Real-Time Anomaly Detection using Average Level-Crossing Rate

Premanand B, V. S. Sheeba

Abstract*: Vibration data collected from piezoelectric sensors serve as a means for detecting faults in machines that have rotating parts. The sensor output that is sampled at the Nyquist rate is stored for analysis of faults in the traditional condition monitoring system. The massive amount of data makes the analysis very difficult. Very complex procedures are adopted for anomaly detection in standard methods. The proposed system works on the analog output of the sensor and does not require conventional steps like sampling, feature extraction, classification, or computation of the spectrum. It is a simple system that performs real-time detection of anomalies in the bearing of a machine using vibration signals. Faults in the machines usually create an increase in the frequency of the vibration data. The amplitude of the signal also changes in some situations. The increase in amplitude or frequency leads to a corresponding increase in the level-crossing rate, which is a parameter indicating the rate of change of a signal. Based on the percentage increase in the average value of the level-crossing rate (ALCR), a suitable warning signal can be issued. It does not require the data from a faulty machine to set the thresholds. The proposed algorithm has been tested with standard data sets. There is a clear distinction between the ALCR values of normal and faulty machines, which has been used to release accurate indications about the fault. If the noise conditions do not vary much, the pre-processing of the input signal is not needed. The vibration signals acquired with faulty bearings have ALCR values, ranging from 3.48 times to 10.71 times the average value of ALCR obtained with normal bearing. Hence the proposed system offers bearing fault detection with100% accuracy.

***Keywords* : Average level-crossing rate, fault diagnosis, Nyquist rate, prognosis.**

I. INTRODUCTION

Most of the engineering systems have rotating parts, and various parameters must be closely monitored for maintaining their health. The situation is very critical in systems such as aircraft and spacecraft in which failure may cause loss of lives [1]. The faults in machines used in industries must be detected long before they become severe so that planned repair work can be scheduled. Most of the faults like imbalance, resonance, misalignment, looseness, drive belt problems, and eccentricity occurring in machines cause some changes in vibration signals.

Revised Manuscript Received on February 28, 2020.
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Hence vibration analysis serves as a means for identifying machine deterioration. Further damage and its severe effects can be avoided if preventive maintenance is carried out soon after a warning signal is received.
Fault diagnosis and prognosis are mainly dependent on sensors and their sensing strategies. A wide variety of sensors are used for condition monitoring of equipment nowadays. The data output from the sensors must be processed for extracting useful information. The processed data must be in reduced form, preserving the features which are needed for detecting anomalies. Piezoelectric accelerometers are most commonly used for measuring all types of vibrations due to their excellent linearity over a wide frequency range, accuracy, and self-generation of power. They also have extreme durability due to the absence of moving parts.

Various approaches for Condition-based maintenance (CBM) of systems and Prognostics and health management (PHM) are explained in [2]. In CBM, conditions of the machines are determined from the run-time data to schedule repair and maintenance. PHM is the prediction of future behavior and the remaining useful life (RUL) from the present data and scheduling of the steps needed so that the machine can be operated for a long time. The general approaches for CBM and PHM are classified into (i) model-based methods, (ii) data-driven methods, and (iii) hybrid methods. In the model-based method, a mathematical model is created to describe the damage in the equipment [3]. In the data-driven method, the measured data is used for fault detection or prediction [4]. Hybrid methods make use of both methods [1]. Different processing methods are used for the analysis of sensor data to extract features for fault detection or condition monitoring. For example, time-domain methods are used for temperature measurement. Peak amplitude, energy, and the rate of change are some of the features used in time-domain for condition monitoring. For vibration data, frequency or wavelet domain are suitable. Failures in systems cause changes in power, entropy, spectrum, and amplitude. From the massive data, useful information has to be extracted for detecting anomalies or faults. Methods for vibration analysis include spectral analysis, envelope detection, spectral emitted energy, phase measurement, and high-frequency detection. Even though efforts have been made to reduce the amount of data by employing compressed sensing [5]-[6], the process involved for feature extraction is very much involved. Machine learning techniques have been used for anomaly detection in [7]. The system must be trained with a lot of data acquired from normal and faulty conditions. Damage detection is not only limited to machines, but can be extended to other applications such as structural health monitoring [8].

