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Hierarchical k-nearest neighbours classification and binary differential evolution for fault diagnostics of automotive bearings operating under variable conditions

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ABSTRACT

Electric traction motors in automotive applications work in operational conditions characterized by variable load, rotational speed and other external conditions: this complicates the task of diagnosing bearing defects. The objective of the present work is the development of a diagnostic system for detecting the onset of degradation, isolating the degrading bearing, classifying the type of defect. The developed diagnostic system is based on an hierarchical structure of K-Nearest Neighbours classifiers. The selection of the features from the measured vibrational signals to be used in input by the bearing diagnostic system is done by a wrapper approach based on a Multi-Objective (MO) optimization that integrates a Binary Differential Evolution (BDE) algorithm with the K-Nearest Neighbor (KNN) classifiers. The developed approach is applied to an experimental dataset. The satisfactory diagnostic performances obtain show the capability of the method, independently from the bearings operational conditions.

1. Introduction

According to both the IEEE large machine survey (Zhang et al., 2011) and the Norwegian offshore and petrochemical machines data, bearing-related defects are responsible of more than 40% of the failure in industrial machines (O'Donnell et al., 1983). Then, in industrial practice it is of great interest to promptly detect the bearing degradation onset, to identify which bearing is degrading, to correctly classify the cause of the bearing degradation (type of defects) and to assess the bearing degradation level. The most critical bearing degradation modes involve the bearing inner race, outer race and balls (Rao et al., 2012; Schoen et al., 1995). At the earliest stage of bearing degradation, information on the bearing health state, and, eventually, on the type of degradation can be obtained by observing the machine vibrational behavior. Thus, a typical approach to fault diagnosis in bearings is based on the extraction of features from the raw vibrational signals (accelerations) and on the use of classification models, such as Support Vector Machine (SVM) (Gryllias and Antoniadis, 2012; Zhu et al., 2014), Relevance Vector Machines (Di Maio et al., 2012a), K-Nearest Neighbours (KNN) (Jiang et al., 2013), Artificial Neural Networks (ANN) (Li and Ma, 1997), neuro-fuzzy techniques (Zio and Gola, 2009; Pan et al., 2014) and multi-symptom-domain consensus diagnosis techniques (He et al., 2001): input to the classifiers are the selected features, whereas the outputs are the detection of the onset of bearing degradation, the isolation of which bearing is degrading, the classification of the degradation mechanism and the assessment of the bearing degradation level.

Approaches to fault diagnosis in bearings have been developed considering the vibrational signals in the time domain, in the frequency domain and in both time and frequency domains. Time-domain approaches are based on the use of statistical indicators of the raw acceleration signals, such as mean, standard deviation, peak value, root mean square error, crest factor, kurtosis and skewness (Martin and Honarvar, 1995). Alternative time domain indicators have been developed (Tao et al., 2007) for dealing with incipient bearing faults, although the most critical shortcoming of all time-domain approaches is their inability to correctly diagnose bearing failures at the last stages of the degradation process, when the signal behaviors tend to be highly unpredictable and random (Ocak et al., 2007). In frequency-domain approaches, the principal frequencies of the vibrational signals and their amplitudes are identified (Chebil et al., 2009). Most of the proposed approaches to fault diagnosis for bearings in the frequency domain assume a

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priori knowledge of the principal frequencies associated to the bearings faults (Chebil et al., 2009). This setting is not realistic in automotive applications where the environmental and operational conditions modify the frequency spectra of the vibrational signals. Furthermore, real bearing spectra are characterized by a large number of frequency components, which can be difficult to be managed (Ocak et al., 2007). Time-frequency approaches, which combine time and frequency domain information, have been reported to provide the most satisfactory performances (Georgoulas et al., 2013). Several time-frequency features have been proposed in literature, such as Short Time Fourier Transforms (STFT) (Kaewkongka et al., 2003), Wigner-Ville Distribution (WVD) (Hui et al., 2006), Wavelet Transform (WT) (Loutas et al., 2012; Abbasion et al., 2007), and Empirical Mode Decomposition (EMD) (Huang et al., 1998; Ben Ali et al., 2015). For example, a multilevel classification approach for bearing diagnosis based on WT has been proposed in (Chebil et al., 2009). Conversely, EMD is suitable and attractive in dealing with highly non-linear, non-stationary signals but can be computationally expensive due to the non-smooth behavior of vibration signals. This limitation can be partially overcome using EMD and the Hilbert Huang transforms for the extraction of a compact set of features (Georgoulas et al., 2013).

