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Observer-biased bearing condition monitoring: From fault detection to multi-fault classification

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ABSTRACT

Bearings are simultaneously a fundamental component and one of the principal causes of failure in rotary machinery. The work focuses on the employment of fuzzy clustering for bearing condition monitoring, i.e., fault detection and classification. The output of a clustering algorithm is a data partition (a set of clusters) which is merely a hypothesis on the structure of the data. This hypothesis requires validation by domain experts. In general, clustering algorithms allow a limited usage of domain knowledge on the cluster formation process. In this study, a novel method allowing for interactive clustering in bearing fault diagnosis is proposed. The method resorts to shrinkage to generalize an otherwise unbiased clustering algorithm into a biased one. In this way, the method provides a natural and intuitive way to control the cluster formation process, allowing for the employment of domain knowledge to guiding it. The domain expert can select a desirable level of granularity ranging from fault detection to classification of a variable number of faults and can select a specific region of the feature space for detailed analysis. Moreover, experimental results under realistic conditions show that the adopted algorithm outperforms the corresponding unbiased algorithm (fuzzy c-means) which is being widely used in this type of problems.

1. Introduction

Bearings are elemental mechanical components in rotary machinery (engines, gearboxes, propellers, turbines, etc.) that have been identified as one of their primary cause of failure, cf. (Yaqub et al., 2012). For example, in induction motors metal bearing faults account up to 40% of all faults (Siyambalapitiya and McLaren, 1990).

Rolling element bearings, such as ball bearings, consist of an inner, an outer race or ring, inside which a set of rolling elements rotate which are all prone to faults. In some models, a cage holds the rolling elements. Bearing faults can have different causes such as excessive load, lubricant failure, or corrosion. Studies exist comparing bearings with different materials and failure mechanisms (Sreenilayam-Raveendran et al., 2013). In general, faults result in abrasion due to steady friction of mechanical parts that, in turn, can have severe consequences for the overall system where the bearing is working in. The healthy condition of the bearings is directly related to the safe and effective operation of mechanical systems (Li et al., 2015). The result of a bearing failure can be catastrophic. This is the case of metal engine bearings supporting a crankshaft. Should this bearing fails the whole engine can disintegrate. Therefore, it is apparent the need for early detection and diagnosis of such faults.

A fault can be classified according to the location where it occurs: at the inner race, outer race, or at the rolling body, cage included. Also, a fault can be classified according to its type: it can be (i) a single point, (ii) localized within a certain region, or (iii) a generalized roughness fault. Often, localized or generalized faults originate from single point faults. The study focuses on metal ball bearings with single point faults. Fig. 1 shows some examples of the considered single-point faults in each one of the main components of a bearing. Different faults can and do occur simultaneously and are considered as well in this work. On the other hand, cage faults are not considered in this study. When present, a cage holds the rolling elements in position and its failure is

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Fig. 1. Examples of the three basic types of bearing faults actually studied in this work: (a) ball bearing fault, (b) inner race fault, and (c) outer race fault.

normally secondary as it is due to the failure of the other 3 main bearing components and, as such, cage faults are not normally studied in bearing diagnosis.

Bearing faults leave a trace in the vibration signal captured by accelerometers, the so-called fault signature. Acoustic, electric, thermal, or oil debris signals, e.g., Navarro et al. (2010), Oskouei and Esmaeili (2012), Oh et al. (2012) can also be used for detecting such faults, however vibration analysis is still one of the more widely used method and is also the method used in this work. This is due mainly to the following two aspects: (i) comparatively to electric, thermal, or oil debris signals, the vibration signal is more sensitive to the local defects of rotating components, and (ii) compared to other sensors such as acoustic emission or oil debris sensors, vibration sensors are much cheaper.

Bearing fault diagnosis involves the following general data pipeline: data acquisition and conditioning, feature extraction, feature selection, and classification. Typically, time, frequency, and time-frequency features are extracted from the collected signals. Feature selection is a critical step for optimizing efficiency, accuracy and for mitigating overtraining. Feature selection can be accomplished by experts with or without the help of feature selection methods. These include the employment of genetic algorithms, e.g., Lei et al. (2007), correlation-based methods such principal component analysis (PCA), e.g., Xu et al. (2009), Vijay et al. (2013), Ben Ali et al. (2015), fuzzy measures, e.g., Liu et al. (2008), rough sets (Zhao et al., 2008), orthogonal fuzzy neighborhood discriminant analysis, e.g., Abed et al. (2014), or entropy based criteria like those used for growing decision trees (Robin et al., 2010). The latter computes the information degree contributed by each feature and is the method adopted here. See Section 3.3 for details.

