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Signal Processing Methods for Identification of Induction Motor Bearing Fault

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***Abstract:** To diagnose early faults as soon as possible, the feature extraction of vibration signals is very important in real engineering applications. Recently, the advanced signal processing-based weak feature extraction method has been becoming a hot research topic. The dominant mode of failure in rolling element bearings is spalling of the races or the rolling elements. Localized defects generate a series of impact vibrations every time whenever running roller passes over the surface of a defect. Therefore, vibration analysis is a conventional method for bearing fault detection. However, the measured vibration signals of rotating machinery often present nonlinear and non-stationary characteristics. This paper deals with the diagnosis of induction motor bearing based on vibration signal analysis. It provides a comparative study between traditional signal processing methods, such as Power Spectrum, Short Time Fourier Transform, Wavelet Transform, and Hilbert Transform. Performances of these techniques are assessed on real vibration data and compared for healthy and faulty bearing.*

***Keywords :** FFT, STFT, WT, Hilbert Transform, TKEO.*

I. INTRODUCTION

Diagnosing the faults and monitoring the condition are important to ensure the continuous operation of any motor driving system. For monitoring as well as diagnosing the fault following are important:

- Sensing and measuring the primary variable;
- Acquisition of data (converting sensed primary variables in digital form);
- Processing the data i.e. identification of information within data;
- Diagnosis i.e. functioning on data processed.

Out of four tasks mentioned, the first two are normally carried out when the motor is in operation mode and last two are executed off-line, but the result obtained by applying these tasks are not able to provide immediate feedback about the working of motor to the operator.

The processing of data is basic premise for monitoring the condition and diagnosis of faults. Various signals i.e. electrical and vibration signals are considered for monitoring as well as diagnosing. Therefore, extraction of legitimate features from these signals is important for the said purpose. Therefore, there is a need of a technique of feature extraction by which signal processing can be applied to get relevant feature parameter from signals recorded for a time period. By applying appropriate algorithm of signal analysis, changes in the signal due to faulty component can be detected. The simplest way is to examine the amplitude of raw signal continuously in time domain. In this case, the processing of signal consists of comparing the current recorded signal with the previous one or with any pre-set or fixed threshold. This variation in signals may be the significance of change in condition of the machine. Spectral analysis is commonly used for processing the signal in frequency domain as it is efficient to process steady state recurrent signal which is actually the case of motor fault monitoring that develops gradually.

The signal obtained by electrical rotating machine can be stationary or non-stationary. Fourier transform is standard feature extraction method for stationary signals but in case of signals which are non-stationary, features that reflect faults in motor does not have regular frequency elements with regards to time. It often exhibits transitory nature and contain minor elements fixed in major recurrent signals. So, Short Time Fourier transform (STFT) are applied to extract the limited fugitive features. But, in STFT fixed windowing is used which suggests permanent time frequency resolution [1]. The disadvantage of STFT is that the information extracted in form of the frequency is restricted due to window length in relation with duration of signal analyzed. To overcome this resolution problem Wavelet Transform (WT) is the alternative to handle this type of fugitive signal, which uses variable size windowing technique is used. WT has some important feature which enables it to perform local analysis [2]. It also exhibits significant properties while doing time domain analysis and that is why it has gained more attention in various engineering field. WT technique also reveal the hidden association between signals and so able to identify the reasons and effects of faults [3].

To know about the internal conditions of any machine, it is required to record the signal. Modern data acquisition units now a day's allow data to be acquired and investigated at a diverse position apart from any significance delay. The recorded signal may be of mechanical, electrical, chemical, and the temperature signal. These recorded signals are having hidden information and it is required to do processing to know the correct information about the machine. Processing can be done on-line or off-line but the choice shall mainly rely on whether the monitoring is d one on regular basis or not.

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It is also dependent on insight how quickly the faults are developed.

The roles of different signal processing algorithms have been playing an important role in identifying the induction machine conditions i.e. healthy or defective. The results obtained from the signal processing technique require human expert to investigate the outcome because unreliable results may lead to misinterpretation of the fault condition of the machine. The consideration of magnitude of recorded signal regularly will be the simplest form of the signal processing with respect to time. It is also necessary to apply all visual assessment techniques or trend analysis. The idea behind the regular basis recording is to compare of the present record with earlier record having some predetermine threshold value.

II. METHODOLOGY

A. *Data Description*

The analysis in this paper is done on the vibration data which have been taken from Case Western Reverse Lab [4]. The recording is done to frame the data set related to bearing installed at motor driven system. A, 3-phase, 2HP induction motor is attached with a dynamometer adaptively coupled with torque sensor. The controlling of dynamometer is done in order to achieve the required torque load. An accelerometer having bandwidth of 5000 Hz was fixed on the housing of motor at the driving end to gather the information of vibration signals of bearing. The data assemblage system comprised a high bandwidth amplifier especially intended for the vibration signal recording having a sampling frequency of 12 kHz.

The vibration signals from healthy and defective bearing of an induction motor have been shown in Fig. 1, 2, and 3 having 0.007, 0.014 and 0.021 inch of fault size. Fig. 1 represents inner raceway faults, Fig. 2 represents rolling ball fault and Fig. 3 represents outer raceway fault. From the Fig. it is difficult to interpret anything regarding the actual condition of the machine. Hence, time domain analysis and various signal processing techniques can be employed to know the fault status of the techniques.

