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Fault Detection of Bearing using Signal Processing Technique and Machine Learning Approach

Manjunatha G[1*], H C Chittappa[2] and Dilip Kumar K[3]

*[1]Research Scholar, Department of Mechanical Engineering, UVCE, Bangalore University, Karnataka, India. Assistant Professor, School of Mechanical Engineering, REVA University, Karnataka, India. *E-mail: manjunathag16@gmail.com*
[2]Professor, Department of Mechanical Engineering, UVCE, Bangalore University, Karnataka, India. E-mail: hcchittappa@gmail.com
[3]Department of Mechanical Engineering, NITTE (Deemed to be University), Nitte 574110, India. E-mail: dil.k333@gmail.com

Abstract

In large- or small-scale industries, machines have rotary element supported by bearings for accurate drive and fixed support. Fault diagnosis has gained much importance in recent times due to increased bearing failures. This demands an efficient diagnosis methodology to detect faults in bearings. In this work, fault diagnosis for the acquired vibration signals of healthy and fault seeded in rolling element bearings were investigated using signal processing technique and online machine learning approach. The research work is carried out in two phases. The first phase of research work investigates fault detection of bearing using conventional signal processing techniques such as time domain analysis and spectrum analysis. The results show that signal processing techniques may be useful for revealing post fault detection information. It was also concluded that the use of different signal processing techniques is often necessary to achieve meaningful diagnostic information from the signals. The second phase of research work describes fault diagnosis of bearing using machine learning approach. Using MATLAB, Discrete Wavelet Features (DWT), were extracted from acquired signals for different rolling element bearing conditions. J48 algorithm was implemented to extract most significant features. Extracted features were used as input to different classifiers to obtain maximum classification accuracy of rolling element bearings. The results showed that machine learning technique could be used to detect and classify the different fault sizes effectively with vibration signals.

Keywords: *Spectrum analysis, DWT, Machine learning, J-48, Bearing fault.*

1.0 Introduction

The toughest job for the engineers is maintenance of machine parts in real time applications. Designers are continuously working towards development of new methodologies and characterizing them for various engineering applications. Rolling element bearings act as vital component in maintaining health and life of machinery. Bearings are one of the prime components in rotary machines. They play a vital role in health and life of machinery. In current competitive world advanced modelling and dynamic analysis of rotary machines has gained popularity. Numerous techniques have emerged for condition monitoring of bearings. System failure could be prevented by using diagnosis algorithms and preemptive fault detection.

Periodic scanning is essential in offline Condition Monitoring. Scanning assets regularly is sufficient for Offline Condition Monitoring. It's a sort of manual surveillance. Vibration signal processing is one of the most commonly

*Corresponding Author

used technique to detect bearing faults. Signal processing analysis techniques come in a variety of forms and they're all intended to offer information on the state of a machine component so that it may be replaced before it fails. The fast Fourier transforms (FFT) are the most widely used method for converting signals from their time domain to their frequency domain. This classical method gives signal strength at different frequencies, which allows the observer to detect different faults in the rotating machine. McFadden et al. [1] proposed a fault identification approach based on FFT analysis for high-frequency vibration caused by a single point defect on the inner race of a rolling element bearing under radial load. Yang et al. [2] used signal-based approaches based on the motor's vibration and phase current measurements to study failure detection and diagnosis for a class of ball bearings. Before the FFT algorithm is utilized for vibration analysis, the envelope detection method is used to preprocess the measured vibration data.

In Online Condition Monitoring, the term "shutdown" does not exist. This aids in cost-cutting and avoids unexpected expenses. Due to rising demand, the cost of lost output and equipment failure is unaffordable in today's competitive world. A computer creates a prediction based on the features of prior training data sets in machine learning. The bearing can be monitored using data from the force, vibration, or sound emission signal received during machining. These signals are usable to extract features that reveal effective and persistent bearing fault trends. Pattern recognition or other classification approaches can be used to forecast the bearing condition once these features have been recovered through preliminary signal processing [3]. Mori et al. [4] proposed the DWT theory for flaw detection at an early stage. Through the use of high pass and low pass filters, DWT decomposes the signals into two frequency sub bands: low frequency and high frequency. The wavelet uses the concept of Fourier. In Fourier, a complex function is approximated as a weighted sum of simpler functions using a basis function. The basis function can be named as a building block. Sinusoidal signal of different frequencies is used as a basis function. V. Purushotham et al. [5] proposed a new wavelet transform-based approach for detecting localized bearing faults. DWT has been used to detect bearing race problems. The impulses come regularly, with a time period that corresponds to the typical defect frequencies. The wavelet transform was used to study the diagnosis of ball-bearing race defects. These findings are compared to data from feature extraction. It has been demonstrated that DWT is a useful method for detecting single and multiple problems in ball bearings. S. Zhang et al [6] proposed a new method for integrated machine failure diagnostics based on discrete wavelet packet bases of vibration signals. The best basis is chosen first and foremost based on its categorization ability. Data mining is then used to extract features, and Bayesian inference is used to make local decisions.

