Feature Extraction for Bearing Prognostics using Correlation Coefficient Weight

Seokgoo Kim[1], Chaeyoung Lim[2], and Joo-Ho Choi[3]

[1,2]*Dept. of Aerospace and Mechanical Engineering, Korea Aerospace University, Goyang-City, Gyenggi-do, Korea*
sgkim@kau.kr
chaee114@naver.com

[3] *School of Aerospace and Mechanical Engineering, Korea Aerospace University, Goyang-City, Gyenggi-do, Korea*
jhchoi@kau.ac.kr

ABSTRACT

Bearing is an essential mechanical component in rotary machineries. To prevent its unpredicted failures and undesired downtime cost, many researches have been made in the field of Prognostics and Health Management (PHM). Key issues in bearing PHM is to establish a proper health indicator (HI) reflecting its current health state properly at the early stage. However, conventional features have shown some limitations that make them less useful for early diagnostics and prognostics. This paper proposes a feature extraction method using traditional envelope analysis and weighted sum with correlation coefficient. The developed methods are demonstrated using IMS bearing data from NASA Ames Prognostics Data Repository. In the end, proposed feature is compared with traditional time-domain features.

1. INTRODUCTION

Bearing is one of the most important components in rotating machineries and its failure leads to catastrophic accidents in the industrial filed. In order to prevent these disasters while extending its use over the designed bearing's life, many researches have been made in field of prognostics and health management (PHM), which consists of feature extraction via signal processing, diagnosis and prognostics. Many review papers have addressed state-of-the-art of the related techniques. Among them, some representative ones are given in (Jardine 2016, Heng et al. 2009, Lee et al. 2014). Up to date, most of the studies have been on the purpose of diagnosis that estimates failure mode and its current severity which can be useful for immediate interruption to avoid critical failures.

On the other hands, prognostics focus on predicting when failure will occur in the future and provides advantages to maintenance readiness in advance. Compared to diagnosis, prognostics still have many challenges to overcome. For an effective prognosis, extracting features which reflect degradation pattern and fault severity properly is the most important stage. And several works have been made in this sense. Siegel et al (2011) used the bearing vibration data from Bearing Prognostics Simulator provided by SpectraQuest and study feature trending using RMS, kurtosis and peak value at bearing fault frequencies acquired from envelope analysis. Randall & Antoni (2011) published bearing diagnostics tutorial especially for envelope analysis and other signal processing techniques to enhance its performance. Li & Zheng (2008) utilized envelope spectrum analysis using Empirical Mode Decomposition (EMD) and Teager-Kaiser Energy Operator (TKEO) for bearing fault detection. Zhang et al. (2011) applied weight window function to envelope spectrum to detect the incipient bearing fault. However, most of them are limited to single failure mode and rarely consider comprehensive health index (HI). There are other approaches using data analytics and machine learning algorithms. Qiu et al (2003) employed Self-Organized-Map (SOM) and used Minimum Quantile Error (MQR) as a feature to obtain monotonic trend. Tobon-Mejia (2011) suggested bearing prognostics using wavelet packet decomposition (WPD) and Hidden Markov Model (HMM). Even though these algorithms show good performance, it is lack of physical meaning and data analytics based algorithms needs many data sets. To overcome these limitations and extract effective feature, this paper suggests the feature extraction methods using correlation coefficient of envelope trends.

This paper is organized as follows: Section 2 introduces the theoretical background of signal processing technique. Section 3 presents the proposal methodology. Section 4 suggest the result of application to IMS bearing data set. Section 5 gives the conclusion.

2. THEORETICAL BACKGROUND

This paper proposes a feature extraction based on correlation weight sum of bearing defect frequency amplitude. For this purpose, signal processing techniques such as Teager-Kaiser Envelope Operator (TKEO), Wavelet Packet Decomposition (WPD) , envelope analysis are employed.