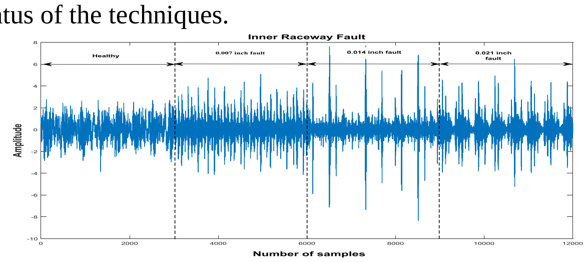


Fig.. 1: Recorded signal from bearing having inner raceway fault

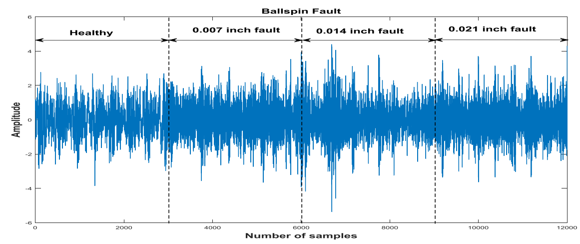


Fig.. 2: Recorded signal from bearing having rolling ball fault

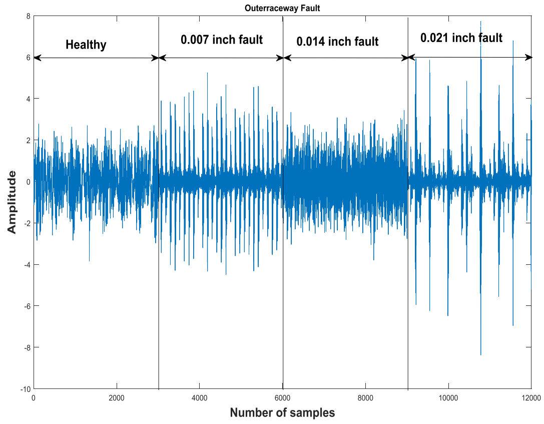


Fig.. 3: Recorded signal from bearing having outer raceway fault

B. *Power Spectrum*

To obtain frequency component from a time domain sequence, DFT is used but it is not very efficient because the calculations in DFT become more complex and lengthy with increase in number of points. To overcome this difficulty, a modified algorithm named FFT was developed which is computationally more efficient. It multiplies the periodicity of sine wave for making transformations thus reducing computation and applied so often for diagnosis of fault and monitoring the condition of induction machine [5].

To obtain the time-domain information into the frequency domain, Fast Fourier Transform (FFT) is applied. This method is very commonly used analysis method of frequency domain and the Fourier transform of a signal $s(t)$ is defined as:

$$S(\omega) = \int_{-\infty}^{\infty} s(t)e^{-j\omega t}dt \qquad (1)$$

In this, ω is frequency of the signal;

In Equation (1), $s(t)$ and $S(\omega)$ are pair of Fourier transforms, implying decomposition of signal $s(t)$ into different component with harmonics $e^{-j\omega t}$ as well as the weighting coefficient $S(\omega)$ shows the magnitude of the harmonics in $s(t)$. The $S(\omega)$ does not have any information about time; it reflects only that component which is stationary by nature.

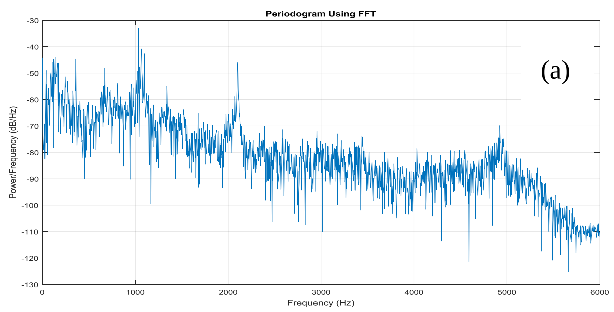
The Fourier transforms translates the time domain function into frequency domain function. The analysis of the signal is done for obtaining frequency content since coefficient of transformed function obtained by FT depicts the provision of Sine and Cosine function at each frequency.

The effectiveness of FFT-based method is to decompose a signal into various harmonics component as segmentation of signal selects the stationary signal segments. The FFT-supported technique is inadaptable signals which are non-stationary, in which the magnitude of frequency component of signal varies with time. Due to fault in motor as well as change in environment condition increases the possibility that signal become non-stationary.

A motor operating under such condition generates non-stationary signals such as vibration, current etc. The main reason of generation of a non-stationary signal from an electrical motor is that the state of motor varies all the time and never run on constant speed. Generally, the non-stationary signal contains rich information of fault. FFT is unsuitable to analyze the non-stationary signal as it can not disclose intrinsic information about that. Therefore, it can be concluded that the major application of Fast Fourier Transform (FFT) based analysis, is for stationary signals. Generally, the stationary signals can be obtained when machine condition is steady state and so FFT method can be used to do signal's frequency domain analysis for detecting the different electrical and mechanical faults.

In the present work mechanical faults are considered only. The most occurrence of a fault under this category is in the bearing of the motor. The fault conceived in roller bearing is confined to raceways, roller balls and cage. Impacts are produced periodically when the ball passes through defective portion and can be computed by conFig.uration of bearing and its speed. Various methods are used to detect faults in bearing through vibration signals [6]. FFT may indicate the characteristic defect frequency with respect to the defect in bearing but occasionally FFT does not reveal the frequency component by virtue of masking of impulses due to noises.