N. G. Nikolaou et al [7] proposed an outstanding demodulation method based on the use of a complex shifted Morlet wavelet. The method aims to fully use the underlying physical ideas of the modulation mechanism, which are present in the vibration response of defective bearings, by using a time-frequency representation of the signal. The results support the overall strategy's soundness. R. Rubini et al. [8] demonstrated the limitations of the Spectral and Envelope techniques by applying them to bearings with various pitting failures that were subjected to a very low radial load. The results are compared to those of an advanced signal processing method based on wavelet transform assessment. Vijay G S et al [9] utilized FFT and DWT to diagnose defects in Rolling Element Bearings. Inner and outer race fault DWT coefficient energies are higher than normal bearing DWT coefficient energies. The DWT coefficients' energy and kurtosis values can be utilized as excellent indicators for detecting defects in rolling element bearings. The findings suggest that DWT can be utilized to successfully diagnose bearing faults.

1.1 Experimental Set Up

Figure 1 shows line diagram of experimental set up. It comprised 1 HP motor, bearing 1, bearing 2 with accelerometer and loading platform. Motor shaft is supported by end bearings. Single point faults were seeded to the test bearing (bearing 2) using supersonic method. The fault diameter of 0.1mm, 0.3mm and 0.5mm were seeded individually at the inner race, rolling element and outer race [10]. Test rig was reinstalled with faulted bearings and accelerometers (not shown) attached to the housing were used to collect vibration data. This experiment runs at a load of 3314 N and speed of 1760 rpm [11] which is same as real time application.

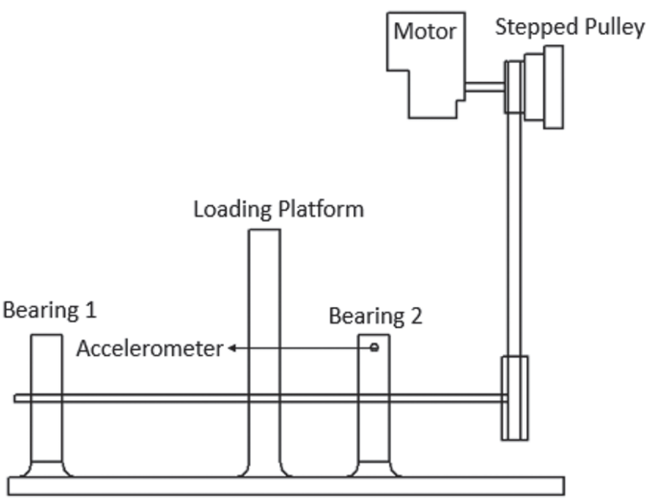
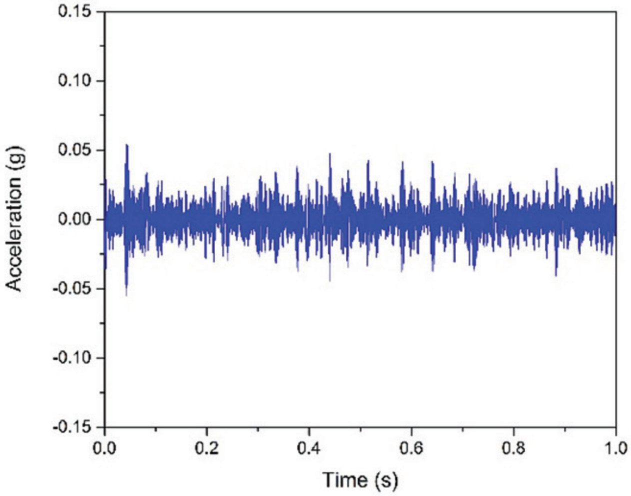
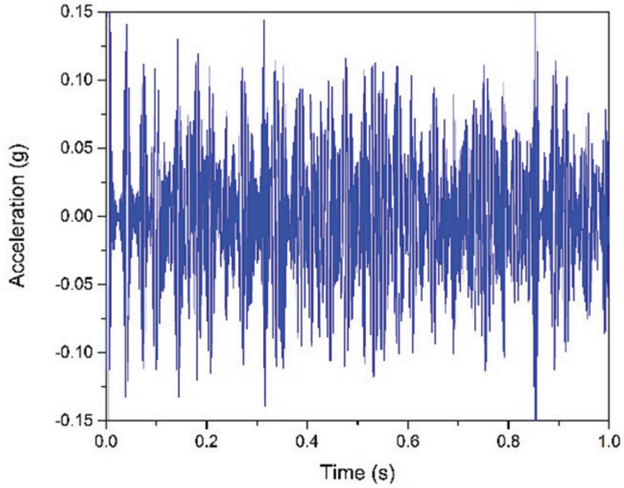