2.1. Teager-Kaiser Energy Operator

Simple energy of signal is the sum of squared absolute values of the signal over a time, which is not the instantaneous summed energy. In order to estimate the instantaneous energy of a signal $x(t)$, Teager-Kaiser Energy Operator (TKEO) is used as an energy tracking operator as follows (Tabrizi, A., et al (2015)).

$$\psi_c[x(t)] = \dot{x}^2(t) - x(t)\ddot{x}(t) \quad (1)$$

For a discrete time signal, TKEO can be expressed as follows as Eq. (2).

$$\psi_D[x(n)] = x^2(n) - x(n-1)x(n+1) \quad (2)$$

To estimate the instantaneous TKEO, only three continuous samples are used. It is adaptive to the instantaneous changes in signals. It has some merits such as low computational cast, high resolution of time and frequency and adaptively to instantaneous feature.

2.2. Envelope analysis

For rolling element bearing, when its outer race, inner race, rolling element or cage has fault, periodic impact is produced exciting the whole structure's high frequency resonance. As a result, amplitude modulation occurs at the associated bearing pass frequencies such as ball pass frequency outer race (BPFO), ball pass frequency inner race (BPFI), ball spin frequency (BSF), fundamental train frequency (FTF) as shown in Figure 1. These bearing pass frequencies calculated from Eq. (3-6). The raw signal often contains little information about bearing faults. Over many years envelope analysis has been established as benchmark method for bearing diagnostics. Envelope analysis provides a mechanism for extracting the periodic excitation of the resonance from vibration signals by demodulating the vibration signals at the resonances. It is realized by applying Hilbert transform and the construction of the analytic signal. Finally, the frequency spectrum of envelope signal is used for feature extraction. The details of the method can be found in reference (Randall & Antoni, 2011).

$$BPFO = \frac{nf_r}{2}\left\{1 - \frac{d}{D}\cos\alpha\right\} \quad (3)$$

$$BPFI = \frac{nf_r}{2}\left\{1 + \frac{d}{D}\cos\alpha\right\} \quad (4)$$

$$FTF = \frac{f_r}{2}\left\{1 - \frac{d}{D}\cos\alpha\right\} \quad (5)$$

$$BSF = \frac{Df_r}{2d}\left\{1 - \left(\frac{d}{D}\cos\alpha\right)^2\right\} \quad (6)$$

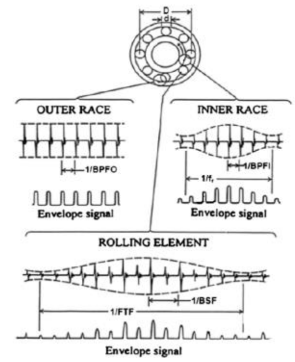


Figure 1. Typical signals and envelope signal from local faults in rolling element bearing (Randall & Antoni, 2011)

2.3. Wavelet Packet Decomposition

Wavelet packet decomposition is becoming effective tool for signal processing. Wavelet packet decomposition uses a pair of low pass and high pass filtering to split the signal into low frequency components (approximations) and the high frequency components (details) at every level. Thus, in general, wavelet packet decomposition divides the frequency space into various parts and allows better frequency localization of signals. Simply the wavelet packet decomposition can be expressed as a tree as shown in Figure 2, which shows level 3 wavelet packet decomposition. Top of the tree is the original signal. The next level of tree means one step of the wavelet transform. (Tobon-Mejia et al. 2011)

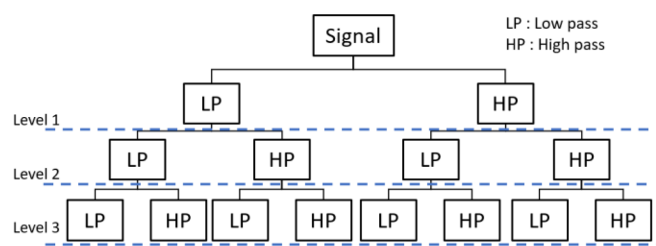


Figure 2. Wavelet packet decomposition

3. METHODOLOGY

The originality of the proposed methods dwells in the fact that raw signal is processed using TKEO, WPD, and envelope analysis to extract the feature. The procedure of proposed methods is given as follows

