# Bearing Fault Diagnosis using DWT& SVM

Rajani J.
Dept. of Avionics
Inst. of Science & Technology, JNTUK
Kakinada, India

VPS Naidu
Multi Sensor Data Fusion Lab
CSIR – National Aerospace Laboratories
Bangalore, India

***Abstract*— Bearings are very critical components in all rotating machines used in the majority of the industries. Vibration analysis based condition monitoring is one of the best approaches for maintenance and diagnosing the faults in the rotating machinery. This paper deals with the vibration-based health condition-monitoring techniques used for bearing fault diagnosis. Discrete wavelet transform (DWT) and support vector machines (SVM) have been presented for the statistical feature extraction and fault classification of the bearings respectively. The useful features from normalized wavelets energy analysis and wavelets variance have been extracted. The results reveal that the vibration based health condition monitoring method is successful in fault diagnosis and clear classification of bearing faults using DWT and SVM.**

***Keywords*— Discrete wavelet transform; Bearing Health Condition Monitoring; Vibration Analysis; SVM***

## I. INTRODUCTION

The majority of the engines used in all industries comprises of rotating parts. The health condition monitoring of these crucial rotating components results in the reduction of maintenance and operating costs, improved security level as well as improved efficiency of the engine. As the condition monitoring has acquired great significance in manufacturing field, the vibration-based techniques for fault diagnosis are widely employed. For revealing the bearing faults vibration based techniques gives best results compared to other techniques. The bearing data used for vibration analysis is Bearing test rig experimental data conducted by National Aerospace Laboratories (NAL) [1].

In this paper, feature extraction and fault diagnosis is carried out using wavelets whereas classification of various bearing faults [2] such as outer race defect (ORD), inner race defect (IRD), roller element (ball segment) defect (BSD) among healthy bearing (HB) is done using Support Vector Machines.

## II. METHODOLOGY

Vibration analysis based bearing health Condition monitoring techniques are of paramount importance because the costs associated with repairs and maintenance is significantly greater than the monitoring cost as well as the time consumption for condition monitored machine maintenance is very less [3]. The information flow diagram of the proposed algorithm for bearing fault detection and classification is shown in Fig. 1.

### *A. Bearing Data Collection*

Faulty bearing component produces vibration. The accelerometer (sensor) mounted on the bearing housing is used for measuring the bearing vibrations. These vibrations are recorded using the data acquisition device called OROS 3x DAQ as shown in Fig. 1 [1].

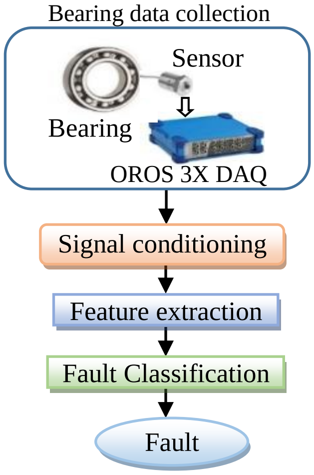


Fig. 1. Information flow for the proposed methodology

### *B. Signal conditioning & pre-processing*

After obtaining data, signal conditioning which is nothing but time derivative of the vibration signal is carried out to enhance the frequency of the vibration signal. Then the signal is divided into 16 segments of each window length 32768 ($2^{15}$) samples (This process is called segmentation) for further processing.

### *C. Feature Extraction*

The signal is processed for diagnosing the fault. The fault diagnosis and type of fault can be analyzed from the bearing signal using vibration analysis. The feature extraction approaches used in vibration analysis are time domain analysis, frequency domain analysis, and time-frequency domain analysis [4].

### *D. Discrete Wavelet Transform:*

The DWTis an efficient mathematical tool for representing the vibration signal in time-frequency domain and for detecting the bearing faults.DWT is extensively used for multiresolution signal analysis [5]. It is an implementation of the wavelet transform, which decomposes the signal as the mutually perpendicular set of wavelets. DWT extracts precise features of time and frequency data at high and low frequencies respectively. First, the signal is decomposed using a high scale, low pass filter (LPF) and the filter output is called as “Approximation coefficient” (A). Simultaneously the signal is also decomposed using a low-scale, high pass filter

(HPF)& the output of this filter is known as "Detailed Coefficient" (D) [6]. This decomposition is repeated to further increase the frequency resolution. Therefore, a series of filters have been used to decompose the vibration signalusing DWT [7].