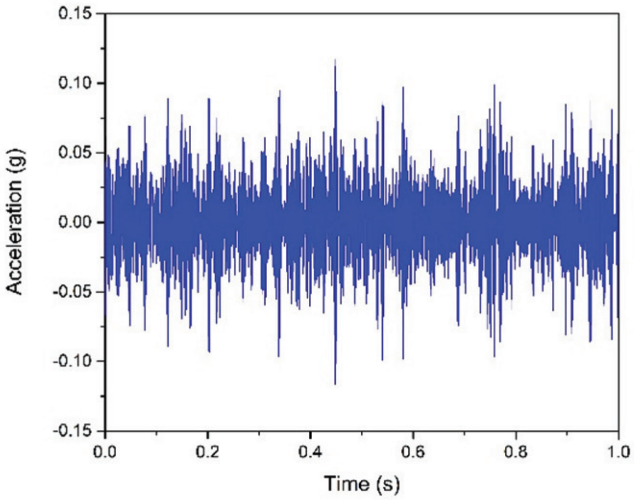
Figure 1: Line diagram of experimental set up



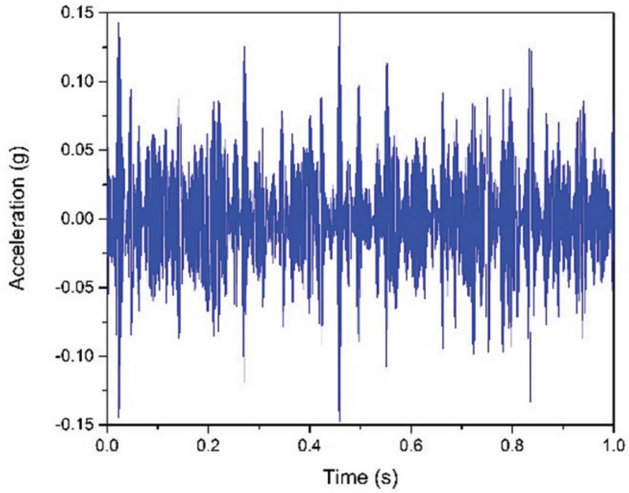
(a) Healthy condition



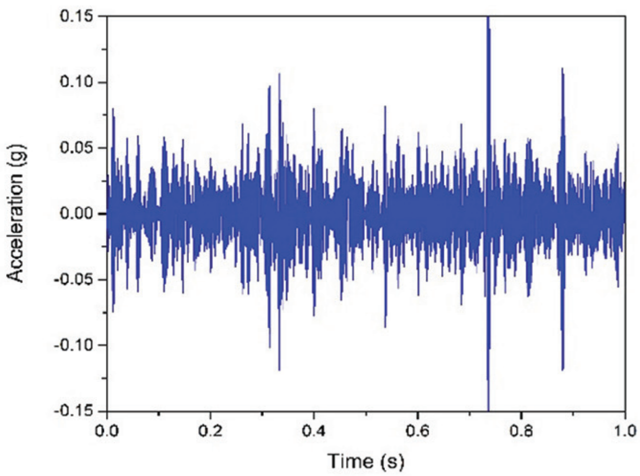
(b) 0.1 mm inner race defect



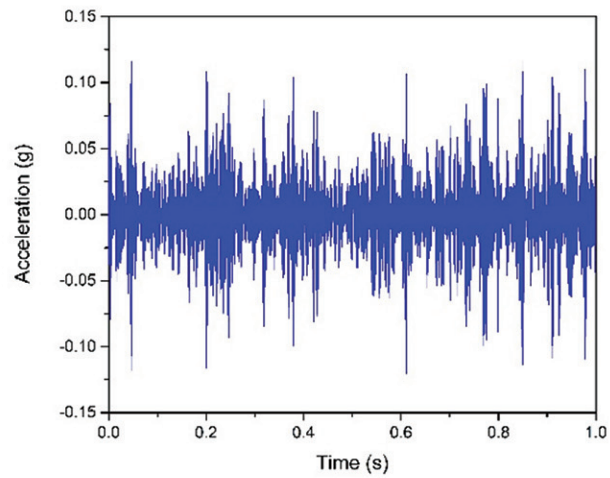
(c) 0.1mm ball defect



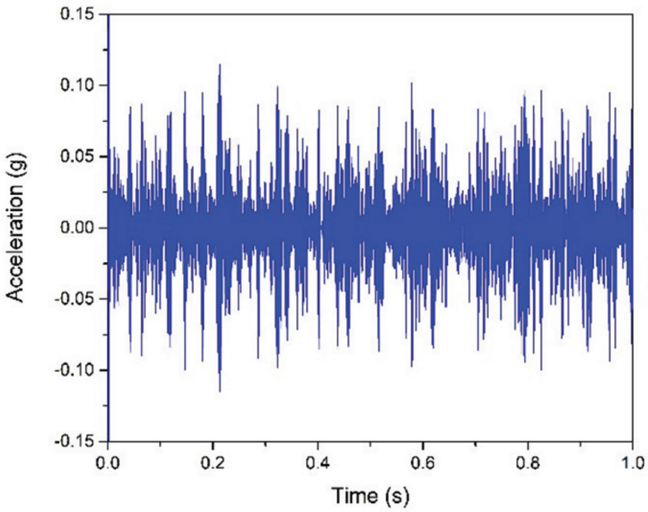
(d) 0.1 mm outer race defect



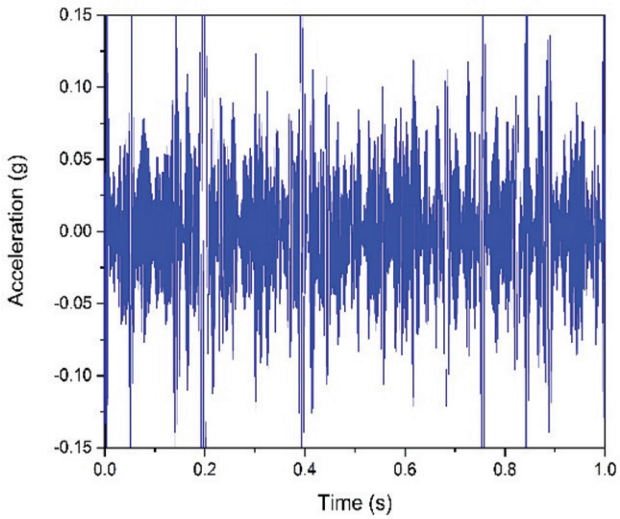
(e) 0.3 mm inner race defect



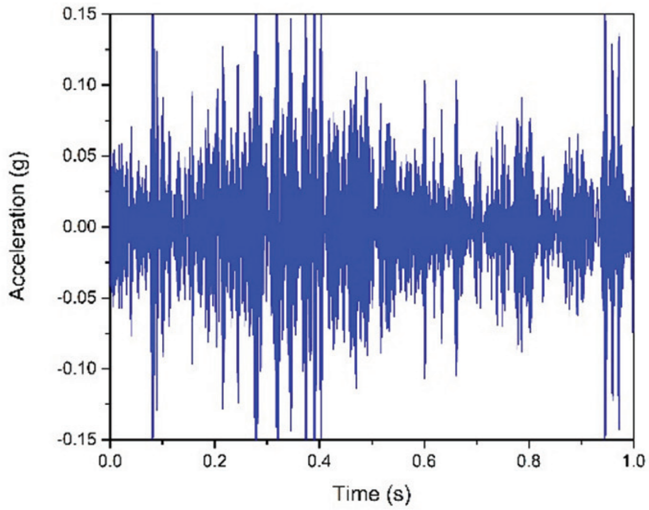
(f) 0.3 mm ball defect



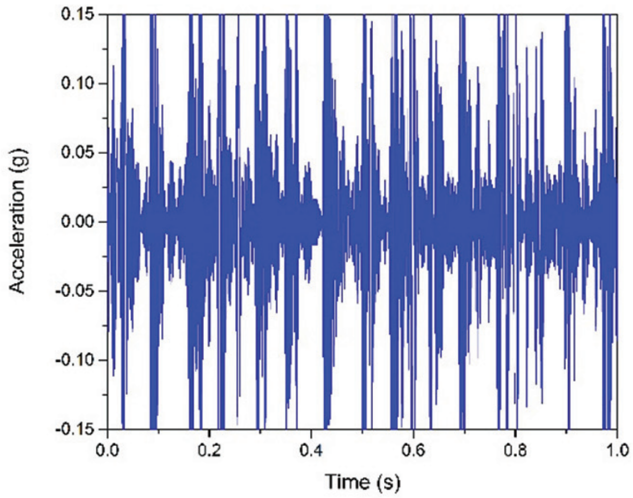
(g) 0.3 mm outer race defect



(h) 0.5 mm inner race defect



(i) 0.5 mm ball defect



(j) 0.5 mm outer race defect

Figure 2: Vibration responses in the time domain

2.0 Time Domain and Spectrum Analysis

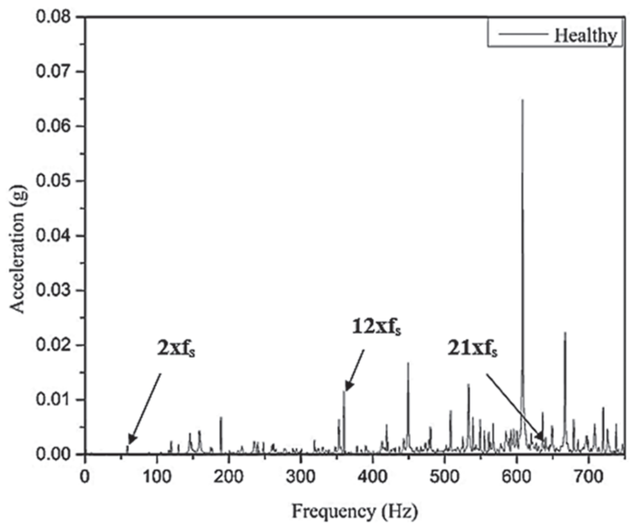
The time domain depicts dynamic responses that are influenced by many system components' interactions. It aids in the detection of any rotating machinery system issue by analyzing the amplitude and phase information of the vibration time signal. Time domain is very useful for analyzing signals from unstable and short transient impulses caused by bearing and gear faults [12-13]. The influence of an emerging fault will be spread in the total vibration signal, if statistical measures like root mean square value are used. This is a key fault in the time domain method, which is greatly minimized by the frequency domain method. Each component of a system has its fault frequency, which corresponds to any problem in the component. These fault frequencies are quite useful in determining the state of a bearing. Jayaswal et al [14] examined the viability of FFT (Fast Fourier Transform) and band pass analysis for fault detection of roller bearings having several defects. They tested different defective and healthy conditions of bearing. It is concluded that filtered signals under three frequency bands can be feasible signatures for identifying the fault.

