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Bearing Fault Diagnosis and Classification Based on KDA and Alpha-Stable Fusion

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Abstract

Bearings are the most critical components in machinery elements. Their failure caused an unexpected disturbance at industrial processes. Many researchers studied diagnose and classification of bearing faults by data vibration analysis. In this regard, an efficient and a new method to extract and classify the bearing-fault may be the application of the Alfa stable extraction and Kernel Discriminant Analysis (KDA) algorithm for improving the diagnosis and classification accuracy. The aim of this paper is to present a methodology by which different levels of bearing defects can be detected and classified. We create and develop a bearing vibration database from an industrial plant, then we accomplish the diagnosis using Hilbert transformation, the extraction is done with entropy and Alfa stable methods, and finally we apply many classifiers to the feature extraction. Experimental results proofs the effectiveness of the proposed method. The analysis and comparison show that the accuracy rate of classification using the KDA based alpha stable is higher than the others algorithms.

Keywords: Machine vibration, Condition monitoring, Diagnosis, classification, bearing, KDA, alpha stable, LDA, PCA, SVM, entropy

1. Introduction

Bearings are found in a wide variety of industrial applications such as pumps, motors, wind power generators and compressors. There failures caused unscheduled downtime, perturbation in machinery operation, unpredictable productivity losses and high maintenance costs. By vibration analysis we can diagnose and classify typical faults such as gear faults, cracked shaft, misalignment, unbalance, rubbing, impellor/blade, motor faults looseness, and bent shaft defects. An accurate bearings dynamical model is hard to construct, because there are many complex sub-parts to model, which include inner race, outer race, cage, etc. Therefore, data driven models based on historical data is preferred in real industrial applications.

The bearing diagnosis can be done in the time or in the frequency domain. In the frequency domain, the enveloping technique has been proven to be an efficient method for bearings faults diagnosis [26, 2]. The probability density moments (skewness, kurtosis), crest factor and RMS are the most popular statistical time domain parameter for bearing defect detection [17, 14]. In recent years, the wavelet transform [8, 15], artificial neural networks and fuzzy logic have emerged as excellent process for fault detection [6, 21].

A bearing fault diagnosis can be decomposed into three parts: data acquisition, feature extraction, and fault condition classification. The aim of this paper is to present a methodology by which different levels of bearing defects can be detected and classified. We present the conception and the exploitation of a bearing vibration database taking in an industrial plant and we present also a new method to extract and classify the bearing-fault by application of the Alfa stable extraction and KDA algorithm for improving the diagnosis accuracy and classification. This proposed method have been compared to entropy extraction, Linear Discriminant Analysis (LDA), Principle Component Analysis (PCA) and multi-class Support Vector Machine (SVM) methods. The experimental measures and treatment are applied to both horizontal and vertical bearing axis. The alpha stable and KDA methods are built and applied to perform to automate the fault diagnosis and classification procedure. Moreover, the fusion between those adopted methods is used to improve the evaluation accuracy of the classifier. We present in Section 2, the adopted approach and the experimental phase including data acquisition, pre-processing and feature extraction, while section 3 gives an account of the obtained results. Finally, concluding remarks are presented in section 4.