The vibration signal has been acquired at a sampling rate/frequency ($F_s$) of 25600Hz. Then, the maximum frequency present in the signal is 12800Hz i.e., ($F_s$/2). The vibration signal is decomposed up to 12 levels because beyond this there are no much useful frequency components present in the signal. Fig. 2 shows the decomposition process using DWT of a vibration signal from the frequency 12800Hz to 3.125Hz.

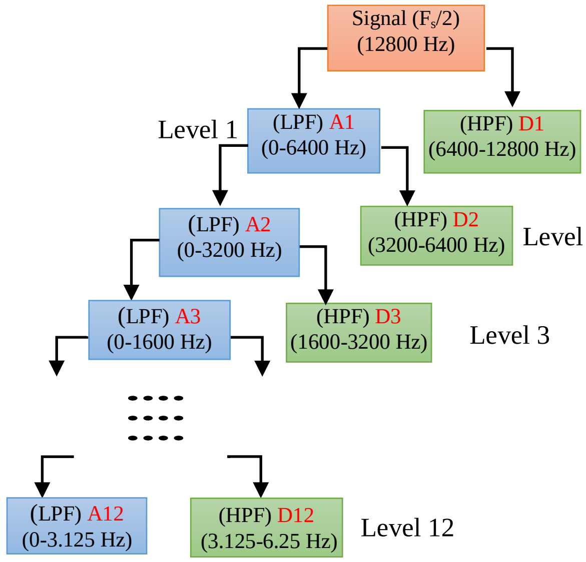


Fig. 2. Decomposition of a signal using DWT

The energy distribution of the bearing vibration signal with different faults is dissimilar at different frequency bands. The energy of the signal at different decomposition levels is the energy of the wavelet coefficients and can be segregated at distinct resolution levels. Theenergy of the detailed coefficients at $j^{th}$ level is computed as [8]:

$$E_j = \sum_{k=1}^{\frac{N}{2^j}} \left| d_{j,k} \right|^2 \quad (1)$$

Where $j = 1,2,\ldots,J$ decomposition level

$k = 1,2,\ldots,\frac{N}{2^j}$ Index of decomposition coefficients and

$N$ Length of the vibration signal

Energy of the approximation coefficients at $J^{th}$ level is computed as:

$$E_{J+1} = \sum_{k=1}^{\frac{N}{2^J}} \left| c_{J,k} \right|^2 \quad (2)$$

The total energy of the vibration signal is:

$$E_{Total} = \sum_{j=1}^{J+1} E_j \quad (3)$$

The time scale density or relative wavelet energy (RWE) of the bearing vibration signal (Eq. (4)) is calculated in such a way that $\sum D_j + A = 100,\ j = 1,2,\ldots,J$ for all wavelet coefficients and it represents the energy corresponding to different frequency bands of the bearing vibration signal.

$$D_j = \frac{E_j}{E_{Total}} 100,\ j = 1,2,\ldots,J$$

$$A = \frac{E_{J+1}}{E_{Total}} 100 \quad (4)$$

The normalized wavelet energy as given in Eq. (4) have been computed for all wavelet coefficients. Then the mean ± standard deviation for the coefficients normalized wavelet energy is calculated to extract the useful features. In addition to that, the variance of the coefficients also calculated for various levels for extracting the features from the bearing vibration signal for classifying the faults.

### *E. Fault Classification*

The support vector machines are used as the classification algorithm to classify the normal and faulty bearings in this study. Support vector machines are supervised and statistical learning models, conventionally described by partitioning hyperplanes, used for both classification and regression challenges. SVMs are having inbuilt leaning techniques/models like SVM Classifier [9]. It analyses, recognizes patterns according to the variation of values in given vibration data, trains itself and then used as a classifier for classifying the bearing faults. Hyper-planes are used to differentiate two or more classes of data with the help of support vectors. These support vectors are the coordinates of each measurement. SVM gives a good margin of separation only when there is a larger distance between the nearest training data of any class & the hyper-plane [10]. The SVM classifier takes useful features extracted from DWT as inputs to classify the bearing faults.