Step 1) Apply the TKEO to raw vibration signal in time domain following Eq. (7) and WPD is performed to select the node showing minimum nodal energy. WPD with decomposition level 1 is used. Then 2 to the power of two of node is obtained as shown in Eq. (8-9)

$$TKEO = \psi[x(t)] \quad (7)$$

$$TKEO \xrightarrow{WPD} Node = (node_1, node_2, \dots, node_{2^{level}}) \quad (8)$$

$$Selected\ Node = \min_i Energy(node_i) \quad (9)$$

Step 2) Envelope analysis is performed on the selected node. Zhang et al. (2011) calculated the weight energy in a frequency band centered on a frequency of interest. Similarly, this paper used the weighted window that has the shape of Blackman-Harris. Window size is corresponding to shaft rotating speed. The summation of weight spectra is calculated. Figure 3 shows example of a weighted window process in detail. Weighted spectra is obtained by multiplying envelope spectrum with window function. The same process is applied to other characteristic frequency. As a result, feature vector is constructed following Eq. (10,11)

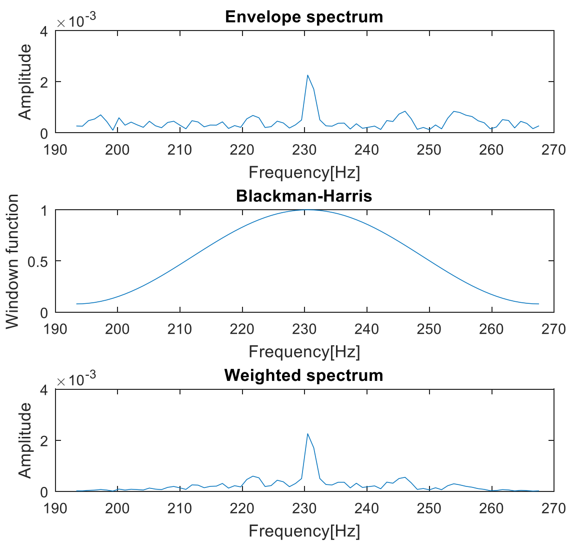


Figure 3. Weighted envelope

$$f = \sum_i weighted\ spectra_i \quad (10)$$

$$feature = (f_{BPFO}, f_{BPFI}, f_{FTF}, f_{BSF}) \quad (11)$$

Step 3) Based on the assumption that a feature which shows monotonic increase over time is the ideal degradation signal, calculate the spearman's rank correlation coefficients to assess monotonic relationship between feature vector and time using Eq. (12). ρ denotes the usual Pearson correlation coefficient, but applied to the rank variables. $\mathrm{cov}(rg_X, rg_Y)$ is the covariance of the rank variables. σ_{rg_X} and σ_{rg_Y} are the standard deviations of the rank variables.

$$r = \rho_{rgx,rgy} = \frac{cov(rgx, rgy)}{\sigma_{rgx}\sigma_{rgy}} \quad (12)$$

Step 4) The feature vector is multiplied by the Spearman's rank correlation coefficients and their sum is used as health index as shown in Eq. (13) For more detail, negative correlation coefficient is all zero padded so that only positive coefficient is weighted to the feature vector. L means the number of failure mode. In case of bearing, L will be 4.

$$Feature = \sum_{l=1}^{L} r_l \cdot f_l \quad (12)$$

4. APPLICATION

The IMS bearing data set in the NASA Ames data repository can be downloaded from 'Bearing Data Set', IMS, University of Cincinnati NASA Ames Prognostics Data Repository (Lee, J et al. 2009.). They were used for the study in reference (Qiu et al. 2006). Four double row bearings (16 rollers) are installed on a shaft as shown in Figure 4, and the rotating speed are radial load are, respectively 200 rpm and 26.7kN. four data sets are made from the repeated experiment under this condition. Vibration data was collected every 20 minute with sampling frequency 20kHz and the data length was 20,480 points. The test was carried out until a significant amount of meta debris was found on the magnetic plug of the test bearing.

