ARTICLE IN PRESS

Mechanical Systems and Signal Processing xx (xxxx) xxxx–xxxx

Contents lists available at ScienceDirect

Mechanical Systems and Signal Processing

journal homepage: www.elsevier.com/locate/ymssp

Condition monitoring of distributed systems using two-stage Bayesian inference data fusion

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ARTICLE INFO

Keywords:
Data fusion
Condition monitoring
Fault diagnosis
Bayesian inference

ABSTRACT

In industrial practice, condition monitoring is typically applied to critical machinery. A particular piece of machinery may have its own condition monitoring system that allows the health condition of said piece of equipment to be assessed independently of any connected assets. However, industrial machines are typically complex sets of components that continuously interact with one another. In some cases, dynamics resulting from the inception and development of a fault can propagate between individual components. For example, a fault in one component may lead to an increased vibration level in both the faulty component, as well as in connected healthy components. In such cases, a condition monitoring system focusing on a specific element in a connected set of components may either incorrectly indicate a fault, or conversely, a fault might be missed or masked due to the interaction of a piece of equipment with neighboring machines. In such cases, a more holistic condition monitoring approach that can not only account for such interactions, but utilize them to provide a more complete and definitive diagnostic picture of the health of the machinery is highly desirable. In this paper, a Two-Stage Bayesian Inference approach allowing data from separate condition monitoring systems to be combined is presented. Data from distributed condition monitoring systems are combined in two stages, the first data fusion occurring at a local, or component, level, and the second fusion combining data at a global level. Data obtained from an experimental rig consisting of an electric motor, two gearboxes, and a load, operating under a range of different fault conditions is used to illustrate the efficacy of the method at pinpointing the root cause of a problem. The obtained results suggest that the approach is adept at refining the diagnostic information obtained from each of the different machine components monitored, therefore improving the reliability of the health assessment of each individual element, as well as the entire piece of machinery.

1. Introduction

As Industrial Processes become more efficient, the machinery used in such processes is subject to increasingly demanding operating conditions. As a result, condition monitoring systems which monitor the health status of the machinery during operation

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http://dx.doi.org/10.1016/j.ymssp.2016.10.004
Received 28 June 2015; Received in revised form 20 August 2016; Accepted 1 October 2016
Available online xxxx
0888-3270/

Please cite this article as: Jaramillo, V.H., Mechanical Systems and Signal Processing (2016), http://dx.doi.org/10.1016/j.ymssp.2016.10.004

are growing in importance. Industrial machines are comprised of a number of connected components that continuously interact with one another in a non-trivial manner. For example, a gas compression installation might be composed of a variable speed inverter connected to a grid, an electric motor, a gearbox and a compressor, compressing the working fluid which is flowing through a complex piping network. Each component in the installation may have its own condition monitoring system that aims to identify the health condition of said component, independently of any connected assets. While considering each component in isolation may appear to simplify the diagnostic analysis, this approach might neglect the additional level of complexity and uncertainty that the interactions between components add. These interactions can lead to difficulty in distinguishing dynamic signatures excited by a fault from those propagated from other healthy components in the system. This added uncertainty can reduce confidence in the outputs of the condition monitoring systems, and can ultimately lead to false or missed alarms.

Traditional condition monitoring approaches attempt to mitigate external influences by only comparing results obtained under similar operating conditions. For example, the ISO 10816-3:2009 standard [1] for the evaluation of machine vibrations states that measurements should only be carried out when the rotating components have reached their normal, steady state operating temperatures and with the machine running under specified conditions. In certain applications in which the load is non-stationary, such conditions can be difficult to realize. Signal processing approaches, that deal with non-stationary operating conditions, have also been developed. For example, Time Synchronous Averaging, or TSA [2], links measurements of vibration to a synchronously recorded shaft angular position, averaging from rotation to rotation to reject components in the vibration signal unrelated to the rotating element under consideration. Whilst these approaches can successfully extract specific fault signatures from measured signals, in doing so they discard other measured data which may also potentially contain useful diagnostic information.

