Journal of Applied Sciences

ISSN 1812-5654

Journal of Applied Sciences 13 (13): 2404-2408, 2013
ISSN 1812-5654 / DOI: 10.3923/jas.2013.2404.2408

Fault Severity Identification of Rolling Bearing Based on Multiscale Entropy

Xiong Guoliang, Huang Wenyi and Zhang Long
East China Jiaotong University, Nanchang, Jiangxi, People's Republic of China

Abstract: CBM (Condition based maintenance) is an effective approach to reduce the fault rate and thus avoid the occurrence of serious failure. Quantitative identification of bearing fault severity is the basis of CBM for bearings. The vibration signals will exhibit nonstationarity and nonlinearity in the presence of bearing faults. Taking into account the mean value and the variations of the entropies over multiple scales, a new index termed Partial Mean of Multiscale Entropy (PMME) is constructed to quantitatively describes bearing fault severity. Experimental results verify that the new index is able to detect incipient bearing fault in a timely fashion and can trend the fault development well.

Key words: Fault severity, fault diagnosis, multiscale entropy

INTRODUCTION

Nonlinear factors such as stiffness, damping and clearance often lead a mechanical system to be in nonlinear and nonstationary states. The traditional signal processing method for stationary signal is not suited to nonstationary signals with time varying frequency characteristics. To date, many time-frequency analysis and fusion diagnosis methods have been available for nonstationary process such as wavelet analysis, Empirical Mode Decomposition (EMD), holo-spectrum, neural network, support vector machines and rough set theory (Jardine *et al*., 2006).

However, most of such methods only identify the fault type and location, lacking a quantitative index to describe the fault severity which is basis of the CBM. Fault development from an incipient state to a mature one is an evolution process. Accurate and timely identification of fault severity on line helps to avoid economic loss and disastrous accidents, which is of great significance to ensure the safe operation of mechanical equipment (Lee, 1996). A quantitative method for fault diagnosis refers to describing the evolution of faults and identifying fault size. Dou studied the damage degree of the rolling bearing in the single damage cases under the experimental simulation based on EMD and Lempel-Ziv indicators, they found the comprehensive index on Lempel-Ziv of inner damage decline with fault aggravating decline, while the index of outer ring increase (Dou and Zhao, 2010). Cong performed the whole life detection of rolling bearing in fatigue experiment using the detection method for AR prediction of white noise based on Kolmogorov-Smirnov test (Cong *et al*., 2011). Jiang proposed a method separating the model for training and evaluation of diagnostic, describing the system structure and realization of software, hardware and the system design, to achieve portable vibration analyzer on-site equipment performance degradation assessment to guide diagnosis and objective of alarm threshold setting, meanwhile they verify the effective of proposed method and the feasibility of system through the test of bearing life in accelerated fatigue test (Jiang *et al*., 2012). Pan proposed a bearing performance degradation assessment method based on wavelet and support vector data, which constitute the wavelet packet decomposition energy of the feature vectors, only under the normal state of the sample data can they using support vector data description to establish the knowledge base, to realize the degradation degree quantitative assessment of the sample to be tested,and verified the feasibility and validity of this method through applying to the detection of whole life cycle of bearing suffer on different defect sizes and acceleration fatigue experiment (Pan *et al*., 2009).

However, the above methods are mostly linear processing method and require long sample data. A nonlinear quantitative evaluation method based on multiscale entropy is proposed in this paper and applied to the experimental signals of rolling bearing fault to verify its practicability.

MULTISCALE ENTROPY AND PARTIAL MEAN OF MULTISCALE ENTROPY

Entropy is intended to measure the complexity of time series. Approximate entropy and sample entropy are proposed by Pincus and Richman, respectively. However, approximate entropy and sample entropy just reflect the information on a single time scale. Multiscale entropy was

Corresponding Author: Xiong Guoliang, East China Jiaotong University, Nanchang, Jiangxi, People's Republic of China

originally proposed by Costa, who pointed out conflicting results will be incurred if the single scale entropy algorithm is applied on the data from the health and disease filed. As such, multiscale entropy was proposed using coarse grain series to replace the original single scale time series and then analyzing the physiological signals in each scale. For rolling element bearing fault, the entropy of vibrations will reduce gradually with the deepening of fault degree, which means that the complexity of fault signal decreases with fault severity. The calculation method of the sample entropy, multiscale entropy and the partial mean of multiscale entropy are introduced as follow:

Sample entropy: Sample entropy is obtained by following steps:

- Assuming that the original data of $X = (x_1, x_2, ..., x_N)$, $X(i) = (x_i, x_{i+1}, ..., x_{i+m-1})$, where $1 = I = N\text{-}m$ and m is the embedding dimension
- The definition of d_{ij} is the distance between X(i) and X(j) which means the maximum absolute value of the difference of corresponding elements of the two
- For each i, calculating distance d_{ij} between X(i) and the rest of the vector X(j), ratio the number of d_{ij} less than r and the distance of the total number of N-m-1, denoted as $B_i^m(r)$:

$$B_i^m(r) = \text{num}(d_{ij}<r)/(N\text{-}m\text{-}1) \quad (1)$$

where, r is the similar tolerance, num $(d_{ij}<r)$ is the number of d_{ij} less than r:

- Then, get the average value $B^m(r)$ of $B_i^m(r)$
- For dimension m+1, repeat 1~4, get $B_i^{m+1}(r)$ and then $B^{m+1}(r)$
- Finally get the expression of sample entropy:

$$\text{Samp En}(m, r, N) = \ln B^m(r) - \ln B^{m+1}(r) \quad (2)$$

SampEn (m, r, N) is related to embedding dimension m, similar tolerance r and data length N. In general, m = 2, r = 0.15*SD (SD is the standard deviation of original data) and N = 500~1000.

Multiscale entropy: The sample entropies of coarse grain series are referred to as multiscale entropy:

- Given the original data $X = (x_1, x_2, ..., x_N)$ with length of N, embedding dimension m and similar tolerance r, then establish a new coarse vector:

$$y_j^{(s)} = \frac{1}{s} \sum_{i=(j-1)s+1}^{js} x_i, \; 1 \le j \le \frac{N}{s} \quad (3)$$

where, the positive integer s = 1,2.... is the scale factor, taking the maximum value of s as $s_{max} = 20$:

- Calculate the sample entropy of each coarse grain series, then get s coarse grain series of sample entropy. Drawing the multiscale entropy as a function of the scale factor s, which called the analysis of multiscale entropy

Multiscale entropy analysis are applied in various research fields. Li applied multiscale entropy to renal sympathetic nerve activity of conscious and anesthetized rats to study, they found that multiscale entropy is more fully reflect on nonlinear characteristics of the nervous system than the sample entropy algorithm (Li *et al*., 2008). He explored multiscale entropy analysis in metallic interconnection electromigration noise and found that electromigration failure process can be characterized by multiscale entropy (8). In the domain of fault diagnosis, Wu reported a fusion diagnosis method including the multiscale entropy analysis and Support Vector Machines (SVM), which seems more excellent than sample entropy analysis for bearing fault diagnosis (Wu *et al*., 2012). Wu showed that it is significant to extract feature in different scales as fault feature in fault diagnosis of bearing (Wu *et al*., 2013).

PMME: Most of the literature on multiscale entropy does not made a quantitative diagnosis of fault. This study presents a fault severity index, which was named as the partial mean of multiscale entropy (denoted as PMME).

It is necessary to get some insights into the skewness before introducing PMME. In order to analyze the overall trend of a set of data, the first step is to calculate the mean value with aim to examine the trend of concentration data. However, mean value fails to fully characterize the whole profile of a data set, so introducing the concept of skewness is the key to compensate the efficiency of the mean. The skewness is greater, the efficiency of the mean is more doubtful, while the skewness is smaller, the efficiency of the mean is more reliable.

In the symmetric condition, there is:

$$x' = M_0 = M_e \quad (4)$$

where, x' is mean, M_0 is mode, M_e is median, in the partial distribution conditions and there exist differences of numerical and position between the three number. The M_e

is located in the middle, x' and M_0 separate on both sides. Therefore, the skew a' can be represent by the absolute difference (distance)of x' and M_0:

$$a' = x'-M_0 \quad (5)$$

The absolute difference of x' and M_0 is greater, the skew degree is greater; the difference is smaller, the skew degree is smaller. When $x'>M_0$, deflection direction is right (positive); otherwise, deflection direction is left (negative).

Due to the fact that the skew a' is expressed in absolute value with the dimension of the original sequence, thus it cannot make a comparison between different sequence. The solution is to calculate the relative values of skewness so as to make different skew of different sequence comparable, which means the absolute value of skewness divided by the standard deviation, resulting in the coefficient of skewness or skewness (denoted as Ske):

$$Ske = (x'-M_0)/SD = 3(x'-M_e)/SD \quad (6)$$

where, SD is the standard deviation, Skewness is the deviation between the arithmetic average and modal dispersion owning the units of standard deviation, so its value is within the range of 0 and ±3. For the case of a = 0, the distribution is symmetrical. For a = +3 or-3, the distribution is ultra-right skewness or ultra-left skewness. According to the definition of the skewness and its relationship with the mean, the partial mean of multiscale entropy is defined as follows:

- Assuming that the multiscale entropy of a fault signal X (the maximum scale factor is s_{max} = 20) is MSE(X) = (MSE (1), MSE (2), ..., MSE (20)) then:

$$PMME = (1+|Ske(MSE)|/3)\bullet mean(MSE) \quad (7)$$

where, the Ske(MSE) and mean(MSE) is the skewness and mean value of the entropies over 20 scales. PMME can reflect the complexity of sample signal more accurately than sample entropy. It has potential to be an important indicator for quantitatively describing bearing fault.