2.1 Time Domain Technique

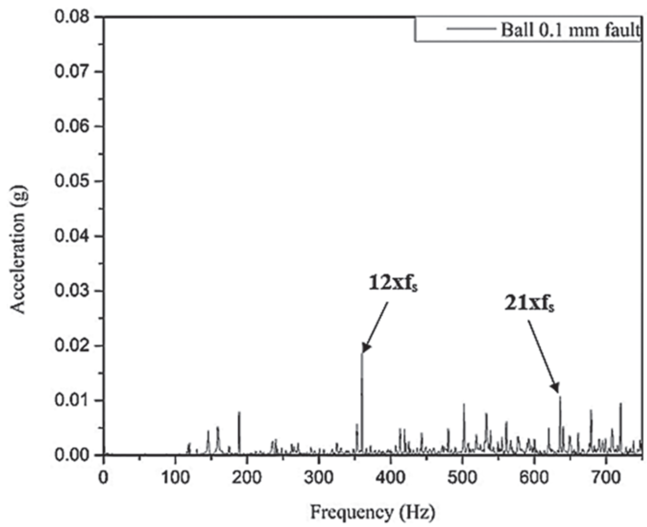
Figure 2 Shows one of the obtained vibration signal samples in the time domain for various bearing conditions. It can be seen from the time domain signals that the acceleration level rises with the severity of the defect., the time-domain analysis provides general vibration levels but not diagnostic information.

2.2 Spectrum Analysis

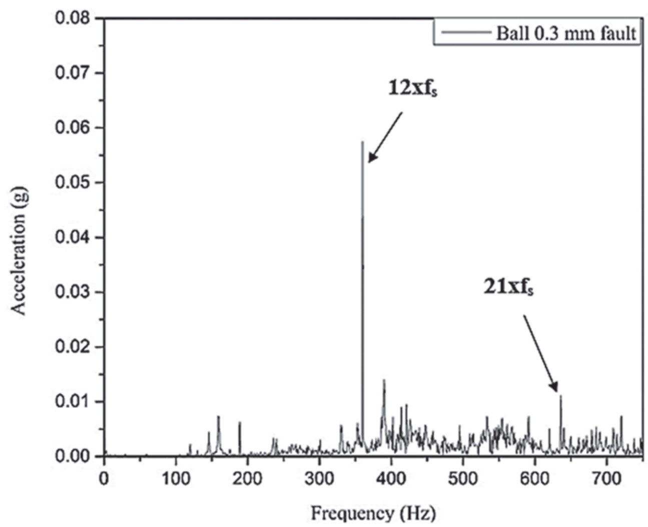
In spectrum analysis, traditional vibration technique presented based on the Fast Fourier Transform (FFT) for bearing fault identification. Figure 3 depicts the experimental observations for various bearing fault circumstances. The component's peak frequency is 30 Hz, which corresponds to the shaft rotation's frequency (fs), can be seen on the spectrum plot, and the majority of the other peaks are multiples of shaft rotating frequencies, with the 12th (360 Hz) and 21st (630 Hz) multiples for shaft speed showing dominance over all other harmonics. In the frequency spectrum, the increase in bearing amplitude with increasing fault severity may be seen. With rolling element, inner race, and outer race defects, the magnitude of healthy bearing increases from 0.01 to 0.05 m/s^2, 0.03 m/s^2, and 0.013 m/s^2, respectively.



