3, described Vibration Data Acquisition with experimental setup to find the bearing fault. Section 4, stated the description of the Results and Observation of proposed method followed by conclusions in section 5.

II. THEORETICAL BACKGROUNDS

The machine availability is a major concern in industrial application. To avoid the failure, it is necessary to monitor the condition of a machine during the period of machine life. Condition monitoring is a field of technical activity in which selected parameters associated with machinery operation are observed for determining integrity presented by Mathew (1997). Condition monitoring is essential for maintenance management in industry, which involves detection of fault and diagnosis of fault. According to Randall (2004), a frequency analysis of raw signals does not provide the desired diagnostic information, where as the frequency spectra of the envelope signals can provide this information. The bearing faults alter the machine dynamics and generate definite vibration patterns which depend upon bearing characteristics frequency. Benbouzid (2000) has presented the vibration characteristics frequencies described for inner race, outer race and ball defects, which is presented in this research. The focus of this research is to find out the defects of bearing that create different types of vibration characteristics. The paper focusing on the outer race defect, inner race defect and ball defect.

2.1. Types of Defect

Vibration monitoring and analysis in rotating machines provides details information about irregularities formed internal structure of the machinery. Vibration in machinery always present during operation of it, but increment in vibration may give failure to the machine. Table 1 represents normal failure of bearing during operation.

Table 1. Bearing failure mechanisms

Failure Means	**Damage Cause**	**Results**
Mechanical damage	Indentation mark by rolling element overload	indentation
Wear damage	Abrasive particle entrained or steady deterioration	Dimensional inaccuracy occur
Insufficient lubrication	Increase the friction	Increase in bearing

		temperature
Corrosion	Surface oxidation due to humid	Produce pits
Fatigue damage	Fatigue after certain operation time	Formation of crack propagation
Plastic deformation	Excessive loading	Indentation of raceway

Vibration in rotary machinery can be measured using various sensors, by measuring displacement at low frequency and acceleration at high frequency. Many techniques can be used to predict the bearing conditions are like: vibration monitoring, Current signature analysis, Tribology, Thermography, etc.

2.2 Fault Models in Bearings

There are many reasons to cause the damage of the bearing in operation process. The bearing will run abnormally due to the fatigue peeling and the abrasion after a period of the service, even if the proper lubrication and maintenance has maintained. Vibration signal is collected to observe the states of the bearing and the type of the rolling bearing fault. Defect bearings present characteristic frequencies depending on the localization of the defect described by McFadden and Smith (1984). Therefore, it is very important to find out the defects of bearing that create different types of vibration characteristics. For this reason, paper first consider to calculate the characteristic vibration frequencies due to the bearings defects, with the help of rotor speed and bearing geometry for each type of defect characteristic frequency varies simultaneously. Here we are focusing on the outer race defect, inner race defect and ball defect. The paper illustrates many characteristic frequencies related to abnormal vibration (time-domain amplitude, frequency-domain amplitude), which identified the fault location can be calculated using the following equations:
The outer race defect frequency is given by:

$$FOD = \frac{n}{2} * \frac{N}{60}\left[1 - \frac{b_d * \cos\varphi}{p_d}\right] \qquad ...(1)$$

where ϕ is the contact angle, p_d is the pitch diameter, b_d is the ball diameter, n is the number of balls and N is the rotational speed in rpm.
The inner race defect frequency FID or the ball pass frequency of the inner race is given by

$$FID = \frac{n}{2} * \frac{N}{60}\left[1 + \frac{b_d * \cos\varphi}{p_d}\right] \qquad ...(2)$$

The ball defect frequency (or ball spin frequency) is given by

$$BOD = \left(\frac{p_d}{2b_d}\right) * \frac{N}{60}\left[1 - \left(\frac{b_d}{p_d}\right)^2 * \cos^2\varphi\right] \qquad ...(3)$$

Vibration signal is non-stationary in nature, i.e., its spectral contents vary with respect to time. Wavelet transform (WT) is effectively used in order to extract the time-frequency domain contents of the vibration signal described by Peng and Chu (2004). In particularly, wavelet packet transform (WPT) discussed by many researchers like Peng and Chu (2004), Eren and Devaney (2004), Teotrakool, Devaney and Eren, (2009) and Lau and Ngan (2010) for decomposition of singnal into multiple frequency nodes and provides multi resolution analysis In earlier Fast Fourier Transform Method is utilized to convert time domain signal in to frequency domain, so that from the frequency domain signal it can be analyze that on which fault frequency peaks of amplitudes are present in the signal. Then we were supposed to know the outcome and predict the fault presence. But the drawback of this approach is that Fourier analysis was limited to stationary signals and what time this peak is coming. In today's world there are many advance approaches are evolving for vibration analysis and prediction of occurrence of faults in machine health condition monitoring. The results of these approaches are further going towards the making of intelligent system.