The available bit rate in launch vehicles is very limited. Several vibration signals are to be tele-metered to the ground, which requires a very high data rate.

The number of vibration signals transmitted to the ground can be reduced to a minimum if on-board anomaly detection is used, and its output alone needs to be transmitted to earth instead of sending the whole sensor data.

Time-domain methods have been applied for fault detection in the planetary gear set in [9], which is based on the change in the peak amplitude of the stator current. Changes in the amplitude of the current may not be due to a faulty condition alone. In another time-domain method [10], artificial modulation of the current signal is done to extract the frequency components due to faults. However, the accuracy of failure detection is dependent on careful selection of the frequency, and measurement of the time gap between zero-crossings.

All the present methods for anomaly detection involve either sophisticated analysis methods or require processing on a massive amount of data collected for this purpose. In most of the methods, noise present in the signals must be removed first for further processing.

A simple signal processing method that provides real-time indications of anomalies in a bearing is presented in this paper. It is based on the changes in the ALCR of vibration signals, and noise removal is not necessary if there is no significant change in noise environments. It is also free from the steps involved in conventional fault detection methods, including sampling, compression, feature extraction, and classification. The system is free from the complex analysis procedures or the big data analysis problem in traditional methods.

This paper is organized as follows. Section II focuses on the concept of average level-crossing rate (ALCR) of signals with illustrations. The block diagram of the system developed for measuring ALCR is presented, along with a comparison of the vibration signals collected with normal and faulty bearings. The proposed method for anomaly detection in machines is explained in section III. Simulation results are presented in section IV, followed by conclusions in section V.

II. AVERAGE LEVEL-CROSSING RATE

A change in the instantaneous value of a vibration signal cannot be used for detecting a faulty condition of a machine. Hence a parameter which is estimated over a small time interval must be selected for this purpose. If there is a faulty condition in the bearing of a machine, there is an increase in the frequency of the vibration signal. There is also an increase in the amplitude that has been observed in most of the cases. Irrespective of the peak value, the average amplitude of a vibration signal will be nearly zero and cannot be used as a parameter for detecting anomalies. Similarly, the energy of a signal cannot be considered for this purpose because it does not change with respect to a change in frequency. Average Level-Crossing Rate (ALCR) of a signal is the best choice for detecting variations in the vibration signal due to a faulty condition in a machine. The level-crossing rate (LCR) is a measure of the rapidity of a signal. LCR is defined as the number of times a signal crosses a certain amplitude level in unit time [11]. ALCR is obtained by summing up the LCR values of all the levels in unit time. It is a time-domain parameter that increases with an increase in either the amplitude or frequency of a signal. The effect of amplitude and frequency is illustrated in fig. 1.

The computation of ALCR value has been explained in [11]. Let x(t) be the analog input signal for which ALCR has to be computed. A level-crossing, $c(j, t_0)$ at a particular level l_j is detected at time t_0, if the condition specified in (1) is satisfied.

$$[x(t_0)-l_j][x(t_0-\delta t)-l_j]<0; \qquad (1)$$

δt is a short time interval. If the above condition is satisfied $c(j, t_0) = 1$, and 0 otherwise. Level-crossing rate (LCR) for a particular level l_j for an interval Δt can be computed at a particular instant as shown in (2).

$$L(j,t_0)=\sum_{t_0-\Delta t}^{t_0} c(j,t_0) \qquad (2)$$

Average level-crossing rate, ALCR is defined in (3).

$$ALCR=\sum_{j=1}^{N} L(j,t_0) \qquad (3)$$

N is the total number of reference levels. The value of ALCR depends on Δv, the amplitude difference between adjacent levels and Δt, the duration for which it is computed.