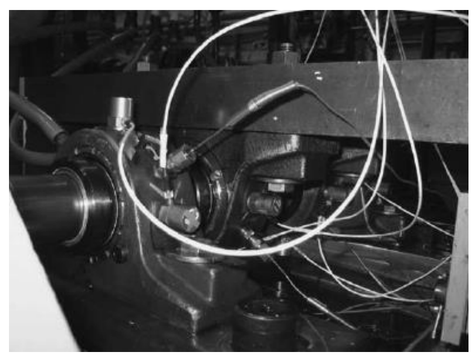
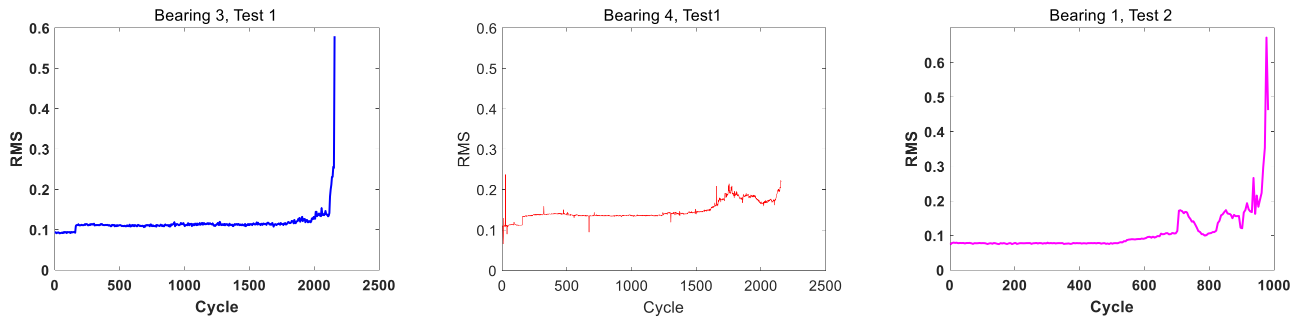


Figure 4. Bearing test rig

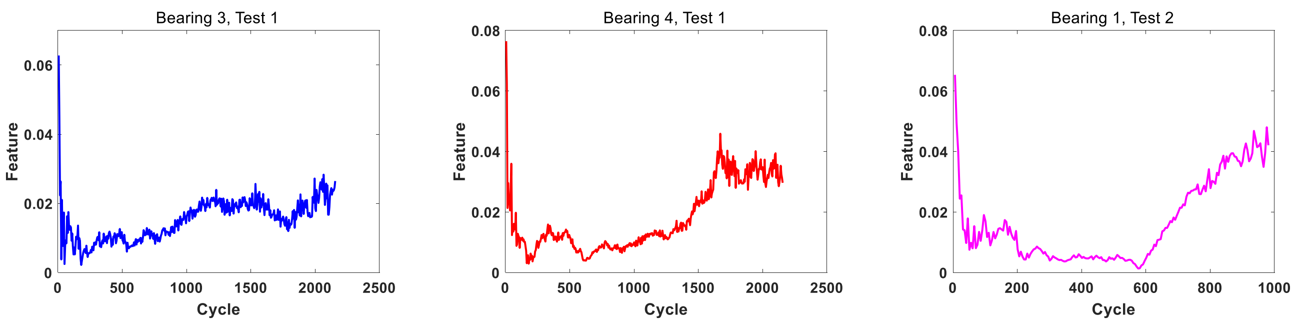
For application purposes, data set which experience the real defect is used. Bearing 3, 4 in test 1 and bearing 1 in test 2 are recognized to have inner race defect, roller element fault and outer race defect as shown in Figure 5.

(a) inner race (b) roller element (c) outer race

Figure 5. Photo of bearing component (a) inner race fault in bearing 3, test 1 (b) roller element fault in bearing 4, test 1 (c) outer fault in bearing 1, test 2



(a) Bearing3, Test 1 RMS trend (b) Bearing4, Test 1 RMS trend (c) Bearing1, Test 2 RMS trend



(d) Bearing3, Test 1 Feature (b) Bearing4, Test 1 Feature (c) Bearing1, Test 2 Feature

Figure 6. RMS trend & proposed feature

4.1. Result

Bearing set 3, 4 in test 1 and set 1 in test 2 are used to demonstrate the proposed methods. Figure 6 (a), (b), (c) shows rapid increase trend which makes the time available for the maintenance crew to respond prior to catastrophic failure after a defect is confirmed, is very short (Qiu et al. 2003). As shown in Figure 6, classical time domain feature, RMS shows good performance in the view of fault detection. However, retaining enough time to make maintenance decision, feature showing monotonic increase or decrease trend and sensitivity in identifying incipient defect is required. In case of bearing 1 in test 2, RMS shows sudden increase around 700 cycle, which makes bearing health estimation inaccurate and increase uncertainty when trending its trajectory. New feature extracted from proposal method has much more sensitivity than the RMS and shows no abrupt increase. It shows smooth increase trend around 700 cycle in contrast with RMS.

