Advance Research in Electrical and Electronic Engineering (AREEE)
Print ISSN : 2349-5804; Online ISSN : 2349-5812; Volume 2, Number 5; April – June, 2015 pp 41 – 46
Krishi Sanskriti Publications
http://www.krishisanskriti.org/AREEE.html

Fault Diagnosis of Bearing of Electric Motor Using Wavelet Transform and Fault Classification Based on Support Vector Machine

Swapna Vora[1], Prof. Jitendra. A. Gaikwad[2], Dr. Jayant. V. Kulkarni[3]
[1,2,3]Department of Instrumentation and Control Engineering, Vishwakarma Institute of Technology Pune, India
[1]*Email: swapihp@gmail.com*
[2]*Email:jitendra.gaikwad@vit.edu*
[3]*Email: jayant.kulkarni@vit.edu*

Abstract: *The bearings of the machines are required to function for longer period of time with reliability since its breakdown can severely affect the productivity of factories. Condition Monitoring (CM) of electrical machines has become vital as more and more processes in the industries are becoming automated. This paper describes fault diagnosis technique for rolling-element bearing based on Wavelet Support Vector Machine (WSVM). The data is acquired and vibration signal is decomposed by Discrete Wavelet Transform (DWT) using db08. Statistical features are extracted from the signal followed by diagnosis of the bearing faults using multiclass Support Vector Machine (SVM) as a classifier. To validate the proposed methodology, an experiment of fault diagnosis has been carried out on rolling-element bearing. The results of this experiment indicate that WSVM can be used to achieve greater accuracy and reliability bearing fault diagnosis.*

1. INTRODUCTION

Rotating machines are immeasurably used in our daily activities. Bearings are critical and core part of any rotating machine used in household applications to heavy duty industrial equipment due to their simple construction and high reliability. When it comes to rotating machines, they have to undergo regular maintenance like break down, preventive and predictive maintenance to avoid fault occurrence. Faults in rotating machines are in stator, rotor, gear and bearing. 40 - 50% issues in rotating machines are due to faults developed in bearing which may further lead to fatal breakdowns of machines. Bearing is a main source of system failure. Bearing is cheap, but the failure of bearing is costly.

So the studies for early detection, diagnosis and classification of faults in engineering studies become inevitable. A CM of electrical motors can further increase their productivity, reliability, life and safety.

CM is process of monitoring several parameters of condition of machine vibrations in order to identify any significant changes which could indicate a potential fault development. CM can be done in different ways like vibration monitoring, acoustic, thermography, infrared, oil condition and wear debris analysis. It pro-vides crucial information about irregularities developed in the internal structure of bearing. Compare to other CM techniques, Vibration Analysis (VA) decrease down time of machine, cost effective and can apply for non-stationary signals.

Amplitude of vibration signal indicates severity of fault and frequency indicates source of fault / defect. VA can be done in time and frequency domain. But due to some drawbacks in each of this analysis joint time and frequency domain techniques have been recommended. These techniques include Short Time Fourier Transform (STFT), Winger–Ville Distribution (WVD) and Wavelet Transform (WT). SVM is a new machine learning method built on statistical learning theory.

SVM has become very popular and widely used with advantages like higher precision and better generalization when the samples are very low in counts. Kernel function, a class of algorithms for pattern analysis plays a vital role in SVM performance. It is useful in mapping of input data into a higher dimensional representational space to make non-separable problem separable. The common kernel functions are Linear, Polynomial and Radial Basis Function (RBF).

In this paper, WSVM is introduced and its use for CM of machine and defect diagnosis is demonstrated. This method is based on WT (db08) and SVM. The acquired vibration signal follows specific pattern which can be classified according to fault occurrence in machine. SVM is widely used for such pattern recognition and machine learning technique.

Signal acquisition is followed by feature extraction i.e. extraction of statistical characteristics from signal since all features in the signal are not useful and they contain irrelevant features. These irrelevant and redundant features should be eliminated for increased accuracy of the SVM classifier otherwise they will degrade its performance. VA technique is useful for CM, predictive maintenance, early fault detection, quality control, maintenance decision and estimating life of bearing.