The power spectrum of a healthy and defective bearing of an induction motor is illustrated in Fig. 4(a) and 4(b) individually. Comparing the spectra of the healthy and defective bearing, the faulty bearing generates broader spectra than the healthy. The main vibration components of the healthy bearing are limited in the lower frequency region (below 2 kHz) and spectrum amplitude is much smaller than the faulty bearing spectrum. In the case of faulty bearing the spectra occurs from the low to the high-frequency region (between 0 kHz to 1 kHz and between 2 kHz to 6 kHz). These observations imply that the resonant frequency is a function of the change of frequency components in the higher region is more sensitive to bearing defect than the frequency component in the lower frequency region. Still, the FFT of the signal is not enough and trustworthy to decide the condition of bearing since it is unable to identify the defect frequency. Finally, it may be concluded that FFT-based analysis has certain drawbacks due to which it is required to discover secondary methods for analyzing non-stationary signals. Further, the time-frequency based method is employed to analyze the signals of motor which is operating under diverse conditions.



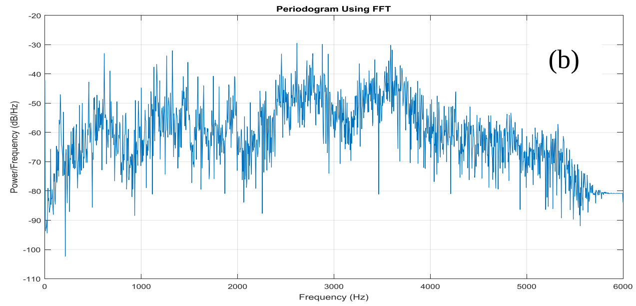


Fig.. 4: Power spectrum of (a) Healthy bearing (b) Defective bearing

C. *Short-Time Fourier Transform (STFT)*

Fourier Transform is widely acceptable with linear time-invariant operators and its affluence makes it more appropriate for processing stationary signals. However, for the transient phenomena, the Fourier Transform is not applicable. Despite that Fourier coefficient is product of $s(t)$ and $e^{-j\omega t}$ i.e. sinusoidal wave of infinite duration as per Equation (1). Hence, with this information it is difficult to do analysis about the indigenous property of signal $s(t)$ as signal is widespread on frequency axis due to abrupt changes in time and so the Fourier transform is not acceptable for non-stationary signals. To conquer this problem a frequency parameter present locally can be considered which helps to assume time window throughout that portion of signal which seems nearly stationary. The process adopted is to shift a short duration window along the signal to acquire the power spectrum. This method is called Short-Time Fourier Transform (STFT) and can be expressed as Equation (2).

$$STFT(\tau, f) = \int_{-\infty}^{\infty} s(t) \otimes g(t-\tau) e^{-j\omega t} dt \qquad (2)$$

Where, $s(t)$ is a stationarysignal over the range window $g(t)$ centered at a particular location τ. Generally, square of the amplitude $|STFT(\tau, f)|^2$ is exhibited on time–frequency diagram, so called spectrogram.

The performance of STFT intensely relies on window $g(t)$ chosen and can be treated as modulated filter bank.

However, at a particular frequency f, signals are filtered at each instant of time by STFT with a band pass filter's impulsive response modulated at that frequency [7]. With this understanding of STFT, fixation of time and frequency transform can be resolved. However, these resolutions are somehow connected to the energy of window $g(t)$, so, the product of both is bounded lower by the principal of uncertainty or Heisenberg inequality, which is described as per equation (3):

$$\Delta t \Delta f \geq \frac{1}{4\pi} \qquad (3)$$

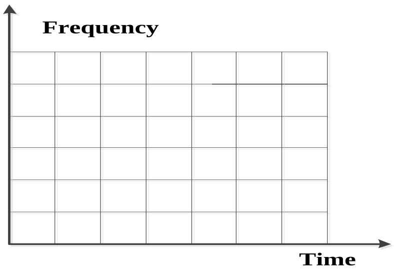


Fig.. 5: Time-frequency plot of a short Time Fourier Transform (STFT)

The limitation of the STFT is its resolution, as identical window is utilized at all frequencies as shown in Fig. 5. The frequency may not be randomly less because when a window is selected, the resolution of time-frequency shall be set through the complete time-frequency plane. Fig. 6 (a) and Fig. 6 (b) represents the STFT of healthy as well as bearing with defect respectively. It reveals that the time and frequency information in the form of magnitude. If the bearing is faulty its characteristic frequency is represented at regular interval but in case of healthy bearing this characteristic frequency exists without interval at the lower range only.

