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Linear feature selection and classification using PNN and SFAM neural networks for a nearly online diagnosis of bearing naturally progressing degradations

Jaouher Ben Ali [a,b,*], Lotfi Saidi [a], Aymen Mouelhi [a], Brigitte Chebel-Morello [b], Farhat Fnaiech [a]

[a] University of Tunis, National Higher School of Engineers of Tunis, Laboratory of Signal Image and Energy Mastery (SIME), 5 Av. Taha Hussein, 1008 Tunis, Tunisia

[b] FEMTO-ST Institute, AS2M Department, UMR CNRS 6174 – UFC/ENSMM/UTBM, 25000 Besançon, France

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ABSTRACT

In this work, an effort is made to characterize seven bearing states depending on the energy entropy of Intrinsic Mode Functions (IMFs) resulted from the Empirical Modes Decomposition (EMD). Three run-to-failure bearing vibration signals representing different defects either degraded or different failing components (roller, inner race and outer race) with healthy state lead to seven bearing states under study. Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) are used for feature reduction. Then, six classification scenarios are processed via a Probabilistic Neural Network (PNN) and a Simplified Fuzzy Adaptive Resonance Theory Map (SFAM) neural network. In other words, the three extracted feature data bases (EMD, PCA and LDA features) are processed firstly with SFAM and secondly with a combination of PNN–SFAM. The computation of classification accuracy and scattering criterion for each scenario shows that the EMD–LDA–PNN–SFAM combination is the suitable strategy for online bearing fault diagnosis. The proposed methodology reveals better generalization capability compared to previous works and it is validated by an online bearing fault diagnosis. The proposed strategy can be applied for the decision making of several assets.

1. Introduction

Anomalous operating condition and fault detection of industrial assets are the core of process engineers in industry. Effective detection ensures the product quality improvement and reduces the cost and the time of repair. Consequently, industrial assets safety and reliability are very important to ensure the continuity of production, to improve process operation, to increase plant throughput, to reduce process downtime and to comply with increasingly stringent environmental rules and safety regulations (Lau et al., 2013).

Rolling Element Bearing (REB) is the most used solution for industrial machinery guiding in rotation. This critical component requires running with high reliability to decrease fault occurrences and fatal breakdowns of machineries (Lei et al., 2007; Konar and Chattopadhyay, 2011). It is well known that bearing defects are one of the most common fault sources in induction machineries (about 40–50%) (Widodo and Yang, 2007; Frosini and Bassi, 2010). Failure surveys by the electric power research institute indicate that bearing-related faults are about 40% among the most frequent faults in induction motors (Bellini et al., 2008). Therefore, accurate strategies for REB defect detection are a trivial task nowadays in the industry.

Over the past few years, various signal processing methods have been proposed to detect and diagnose bearing defects. These methods may be roughly classified into vibration and acoustic measurements, temperature measurements and wear debris analysis (Nandi et al., 2005). The mechanical bearing vibration signals remain the most immediate, simplest, and richest source of information for understanding phenomena related to bearing defects (Seungdeog et al., 2011; Žvokelj et al., 2011). Certainly, vibration analysis is a powerful source to extract interesting information and to apply appropriate techniques. However, REB accelerations are considered as non-stationary and nonlinear (Randall and Antoni, 2011). Besides, noises present a serious trouble in the study of this type of signals (Zhang and Randall, 2009). Moreover, the relatively weak bearing signals are always affected by quite stronger signals (gear meshing, unbalance, bars, etc.) (Randall and Antoni, 2011).

Several efforts based on vibration signals have been recently proposed in the open literature to deal with the diagnosis of bearing faults. When a fault occurs on one bearing surface, the acceleration is characterized by the presence of periodic repetitive

* Correspoding author. Tel.: +216 96 568 115, +216 52 276 629.
E-mail address: benalijaouher@yahoo.fr (J. Ben Ali).

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sharp peaks and further modulated by a number of harmonic frequencies (Zhang and Randall, 2009). However, interesting information is often contained in the periodicity of impacts, rather than in the rest of the signal frequency content. Thereby, vibration signals are non-stationary and always are masked by machine noise (Randall and Antoni, 2011). For this reason, conventional vibration analysis techniques, which were successfully employed for stationary signals such as fast Fourier transform, have not provided good and significant results based on REB vibration signals (Braun and Feldman, 2011).

In the literature, non-stationary or transient signals are often decomposed into sub-bands where stationary and linear characteristics could be obtained and fault patterns are easily extracted (Priestley, 1988). Consequently, Wavelet Transforms (WT) (Wang et al., 2015), Empirical Mode Decomposition (EMD) (Liu et al., 2015), Local Characteristic-scale Decomposition (LCD) (Zheng et al., 2013a), Ensemble Empirical Mode Decomposition (Wang et al., 2014), and Generalized Empirical Mode Decomposition (Zheng et al., 2013b) were widely used for the processing of bearing vibration signals in the presence of nonlinear and non-stationary data. By analyzing some series of decomposed REB signals based on WT and EMD, it was demonstrated that the energy entropy changes in different frequency bands when a bearing fault occurs. Besides, EMD is more highlighted than WT in terms of mean fault characterization (Tavakkoli and Teshnehlab, 2007).

