Bearing Health Assessment Using Gaussian Mixed Model Based on a Hybrid Feature Extraction Schemer

Zhipeng Wang, Chen Lu[1], Zili Wang and Jian Ma
School of Reliability and Systems Engineering, Beihang University, Beijing, 100191, China
Science & Technology Laboratory on Reliability & Environmental Engineering, Beijing, 100191, China

E-mail: luchen@buaa.edu.cn

Abstract. Bearings, as important components, are widely used in almost all forms of rotary machines. Bearing failure is one of the foremost causes of breakdown in rotating machinery. Such failure can be catastrophic and often results in lengthy industrial downtime that has economic consequence. In order to prevent unexpected bearing failure, this paper presents a health assessment method using Gaussian mixture model (GMM) based on a hybrid feature extraction method. This hybrid feature extraction method combines Empirical Mode Decomposition (EMD) and Singular Value Decomposition (SVD) to process the nonlinear and non-stationary vibration signal of bearing. Then, the health condition of bearing can be assessed and tracked in terms of confidence values (CVs) obtained by GMM. This method can be employed only using normal condition datasets without the need of failure data, which is a notable indicator for bearing health tracking and defect detection at the incipient stage. Its performance and effectiveness has also been validated via a bearing test-bed.

1. Introduction

Diagnosis of bearings has been studied extensively for decades. Nowadays, a variety of data-driven methods exist for condition monitoring, such as principal component analysis [1], fuzzy logic [2], wavelet packet [3], proportional hazard model [4] and artificial neural networks [5-7]. However, considering the damage that the failed bearing can cause, it becomes increasingly important in contemporary manufacturing to predict and prevent bearing failures, instead of allowing the bearing to fail and then react to the failure. The need to achieve near-zero-downtime performance has been driving the shift from the traditional "fail and fix" (FAF) practice to the "predict and prevent (PAP) paradigm [8, 9]. Therefore, the research on health assessment has attracted much attention.

Nowadays, most health assessment methods require fault data to extract the condition feature, whereas fault data is rare in real situations. So, how to accurately track the health condition of bearing using normal condition data is a current highlight in condition-based maintenance. To solve this problem, Gaussian mixture model (GMM) is employed for health assessment in this paper.

Bayesian inference based GMM, as a data-driven method, has shown strong capability in monitoring non-Gaussian processes, which consist of multiple modes and have significant multi-Gaussianity in monitoring data [10]. When GMM is employed, there is no need for fault data.

Meanwhile, for the purpose of the employment of GMM as a health assessment algorithm, there is an significant process ahead: extracting the suitable features from the raw data. The features are inputs of the GMM. As well known, in most cases, garbage in, garbage out. To ensure the efficiency of the GMM, well-done feature extraction is also very important. Therefore, an investigation for feature extraction is needed.

In the most recent studies, the time-frequency analysis methods are widely used in analysis of rotating machinery vibration signal [11-14]. From the past decades, wavelet transform has become one of the fast-evolving mathematical and signal processing tools. The basic operation of wavelet transform involves the operations of dilation and translation, which lead to a multi-scale analysis of the signal. Wavelet transform is capable of analyzing non-stationary signals, but it still has some

[1] Author to whom any correspondence should be addressed.

inevitable deficiencies [15]. One of them is that the commonly used wavelet analysis is essentially a kind of Fourier transform with adjustable windows and suffers many shortcomings of Fourier spectral analysis [16]. Another disadvantage of wavelet analysis is its non-adaptive nature. Once the wavelet function is selected, one will have to use it to analyze all the data [15, 17].

To avoid the disadvantages of wavelet transform, a self-adaptive method for nonlinear and non-stationary signals is needed. In 1998, Huang et al. proposed Empirical Mode Decomposition (EMD) which is based on local time and scale characteristics of signal and decompose signal into a number of intrinsic mode functions (IMF). IMF not only relates to sampling frequency but also changes with signal itself, so the method is a self-adaptive method to decompose nonlinear and non-stationary signals [17]. Nowadays, it has been broadly used in fault diagnosis [16, 18, 19]. Therefore, EMD is available for feature extraction in this paper.

Meanwhile, considering the vibration signal usually unfolds a feature similar to periodic impulse when local fault appears in bearing, matrix singular value decomposition (SVD) techniques can be used to extract the features [18]. And according to the matrix theory, singular values are the intrinsic characteristics of matrix, with favorable stability, invariant ratio and rotation. Generally, SVD can be used as a tool for signal regularization, noise reduction, signal detection and estimation, etc [20]. But there is still a drawback in implemetation of SVD: how to construct the initial matrix? Usually, phase space reconstruction in chaos theroy is employed [18, 21]. However, it is required to determine the reconstruction parameters, such as delay time and embedding dimension, which will need extensive computational requirements. Thus, this construction method is unavailable in application. Whereas, EMD can decompose signal into a number of IMFs, which can be used to construct the original matrix for SVD. Therefore, a hybrid feature extraction method combined with EMD and SVD is proposed for the nonlinear and non-stationary signal.

