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Automatic bearing fault diagnosis using particle swarm clustering and Hidden Markov Model

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ABSTRACT

Ball bearings are integral elements in most rotating manufacturing machineries. While detecting defective bearing is relatively straightforward, discovering the source of defect requires advanced signal processing techniques. This paper proposes an automatic bearing defect diagnosis method based on Swarm Rapid Centroid Estimation (SRCE) and Hidden Markov Model (HMM). Using the defect frequency signatures extracted with Wavelet Kurtogram and Cepstral Liftering, SRCE+HMM achieved on average the sensitivity, specificity, and error rate of 98.02%, 96.03%, and 2.65%, respectively, on the bearing fault vibration data provided by Case School of Engineering of the Case Western Reserve University (CSE) which warrants further investigation.
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1. Introduction

Fault detection and diagnosis (FDD) plays an important role in process engineering (Venkatasubramanian et al., 2003). Early detection of faults while a plant is still operating in a controllable region can help to avoid abnormal event progression, minimize productivity loss, as well as improve stability of manufacturing processes and the quality of end products (Venkatasubramanian et al., 2003; Huang et al., 2009). Industries have generally acknowledged the importance of FDD (Huang et al., 2009; Venkatasubramanian et al., 2003; Guo et al., 2013; Wall et al., 2011). For example, petrochemical industries estimated an annual loss of 20 billion dollars attributed to faults alone and have therefore put fault management as critical priority (Venkatasubramanian et al., 2003). Semiconductor and TFT-LCD factories employ periodic sampling to monitor the stability of manufacturing processes (Huang et al., 2009). Scientists develop statistical machine learning model for automatic FDD in Heating Ventilation and Air Conditioning (HVAC) systems (Wall et al., 2011). Considerable interest has therefore been expressed in this field from both industrial practitioners and academic researchers (Venkatasubramanian et al., 2003; Yuwono et al., 2013a).

Bearings play a critical role especially in modern machineries, power generators, motor vehicles, trains, industrial robots, manufacturing machines, mining equipments, heavy vehicles, construction cranes, and general purpose electro-mechanical machines (Slocum, 2008). Newer inventions often require the need for extreme precisions, greater capacities, and faster rotations which makes maintaining healthy bearings increasingly important. Poor operating environments, particularly moist or contaminated areas and improper handling practices often give rise to premature bearing failures which would shorten the lifetime of the corresponding machine and ultimately impair the robustness of product quality (Publications, 2007).

Bearings are most commonly associated as a supporting element in rotating manufacturing machineries such as in conveyer belts. This type of bearing is known as contact bearing, as mechanical contact exists between the load and the bearings. Contact bearings, an area of focus in this paper, have developed extensively from their early use in bicycles to construction cranes. More specifically, we will focus on deep-groove ball (roller) bearings, also known as Conrad ball bearings, with the primary goal of detecting faults in the following compositions of the bearings: outer race, inner race and the ball itself (Randall and Antoni, 2011).

A Conrad ball bearing is designed to support radial or bi-directional axial loads. Faults commonly found in this type of bearings include outer race, inner race and ball/rolling element