A brief review of vibration monitoring techniques has been detailed illustrated by Davis (1998) and a mathematical tool like fast Fourier transform (FFT) to identify the changes in frequency spectrum for motor fault detection has been presented by Lau and Nagan (2010). These methods have traditionally been applied, separately, in the time and frequency domains. A time-domain analysis focuses principally on statistical characteristics of the vibration signal such as peak level, standard deviation, skewness, kurtosis and crest factor. A frequency-domain approach uses Fourier methods to transform the time-domain signal to the frequency-domain where further analysis is carried out. In case of vibration signal, not the entire frequency band contains the true information about the fault vibration signal, only sub-portion of the whole frequency spectrum contains true fault signature presented by Yaqub, Gondal and Kamruzzaman, (2011). In wavelet packet decomposition, the vibration data is decomposed into different frequency sub-bands and feature vector is extracted from these frequency sub-bands and feature vector is extracted from these frequency sub-bands. However, a relatively new signal processing technique, called wavelet analysis, is adopted here and used to develop vibration signal processing procedures for bearing fault detection. The wavelet approach has advantages over traditional Fourier methods for signal analysis, particularly for signals containing discontinuities and shape spike. The ability of the wavelet transforms approaches to represent simultaneously both time-domain and frequency-domain information is a significant advantage. The use of the continuous wavelet transforms to study bearings with outer race and inner race defects is presented by Cheng, Yu, and Yang (2007). Li and Ma (1997) have used wavelet transforms to study bearings with outer race and rolling element defects under a range of load and speed conditions.

2.3 Wavelet Packet Transform

Wavelet packet transform (WPT) is a time-frequency analysis method, which decomposes a signal into a full binary tree of frequency bands. Each decomposition unit contains the information of frequency band and time series. WPT is proficient of processing both stationary and non-stationary vibration signals with numerous advantages over conventional methods, as WPT has various resolutions in different frequency band. Wavelet transform (WT) cannot decompose the signal into a full binary tree in the frequency domain, while WPT can perform it. By comparing with Hilbert-Huang Transform (HHT)'s decomposition, WPT is an orthogonal decomposition method while HHT is not. Therefore, WPT has been widely used to perform condition monitoring for rolling bearing. Tang, Miao and Pecht (2011) have stated that to diagnosis bearing fault, WPT can be combined with energy demodulation operator for good result. Wavelet packet can be decomposed by the following recursive equations:

$$w_{2n} = \sqrt{2}\sum_j h_{0j} W_n(2t-j) \qquad ...(1)$$

$$w_{2n+1} = \sqrt{2}\sum_j h_{1j} W_n(2t-j) \qquad ...(2)$$

where $w_0(t)$ is the scaling function, $w_1(t)$ is the basic wavelet function, h_{0j} is the low pass-filter, h_{1j} is the high pass-filter. Then the wavelet packet functions are formed as:

$$W_{ij}^n(t) = 2^{i/2} w^n(2^i t - j) \qquad ...(3)$$

Correction Coefficient: Pearson Correlation Coefficient (PCC) is a measure of linear dependence of two variables. In this paper it is used to measure the linear dependence between the decompositions of the testing signal and the reference signal (bearing signal with known fault). The PCC used in this research is defined as:

$$corr_a(i) = \frac{\mathrm{cov}(s_a(t) * c_i(t))}{\sigma_{s_a}(t) * \sigma_{c_i}(t)} \qquad ...(4)$$

where $corr_a(i)$ is the correlation coefficient between the ith decomposition unit of the test signal and the reference signal, $s_a(t)$ is the bearing fault signal used as reference and $c_i(t)$ is the ith decomposition unit of the test signal.

III. VIBRATION DATA ACQUISITION

The experiments presented in this paper used the vibration data from the experimental run the machine described in Figure 1. The data were collected from an accelerometer mounted on the bearings housing of a motor system coupled to a load that can be varied within the operating range of the motor. The accelerometer is connected with the FFT analyzer DL 2400 with LCD display and this is connected with a DOS based computer system.

