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Application of empirical mode decomposition and artificial neural network for automatic bearing fault diagnosis based on vibration signals

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ABSTRACT

Condition monitoring and fault diagnosis of rolling element bearings (REBs) are at present very important to ensure the steadiness of industrial and domestic machinery. According to the non-stationary and non-linear characteristics of REB vibration signals, feature extraction method is based on empirical mode decomposition (EMD) energy entropy in this paper. A mathematical analysis to select the most significant intrinsic mode functions (IMFs) is presented. Therefore, the chosen features are used to train an artificial neural network (ANN) to classify bearings defects. Experimental results indicated that the proposed method based on run-to-failure vibration signals can reliably categorize bearing defects. Using a proposed health index (HI), REB degradations are perfectly detected with different defect types and severities. Experimental results consist in continuously evaluating the condition of the monitored bearing and thereby detect online the severity of the defect successfully. This paper shows potential application of ANN as effective tool for automatic bearing performance degradation assessment without human intervention.

1. Introduction

Today, diagnosis is a very important research area in industry. Traditional concepts of preventive and corrective maintenance are gradually supplemented by diagnosis form. The main objective of this maintenance type is to ensure the dependability of industrial systems and increase their availability with lower cost. However, fault diagnosis is not an easy task; it is essentially a problem of pattern recognition. The most effective feature extraction and more accurate classifier are needed to obtain higher diagnostic accuracy [1].

Rolling element bearings (REBs) are widely used in industrial and domestic applications. REB is one of the most common components in modern rotating machinery and their failure is one of the most frequent reasons for machine breakdown. Approximately 45% of the failures are due to the bearing faults [2]. Failure surveys by the electric power research institute (EPRI) indicate that bearing-related faults are about 40% among the most frequent faults in induction motors [3].

Although the development of this critical component has progressed in a rapid manner, the development of an expert system for the diagnosis remains an important focus of research. One of the fundamental problems currently facing a wide range of industries is how to identify a bearing fault before it reaches a critical level and catastrophic failure.

Analyzing vibration signals is a quite common technique for mechanical system monitoring thanks to the great information that contain [4]. However, REB vibration signals are considered as non-stationary and non-linear [5]. Besides, noises present a serious trouble in the study of this type of signals [6]. Moreover, the relatively weak bearing signals are always affected by quite stronger signals (gears, bars…) [5]. All these constraints lead us to converge to a single question: What is the most effective method for bearing fault diagnosis?

To answer this question, many research lines have been developed and many techniques are being used. In [7], artificial neural networks (ANN) and principal components analysis (PCA) are used to diagnose the severity of bearing outer race faults. Four bearing classes were examined; the no-fault class and three different notches in the outer race (0.15, 0.50 and 1.00 mm wide).

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In [8], generalized empirical mode decomposition (GEMD), empirical envelope demodulation (EED) and Hilbert–Huang transform (HHT) were used to analyze REBs vibration signals. The simulation results are based on the data set of bearing data center of Case Western Reserve University (BDCWRU). An electro-discharge machine was used to introduce REBs faults with different fault diameters and depths.

In [9], the semi-supervised kernel Marginal Fisher analysis (SSKMFA) was used for bearing feature extraction and the K-nearest neighbor (KNN) classifier was added afterwards to distinguish different fault categories and severities. To validate the proposed method, bearings data set of BDCWRU was used. The classification results of the four classes (healthy, inner race failure, outer race failure, ball failure) were very important.

Although the results were very satisfactory in terms of classification in [7–9], like the majority of bearing diagnostic works, these works were based on synthetic bearing defects which were always introduced by the user (holes with different diameters and depths). In reality, this is not the case of a bearing defect in industrial environment. Many factors can cause deterioration of bearings such as

- Contamination and corrosion.
- Lack of lubrication causing heating and abrasion.
- Defect of bearing's mounting, by improperly forcing the bearing onto the shaft.
- Misalignment defects.

REBs degradation is a highly non-linear phenomenon; using the same type of bearing in the same experimental conditions never produces the same kind of failure in terms of time, type, and severity. This property is confirmed by Intelligent Maintenance Systems (IMS) bearing run-to-failure data set [10].

Relatively, only few papers discussed the bearing diagnosis based on run-to-failure vibration signals. This is due to the difficulties in processing these signals. The major problem is the noise; it is very difficult to detect degradation when it is smaller than the noise measurements. This form of degradation is often known as "degradation at early stage". Even though many researchers have performed fault bearing detection, they do not perform the diagnosis and identification of degradation at early stage.