2. Vibration Analysis Theory Review

2.1. Vibration Analysis Techniques

Every healthy bearing produces certain amount of vibrations. The existence of bearing faults can be determined from analysis of acquired raw acceleration signals using following approaches:

- Time Domain approach
- Frequency Domain approach
- Joint Time and Frequency Domain approach

2.1.1. Time Domain Approach

This is the most simplistic and elementary method used for finding bearing faults by analyzing vibration signals. The signals are captured by accelerometers and compared with standard values to plot results over time axis. There are different parameters like skewness, kurtosis, RMS and crest factor that can be constantly monitored and examined for bearing fault finding in time domain.

The comparison of vibration parameters like crest factor, peak and RMS etc. is prepared by Tandon [4][5] for the defect diagnosis in rolling-element bearings. The disadvantage of the statistical analysis for rolling-element bearing is that the location of the fault cannot be determined. Many of these parameters are sensitive to operating conditions and noise. McFadden and Smith have developed vibration model which is extended by Su and Lin [11] for description of the bearing vibration under diverse loading. For reliable monitoring Su and Lin [11] have reported the need of time domain analysis along with frequency domain. Time domain analysis is advantageous for detecting severity of faults. But it cannot be used to detect fault type and location of faults.

2.1.2. Frequency Domain Approach

In this approach Fast Fourier Transform (FFT) is used to convert time domain vibration signals into discrete frequency components. The primary advantage of this method is that, the repetitive frequency in the frequency spectrum clearly appears as peak which distinctly indicates the repetitive vibration. This approach is fundamentally used for fault diagnosis in bearing. Characteristic frequency components of the spectra indicates the fault if any. It's analysis is used for evaluation of health of bearings. Fourier analysis is classical tool for conversion of data into a form which can be used for analyzing frequencies. JayaswalPratesh [7] performed investigations for the feasibility of FFT for fault detection in bearings with multiple defects. Some techniques used in frequency domain are Spectrum analysis, FFT, Ceptrum Analysis and Envelope Analysis.

Frequency domain approach is advantageous to locate source of vibration and it is easier to detect certain frequency components of interest. But it cannot be used for non-stationary signals.

2.1.3. Joint Time and Frequency Domain Approach

Non-stationary or transitory characteristics require both time and frequency domain analysis such as Short Time Fourier Transform (STFT) [7] and WT.

a) Short Time Fourier Transform (STFT):

STFT provides some information about when and at what frequencies a signal event occurs. The accuracy of extraction of frequency information is governed by size and shape of window relative to duration of signal.

b) Wavelet Transform (WT):

Certain seismic signals can be modeled appositely by combining translation and dilations of a simple, oscillatory function of finite duration called wavelet. WT provides combined time and frequency representation of signal. It is capable to perform local analysis of a signal. Peng and Chu [1] prepared detailed analysis of the application of WT in the diagnosis of machine fault. De-noising and feature extraction techniques based on wavelet analysis are studied by Chen and Gao [10] and they have proposed improved wavelet thresholding algorithm. This algorithm is applied for bearing health monitoring system. Chebil [2] used DWT and Discrete Wavelet Packet (DWP) for fault detection in rotating equipment. Prabhakar [9] has studied the diagnosis of faults in single and multiple rotating-elements bearing ring using DWT. WT is widely used for decomposition, de-noising and signal analysis of non-stationary signal.

i) Continuous Wavelet Transform (CWT):

The CWT is represented by equation 1.

$$W(a,b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{+\infty} f(t)\ \psi * \left(\frac{t-b}{a}\right) dt \qquad (1)$$

where, a - scaling factor, b - shifting factor, f(t) - signal to be analyzed, $*$ - complex conjugate, ψ (t) - mother wavelet

ii) Discrete Wavelet Transform (DWT):

Implementation of DWT is easy and it also reduces computational time. S. Mallat [3] describes DWT technique that breaks down total vibration signal into smaller parts. DWT provides zooming of signal into levels of approximations and details for better analysis. Thus DWT is used for fault finding of bearings where alone time and frequency domain analysis fails. The signal is breaking up and obtains one high and one low frequency term i.e. detail and an approximation level as shown in fig.1. This approximation is again split into detail and an approximation level, called 2ndlevel of decomposition and so on.The decomposition layer is always decided by characteristics of the signal and actual needs. Selection of the best decomposition level plays an important role in bearing fault diagnosis.

