Data-Driven Roller Bearing Diagnosis Using Degree of Randomness and Laplace Test

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ABSTRACT

In this paper, we present a new diagnosis and prognosis method using the degree of randomness (DoR) measure and Laplace test procedure. The abnormal events are detected based on changes of randomness of vibration signals. The trend of randomness is resulted from faulty components such as roller bearings. We aim at the early detection of semi-failure events through the use of Laplace test statistic which measures the rate changes of abnormal event occurrence. Algorithms are data-driven and capable of making fault detections at its early stages. They have also been integrated into a real-time diagnosis system.*

1 INTRODUCTION

A bearing is one of the most common elements in many mechanical systems and its failure can sometimes have catastrophic consequences. In general, bearing faults can be reflected through rising temperature, periodic acoustic emissions, larger torque amplitude, higher vibration magnitude, increasing stator current, and wear debris accumulation. The vibration, stator current (Obaid, 2003), and wear debris related approaches (Dempsey, 2004) have dominated recent research, as evident by publications in the open literature. Among them, the vibration-based techniques have attracted more attention because vibration signals mainly reflect the local properties and are not sensitive to operation environment changes.

The dominant failure mode of roller bearings is spalling of the races related to the fatigue crack that commonly begins below the metal surface and eventually produces a small pit or spall as the crack propagates to the surface. Whenever a local defect on the bearing interacts with its mating element, abrupt changes in the contact stresses generate vibration that can sometimes be used to monitor the health status of the bearings. Although spalling-related frequencies can be estimated, they are usually buried in noise until damage becomes appreciable and system fault imminent (Roemer, 2007).

Many diagnosis methods have been developed for monitoring bearing damage in rotating machinery. For example, the characteristic frequencies of bearing damage are used to monitor and detect certain frequency components emanating from vibration (Ilonen, 2005). The methods used to analyze these signals include shock pulse methods (SPM) (Morando, 1996), wavelet (Tse, 2001), intrinsic mode functions (IMF) (Yang, 2007), independent component analysis (ICA) (Fan 2007), high order statistics (Antoni, 2006), and amplitude modulation (Stack, 2004). Although these approaches deal with the bearing fault diagnosis in different directions, the core problems that they face are quite similar. The local fault makes the bearings produce the vibrations that correspond to a linear modulation signal, which usually superimposes on other vibration sources in the rotating machinery.

For diagnosis and prognosis of bearing faults, one key issue is how to make early fault detection. Common methods include monitoring the vibration magnitude and related kurtosis estimates. However, these methods are often ineffective for the purpose of detecting system faults in their early stages. Because of the complexity of physics underlying the bearing failure progression, it is often difficult, if not impossible, to develop viable physics-based models for bearing diagnosis and prognosis.

In our previous work (Ling et. al, 2009), we reported the development of a new approach for the diagnosis of ball bearing faults using Hidden Markov Model with degree of randomness (DoR) used as the features. We have demonstrated that the measure of degree of randomness is sensitive in detecting abnormal signals embedded in normal signals. In this paper, we present the latest algorithm improvement of DoR and Laplace test. We test the DoR trend and detect the fault events through its changes. We aim at the detection of semi-failures using Laplace test statistic. Test results using roller bearing data downloaded from NASA Prognostic Data Repository have shown that, with ground truth, our algorithms can detect the roller bearing faults about 10 days in advance of occurrence of failure.

This paper is organized as follows: In Section 2, we present a new method for automated window size selection. Degree of randomness and its analysis is given in Section 3. Laplace test is introduced in Section 4. Finally, in Section 5, test results of roller bearing data are given.

2 AUTOMATED WINDOW SIZE SELECTION

Data window size is important for signal processing. Features often extracted from the data segment windowed out with fixed or variable sizes. There is currently no systematic way to automatically estimate the data window size. In this paper, we present a data-driven approach to estimate the window size.

If the window size is selected appropriately, the data segment should possess enough information for signal processing such as feature extraction. If the data segment mostly contains random signals, it is generally impossible to extract meaningful features. Kolmogorov Complexity (Watanabe, 1992) can be used to measure the complexity of the data to be processed.