2. Methodology

2.1. Empirical Mode Decomposition

EMD method is developed from the simple assumption that any signal consists of different simple intrinsic modes of oscillations. Each signal could be decomposed into a number of intrinsic mode functions (IMFs), each of which must satisfy the following definition [17]: (1) In the whole data set, the number of extreme and the number of zero-crossings must either equal or differ at most by one; (2) At any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero.

With the definition, any signal can be decomposed [17]. We finally obtain:

$$x(t)=\sum_{j=1}^{n} c_j(t)+r_n(t) \tag{1}$$

Thus, one can achieve a decomposition of the signal into n-empirical modes and a residue $r_n(t)$, which is the mean trend of $x(t)$. Each IMF $c_1(t), c_2(t), \cdots c_n(t)$ contains lower-frequency oscillations than the prior-extracted one, while $r_n(t)$ represents the central tendency of signal $x(t)$.

2.2. Singular Value Decomposition

SVD, as a powerful and effective tool for feature extraction in Linear Algebra, has been used for fault diagnosis of rotating machinery [21]. The SVD is defined as follows:

Let X denote an $m \times n$ matrix with $m \geq n$, according to the SVD theorem, the matrix X can be decomposed in the form [22]

$$X = U\sigma V^T \tag{2}$$

where $U(m\times m)$ and $V(n\times n)$ are orthogonal matrix, and σ is an $m\times n$ diagonal matrix of singular values ($\sigma_{ij}\neq 0$, if $i=j$ and $\sigma_{11}\geq\sigma_{22}\geq\cdots\geq 0$). The columns of the orthogonal matrix U and V are called the left singular vector and right singular vector, respectively.

2.3. Health assessment based on Gaussian mixed model

Quantitative health assessment can be described by evaluating the overlap between the most recently observed signatures and those observed during normal machine operation. This index is introduced by Jay Lee [9, 23], and has been accepted by some researchers [24-26]. In this paper, Gaussian mixed model (GMM) is employed.

GMM is a statistical model that using a weighted sum of probability density functions of multiple Gaussian distributions to depict the distribution of a vector in the probability space [24]. It can theoretically be applied to approximate an arbitrary feature distribution within an arbitrary accuracy [23]. The mathematic model of GMM is parameterized by mixture weights α, mean vectors $\vec{\mu}$, and the covariance $\sum$ from all the M mixture components and can be denoted as:

$$\lambda=\{\alpha_i,\vec{\mu}_i,\sum{}_i;i=1,2\cdots M\} \tag{3}$$

GMM can be given as:

$$P(x)=\sum_{i=1}^{M}\alpha_i p(x|\theta_i) \tag{4}$$

$$p(x|\theta_i)=\frac{1}{(2\pi)^{d/2}|\sigma_i|^{1/2}}\exp\left(-\frac{1}{2}(x-\vec{\mu}_i)'\sigma_i^{-1}(x-\vec{\mu}_i)\right) \tag{5}$$

where $p(x|\theta_i)$ is a single Gaussian function, x is the d-dimensional feature vector, M is number of mixtures, and θ_i stands for the parameters of the ith Gaussian function, including mean vector $\vec{\mu}_i$ and covariance matrix σ_i.

For health assessment, given training feature vectors from normal machine condition, the goal of model training is to estimate the parameters of the GMM built on normal machine condition [24]. There are several methods available for estimating parameters of GMM. Maximum likelihood (ML) estimation, which is the most popular and well-established method, is used in this work. The estimation of ML parameters can be obtained iteratively by the expectation maximization (EM) algorithm [25-28].

After establishing the GMMs for normal condition and monitoring condition separately, the CV can be calculated by the overlap of the GMMs.

$$CV=overlap=\frac{\int g_1(x)g_2(x)dx}{\sqrt{\int(g_1(x))^2dx}\sqrt{\int(g_2(x))^2dx}} \tag{6}$$

where $g_1(x)$ and $g_2(x)$ are GMMs which represent the normal and current monitoring condition, respectively. In this paper, the authors will use only normal condition datasets for overlap calculation, where each overlap value between the clustered normal dataset and online measurement data can be considered as CV, and health degradation state tracking as well.