## III. RESULTS AND DISCUSSIONS

The vibration signals for healthy and defective (BSD, IRD & ORD) bearings are shown in Fig. 3. It is observed that all the four signals are looks like the noise. The inner and outer race defective bearing signals have greater magnitude compared to ball defective and healthy bearing vibration signals. It can also be observed that the magnitude of ball defective and healthy vibration signals are looks like same.

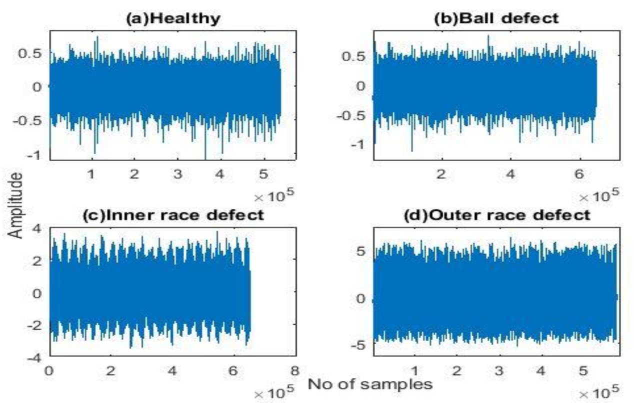


Fig. 3. Vibration signal of the bearing with different Faults

Thirteen features viz., A, D1, D2, …,D12 are computed using eq. (4). The mean ± standard deviation of these features for12 decomposition levels are as shown in Table I. From this Table, the features viz., A, D1 to D5 (marked as green in color) are useful features as these features are giving clear classification when the raw vibration signal is used in the analysis. For time derivative of the bearing vibration signal, the following features viz., D1, D3 to D9 are perfectly classifying the faults. The features marked as yellow color in Table I are partially classifying the bearing faults. Similarly, Table II represents the wavelets variance of both time derivative and the raw vibration signal.

From Table II, it can be observed that for the raw signal, the features D1 and D2 are best classifying the faults & for time derivative signal, D1 to D4 are useful features to classify the bearing faults, which are highlighted with green color.

The RWE of 12th level detailed coefficient for raw & time derivative vibrational signal is shown in Fig. 4. It can be observed that it is very difficult to classify the faults (HB,BSD & IRD) except ORD since the feature (D12) for faults are overlapping while the raw signal is considered. Whereas for time derivative signal, except for HB, remaining all bearing faults are overlapped each other. Therefore, D12 (Detailed coefficient of level 12) marked as white color in Table I andis not a useful feature in fault classification. Fig.5 shows the RWE at 5th level(D5) of the vibration signal.

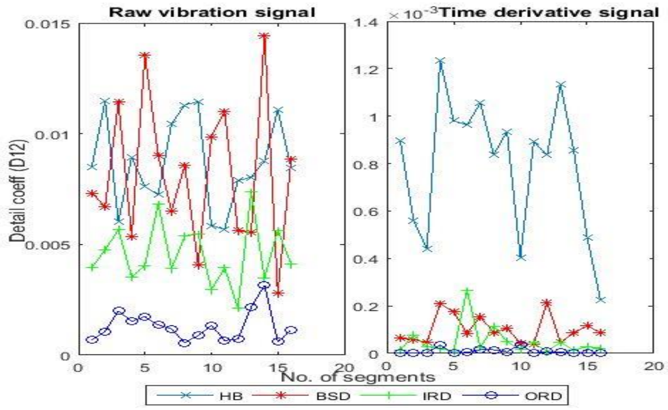


Fig. 4. Detailed coefficient (D12) for fault classification

From Fig.5, it is observed that all the faults are clearly distinguished for both time derivative and raw vibration signal. Therefore, D5 is a very useful feature for classifying the faults (marked as green color in Table I). The statistical and useful features obtained from the DWT have been formed into feature vectors. The SVM classifier uses all these useful features (support vectors) from normal and faulty bearings as inputs to classify between the faults.