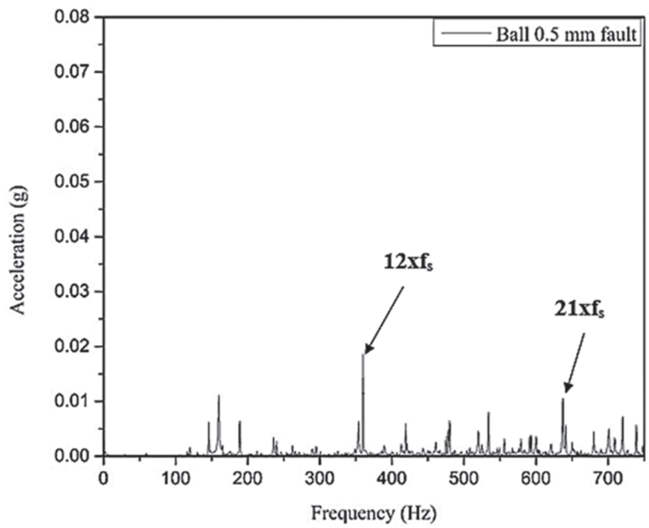
(a) Healthy bearing



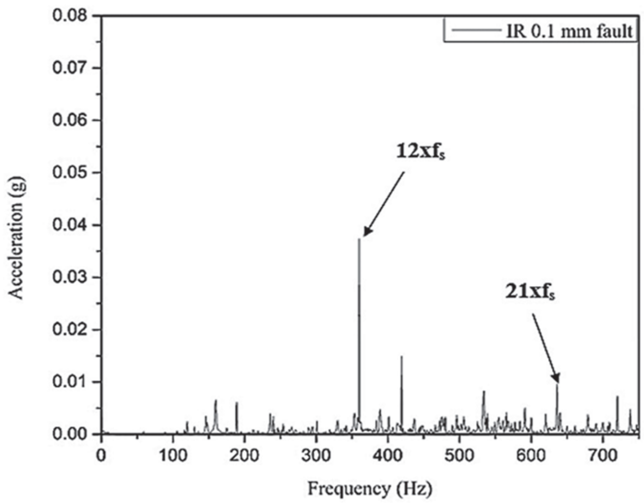
(b) Ball with 0.1 mm fault



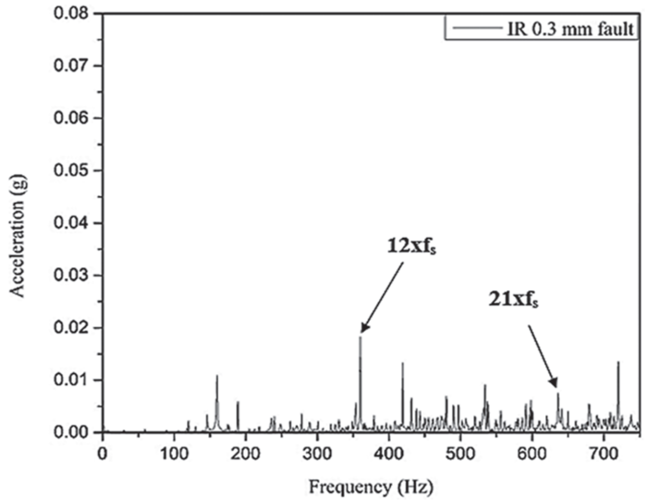
(c) Ball with 0.3 mm fault



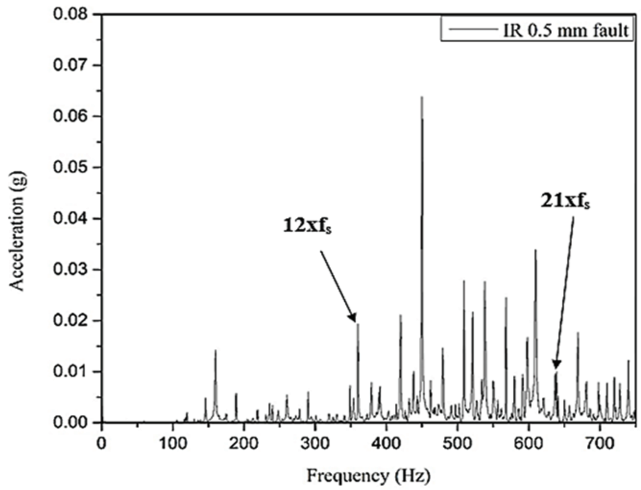
(d) Ball with 0.5 mm fault



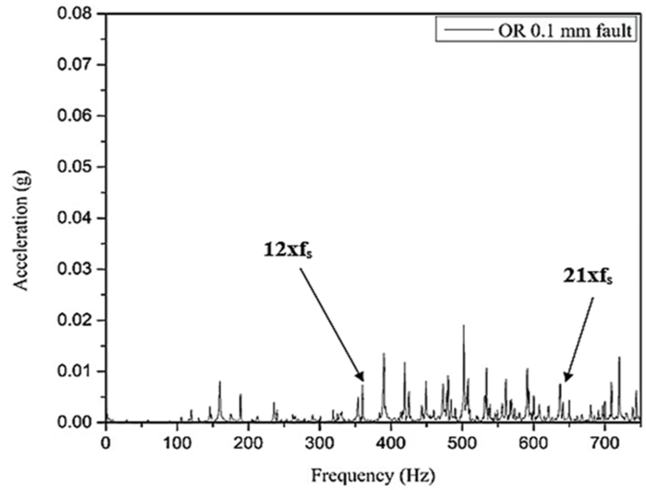
(e) IR with 0.1 mm fault



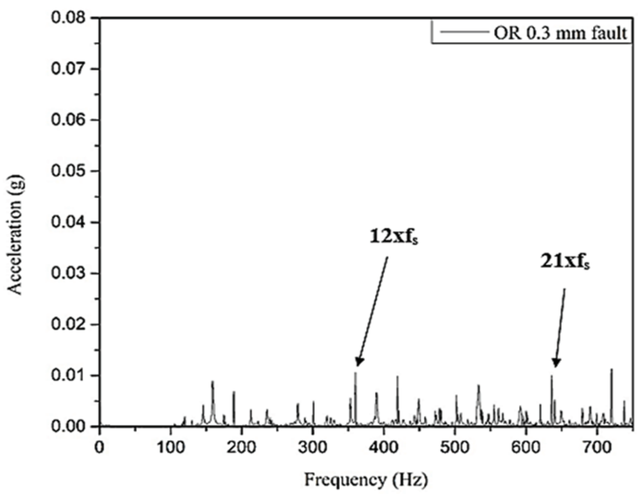
(f) IR with 0.3 mm fault



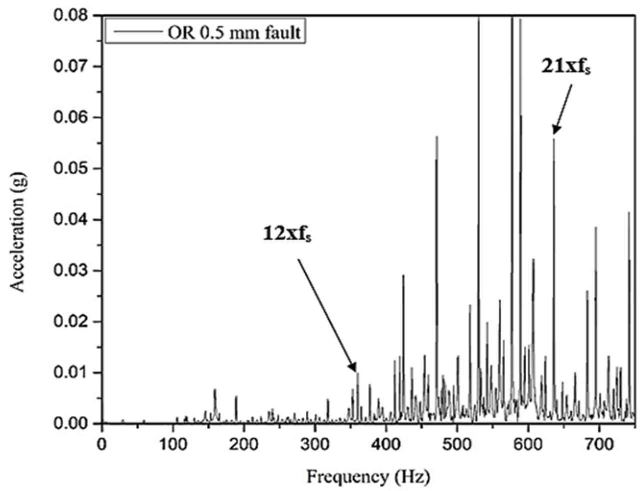
(g) IR with 0.5 mm fault



(h) OR with 0.1 mm fault



(i) OR with 0.3 mm fault



(j) OR with 0.5 mm fault

Figure 3: Vibration responses in the frequency domain

3.0 Machine Learning Approach

The method of detecting bearing defects by mapping information obtained in the measurement space or feature space. The mapping technique is also known as pattern recognition or machine learning. Manual pattern identification necessitates knowledge of the diagnostic application's specific domain. As a result, highly qualified and skilled employees are required. Therefore, pattern recognition software that recognizes patterns automatically is quite useful. This can be accomplished using machine learning approaches to classify signals based on the information retrieved from the signals. In this work, 20 vibration signals from bearings (each signal with 24000 samples) were collected for healthy and defect seeded diameters. Discrete wavelet transform (DWT) features were extracted from vibration signals to detect the bearing condition. Important feature selection/reduction from extracted features was accomplished using the decision tree (J48 algorithm).

3.1 Discrete Wavelet Transform

The discrete wavelet transform (DWT) of the time domain vibration signal (s), C (a, b) can be expressed using the following equation,

$$C(a,b) = \int_R S(t) \frac{1}{\sqrt{a}} \psi\left(\frac{t-b}{a}\right) dt \qquad \text{... (1)}$$

Here DWT represents the discrete form of continuous wavelet transform [15].

In practice, the DWT can be implemented by low-pass scaling filter and high-pass wavelet filter. These filters are created from (t) and scaling function (t) that can be represented by the following.

