Automatic Fault Classification of Rolling Element Bearing using Wavelet Packet Decomposition and Artificial Neural Network

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Abstract: **In this work an automatic fault classification system is developed for bearing fault classification of three phase induction motor. The system uses the wavelet packet decomposition using 'db8' mother wavelet function for feature extraction from the vibration signal, recorded for various bearing fault conditions. The selection of best node of wavelet packet tree is performed by using best tree algorithm along with minimum Shannon entropy criteria. The ten statistical features such as peak value, root mean square value (RMS), kurtosis, skewness etc. are extracted from the wavelet packet coefficient of optimal node. The extracted feature then was used to train and test neural network fault classification. The artificial neural network system was designed to classify the rolling element bearing condition: healthy bearing (HB) rolling element fault (REF), inner race fault (IRF) and Outer race fault (ORF) for fault classification. The over all fault classification rate is 98.33% of the artificial neural network fault classifier.**

Keywords: Artificial neural network (ANN), Rolling Element bearing, Shannon Entropy, Wavelet packet decomposition (WPD.)

I. INTRODUCTION

Rolling element bearings are considered to be the most important components in rotating machinery. Faulty bearings is the primary cause of failures in rotating electrical machines and this accounts for the need of detailed study of the rolling element bearing fault detection. Many studies have been carried out on fault detections and the major causes of bearing failures [1] in induction motor. The most critical situation arises due to inadequate maintenance as winding failure within the machine can be the worst outcome of this negligence. Therefore fault diagnosis and monitoring the condition of rotating machines on periodic basis can guarantee efficient, safe and healthy running of rotating machines, thus leading to increased productivity and reduction in capital loss in industries.

Among the most frequently used methods for detection and diagnosis of bearing defects, vibration based techniques, both in the time and frequency domains are well established. These different techniques have been stated in [2]-[3].The two approaches can be differentiated in the sense that time domain methods are based on analysis of peak value, standard deviation, skewness etc which are the statistical characteristics of the vibration signal whereas in frequency domain based analysis Fourier transformations are employed to transform time domain signals into frequency domain. Further analysis is done on vibration amplitude and power spectrum. The key point in both the analysis techniques is that the direct use of informational content in one domain is excluded when the other domain is employed.

A major revolution in the signal processing techniques is brought by the introduction of wavelet analysis as it is capable of revealing aspects of data that other signal analysis techniques could not. One major advantage afforded by wavelets is the ability to perform analysis for non stationary signals, that is, signals containing discontinuities and shape spike. In the present work bearing fault detection is performed by wavelet packet analysis to overcome the limitations of well known Fourier transformation. The major disadvantages of Fourier analysis considered here can be cited as information loss and difficulty in interpreting the signals when moving from time domain to frequency domain, particularly in non stationary signals. Due to highly non stationary nature of the vibration signals wavelet approach is done since it offers a remarkable advantage of representing both time domain and frequency domain simultaneously. Thus the signal is represented using shifted and scaled versions of a so-called mother wavelet and therefore evolving the frequency information with the time parameter.

This paper presents a wavelet based methodology for feature extraction and artificial neural network application for fault classification of different bearing conditions such as healthy bearing(HB),rolling element fault(REF),inner race fault(IRF),outer race fault(ORF). The test results indicate that the proposed method has a good success rate to improve the accuracy to a considerable extent.

II. IMPLEMENTATION OF PROPOSED METHOD

In this method vibration signal are obtained from self designed bearing test bench for different bearing faults. Features are extracted from acquired vibration signals and subsequently classified to assess bearing conditions. The feature extraction process utilizes the wavelet packet decomposition through best tree algorithm. The statistical parameters such as, peak value, root mean square value (RMS), crest factor, kurtosis, skewness, shape factor, impulse factor, clearance factor, upper bound and lower bound were derived from wavelet packet coefficients signal. Before applying the input features in neural network, all the features were normalized. A feed forward neural network (FFNN) was used to classify bearing condition based on features obtained. The training and testing of the neural network is done for various bearing condition determination of healthy bearing (HB), outer race fault (ORF), inner race fault (IRF) and rolling element fault (REF). The block diagram of proposed method is shown in Fig 1.