The Kolmogorov Complexity (KC) is defined as the minimum number of bits into which a string can be compressed without losing information. This is defined with respect to a fixed, but universal decompression scheme, given by a universal Turing machine. In other words, Kolmogorov Complexity can be measured by the length of the shortest program for a universal Turing machine that correctly reproduces the observed string. The program can be as simple as copy and paste.

Definition of Kolmogorov Complexity: For every language L, the Kolmogorov complexity of the bit string *x* with respect to L is defined as

$$C(x) = \min_{p:L(p)=x} l(p) \tag{1}$$

where *p* is a program represented as a bit string, L(*p*) is the output of the program with respect to the language L, and *l*(*p*) is the length of the program, or more precisely, the point at which the execution halts.

In his work on algorithm complexity, Kolmogorov intended to formalize the notion of a random sequence (string). In theory, if a string *x* is an element of a "simple" finite set A, the Kolmogorov Complexity, C(*x*), cannot be much greater than the binary logarithm log|A| , where |A| is the size of the finite set.

There are basically two different approaches of Kolmogorov Complexity (KC) for window size estimation:

Approach 1 – Fix the window size of data, and calculate the Kolmogorov Complexity over time. If KC converges to a constant, one concludes that the data shows certain deterministic patterns over time.

Approach 2 – Get sets of data with varying window sizes and subsequently calculate KC associated with each set. If KC converges to a constant as the window size increases, one concludes that there is a smallest window size which provides enough discrimination power.

For automated window size estimation for our bearing diagnosis application, we have chosen the second approach.

The original KC is known to be computationally intractable. Instead the Lempel-Ziv measure (Lempel, 1976) can be used to approximate KC . For a string of length *n*, it has been shown by Lempel and Ziv that, for almost all $x \in [0, 1]$, the complexity $C(x)$ tends to the same value, which can be expressed as

$$\lim_{n \to \infty} C(x) = \frac{n}{\log_2 n} \tag{2}$$

The philosophical implication of Eq. (2) is that almost all strings that correspond to a binary representation of a number $x \in [0, 1]$ should be random and have the maximum complexity, $n/\log_2 n$. If $C(x)$ is large, one may conclude that the string is more random. However, if $C(x)$ is small, the corresponding string is less random, or the string exhibits some "deterministic" patterns.

We have developed this automated window size estimation algorithm using various types of data including those of ball bearing vibration, roller bearing vibration, battery voltage, and acoustic emission of air pumps. Figure 1 shows the vibration data of a roller bearing.

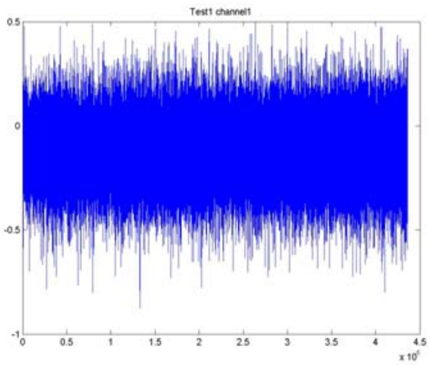

Figure 1: Roller bearing vibration data

We selected a number of data points from this data set and form a sequence of data segments with increasing window sizes. Kolmogorov Complexity is estimated for each of the data segments. Figure 2 shows a curve of KC values associated with data segments with increasing lengths.

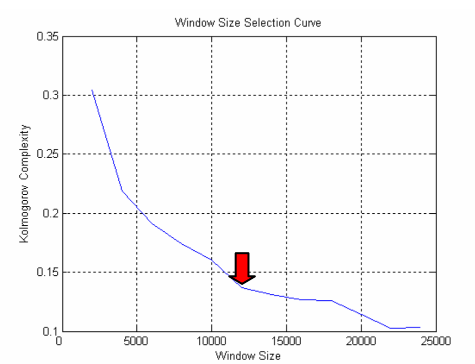

Figure 2: A curve of KC values v.s. window size

From Figure 2, it can be seen that KC-curve decreases sharply when data window size is small and gradually becomes flat at the window size about 12,000. This implies that KC approaches to a relatively constant once the window size is larger than 12,000. This also implies that data in the window with size of 12,000 or larger are less random, or showing certain patterns. The corresponding smallest window size can be selected as the window size for subsequent signal processing. The raw data were used in the estimation of window sizes.