(a)

(b)

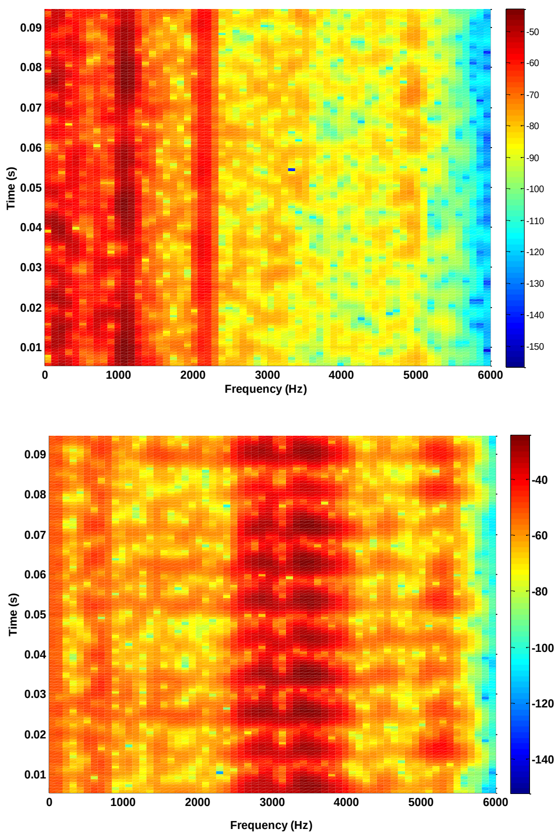


Fig.. 6: STFT of (a) Healthy bearing and (b) Defective bearing

D. *Wavelet Transform*

The STFT is able to analyze only stationary signals and extract only transient localized features. It provides information with limited precision about when and at what frequency the signal event is occurring, subject to the size of window. However, the fixed window size utilized in the STFT suggests fixed time–frequency resolution. The drawback of STFT is that it provides limited information because of confined window length. But the requirement is to adopt a flexible approach which is able to provide more accurate information, therefore, Wavelet analysis can be applied for that. The Wavelet Transform (WT) approach is coming under the category of time–frequency analysis and used for decomposition of given signal into family of 'wavelets'. The wavelets are fixed in structure but can be shifted and expanded. Wavelet transform has merits overcoming the disadvantages embedded in STFT, which represents same preservance for all frequencies as it utilizes the same window for analyzing signal $s(t)$. On the other hand, WTs gives multiple-resolution, because during the process of calculation wavelet coefficient uses diverse window functions to study separate frequency bands of the signal $s(t)$. Thus, Wavelet analysis is a kind of technique which uses variable window-size. It permits to use long time intervals, if accurate low-frequency information is needed and short intervals when high-frequency is needed. Wavelet transforms is advantageous if the signal is non-stationary since it is capable to analyze in time as well as frequency domains [8].

E. *Continuous Wavelet Transform (CWT)*

The filtering operation of the signal is one of the special attribute, which can be obtained using wavelet transform. By using translation and dilation of the analyzing wavelet, various frequency segments can be obtained. The Continuous Wavelet transform has the capability to fabricate the time-frequency depiction of signal which reflects better time-frequency deposition. Unlike Fourier transform, the Wavelet transforms is applicable to time domain signal which may not be periodic and can be rebuilt utilizing series of the small waveform which is transitioned in time and scaled in magnitude. Conventionally, CWT is applied to partition a continuous-time function into wavelets. For an example, a time signal $s(t)$ along with selected mother wavelet function $\psi(t)$, then the equivalent wavelet transform, $\psi(a,b,t)$; can be represented as [9]:

$$w(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} s(t)\psi\left(\frac{t-b}{a}\right) dt \tag{4}$$

Where, a is dilation factor, b is the translation factor, $\psi(t)$ represents the mother wavelet.

Equation (4) represents that the wavelet analysis is actually a time-frequency analysis, or a time scale analysis more precisely.

Actually, the wavelet coefficient $w(a,b)$ counts the correspondence between the signal $s(t)$ and mother wavelet $\psi(t)$ at various scales which is determined by the parameter a, and various time positions determined by the parameter b. The factor $a^{-1/2}$ is used for energy preservation. It is also observed that at larger scales, there is improvement in frequency resolution and decrement in the time resolution. A scale is the inverse of its corresponding frequency.

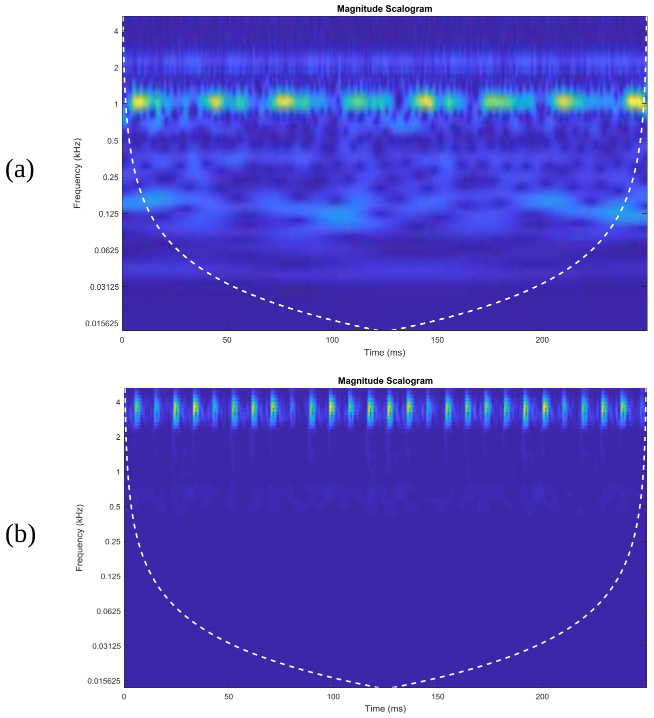


Fig.. 7: CWT of (a) Healthy bearing and (b) Defective bearing

Fig. 7 shows the plot of continuous wavelet transform which comprises frequency information as well as the time information which was not available in frequency domain analysis. Fig. 7 (a) represents a measured vibration signal of healthy bearing and it has been observed that the small amplitude of frequency occurs at lower frequency region around at 1000Hz. Fig. 7 (b) shows a measured vibration signal of a faulty bearing and it was observed in the Fig. that a higher value of amplitude at higher frequency region (2 kHz to 5kHz) present all the time since the fault, use each time a ball passes the fault; the resulting impact excites the resonance in the structure. But, the diagnosis of fault is difficult by examining the frequency spectrum [10].