Recently, new condition monitoring approaches have been developed that embrace the interactions between the components. An example of this is the use of electrical signals measured from a motor or inverter to monitor connected load components. The coupling between the speed, torque and stator currents and voltages allows variable speed drives to control motors to a defined set-point without the need for additional speed transducers [3,4]. Similarly, torsional oscillations from faulty components connected to a motor or generator modulate stator currents and voltages, generating signal features that can be used to identify faults in the connected components. Such an approach has been used to identify faults in gearboxes [5–9], compressors [10,11], pumps [12] and fans [13]. Evidently, it is possible for fault signatures to propagate between components and be observed in measurements recorded throughout the system. As a result, in the case of a condition monitoring system focused on a specific component, understanding the source of a dynamic signature can represent a challenge. On the other hand, a more holistic condition monitoring system which has the capability of combining information from multiple components in a system, offers the opportunity to provide a more complete and reliable diagnostic assessment.

There are also further reasons why incorporating data from multiple sources into a condition monitoring system can improve the reliability of analysis. It is well known that a number of different fault modes can excite similar fault signatures. For example, among others, imbalances, eccentricities or misalignments can all result in increased vibration levels at the rotation speed of a piece of rotating machinery. Comparing vibrations or fusing the data recorded at multiple locations along the shaft line can help inform on which of these fault modes is the most likely to be present. Similar approaches have also been applied in Structural Health Monitoring (SHM) applications where data recorded from multiple sensors of similar type but located at different positions across the structure is fused in order to improve the assessment of the system. Vanik et al. [14] proposed a methodology based on Bayesian Inference that makes use of modal parameters, previously identified via simulation, to identify potential health state changes by analyzing the probability of a change in system stiffness parameters. Yuen et al. [15] used this approach in the development of a two-stage health assessment approach for benchmark tests. Similarly, Wang et al. [16] proposed a two-stage based Bayesian inference method that makes use of a network of sensors to identify structural problems in plates. SHM represents a vast field in which a number of approaches have been utilized for fusing data from sensors distributed across a structure. For a greater overview of structural health monitoring methods and associated applicable machine learning based techniques, readers are guided to the work of Farrar and Worden [17].

While monitoring approaches based on combining data from identical (or similar) sensors positioned at various locations across a system are well established for applications such as judging installation problems in rotating machinery or for identifying anomalies in structures, even greater gains may potentially be achieved by combining data from even more diverse sources [18]. Specifically, including data from different sensor types, recording physical quantities such as temperature [19,20], oil quality [21], or acoustic emissions [22] can also increase the reliability of a condition monitoring system, particularly as some approaches are more reactive to certain fault modes than others. Various researchers have described methods of combining signals from different sensor types in order to improve the reliability of condition monitoring analyses. For example, Yang and Kim fused electric currents and vibrations in order to diagnose faults in electric motors [23]. Basir and Yuan [24] described the fusion of vibration, sound, pressure and temperature in order to assess the condition of combustion engines whilst Salahshoor et al. [25] combined the same signals when assessing the health of turbines. Various authors have fused the signals acquired from oil debris sensors with vibration signals for the successful diagnostics of gearboxes [26,21,27]. Sadizadeh and Latifi [28] proposed combining data from an accelerometer and a load cell to diagnose bearing defects, showing that the load cell was excellent in identifying a faulty bearing whilst the accelerometer was useful to detect the location of the fault.

These multi-sensor data fusion approaches are based on Machine Learning techniques for combining data and providing a health assessment of the system by conducting pattern recognition. Machine Learning techniques typically used in multi-sensor data fusion range from Support Vector Machines (SVM) [29–31], Neural Networks (NN) [27,24,32], Fuzzy logic [33], Fuzzy measure and fuzzy integral data fusion [34] or Decision Trees [35,36], to the combination of different Machine Learning techniques, such as NN with Dempster–Shafer inference theory [23] or SVM with NN [25], among others.