$$(t) = \sqrt{2} \sum k \; \square \; (k) \; \phi \; (2t - k) \qquad \text{... (2)}$$

$$(t) = \sqrt{2} \sum k \; (k) \; (2t - k) \qquad \text{... (3)}$$

The technique of "dividing the signal into low frequency and high-frequency components" is known as decomposition. A signal can be divided into multiple lower-resolution components using wavelets, which can be determined continuously with subsequent approximations. The 'wavelet decomposition tree' is the name given to this method. The discrete wavelet transform (DWT) is a powerful tool for creating features. The feature vector is made up of all of these features.

3.2 Classification with DWT Features

DWT was used to extract eight discrete wavelet features from vibration data obtained from healthy and damaged bearings belonging to ten different classes. Only two examples from each class are provided in Table 1, which illustrates the retrieved features using the DWT technique.

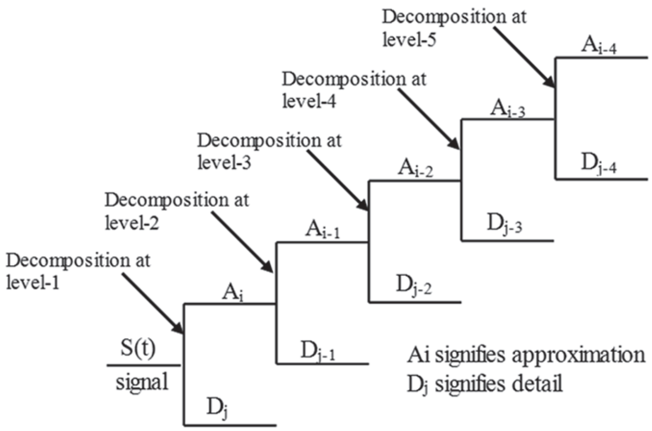


Figure 4: Wavelet decomposition tree

4.0 Results and Discussion

Different fault conditions were induced to bearing and vibration signal were acquired. Overall vibration level could be determined with vibration signal analysis. But this doesn't provide diagnostic information. Hence DWT features were extracted from signals acquired and fed as input to J48 algorithm. Different classifiers were used to classify different fault conditions from reduced features.

4.1 Feature Reduction and Classification

As shown in Table 1 DWT features were extracted in large number from signals. Not all the features extracted have relevant information. Accuracy of classifier is affected by irrelevant information making computation more difficult and wastage of system resources. J48 algorithm was fed with 8 DWT features as input. Four among them were ignored as their contribution to classification was negligible. From extracted DWT features, four most significant contributors were identified using J48 algorithm. Machine learning was leveraged for classification of selected features using different classifiers. Table 2 provides information on classification accuracy and time required to classify the instances for the extracted DWT features.