In [11], the one class support vector machine (v-SVM) was used to detect characteristic changes of the monitored bearing vibration signals in order to detect REB defects. To validate the proposed non-destructive diagnostic method, the IMS bearing data set was exploited.

In [12], the combination of locality preserving projections (LPP) and exponential weighted moving average (EWMA) were presented. The non-monotonic EWMA performance quantification index shows undesirable results, in terms of false alarm creation. Motivated by the Gaussian mixture model (GMM) and the negative log likelihood probability (NLLP) advantages, experimental results were improved but they still have false alarms [13].

In this paper, to overcome the non-stationarity problem of REB vibration signals, we tend towards the application of the empirical mode decomposition (EMD) method. Based on the energy entropy of the different intrinsic mode functions (IMFs), a statistical analysis is detailed to determine the most appropriate IMFs for bearing fault diagnosis. The combination of EMD energy entropy, statistical features and ANN shows that it's very helpful for bearing state classification task. Thereby, the IMS run-to-failure vibration signals are used to detect seven bearing states (healthy, degraded inner race, degraded outer race, degraded roller, failure inner race, failure outer race and failure roller). The majority of the previous works defined just four bearing states however in this paper seven classes are defined to follow bearing degradation over time. To detect early stage bearing degradations in real time, this work proposes a health index (HI). This new approach is successfully applied and it identifies reliably early stage REB degradations base on vibration signals.

The paper is organized as follows: Section 2 presents in details the experimental setup and data recording. The different steps of the EMD method are also given in this section. Section 3 presents a mathematical analysis to select the most effective features for REBs diagnosis. Section 4 presents a good discussion and analysis of the experimental results by comparing the performances of the proposed method with previous methodologies in literature. Finally, our conclusions are provided in Section 5.

2. Materials and methods

2.1. Experimental setup

The used data set in this paper is generated by the NSF I/UCR Center for Intelligent Maintenance Systems (IMS) with support from Rexnord Corp.

Rexnord ZA-2115 double row bearings shown in Fig. 1 are installed on the shaft. Bearings contain 16 rollers in each row, a pitch diameter of 2.815 in., a roller diameter of 0.331 in. and a tapering contact angle of 15.17° [14].

PCB 353B33 High Sensitivity Quartz ICP accelerometers are installed on the bearing housing. All failures occurred after exceeding designed life time of the bearing which is more than 100 million revolutions. The test rig and sensors placement are shown in Fig. 2.

Four bearings are installed on a shaft. The rotation speed is kept constant at 2000 rpm by an alternative current motor coupled to the shaft via rub belts. A radial load of 6000 lbs is applied onto the shaft and bearings by a spring mechanism. All bearings are lubricated.

The test is carried out for 35 days until a significant amount of metal debris is found on the magnetic plug of the tested bearing [14]. In this way it is possible to obtain bearing run-to-failure data sets with known defects. Fig. 3 shows failure bearing components after test. It is clear that real bearing defects does not seem like holes with different diameters and depths.

Three tests were made. Each test is an experience of 4 bearings. In this way 12 bearings are used but only 4 bearings have reached failure with known defects. Each data set describes a run-to-failure experiment. It consists of individual files that are 1-s vibration signal snapshots recorded at specific intervals (every 10 min). Each file consists of 20,480 points with the sampling rate set at 20 kHz. Records (row) in the data file are data points. Data collection is provided by NI DAQ Card 6062E [14].

Three data sets are included in the data package. Each data set contains simultaneous testing of four bearings. The vibration bearing data set is provided by the Center on Intelligent Maintenance Systems (IMS), University of Cincinnati, USA [10].

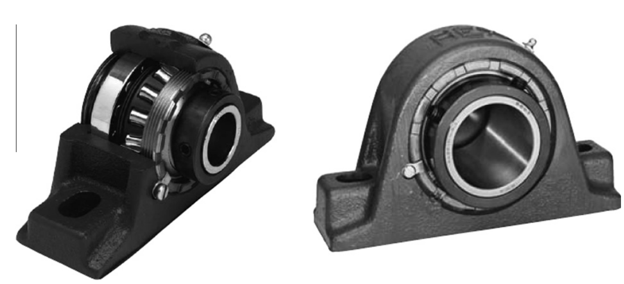

Fig. 1. Rexnord ZA-2000 bearing series.