Three sinusoidal signals of equal durations, $x_1(t)$, $x_2(t)$, and $x_3(t)$ are shown in fig. 1. Denoting the number of level-crossings occurring in a duration 't' as 'N_t,' its value for $x_1(t)$ is 16. The frequency of the signal $x_2(t)$ is equal to that of $x_1(t)$, but its peak value is almost half of $x_1(t)$. The value of N_t for $x_2(t)$ is eight. The peak amplitude of $x_3(t)$ is almost equal to that of $x_1(t)$, but the frequency is almost double. The value of N_t for $x_3(t)$ is 32, which is double that of $x_1(t)$. If a fault condition occurs in a machine, there will be an increase in frequency, and amplitude of the vibration signal, which cause a corresponding increase in the value of ALCR. ALCR has been used for automatic speech segmentation [11].

As shown in fig. 2(a), an arbitrary analog signal x(t) is applied to a level-crossing detector (LCD). The reference voltage levels l_1 to l_6 are placed uniformly at Δv apart. The instantaneous amplitude of the signal x(t) is compared with these levels. The dark dots on x(t) indicate instants at which level-crossings take place. These instants are shown as t_1 to t_{13} on the time axis. The signal crosses the level l_2 at time instant t_1. The corresponding output of the level-crossing detector (LCD) is shown in fig. 2(b). LCR is dependent on the value of Δv, the signal amplitude A, and the frequency of the signal.

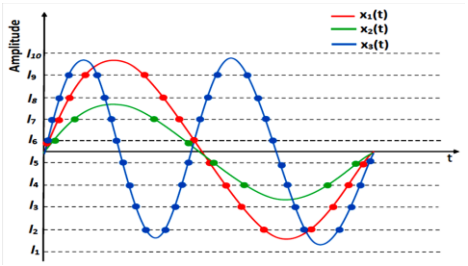

Fig. 1. Illustration of level-crossing

International Journal of Innovative Technology and Exploring Engineering (IJITEE)
ISSN: 2278-3075 (Online), Volume-9 Issue-4, February 2020

