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An open set recognition methodology utilising discrepancy analysis for gear diagnostics under varying operating conditions

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A B S T R A C T

Historical fault data are often difficult and expensive to acquire, which can prohibit the application of supervised learning techniques in the condition-based maintenance field. Hence, novelty detection techniques such as discrepancy analysis are useful because only healthy historical data are required. However, even if discrepancy analysis is implemented on a machine, some historical fault data will become available during the operational lifetime of the machine and could be utilised to improve the efficiency of the condition inference process. An open set recognition methodology relying on discrepancy analysis is proposed that is capable of detecting novelties when only healthy historical data are available. It is also capable of inferring the condition of the machine if historical fault data are available and it is further able to detect novelties in regions not well supported by the historical fault data. In the condition recognition procedure, Gaussian mixture models are used with Bayes' rule and a decision rule to infer the condition of the machine in an open set recognition framework, where it is emphasised that it is beneficial to use the complete datasets (i.e. data acquired throughout the life of the component) for optimising the models. The benefit of the open set recognition model is that it is easy to incorporate new historical data in the framework as the data become available. In this work, practical aspects of the condition inference process such as the importance of good decision boundaries are highlighted and discussed as well. The methodology is validated on a synthetic dataset and experimental datasets acquired under varying operating conditions and it is also compared to a conventional classification process where discrepancy analysis is not used. The results indicate the potential of using the proposed methodology for rotating machine diagnostics under varying operating conditions.

1. Introduction

Reliable condition monitoring techniques are essential when performing condition-based maintenance on expensive rotating machine assets [1,2]. Advanced signal processing [3–13] and sophisticated supervised machine learning techniques [14–23] are actively investigated to improve the condition monitoring task. Deep learning techniques have also recently

Abbreviations: CCP, Conventional Classification Procedure; CSR, Closed Set Recognition; CWT, Continuous Wavelet Transform; DR, Decision Rule; EM, Expectation Maximisation; GMM, Gaussian Mixture Model; GNB, Gaussian Naive Bayes; LDA, Linear Discriminant Analysis; LR, Logistic Regression; NLL, Negative Log-Likelihood; PCA, Principal Component Analysis; QDA, Quadratic Discriminant Analysis.

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been used to not only infer the condition of the machine, but also to extract features from the raw dataset i.e. it is not necessary to manually extract the features [24,25].

However, many supervised machine learning techniques assume that all class labels are available at time of training and therefore the techniques require much historical fault data to be available, which can be expensive and impractical to acquire. This has resulted in novelty detection techniques [26–28] and techniques which address the class imbalance between healthy and damaged states [25] to be investigated for machine condition monitoring applications. Another shortcoming of standard supervised learning techniques in the condition monitoring field is that the condition classification task is implicitly addressed as a Closed Set Recognition (CSR) problem as opposed to an Open Set Recognition (OSR) problem. In the OSR framework, it is assumed that the historical datasets are samples from a population of damage modes and therefore the class label can only be assigned to data that are well supported by a class from the historical dataset [29–34]. This is in contrast to a CSR framework where it is assumed that the class label can only originate from the class labels in the historical dataset and is implicitly used in most supervised machine learning approaches for condition monitoring.

The differences between the decision boundaries of CSR and OSR frameworks are shown in Fig. 1(a) and (b) for a machine with healthy historical data and historical fault data of two damage modes. In the OSR framework (i.e. Fig. 1(b)), predictions are only made in regions supported by historical data as opposed to the CSR (i.e. Fig. 1(a)). Hence, the CSR framework can lead to erroneous results when used for data from a new class or data not supported by the historical data, i.e. outliers. However, it has to be emphasised that both CSR and OSR frameworks are supervised learning problems where the labels are used in the loss function during model optimisation. The key distinction between the aforementioned frameworks is the assumption that is made of the class labels; if a complete representation of the potential class labels is available at the time of training, it is a CSR problem, otherwise, it is a OSR problem. The open set recognition problem does not only compromise the ability of conventional classifiers to correctly predict the condition of the machine, it can also potentially compromise the effectiveness of automatic feature extraction methods. This is because the automatic feature extraction methods for example are optimised based on the data available at the time of training the model and may not be the optimal features to separate new or unseen damage modes in the feature space.

Throughout the operational lifetime of a machine, the machine transitions from a healthy state to some damaged state e.g. a crack initialises and grows. However, this results in problems when using the OSR framework shown in Fig. 1(b); only the discrete conditions can be labelled with a class label, with the transitions between conditions labelled as novelties when the conditions are well-separated in the feature space. Hence, it is necessary to exploit the complete dataset (i.e. as the machine transitions from a healthy state to a damaged state) to learn the transition path of the features so that the correct label can be assigned as the machine transitions between conditions. This results in decision regions shown in Fig. 1(c). It is also easier to assign class labels to the approach in Fig. 1(c) as opposed to 1(b), because the damage initiation time and the

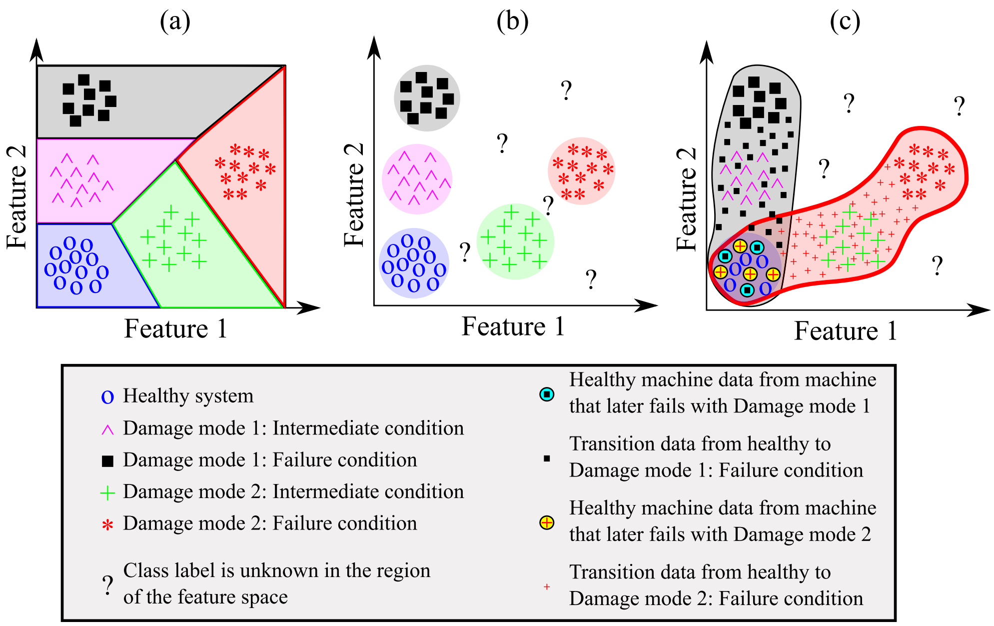

Fig. 1. The differences between the decision boundaries of a Closed Set Recognition (CSR) framework and an Open Set Recognition (OSR) framework are shown in (a) and (b) respectively for artificial data. The proposed decision boundaries that are required for an ideal OSR framework for machine condition monitoring are shown in (c). In (c), the five classes used in (a) and (b) are reduced to three classes i.e. healthy, damage mode 1 and damage mode 2. The intermediate condition refers to a machine that is somewhere between a healthy and a failure state.