3.1 Experimental Setup

Each defective bearing element produces a specific frequency, which permits for localizing different occurring concurrently. Ball Pass Frequency on an outer race (BPFO) defect, Ball Pass Frequency on an inner race (BPFI) defect, Fundamental Train Frequency (FTF) and Ball Spin Frequency (BSF) – as well as their harmonics, modulating frequencies has been calculated from kinematics consideration and presented by Sassi, Badri, and Thomas (2007) and Norton and Karczub (2003). Like frequency, time-domain has been widely employed as input features to train a bearing fault diagnosis classifier. Time-domain indicators allow for representing the vibration signal through a single scalar value.

Experimental data were collected from double row, self aligning bearings mounted on a shaft driven by a 3-phase electric motor (0-55KW, 220-240V) of a Vibration Simulator. This Vibration simulator has facility for easy removal of bearings to be tested. The bearings housing of the Simulator has a facility for the placement of sensors on it. The motor connected with the shaft rated max 3310 rpm. Accelerometer is placed on the upper side on the bearing housing in radial position for sensing the vibration produced by the bearing to be tested. This accelerometer is connected with the FFT analyzer DL 2400 with LCD display and this is connected with a DOS based computer system. The complete experimental setup has been shown in Figure 1.

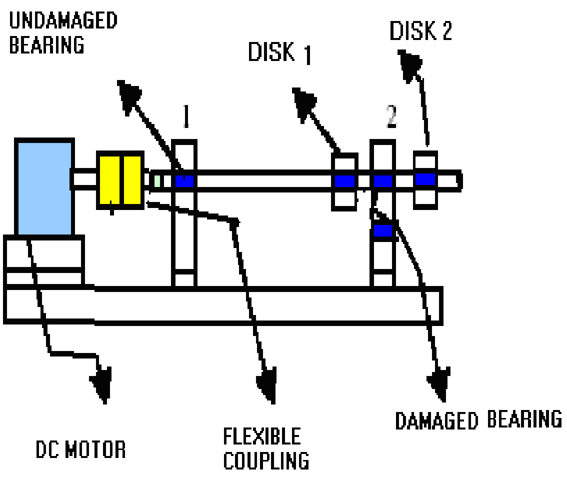

Fig. 1. complete view of experimental setup

3.2 Bearings Used

The bearings used in the experiment are double row self aligning by SKF have 13 balls in a row. There are three types of faulty bearings used in our experiment and one healthy bearing for the comparison. The details of these faulty bearings are tabulated in Table 2.

Table 2. Details of Bearings used

Bearing Name	**Bearing Defect**	**Location of defect Number of defects**	**Defect size**
Faulty-1	Ball Defect	2 balls in one row, one by one	1*1 mm, 0.1 mm deep
Faulty-2	Inner Race defect	3 defects at each row. 3 mm distance, both rows with defects	1*1 mm, 0.2 mm deep
Faulty-3	Outer Race defect	3 defects at each row. 3mm distance, both rows with defects.	1*1 mm, 0.2 mm deep

In this research, the vibration signature analysis via wavelet packet decomposition is used to detect the ball bearing defects. First the RMS data using accelerometer as pick up is collected. The FFT of this data do not have the further perspective so shifted towards the wavelet transform. The signal is decomposed into wavelet packets using debauchee's db8 filter into six levels. The selection of db8 is based on the result of analysis, as previous to db8 all were not giving significant difference. Wavelet Packet Coefficients (WPC) of the nodes used to compute the RMS values. The nodes reviewed for this analysis are 62 that presents up to fifth level of decomposition has been shown in Figure 2.