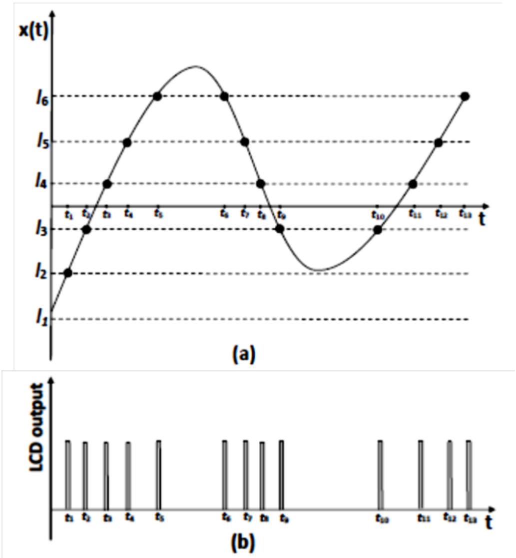

Fig. 2. (a) Input signal (b) LCD output

The ALCR of a signal can be monitored by comparing the instantaneous value of the signal with a set of reference levels. There are two commonly used methods for the generation of the threshold levels, and for the comparison of these levels with the signal amplitude. One method resembles the front-end of a flash type analog to digital converter [12]. Different reference levels are connected to the inputs of each of the comparators, with the signal input connected as the universal input. The number of comparators required is equal to the number of reference levels, and hence the hardware complexity of this type of circuit increases with the number of levels. A requirement for prior knowledge about the peak amplitude of the input signal is another limitation. The second realization is in the form of an asynchronous delta modulator [13]. The block diagram of the system simulated for ALCR computation is shown in fig. 3. At any instant, the present input amplitude is compared with the reference levels V_H and V_L. V_H and V_L are increased or decreased by the step size Δv depending upon the output of the comparators. An offset voltage, which is slightly greater than $\Delta v/2$ is used to produce V_H and V_L, which are the updated reference levels for the window comparator. A pulse signal is produced at the output of LCD whenever the input signal crosses any of the reference levels. LCD is an integral part of level-crossing sampling, which is an activity-dependent sampling method resulting in non-uniform samples. LCD output is fed to a counter which counts the number of level-crossings in a particular duration, Δt for which ALCR is computed. For this purpose, a timer which resets the counter at the end of every Δt is used.

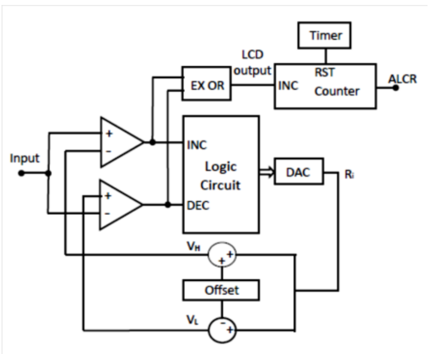

Fig. 3. Block diagram for ALCR measurement

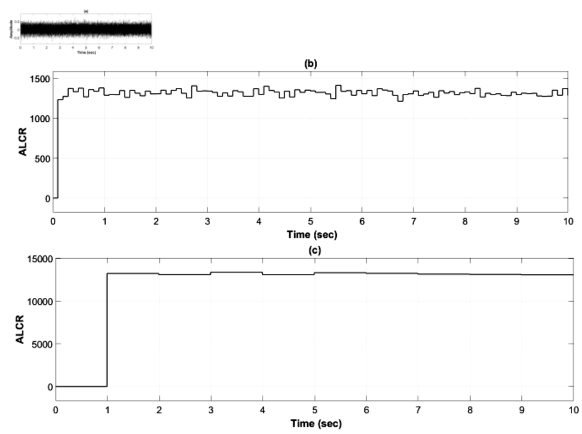

Fig. 4. (a) Vibration signal (X097_DE), (b) ALCR with Δt=0.1 second, (c) ALCR with Δt=1 second

The data set consisting of vibration signals from normal and faulty bearings are provided as online resources by Case Western Reserve University [14]. The data was the output from accelerometers, which were attached to the housing of the motor using magnetic bases. Vibration data was also collected after introducing faults in the bearings with the electro-discharge machining technique. A vibration signal, 'X097_DE' is shown in fig. 4(a), and ALCR in fig. 4(b) and fig. 4(c). ALCR values in fig. 4(b) are computed for Δt of 0.1 second. Fig. 4(c) shows the ALCR value of the same signal taking Δt as 1 second. Even though ALCR computed with Δt of 1 second shows a smooth variation in ALCR, the maximum delay for delivering the warning signal will be 1 second compared to 0.1 second in the earlier case. If a signal is applied to the LCD, the value of ALCR will be computed at the end of every Δt seconds. This is the reason why ALCR is seen to be zero during the initial time period of Δt.

III. THE PROPOSED METHOD

A vibration signal, 'X100_FE' with a normal bearing and its spectrum are shown in fig. 5(a), and fig. 5(b) respectively. The significant frequency components in the spectrum extend approximately up to 2kHz. ALCR values of this signal are computed, and shown in fig. 5(c).

The average value of ALCR is 1500. Fig. 5(d) shows another signal, 'X106_FE', acquired from the same machine with a faulty bearing.

The spectrum of this signal is shown in fig. 5(e) in which the significant frequency components are seen to be extended above 4kHz. There is also an increase in the maximum amplitude of the signal acquired from the faulty machine. The corresponding ALCR is plotted in fig. 5(f).

There is a huge increase in the ALCR values for this signal from the previous case, and is computed as 8391.