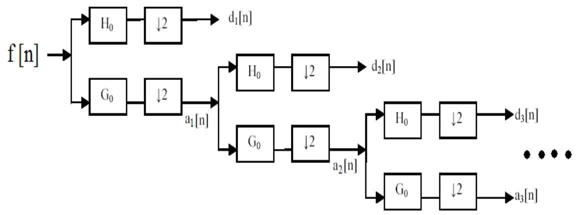

Fig 1 Decomposition of signal up to 3rdlevel

where f[n] signal to be decomposed, H_0 is High Pass Filter, G_0 is low pass Filter, $d_i[n]$-detail, $a_i[n]$ approximation.

2.2. Support Vector Machines (SVM)

The original SVM proposals are used for binary and multiclass classification problem. The binary classification considers only two possible classification classes while the later considers more than two classification classes.

Binary linear SVM classification performs the calculations of optimal hyper plane decision boundary, separating one class from the other on the basis of training data set. This decision boundary is completely determined by so called Support Vectors, a subset of training input vectors which by themselves alone lead to same decision boundary.

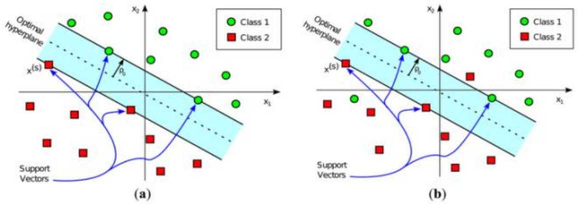

Fig 2 SVM classifier [8] (a) Linear pattern separation with hyperplane dividing green circles from redsquares. (b) A non-linear pattern separation with no hyperplane dividing all the green circles from red squares.

Tuple$(xi, yi) where\ i = 1 \ldots N$, as exemplars from training set of images with and without hidden images.yi = Class of data points.

The points which lie on the hyperplane satisfy the constraint:

$$w.x + b = 0 \qquad (2)$$

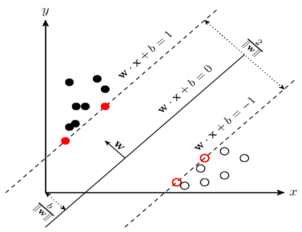

Fig 3 Classification of two classes using SVM (Ref. http://blog.pengyifan.com)

As shown in Fig 3 where ‘w’ is a vector normal to hyperplane, b/||w|| is perpendicular distance from origin to hyperplane. Margin to any hyperplane is the sum of the distances from the hyperplane to the nearest positive and negative exemplar.

Hyperplane exist within a scale factor

$$w.x + b \geq 1 \quad if\ yi = 1 \qquad (3)$$

$$w.x + b \leq -1\ if\ yi = -1 \qquad (4)$$

For any hyperplane that satisfies the above constraint, margin is 2/||w||.

A kernel function is similarity function, computes similarity between images. It helps to work with highly complex data with fast and easy calculations. Radial Basis Function (RBF) [14] is the most widely used kernel function, expressed as,

$$K(x, xi) = exp\left(-\frac{\|x - xi\|^2}{2\sigma^2}\right) \qquad (5)$$

$K(x, xi)$is a kernel function which represent the inner product

$$K(x, xi) = \langle \varphi^T(x).\varphi(xi) \rangle \qquad (6)$$

3. EXPERIMENTAL STUDIES

The bearing structure consists of outer race, inner race, cage and rolling-element. Bearing characteristic frequency is the fundamental frequency is needed in the detection of bearing faults using frequency spectrum. It is the predicted frequency from the bearing and the speed at which bearing rotate is required to find faults.