EXPERIMENTAL TEST

Experiment introduction: The experimental data was obtained from the center for Intelligent Maintenance Systems (IMS). Rolling element bearings were subjected to run-to-failure tests under constant load conditions on a specially designed test rig as shown in Fig. 1 (Qiu *et al*., 2003; Lee *et al*., 2007). The bearing test rig hosts four Rexnord ZA-2115 double row bearings on one shaft. The shaft is driven by an AC motor and coupled by rub belts. The rotation speed was kept constant at 2000 rpm. A radial load of 6000 lbs is applied on the shaft and bearings by a spring mechanism. An oil circulation system regulates the flow and the temperature of the lubricant. A magnetic plug installed in the oil feedback pipe collects debris from the oil as evidence of bearing degradation. A test will stop when the accumulated debris adhered to the magnetic plug exceeds a certain level and cause a switch to turn off. The test bearing have 16 rollers in each row, a pitch diameter of 2.815 in, roller diameter of 0.331 in. and a tapered contact angel of 15.17°C. A PCB 353b33 High Sensitivity Quartz ICP Accelerometer was installed on each bearing housing.

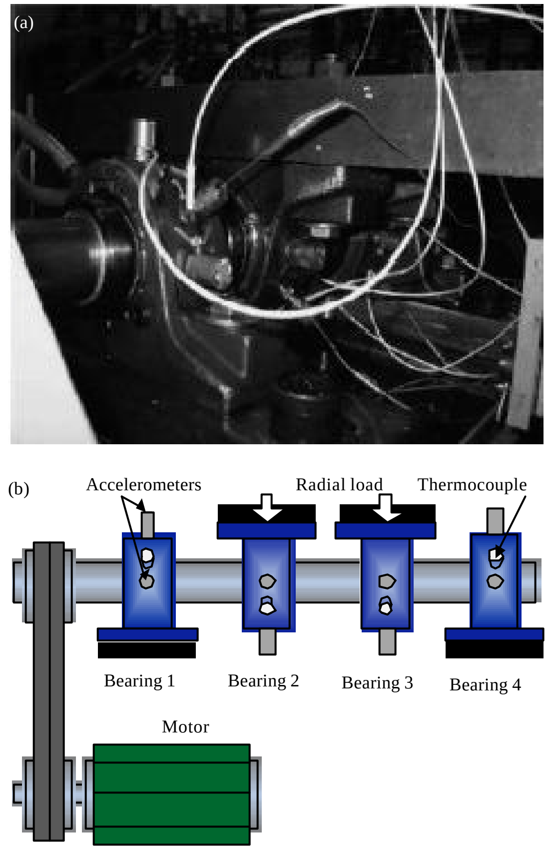

Fig. 1(a-b): (a) Bearing fatigue test bench and (b) Sketch map of test bench

Data collection started form 2004.2.12 10:32:39 to 2004.2.19 06:22:39 with an interval of 10 min during acquisition time and thus there are totally 984 data files collected during the experimental process. The sampling