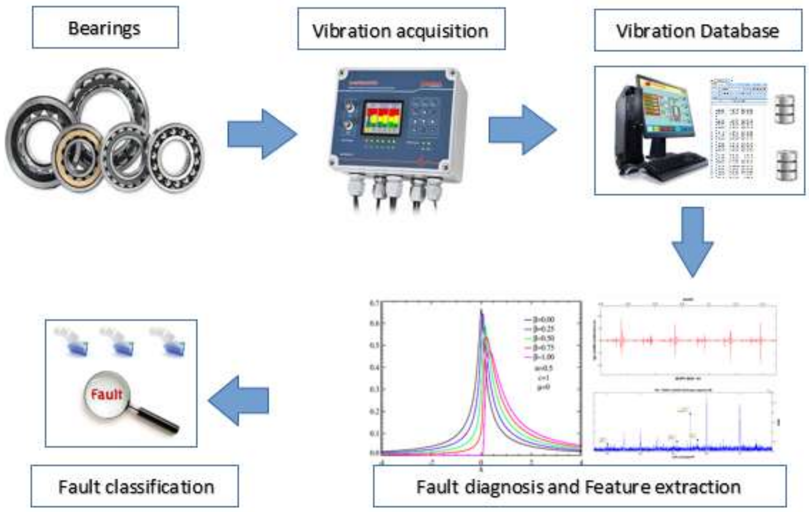

Figure 1: Bearing fault classification

2. Proposed method

2. 1 Adopted approach

To diagnose bearing faults, we process in three phases: Data acquisition, a learning phase by a feature extraction, and fault condition classification (see Figure 1). In the first phase, we construct a bearing vibration data base recorded by the sensors, in the second one, we apply some diagnosis faults methods based Hilbert transformation and we extract reliable features based entropy and α-stable distribution which are the best representation the observed sequence of vibration data. These features are then used to learn several behavioral models of stable distribution coefficients (μ, c, α and β) and PE corresponding to different initial states and operating conditions of bearing (normal and fault states). The last phase, we detect the component's current condition by exploiting the learned models, in this phase we propose using Kernel discriminant analysis (KDA) algorithm as classifier for estimate machine state and we compute the recognition accuracy results compared to different classification methods (Permutation Entropy (PE), SVM, LDA, PCA). The learned models are exploited to identify the current machine state and the bearing fault severity (in our study we have considered 4 bearing default classes: Normal, slight faults, medium faults and serious faults).

2.1.1 Alpha Stable distribution

Alpha Stable distribution was developed from the generalized central limit theorem. It includes as, three special cases, Gaussian, Cauchy and Levy distributions. The general characteristic function for this probability density is characterized by a four-parameter family of continuous probability distributions form parameterized by location and scale, and two shape parameters and, roughly corresponding to measures of asymmetry and concentration. The theory and procedure of Alpha Stable distribution can be found in [18, 20]. The general characteristic function is used to describe its statistical properties and can be expressed as:

$$\varphi(u) = \exp\left\{ j\delta u - \gamma |u|^{\alpha} \left[1 + j\beta \operatorname{sgn}(u)\omega(u,\alpha)\right]\right\} \tag{1}$$

where $$\omega(u,\alpha) = \begin{cases} \tan(\pi\alpha/2), \alpha \neq 1 \\ (2/\pi)\log|u|, \alpha = 1 \end{cases} \tag{2}$$

and $$\operatorname{sgn}(u) = \begin{cases} 1, u > 0 \\ 0, u = 0 \\ -1, u < 0 \end{cases} \tag{3}$$

As the equation (1) shows, the statistical characteristics of Alpha Stable distribution are completely determined by four parameters (α, β, γ, δ). In reference [25, 5], it has been proved that the use of the four parameters of Alpha Stable distribution as the fault features in fault diagnosis of rolling bearings is operable. The calculated features represent the degradation of bearing. The selected features gives the best separation between classes and we compare the obtained result with the four features obtained from stable distribution.

2.1.2 Classification by PE, LDA, PCA, SVM and KDA

We use as traditional classifiers, the Permutation Entropy (PE) [23, 3] which estimates the complexity of time series through the comparison of neighboring values, the Linear Discriminant Analysis (LDA) a statistical technique used for linear dimension reduction by minimizing the within-class scatter and maximizing the between-class scatter [9, 16], the multi-class Support Vector Machine (SVM) a computational learning method used for classification and regression which employs structural risk to minimize an upper bound on the expected risk [1, 7, 11], The Principle Component Analysis (PCA) dimensionality reduction method based on a transformation of a number of possibly correlated variables into a smaller number of uncorrelated variables to reduce data complexity [13, 19]. Kernel Discriminant Analysis (KDA) [13, 4] a kernelized version of linear discriminant analysis employs the kernel trick to perform LDA in a new feature space by a non-linear mapping, which allows non-linear mappings to be learned. KDA can, simultaneously, maximize the between-class scatter and minimize the within-class scatter of the signal processing. Kernel discriminant analysis has been used in different applications, for examples: Palmprint recognition [22], Face recognition [10] and handwritten recognition [24].

2.2 Experimental section

The experiment was carried on many motors bearings as shown in the Figure 2. Those bearings are mounted in three phases 200 Kw. The reference of chosen bearing used for the experimental work is SKF NU 326 cylindrical roller bearing.