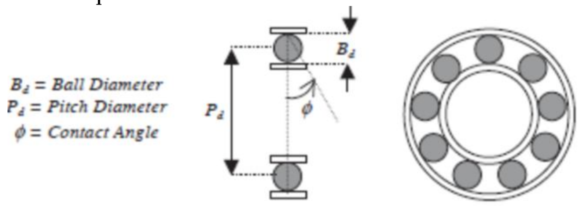

Fig 4Bearing structure [8]

The bearing characteristic frequencies are Ball Pass Frequency of Outer race (BPFO), Ball Pass Frequency of Inner race (BPFI) and Ball Spin Frequency (BSF) which are expressed as:

$$BPFO = \frac{Nb}{2}\left[1 - \left(\frac{Bd}{Pd}\right)\cos\Phi\right]fs \qquad (7)$$

$$BPFI = \frac{Nb}{2}\left[1 + \left(\frac{Bd}{Pd}\right)\cos\Phi\right]fs \qquad (8)$$

$$BSF = \frac{Nb}{2}\left[1 - \left(\frac{Bd}{Pd}\right)^2\cos\Phi\right]fs \qquad (9)$$

where, $Nb, fs, Bd, Pd\ and\ \Phi$ are number of balls, revolutions per second of the inner race or the shaft, ball diameter, pitch diameter and the contact angle respectively.

3.1. Introduction and Description

The experimental set up is shown in Fig 5 consist of PMDC motor with load of 1 kg, speed regulator, two vibration measurement sensors accelerometers, DAQ - Data Acquisition device and computer [12].

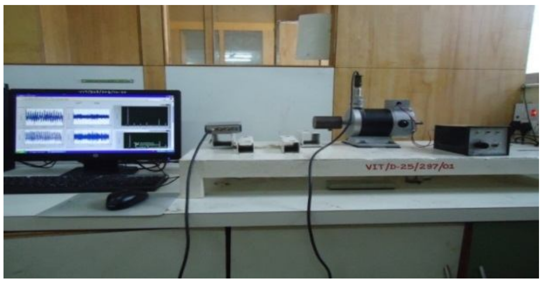

Fig 5Experimental setup [12]

Two accelerometers viz. MIL 521 are attached vertically and horizontally to the case of motor to acquire vibration signals generated by front bearing. Vibration signals with load conditions are considered for study purpose. SKF 6203 2RS bearing is used for study with Pd = 28.7 mm, Bd = 6.747 mm, Nb = 8 and Φ = 0. Artificial faults were created in Outer + Inner (O+I) race.

Table 1. Fault details of ball bearings.

Sr. No	Bearing Fault Loc	Dimension	Remark
I	No Fault	----	----
II	O+I Race	2 mm Ea	2 Faults
II	Outer Race	2 mm	1 Fault

To get correct results of vibration signal, bearing must be pressed to axial & radial load, for that load of 1 kg is applied to the shaft of the motor. Inner race is rotated at various speeds keeping outer race stationary. The sampling frequency is set to 2.5 KHz (0.4s) with sensitivity = 100 mV/g.

3.2. Feature Extraction and Diagnosis of Fault

3.2.1. Feature Extraction

The vibrations signals are extracted from bearing are used for detection and diagnosis of faults in bearing. Decomposition of acquired signal is done into detail level 4 and an approximation level 4 using DWT (db08). The statistical parameters are then extracted viz. RMS, crest factor, kurtosis and skewness using Lab-VIEW software.

3.2.2. Detection and Diagnosis of Bearing

After feature extraction, all data is feed to the SVM classifier as training data. MATLAB code is developed for binary SVM classifier which classifies the faults and gives location of defect in the bearing.

4. RESULTS

4.1. Wavelet Transform Analysis

Results of DWT analysis for good and faulty bearing are collected at 2400 rpm.

Fundamental Shaft Frequency (FSF) = No. of RPM/ 60

FSF = 2400/60, FSF = 40 Hz

4.1.1. Results for Good Bearing:

FSF at 40Hz and its harmonics at 80 Hz, 120 Hz, and 160 Hz are checked.

