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Bearing Health Condition Monitoring: Wavelet Decomposition

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Abstract

Background/Objectives: Condition monitoring is one of the important functions to be carried out in the maintenance of any machine. In condition monitoring, there are several techniques among which the most commonly used technique for rotating machines is the vibration analysis. **Methods/Statistical analysis**: Discrete Wavelet Transform is used to decompose the vibration signal into 9 levels. For each level, mean ±std (standard deviation) are computed for both approximated and detailed coefficients. **Findings**: Bearing data obtained from the bearing test rig of Case Western Reserve University are used to test the algorithm. The standard of coefficients in level to 3 shows distant classification of faults. The levels which show clear classification among the bearings are those frequency bands in which the characteristic defect frequencies of faults occur. It is inferred that, the wavelet decomposition classifies the ball defect clearly than the frequency domain methods. **Application/Improvements**: Wavelet based bearing health condition monitoring technique can be used for bearing fault diagnosis and it can be extended for prognosis.

Keywords: Bearing Health Diagnosis, Condition Monitoring, Failure Analysis, Vibration Analysis, Wavelet Decomposition

1. Introduction

In recent years, condition monitoring has gained a lot of importance in the manufacturing sector. This is because of the fact that, the costs involved in performing condition monitoring of a machine is much lesser than the amount required for repairing the machine once it has become completely deteriorated. The time spent in maintenance will also be lesser for a machine undergoing condition monitoring. There are lot of techniques for condition monitoring such as static, dynamic, thermal and Tribology[1], among which vibration falls under the dynamic techniques.

Bearing is one of the crucial components of an engine. If a bearing defect is detected in earlier stages, then the bearing can be replaced than replacing the entire motor, which saves a lot of cost[2]. It is the main component of any rotating machine. It is used to transfer load between components which in turn reduces friction between them and it facilitates smooth rotation. In this paper, deep groove ball bearing is considered. The rolling element in this bearing is ball. The components of a bearing are the outer race (ring), inner race (ring), balls and cages (separator). The cages are used to prevent friction among the balls. Bearing fault may occur in any of these components. The basic structure of the bearing explaining the components of the bearing is shown in Figure 1.

In vibration based condition monitoring, there are three techniques. Time domain analysis consists of finding different parameters and classifying them according to the

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mean ± standard deviation values of those parameters. In Reference [3], time domain analysis has been carried out using the raw vibration signal, time derivative and time integral of the raw vibration signal and the faults were classified using the values of mean ± standard deviation of the parameters. In Ref.[1], frequency domain analysis was carried out in which several characteristic defect frequencies were calculated based on the dimensions of the bearing and the frequency spectrum was obtained using methods such as Fast Fourier Transform (FFT), Envelope Analysis and Resampling. In these frequency spectrums, the characteristic defect frequencies of the bearing and the harmonics were obtained as peaks corresponding to the particular defect.

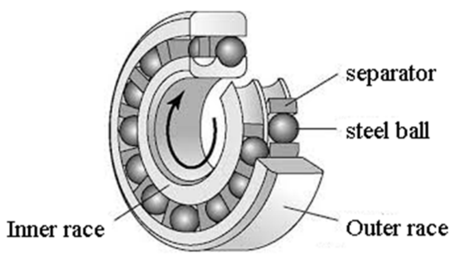


Figure 1. Components of a Ball Bearing[3].

There are three types of time frequency methods such as Short Time Fourier Transform (STFT), Wavelet Transform and Wigner-Ville Distribution (WVD). These give both time information and frequency information. Ref.[4] gives a detailed review on the techniques used in time frequency method. Apart from the above techniques, there is another type of wavelet transform, which is wavelet decomposition. It is the process where the signal is divided into several frequency bands called levels and filters are applied to each level to find out various coefficients which in turn help in classifying the fault in the bearing.

2. Wavelet Decomposition

In Discrete Wavelet Transform (DWT), the signal is divided into many segments, where each segment has several levels. Each level has a high frequency range and a low frequency range. The part with a low frequency range and high-scale is called as 'Approximation' part and the one with high frequency range and low-scale is called as 'Details' part[5]. DWT forms the basis for wavelet decomposition. The approximation part is obtained by passing the signal through Low Pass Filter (LPF) and Detail part is obtained by passing it through High Pass Filter (HPF). The procedure by which this is done is called mallat (pyramidal) algorithm. This concept is illustrated in Figure 2.