The designed rpm of motors is 1500 rpm and the operating conditions of the bearings are full load condition running at 1470 rpm. Vibration signals of four bearings are obtained by the piezoelectric accelerometers mounted on the bearing housing along horizontal and vertical axis with magnetic bases.

Figure 2: Experimental measurement

The accelerometers used are industrial ICP accelerometer model 603C01. They are connected to the computer via the NI CompactRIO- 9022 controller which contains a vibration module NI 9234.
The sampling rate is set to 25.6k and the duration is 40 seconds for each bearing. LABVIEW software (Real-time & FPGA) is used to obtain the acceleration spectrum data. The acceleration data for all bearings are obtained and are recorded by the equipment as shown in the Figure 3.

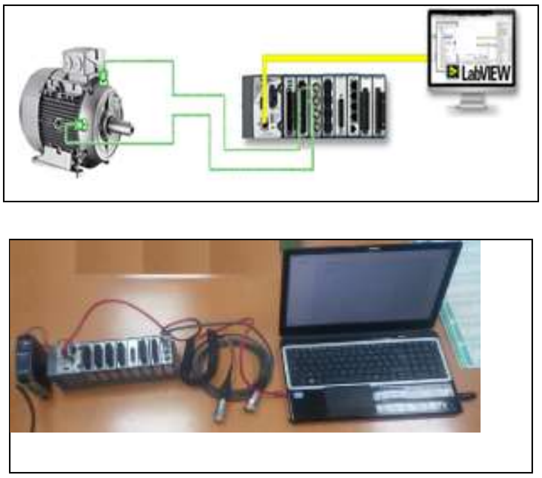

Figure 3: Data acquisition equipment

The obtained acceleration data is used to extract signal features for fault diagnosis and classification. We consider four different conditions of bearing: (a) normal healthy bearing, (b) bearing with lowest defect, (c) bearing with medium defect, (d) bearing with extreme defect.
All signals are filtered by using a 1KHz – 10KHz pass-band filter and the obtained results from horizontal axis data are exposed in Figure 4.

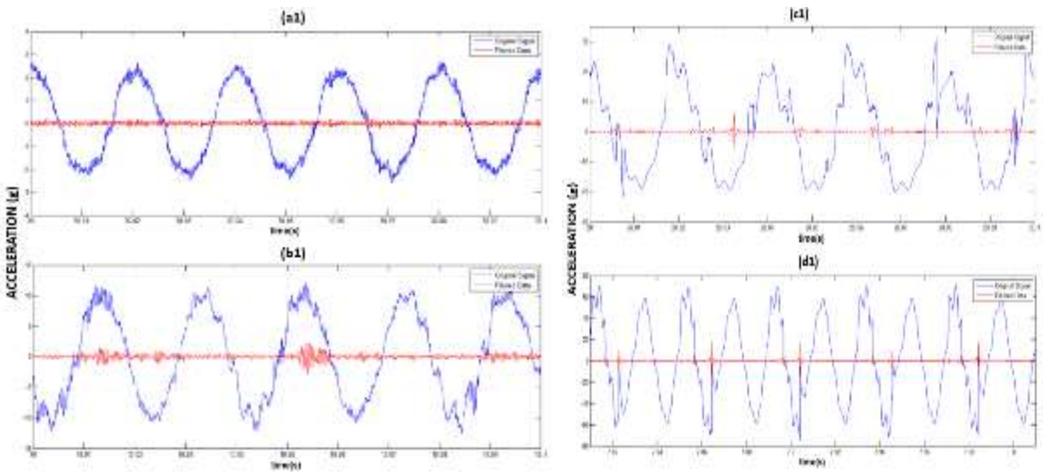

Figure 4: Filtered acceleration signals based horizontal axis data, (a) healthy bearing, (b) bearing with lowest defect, (c) bearing with medium defect, (d) bearing with extreme defect

To diagnose those bearings. We consider the evaluation of some temporal parameters like Crest factor/Kurtosis as shown in in Figure 5. We see the difference between the four bearings in values and in variation of the Crest factor and Kurtosis parameters in both axis. High value and huge variation are correlated with the defect level.