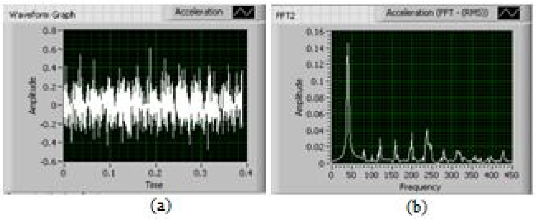

Fig 6 (a) Time Domain Analysis. (b)FFT of time domain signal

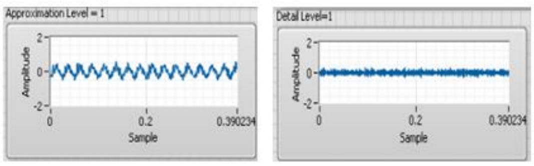

Fig 7Approximation and detail level 1

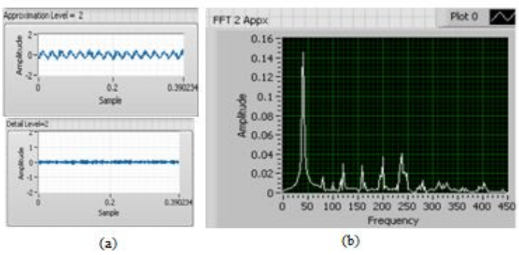

Fig 8 (a) Approximation and detail level 2. (b)FFT of approximation level 2

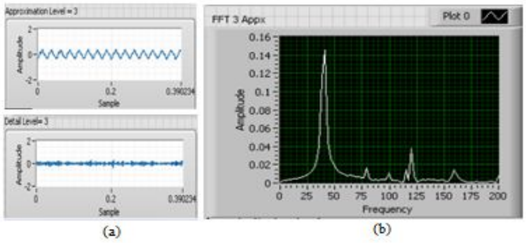

Fig 9 (a) Approximation and detail level 3. (b) FFT of approximation level 3

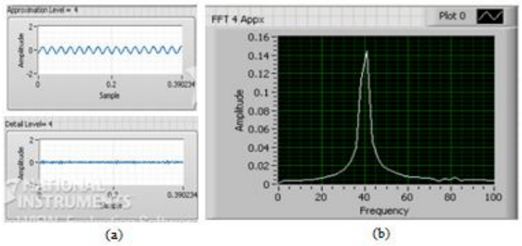

Fig 10 (a) Approximation and detail level 4(b) FFT of approximation level 4

4.1.2. Results for outer race fault:

FSF at 40 Hz and BPFO at 122.38 Hz and it's harmonics at frequency 244.76 Hz is calculated using equation (7)

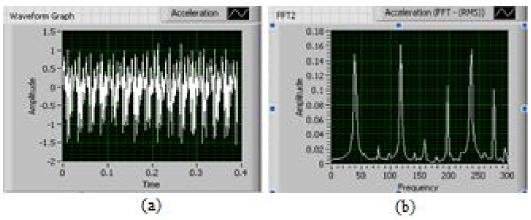

Fig 11 (a)Time Domain signal for outer race fault. (b)Frequency Domain signal for outer race fault

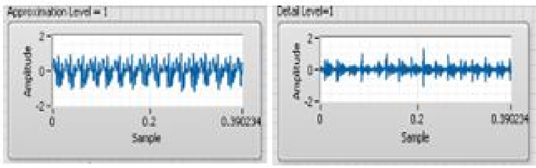

Fig 12Approximation and detail level 1

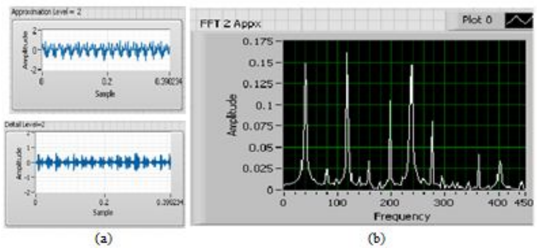

Fig 13 (a) Approximation and detail level 2 (b) FFT of approximation level 2

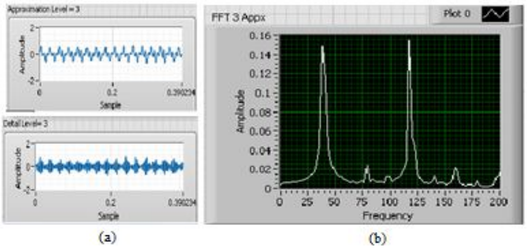

Fig 14 (a) Approximation and detail level 3 (b) FFT of approximation level 3

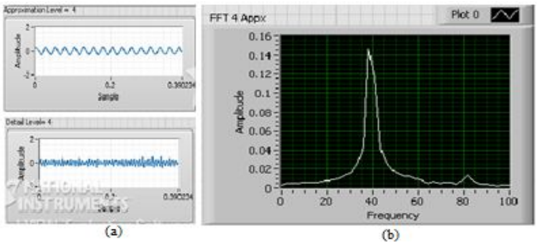

Fig 15 (a) Approximation and detail level 4 (b) FFT of approximationlevel 4

4.1.3. Results for O+I race fault:

BPFO = 122.38 Hz and its harmonics at frequency 244.76 Hz using equation (7)

