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Hybrid vibration signal monitoring approach for rolling element bearings

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Abstract. New approach to identify different lifetime stages of rolling element bearings, to improve early bearing fault detection, is presented. We extract characteristic features from vibration signals generated by rolling element bearings. This data is first pre-labelled with an unsupervised clustering method. Then, supervised methods are used to improve the labelling. Moreover, we assess feature importance with each classifier. From the practical point of view, the classifiers are compared on how early emergence of a bearing fault is being suggested. The results show that all of the classifiers are usable for bearing fault detection and the importance of the features was consistent.

1 Introduction

In general terms, rolling-element bearings (REBs) are common elements in various rotating machines and the failure of a bearing is a common cause of machine breakdowns. Economical and human losses due to an unexpected failure of a critical bearing can be extensive [1]. They can be prevented and significantly reduced by applying a proper maintenance strategy [2]. Vibration measurements are the most widely used method for detection and diagnosis of bearing faults [3]. Signal processing methods are continuously developed for bearing fault detection. These methods focus to extract characteristic features from vibration signals.

Wear, a measure of condition, accumulates over time and the cumulative wear is measured at chosen times in the machine condition monitoring systems [4]. Presentation of the wear evolution process as a time series describes the wear interaction and evolution at different lifetime stages. El-Thalji et al. introduced a five-stage descriptive model of wear evolution including: running-in, steady-state, defect initiation, defect propagation, and damage growth [5]. The main period of interest is between the steady state and the defect initiation and the propagation stages. Hence, in general we try to identify the time-instance of the occurrence of such a concept drift [6].

In doing so, the feature data is pre-labelled with an unsupervised method for a preliminary identification of the defect initiation. A similar time-series clustering approach was also used in[7]. Then, three popular supervised classification techniques [8], also central for the determination of concept drift [6], are applied and tested to sharpen the unsupervised result. Note that recently a combination of unsupervised fuzzy clustering and supervised learning to improve a machine

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learning method referred as minimum learning machine was proposed in [9]. Our study confirms that the proposed novel, hybrid combination of methods is useful, real-time applicable, and reliable for early bearing fault detection.

2 Methodological Background

As described above, condition monitoring and preventive maintenance are based on proper processing of measurement data [10, 2]. We describe next the basics of those methods that will be applied as part of the proposed approach.

2.1 Unsupervised learning

Fuzzy clustering algorithms, especially the fuzzy c-means (FCM) which was originally developed by Ruspini [11], generalize the k-means by allowing data points to belong to multiple clusters. This relation is represented with a membership function. Such an approach is appealing especially in the condition monitoring setting, where we have no fixed change-points but a gradual evolution of different lifetime stages [5]. The FCM algorithm was further developed by Dunn and Bezdek [12, 13].

We use FCM clustering to identify the different REB lifetime-stages. The number of centroids corresponds to number different life-time stages. Our techniques are different but the basic idea is similar to [7]. Transition states between lifecycle stages are not characterized by sudden changes in the characteristic features of vibration signals. Consequently, FCM clustering produces overlapping clusters. Yiakopoulos et al. introduced a k-means clustering approach for the diagnosis of the bearing faults [14]. They used a set of features based on vibration energies in the frequency domain and statistical time-domain indices [14].

2.2 Supervised learning

In this experimental study, we examine different supervised classification methods, namely K-nearest-neighbors (KNN), Naive Bayes (NB), and Support Vector Machine (SVM), in terms of how well they are able to generalize the lifetime stage labelling from characteristic features of vibration signals. Previously, performance of various supervised classifiers (including the techniques here) on acoustic emission measurements of REBs were compated in [8]. The KNN classifier was found as the best suited there.

The K-nearest neighbor classification rule was originally introduced by Cover and Hart [15]. The KNN rule is applicable on data that is in the metric space and it does not make assumptions on the distribution of data. Support vector machine (SVM) is a supervised machine learning algorithm that can be used for both classification and regression problems. General review of the use of SVM in condition monitoring and fault diagnostics was given in [16]. The naive Bayes (NB) classifier is a probabilistic classifier that is based on the Bayes theorem.

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The NB classifier considers prior probability of the predicted class when the likelihood of that class is calculated [17].

Quality of the classifiers was assessed using ten-fold cross-validation with misclassification in percentages (MCP) as error measure. We used Distribution Optimally Balanced Stratified Cross Validation (10-DOB-SCV), which tries to keep data distribution as similar as possible between the training and test data by minimizing the covariate shift [18, 19]. Analysis of feature saliency (importance) was carried out with each classifier, to identify the most informative features. It was estimated using backward elimination of individual features one-by-one [20, 21]. All MCP errors $\{e_i\}_{i=1}^{n}$ are sorted to the descend order in order to identify the ranking of features, where n is the number of features. Moreover, relative importance of each feature in percentages, MCP order, is estimated simply by taking $100\frac{e_i}{\sum_{i=1}^{n} e_i}$.

3 Experimental results

Vibration data were generated by the NSF I/UCR Center for Intelligent Maintenance Systems (IMS) with support from Rexnord Corp. in Milwaukee, WI [22]. The vibration data was collected from the IMS bearing test rig. Total of four bearings (Rexnord ZA-2115) were installed on a shaft. All the tests were "run-to-a-failure" tests. We use vibration signals from two test runs. The first case includes an inner race fault in the bearing. The second case includes an outer race fault in the bearing. The sampling rate of the vibration measurements was 20 kHz and the measurements were recorded every ten minutes. The total number of vibration measurements were 2156 and 4448 in these two datasets.