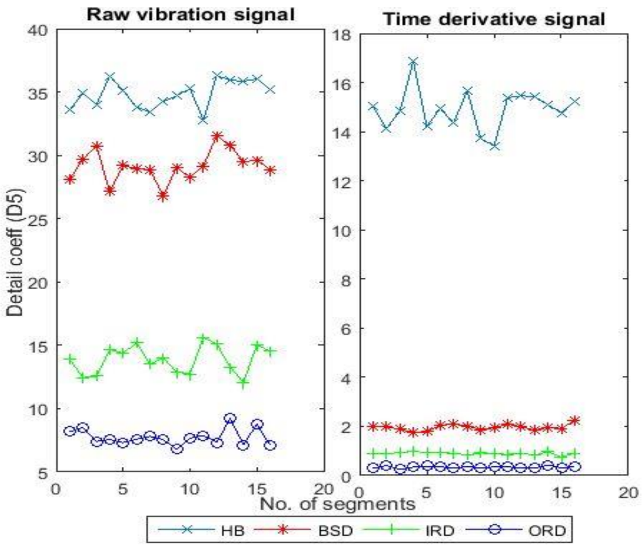


Fig. 5. Detailed coefficient (D5) for fault classification

Fig. 6 shows the bearing fault classification with SVM classifier using wavelets energy features D10 (Level 10 Detailed coefficients) and D12 (Level 12 Detailed Coefficients). It can be observed that healthy, ball defective vectors have been completely merged. Therefore, there is no clear classification between the faults by choosing these features. A similar observation has been made with the features marked with white color in Table I & II.

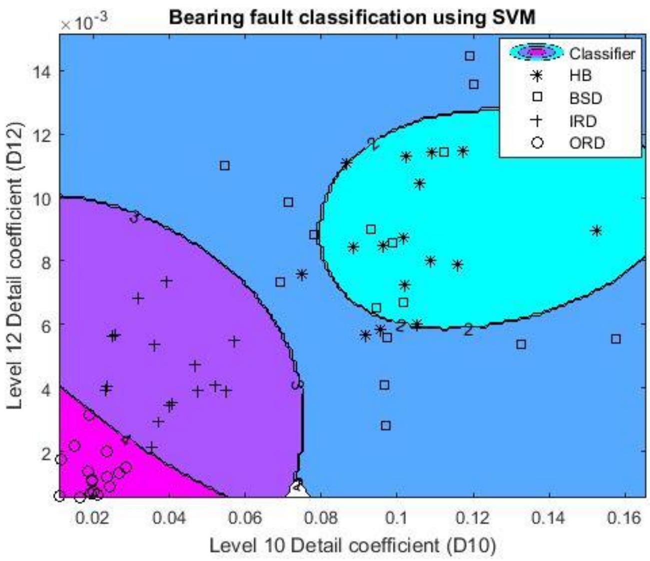


Fig. 6. SVM bearing fault classification using D10 and D12

SVM classification using D4 and D5 variance features are shown in Fig. 7. It can be observed that the SVM classifier using these features clearly classify the outer and inner race failures but it fails to classify the ball defect and healthy bearings. Same observation has been made with the features marked in yellow color in Table II.

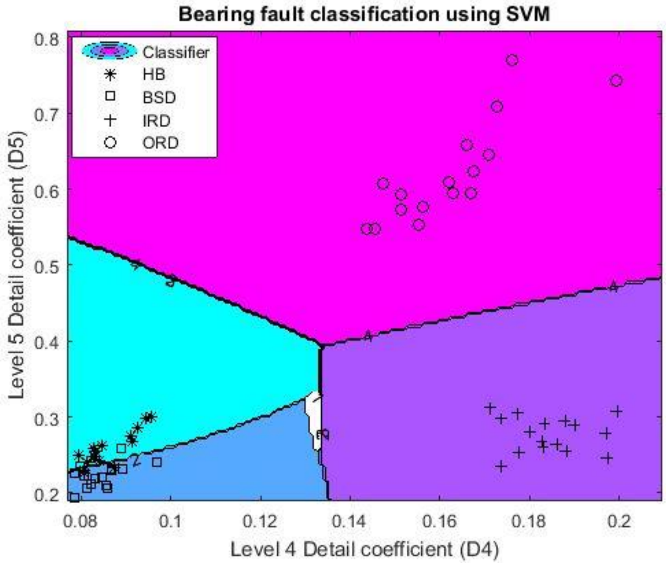


Fig. 7. SVM bearing fault classification using D4 and D5

The SVM classifier for bearing fault classification using the features of approximation coefficients (A) and detailed coefficients at level 1 (D1) is shown in Fig. 8. It can be observed thatthese features can be useful to classify the bearing faults very clearly. The features shown in green color in Table I & Table II are very useful for bearing fault classification.