BPFI = 197.61 Hz and its harmonics at frequency 395.22 Hz using equation (8)

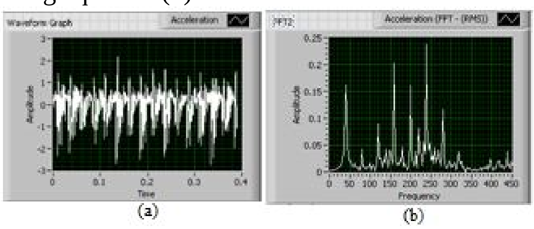

Fig 16 (a)Time Domain signal for O+I race fault. (b)Frequency Domain signal for O+I race fault

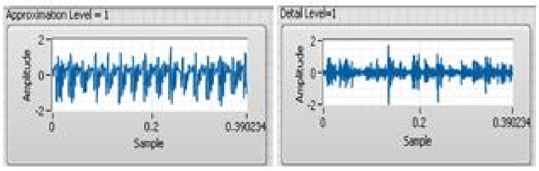

Fig 17Approximation and detail level 1

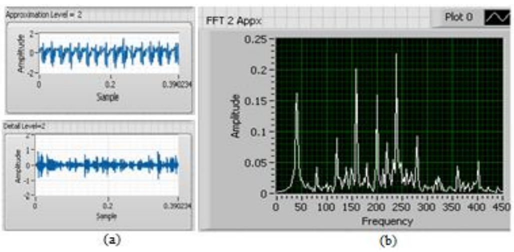

Fig 18 (a) Approximation and detail level 2 (b) FFT of approximation level 2

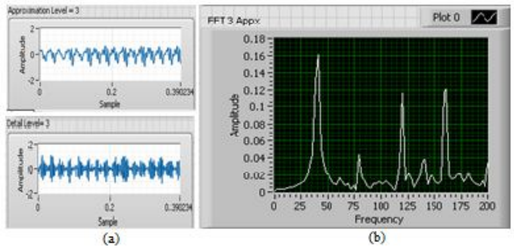

Fig 19 (a) Approximation and detail level 3 (b) FFT ofapproximation level 3

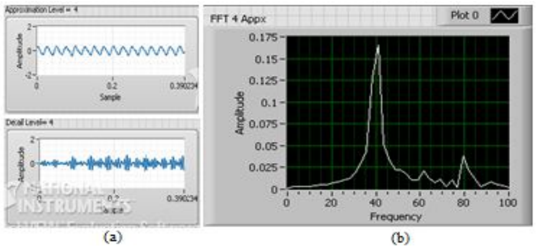

Fig 20 (a)Approximation and detail level 4. (b) FFT of approximation level 4

4.2. Support Vector Machine

MATLAB code is developed for binary SVM classifier.

a. **Fault classification using RMS and Kurtosis:**

The random values of RMS and kurtosis are entered for O+I race fault (Fig 21 (a)) and outer race fault (Fig 21 (b)) from vibration signals in MATLAB code. The results are classified based on condition of fault in the bearing as:

1. Good bearing
2. O+I Race fault (O+I)
3. Outer Race fault

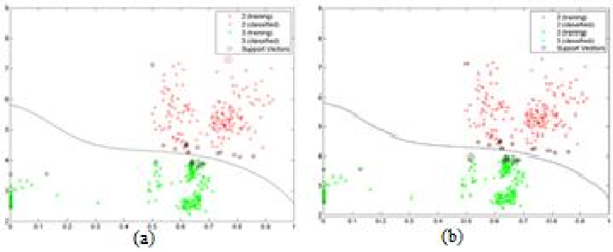

Fig 21 (a) Fault classified as 2 i.e.(O+I) race fault RMS=0.768, kurtosis=7.309 (b) Fault classified as 3 i.e. outer race fault RMS=0.513, kurtosis=3.949

b. Fault classification using Skewness and CF:

The random values of Skewness and Crest factor (CF) are entered for O+I race (Fig22 (a)) and outer race (Fig22 (b)) fault from vibration signals in MATLAB code. The results are classified based on condition of fault in the bearing as:

1. Good bearing
2. O+I Race fault (O+I)
3. Outer Race fault

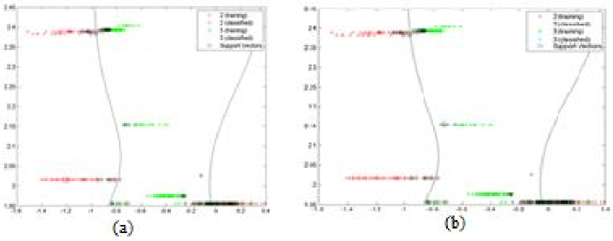

Fig 22 (a) Fault classified as 2 i.e. (O+I) race fault skewness = -1.206, crest factor = 2.016 (b) Fault classified as 3 i.e. outer race fault skewness = -0.731, crest factor =2.154

5. CONCLUSION

DWT analysis gives better results compared to FFT and is a good technique for denoising of vibration signal. SVM is a reliable technique for fault classification. Wavelet with SVM gives better results for fault diagnosis and detection. It is recommended to use for CM and predictive maintenance tools for various electrical motors. WSVM can achieve greater accuracy and reliability.

6. REFERENCES

[1] Cheng Junsheng, Yu Dejie et al (2007) "Application of an impulse response wavelet to fault diagnosis of rolling bearings", *MechSyst Signal Pr*, vol. 21, pp. 920-929

[2] J. Chebil, G. Noel et al (2009) "Wavelet decomposition for the detection and diagnosis of faults in rolling element bearings", *Jordan-J of Mechanical and Industrial Engineering*, vol.3, pp. 260-267

[3] Mallat S.G (1989) "A theory for multi resolution signal decomposition: The wavelet representation", *IEEE Trans. Pattern Anal. Mach. Intell.*; 11(7):674-93

[4] N. Tandon (1994) "A comparison of some vibration parameters for the CM of rolling element bearings", *Measurement*, vol. 12, pp. 285-289

[5] N. Tandon, A.Choudhury (1999) "A review of vibration and acoustic measurement methods for the detection of defects in rolling element bearings", *Tribol Intl*, vol. 32, pp. 469-480

[6] P.D.McFadden and J.D.Smith (1984) "Vibration monitoring of rolling element bearings by the high frequency resonance technique-A review". *TribolInt*, vol.17, no. 1, pp.3-10

[7] PrateshJayaswal, A.K.Wadhwani et al (2008) "Rolling element bearing fault detection via vibration signal analysis", *The Icfai University J of Science &Technology*, vol. 4, no.2, pp. 7-20

[8] Ruben Ruiz-Gonzalez, Jaime Gomez-Gil et al (2014) "An SVM-based classifier for estimating the state of various rotating components in Agro-Industrial machinery with a vibration signal acquired from a single point on the machine chassis", *Sensors*, 14(11), 20713-20735

[9] S. Prabhakar, A.R. Mohanty et al (2010) "Application of discrete wavelet transform for detection of ball bearing race faults", *TribolInt*, vol. 35, pp. 793–800

[10] Xiang-jun Chen, Zhan-fengGao (2011) "Data processing based on wavelet analysis in structure health monitoring system", *J of Computers*, vol. 6 no.12, pp. 2686-2691

[11] Y. T. Su and S. J. Lin (1992) "Initial fault detection of a tapered roller bearing: frequency domain analysis", *J of Sound Vib*, vol. 155, no.1, pp. 75-84

[12] Yogita K Chaudhari (2014) "Vibration Analysis for Bearing Fault Detection in Electrical Motors", *ICNSC-14*

[13] Z. K. Peng, F. L. Chu (2004) "Application of the wavelet transform in machine condition monitoring and fault diagnostics: a review with bibliography", *MechSyst Signal Pr*, vol. 18, pp. 199-221

[14] ZhiwenLiu,Hongrui Cao, Xuefeng Chen et al (2013) "Multifault classification based on wavelet SVM with PSO algorithm to analyze vibration signals from rolling element bearings", *Neurocomputing Science Direct* 99, 399-410