Commonly used statistical time-domain degradation features are used: 1.Root mean square 2.Crest factor, 3.Shape factor, 4.Impulse factor, 5.Mean frequency, 6.Skewness, 7.Kurtosis and 8.Entropy [23, 24]. The ninth (9.) feature, which is the only frequency-domain feature, refers to the amplitude of the characteristic bearing fault frequency in envelope spectrum. Later in the results, the features are referred to by order number.

3.1 Unsupervised clustering

FCM clustering is performed with four centroids for the unsupervised vibration features data. The moving median of 50 samples is used to smoothen the feature data before the fuzzy c-means. Length of the median window is c. 8.3 hours that gives good resolution for life-time stage identification. Vibration data covers almost the entire lifetime of the investigated bearings. Figure 1 presents the FCM clustering results for both cases. The classification indicator is a floating point value between zero and one. The first indication of a bearing fault is seen as an increment in the indicator values of the first class (1) in both cases. This change point is interpreted as the beginning of the defect initiation stage (the first black dotted line). When the defect initiation stage shifts to the propagation stage, changes are seen in the second class (2). The assumed beginning of the damage growth stage begins when the indicator value of the third class (3) increases.

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The defect initiation, the defect propagation and the damage growth stages are clearly separated by fuzzy c-means clustering.

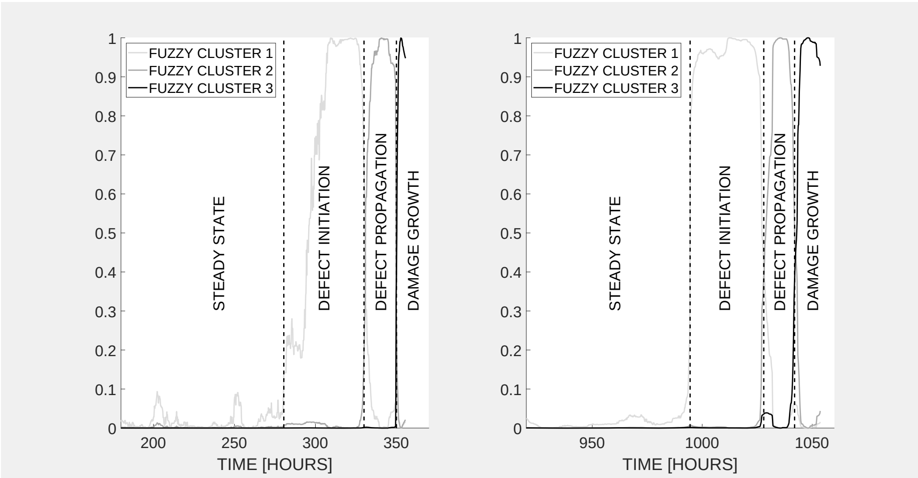

Fig. 1: Lifetime stage identification using c-means fuzzy clustering (Case 1 on the left side, Case 2 on the right side)

3.2 Supervised classification

The evaluation of the classifiers is done for the merged data of both cases, containing 4481 feature data points. Moreover, results from the unsupervised processing were used to introduce binary labelling of the time-series, where the label changes corresponded to the unsupervised identification of the time instances for the emergence of the defect initiation stage. The feature data split by 10-DOB-SCV and the bearing fault detection is done for the partitioned data. Hence, the start time of the defect initiation state was set as a zero point to compare how early different classifiers detect the bearing fault.

The quantified results of the evaluation of the classifiers and the bearing fault detection estimations are listed in Table 1. First, the optimal number of nearest neighbors (k) for the KNN classifier is estimated by using 10-DOB-SCV, i.e., by seeking the minimal CV-error. As a result k=5 was fixed. In each experiment, the CV-errors were calculated separately for all classifiers. All the calculations were repeated for 15 times. Average of the CV-errors for the KNN, SVM and NB classifiers are roughly equal 3.5%, 3.3% and 3.3%, respectively. The standard deviation of the CV-errors are fairly unobtrusive. The MCP order (%) range is between 9.3% - 11.1% for all features (1-9), which means that every feature is important in the classification for all classifiers. The KNN classifier detected the bearing fault about 51 hours before the zero point, i.e., before the first suggestion of the unsupervised FCM. The SVM- and NB-classifiers also detected the bearing fault c. 31 hours and c. 46 hours before the zero point, respectively.

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	KNN	SVM	NB
CV-error mean	0.035	0.033	0.033
CV-error std	0.006	0.006	0.006
Earlier fault detection mean [hours]	51	33	46
Earlier fault detection std	2.7	3.7	1.8

Table 1: Supervised classification results (15 runs).

4 Conclusions

Our experiments confirmed that the results from FCM clustering can be used for the initial identification of different lifetime stages of rolling element bearings. Identification of the defect initiation, the defect propagation and the damage growth stages succeeded quite well. Utilization of the FCM clustering was straightforward. However, the feature data were smoothen by median averaging.

The studied supervised classification methods were not easy to implement with the presented feature data of vibration signals. The affecting parameters of the classifiers need to be configured properly and the sensitivity of the classifiers must be evaluated for reliable results. Our case studies showed that all the classifiers gave reliable results in bearing fault detection. The KNN classifier gave slightly the earliest fault detection for the presented vibration signal features. The importance of the features was consistent and none of the features needed to be discarded. As a result, several classifiers with different models were obtained. Future research will focus how to find the best of these models and apply it to separate case studies to detect bearing faults.

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