3 DEGREE OF RANDOMNESS

We hypothesize that the vibration signal associated with faulty bearings is primarily superimposed of two independent vibration signals –one from the surrounding environment such as bearing platform and the other from the faulty bearings. This concept is illustrated in Figure 3.

Figure 3: Linear combination of random signals associated with surrounding environment and faulty components

Let X and Y be two statistically independent random variables. For example, in a bearing system, X can be the vibration signal associated with the platform such as bearing housing, and Y the vibration signal from faulty bearings. The properties of sum of two random variables (discrete or continuous) have been studied over the past several decades. Suppose the random variables X and Y have density functions $f_X(x)$ and $f_Y(y)$, respectively. It is known that the sum $Z = X + Y$ is also a random variable with density function $f_Z(z)$ as the convolution of f_X and f_Y given as

$$f_Z(z) = (f_X * f_Y)(z) = \int_{-\infty}^{\infty} f_X(z-y) f_Y(y) dy \tag{3}$$

Although the probability density function of a random variable can be used to derive many useful statistical properties, it is not effective in estimating the degree of randomness (DoR) of random variables. In fact, the variance derived from a density function cannot be used to infer the degree of randomness. For example, suppose X is a uniformly distributed variable over an interval of [-1 1]. It can be shown that var(X) = 1/3. One can easily generate a random variable with variance larger than 1/3. However, it is known that the uniformly distributed variables have the largest degree of randomness, which implies that the variance is not an effective measure of randomness.

We are more interested in the measure of randomness of a random variable. Denote DoR of X and Y as R_X and R_Y. Specifically, we want to estimate DoR of the new random variable, $Z = X + Y$. In other words, if we define DoR of z as R_Z, we want to know whether or not the following inequality holds

$$R_Z \geq \max(R_X, R_Y) \tag{4}$$

If Eq. (4) is satisfied, we conclude that the random variable $X + Y$ is more random than X or Y.

The majorization technique has been used to define the randomness of a random variable (Hickey, 1983). Majorization is a partial ordering on vectors which determines the degree of similarity between the vector elements. Let Θ denote the class of all discrete probability vectors. For P = (p_1, p_2, …) and Q = (q_1, q_2, …) in Θ, assume that all elements of P and Q are arranged in a non-increasing order. We say that P is majorized by Q (written as P $\prec$ Q) if

$$\sum_{i=1}^{r} p_i \leq \sum_{i=1}^{r} q_i \quad (5)$$

for all $r > 0$. We now state the following definition of randomness (Hickey, 1983):

Definition of Randomness: For P, Q $\in \Theta$ we say that there is at least as much randomness in P as in Q if P $\prec$ Q. If P $\prec$ Q and the elements of P cannot be obtained by permuting those of Q we say that P has greater randomness than Q.

From this definition, it follows that a degenerate distribution (i.e., one for which all the probability is concentrated at a single outcome) is less random than every other non-degenerate distribution. The uniform distribution ($1/n$, …, $1/n$) is more random than every other distribution having at most n positive probabilities. The best-known measure satisfying the definition above is the Shannon entropy given as

$$H = -\sum_{i=1}^{K} p_i \ln p_i \quad (6)$$

where H is a real-valued function and K is the number of possible categories. Therefore, Shannon entropy can be used to measure the randomness of a random variable. The DoR of $X + Y$ can be summarized by the following theorem:

Theorem (Hickey, 1983): Let X and Y be independent discrete random variables. The distribution of $X + Y$ is more random than that of X or Y unless one of these distributions, say that of Y, is degenerate in which case $X + Y$ and X are equally random.

This theorem implies that, in general, the random variable $X + Y$ is more random than either X or Y. Therefore, by monitoring the randomness of vibration signals, we can detect the existence of a new independent random variable associated with the faulty components. There are some other randomness measures. For example, based on Random Matrix Theory (RMT), the largest eigenvalue of a covariance matrix can be used to measure DoR of a random variable (Ling et. al, 2009).