F. *Discrete Wavelet Transform (DWT)*

From the spectrum analysis, it can be concluded that the signal which is obtained from the faulty bearing generally have both low-frequency and high-frequency components both. The low-frequency component varies slowly with time hence, requires fine frequency and coarse time resolution and on other hand, high-frequency component varies rapidly with the time and so it requires fine time and coarse frequency resolution. In order to deal the above problem Multi-Resolution Analysis (MRA) method is applied to deal with the signal which has both low and high-frequency components. MRA has the ability to decompose a signal using different window size at a diverse scale. A large window size for lower scale and a small window size for higher scale. This allows to capture short time high frequency as well as long time low frequency components of the signal.

The DWT implementation for digital computation, there is an efficient algorithm that is well-suited for MRA. The MRA decomposes the signal recursively with two-channel filter bank and down sampling process[11]. The DWT is executed by selecting fixed values $a = 2^m$ and $b = n \times 2^m$, where, m and n are integers. Thus wavelets $\psi_{m,n}(t) = 2^{-m/2}\psi\left(2^{-m}t - n\right)$ can be built, which constitutes an orthonormal basis. The discrete wavelet analysis can be employed by using scaling filter $h(n)$ i.e. low pass filter associated to the scaling function $\varphi(t)$ and the wavelet filter $g(n)$ i.e. high pass filter associated to the wavelet function $\psi(t)$

$$h(n) = \frac{1}{\sqrt{2}}\langle \varphi(t), \varphi(2t-n) \rangle \tag{5}$$

$$g(n) = \frac{1}{\sqrt{2}}\langle \phi(t), \phi(2t-n) \rangle = (-1)^n h(1-n) \tag{6}$$

The estimation and the properties of these filters are broadly analyzed. The elementary procedure of a fast wavelet algorithm has been shown in Fig. 11 and can be employed in both directions opposite to each other, such as decomposition and reconstruction.

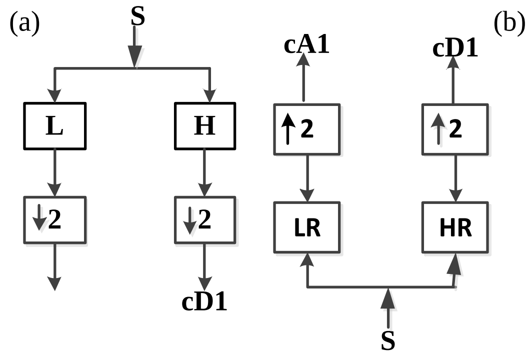


Fig.. 8: Step used for (a) Decomposition and (b) Reconstruction by Wavelet Transform

In decomposition as shown in Fig. 8 (a), the discrete signals convolves with a low pass filter L and high pass filter H, which results in two vectors A_1 and D_1. Vector A_1 is termed as a approximation coefficients and the vector D_1 is termed as detail coefficients. The symbol $\downarrow 2$ represents down sampling, i.e. neglecting the odd indexed elements of the filtered signal so that the number of the coefficients generated by the basic step is almost same as the number of elements of the discrete signal "S".

Fig. 8 (b) represents the reconstruction process of a pair of low-pass and high-pass filters LR and HR by vectors A_1 and D_1. Two signals are evolved resulting in rebuilding the signal A_1 known as approximation and a signal D_1 called detail coefficients.

The symbol $\uparrow 2$ represents upsampling by introducing zeros between the elements of the vectors A_1 and D_1 by following steps:

$$S = A_1 + D_1 \tag{7}$$

These basic steps are repeated on the approximation vector A_1 and successively on every new approximation vector A_j. The same concept is followed for j levels of wavelet tree, where j is the number of iterations. In Fig. 9, wavelet decomposition of the wavelet tree for $J = 2$ is demonstrated. Each vector A_j comprises $N_t / 2^j$ coefficients approximately, where N_t is the length of signal S and informs about a frequency band $[0, F_s / 2^{j+1}]$, where F_s is the sampling rate. The reconstructed signals A_j and D_j satisfies the following equation:

$$A_{j-1} = A_j + D_j \tag{8}$$

$$s = A_j + \sum_{i \le j}^{n} D_i \tag{9}$$

Where, i and j are positive integers.

This time and frequency localization of DWT are special attributes which are widely applied in signal processing techniques [12]. The inconsistency of the time-frequency division enhances the competence of capturing features of signal. It is applicable to transient signal analysis to detect faults. It also provides the ability to find a fault either in the beginning or during transition. The traditional diagnostic methods are not able to find incipient faults in motor but it is possible by the DWT analysis. Therefore, DWT is an essential tool for diagnosing faults if operating condition is non-stationary. Moreover, the multi-scale feature of the DWT can be employed on bearing vibration signal and allows the decomposition of the signal into different scales. The whole process of decomposition is on the basis of fact that cracks are interpreted into transient and high-frequency occurrences in the vibration signal. Therefore, the abnormality in conduct may be observed by examining the detail coefficient in high frequency.