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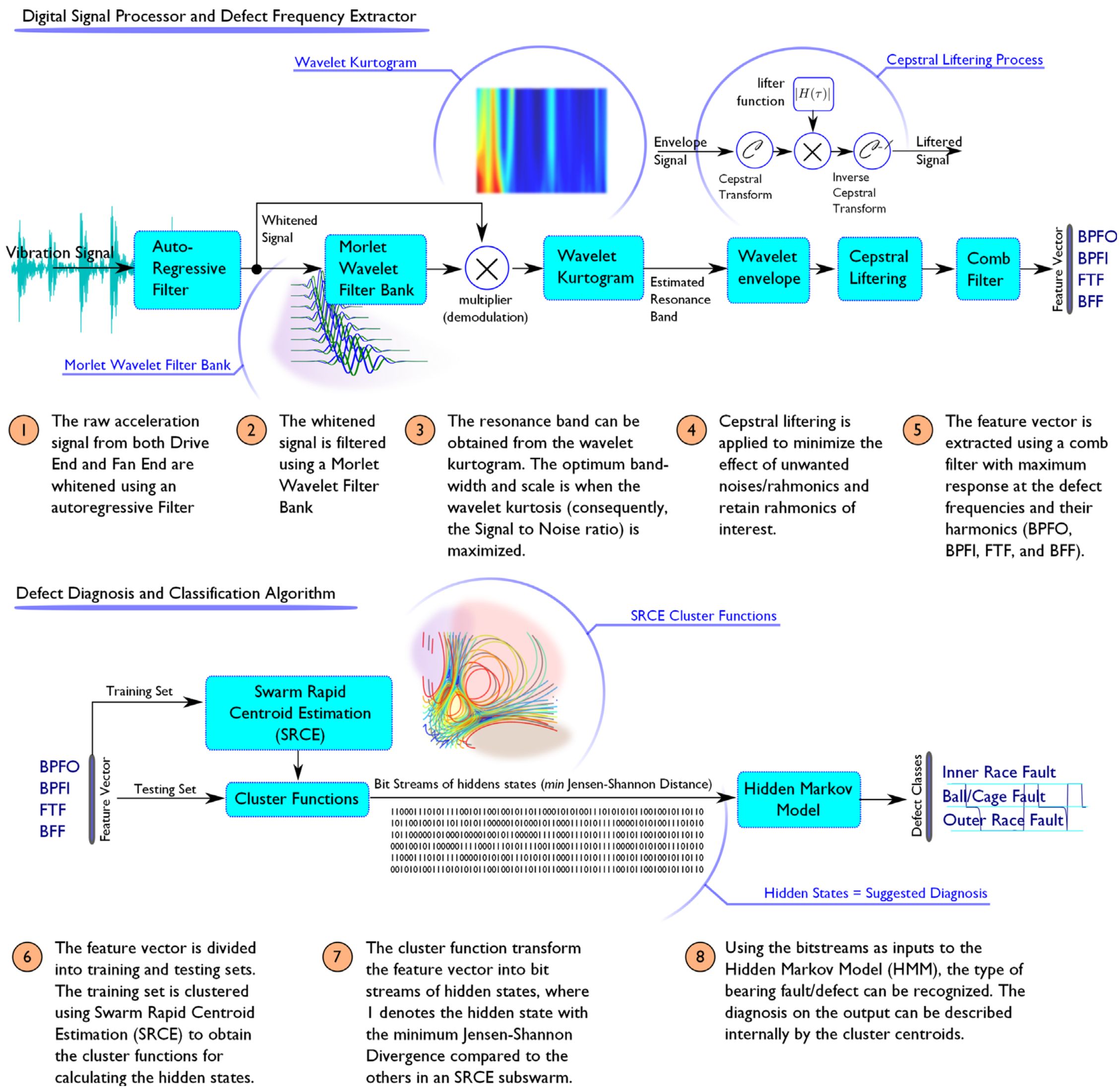

Fig. 1. Block diagram of the proposed bearing defect diagnosis system.

faults (Randall and Antoni, 2011; Li and Wen, 2014). In order to identify these faults, time and frequency domain analysis of vibration signals along with clustering technique is employed. Prior studies (Kulkarni and Sahasrabudhe, 2013; Fang and Zijie, 2007; Randall and Antoni, 2011) have revealed that the classical signal processing techniques such as the Fast Fourier Transform (FFT) has succeeded in terms of analyzing frequencies, but its discrete nature poses a significant challenge in capturing the rather aperiodic and finite signals observed in practice (Randall and Antoni, 2011). Another difficulty in applying the FFT occurs with the existence of noise over signal. This issue leads to the use of Wavelet Transform (WT) (Fang and Zijie, 2007; Kulkarni and Sahasrabudhe, 2013; Sawalhi and Randall, 2005) in extracting weaker signals due to its capability to handle frequency transients.

The essential signal processing guidelines for the rolling bearing fault diagnosis are well established (Randall and Antoni, 2011; Fang and Zijie, 2007; Kulkarni and Sahasrabudhe, 2013; Sawalhi and Randall, 2005; Randall and Hee, 1981). Fang and Zijie (2007) observe a distinctive wavelet energy pattern in various bearing faults. Kulkarni and Sahasrabudhe (2013) discover that fault frequency signatures can be isolated, denoised and monitored using WT. Sawalhi and Randall (2005) show that the resonance band can be estimated using Wavelet Kurtogram. Randall points out that multiple faults may be well discerned in the envelope cepstral domain given proper demodulation (Randall and Hee, 1981).

In this paper we are interested in augmenting the available signal processing technique with swarm intelligence and Markovian probabilistic framework. This paper contributes a novel automated method for detection and diagnosis of defects using Swarm Rapid Centroid Estimation (SRCE) (Yuwono et al., 2013a,b, 2014) and Hidden Markov Model (HMM) (Guo et al., 2012, 2013; Zoubin, 2001). The algorithm uses the (continuous) wavelet kurtogram (Randall and Antoni, 2011; Lei et al., 2011; Valeriu Vrabie and Pierre Granjon, 2003) and cepstral liftering (Randall and Hee, 1981) as the feature extraction method. The proposed method is tested against an openly available bearing fault dataset published by the Case School of Engineering of the Case Western Reserve University (CSE) (Case Western Reserve, 2014). The block diagram of the method can be seen in Fig. 1.

The rest of the document is structured as follows. Section 2 gives a general overview of the vibrational behavior of a rolling bearing system under fault. Section 3 gives a detailed explanation

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