We have developed the algorithms for the estimation of DoR using Shannon entropy. As an example, Figure 4 shows the acoustic data taken from an air pump. In the experiment, the air pump was running under normal condition with both air outlets open. The sound produced by the air pump was recorded. The fault was introduced by blocking one air outlet. As the internal air pressure builds up, the air pump produces a different sound which was recorded as well. The faulty condition was removed by opening the air outlet again and making the air pump operate under normal condition again. From the acoustic wave form shown in Fig. 4, it can be observed that the magnitude of acoustic wave signal has slightly changed over the time period when the fault was introduced.

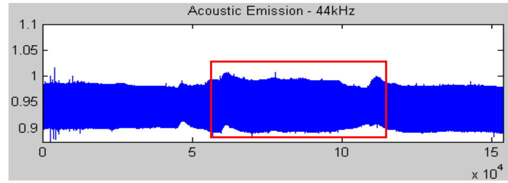

Figure 4: Air pump acoustic emission with faults introduced

We have calculated the degree of randomness for the acoustic data shown in Figure 4. Its curve over time is shown in Figure 5. It is clear that DoR has successfully captured the faults introduced during the experiment. The increase of DoR implies that the acoustic signal becomes more random when fault was introduced, which is expected. Although the magnitude change in Fig. 4 is not significant, DoR clearly shows a trend which can be used for further analysis.

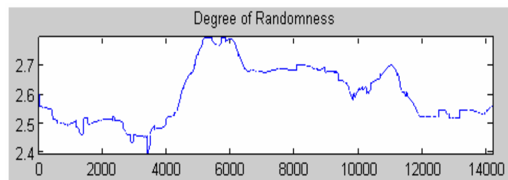

Figure 5: DoR curve calculated from data shown in Fig. 4

We must point out that DoR can increase or decrease. Its trend depends on the underlying physical system one deals with. For example, for some battery data, we have found that DoR associated with the charging voltage actually decreases as the charging process goes on. Therefore, faults can be inferred from DoR curve through its change, either increasing or decreasing. If DoR trend is relatively flat, one can conclude that the system being monitored is in normal conditions, i.e., no faults exist.

4 LAPLACE TEST STATISTIC

Based on the test results using a large amount of test data, we hypothesize that, when the object being monitored is in healthy state, its DoR is relatively *constant*. As its faulty conditions progress, the DoR gradually *increases* or *decreases*. When it is in the failure state, the DoR is becomes relatively *constant* again. In other words, when the object being monitored is failing or in semi-failure stages, its DoR will show certain trend (increasing or decreasing). By testing this trend, we can determine whether or not the health of this object is deteriorating or failing.

There are many different methods which can be used to detect whether or not certain time series show trends. The easiest approach is to test the change of slopes through regression analysis. More sophisticated approach is to use statistical nonparametric hypothesis test procedures. Although it is not straightforward to determine which approach is best, the statistical hypothesis test approach is preferred if the data are noisier.

Once DoR trend is confirmed in the data, an abnormal event or fault is detected. A binary value can be assigned to the detected event, resulting a pulse train. Figure 6 shows an example of detected events based on DoR trend changes. The dense pulses are resulted from DoR changes over a longer period of time.

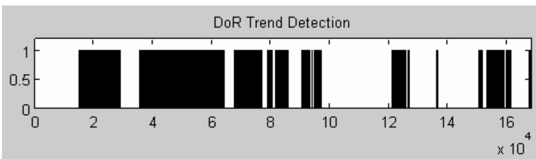

Figure 6: Pulse train of detected events

Although abnormal events can be detected through the use of DoR change test, it is difficult to determine when the failure will actually occur. For mechanical systems, the complete failure occurs over time and many semi-failure events can be captured long before this complete failure occurs. Therefore, it is important to detect these semi-failure events to provide the capability of early failure detection. From abnormal events detected from DoR changes (see Fig. 6), it is not easy to determine the semi-failure events. Laplace test statistic can be used for this purpose.

The Laplace test statistic has been used for reliability analysis (Ascher, 1992). It can be used to detect the rate changes of certain event occurrence from a relatively constant to an increasing trend. Here we apply Laplace test to the events detected from DoR trend changes. Suppose we have detected m abnormal events. Denote the first m-1 arrival time instants as T_1, T_2, …, T_{m-1}. The Laplace test statistic is defined as

$$U = \frac{\frac{1}{m-1}\sum_{i=1}^{m-1} T_i - \frac{T_m}{2}}{T_m\sqrt{\frac{1}{12(m-1)}}} \qquad (7)$$

It can be shown that Laplace test statistic is Gaussian distributed. Figure 7 shows an example of this distribution from the data shown in Fig. 6. The normality characteristic of Laplace test statistic makes it possible to make the semi-failure detections under certain confidence level such as 95%.