3. Experimental results

3.1. Experimental Setup

In order to verify the proposed method, datasets from a bearing test rig have been used. The datasets is generated from bearing run-to-failure tests performed under constant load condition by NSF I/UCR Center on Intelligent Maintenance Systems. Experimental test rig in NSF IUCR center is as shown in figure 1. Rexnord ZA-2115 double row bearing is selected in this run-to-failure test. The rotation speed is kept constantly at 2000RPM. 6000lb radial load is placed onto the shaft and bearing by a spring mechanism [29]. Vibration data is collected every 20 min, with a sampling rate of 20kHz. Test is stopped until a significant amount of metal debris was found on the magnetic plug of the test bearing. Test ends up with an inner race fault in bearing.

Figure 1. Experimental test rig in NSF I/UCR center.

3.2. Feature extraction

Firstly, the vibration signal of the dataset is decomposed into a *n*-empirical modes, which contains lower-frequency oscillations than the prior-extracted one, and a residue $r_n(t)$. As the information of bearing health condition is considered in the high frequency bands. Therefore, in this paper, n is designated as 7. The first seven IMFs and a residue $r_7(t)$ are extracted to construct the feature matrix for the following SVD processing. Secondly, the constructed feature matrix is decomposed, and an 8-dimensional feature vector of singular values is obtained.

3.3. Health assessment using only normal condition data

Considering the first 400min collected datasets as normal condition data, with equation 6, the CVs from the beginning to the end of the life testing of the bearing are calculated, as shown in figure 2.

From the blue curve, the health degradation can be detected. Approximately, in the first 900min, the bearing is in good health condition, considered as “normal stage”; from around 900min to 5400min, the initial defects appear and propagate, so the CV decreases, considered as “defect stage”; from around 5400min to 6400min, defects become extremely bad and the CV decreases rapidly, considered as “danger stage”. A few minutes later after 6400min, fault occurs, considered as “failure stage”. Thus, as figure 2 shown, several thresholds are selected: 0.8, 0.4, and 0.1. With those thresholds, the health scale of the bearing can be distinguished, which is significant for condition-based predictive maintenance.

4. Conclusion

Health assessment is the main technique for intelligent maintenance systems. The strong nonlinearity features in the vibration signals of bearing bring difficulties for health assessment. This paper presents a health assessment method based on EMD, SVD and GMM. Targeting nonlinear and non-stationary signal of bearing, EMD-SVD method is employed for feature extraction. Then, GMM is used for health assessment, which has been verified by experimental datasets. The results indicate that this method can be used without fault datasets in applications and detect the defect at its incipient stage.

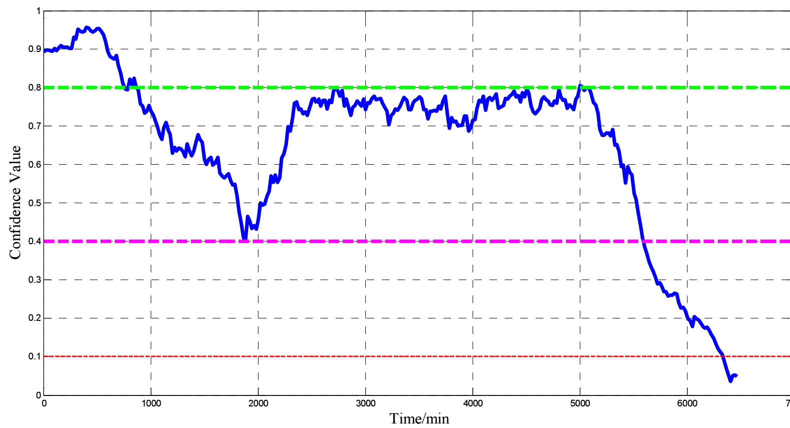

Figure 2. CVs obtained by the proposed method.

Acknowledgments
This research was supported by the National Natural Science Foundation of China (Grant No. 61074083, 50705005 and 51105019), the Technology Foundation Program of National Defense (Grant No. Z132010B004), as well as the Innovation Foundation of BUAA for PhD Graduates.

References

[1] Yu J 2011 A hybrid feature selection scheme and self-organizing map model for machine health assessment *Applied Soft Computing* **11** 4041–54.

[2] Li B, Liu P, Hu R, Mi S and Fu J 2012 Fuzzy lattice classifier and its application to bearing fault diagnosis *Applied Soft Computing* **12** 1708–19

[3] Pan Y, Chen J and Guo L 2009 Robust bearing performance degradation assessment method based on improved wavelet packet-support vector data description *Mechanical Systems and Signal Processing* **23** 669–81

[4] Van Tung Tran, Pham H T, Yang B and Nguyen T T 2012 Machine performance degradation assessment and remaining useful life prediction using proportional hazard model and support vector machine *Mechanical Systems and Signal Processing* 320–30