In this paper, DWT is applied to decompose the vibration data having sampling frequency 12000 sample/sec for healthy and defective bearing by applying mother wavelet Daubechies (db10). A three level decomposition has been done to obtain fault. The DWT has been applied on healthy and bearing with defect and obtained decomposition of the original signal. The recorded signal is decomposed into different components: third level approximation A3, third level detail D3, first and second level detail D1 and D2 as shown in Fig. 10. The frequency sub-bands with respect to each component of the signal are shown in Table 1.

The application of this approach on the available data reveals that for defective bearing detail coefficient at high frequency band is much more than the healthy bearing. The similar result is obtained by computing energy percentage at each sub bands as shown in Fig. 11. The Fig. exhibits highest average energy in the A3 band for healthy bearing while for faulty bearing other frequency band has highest average energy. This result signifies efficient distinction between healthy and faulty bearing behavior through average energy of each sub-bands.

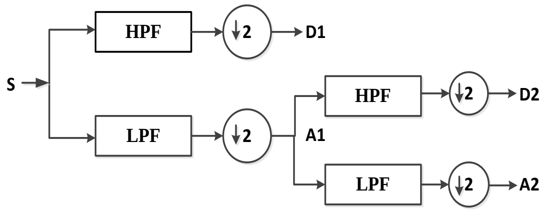


Fig.. 9: Two level wavelet tree

Table 1: Frequency bands at different levels

Level	Frequency band (Hz)
D1	3000-6000
D2	1500-3000
D3	750-1500
A3	0-750

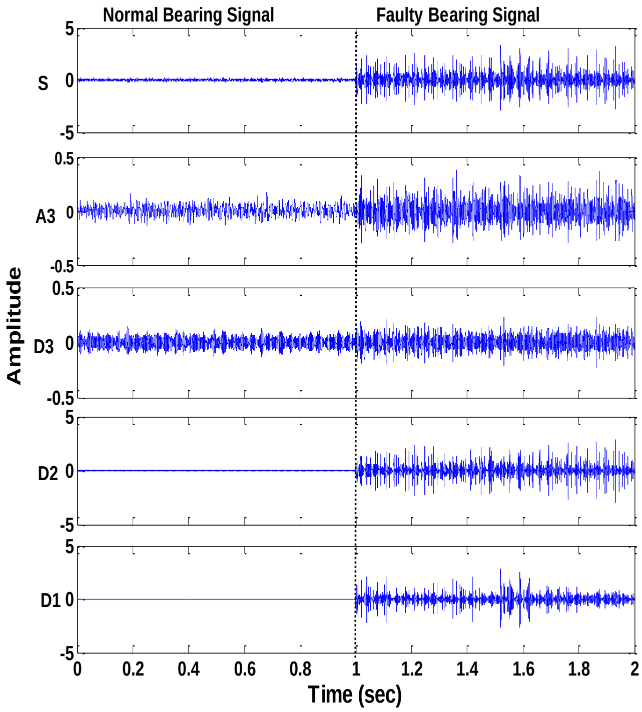


Fig.. 10: Decomposition of signal for healthy and faulty Bearing by DWT

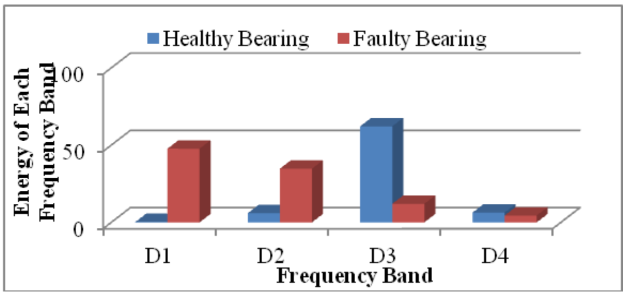


Fig.. 11: Average energy of vibration signal for healthy and faulty bearing in the frequency sub-bands

G. *Wavelet Packet Transform (WPT)*

Wavelet Packet Transform (WPT) is a method of decomposing the signal regularly into consecutively high and low frequency components. Wavelet transform does signal analysis in time as well as frequency domain, hence it is applicable to non-stationary signals.

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WPT is dissimilar from DWT in the manner that it decomposes the signal into approximation as well as detail coefficients. So, WPT is more flexible for signal processing as it separates low frequency and high frequency sub bands. Since it divides the signal into approximation and detail coefficients, which is further partitioned into second level of coefficients and so on. WPT also has the ability to detect multi resolution damage as it localizes multi frequency bands in time domain. Therefore, WPT is used very often for health monitoring and detection of damage in the machine which is based on vibration signal [13], [14].

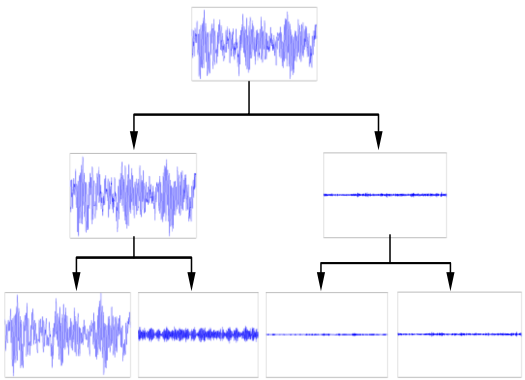
It is necessary to determine the decomposition level considering the separation of natural fundamental frequency into wavelet packets. Those wavelet packets are selected which includes natural frequency with respect to the fundamental modes which are more influenced by damage of components than others. Therefore, decomposition of recorded signal is done up to two levels of WPT followed by reconstruction as the frequency of interest is obtained up to this. Four distinct components having different frequency band and obtained at level two. This enhanced ability makes WPT more appealing for detection as well as discriminating transient elements having high frequency bands.