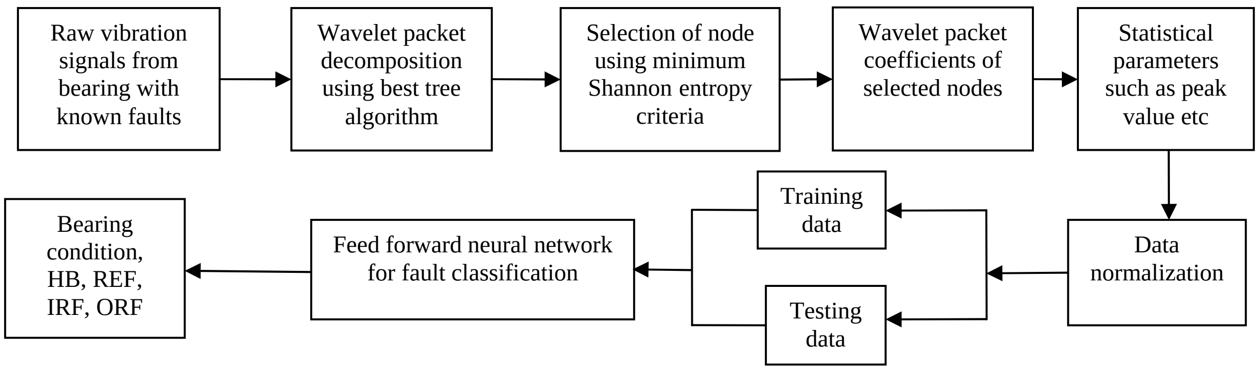


Fig .1 Block Diagram of Proposed Method

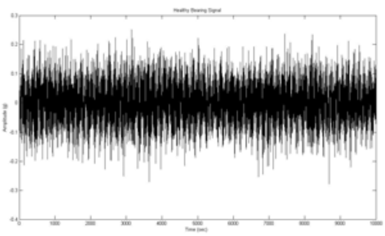
III. EXPERIMENTAL SETUP

The experiment was carried out on the self designed bearing test bench is shown in Fig 2. The raw vibration signals were collected from bearing housing of the test bench. The shaft is extended from induction motor through a flexible coupling. The motor used for experimentation purpose is 3-phase, 4-pole, 50Hz, 5hp (3.7kw), 414V and 1440 rpm. ZKL 1207 EK series rolling element bearing is used for analysis. Single point faults are introduced into the bearing using electric discharge machining with a fault diameter of 0.18mm and a depth of 0.24mm in the outer race and inner race of bearing and dent type fault in rolling element of bearing. Vibration data is acquired using RACC/001/U2/10K accelerometer sensor which is attached to the bearing housing with magnetic base. The signal from accelerometer were transmitted to the Advantech USB 4711A card and sample at a rate of 4000 samples/sec and personnel computer is used for storing the vibration data and further analysis of data using Mat lab 7.9 toolbox.

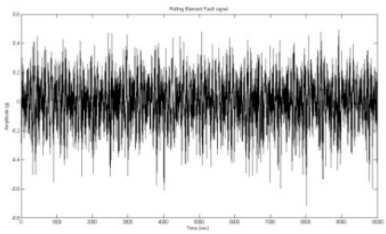
a. Accelerometer attached with bearing housing
b. Induction Motor
c. Bearing Test Bench without Load
d. Personal Computer
e. DAQ USB 4711 Card

Fig 2. Experimental Setup without Load

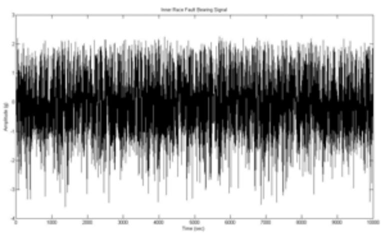
The time waveform of vibration signal for four different conditions of the bearing; healthy bearing (HB), outer race fault (ORF), inner race fault (IRF), rolling element fault (REF) is show in Fig 3.



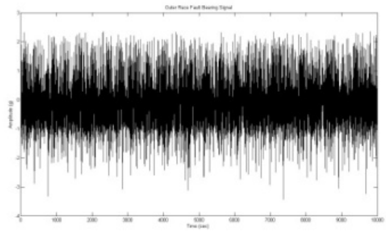
(a) Healthy Bearing



(b) Rolling Element Fault



(c) Inner Race Fault



(d) Outer Race Fault

Fig.3. *The Recorded Raw Vibration Signal of Bearing*

IV. FEATURE EXTRACTION USING WAVELET PACKET DECOMPOSTION (WPD)

Wavelet packets form a redundant dictionary of bases from which the best basis to represent a given signal can be selected. Wavelet packets are composed of elementary functions called wavelet packets

$$W_{j'n'k}(x) = 2^{-\frac{j}{2}} W_n(2^{-j}x - k) : j, k, n \epsilon Z \quad (1)$$

where j, k and n represents the index of scale, position and degree of oscillation respectively.