5 TEST RESULTS

We have tested the algorithms described in this paper using the roller bearing data downloaded from NASA Prognostic Data Repository available to general public

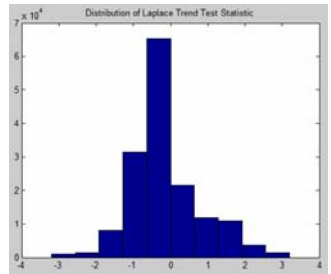

Figure 7: Normal distribution of Laplace test statistic

(http://ti.arc.nasa.gov/project/prognostic-data-repository/). The data description can be found in (Qiu, 2006).

The roller bearing data used for the test were collected from a lab system with its setup shown in Figure 8. Rexnord ZA-2115 double roller bearings were used in the experimental system. The bearings have 16 rollers, a pitch diameter of 2.815', roller diameter of 0.331', and a tapered contact angle of 15.17°. There are four bearings in the system. For each bearing, there are two accelerometers, one in x-direction and the other y-direction.

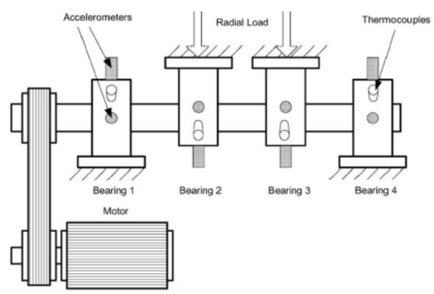

Figure 8: Experimental system setup

There are a total three datasets named as Test1, Test2 and Test3. In this paper, we only report the test results using the first dataset (Test1) which has the measurement data from four sensors mounted on four different bearing housings shown in Fig. 8.

During the experiment over 35 days, the bearing #3 developed an inner race defect and bearing #4 had a roller element defect and outer race defect. These defects were occurred during the 30th day and are shown in Figure 9.

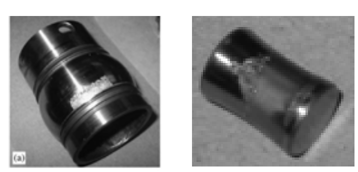

Figure 9: Defects in bearings #3 (left) and #4 (right) given in (Qiu, 2006)

Figure 10 shows the vibration signals of sensor #4 in *x*-direction (top) and *y*-direction (bottom). This sensor is mounted on the housing of #4 bearing shown in Fig. 8. It can be observed that there are large variations in the magnitude of vibration data, which indicates that bearing faults occurred.

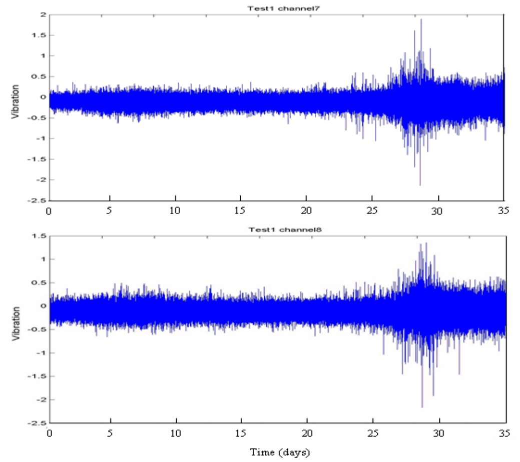

Figure 10: Vibration data of sensor #4 in *x*-direction (top) and *y*-direction (bottom)

These bearing faults can be easily detected using kurtosis as shown in Figure 11 which is also given in (Qiu, 2006). The large kurtosis provides a clear indication that bearing #4 has developed some faults.

We aimed at the early detection of bearing #4 faults. Figure 12 shows the DoR trend and semi-failure indicators using the data of sensor #4 in *x*-direction. The results are obtained from the algorithms described in this paper. It can be seen that DoR developed an increasing trend around the 20^{th} day, which is also detected by Laplace test statistic.