When a fault appears, the amplitude and distribution of its vibration signal are different from those of normal in the time domain and the entropy of fault frequency corresponding to various faults also will change remarkably in the frequency domain [15], [16]. Fig. 12 (a) shows the two-level wavelet packet decomposed frequency band of the signal via db10 of normal bearing and Fig. 13 (a) shows the two-level wavelet packet decomposition frequency band of the signal by db10 wavelet packet decomposition of faulty bearing vibration signal. By comparing the Fig. 12 (a) and 13 (a) the difference in frequency band of healthy and defective bearing can be observed. Moreover, the energy entropies calculated by Equation (10) are shown in Fig. 12 (b) and 13 (b) for each node. It is found that the entropy of the faulty bearing is different from that of the healthy one. Entropy The energy entropy can be obtained by equation:

$$H_e = -\sum_{j=1}^{J} p_j \log p_j \tag{10}$$

Where, $p_j = E_j / E$ is the percentage of the energy of the j^{th} frequency band signal of WPT and E is the $\sum_{j=1}^{J} E_j$.

(a)



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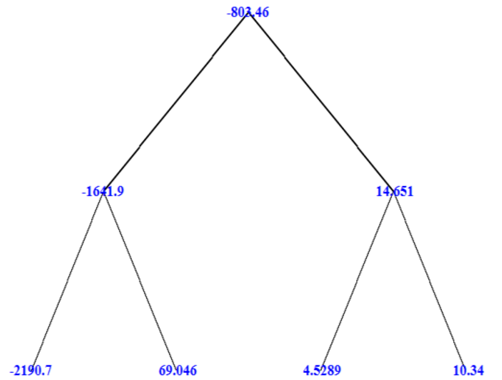
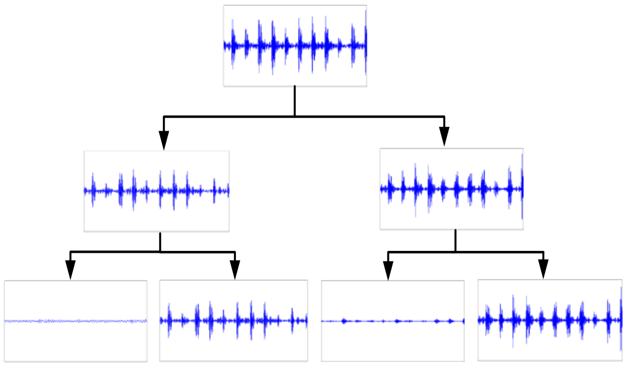


Fig.. 12: A two level WPT decomposition of healthy bearing vibration signal with entropy

(a)



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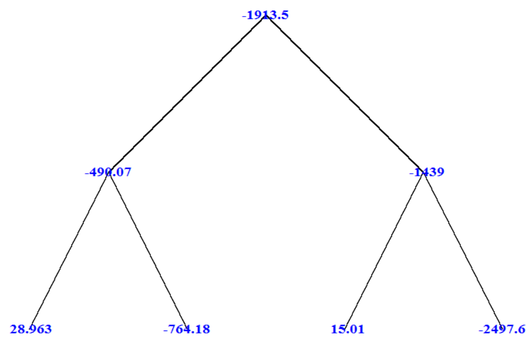

Fig.. 13: A two-level WPT decomposition of defective bearing vibration signal with entropy

On the basis of above analysis, it is concluded that distribution of energy of frequency band is changed with bearing health condition. Thus, the entropy associated with frequency-band signals will be additional information for detection of damage in bearing in time frequency domain.

H. *Hilbert Transform (HT)*

The Hilbert transform is actually the connection between the real and imaginary parts of FFT of one-sided function. Hilbert transform $H\left[s(t)\right]$ of a signal *s(t)* is given by equation [17]:

$$H[s(t)] = \frac{1}{\pi} \int_{-\infty}^{+\infty} \frac{s(\tau)}{t-\tau} d\tau \tag{11}$$

Where, t is time and τ is translation parameters.

Hilbert transform is a frequency independent time domain involution that maps real time-domain value into other value. It is also called 90^0 phase shifter and has no effect on non-stationary characteristic of a modulating signal. Actually, fault in machine causes modulation; therefore, demodulation is required for obtaining signature related to fault. This can be obtained analytically by following equation:

$$B(t) = s(t) + iH[s(t)] = be^{\phi(t)} \tag{12}$$

$$b(t) = \sqrt{s^2(t) + H^2[s(t)]}, \phi(t) = \arctan\frac{H[s(t)]}{s(t)},$$

and

$i = \sqrt{-1},\ b(t)$ is the envelope of $B(t)$.