As with the wavelet transform, wavelet packets can be represented by a filter bank constructed from the quadrature mirror filters. The construction of the wavelet packet bases can be expressed as. A wavelet packet base allows any dyadic tree structure. At each point in the tree we have an option to send the signal through the low pass and high pass filter bank.

Wavelet packets are generated by the following iterations.

$$W_{2n}(x) = \sqrt{2}\sum_{k=0}^{2N-1} h\,(x) W_n(2n-k) \tag{2}$$

$$W_{2n+1}(x) = \sqrt{2}\sum_{k=0}^{2N-1} g\,(x) W_n(2n-k) \tag{3}$$

Where h(x) and g(x) represent the respective high and low pass quadrature mirror filters and w_0 and w_1 correspond to the father wavelet (scaling function) and mother wavelet (analyzing function).

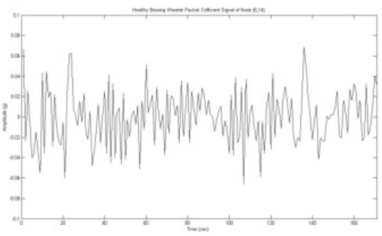
For a given signal the wavelet packet coefficients can be iteratively computed by the following equations.

$$C_{2n,1}^{j-1} = \sum_k h_{k-2l}\, C_{n,k}^{j} \tag{4}$$

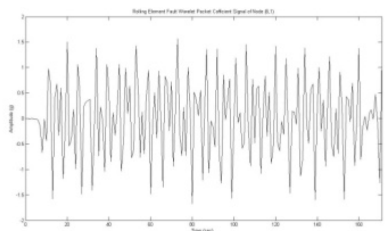
$$C_{2n+1,1}^{j-1} = \sum_k g_{k-2l}\, C_{n,k}^{j} \tag{5}$$

Best tree algorithm is used for wavelet packet decomposition of raw vibration signal. According to this algorithm if entropy of parents node is greater than the sum of child node then given node is interesting node otherwise it is discarded.

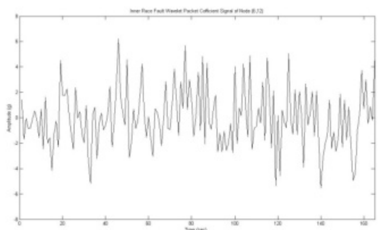
In this work wavelet packet decomposition of vibration signal obtained using ‘db8’ mother wavelet function. The signal is decomposed up to sixth level, so that the frequencies up to 171Hz can be obtained at the lowest level. After decomposition minimum Shannon entropy criteria are used for wavelet packet coefficient signal selection and statistical parameters are obtained from corresponding vibration signal of rolling element bearing faults. The wavelet packet coefficient signal of different bearing condition is obtained on the basis of minimum Shannon entropy criteria. The wavelet packet coefficient of best node obtained for each fault case is shown in Fig 4.



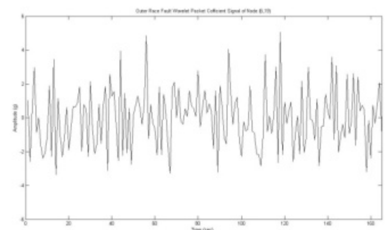
(*a) Healthy Bearing of Node (6, 14)*



(*b) Rolling Element Fault of Node(6,1),*



(*c) Inner Race Fault of Node (6, 12)*



(*d) Outer Race Fault of Node (6,19)*

Fig. 4 *Wavelet Packet Coefficient of Best Node*

Statistical parameters such as peak value(P_k), root mean square value (RMS), crest factor(C_{rf}), kurtosis(K_v), Skewness(S_w), shape factor(S_{hf}), impulse factor(I_{mf}), clearance factor (C_{lf}),upper bound (UB)and lower bound(LB) is measured from wavelet packet coefficient of preprocessed signal was used as feature vector of the neural network. In these work total 100 samples of vibration signal is used for training/testing of neural network. Out of 100 samples one input feature vector of the neural network is shown in Table.I

TABLE.I Statistical Parameters value is calculated from WPC signal using minimum Shannon entropy criteria

S. No.	Bearing Condition	P_k	RMS	C_{rf}	K_v	S_w	C_{lf}	I_{mf}	S_{hf}	UB	LB
1	*HB*	0.068	0.026	2.586	2.710	0.0360	3.676	3.167	0.194	0.069	-0.066
2	*REF*	1.567	0.756	2.061	2.415	-0.097	3.049	2.534	1.073	1.576	-1.684
3	*IRF*	6.199	2.305	2.689	3.440	0.264	4.138	3.446	1.883	6.233	-5.575
4	*ORF*	5.055	1.757	2.877	2.749	0.296	4.127	3.545	1.587	5.080	-3.394