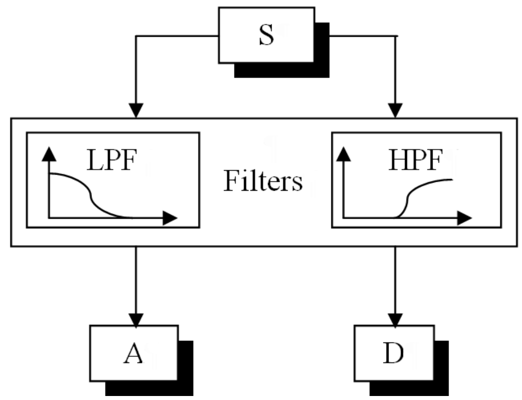


Figure 2. Signal Decomposition[5].

In Figure 2, S is the raw vibration signal; A and D represent the Approximation and Details part respectively. Each Approximation part is further decomposed into approximation and details parts, whereas the details part is not further decomposed. If this is done for only one level, it is called discrete wavelet transform. When this low pass and high pass filtering process is carried on further for many levels, the discrete wavelet transform is called as wavelet decomposition.

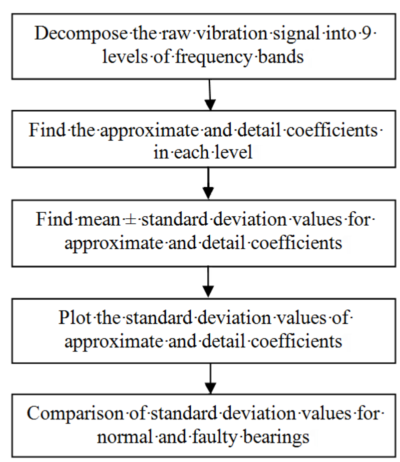


Figure 3. Overall Flow of Wavelet Decomposition Process.

At any decomposition level j, the raw vibration signal can be represented as the sum of approximation and detail coefficients, as given by equation (1).

$$S = A_j + \sum D_i \, (i \leq j) \quad (1)$$

Where, A_j is the approximation coefficient at the j^{th} level

D_i is the detail coefficient

Wavelet packet decomposition is a type of wavelet transforms where there are more filters than the DWT. The difference between wavelet decomposition and wavelet packet decomposition is that, in wavelet decomposition, only the approximation parts are decomposed further, whereas in wavelet packet decomposition, the details part is also decomposed into several levels[6].

Once different levels are obtained for each frequency band, mean ± standard deviation values can be calculated for each segment as well as the overall mean ± standard deviation values for each level. In addition to that, the standard deviation values can be plotted in order to obtain classification of faults in the bearing. In Reference [7], wavelet decomposition has been performed and variance of coefficients was found for various levels for classifying between the normal and faulty bearings. Good classification was obtained using variance and the bands in which characteristic defect frequencies were present were also found out using scatter plot. In this paper, nine levels of decomposition have been carried out. The number of levels has been chosen as nine since the cage frequency falls in the frequency band of 0-24 Hz and if it is split further, the frequency information will be lost.

The overall flow of the process is explained in Figure 3.

3. Results and Discussions

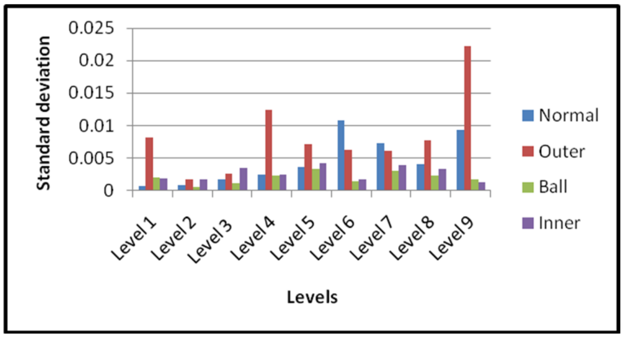
The wavelet decomposition was carried out on the bearing data obtained from the bearing test rig of Case Western Reserve University[8]. In this data, the sampling frequency is 12000 Hz. The total number of samples is divided into ten segments of 12000 samples each and then the mean ± standard deviation values were calculated. The nine decomposition levels with the frequency range of the approximate and detail components and the mean ± standard deviation values of approximate and detail coefficients for each level are shown in Table 1.