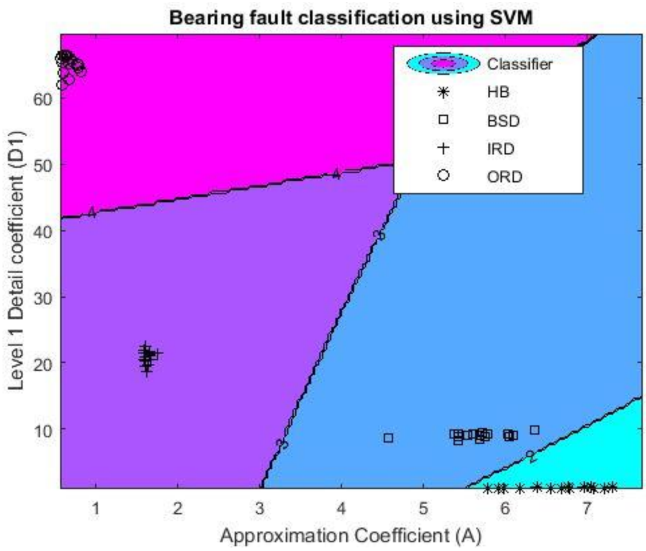


Fig. 8. SVM bearing fault classification using A and D1

All the features have been summarized and their usefulness in classifying the faults are shown in Table III.The features that are very useful for bearing faults classification using SVM classifier are shown in Table III with green color. Similarly, the features shown with yellow color in Table III are marginally classifying the faults. Other features that are shown with white color in the Table are not useful features for bearing fault classification. Therefore, the wavelets energy features D1, D3, D4 & D5 and the wavelets variance features D1 and D2 (marked completely with green color in Table III) are best features in all the cases to classify the bearing faults. Hence, only the above-mentioned features are useful features and the remaining features are not much useful and unable to classify the bearing faults.

## IV. CONCLUSION

This papermainly focuses on the vibration based bearing health condition monitoring techniques that can be efficiently used for bearing fault diagnosis and classification of faults. Discrete wavelet transforms are used for the decomposing the bearing vibration signal into different frequency bands. Features such as wavelets energy and variance of the coefficients for all decomposition levels have been calculated. These features were fed to the SVM classifier to classifying the bearing faults. The results reveal that the proposed algorithm for vibration-based health condition monitoring is successful in bearing faults diagnosis as well as clearfault classification byusing discrete wavelet transform and support vector machines. The proposed algorithm is very simple and easily adoptable for other applications.

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## REFERENCES

[1] Sarvajith M, BrijeshKumar Shah, DushyanthN.D and S. Jana, “A Novel Approach for Bearing Fault Detection and Classification using AcousticEmission Technique”, UACEE International Journal of Advances in Electronics Engineering, Volume 2, Issue 2, pp.73-76, 2012.

[2] J. Rajani and VPS Naidu., “Bearing Health Condition Monitoring using Time Domain Analysis and SVM”, CADFEJL Vol. 1, No. 5, pp. 02-11, Sep-Oct 2017.

[3] S. Devendiran and K. Manivannan, “Vibration Based Condition Monitoring and Fault Diagnosis Technologies for Bearing and Gear Components-A Review”, International Journal of Applied Engineering Research ISSN 0973-4562, Volume 11, Number 6, pp.3966-3975,2016.

[4] Hongyu Yang, “Automatic Fault Diagnosis of Rolling Element Bearings Using Wavelet Based Pursuit Features”, Ph. D. thesis paper Queensland University of Technology, October 2004.

[5] Boufenar M, Rechak S,Rezig M.,“Time-Frequency Analysis Techniques Review and their Application on Roller Bearings Prognostics”, Proceedings of the Second International Conference on Condition Monitoring of Machinery in Non-Stationary operations (CMMNO’2012). Springer. 2012. p. 239–46.

[6] V. Shanmukha Priya, P. Mahalakshmi, and VPS Naidu, “Bearing Health Condition Monitoring: Wavelet Decomposition”, Indian Journal of Science and Technology, Vol 8(26), IPL0569, October 2015.