V. DATA NORMALIZATION

During training of the neural network, higher valued input variables may tend to suppress the influence of the smaller one. To overcome this problem and in order to make neural networks perform well, the data must be well processed and properly scaled before inputting to the ANN. The raw data are normalized in the range 0.1 to 0.9 to minimize the effect of input variable. The range 0.1 and 0.9 is selected instead of zero and one because zero and one can not be realized by the activation function (sigmoid function). All the component of feature vector are normalized using the following equation.

$$X_i = 0.8\frac{\left(x_i^{old} - \min\left(x_i^{old}\right)\right)}{\left\{\max\left(x_i^{old}\right) - \min\left(x_i^{old}\right)\right\}} + 0.1 \qquad (6)$$

Where, x_i^{old} is actual data, max (x_i^{old}) and min (x_i^{old}) are the maximum and minimum value of the data and X_i is the normalized data.

VI. DESGIN OF FEED FORWARD NEURAL NETWORK CLASSIFIERS

In this paper, three layer feed forward neural network (FFNN) is designed for the fault classification of the rolling element bearing condition. It consists of the input layer, hidden layer and output layer. For training and testing purpose the number of input layer is ten, five hidden layer and four output layer. The output layer of the neural network comprises of four nodes which represents the class of the bearing conditions. Healthy bearing (HB), outer race defect (ORF), inner race fault (IRF) and rolling element fault (REF) respectively. The target vector of output layer nodes of all bearing condition is shown in Table II.

TABLE II. *Target vector for output layer nodes*

***S.N**o*	Bearing defect	Target			
		Node 1	*Node 2*	*Node 3*	*Node 4*
1	*Healthy Bearing(HB)*	0.9	0.1	0.1	0.1
2	*Rolling Element Fault(REF)*	0.1	0.9	0.1	0.1
3	*Inner Race Fault(IRF)*	0.1	0.1	0.9	0.1
4	*Outer Race Fault(ORF)*	0.1	0.1	0.1	0.9

The neural network is trained using an error back propagation algorithm. The training can cease according to the criteria of either mean square error (MSE) reach to certain value or that the epoch of training reaches certain value. In our application a target mean square error of 10^{-5} and a maximum iteration number (epoch) of 1000 is setup. The training process would stop if any of these conditions were met. The initial weights and biases of the network were generated automatically by the program. During our training processes generally the iteration is reached first. The mean square error at this time is used as a criterion for appraising the training performance of the neural network and the classification rate as the criterion for appraising each diagnosis procedure.

VII. RESULT AND DISCUSS

The total of five vibration signal corresponding to each bearing condition is recorded for fault classification. The length of the each signal is 50000. This 50000 data is segmented into five so that signal length is 10000. Therefore number of vibration signal recorded for one bearing condition are 5*5=25sample. Hence for four bearing faults total 100 vibrations recorded signal are available for fault classification. Out of 100 samples 40% of data is training purpose and 60% of data is testing purpose in the neural network for fault classification .The classification rate of bearing fault is shown in Table III.

TABLE III. *Classification rate of Rolling Element Bearing Faults*

Total number of samples 100						
S. No	*Fault type*	*Training sets*	*Testing sets*	*Correct classification*	*Misclassification*	*Classification rate*
1	HB	10	15	15	0	100%
2	REF	10	15	15	0	100%
3	IRF	10	15	14	1	93.33
4	ORF	10	15	15	0	100%
Total		40	60	59	1	98.33%

Out of these testing data sets 15, 15, 14 and 15 is correctly classified and 0,0,1,0 is misclassified for rolling element bearing faults, HB, REF, IRF, ORF respectively. It is observed form Table 3.The classification rate of individual bearing faults is 100%, 100%, 93.33%, 100% HB, REF, IRF, and ORF respectively. The overall fault classification rate is 98.33% of the artificial neural network fault classifier.

VIII. CONCLUSION

This paper has investigated the feasibility of applying wavelet packet decomposition for feature extraction of vibration signals. To alleviate the time-invariant characteristics of the wavelet packet coefficients and to reduce the dimensionality of the input to the neural network, the statistical parameters are used to measure the features value of the signal. The features obtained by proposed method for vibration signal yields nearly 98.33% correct classification when used as input to a neural network classifier

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