A common characteristic of the frequency and time-frequency domain approaches is that they typically generate feature sets of very high dimensionality. Reducing the dimensionality of the feature set allows to remarkably reduce the computational burden. Furthermore, it has been shown that irrelevant and noisy features unnecessarily increase the complexity of the classification problem and can degrade modeling performance (Emmanouilidis et al., 1999). Thus, in this work, the development of classification algorithms for bearing diagnosis is accompanied by the application of feature extraction methods which map the n-dimensional data being classified onto an m-dimensional space, where $m < n$ (Dash and Liu, 1997). Examples of feature extraction methods are Kernel Principal Component Analysis (KPCA) (Schölkopf et al., 1998), Kernel Fisher Discriminant Analysis (KFDA) (Mika et al., 1999; Baudat and Anouar, 2000) or Semi-supervised Kernel Marginal Fisher Analysis (SKMFA) (Jiang et al., 2013), Linear Local Tangent Space Alignment (LLTSA) (Li, 2013), Self-Organizing feature Map (SOM) (Kohonen, 1982). A special case of feature extraction is feature selection, whereby $(n - m)$ irrelevant features are discarded. More specifically, the objective of feature selection is that of finding a subset of the original features such that the classification algorithm based on these features generates a classifier with the highest possible performance (Zio et al., 2006). In general, feature selection methods can be classified into two categories: filter and wrapper methods (Kohavi and John, 1997). In filter methods, the feature selector algorithm is used as a filter to discard irrelevant and/or redundant features a priori of the construction of the classification algorithm. A numerical evaluation function is used to compare the feature subsets with respect to their classification performance (Dash and Liu, 1997). On the contrary, in wrapper methods the feature selector behaves as a wrapper around the specific learning algorithm used to construct the classifier. The feature subsets are compared using as criterium the classification performance achieved by the classification algorithm itself (Zio et al., 2008).

This work is motivated by the interest of investigating the possibility of effectively performing in practice fault diagnostics of bearings installed on the powertrain of a Fully Electric Vehicle (FEV). The research is part of the European Union funded project Electrical power train Health Monitoring for Increased Safety of FEVs (HEMIS, www.hemis-eu.org) (Sedano et al., 2015; Baraldi et al., 2013), which aims at the development of a Prognostics and Health Monitoring System (PHMS) for the most critical components of FEVs. The difficulty of the fault diagnostics task is that automotive motors differ from other industrial motors since they work in operational conditions characterized by variable load, rotational speed and other external conditions which can cause major modifications of the vibrational signal behavior. Electrical machines and drive systems are subject to many different types of faults which include: 1) stator faults such as stator winding open or short circuited; 2) rotor electrical faults such as rotor winding open or short circuited for wound rotor machines and broken bar (s) or cracked end-ring for squirrel-cage machines; 3) rotor mechanical faults such as bearing damage, eccentricity, bent shaft, and misalignment; and 4) failure of one or more power electronic components of the drive system (Bellini et al., 2008). (Bonnett and Yung, 2008) describes the distribution of induction motor faults and shows possible scenarios for after fault, detailing the repair-replace decision process. The distribution of induction motor faults is listed in Bellini et al. (2008) as bearing (69%), rotor bar (7%), stator windings (21%), and shaft/coupling (3%). Fault diagnostics of bearing installed on the powertrain of electric machines is an attracting research field. In Tian et al. (2016), different features are extracted from spectral kurtosis and then combined to build a health index based on PCA and a semi-supervised KNN distance measure to detect incipient faults and diagnose the locations of the bearings faults. In Abed et al. (2015), DWT is used to extract features from stator current and lateral vibrations current measurements. The obtained features are further reduced via the applications of orthogonal fuzzy neighbourhood discriminant analysis. Finally, a Recurrent Neural Networks (RNN) is used to detect and classify the presence of bearing faults. In Geramifard et al. (2013), a semi-nonparametric approach based on a hidden Markov model classifier is introduced for fault detection and diagnosis of bearings in syncrounous motors. In Zhang and Zhou (2013), a procedure based on Ensemble Empirical Mode Decomposition (EEMD) and SVM for multi-fault diagnosis of bearings in induction motors is discussed. In Dalvand et al. (2016) the kurtosis of instantaneous frequency of motor voltage is used for the identification of defective bearings. In Jin et al. (2014), Trace Ratio Linear Discriminant Analysis (TRLDA) is used to deal with high dimensional non-Gaussian fault data for dimension reduction and fault classification of bearings in induction motors. Although the listed works have been reported to achieve satisfactory performance, the industrial applicability of these methods is limited by the fact that the features extrated to train the empirical model for the diagnosis are not independent from operational conditions: fault diagnostics is tacitily based on the hypothesis that the training patterns and the testing patterns are similar. As a result, if the diagnostic model is used in working conditions different from those considered to train the model, its performance may be unsatisfactory. To overcome this limitation, the main contribution of this work is the development of a novel feature selection approach to identify features independent from operational conditions. This is expected to allow developing a diagnostic system that can be used independently from the operational and environmental conditions that the FEV is experiencing. A further novelty of the work is that the feature selection problem is embedded into a multi-classification problem, where several classifiers developed for different scopes (detection, isolation, degradation mode classification and degradation level assessment) are integrated. The proposed diagnostic system is based on an hierarchical model of K-Nearest Neighbor (KNN) (Jiang et al., 2013) classifiers. A multi-objective (MO) Binary Differential Evolution (BDE) optimization algorithm has been used for the identification of the feature set to be used. The optimization aims at the identification of a feature set, which allows to obtain a high classification performance by using a low number of features extracted from a low number of vibrational signals. Notice that the use of a low number of features allows