[7] Theodoros Loutas, Vassilis Kostopoulos, “Utilising the Wavelet Transform in Condition-Based Maintenance: A Review with Applications”, Advances in Wavelet Theory and Their Appl. in Eng. Physics and Technol. ISBN: 978–953-51–0494-02012, pp 273-312, April 2012.

[8] Ling Guo, Daniel Rivero, Jose A.Seoane and Alejandro Pazos, “Classification of EEG signals using relative wavelet energy and artificial neural networks”, GEC ’09 Proceedings of the first ACM/SIGEVO Summit on Genetic and Evolutionary Computation, ISBN: 978-1-60558-326-6, DOI: 10.1145/1543834.1543860, January 2009.

[9] https://en.wikipedia.org/wiki/Support_vector_machine, “Support vector machine”, accessed on January 1, 2018.

[10] Shanmukha Priya V., M. R. Ramesh, and VPS Naidu, “Bearing fault Classification using Support Vector Machines” Paper No. T01, pp.1-8, ASI-HMFD 2015, organized by VSSC, Trivandrum, May 22-23, 2015.

TABLE I. THE MEAN ± STANDARD DEVIATION OF NORMALIZED WAVELETS ENERGY

| Coeff. | Raw Data | | | | Time Derivative Data | | | |
|---|---|---|---|---|---|---|---|---|
| | *HB* | *BSD* | *IRD* | *ORD* | *HB* | *BSD* | *IRD* | *ORD* |
| **A** | 6.67581 ± 0.491487 | 5.659205 ± 0.404676 | 1.627159 ± 0.041347 | 0.669106 ± 0.081293 | 0.0003 ± 0.000196 | 4.49E-05 ± 2.35E-05 | 1.13E-05 ± 1.48E-05 | 4.11E-06 ± 7.55E-06 |
| **D1** | 1.142558 ± 0.061398 | 9.066008 ± 0.40303 | 20.83839 ± 0.947702 | 64.99424 ± 1.299243 | 25.2523 ± 0.761501 | 76.41855 ± 0.597494 | 73.24542 ± 0.958392 | 88.80041 ± 0.073531 |
| **D2** | 3.061952 ± 0.110142 | 5.311781 ± 0.2352 | 14.05252 ± 0.701104 | 7.492921 ± 0.288064 | 15.95002 ± 1.813693 | 10.09764 ± 0.455621 | 13.57934 ± 0.473321 | 5.052015 ± 0.206165 |
| **D3** | 9.40048 ± 0.179102 | 10.1629 ± 0.209474 | 20.3478 ± 0.591977 | 5.58935 ± 0.240153 | 16.02055 ± 0.550086 | 7.206271 ± 0.166744 | 9.116643 ± 0.587471 | 5.083049 ± 0.168922 |
| **D4** | 23.31539 ± 0.488664 | 22.03825 ± 0.759546 | 18.46013 ± 0.756347 | 4.047846 ± 0.301875 | 22.76777 ± 1.096602 | 3.712715 ± 0.168231 | 2.935694 ± 0.24267 | 0.651449 ± 0.071971 |
| **D5** | 34.83552 ± 1.101111 | 29.14137 ± 1.239851 | 13.87262 ± 1.115626 | 7.742929 ± 0.648059 | 14.90887 ± 0.83378 | 1.964814 ± 0.12583 | 0.895306 ± 0.057874 | 0.337641 ± 0.047698 |
| **D6** | 14.38361 ± 0.641283 | 11.97167 ± 0.772466 | 7.642429 ± 0.725722 | 7.874698 ± 0.701372 | 3.820697 ± 0.270275 | 0.447249 ± 0.037432 | 0.165275 ± 0.020312 | 0.059928 ± 0.007778 |
| **D7** | 4.871529 ± 0.379681 | 4.406722 ± 0.356306 | 2.292727 ± 0.202045 | 1.026885 ± 0.073611 | 1.015427 ± 0.07834 | 0.122447 ± 0.009629 | 0.048587 ± 0.007142 | 0.010976 ± 0.002672 |
| **D8** | 1.745955 ± 0.17257 | 1.741607 ± 0.178921 | 0.656592 ± 0.11525 | 0.388579 ± 0.046984 | 0.202963 ± 0.029606 | 0.022618 ± 0.002718 | 0.010507 ± 0.00202 | 0.003255 ± 0.000911 |
| **D9** | 0.421993 ± 0.0806 | 0.357751 ± 0.053837 | 0.14969 ± 0.037383 | 0.147345 ± 0.05682 | 0.046189 ± 0.008156 | 0.005789 ± 0.001009 | 0.002345 ± 0.000635 | 0.000954 ± 0.000302 |
| **D10** | 0.10338 ± 0.017202 | 0.099619 ± 0.02549 | 0.038494 ± 0.011031 | 0.019899 ± 0.004881 | 0.011222 ± 0.00215 | 0.001376 ± 0.000447 | 0.0007 ± 0.000518 | 0.000263 ± 0.000176 |
| **D11** | 0.033152 ± 0.013546 | 0.034952 ± 0.008896 | 0.016879 ± 0.006215 | 0.004905 ± 0.001636 | 0.002887 ± 0.001135 | 0.000385 ± 0.000162 | 0.000114 ± 7.28E-05 | 4.80E-05 ± 3.15E-05 |
| **D12** | 0.008672 ± 0.001996 | 0.008166 ± 0.0033 | 0.004576 ± 0.001403 | 0.001299 ± 0.0007 | 0.000796 ± 0.000287 | 0.000101 ± 5.82E-05 | 4.89E-05 ± 6.44E-05 | 9.08E-06 ± 1.15E-05 |