All the vibration signals collected from the machine which is having a faulty bearing

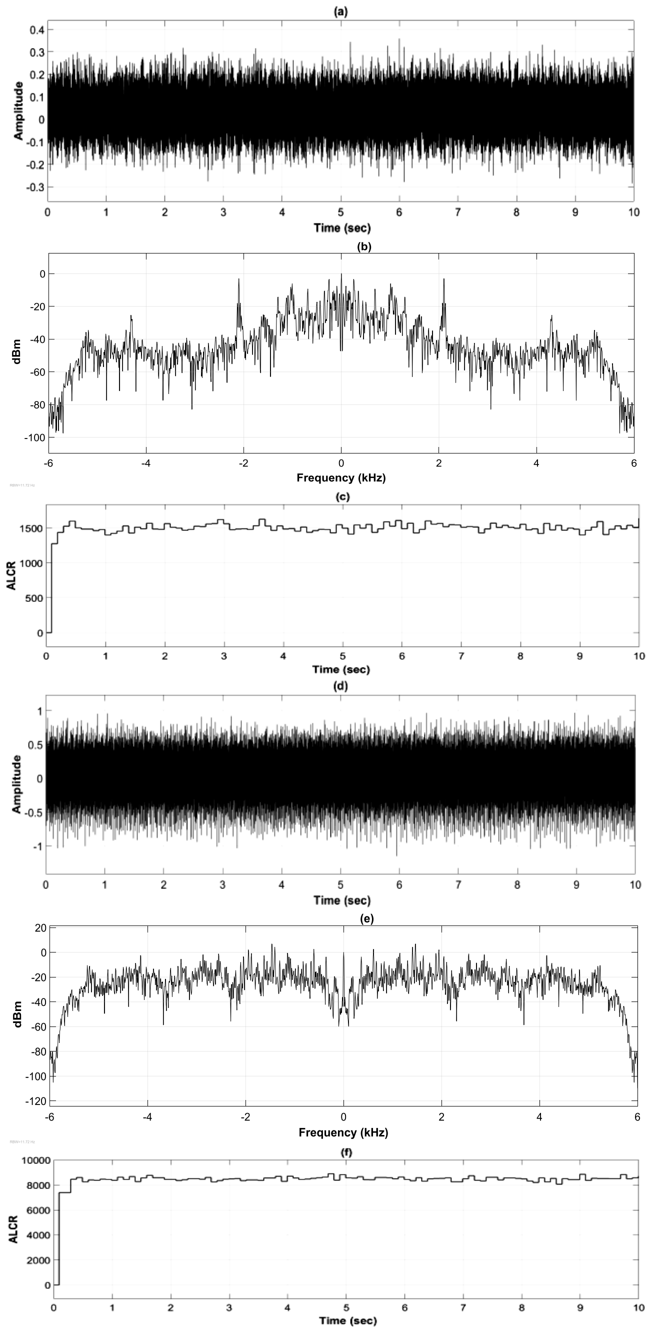

Fig. 5(a) The vibration signal from a normal bearing (X100_FE) (b) Spectrum of X100_FE (c) ALCR of X100_FE (d) The vibration signal from a faulty bearing (X106_FE) (e) Spectrum of X106_FE (f) ALCR of X106_FE

is spread in its bandwidth with some increase in the peak amplitude. This is illustrated in fig. 5, where a significant increase in the ALCR value of a vibration signal collected from a faulty bearing is noticed, compared to that from a normal bearing. Variations in ALCR values are used for the detection of faults. Fig. 6 depicts the method of detection of anomalies in the machine using ALCR values.