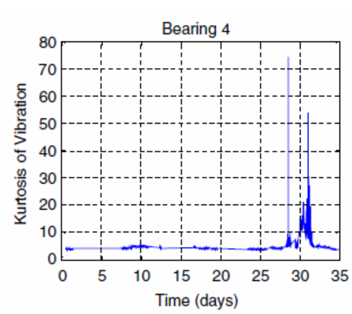

Figure 11: Kurtosis of sensor #4 in *x*-direction.

The binary indicators shown in Fig. 12 are generated from the Laplace test statistic at 95% confidence level. Therefore, with the ground truth, we are able to detect the “complete” failure about **10 days** earlier. From the vibration data, it is send that the vibration signals have not shown any significant increases in the 20^{th} day. From Fig. 12, it can also be seen that there are detections in the beginning of the experiment. We believe the data in that time period were abnormal, which can also be observed from the vibration data (smaller magnitude).

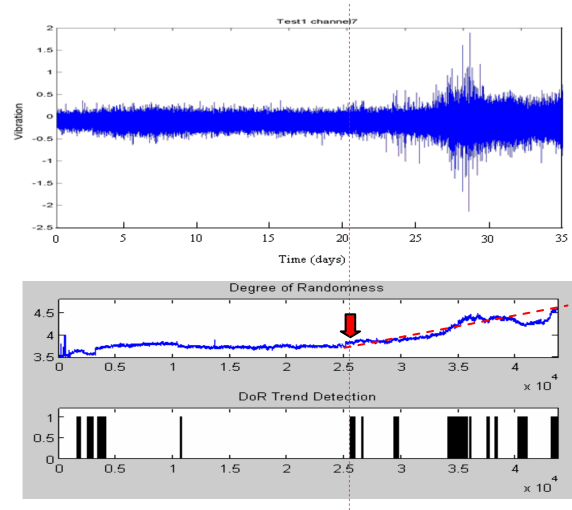

Figure 12: Early detection using sensor #4 in *x*-direction

We have also tested the data of sensor #4 in *y*-direction. We have found that the *y*-direction vibration data can also be used for the early detection of failures. The test results of sensor #4 in *y*-direction are given in Figure 13. One interesting observation is that the results using *y*-direction sensor data only predicts the semi-failure about 6 days earlier, instead of 10 days prediction using *x*-direction data. Another difference is that there is less number of detections in the beginning of the data. This finding indicates that the y-direction data of sensor #4 is less sensitive for the faults developed in the bearing #4, which makes sense in mechanics.

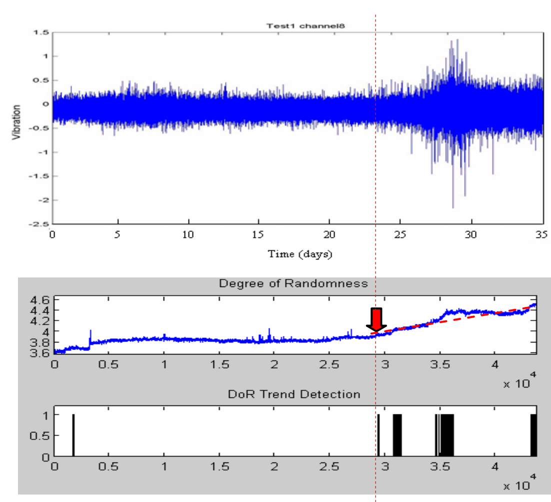

Figure 13: Early detection using sensor #4 in *y*-direction

The test results shown here clearly indicate that our DoR-based detection methods can be used for the diagnosis and prognosis of roller bearing faults. We are currently in the process of further improving the algorithm performance through the test of more datasets.

6 CONCLUSIONS

In this paper, we present a new diagnosis and prognosis method using degree of randomness (DoR) measure and Laplace test procedure. The abnormal events are detected through the measure of change of randomness of vibration signals. The changes of randomness are resulted from the faulty components such as roller bearings. We aim at the early detection of semi-failure events through the use of Laplace test statistic which measures the rate changes of the abnormal event occurrence. Test results using roller bearing data downloaded from NASA Prognostic Data Repository have shown that our algorithms can detect the roller bearing faults 10 days in advance of the occurrence of failure. -

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