Classification accuracy and time complexities are listed in Table 2 for different classifiers. Based on these parameters users would have to choose relevant algorithms for classification. In comparison with other classifiers K-star classifier needs less time for classification and yields high accuracy. Confusion matrix of K-star algorithm [16] with DWT features is shown in Table 3.

From Table 3, out of 200 samples only 02 instances are misclassified. This yields a classification efficiency of 99%,

Table 1: Extracted features using DWT method

Class	Sample No.	Wavelet coefficient							
		V1	V2	V3	V4	V5	V6	V7	V8
Healthy	1	0.0006	0.0031	0.0081	0.0075	0.0155	0.0445	0.0505	0.0122
	2	0.0006	0.0032	0.0086	0.0079	0.0152	0.0377	0.0655	0.0130
IR 0.1	1	0.0061	0.0431	0.2319	0.4036	0.2200	0.1657	0.0682	0.0530
	2	0.0062	0.0426	0.2213	0.4299	0.2355	0.1646	0.0621	0.0461
RE 0.1	1	0.0014	0.0102	0.0581	0.1194	0.0188	0.0315	0.0329	0.0160
	2	0.0014	0.0103	0.0613	0.1152	0.0192	0.0309	0.0299	0.0187
OR 0.1	1	0.0978	0.7098	4.4623	5.0595	0.1086	0.3037	0.3972	0.1194
	2	0.0995	0.7261	4.0854	6.0497	0.1071	0.3926	0.4768	0.1382
IR 0.3	1	0.0044	0.0330	0.2077	0.5705	0.0343	0.0929	0.0820	0.0308
	2	0.0041	0.0304	0.1897	0.5363	0.0324	0.0860	0.0860	0.0313
RE 0.3	1	0.0019	0.0143	0.0687	0.2278	0.0295	0.1052	0.1560	0.0247
	2	0.0017	0.0125	0.0733	0.1816	0.0333	0.1440	0.0957	0.0386
OR 0.3	1	0.0014	0.0100	0.0572	0.1237	0.0122	0.0327	0.0211	0.0237
	2	0.0017	0.0127	0.0686	0.1616	0.0117	0.0295	0.0349	0.0233
IR 0.5	1	0.0190	0.1431	0.8662	2.5654	0.1694	0.4748	0.3780	0.1494
	2	0.0198	0.1483	0.8677	2.7155	0.1809	0.4806	0.3480	0.1390
RE 0.5	1	0.0018	0.0134	0.0817	0.2060	0.0206	0.0324	0.0378	0.0224
	2	0.0025	0.0186	0.1120	0.2928	0.0226	0.0362	0.0544	0.0294
OR 0.5	1	0.0295	0.2179	1.2917	2.4400	0.3346	0.8400	0.4095	0.2584
	2	0.0270	0.1949	0.8420	2.8270	0.3156	0.8097	0.3822	0.2226

Table 2: Comparison between various classifiers against classification accuracy and computational time

	Classifier	Classification accuracy (%)	Computational Time (Sec)
1.	Artificial neural network	89.0	0.47
2.	Naïve Bayes	98.5	0.02
3.	Bayes net	98.0	0.02
4.	Support vector machine	85.0	0.33
5.	K-Star	99.0	0.0
6.	J-48	95.0	0.0

Table 3: Confusion matrix of K-star algorithm with DWT features

i	ii	iii	iv	v	vi	vii	viii	ix	x	Class
20	0	0	0	0	0	0	0	0	0	i-Healthy
0	20	0	0	0	0	0	0	0	0	ii-IR 0.1
0	0	20	0	0	0	0	0	0	0	iii-RE 0.1
0	0	0	20	0	0	0	0	0	0	iv-OR 0.1
0	0	0	0	20	0	0	0	0	0	v-IR 0.3
0	0	0	0	0	20	0	0	0	0	vi-RE 0.3
0	0	0	0	0	0	20	0	0	0	vii-OR 0.3
0	0	0	0	0	0	0	20	0	0	viii-IR 0.5
0	0	1	0	1	0	0	0	18	0	ix-RE 0.5
0	0	0	0	0	0	0	0	0	20	x-OR 0.5

which is greater than other classifiers. With notably high classification efficiency, K-star classifiers with DWT features for fault diagnosis of bearing looks attractive.

4.0 Conclusion

It can be seen from the bearing vibration spectrum that identifying the fault frequency is difficult even when there is a flaw in the bearing. Hence, it is difficult to identify the defect in a component with vibration spectrum analysis for different conditions of bearing. This can be avoided by employing a machine learning strategy. Vibration signals were acquired from different fault bearing conditions and were fed as input to MATLAB to extract DWT features. Different classifiers were used to compare the extracted features. Among them K-star classifier yields a classification efficiency of 99% which is promising for a high accuracy diagnosis of fault bearing. Hence could be used to monitor condition of bearing in various applications. Future research could focus on prediction of early faults in bearings by comparing different bearing conditions with different algorithms.

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