$\hat{B}(i\omega)$ the Fourier transform of signal $B(t)$ and its properties are given by:

$$\hat{B}(i\omega) = \begin{cases} 2\hat{s}(i\omega) & 0 \le \omega \\ 0 & \omega < 0 \end{cases} \tag{13}$$

Where, $\hat{s}(i\omega)$ is Fourier transform of $s(t)$ and ω is angular frequency of $\hat{B}(i\omega)$

Fig. 14 shows the Hilbert transform of healthy and faulty bearing signal. From Fig., it is difficult to make a final decision about the presence of a fault. In literature, it has been observed that, to identify the fault frequencies, Power Spectral Density is further applied. Z. Peng et al. effectively applied Hilbert transform for identifying the fault location [18].

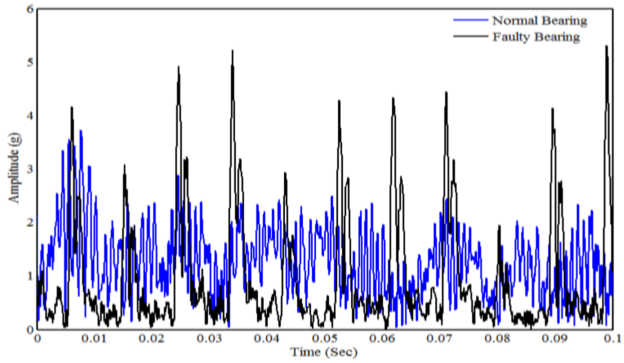

Fig.. 14: Hilbert transform of healthy and defective bearing

I. *Teager Kaiser Energy Operator (TKEO)*

TKEO is a non-linear operator that can track the energy and identify the instantaneous frequency and instantaneous amplitude of signal at any instant. TKEO detects a sudden change of energy stream without any priori assumption of the data structure; it can be utilized for vibration based condition monitoring (non-stationary signals).

The TKEO application on a real-valued signal $s(t)$ of induction motor bearing vibration signal are given by Equation 14 [19].

$$\psi_c[s(t)] = \dot{s}(t)^2 - \ddot{s}(t)s(t) \tag{14}$$

Where, $\dot{s}(t)$ is first time derivative and $\ddot{s}(t)$ is second time derivatives of $s(t)$. $\psi_c[s(t)]$ is the Teager energy of the signal. Its discrete form is given by Equation 15.

$$\psi_c[s(t)] = s(n)^2 - s(n+1)s(n-1) \tag{15}$$

TKEO shows instantaneous behavior due to requirement of only three samples which are essential for the energy calculation at each time of instant. Moreover, this simple operator has ability to capture the energy fluctuations as well as efficient in implementation. P. Marago developed the algorithms so-called discrete energy separation algorithms (DESAs) to estimate the amplitude envelope $|a(n)|$ and the instantaneous frequency $f(n)$ of discrete time signal to achieve mono-component AM-FM signal demodulation [20], [21]:

$$f(n) \approx \frac{1}{2\pi}\sqrt{\frac{\psi[\dot{s}(n)]}{\psi[s(n)]}} \tag{16}$$

$$|a(n)| \approx \frac{\psi[s(n)]}{\psi[\dot{s}(n)]} \tag{17}$$

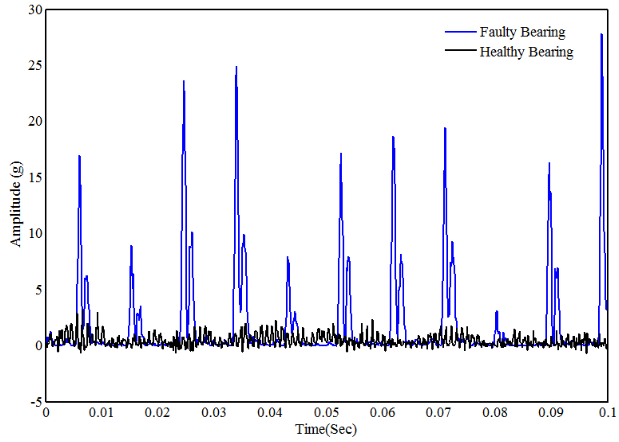

Fig.. 15: TKEO for Healthy and Defective Bearing

The energy parting algorithm is simply AM-FM demodulation technique. The best part TKEO is that it has better time resolution than the conventional method like Hilbert transform due to less computational complexity. Sensitivity is a major concern of this operator when it is applied to a noisy signal. TKEO successfully applied in the area of speech processing also. Fig. 15 shows the TKEO of the faulty and healthy signal of the induction machine. From the Fig., it can be easily observed that the TKEO amplitude of faulty bearing is much higher than the healthy bearing. If Hilbert Transform and TKEO are compared it is found that TKEO is the winner because of its clearly separable capability between healthy and faulty condition of the bearing.

III. CONCLUSION

The vibration signals contain strong background noises during the early fault stage, making it difficult to extract fault information. In order to effectively analyze (14) the non-stationary vibration

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signals, massive research efforts have been made in last two decades to develop various signal processing technologies, These techniques gives the pictorial view which is used for comparison in order to identify the induction motor bearing condition such as healthy or bearing with defect and successfully achieved by Power Spectrum, STFT, Continuous Wavelet Transform. Further, the same information is identified by comparing energy calculation with the help of Discrete Wavelet Transform and wavelet packet Transform. These techniques are successfully able to discriminate between healthy and bearing having defect but fails to detect the location of fault such as inner race, outer race or in rolling ball as it produces similar nature of images for all located faults.

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