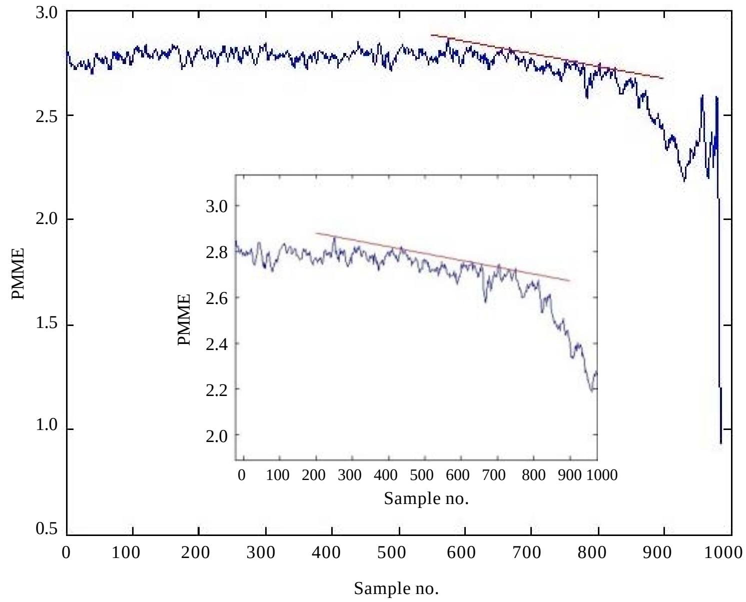

Fig. 2: PMME of experimental data

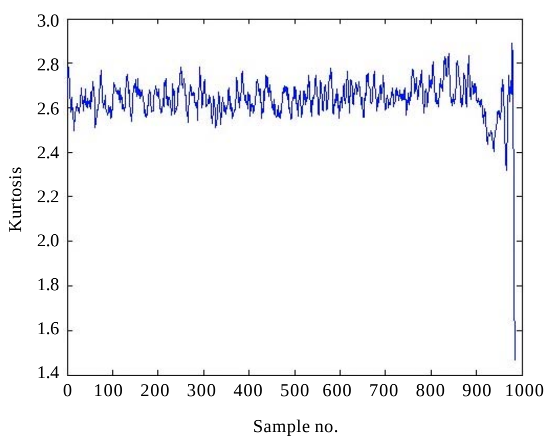

Fig. 3: Kurtosis of experiment data

frequency is set as 2000 Hz and each sensor collect 20480 data every time. The analyzed is the 8192 data of the second file (Bearing 2).

Experimental results analysis: Calculating the PEME of 984 groups of experimental data, the smoothed result is shown in Fig. 2. It is observed that the PMME values continue to decline from the 575th data sets and sharply decline from the 778th sets of data.

Comparison with the conventional method: Kurtosis has been considered as an important indicator for the determination of bearing fault severity. The kurtosis of the experimental data is shown in Fig. 3. The comparison between the results shown in Fig. 2 and 3 demonstrates that the proposed PMME can clearly reveal the severity characterization of bearing failure and give warning in the early stage of bearing faults.

CONCLUSION

A novel bearing health condition index termed partial mean of multiscale entropy (PMME for short) is proposed for quantitatively describing fault severity. The PMME is construed by the mean value and the skewness of the entropies over multiple scales, which takes into account the value and the variation of multiscale entropy. The results on a bearing run-to-failure test data set shows the PMME is able to detect incipient bearing fault at its early stage and trend the fault evolution process well. Furthermore, comparison with conventional statistical index like kurtosis highlights the merits of the proposed PMME index.

ACKNOWLEDGMENT

This study was supported by the Natural Science Foundation of China (Grant No. 51205130, 51265010) and the Foundation of Jiangxi Educational Committee (Grant No. GJJ12318).

REFERENCE

Cong, F., J. Chen and Y. Pan, 2011. Kolmogorov-smirnov test for rolling bearing performance degradation assessment and prognosis. J. Vibration Control, 17: 1337-1347.

Dou, D.Y. and Y.K. Zhao, 2010. The identification study of rolling bearing damage based on EMD and Lampel-Ziv index. J. Vibration Shock, 3: 5-8.

Jardine, A.K.S., D. Lin and D. Banjevic, 2006. A review on machinery diagnostics and prognostics implementing condition-based maintenance. Mech. Syst. Signal Proc., 20: 1483-1510.

Jiang, R.L., J. Chen, T. Liu and W.B. Xiao, 2012. Equipment performance degradation assessment used in routing inspection system. J. Vibration Shock, 16: 134-137.

Lee, J., 1996. Measurement of machine performance degradation using a neural network model. Comput. Ind., 30: 193-209.

Lee, J., H. Qiu, G. Yu and J. Lin, 2007. 'Bearing data set?, IMS. NASA Ames Prognostics Data Repository, NASA Ames, Moffett Field, CA., University of Cincinnati.

Li, Y.T., R. Yan and Z. Yan, 2008. Multiscale entropy analysis of awake and anesthetized renal sympathetic nerve activity in rats. Chinese J. Biomedical Eng., 4: 498-501.

Pan, Y., J. Chen and L. Guo, 2009. Robust bearing performance degradation assessment method based on improved wavelet packet-support vector data description. Mech. Syst. Signal Proc., 23: 669-681.

Qiu, H., J. Lee, J. Lin and G. Yu, 2003. Robust performance degradation assessment methods for enhanced rolling element bearing prognostics. Adv. Eng. Inform., 17: 127-140.

Wu, S.D., C.W. Wu, T.Y. Wu and C.C. Wang, 2013. Multi-scale analysis based ball bearing defect diagnostics using mahalanobis distance and support vector machine. Entropy, 15: 416-433.

Wu, S.D., P.H. Wu, C.W. Wu, J.J. Ding and C.C. Wang, 2012. Bearing fault diagnosis based on Multiscale permutation entropy and support vector machine. Entropy, 14: 1343-1356.