Signal Processing for Health Monitoring

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Abstract - Applying signal processing techniques for health monitoring of rotary machines becoming of greater importance. The aim of our work is verification of basic signal processing techniques for bearings faults with the help of MATLAB. Scattergram images and Statistical indicators from time-domain, frequency domain, time-frequency domain are calculated to extract features from signals for fault detection. Public bearing datasets from the Case Western Reserve University are utilized and the complete analysis is finalized by MATLAB. These tests reveal that strong evidence of health indicators and scattergram images is found in separating bearing states.

Keywords - discrete wavelet transform (DWT) , envelope spectrum, matlab, scattergram, signal processing.

I. Introduction

In the literature, there are a surprising number of examples showing the application of signal processing for bearing fault detection. In particular, health indicators gained a lot of popularity in condition monitoring as a feature extraction of transient and non-stationary signals. Feature extraction typically—but not always—provides the input to an expert system for data-driven prognostics and monitoring. Researchers proved the effectiveness of using features from three domains to better classify bearings faults of an aero-engine [1]. Other investigators improved the ability of the selected features from time, frequency and wavelet domain in separating bearing statues at various speeds [2]. Other researchers proposed a multi-feature fusion method that can effectively improve the diagnosis accuracy [3]. In [4], authors calculated kurtosis of all sub-signals obtained by adaptive scale decomposition method to remove the fault irrelevant components. Authors proposed a multi-angle feature extraction method to form a new dataset in experience pool of the neural network structure, which will be transmitted to kernel function for feature mapping, the results confirmed that the proposed method is more effective compared to other intelligent method [5]. The results obtained from [6], showed the great practical application prospects of using health indicators for suppressing interference components and quantifying the bearing degradation process. Researchers in [7], found a very satisfying results by using statistical indicators from time and frequency domain to train AI models for ball bearing multiple failure diagnosis. In [8], a set of features from time and frequency domain were used to fed a different ML algorithms, resulting in successful detection and classification of bearing faults.

This paper is organized as follows: the first section a case study is presented to diagnose bearing defects. The second section discusses the main results. Our conclusions are drawn in the final section**.**

II. Signal Processing Basic Techniques For Bearing Fault Detection

Signal processing methods are widely used for bearings health monitoring to extract the hidden features of the signal from various domains, such as time-domain, frequency-domain, and time–frequency [9].

A) Data Acquisition

In our work, the vibration data are obtained from the Case Western Reserve University Bearing Data Center Website [10]:

The rotational speed of the driving shaft is set to 30 Hz, while the sampling frequency is 48000 Hz. Two types of data sets have been used including; healthy bearing, inner race faulty bearing. Raw vibration data of two bearing states is shown in Fig. 1.

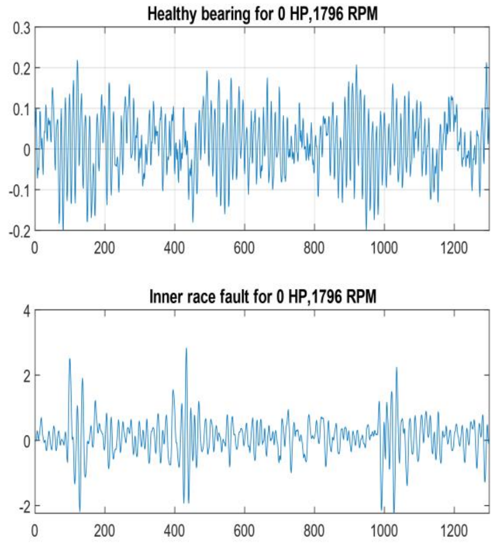

Fig. 1. Raw vibration signals

TABLE 1. RESULTS OF COMPUTED TIME-DOMAIN HEALTH INDICATORS

Bearing state	Healthy	Inner race fault
Mean	0.0141	0.08668
Median	0.01189	0.08514
Max	0.2483	3.292
Min	-0.2866	-2.773
Standard deviation	0.0727	0.584
Magnitude range	0.5349	6.065
Kurtosis	2.76	6.03

B) Signal Processing Techniques

1. Envelope spectrum

Envelope spectrum analysis has been used to visualize the frequency peaks. In case of inner race faulty bearing, the fault characteristic frequency is 162.08 Hz. As mentioned earlier, the rotating speed of the shaft is 29.93 Hz, which can be seen in the following Fig. 2-3.

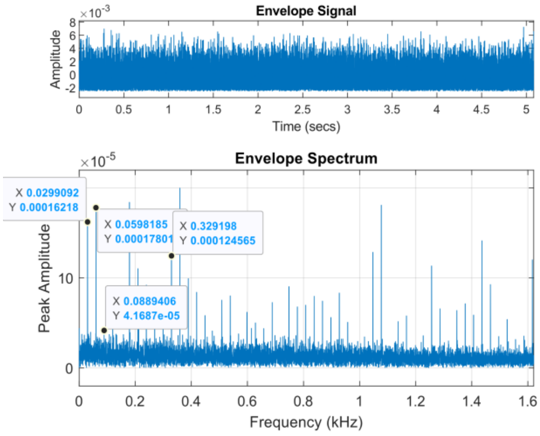

Fig. 2. Envelope spectrum of healthy bearing

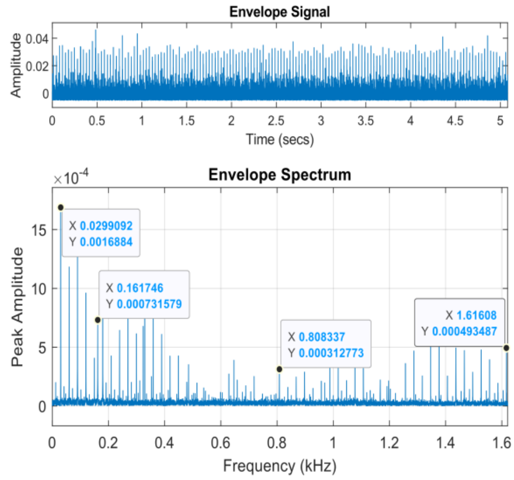

Fig. 3. Envelope spectrum of inner race faulty bearing

2. Discrete Wavelet Transform

TABLE 2. RESULTS OF COMPUTED MAGNITUDE RANGE OF APPROXIMATION COEFFICIENTS FOR HEALTHY AND FAULTY BEARING

Approximation Coefficients	Magnitude range (Healthy)	Magnitude range (Inner fault)
Level 1	0.749	8.51
Level 2	1.0348	11.571
Level 3	0.7983	11.464
Level 4	0.9402	6.197
Level 5	1.0115	4.139
Level 6	0.6836	1.5155
Level 7	0.4889	0.9933
Level 8	0.27539	0.611

TABLE 3. RESULTS OF COMPUTED MAGNITUDE RANGE OF DETAIL COEFFICIENTS FOR HEALTHY AND FAULTY BEARING

Detail Coefficients	Magnitude range (Healthy)	Magnitude range (Inner fault)
Level 1	0.0462	0.19457
Level 2	0.2165	1.7806
Level 3	0.9817	11.379
Level 4	0.5498	13.175
Level 5	0.6584	8.004
Level 6	1.0951	5.463
Level 7	0.6903	1.619
Level 8	0.5714	1.2184

3. *Scattergram*

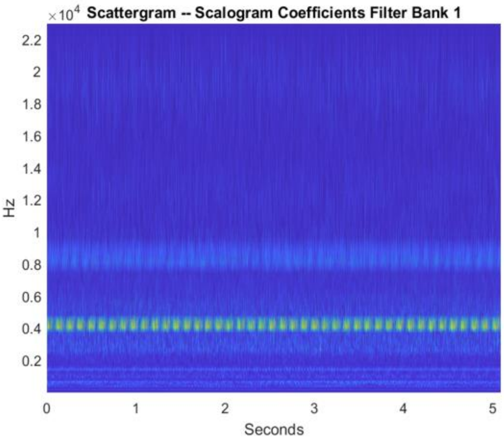

Fig. 4. Scattergram of healthy bearing

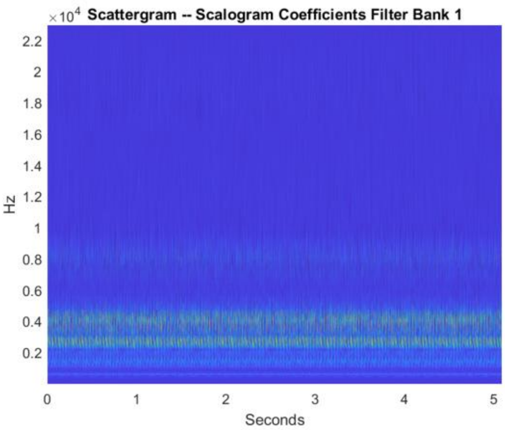

Fig. 5. Scattergram of inner race faulty bearing

III. RESULTS AND DISCUSSIONS

It can be seen from TABLE I, that statistical indicators provide a precise information about the state. The value increases dramatically for each indicator due to the existence of defect.

It can be seen from (Fig. 2, Fig. 3), which shows the envelope spectrum of the vibration signal that bearing in healthy state has low magnitude peaks compared to the faulty state. It is also observed that signal of healthy bearing has no periodic peaks whereas signal of faulty bearing has periodic peaks at the fault frequency.

