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A data mining approach for fault diagnosis: An application of anomaly detection algorithm

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ABSTRACT

Rolling-element bearing failures are the most frequent problems in rotating machinery, which can be catastrophic and cause major downtime. Hence, providing advance failure warning and precise fault detection in such components are pivotal and cost-effective. The vast majority of past research has focused on signal processing and spectral analysis for fault diagnostics in rotating components. In this study, a data mining approach using a machine learning technique called anomaly detection (AD) is presented. This method employs classification techniques to discriminate between defect examples. Two features, kurtosis and Non-Gaussianity Score (NGS), are extracted to develop anomaly detection algorithms. The performance of the developed algorithms was examined through real data from a test to failure bearing. Finally, the application of anomaly detection is compared with one of the popular methods called Support Vector Machine (SVM) to investigate the sensitivity and accuracy of this approach and its ability to detect the anomalies in early stages.

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1. Introduction

Low speed rotating machineries are widely applied in many heavy industries such as steel pipe, mining and wind turbine power plants. Rolling element bearing condition monitoring has become the center of attention in recent years, since the majority of rotating machine defects are caused by faulty bearings and it offers considerable economic savings and easy implementation. According to the Department of Trade and Industry in the UK (DTI), the benefit of Condition Based Maintenance (CBM) in wind turbine rolling elements has achieved total savings of £1.3 billion per year in the device's lifetime [1]. Condition

Monitoring Systems (CMS) or Health Monitoring Systems (HMS) plays important roles in organizing condition-based maintenances and repairs (M&R). One means of achieving this objective is applying an efficient fault diagnosis technique that has greater sensitivity to find very minor defects.

Bearing faults are one of the foremost causes of failures in rotating mechanical systems (40–50% in wind turbines [2]) for they include some or numerous bearings to provide smooth rotation with minimal losses, and their faults can be directly contributed to consecutive problems in other major components. Since the time of occurring principal failures varies for inner race, outer race, ball, and rolling element, the accuracy and sensitivity of the maintenance techniques are essential to detect incipient faults in bearings. The majority of existing works have focused on classified fault types on the basis of availability of fault samples, in practice collecting all types of faulty data from bearing defects is very difficult if not impossible. This is

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due to the fact that some faults occur very occasionally and also each type of machine has specific failure vibration patterns [3–5]. Some previous studies have overcome the problem by applying data-mining algorithms and machine learning classification technologies, which use a historical database of the system to predict failures.

Among various methods that have been used machine learning, artificial neural networks (ANN) have experienced the fastest development over the past few years [6]. Nevertheless, there are some drawbacks with neural networks, such as structure identification difficulties, Orthogonal Weight Estimators (OWE) learning, local convergence, and poor generalization abilities, since they originally applied Experienced Risk Minimization (ERM). The other method, Support Vector Machines (SVM), was a better solution to overcome the disadvantages mentioned [7,8] and rapidly became the center of attention in recent research. Basically, in SVM the algorithm deals with binary classification problems, and furthermore various kinds of SVM fault classifications suffer from huge amounts of computation which causes some restrictions.

The aim of this research is to propose a fault diagnosis method that is able to overcome all the above mentioned drawbacks, provide system with higher sensitivity in fault detection and the most important point is it does not need huge historical data with fault samples. This method is based on anomaly detection approaches to create models of normal data and then attempts to detect abnormalities from the normal model in the observed data. Machine learning technique develops algorithms that are able to find different patterns in data and adjust program actions according to the training dataset. Hence, the anomaly detection algorithm is able to recognize the majority of new types of intrusion [9,10]. This method provides the ability to classify data where generally we only have access to a single class of data, or a second class of data is under-represented. However, this method needs a purely normal data set to train the algorithm. The algorithm may not recognize future failures and will assume they are normal if the training data set includes the effects of the intrusions. The aforementioned feature contributes to diagnosing faults and fatigues in early stages, and because of the high sensitivity in its nature this method is extremely rigorous in comparison with previous algorithms.

This paper is organized as follows. Section 2 discuss about the existing analysis techniques and feature extraction. Section 3 contains the methodology proposed for fault detection and diagnosis. In Section 4, the experimental data from a test rig is used to validate the proposed algorithm. In Section 5, the implication of the methods for both researchers and practitioners are explained, and finally the conclusion closes the paper in Section 6.

2. Analyzing techniques

Fault diagnosis and CM, using vibration analysis are commonly applied in a variety of industrial tasks. In rotating components, vibration signals are generated and can be observed via sensors [11]. These vibration signals can provide information on the health state of the rotating

component and relevant features of vibration signals can be extracted for signal processing. Various analysis techniques have been conducted on the raw vibration data collected from the sensors [12–14]. The techniques normally include time-domain processing, frequency-domain processing and time–frequency techniques. These are the three main classes among numerous techniques that have been developed for waveform and data analysis, and interpretation. Frequency-domain techniques have previously been employed to show that a localized defect can generate a periodic signal with a singular characteristic frequency [15]. This approach identifies and isolates the added frequency component to diagnose faults. However, this approach is suitable for defect information where the collected data contains a waveform signal with certain harmonic attributes. Time-domain techniques are primarily descended from statistical behaviors of signal waveforms. There are several characteristic features like peak-to-peak amplitude, Root-Mean Square (RMS) energy, standard deviation, skewness and kurtosis. These statistical features and their probability density functions can experience modifications when abnormalities are observed in the input data.

2.1. Kurtosis

In this paper we will apply one of time-domain features called kurtosis, which is defined as the fourth statistical moment, normalized by the standard deviation to the fourth power. It represents a measure of the flattening of the density probability function near the average value. Kurtosis is a measure of how outlier-prone a distribution is. The kurtosis of the normal distribution is 3. Distributions that are more outlier-prone than the normal distribution have kurtosis greater than 3; distributions that are less outlier-prone have a kurtosis value less than 3 [16]. The kurtosis value can be calculated using the following equation:

$$K = \frac{1}{N\sigma^4} \sum_{i=1}^N (x_i - \mu)^4 \quad (1)$$

μ = mean of $x[i]$ and σ = standard deviation of $x[i]$.

2.2. Non-Gaussianity Score (NGS)

One of the quantitative measurements of a data set which arises of the deviation from Gaussianity is the Non-Gaussianity Score (NGS). The NGS feature which is assigned to symbol ψ is developed to measure the non-Gaussianity for a segment of data [17]. To calculate ψ for data $x[i]$ first the inverse normal cumulative distribution function (CDF) for the data should be obtained from the following equations:

$$\gamma = F^{-1}(p|\mu, \sigma) = \{\gamma : F(\gamma|\mu, \sigma) = p\} \quad (2)$$

where,

$$p = F(\gamma|\mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^{\gamma} e^{-\frac{(t-\mu)^2}{2\sigma^2}} dt \quad (3)$$

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