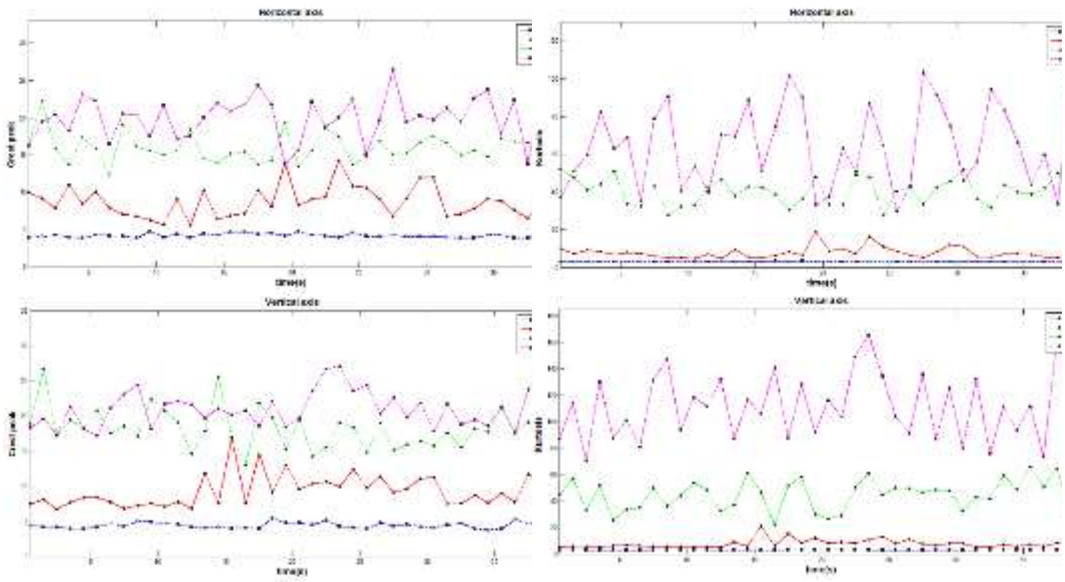

Figure 5: Crest factor/Kurtosis based horizontal and vertical axis data, (a) healthy bearing, (b) bearing with lowest defect, (c) bearing with medium defect, (d) bearing with extreme defect

To diagnose and to identify specified bearings faults, we use as exposed in Figure 6 and Figure 7, Hilbert spectrum based on horizontal/vertical bearing acceleration and correlated with SKF bearing frequency specifications.

Bearing acceleration and spectrum are normal for the first bearing condition (a1, a2) and indicate a healthy bearing. The second bearing condition (b1, b2) indicate a slight bearing cage defect, as appear in the rotational frequency of the rolling element and cage assembly 10.1 Hz.

