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A novel intelligent method for bearing fault diagnosis based on affinity propagation clustering and adaptive feature selection

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ABSTRACT

Bearings faults are one of the main causes of breakdown of rotating machines. Thus detection and diagnosis of mechanical faults in bearings is very crucial for the reliable operation. A novel intelligent fault diagnosis method for roller bearings based on affinity propagation (AP) clustering algorithm and adaptive feature selection technique is proposed to better equip with a non-expert to carry out diagnosis operations. Ensemble empirical mode decomposition (EEMD) and wavelet packet transform (WPT) are utilized to accurately extract the fault characteristic information buried in the vibration signals. Moreover, in order to improve the efficiency of clustering algorithm and avoid the curse of dimensionality, a new adaptive features selection technique is developed in this work, whose effectiveness is verified in comparison with other methods. The proposed intelligent method is then applied to the bearing fault diagnosis. Results demonstrate that the proposed method is able to reliably and accurately identify different fault categories and severities of bearings.

1. Introduction

Rolling element bearings are among the most important components in a rotating machine. Defects in bearings can lead to machine malfunction, even to economical loss and human casualties. Thus, fault diagnosis of rolling element bearings plays an important role in machinery maintenance. Various methods have been developed for bearing diagnosis, such as vibration analysis, acoustic emission (AE), temperature trend analysis and wear debris analysis [1]. However, costly training and highly skilled operators are needed, because diagnosis operations require expertise to have a domain specific of maintenance and knows the “ins-and-outs” of the system [2]. Therefore, intelligent approaches are necessary for unskilled operators to make reliable maintenance decisions.

Growing efforts in clustering/classification have been made to explore innovative methods for intelligent fault diagnosis. For example, adaptive neuro-fuzzy inference system [3], genetic algorithm [4], fuzzy C-means cluster algorithm and compensation distance evaluation technique [5], radial basis function network [6] have been often adopted to solve the classification/clustering issues. In [2], Dou proposed a rule-based intelligent approach which combines EMD with fault decision table technique. Recently, a novel intelligent fault diagnosis method with multi-variable ensemble-based incremental support vector machine was given in [7], which can effectively correlate monitored multiple variables with different defects. Meanwhile, Qu proposed a multiple classifier fusion method based on dual-tree complex wavelet packet transform [8]. Moreover, in order to detect incipient fault and to identify potential problems, four classifying methods used in the intelligent fault diagnosis of rotating machinery have been thoroughly investigated in [9]. It is important for these mentioned techniques to successfully identify a subset of representative examples for the purpose of pattern recognition. However, these methods are sensitive to the initial selection of cluster centers, and they usually must run many times with different initializations in order to find a good solution. They works well only when the number of clusters is small and chances are good that at least one random choice of clustering examplars is close to a good solution [10].

Affinity propagation (AP) pioneered by Brendan J. Frey et al. in [10] is an innovative and readily-extensible clustering algorithm. AP shows some significant improvements in comparison with those other conventional clustering methods, such as *K*-means, spectral clustering and super-paramagnetic clustering. One of the important advantages of AP is that the number of examplars needs not to be specified beforehand. Moreover, AP usually achieves comparable or better results in far less time for large datasets. Due to these good performances, AP has been successfully employed in many fields, such as images clustering, gene-expression data and large scale data analysis [10]. It should be mentioned that AP technique has been also successfully employed for the fault diagnosis of metro vehicle auxiliary inverter [11], trend prognosis of aero-

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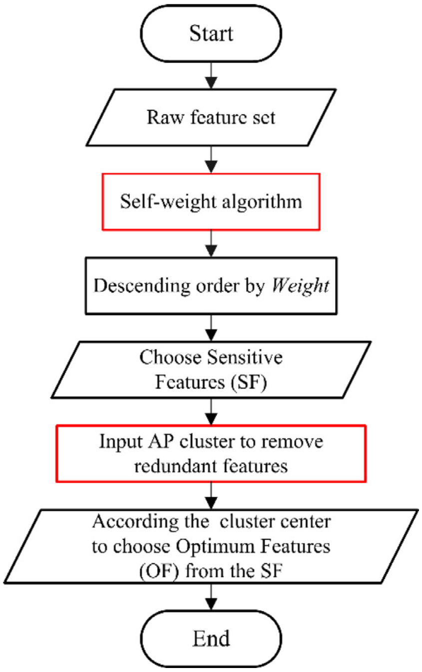

Fig. 1. Flowchart of the proposed adaptive feature selection technique.