-Perfect classification; - Moderate classification; - Poor classification

TABLE II. THE MEAN ± STANDARD DEVIATION OF WAVELET COEFFICIENTS VARIANCE

| Coeff. | Raw Data | | | | Time Derivative Data | | | |
|---|---|---|---|---|---|---|---|---|
| | *HB* | *BSD* | *IRD* | *ORD* | *HB* | *BSD* | *IRD* | *ORD* |
| **A** | 0.004124 ± 0.001841 | 0.003836 ± 0.002221 | 0.004558 ± 0.002288 | 0.006372 ± 0.002325 | 1.43E-05 ± 9.24E-06 | 1.80E-05 ± 9.66E-06 | 2.60E-05 ± 3.24E-05 | 0.000121 ± 0.000218 |
| **D1** | 0.000526 ± 3.09E-05 | 0.004322 ± 0.000128 | 0.026017 ± 0.001284 | 0.325819 ± 0.022137 | 00.000531 ± 3.19E-05 | 0.013209 ± 0.000375 | 0.075898 ± 0.003016 | 1.157344 ± 0.077864 |
| **D2** | 0.00282 ± 0.000177 | 0.00507 ± 0.000269 | 0.035075 ± 0.001523 | 0.075074 ± 0.004779 | 0.000673 ± 0.000107 | 0.003494 ± 0.000233 | 0.028129 ± 0.001106 | 0.131586 ± 0.008894 |
| **D3** | 0.01732 ± 0.000997 | 0.019404 ± 0.000783 | 0.10165 ± 0.003968 | 0.112128 ± 0.009204 | 0.001347 ± 7.25E-05 | 0.004984 ± 0.00022 | 0.037778 ± 0.002652 | 0.265231 ± 0.022575 |
| **D4** | 0.085948 ± 0.005361 | 0.084193 ± 0.004963 | 0.184379 ± 0.00881 | 0.162202 ± 0.014123 | 0.003827 ± 0.000247 | 0.005133 ± 0.000223 | 0.024337 ± 0.002213 | 0.067731 ± 0.007284 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **D5** | 0.257365 ± 0.023134 | 0.222885 ± 0.015691 | 0.277372 ± 0.023565 | 0.621641 ± 0.067835 | 0.005017 ± 0.000374 | 0.005435 ± 0.000354 | 0.014842 ± 0.001056 | 0.070573 ± 0.013253 |
| **D6** | 0.212181 ± 0.016336 | 0.18297 ± 0.017202 | 0.30495 ± 0.031552 | 1.262361 ± 0.129428 | 0.002571 ± 0.000196 | 0.002473 ± 0.000187 | 0.005469 ± 0.000691 | 0.024958 ± 0.00346 |
| **D7** | 0.143736 ± 0.011508 | 0.134762 ± 0.012784 | 0.183705 ± 0.017197 | 0.329089 ± 0.01829 | 0.001368 ± 0.000107 | 0.001352 ± 0.00011 | 0.003215 ± 0.00049 | 0.009156 ± 0.002341 |
| **D8** | 0.102626 ± 0.01398 | 0.1065 ± 0.009821 | 0.104856 ± 0.018225 | 0.248823 ± 0.033224 | 0.000542 ± 9.04E-05 | 0.000499 ± 6.33E-05 | 0.001392 ± 0.00028 | 0.005408 ± 0.001477 |
| **D9** | 0.040819 ± 0.006481 | 0.038111 ± 0.005227 | 0.047101 ± 0.011688 | 0.116929 ± 0.01586 | 0.000245 ± 4.42E-05 | 0.000256 ± 4.96E-05 | 0.000616 ± 0.000159 | 0.003137 ± 0.00108 |
| **D10** | 0.023063 ± 0.004036 | 0.024175 ± 0.006195 | 0.02436 ± 0.007714 | 0.050998 ± 0.011384 | 0.000118 ± 2.41E-05 | 0.000122 ± 4.15E-05 | 0.000373 ± 0.000279 | 0.00178 ± 0.001282 |
| **D11** | 0.016039 ± 0.006277 | 0.017574 ± 0.005026 | 0.022473 ± 0.008348 | 0.023597 ± 0.008338 | 6.15E-05 ± 2.67E-05 | 6.58E-05 ± 2.76E-05 | 0.000119 ± 7.73E-05 | 0.000656 ± 0.000461 |
| **D12** | 0.008118 ± 0.002556 | 0.008431 ± 0.003723 | 0.012835 ± 0.004332 | 0.012375 ± 0.005559 | 3.42E-05 ± 1.34E-05 | 3.27E-05 ± 1.83E-05 | 0.000103 ± 0.000145 | 0.000233 ± 0.000298 |