5. Conclusion

In the view of prognostics and health management, feature extraction is one of the most important step. This study proposes a feature extraction using correlation coefficient weighted sum of defect frequency amplitude and compared with the simple time domain feature RMS. A new feature shows good performance in monotonicity and early trending.

Acknowledgement

This paper was supported by Korea Agency for Infrastructure technology Advancement (KAIA) in 2017.

(17RTRP-B104370-04-000000)

References

Heng, A., Zhang, S., Tan, A. C., & Mathew, J. (2009). Rotating machinery prognostics: State of the art, challenges and opportunities. *Mechanical systems and signal processing*, vol.23, pp. 724-739.

Jardine, A. K., Lin, D., & Banjevic, D. (2006). A review on machinery diagnostics and prognostics implementing condition-based maintenance. *Mechanical systems and signal processing*, vol. *20*, pp. 1483-1510.

Lee, J., Qiu, H., Yu, G., & Lin, J. (2009). Rexnord Technical Services (2007).'Bearing Data Set', IMS, University of Cincinnati. NASA Ames Prognostics Data Repository.

Li, H., & Zheng, H. (2008). Bearing fault detection using envelope spectrum based on EMD and TKEO. *Fuzzy Systems and Knowledge Discovery, 2008. FSKD'08. Fifth International Conference on*, vol. 3, pp. 142-146

Qiu, H., Lee, J., Lin, J., & Yu, G. (2003).Robust performance degradation assessment methods for enhanced rolling element bearing prognostics. *Advanced Engineering Informatics*, vol. 17, pp. 127-140

Randall, R. B., & Antoni, J. (2011). Rolling element bearing diagnostics—a tutorial. *Mechanical systems and signal processing*, vol. 25, pp. 485-52

Siegel, D., Lee, J., & Ly, C. (2011, June). Methodology and framework for predicting rolling element helicopter bearing failure. *Prognostics and Health Management (PHM), 2011 IEEE Conference on*, pp. 1-9

Tabrizi, A., Garibaldi, L., Fasana, A., & Marchesiello, S. (2015). A novel feature extraction for anomaly detection of roller bearings based on performance improved ensemble empirical mode decomposition and Teager–Kaiser energy operator. *International Journal of Progn Health Management*, vol. 6, pp.1-10.

Tobon-Mejia, D. A., Medjaher, K., Zerhouni, N., & Tripot, G. (2011). Estimation of the remaining useful life by using wavelet packet decomposition and HMMs. In *Aerospace Conference, 2011*, pp. 1-10

Zhang, B., Sconyers, C., Byington, C., Patrick, R., Orchard, M. E., & Vachtsevanos, G. (2011). A probabilistic fault detection approach: Application to bearing fault detection. *IEEE Transactions on Industrial Electronics*, vol. *58*.

BIOGRAPHIES

Seokgoo Kim received the B.S degree of mechanical engineering from Korea Aerospace University in 2016. He is now M.S student at Korea Aerospace University. His current research is focused on the prognostics and health management for rotary machines.

Chaeyoung Lim received the B.S degree of mechanical engineering from Korea Aerospace University in 2017. She is now M.S student at Korea Aerospace University. Her current research is bearing diagnsotics.

Joo-Ho Choi received the B.S. degree of mechanical engineering from Hanyang University in 1981, the M.S. degree and Ph.D. degree of mechanical engineering from Korea Advanced Institute of Science and Technology (KAIST) in 1983 and 1987, respectively. During the year 1988, he worked as a Postdoctoral Fellow at the University of Iowa. He joined the School of Aerospace and Mechanical Engineering at Korea Aerospace University, Korea, in 1997 and is now Professor. His current research is focused on the reliability analysis, design for life-time reliability, and prognostics and health management.