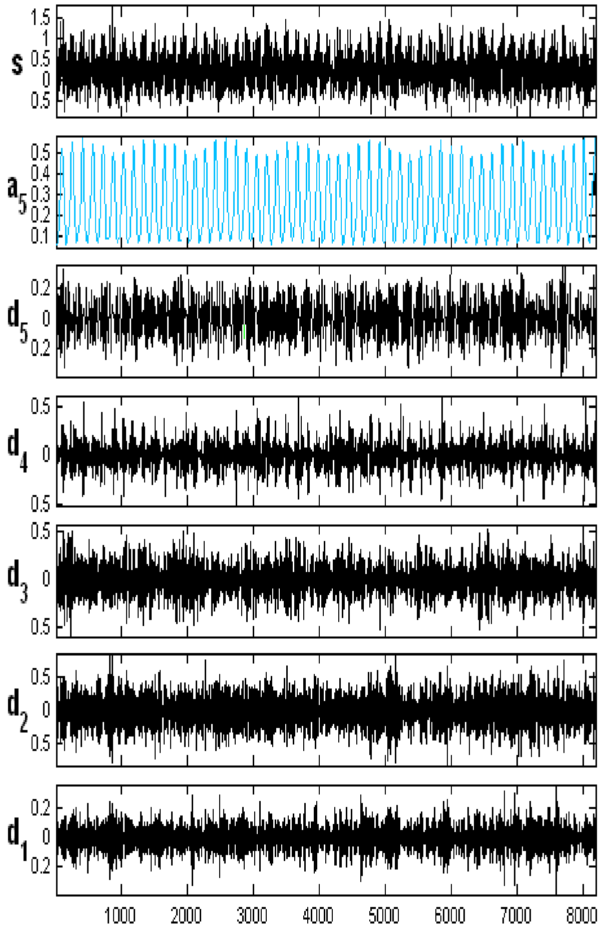

Fig. 2. 5 level decomposition of the original signal's

IV. RESULTS AND OBSERVATIONS

The main focus of this study is to find out the presence of fault and to predict the nature of fault in the bearings used in this work. The data for all the bearings were analyzed by using wavelet transform. Decomposition was done up to 62 nodes and then for each node RMS value has calculated and analyzed for finding the nodes which is giving significant differences in different faulty or healthy condition. All the 62 nodes are tested for the difference among the value of each node corresponding to different fault nodes and healthy bearing nodes. Out of these 13 nodes are found with significant difference used for classifying faults. The results obtained for the proposed WPT techniques have been shown in the Table 3.

Table 3. Nodes with significant difference

S. No.	Node		Healthy Bearing	Ball Fault	Outer race Fault
1	4	max(rms)	0.42828	0.56803	0.6199
		min(rms)	NA	0.44723	0.54767
2	6	max(rms)	0.19587	0.25084	0.22477
		min(rms)	NA	0.14546	0.19878
3	8	max(rms)	0.48283	0.82885	0.58867
		min(rms)	NA	0.60331	0.47476
4	10	max(rms)	0.42614	0.63278	0.64296
		min(rms)	NA	0.34424	0.57033
5	15	max(rms)	0.13355	0.12292	0.15341
		min(rms)	NA	0.077402	0.18224
6	18	max(rms)	0.49223	0.63146	0.3828
		min(rms)	NA	0.51383	0.54771
7	21	max(rms)	0.3725	0.75651	0.5062
		min(rms)	NA	0.35906	0.46081
8	22	max(rms)	0.4837	0.75651	0.78272
		min(rms)	NA	0.35108	0.669
9	35	max(rms)	0.31199	0.41045	0.43667
		min(rms)	NA	0.2832	0.3598
10	36	max(rms)	0.6175	1.1706	0.82643
		min(rms)	NA	0.9308	0.64784
11	38	max(rms)	0.48063	0.73922	0.58488
		min(rms)	NA	0.56332	0.40832
12	39	max(rms)	0.2202	0.25116	0.33246
		min(rms)	NA	0.13919	0.25187
13	43	max(rms)	0.31584	0.36376	0.5349
		min(rms)	NA	0.25327	0.45345

In the above table each colored bars indicate its differences with the others. These 13 nodes indicate that each type of fault differs in RMS value with the other. By using this result can be predicted by making some relations among them. In Table 2, it has been shown that if the maximum RMS value for healthy bearing is less than the minimum RMS value of the other two faulty bearings it will clearly indicate the presence of the fault.

V. CONCLUSION

In this paper, a new strategy based on the Wavelet Packet Transform has been used in order to reduce noise effect in bearing fault diagnosis systems. The paper has worked on three types of different bearings in the experimental setup used. Due to the defects presented in the bearings the vibration signature is hardly a stable on. Traditional time domain analysis or frequency domain approaches dictate the compromise of frequency resolution, but wavelet transform have no such limitations and therefore it is more suitable for the processing of vibration signature. The wavelet packed decomposition (WPD) is one of the many wavelet transforms, which is giving a good difference among all the bearings for getting optimum results.
The outcomes of this study are:

1. The RMS value is a significant signature for the fault identification.
2. The Wavelet Packet Decomposition is capable of predicting the presence and the nature of the fault.
3. After generating more rules from above approach, it can easily train the expert system to make the monitoring on line (Future Scope of this research).

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