Table 1 can be plotted in bar chart form in order to obtain a clear idea on the standard deviation values as shown in Figure 4a and 4b.

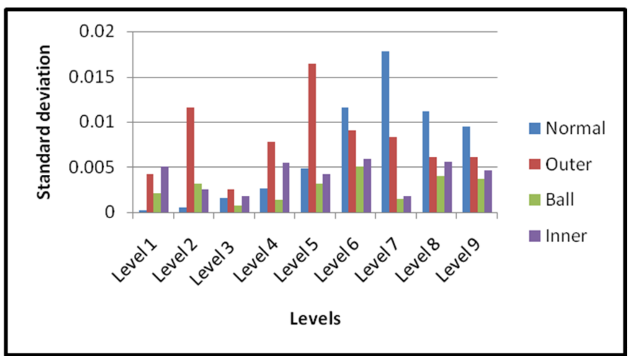
Table 1. Mean ± standard deviation values of approximate and detail coefficients

Level	Low freq	High freq	Mean ± std of Approx/Detail coefficients							
			Normal		Outer race defect		Ball defect		Inner race defect	
			Approx	Detail	Approx	Detail	Approx	Detail	Approx	Detail
1	0-6000	6000-12000	0.0166 ± 0.0007	1.49e-07 ± 0.00017	0.0055 ± 0.0082	-3.15e-07 ± 0.0042	0.0065± 0.0021	-1.35e-06 ± 0.0021	0.0064 ± 0.0019	-4.88e-07 ± 0.0051
2	0-3000	3000-6000	0.0235 ± 0.0009	1.53e-06 ± 0.00055	0.0078 ± 0.0017	-0.0012 ± 0.0116	0.0091 ± 0.0006	-0.0026 ± 0.0032	0.0091 ± 0.0018	-0.0004 ± 0.0025
3	0-1500	1500-3000	0.0333 ± 0.0018	-6.17e-05 ± 0.0016	0.0111 ± 0.0027	-0.0015 ± 0.0025	0.0129 ± 0.0012	-5.53e-05 ± 0.00071	0.0129 ± 0.0035	0.0004 ± 0.0018
4	0-750	750-1500	0.0471 ± 0.0025	0.00016 ± 0.0026	0.0157 ± 0.0125	-0.0001 ± 0.0078	0.0183 ± 0.0024	-4.30e-05 ± 0.0014	0.0182 ± 0.0025	0.0011 ± 0.0055
5	0-375	375-750	0.0666 ± 0.0036	4.28e-05 ± 0.0048	0.0221 ± 0.0072	-0.0106 ± 0.0164	0.0258 ± 0.0033	-0.0003 ± 0.0032	0.0258 ± 0.0042	-0.0002 ± 0.0042
6	0-188	188-375	0.0939 ± 0.0108	-0.0019 ± 0.0116	0.0311 ± 0.0063	-0.0003 ± 0.0091	0.0366 ± 0.0014	0.0001 ± 0.0051	0.0365 ± 0.0018	-0.0005 ± 0.0059
7	0-94	94-188	0.1328 ± 0.0073	-0.0094 ± 0.0178	0.0439 ± 0.0062	0.0001 ± 0.0083	0.0518 ± 0.0031	-0.0009 ± 0.0015	0.0516 ± 0.0040	-0.0012 ± 0.0018
8	0-47	47-94	0.1878 ± 0.0041	0.0065 ± 0.0112	0.0621 ± 0.0078	0.0013 ± 0.0061	0.0733 ± 0.0023	-0.0003 ± 0.0040	0.0730 ± 0.0033	0.0004 ± 0.0056
9	0-24	24-47	0.2630 ± 0.0093	-0.0019 ± 0.0095	0.0864 ± 0.0222	0.0021 ± 0.0061	0.1037 ± 0.0018	-0.0004 ± 0.0037	0.1032 ± 0.0013	0.0011 ± 0.0046

Through Figure 4a and 4b, it can be inferred that, the standard deviation values show a good difference among the normal and faulty bearing values. The following results illustrate the standard deviation of approximate and detail coefficients for each level. Figure5 shows standard deviation of approximate and detail coefficients for level 1.



(a)



(b)

Figure 4. (a) Standard deviation of approximate coefficients and (b) Standard deviation of detail coefficientsts.