-Perfect classification; - Moderate classification; - Poor classification

TABLE III. USEFULNESS OF FEATURES IN FAULT CLASSIFICATION

| Coeff | Wavelets Energy (RWE) | | | | | | | | Wavelets Variance | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Raw signal | | | | Time derivative signal | | | | Raw signal | | | | Time derivative signal | | | |
| | *HB* | *BSD* | *IRD* | *ORD* | *HB* | *BSD* | *IRD* | *ORD* | *HB* | *BSD* | *IRD* | *ORD* | *HB* | *BSD* | *IRD* | *ORD* |
| **A** | ✓ | ✓ | ✓ | ✓ | ✓ | × | × | × | × | × | × | × | × | × | × | × |
| **D1** | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| **D2** | ✓ | ✓ | ✓ | ✓ | ☑ | ✓ | ☑ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| **D3** | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ☑ | ☑ | ✓ | ✓ | ✓ | ✓ |
| **D4** | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | × | × | ☑ | ☑ | ✓ | ✓ | ✓ | ✓ |
| **D5** | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ☑ | ☑ | ☑ | ✓ | × | × | ✓ | ✓ |
| **D6** | ✓ | ✓ | × | × | ✓ | ✓ | ✓ | ✓ | ☑ | ☑ | ✓ | ✓ | × | × | ✓ | ✓ |
| **D7** | × | × | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ☑ | ☑ | ✓ | ✓ | × | × | ✓ | ✓ |
| **D8** | × | × | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | × | × | × | ✓ | × | × | ✓ | ✓ |
| **D9** | ☑ | ☑ | × | × | ✓ | ✓ | ✓ | ✓ | × | × | × | ✓ | × | × | ✓ | ✓ |
| **D10** | × | × | ✓ | ✓ | ✓ | ☑ | ☑ | ☑ | × | × | × | ✓ | × | × | ☑ | ☑ |
| **D11** | × | × | ☑ | ✓ | ✓ | ✓ | × | × | × | × | × | × | × | × | × | ✓ |
| **D12** | × | × | × | ✓ | ✓ | × | × | × | × | × | × | × | × | × | ☑ | ☑ |

Note: Here, ✓ represents clear or perfect classification, ☑ moderate classification and × represents very poor classification.