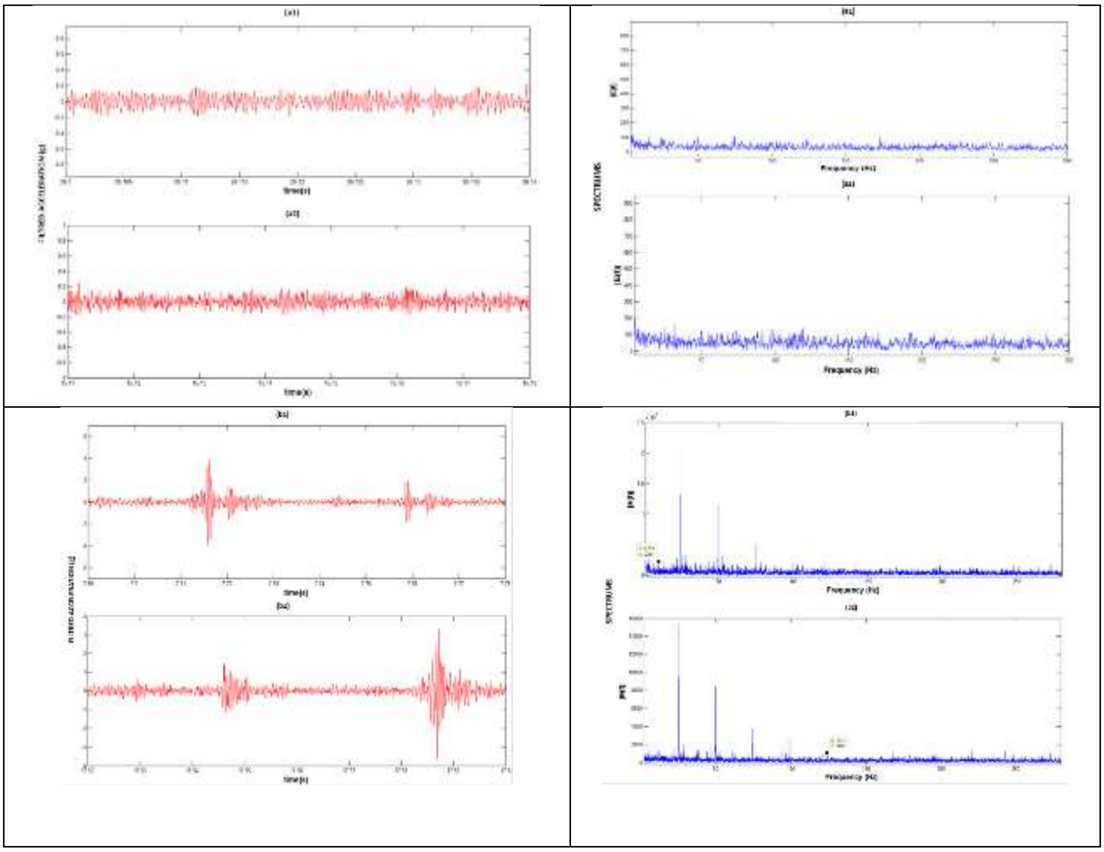

Figure 6: Raw Acceleration signals (left) and their corresponding Hilbert spectrums (right): (a) healthy bearing, (b) bearing with lowest defect. The subscript 1 and 2 represent the horizontal and vertical axis, respectively

Bearing acceleration and spectrum for the third bearing condition (c1, c2) is distinct by a medium ball fault as appear in the f_{rp} "over-rolling frequency of one point on a rolling element" 124.5 Hz.

The forth bearing condition (d1, d2) is characterized by a serious defect level with mixed faults: Ball defect in f_{rp} 124.5 Hz, cage defect in f_c 10.1 Hz and outer ring defect in the f_{rp} "over-rolling frequency of one point on the outer ring" 141.2 Hz.