The input signal is applied to the LCD, which produces non-uniformly spaced pulse signals at the instant of each

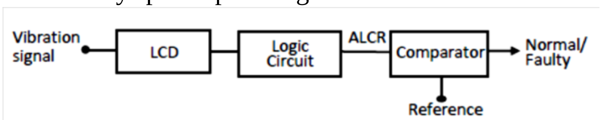

Fig. 6. The proposed method

level-crossing. The logic circuit counts the number of pulses produced in a fixed duration, which is the value of ALCR. A threshold value of ALCR can be manually set with prior knowledge of the vibrations produced under normal working conditions. Alternatively, the initial ALCR value can be stored as a reference for detecting a specified percentage increase in the observed value.

IV. RESULTS AND DISCUSSION

The vibration data from standard databases, which are samples acquired at the Nyquist rate, are interpolated to convert them into the analog form. These analog signals are analyzed by observing the variations in their ALCR values, using the block shown in fig. 3. Simulation has been performed with Simulink. Vibration data set consisting of signals acquired under normal and faulty conditions provided by Case Western Reserve University are used. The bandwidth of the signals collected with faulty bearing has increased, and increase in the amplitude is also observed. A significant increase in ALCR values has been noticed in the signals collected from faulty machines, compared to the values corresponding to a normal machine. Δv is selected as 25mv, and ALCR is computed as the total number of level-crossings during a period of 0.1 seconds. The simulation results are shown in table I. The first column indicates the signal, and the second one indicating whether the signal was acquired under normal or faulty conditions.

The corresponding ALCR values are entered in the third column. The abbreviations DE and FE, along with the signal number, represent "Door End and Fan End," which are the positions of the sensors. ALCR values of each signal are also plotted in fig. 7. The increase in ALCR values is used for anomaly detection in the proposed method. Besides offering a real-time operation, the system avoids the necessity of sampling the signal, storing the data, feature extraction, classification, and big data analysis.

The algorithm has also been tested with NASA bearing data set [15]. The data set includes three sets of vibration data, which are the output of accelerometers placed at

Table I: Vibration signals and the ALCR values

Signal	Normal/ faulty	ALCR value
X097_DE	Normal	1308
X098_FE	Normal	1302
X098_DE	Normal	1157
X099_DE	Normal	1265
X099_FE	Normal	1366
X100_DE	Normal	1345
X100_FE	Normal	1500
X105_DE	Faulty	12200
X105_FE	Faulty	9296
X106_DE	Faulty	12160
X106_FE	Faulty	8391
X108_DE	Faulty	12890
X119_DE	Faulty	7340
X121_DE	Faulty	8006
X130_FE	Faulty	14140
X133_DE	Faulty	13240
X169_FE	Faulty	5960
X172_DE	Faulty	6353
X185_DE	Faulty	5648
X200_DE	Faulty	4595

International Journal of Innovative Technology and Exploring Engineering (IJITEE)
ISSN: 2278-3075 (Online), Volume-9 Issue-4, February 2020

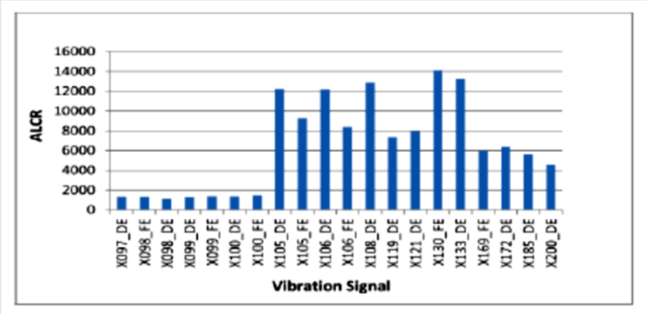

Fig. 7. The plot of ALCR vs signals

different locations inside the bearing housing of an AC motor. The rotation speed of the motor was 2000 rpm, with a radial load of 6000 lbs. Each data set was the output of a test-to-failure experiment and consists of data acquired under failure conditions. It was reported that the inner race defect occurred in bearing 3 at the end of the experiment, which is shown in fig. 8(a). Vibration signals of channels 5 and 6 from bearing 3 acquired in the last 45 seconds of the test are shown in fig. 8(a) and in fig. 9(a). At around 13 seconds, there is a change in the amplitude and spectrum, and another sudden hike occurs at around 42 seconds. The corresponding values of ALCR are plotted in fig. 8(b). It can be noticed that there is a significant change in the ALCR values at 13 and 42 seconds.