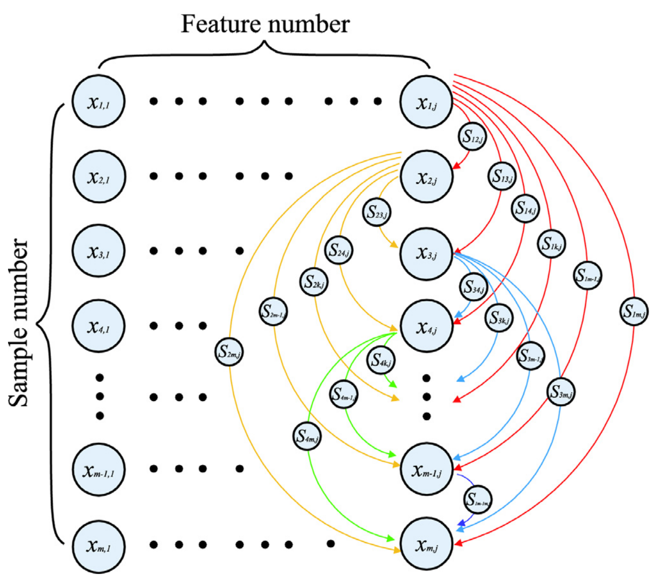

Fig. 2. The calculation of self-similarity factor.

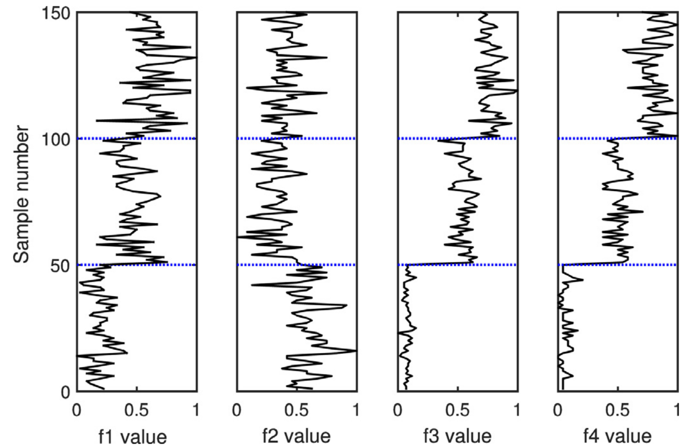

Fig. 3. Iris data.

engine abrupt failure [12] as well as evolving machinery fault diagnosis [13]. However, most of these applications of AP only used the original features for the cluster analysis.

As is well known, more and more features have been involved in the condition monitoring system and fault diagnosis with the rapid development of signal processing techniques [14]. Moreover, different feature sets may be produced via modern signal processing and feature extraction methods, for example, empirical mode decomposition (EMD) [15], ensemble empirical mode decomposition (EEMD) [16], wavelet packet transform (WPT) [17], variational mode decomposition (VMD) [18] and sparse regularization [19]. EEMD and WPT technology are used in this work to produce the original feature sets, respectively. Thus, in order to improve the diagnosis accuracy and reduce the computation burden, a few sensitive features should be selected from the original feature set [5]. Presently, many methods have been utilized for feature selection such as distance evaluation technique [20], the decision tree-based attribute weighting filter method [21] and the attribute estimation with Relief-F [22]. Meanwhile, a new robust metric was proposed in [23], which is different from the Euclidean distance and greatly improves the robustness of fuzzy C-means. Besides kernel mapping, feature weighting is also an effective way in improving the efficiency and capabilities of clustering methods [24]. For example, Shen [25] introduced a weighted fuzzy kernel clustering algorithm to deal with the incomplete data. Iterative relief [26] eliminated the effects of the outliers and noisy data as well as solved the issues of Relief when the nearest neighbors of the samples defined in the original measurement space were inappropriate. However, prior knowledge is required for these techniques to calculate the values of attribute weight and to evaluate different features. Nevertheless, it is practically hard to know this information in advance. Consequently, adaptive feature selection techniques should be further explored in order to self-adaptively choose optimal and sensitive features.

A self-adaptive feature selection technique combined with AP clustering algorithm is proposed for bearing intelligent fault diagnosis in this work. The performance of the proposed feature selection approach is also compared with the Relief-F and distance evaluation technique. The rest of this work is organized as follows: The basic theory of AP clustering is briefly reviewed in Section 2. Feature extraction and the proposed adaptive feature selection technique are illustrated in Section 3. The effectiveness of the proposed methods is evaluated by experimental data in comparison with other methods in Section 4. Conclusions are drawn in Section 5.

2. Briefly review of AP

Different from the common clustering methods, AP simultaneously considers all data points as potential exemplars in a network, and real-valued messages are transmitted along edges of the network until a good set of exemplars and their corresponding clusters are achieved. Clustering centers are found through maximizing the sum of the similarity degree between samples and the nearest clustering center.

$$E(c) = -\sum_{i=1}^{N} s(i, c_i) \tag{1}$$

in which label c_i indicates the exemplar of the data point i, and $s(i, c_i) \leq 0$ is the similarity between data point i and its exemplar c_i. The process of AP can be viewed as a message passing with two kinds of messages exchanged between data points, namely, responsibility and availability [10]. The algorithm is briefly stated as follows: