Fault Detection of Bearings with Time Series Analysis: A Pilot Study

Özlem Gülsüm Kılıçkaya[1], Derya Yılmaz[2]

[1]Department of Defense Technologies and Systems
Başkent University, Ankara, Turkey.
21910166@mail.baskent.edu.tr, ozlemgulsumkilickaya@gmail.com

[2] Department of Electrical and Electronics Engineering
Başkent University, Ankara, Turkey.
derya@baskent.edu.tr

***Abstract*— Electric motors failure is an important issue in industry. This situation may cause interruptions in manufacturing but it may also affect the operator safety. Traditional linear methods may not effectively detect failures. In order to overcome this problem, monitoring and diagnosis methods are tried to be developed. This study presents a time series analysis for healthy and faulty bearing and aims to contribute systematic comparison among different methods from frequency, nonlinear and statistical domains for characterizing working status of ball bearings. The results obtained from healthy and faulty bearing signals were found as distinctive from each other and it is suggested that these methodologies can be used for fault detection. Alternatively, the same analysis might be applied on ball race and outer race. On the other hand, it might be applied on different manufacturing, electro-mechanical and robotic systems and all other industrial applications that electric motors are used. Automatic diagnostic tools for differentiating the healthy and faulty bearing states can be improved with identifying changes, and by using presented way bearing signals are measured. This data is aimed to be used for predictive maintenance and fault detection. Intelligent systems for fault detection can be designed by utilizing this data documented for maintenance, test conditions and fault status.**

***Keywords*— Fault detection, predictive maintenance, bearings, time series analysis.**

I. Introduction

Bearings are widely in common every rotating machine system. It reduces the rotational friction and supports radial and axial loads [24]. It is well known that during the machine operations structural transmutation and friction may occur. According to these phenomena, signals generated from the machines are non-stationary and nonlinear. Therefore, traditional linear analysis methods may be insufficient and may not effectively detect the failures [24]. In literature, there are some studies are conducted by using nonlinear time series analysis in order to overcome this problem. In these studies, different parameters are analyzed. Lyapunov exponent, correlation dimension and entropy are some of them [3,4,5,6,13,14,21,24]. Some algorithms were developed to analyze the complexity of a system, and the studies that are used in order to use the related techniques for limited, noisy and stochastically derived time series were not accomplished this goal. The correlation integral algorithm and the Kolmogorov–Sinai entropy works successfully in real dynamic systems, however even a small amount of noise makes those algorithms unsuccessful since the values tend to go to infinity [1]. Approximate Entropy is an effective parameter in order to distinguish the health state of a machine system [14].

According to literature survey, there are similar studies for bearings [6,13,14,15,24]. In these studies, there is no research conducted that contain most of the nonlinear time series analysis parameters. Also, there is no comparison between healthy and faulty bearings to distinguish them by nonlinear time series analysis parameters.

Aim of this study is to provide diagnostic analysis parameters in order to distinguish healthy bearings from faulty bearings. This will also be useful for predictive maintenance. Nowadays, such parameters were used in industry for machine learning to predict possibility of failure and remaining life of the bearing. Predictive maintenance increases the productivity and reduces the frequency and cost of the maintenance [8,24].

In order to realize predictive maintenance sensors are put into the system that will monitor and collect data about its operation. Data used for predictive maintenance is time series data [8,24].

In this study healthy and faulty bearing signal were evaluated by using different signal analysis methods. These are given as follows; mean, median, standard deviation, periodogram, spectrogram-short time Fourier transform, histogram, auto-correlation, average mutual information, phase space reconstruction, correlation dimension, Lyapunov exponent and approximate entropy. By this way, systematic comparison among different frequency, nonlinear and statistical parameters and was achieved in order to characterize operation status of bearings. Results for these methods were shown and evaluated, in results and discussion section.

II. MATERIALS AND METHODS

A. Data

The related data that used in this study had been obtained from the U.S. Case Western Reserve University-Bearing Data Center [17]. The testing setup used in order to measure data is shown in the following Figure 1. There is a 2 Hp motor, coder and motor spindle that used to support the bearing at left. There is a dynamometer at right. Accelerometers had been placed at the 12 o'clock position for both the drive end and fan end of the motor housing in order to obtain data. Cross sectional view of ball bearing had been shown in Figure 2.

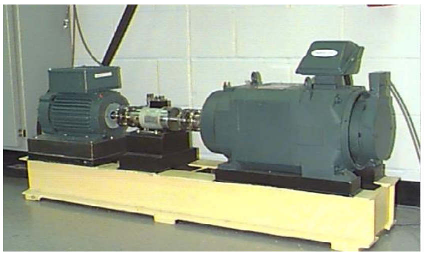


Figure 1. Data testing platform [17].

U.S. Case Western Reserve University-Bearing Data Center provides test data of the healthy and faulty ball bearing. Table 1 shows the properties of the bearing data in various states provided by U.S. Case Western Reserve University-Bearing Data Center where each faulty state of the bearing has three fault diameters. The faulty bearings are tested according to the motor load of 0–3 Hp, and the vibration signals of different fault states are intercepted at sampling frequencies of 12 K/48 K. Cross sectional view of ball bearing is shown in Figure 2.

TABLE I
BEARING FAULT STATE CLASSIFICATION [18].

System Quantities	Values/Conditions
Sampling frequency	12K/48 K (Hz)
Motor load	0/1/2/3 (Hp)
Fault diameter	7/14/21 (mil)
Fault depth	11(mil)
Fault state	Normal/inner ring fault/outer ring fault/ball fault

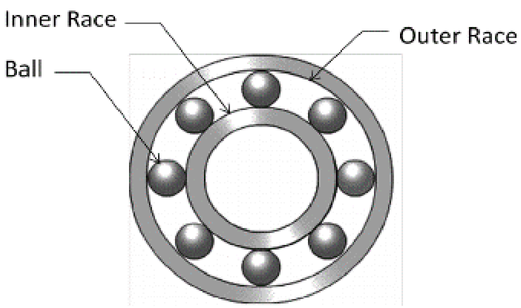


Figure 2. Cross sectional view of ball bearing [23].

In this study, nonlinear time series analysis was applied on inner race of the bearing. Sampling rate is 48 KHz, fault diameter is 0.021 inches (0.53 mm) and state of the bearing is no-load fault state.

B. *Analysis Methods*

Two signals from healthy and faulty bearing were analyzed by using some methods come from statistical, frequency and nonlinear domains. Firstly, the signals were normalized and then mean, median and standard deviations, which are statistical properties, were calculated. The relationship between the values of the signals at different times was observed with the autocorrelation function. Autocorrelation represents the degree of similarity between a time series and shifted copies of that series at specific time intervals. In other words, autocorrelation measures the relationship between the current value of a variable and its previous values. While autocorrelation gives the relationship of the signal with itself on a linear basis, the average mutual information function, another method that calculates this relationship statistically, was also obtained. The first minimum value of this function gives the number of signal samples in which the relationship is the weakest. Histograms were also obtained to reveal the distribution characteristics of the signals. For frequency domain analysis, the frequency components of these two signals and their powers at these frequencies were obtained by estimating the periodograms and spectrograms [7,8,19].

In nonlinear analysis, the attractor belonging to the signal from system is obtained by applying the phase space reconstruction [9,12]. The attractors of the systems may appear in different structures. Some nonlinear features, such as Lyapunov exponent and correlation dimension, are calculated on the system's attractor. Therefore, phase space reconstruction is the first step to be taken in nonlinear analysis. The Lyapunov exponent is a measure that characterizes the rate of separation or convergence of very close orbits on the attractor of a dynamic system [12]. A positive value of the largest Lyapunov exponent indicates that the system has nonlinear dynamics. The correlation dimension is the area occupied by the points that make up the attractor of the system and, is generally fractal for chaotic systems. The correlation dimension of random systems is infinite [12]. Approximate entropy is used to measure the regularity of a signal [12]. Approximate Entropy is a parameter that used to measure correlation, persistence or regularity. According to the sense that low approximate entropy values reflect the system. This means that system is very persistent, repetitive and predictive by the significant patterns that repeat themselves throughout of the series for low values. On the other hand, high values mean independence between the data, this provides a low number of repeated patterns and randomness. This definition is compatible with the idea that the systems which have more random probability must have higher entropy [1,2]. In this study, the largest Lyapunov exponent, correlation dimension and approximate entropy methods were applied to the bearing signals.

III. RESULTS AND DISCUSSION

Results are presented with some figures and table in this section, in order to provide ease for comparison between faulty and healthy bearing. These two bearing signals and their normalized values are given in Figure 3. Results are presented with the Figure 4, 5 and Table 2. Then, these results are interpreted below.

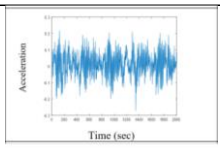
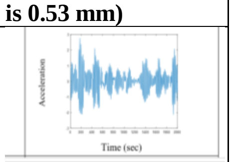
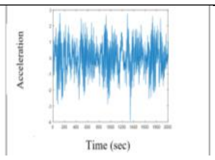
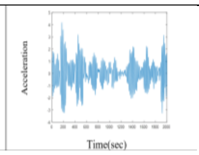
Operations	**Healthy Bearing**	**Faulty Bearing (Inner race fault and fault diameter is 0.53 mm)**
Plot versus time		
Normalization/ Standardization		

Figure 3. Bearing signals from healthy and faulty state

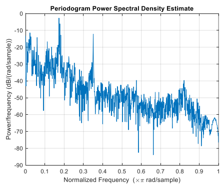
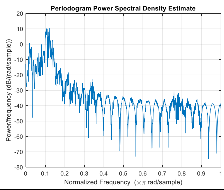
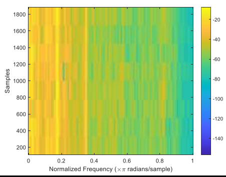
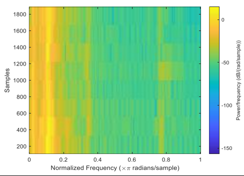
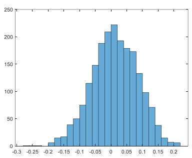
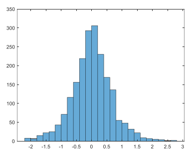
Operations	**Healthy Bearing**	**Faulty Bearing (Inner race fault and fault diameter is 0.53 mm)**
Periodogram		
Spectrogram (Short time Fourier transform)		
Histogram		

Figure 4. Periodograms, spectrograms and histograms.

The periodograms, spectrograms and histograms of signals are presented in Figure 4. Referring to the Figure 4, the periodogram is used to identify the dominant periods (or frequencies) of a time series. In spectrogram after 0.3 value of normalized frequency for faulty bearing, power/frequency becomes higher (there are green and blue when compared to yellow). Faulty and healthy bearing can also be distinguished visually from these plots. Spectral kurtogram and kurtosis might be also used in this stage [7,8,19].

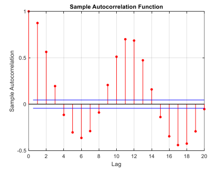
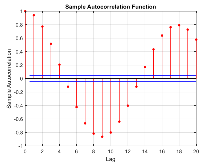
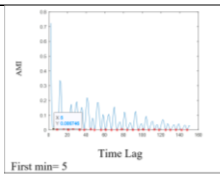
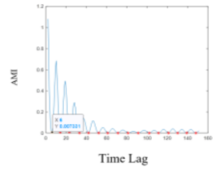
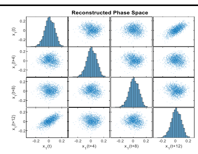
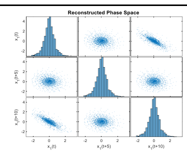
Operations	**Healthy Bearing**	**Faulty Bearing (Inner race fault and fault diameter is 0.53 mm)**
Autocorrelation		
Average mutual information		
Phase space reconstruction	 x1(t+4) and x1(t+8) are the phase space reconstruction states for the eLag (estimated lag) value of 4. The diagonal plots (1,1), (2,2), (3,3) and (4,4) shows the histogram of x1(t), x1(t+4), x1(t+8)and x1(t+12) data, respectively. eDim=4 eLag=4	 x1(t+5) and x1(t+10) are the phase space reconstruction states for the eLag(estimated lag) value of 5. The diagonal plots (1,1), (2,2), and (3,3) shows the histogram of x1(t), x1(t+5) and x1(t+10) data, respectively. eDim = 3 eLag =5

Figure 5. Autocorrelation, average mutual information and phase space reconstruction

Histogram of the healthy bearing is symmetric. It is a good fit. Histogram of the faulty bearing is left skewed and it has negative skewness. It is a poor fit [10,16,20]. The results of autocorrelation, average mutual information and phase space reconstruction methods are shown in Figure 5. Autocorrelation measures the similarity between the signal and a lagged version of itself. As described before healthy bearing is symmetric but faulty bearing has negative skewness. So, negative correlation is obtained for faulty bearing. Mutual information is the measure of information that we can learn from one random variable about another. The first minimum of this function is interpreted as statistically independent point. From here it is understood that healthy bearing has more random variables and randomness is high in that case [10,16,20]. Reconstructed phase space for both healthy and faulty bearing can also be seen in Figure 5. Healthy bearing has symmetrical structure and it is equally distributed. However faulty bearing has tendency to concentrated distribution at some points [10,16,20].

The quantitative properties calculated for healthy and faulty bearing signals are given in Table 2. According to the Table 2, in case of healthy bearing, the mean and the median values were found as equal. This result is obtained if the distribution is symmetric and it has zero skewness. In case of faulty bearing, the mean value was found as smaller than the median. There is negative skewness.

TABLE II

THE QUANTITATIVE FEATURES FOR HEALTHY AND FAULTY BEARING

Features	**Healthy bearing**	**Faulty bearing (Inner race fault and fault diameter is 0.53 mm)**
Mean	0.0123	0.0128
Median	0.0123	0.0164
Standard Deviation	0.0729	0.6585
Correlation Dimension	3.8076	2.3167
Lyapunov Exponent (largest)	0.5207	0.680
Approximate Entropy	0.2070	0.7165

Correlation dimension is a method to compute attractor dimension. Correlation dimension for healthy bearing is higher than faulty bearing. These results indicated that the number of degrees of freedom of the healthy bearing system is higher than faulty.

Random and chaotic, both systems will give positive Lyapunov exponent. In other words, periodic orbits have Lyapunov exponents that are near zero and chaotic orbits have at least one positive Lyapunov exponent and random orbits have still larger Lyapunov exponents. So, the higher the Lyapunov exponent the more unpredictable the future trajectory is based on its past values. In our case, faulty bearing has higher Lyapunov exponent value. The approximate entropy of faulty bearing is also higher than healthy so it can be stated that healthy state is more predictable than faulty. So, the means of these results that when healthy and faulty bearings are compared with each other it is understood that healthy bearing is more chaotic [1,2,10,14,16,20].

IV. Conclusions

In this study, some signal analysis methods were applied to the ball bearing signals in order to provide comparison between faulty and healthy bearing states. According to literature survey, there are similar studies for bearings [6,13,14,15,24]. In these studies, there is no research conducted that contain most of the nonlinear time series analysis parameters. Also, there is no comparison between healthy and faulty bearings to distinguish them by nonlinear time series analysis parameters.

The results showed that these analysis approaches can give useful outcomes for distinguishing healthy and faulty case. As it can be seen in results section, there is a significant difference between healthy and faulty bearings for parameters.

In addition to all of these methods, spectral kurtosis can also be added to these analyses [15].

As it is defined in introduction of this study, aim of this study is to provide diagnostic analysis parameters in order to distinguish healthy bearings from faulty bearings. This will be useful for predictive maintenance. Nowadays, such parameters were used in industry for machine learning to predict possibility of failure and remaining life of the bearing [8,24]. Predictive maintenance increases the productivity and reduces the frequency and cost of the maintenance [8,24].

In order to realize predictive maintenance sensors are put into the system that will monitor and collect data about its operation. Data used for predictive maintenance is time series data [8,24].

Alternatively, the same analysis might be applied on ball race and outer race. On the other hand, it might be applied on different manufacturing, electro-mechanical and robotic systems. This data is aimed to be used for predictive maintenance and fault detection. Intelligent systems for fault detection can be designed by utilizing this data.

In conclusion, this study will contribute to archival literature since there is no research conducted in literature that contain most of the nonlinear time series analysis parameters. Besides, by this data healthy and faulty bearings can be distinguished significantly from each other for the related parameters in which is another advantage of this study.

References

[1] Alfonso Delgado-Bonal and Alexander Marshak. “*Approximate Entropy and Sample Entropy:A Comprehensive Tutorial”*.

[2] Andrew L. Rukhin, “*Approximate entropy for testing randomness, 2000”*.

[3] Antoni, Jérôme. "*Fast computation of the kurtogram for the detection of transient faults*." Mechanical Systems and Signal Processing. Vol. 21, Number 1, 2007, pp. 108–124.

[4] Antoni, Jérôme. "*The spectral kurtosis: a useful tool for characteristing non-stationary signals."* Mechanical Systems and Signal Processing. Vol. 20, Number 2, 2006, pp. 282–307.

[5] Bechhoefer, Eric. "*Condition Based Maintenance Fault Database for Testing Diagnostics and Prognostic Algorithms*." 2013.

[6] Chen R. and Huang R. “*Fault diagnosis of mechanical system based on nonlinear time series model.”, 2012.*

[7] Ivan Zelinka, Mohammed Chadli, Sofiane Bououden, Salim Ziani. *Advanced Control Engineering Methods in Electrical Engineering Systems* (pages 390-410).

[8] Infoq, Available: https://www.infoq.com/articles/machine-learning-techniques-predictive-maintenance/, 20.07.2020.

[9] Jiafei Yan, Ming Qiu, Long Chen, Yingchun Li. *Bearing Tribology: Principles and Applications.*

[10] Kantz, H., and Schreiber, T. *Nonlinear Time Series Analysis*. Cambridge: Cambridge University Press, Vol. 7, 2004.

[11] Kantz, Schreiber, *Nonlinear Time Series Analysis* (Cambridge 2004)(2nd ed)

[12] Pincus, S. M. (1991). “Approximate entropy as a measure of system complexity.” *Proceedings of the National Academy of Sciences*. 88 (6): 2297–2301.

[13] Randall, Robert B., and Jerome Antoni. *"Rolling element bearing diagnostics—a tutorial."* Mechanical Systems and Signal Processing. Vol. 25, Number 2, 2011, pp. 485–520.
[14] Robert X.Gao and Ruqiang Jan. *"Approximate Entropy as a diagnostic tool for machine health monitoring."*, 2017.
[15] Rolling Element Bearing Fault Diagnosis, https://www.mathworks.com/help/predmaint/ug/Rolling-Element-Bearing-Fault-Diagnosis.html, 10.06.2020.
[16] Steven H. Strogatz, *Nonlinear dynamics and chaos with applications to Physics, Biology, Chemistry and Engineering.*
[17]U.S. Case Western Reserve University-Bearing Data Center Available: https://csegroups.case.edu/bearingdatacenter/pages/apparatus-procedures, 10.06.2020.
[18] Wikipedia. https://en.wikipedia.org/wiki/Periodogram
[19] Wikipedia. https://en.wikipedia.org/wiki/Spectrogram
[20] Williams G.-*Chaos Theory Tamed*
[21] Wolfram Hardt, Yanjin Altankhuyag- "*Automated Noise Analysis for Fault Detection.", 2017.*
[22] Yılmaz D and Güler NF (2006). *A study on the chaotic time series analysis.* Journal of the Faculty of Engineering and Architecture of Gazi University, 2006, 21(4):759-779.
[23] Ying-Che Kuo , Chin-Tsung Hsieh , Her-Terng Yau and Yu-Chung Li. "*Research and Development of a Chaotic Signal Synchronization Error Dynamics-Based Ball Bearing Fault Diagnostor.", 2014.*
[24] Yongbin Liu, Robert X. Gao, Ruqiang Yan. "*A nonlinear time series analysis method for health monitoring of rolling bearings.", 2010.*