From Figure 5 It can be observed that, there is a clear differentiation among the normal and different faulty bearings for standard deviation of both approximate and detail coefficients for level 1. Figure 6 Shows standard deviation of approximate and detail coefficients for level 2.

Similar to Figure 5 Figure 6 Also shows a clear differentiation among the normal and faulty bearings with both approximate and detail coefficients. Figure 7 Shows standard deviation of approximate and detail coefficients for level 3.

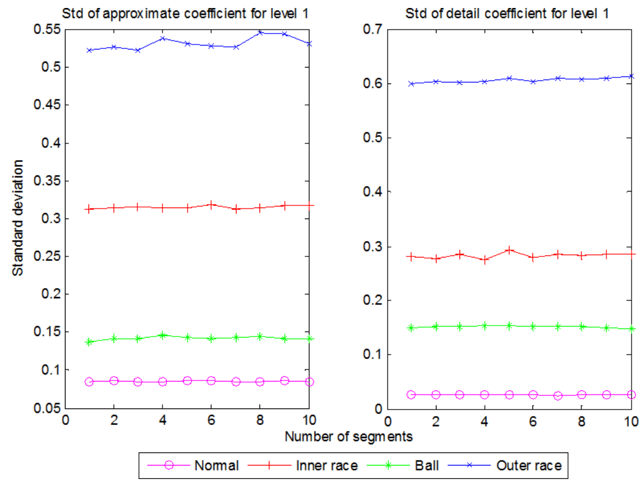


Figure 5. Standard deviation of approximate and detail coefficients for level 1.

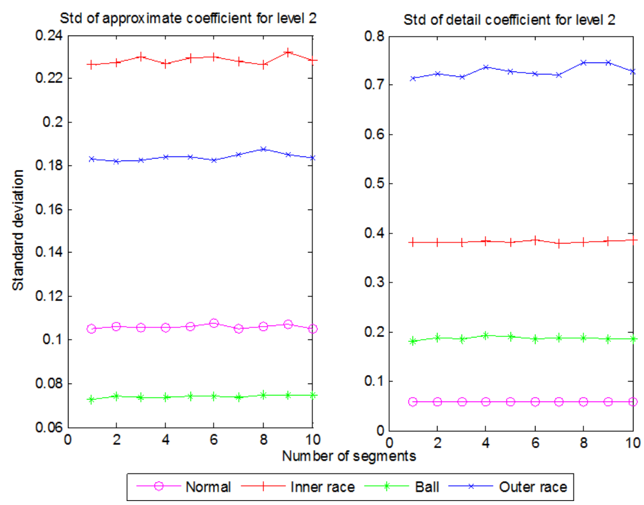


Figure 6. Standard deviation of approximate and detail coefficients for level 2.

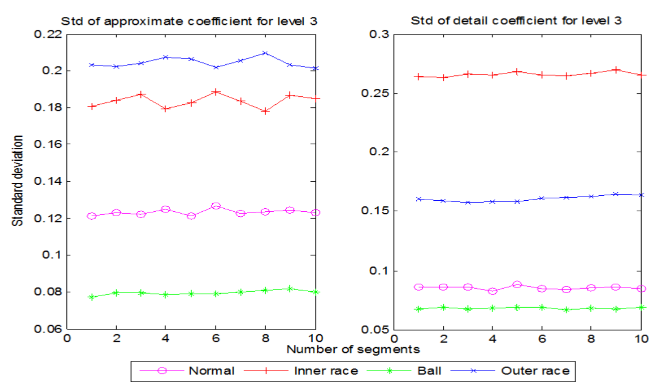


Figure 7. Standard deviation of approximate and detail coefficients for level 3.

From Figure 7 It can be observed that, standard deviation values of approximate and detail coefficients for level 3 classify the faults properly similar to the previous levels. Figure 8 Shows standard deviation of approximate and detail coefficients for level 4.

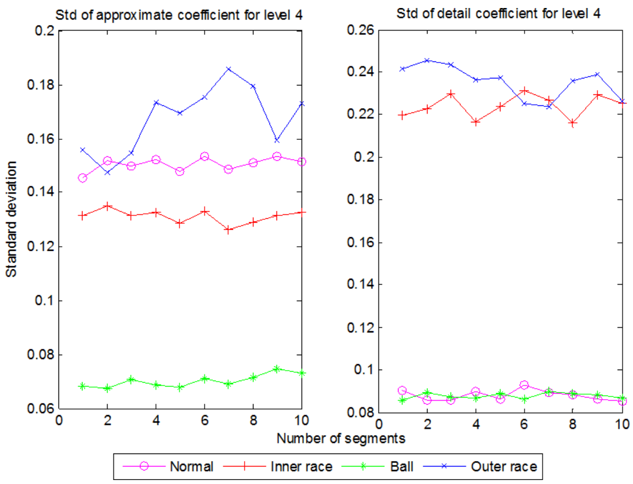


Figure 8. Standard deviation of approximate and detail coefficients for level 4.

