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A discrepancy analysis methodology for rolling element bearing diagnostics under variable speed conditions

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ABSTRACT

Performing condition monitoring on critical machines such as gearboxes is essential to ensure that the machines operate reliably. However, many gearboxes are exposed to variable operating conditions which impede the condition inference task. Rolling element bearing component failures are important causes of gearbox failures and therefore robust bearing diagnostic techniques are required. In this paper, a rolling element bearing diagnostic methodology based on novelty detection is proposed for machines operating under variable speed conditions. The methodology uses the wavelet packet transform, order tracking and a feature modelling approach to generate a diagnostic metric in the form of a discrepancy measure. The probability distribution of the diagnostic metric, statistically conditioned on the corresponding operating conditions is estimated, whereafter the condition of the rolling bearing element is inferred. The rolling element bearing diagnostic methodology is validated on data from a phenomenological gearbox model and two experimental datasets.

1. Introduction

Gearboxes found in air-cooled condenser fans, wind turbines and draglines operate under variable operating conditions, which impede the vibration-based condition monitoring task [1–3]. Lin et al. [4] found that gearbox failures are one of the main causes of wind turbine failures, with rolling element bearing failures being one of the main reasons behind gearbox failures. This emphasises the need for reliable diagnostic techniques that allow incipient rolling element bearing damage to be detected, located (i.e. determine which component is damaged and which damage mode is present) and trended as the bearing deteriorates under varying operating conditions.

A wide variety of techniques have been developed and used for rolling element bearing diagnostics [5], such as envelope analysis which has been extended by [6,7] for variable speed applications, cyclostationary analysis [8,9] which can be seen as a generalisation of envelope analysis [8], regression analysis for variable loads [10], empirical mode decomposition and its extensions [11,12], wavelet analysis [13–16], the spectral kurtosis [17], the kurtogram and its variants [18,19], the sparsogram [20] and the infogram [21]. Varying rotational speeds complicate the condition monitoring process due to its influence on the properties of the vibration signal [7,22,23] and the rotational speed information of the shaft is also required. The rotational speed information can be difficult and impractical to measure for some machines; this makes tacholess order tracking

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methods very important for condition monitoring under varying speed conditions [24–27]. It can also be quite challenging to infer the condition of the bearing by using wavelet analysis for example. This is because small changes occur in the time-scale distribution of the vibration signal as the bearing deteriorates, which can be difficult to detect. This motivates many researchers to use machine learning techniques to aid with the condition inference task.

Machine learning techniques are extensively used in the condition monitoring field as a data-handling tool which allow inferences to be made from complicated data distributions in multi-dimensional spaces. Artificial neural networks [28], support vector machines [28–30], k-means clustering [31], Gaussian mixture models [32] and hidden Markov models [14,32–34] are some examples of the approaches which have been used for bearing diagnostics. However, many of the approaches are based on the assumption that much historical fault data are available for model optimisation, which is rarely achieved in practice. Hence, physics-based models [29] and novelty detection approaches [30,35–42] have been investigated for the condition inference task when only a physical model of the relationship between the damage modes and the vibration signal or only healthy data are available for feature model optimisation. A few different novelty detection categories can be used as summarised in Ref. [38]. The basic principle of novelty detection is to assign a novelty score to the data with a model only optimised on a healthy dataset. Depending on the novelty score, the label of the data is either normal or a novelty. Support vector machines and related techniques [30,41,43], self-organising maps [40], hidden Markov models [34] and Gaussian models [42] are some examples of models used for bearing novelty detection. In the paper by Timusk et al. [39], many novelty detection techniques are compared for gearbox and motor novelty detection and it was found that a combination classifier algorithm performs the best for novelty detection of transient signals. Georgoulas et al. [44] found that a majority voting anomaly detection scheme improves the novelty detection capabilities of individual models for bearing fault detection.

Discrepancy analysis is a novelty detection approach which has been successfully used for gear diagnostics under varying operating conditions [36,37,45,46] and is investigated for rolling element bearing diagnostics under variable speed conditions in this paper. In discrepancy analysis, localised discrepancy measures are obtained for the dataset under consideration using a model of the healthy data. The localised discrepancy measure is a novelty detection score that quantifies the deviation of the segment under consideration from the feature model of the healthy data and can be obtained from Gaussian models, Gaussian mixture models [37], neural networks [36] and hidden Markov models [46]. The discrepancy measure is used to form a discrepancy signal which is processed so that the condition of the component can be inferred. The difference between discrepancy analysis and other novelty detection techniques is that a localised novelty score is given as opposed to a novelty score for the whole measurement. The generated discrepancy signal can be processed into more useful information which allows not only a novelty to be detected, but the characteristics of the novelty i.e. the damaged component can be inferred as well [46].

The new contributions of the current work can be summarised as:

- A framework for rolling element bearing diagnostics is developed using discrepancy analysis for machines operating under varying speed conditions. This methodology allows for the detection, the localisation and trending of bearing faults.
- Discrepancy signal processing tools are investigated and proposed to assist with the condition inference task. An estimate of the conditional model of the discrepancy measure given the rotational speed is used to mitigate the adverse influences of the varying speed conditions.

The objective of the proposed methodology is not to replace classical bearing diagnostic techniques such as wavelet analysis or envelope analysis, but rather to develop a novelty detection framework into which the aforementioned techniques can be naturally incorporated.

The layout of the paper is as follows: The methodology is firstly presented in Section 2. Moreover it is validated on phenomenological gearbox model data in Section 3 and on experimental data in Section 4, respectively. Furthermore, conclusions and recommendations are made in Section 5. For the sake of completeness, additional information concerning the discrepancy processing technique, presented in Section 2.5, has been added in A. Finally in B the parameters of the phenomenological gearbox model, presented in Section 3, can be found.

2. Diagnostic methodology

2.1. Overview

The general process diagram for discrepancy analysis is presented in Fig. 1. The exact discrepancy analysis procedure implemented in this paper is presented in Fig. 2 and is used throughout this work. However, one of the benefits of the proposed methodology is that sub-processes such as the feature extraction procedure can be replaced with a more appropriate

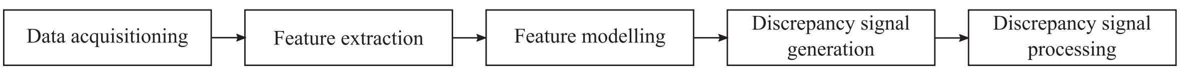

Fig. 1. The key steps in the rolling element bearing diagnostic methodology.