After decomposing bearing accelerations into some linear and stationary signals, it is recommended to extract the most useful features. Bearing fault diagnosis is not an easy task, it is essentially a problem of pattern recognition. The most effective features and accurate classifiers are needed to obtain higher diagnostic accuracy (Li and Zhang, 2011).

Several previous works based on feature extraction and classification techniques have been proposed for bearing fault diagnosis. Yang et al. have used the discrete WT to decompose vibration and acoustic signals into different frequency levels. Then, some statistical measures were extracted from the first-four levels. Also, an Artificial Neural Networks (ANNs) combined with a Support Vector Machine (SVM) were used to classify the faults of small reciprocating compressor used in refrigerators (Yang et al., 2007). In Lin (2010), the EEMD was applied to decompose vibration signals into different Intrinsic Mode Functions (IMFs) and then the Hilbert spectrum was computed to extract bearing fault features. Bin et al. (2012) have demonstrated that the WT generally has some shortcomings and difficulties in selecting suitable basic function because there are no standards or general selection rules for different tasks. However, the EMD is an automated method that extracts easily failure patterns thanks to the use of a wide scale of frequency. Saidi et al. (2014) have presented a combination of EMD and bi-spectrum. The computation of the bi-spectrum was based on the first IMF which contains more information. The proposed combination was promising but it needs always an expert intervention for the analyses of the bi-spectrum plot. Unfortunately, all these methods presented an offline bearing fault detection. Generally, some holes were created in the tested REB and subsequently the fault detection efficiency of the proposed method was given. In this case, the bearing vibration signals increase and the fault detection task become effortless. In an industrial environment, REBs are in continuous rotation where fault characteristics are always submerged and hidden by noises. So, it is recommended to investigate bearing defects online by using run-to-failure histories.

The online bearing monitoring is very important to avoid unexpected breakdowns where the breakdown of a single machine can halt the production of the entire process chain. However, investigations related to naturally induced and naturally progressed defects of REBs are relatively scarce. In fact, online detection of REB degradation for naturally progressing defect in damage stages is not available in the literature (Shakya et al., 2014). Recently, some approaches have been proposed for the online bearing health monitoring. Pan et al. (2014) have proposed a new approach based on dynamic fuzzy neural networks where only consequent parameters were updated online. In Shakya et al. (2014), various damage stages for naturally progressing REB defect were given online. For this, time domain, frequency domain and time–frequency domain were together under study. The Mahalanobis distance was used as a trend parameter for bearing fault diagnosis. In Loutas et al. (2011), the combination of vibration, acoustic emission and oil debris measures is used in an online condition monitoring of bearings and gearboxes. Several techniques were combined such as fusion technique, Principal Component Analysis (PCA) and Independent Component Analysis (ICA) to identify different damage modes. The computational time was not discussed in this work and with respect the definition of failure thresholds was arbitrary. In Ben Ali et al. (2015b), the combination of traditional statistical features and EMD energy entropy were jointed with the back propagation neural network for an online bearing fault diagnosis. The classification results were relatively low (93%) that is why the authors have proposed a health index for a more reliable online monitoring.

In this paper, an attempt is made to diagnose the state of bearings using a new nearly online method. The proposed method is based on the EMD feature extraction, linear feature reduction and feature classification using neural networks. The validation of the proposed method is based on bearing run-to-failure histories. This method is able to detect online perfectly the state of the bearing. The remainder of this paper is organized as follows: Section 2 is devoted to describing the used techniques in this work. This section describes the different steps of the EMD method. Also, a brief description of Linear Discriminant Analysis and Principal Component Analysis algorithms is given. Besides, this section details the different steps to implement the used neural networks in this work. Section 3 is dedicated to the experimental results by analyzing the proposed feature extraction, feature reduction and feature classification techniques. Section 4 gives a numerical analysis of the most effective features based on a mathematical criterion. Also, a good discussion and analysis of the experimental results by comparing the performances of the proposed method with some previous works is provided in this section. Finally, conclusions and prospects of this work are given in Section 5.

2. Methods

2.1. Empirical Mode Decomposition (EMD)

EMD algorithm is developed from the simple assumption that any signal consists of different simple intrinsic modes of oscillations called Intrinsic Mode Functions (IMFs). This adaptive decomposition method is especially applicable to the analysis of nonlinear and non-stationary signals (Yu et al., 2006).

By the definition, any signal $x(t)$ can be decomposed as detailed in Table 1 (Huang et al., 2011).

The step (G) in Table 1 presents a stoppage criterion for the EMD which is one of the weaknesses of this algorithm (Lei et al., 2013). Huang et al. (1998) proposed a robust way to access the IMF component of a signal as “Sifting process”. The sifting process is stopped by limiting the size of the standard deviation (S_D), computed from two consecutive results as

$$0.2 < S_D = \sum_{t=0}^{T} \frac{\left[h_{k-1}(t) - h_k(t)\right]^2}{h_{k-1}^2(t)} < 0.3 \tag{1}$$

Numerous publications of the EMD for bearing fault diagnosis have shown several advantages and very encouraging results.