In Figure 8 it can be seen that, the standard deviation values of normal bearing coincides with the outer race defective bearings in case of approximate coefficients. On the other hand, inner and outer race coincide with each other and normal and ball defective bearings coincide with each other in case of detail coefficients. Figure 9 Shows standard deviation of approximate and detail coefficients for level 5.

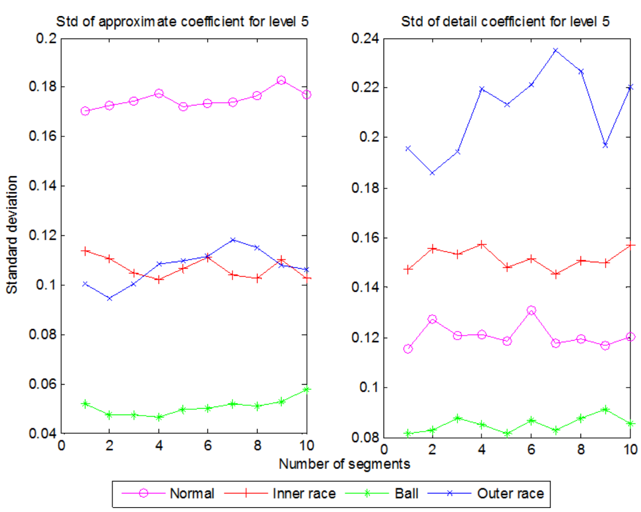


Figure 9. Standard deviation of approximate and detail coefficients for level 5.

In Figure 9 Though all the cases are clearly differentiated from each other in detail coefficients, there is an overlap of values between inner and outer race defective bearings in approximate coefficients. Figure10 Shows standard deviation of approximate and detail coefficients for level 6.

From Figure 10 It can be seen that, in both approximate and detail coefficients, there is an overlap of standard deviation values between the inner and outer race defective bearings. The remaining cases of bearings are clearly classified. Figure 11 Shows standard deviation of approximate and detail coefficients for level 7. \

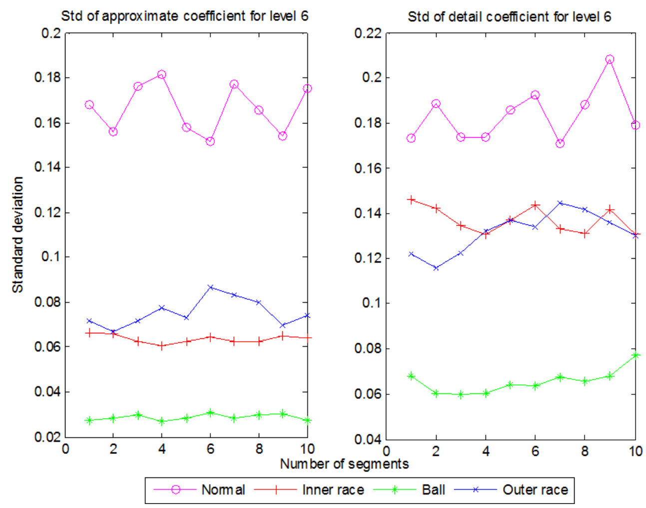


Figure 10. Standard deviation of approximate and detail coefficients for level 6.

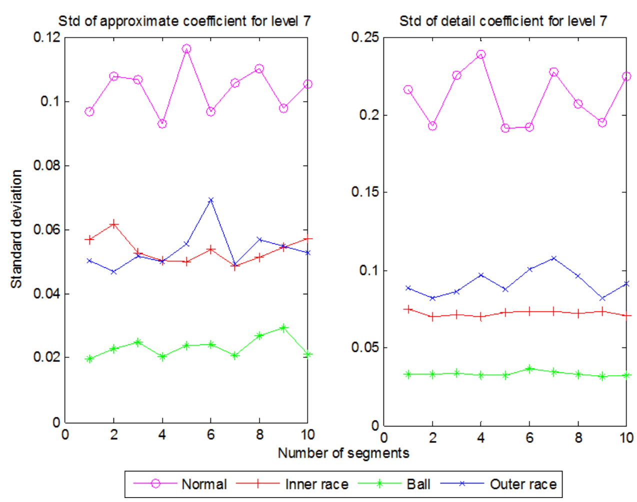


Figure 11. Standard deviation of approximate and detail coefficients for level 7.