According to Table 2, the approximation coefficient of healthy bearing reaches its maximum range value at level 2 (1.0348) than decreases reaching its minimum range value at level 8 (0.27539), whereas the approximation coefficient of inner race and rolling element faulty bearing reaches its maximum range value at level 2 (11.571, 4.977) than decreases reaching its minimum value at level 8 (0.611, 0.3449). It is observed from these results that the maximum value of healthy bearing (1.0348) is less than the maximum value of faulty bearing (11.571 for inner race, 4.977 for rolling element) which means the approximation coefficient at level 8 is sensitive to inner/rolling element fault.

According to Table 3, the detail coefficient of healthy bearing reaches its maximum range value at level 6 (1.0951) than decreases reaching its minimum range value at level 1 (0.0462), while the detail coefficient of inner race and rolling element faulty bearing reaches its maximum range value at level 4 (13.175, 2.784) than decreases reaching its minimum value at level 1 (0.19457, 0.02357). It is can be concluded that the maximum value of faulty bearing (13.175, 2.784) is higher than the maximum value of healthy bearing (1.0951) which means that the detail coefficient range value at level 4 is sensitive to the fault.

It can be seen from (Fig. 4, Fig. 5), an increasing on the energy of the bearing in faulty state. Which indicates the existence of a degradation.

IV. CONCLUSION

The findings of this study indicate how powerful is signal processing-based techniques on detecting, locating, and quantifying the severity of degradation for a given speed and load. According to the results, it can be concluded that, health indicators are efficient for bearing fault separation. Therefore, scattergram images can be easily used for bearing fault detection. we believe our work could be a starting point for beginners on this field. In the future, we will investigate methods to extend machine learning with additional indicators in order to automate analysis.

REFERENCES

[1] X. Guan and G. Chen, "Sharing pattern feature selection using multiple improved genetic algorithms and its application in bearing fault diagnosis," *J Mech Sci Technol, vol. 33*, no. 1, pp. 129–138, Jan. 2019, doi: 10.1007/s12206-018-1213-6.

[2] S. Nezamivand Chegini, A. Bagheri, and F. Najafi, "A new intelligent fault diagnosis method for bearing in different speeds based on the FDAF-score algorithm, binary particle swarm optimization, and support vector machine," *Soft Comput, vol. 24*, no. 13, pp. 10005–10023, Jul. 2020, doi: 10.1007/s00500-019-04516-z.

[3] Z. Shan, Z. Wang, J. Yang, Q. Ma, and T. Gong, "Novel Time–Frequency Mode Decomposition and Information Fusion for Bearing Fault Diagnosis Under Varying-Speed Condition," *IEEE Transactions on Instrumentation and Measurement, vol. 72*, pp. 1–10, 2023, doi: 10.1109/TIM.2023.3260275.

[4] J. Chen, C. Hua, D. Dong, and H. Ouyang, "Adaptive scale decomposition and weighted multikernel correntropy for wheelset axle box bearing diagnosis under impact interference," *Mechanism and Machine Theory, vol. 181*, p. 105220, Mar. 2023, doi: 10.1016/j.mechmachtheory.2022.105220.

[5] L. Zheng, Y. Xiang, and C. Sheng, "Optimization-based improved kernel extreme learning machine for rolling bearing fault diagnosis," *J Braz. Soc. Mech. Sci. Eng., vol. 41*, no. 11, p. 505, Oct. 2019, doi: 10.1007/s40430-019-2011-5.

[6] R. Yao, H. Jiang, C. Yang, H. Zhu, and C. Liu, "An integrated framework via key-spectrum entropy and statistical properties for bearing dynamic health monitoring and performance degradation assessment," *Mechanical Systems and Signal Processing, vol. 187*, p. 109955, Mar. 2023, doi: 10.1016/j.ymssp.2022.109955.

[7] R.-C. Cheng and K.-S. Chen, "Ball bearing multiple failure diagnosis using feature-selected autoencoder model," *Int J Adv Manuf Technol, vol. 120*, no. 7, pp. 4803–4819, Jun. 2022, doi: 10.1007/s00170-022-09054-x.

[8] M. Altaf, T. Akram, M. A. Khan, M. Iqbal, M. M. I. Ch, and C.-H. Hsu, "A New Statistical Features Based Approach for Bearing Fault Diagnosis Using Vibration Signals," *Sensors, vol. 22*, no. 5, Art. no. 5, Jan. 2022, doi: 10.3390/s22052012.

[9] R. Varghese P, M. S. P. Subathra, S. T. George, N. M. Kumar, E. S. Suviseshamuthu, and S. Deb, "Application of signal processing techniques and intelligent classifiers for high-impedance fault detection in ensuring the reliable operation of power distribution systems," *Frontiers in Energy Research, vol. 11*, 2023, Accessed: May 14, 2023. https://www.frontiersin.org/articles/10.3389/fenrg.2023.1114230

[10] "Bearing Data Center | Case School of Engineering | Case Western Reserve University." Accessed: Aug. 05, 2023. https://engineering.case.edu/bearingdatacenter