Output from channel 6 of the same bearing is shown in fig. 9(a). Increases in the corresponding ALCR values are the indications for the faults occurred at the instants explained above. All the faulty conditions in bearings have created significant increases in the ALCR values, as indicated in fig. 9(b), and have been accurately detected.

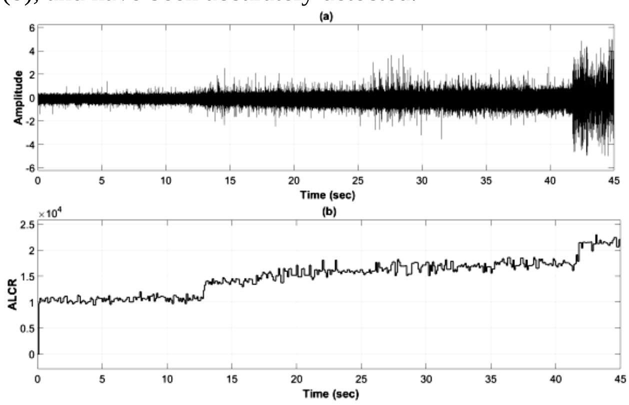

Fig. 8. (a) NASA bearing 3 signal, channel 5 (b) ALCR

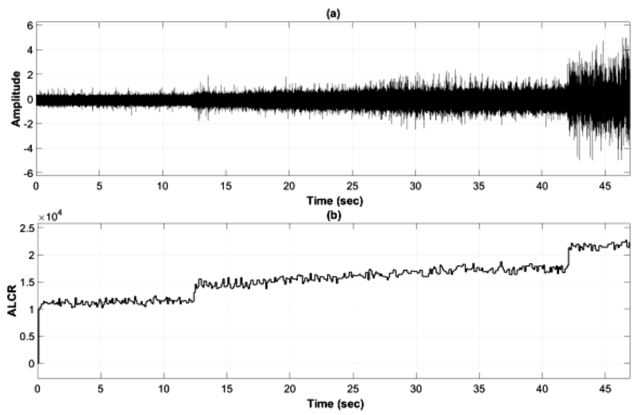

Fig. 9. (a) NASA bearing 3 signal, channel 6 (b) ALCR

II. CONCLUSION AND FUTURE SCOPE

In this paper, a signal processing method, based on ALCR is proposed for detecting bearing faults in machines. ALCR based method is the low cost alternative to the conventional condition-monitoring systems. Bearing faults in machines cause observable changes in the ALCR values of vibration signals. By monitoring the variations in the ALCR, anomalies in machines can be very easily detected. The proposed algorithm is found to be very effective for detecting bearing faults in machines. Compared to the conventional condition-monitoring systems, an ALCR based system is simple and low-cost. It is capable of delivering real-time indications about the operating conditions of a machine. It is especially suitable for systems where computational requirements and the requirement for big data analysis cannot be afforded. The bit rate requirement in launch vehicle telemetry can be reduced to a minimum if on-board anomaly detection mechanism is used, which works directly on the sensor output. Instead of transmitting the entire vibration data from a spacecraft, a few numbers of ALCR values are sufficient for fault analysis. The analog sensor output can be directly applied to the LCD for ALCR measurement, and it provides real-time indication of faults in the machine. ALCR can be used as a parameter for predicting RUL. Generally, for the prediction of RUL, a massive amount of vibration data is needed. The same task can be achieved by making use of ALCR values, which are very few in number compared to the number of samples in the vibration data. Further study is required to find the effect of noise under varying noise conditions.

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