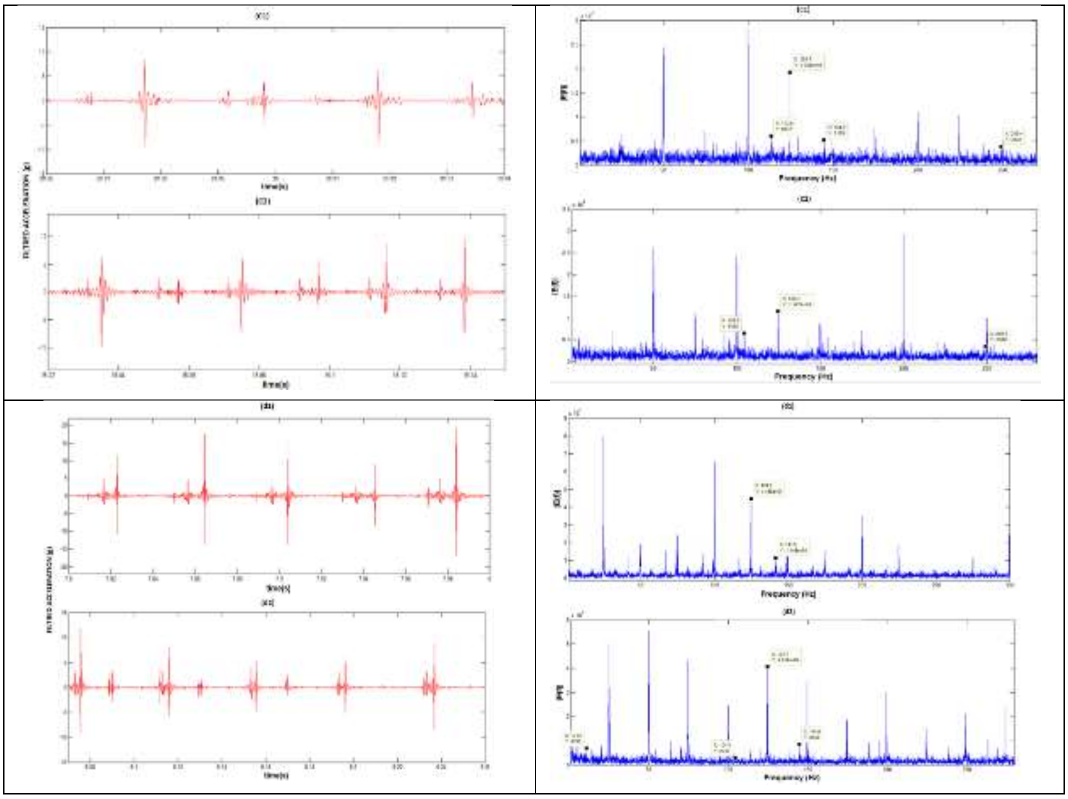

Figure 7: Raw Acceleration signals (left) and their corresponding Hilbert spectrums (right): (c) bearing with medium defect, (d) bearing with extreme defect. The subscript 1 and 2 represent the horizontal and vertical axis, respectively

3. Results and Discussions

To further show the effectiveness of the proposed method, a comparison between our proposed method Alpha stable based KDA, and Alpha stable based PCA, Alpha stable based LDA, PE, Alpha and stable based SVM that use the same real data from our experimental setup is detailed in tables 1, 2 and 3. Horizontal and vertical accelerometers measurement are organized as 40 sets of data in each direction each bearing. We use different amount of training windows: 10%, 20%, 30%, 40% and 50% windows of readings were taken for each bearings to calculate the frequency domain statistical features. The features calculated are used as input to different classification algorithms (PCA, LDA, PE, SVM and our proposed approach Alpha stable based KDA).

For the training purpose the input data is split into three parts. Out of the total inputs 10 to 50% is used for training, the rest is used for validation and testing. The classification is done using PE based entropy extraction and PCA, LDA, SVM, KDA based Alpha Stable extraction.

Table 1: Recognition accuracy of proposed approach* compared with other algorithms based horizontal data

Amount of training windows	10%	20%	30%	40%	50%
PCA (%)	75.23	76.25	77.50	76.25	76.00
LDA (%)	80.41	81.25	85.36	84.58	88.00
PE (%)	83.78	85.31	87.50	89.17	91.50
SVM (%)	85.97	86.65	88.04	89.87	92.07
KDA*(%)	**87.01**	**88.12**	**90.00**	**92.08**	**94.00**

Table 2: Recognition accuracy of proposed approach* compared with other algorithms based vertical data

Amount of training windows	10%	20%	30%	40%	50%
PCA (%)	77.22	81.25	81.79	85.83	88.50
LDA (%)	89.44	91.87	92.14	92.08	93.50
PE (%)	93.06	93.75	94.64	95.42	96.50
SVM (%)	93.26	93.91	94.86	95.57	96.71
KDA*(%)	**95.00**	**96.25**	**95.71**	**97.08**	**98.00**

Table 3: Recognition accuracy of proposed approach* compared with other algorithms with an Horizontal & Vertical data score fusion

Amount of training windows	10%	20%	30%	40%	50%
PCA (%)	82.41	83.55	84.80	85.55	89.30
LDA (%)	90.30	91.95	93.66	93.88	94.30
PE (%)	94.07	94.61	94.80	96.47	97.80
SVM (%)	94.43	94.07	95.98	96.58	97.93
KDA*(%)	**96.17**	**96.72**	**97.21**	**98.75**	**99.50**

It was seen that for Alpha stable based KDA the bearings classification was excellent (see Tables 1, 2, 3). From the above results, it was inferred that our proposed approach is more efficient classifier than the other algorithms.

4. Conclusions

In this paper we study four different bearings behaviors, one healthy and three with different defect levels were used. The vibration acceleration data for each bearing were obtained using horizontal and vertical accelerometers. It was seen that the percentage of correct classification was 99.5% for our proposed approach with an Alpha stable extraction based KDA classifier algorithm provides a significantly higher accuracy of classification than the others methods. It can serve as a promising alternative for diagnose and classify some rotating machines components like gearbox.

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