[5] Yang Y, Liao Y, Meng G and Lee J 2011 A hybrid feature selection scheme for unsupervised learning and its application in bearing fault diagnosis *Expert Systems with Applications* **38** 11311–20

[6] Pan Y, Chen J and Guo L 2009 Robust bearing performance degradation assessment method based on improved wavelet packet-support vector data description *Mechanical Systems and Signal Processing* **23** 669–81

[7] Zhu X, Zhang Y and Zhu Y 2013 Bearing performance degradation assessment based on the rough support vector data description *Mechanical Systems and Signal Processing* **34** 203–17

[8] Djurdjanovic D, Lee J and Ni J 2003 Watchdog Agent—an infotronics-based prognostics approach for product performance degradation assessment and prediction *Advanced Engineering Informatics* **17** 109–25

[9] Liao L and Lee J 2010 Design of a reconfigurable prognostics platform for machine tools *Expert Systems with Applications* **37** 240–52

[10] Yu J 2012 A nonlinear kernel Gaussian mixture model based inferential monitoring approach for fault detection and diagnosis of chemical processes *Chemical Engineering Science* **68** 506–19

[11] Oehlmann H, Brie D, Tomczak M and Richard A 1997 A method for analysing gearbox faults using time – frequency representations *Mechanical Systems and Signal Processing* **11** 529–45.

[12] Yan R and Gao R X 2005 An efficient approach to machine health diagnosis based on harmonic wavelet packet transform *Robotics and Computer-Integrated Manufacturing* **21** 291–301

[13] Zou J and Chen J 2004 A comparative study on time – frequency feature of cracked rotor by Wigner – Ville distribution and wavelet transform *Journal of Sound and Vibration* **276** 1–11.

[14] Baydar N and Ball A 2001 A comparative study of acoustic and vibration signals in detection of gear failures using Wigner – Ville distribution *Mechanical Systems and Signal Processing* **15** 1091–107

[15] Tse P W, Yang W and Tam H Y 2004 Machine fault diagnosis through an effective exact wavelet analysis *Journal of Sound and Vibration* **277** 1005–24

[16] Junsheng C, Dejie Y and Yu Y 2006 Research on the intrinsic mode function (IMF) criterion in EMD method *Mechanical Systems and Signal Processing* **20** 817–24

[17] Huang N E, Shen Z, Long S R, Wu M C, Shih H H, Zheng Q, Yen N, Tung C C and Liu H H 1998 The Empirical Mode Decomposition and the Hilbert Spectrum for Nonlinear and Non-Stationary Time Series Analysis *Proceedings: Mathematical, Physical and Engineering Sciences* **454** 903–95

[18] Cheng J, Yu D, Tang J, and Yang Y 2009 Application of SVM and SVD technique based on EMD to the fault diagnosis of the rotating machinery *Shock and Vibration* **16** 89–98

[19] Yu D, Cheng J and Yang Y 2005 Application of EMD method and Hilbert spectrum to the fault diagnosis of roller bearings *Mechanical Systems and Signal Processing* **19** 259–70

[20] Van Der Veen A, Deprettere E F and Swindlehurst A L 1993 Subspace-based signal analysis using singular value decomposition *Proceedings of the IEEE* **81** 1277–308

[21] Sandy J 1988 Monitoring and diagnostics for rolling element bearings *Sound and Vibration* **22** 16–20

[22] Wade M J, Sánchez A and Katebi M R 2005 On real-time control and process monitoring of wastewater treatment plants: real-time process monitoring *Transactions of the Institute of Measurement and Control* **27** 173–93

[23] Liao L and Lee J 2009 A novel method for machine performance degradation assessment based on fixed cycle features test *Journal of Sound and Vibration* **326** 894–908

[24] Yu G, Sun J and Li C 2008 Machine performance assessment using Gaussian mixture model (GMM) Shenzhen China

[25] Yu J 2011 Bearing performance degradation assessment using locality preserving projections and Gaussian mixture models *Mechanical Systems and Signal Processing* **25** 2573–88

[26] Liu W, Zhong X, Lee J, Liao L and Zhou M 2011 Application of a novel method for machine performance degradation assessment based on Gaussian mixture model and logistic regression *Chinese Journal of Mechanical Engineering (English Edition)* **24** 879–84.

[27] Zhang B, Zhang C and Yi X 2004 Competitive EM algorithm for finite mixture models *Pattern Recognition* **37** 131–44

[28] Huda S, Yearwood J and Togneri R 2009 A stochastic version of Expectation Maximization algorithm for better estimation of Hidden Markov Model *Pattern Recognition Letters* **30** 1301–09

[29] Qiu H, Lee J, Lin J and Yu G 2003 Robust performance degradation assessment methods for enhanced rolling element bearing prognostics *Advanced Engineering Informatics* **17** 127–40