In Figure 11 Approximate coefficients case is similar to the previous case in that, the standard deviation values of inner and outer race defective bearings overlap, whereas in details coefficients case, the differentiation is clear among all the cases of bearing. Figure 12 Shows standard deviation of approximate and detail coefficients for level 8.

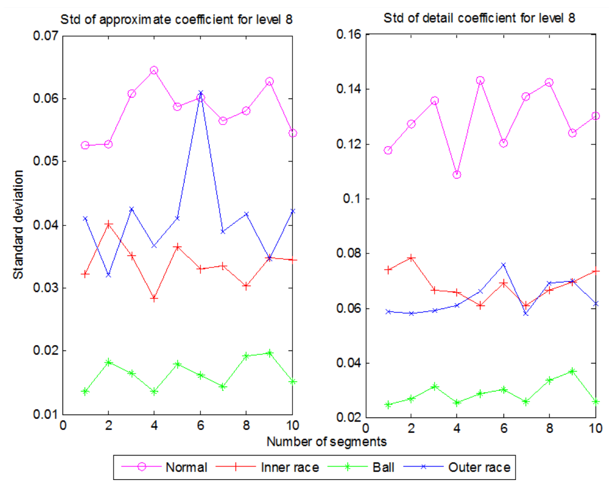


Figure 12. Standard deviation of approximate and detail coefficients for level 8.

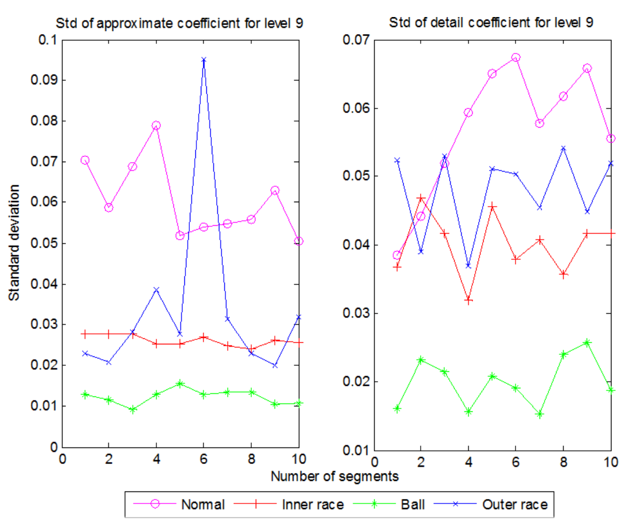


Figure 13. Standard deviation of approximate and detail coefficients for level 9.

From Figure 12 It can be observed that, there is a complete overlap between inner and outer race defective bearings and one standard deviation value is coinciding between normal bearings and outer race defective bearings in case of approximate coefficients. In case of detail coefficients, inner and outer race defective bearings coincide with each other, but the normal and ball defective bearings are clearly separated. Figure 13 Shows standard deviation of approximate and detail coefficients for level 9.

From Figure 13 It can be inferred that, in both the cases, i.e., approximate and detail coefficients, except ball defective bearings, standard deviation values of all the remaining bearings overlap with each other.

Overall, it can be summarized that, the levels which show clear classification among the bearings are those frequency bands in which the characteristic defect frequencies of faults occur. In addition to that, it can be inferred that, the wavelet decomposition classifies the ball defect clearly than the frequency domain methods.

4. Conclusion

In this paper, the wavelet decomposition, one of the types of discrete wavelet transform was discussed in detail and was tested on the bearing data obtained from the bearing test rig of Case Western Reserve University. The mean ± standard deviation values of the approximate and detail coefficients have been found out for nine levels of wavelet decomposition of the signal. The standard deviation of the approximate and detail coefficients were plotted and it was found that, this method classifies the bearing faults in an accurate manner and that, it classifies ball defect better than the frequency domain and time domain techniques considered individually.

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