This work focuses on the employment of fuzzy clustering for fault detection and classification. The notions of cluster and clustering can have different meanings. In this paper, we are interested in (partition-based) clustering algorithms that can be viewed as a function mapping patterns (or observations) in a finite, otherwise unlabeled multi-variate date set $\mathbf{X}$ to partitions in $\mathcal{P}$, the set of all $\mathbf{X}$ dimensional compatible partitions. The problem is to partition $\mathbf{X} \subset \mathbb{R}^d$ space into groups (clusters) so that data in one group are similar to each other and are as dissimilar as possible from data in other groups. The (dis)similarities are evaluated through a suitable distance function that satisfies the three properties of a metric: reflexivity, symmetry, and triangle inequality.

Essentially, fuzzy clustering differs from conventional (hard) clustering in the sense that it allows an observation to belong, with different membership degrees, to more than one cluster, cf. (Valente de Oliveira and Pedrycz, 2007). Each membership degree can express how ambiguously or definitely an observation belongs to a given cluster and, under appropriated constraints, can be interpreted as the probability of an observation be a member of a cluster.

Currently there is a wealth of clustering algorithms available. The following focuses only on the algorithms used in studies on bearing fault diagnosis. For a broader perspective on the currently available fuzzy clustering algorithms the interested reader is referred to Valente de Oliveira and Pedrycz (2007).

1.1. Fuzzy clustering algorithms in bearing fault diagnosis

Fuzzy c-means (FCM) is the most popular and widely used fuzzy clustering algorithm in bearing fault diagnosis. Despite being well-known the algorithm is briefly revised here for easy reference. FCM aims at minimizing the objective function J (1) for a specified number of cluster c and a given set of observations $\mathbf{X} = \{\vec{x}_1, \ldots, \vec{x}_j, \ldots, \vec{x}_N\}$

$$J = \sum_{i=1}^{c} \sum_{j=1}^{N} u_{ij}^m \| \vec{x}_j - \vec{v}_i \|^2 \tag{1}$$

under the constraints $u_{ij} \in [0, 1]$, $\sum_{j=1}^{N} u_{ij} > 0$, and $\sum_{i=1}^{c} u_{ij} = 1$, where u_{ij} represents the membership of observation $\vec{x}_j (j = 1, \ldots, N)$ in the i-th cluster $(i = 1, \ldots, c)$, $\vec{v}_i$ refers to the centroid of the i-th cluster, $\| . \|$ stands for a norm distance in $\mathbb{R}^d$, $m > 1$ being the so-called fuzziness parameter. Increasing m increases the overlapping among the clusters. On the other hand, when $m \to 1$ FCM degenerates into k-means. FCM optimizes J through an iterative process where in each iteration, the centroid of the i-th cluster is updated using:

$$\vec{v}_i = \frac{\sum_{j=1}^{N} u_{ij}^m \vec{x}_j}{\sum_{j=1}^{n} u_{ij}^m} \tag{2}$$

The elements of the partition matrix, u_{ij}, i.e., the membership degrees are computed as follows:

$$u_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{\| \vec{x}_j - \vec{v}_i \|}{\| \vec{x}_j - \vec{v}_k \|} \right)^{\frac{2}{m-1}}} \tag{3}$$

FCM has been extensively studied in bearing fault diagnosis as an exploratory tool (Jia et al., 2005; Guan et al., 2006; Wadhwani et al., 2006; Cui et al., 2008; Pan et al., 2009, 2009; Sui et al., 2010; Fu et al., 2011; Jiang et al., 2011; Ye et al., 2011; Zhang et al., 2011; Cao et al., 2012; Liu and Han, 2012; Xu et al., 2012; Xinbin et al., 2012; Wang et al., 2012b,a, Zanoli and Astolfi, 2012; Liu and Han, 2013; Vijay et al., 2013; Liang et al., 2015; Ou and Yu, 2014; Wang et al., 2014; Meng et al., 2014; Liu et al., 2014; Zhang et al., 2014; Zheng et al., 2015).

Other authors studied specific variants of the algorithm. This is the case of Jiang et al. (2010) in which a specific cost-functional based partitioning clustering algorithm is derived, and the work in Sui et al. (2008), Zhang et al. (2009), Cao et al. (2012) that uses the kernel-based fuzzy c-means.