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Vibration Analysis Approach for Corrosion Pitting Detection Based on SVDD and PCA

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Abstract— **This study is focused on corrosion pitting on the raceways and ball in rolling bearings. We analyze 224 records in the time domain, and combine support vector data description (SVDD) with principal component analysis (PCA) algorithm to improve diagnostic accuracy. Experiment results show that the proposed method can achieve good accuracy based on an imbalanced dataset. The new method is thus well-suited for corrosion pitting detection in rolling bearings.**

***Keywords*—machine learning; rolling bearing; corrosion pitting; SVDD; PCA**

I. INTRODUCTION

By comparing vibrant signals of a rolling bearing running in normal and faulty conditions, local faults including cracks, corrosion pitting, spall on the rolling surfaces is possible based on the non-linear signals of rotor bearing system. Much effort has been devoted to detecting these faults. In the past few years, data mining (DM) techniques, such as discrete wavelet transform (DWT), artificial neural networks (ANN), intelligent algorithms, fuzzy sets, and support vector machines (SVM), have found application of fault diagnosis in machine condition monitoring field.

The model is developed to describe the vibration produced by a single point defect on the inner race of a rolling element bearing under constant radial load. McFadden proposed a effective model describing the vibration used by a single point defect on the inner race of a rolling element bearing, based on bearing geometry, shaft speed, bearing load distribution, transfer function and the exponential decay of vibration in 1984 [1]. Then, the model is extended to describe the vibration produced by multiple-point [2]. There are several methods to detect bearing local defects as given in an excellent review [3].

The characteristic frequencies present corresponding to the bearing local defects using Fast Fourier Transform (FFT) [4]. Signal processing techniques such as a processing technique based on averaging technique, adaptive noise canceling and high frequency resonance technique (HFRT) have been developed to overcome the noise problem for detection local defects of rolling bearings. Prabhakar proposed DWT model that the correctly diagnosed single and multiple ball bearing race faults [5]. Li presented the method that combined HMM with FFT to diagnose the faults based on dynamic time series of peed-up and speed-down process for rotating machinery [6]. In addition, the accuracy is dependent on the two parameters, namely the learning rate coefficient and the momentum has been found, in addition to the input and hidden layer architecture. Two new approaches based on wavelet transform, artificial neural network and

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fuzzy rules are proposed for detecting local defects in rolling element bearings [7]. SVM is a general machine-learning tool based on the structural risk minimization (SRM). Yuan proposed a hybrid method based on combining SVM with Artificial immunization algorithm (AIA) to diagnose defects of turbo pump rotor [8]. Fault diagnosis based on SVM has given in an excellent review [9, 10].

This study presents a dimensionality reduction and classification method for corrosion pitting on the raceways and ball in rolling bearings. Vibration data are collected as the time domain signal for the normal bearing and bearing with corrosion pitting. A dimensionality reduction technique is first applied to refine the vibration dataset. Then, a method employs a one-classification algorithm to distinguish between healthy and local defect with corrosion pitting based on a vibration dataset.

This paper is organised as follows. Section 2 describes our dataset, the dimensionality reduction method, and the diagnostic method. Section 3 describes the two steps in diagnostics: dimensionality reduction using PCA and actual diagnosis. Section 4 summarises our conclusions.

II. MATERIALS AND METHODS

A. Vibration analysis

Features are extracted from the time domain signal by statistical method. It comprises of 224 records containing 13 features: Mean, Standard deviation, Variance, Skewness, Kurtosis, Peak value, Peak-peak value, Square amplitude, Average amplitude, Waveform index, Peak index, Pulse index, Margin index, and Label (Table 1). There are 203 healthy samples and 21 fault samples with corrosion pitting.

TABLE I. FEATURE ITEMS OF VIBRANT SIGNAL IN TIME DOMAIN

Feature	**Description**
Mean	-
Std	Standard deviation
Var	Variance
Skewness	-
Kurtosis	-
Peak	Peak value
PP	Peak-peak value
SA	Square amplitude
AA	Average amplitude
WI	Waveform index
PI	Peak index
PUI	Pulse index
MI	Margin index
Label	Normal: 1 corrosion pitting:-1

B. Principal component analysis (PCA)

PCA is basically a statistical technique used in dimensionality reduction that seeks projection in the directions of maximum variability [11]. It is a linear coordinate transformation that rotates a coordinate system in a particular way that does not suffice to extract all of the important signals.

C. Support vector data description (SVDD)

SVDD [12,13] is inspired by the global optimization problem and Support Vector Machines which was put forward at the 5th annual ACM Workshop on Computation Learning Theory (COLT) for the first time. SVDD is a method for one-class classification to obtain an accurate estimate of a set of observations [14]. Generally, the data description problem differs from two classification problems including two-class or multi-class classification. SVDD is interested in a single type in that a normal data set is used to separate this set from a few abnormal data (also called outlier points), and is a popular kernel method for outlier detection, which tries to fit one-class data with a super-sphere.

To begin, we assume vectors x are column vectors and have a data set

$$\{x_i\} \subseteq \chi, \chi \subseteq \Re^d \quad (1)$$

where i =1, ... , n. N is the number of the vector , d is the dimension of the vector. The data set is mapped to a high dimensional feature space, where we try to search for the minimal enclosing hyper-sphere, by means of a Gaussian kernel function. Soft constraints are described by

$$\left\|\Phi(x_j) - a\right\|^2 \le R^2 + \xi_j \quad \forall j, \xi_j \ge 0, \quad (2)$$

where $\|\cdot\|$ is the Euclidean norm, a is the center of the hyper-sphere, R is the radius, and ξ is a slack variables.

The minimum hyper-sphere can be formulated into

$$R^2 + C\sum_j \xi_j, \tag{3}$$

where C is a penalty constant. To solve this optimization problem we introduce the Lagrange multipliers, set to zero the derivative of Lagrangian with respect to R, a and ξ, and transform into the Wolfe dual form with respect to the Lagrange multipliers α_j:

$$W = \sum_j \Phi(x_j)^2\alpha_j - \sum_{i,j}\alpha_i\alpha_j\Phi(x_i)\cdot\Phi(x_j)$$
$$with \quad 0 \le \alpha_j \le C, \sum_j \alpha_j = 1, a = \sum_j \alpha_j\Phi(x_j) \tag{4}$$

Then, we represent the dot products by a position definite kernel, or Mercer kernel $K(x_i, x_j)$. In this paper we use the Gaussian kernel:

$$\Phi(x_i)\cdot\Phi(x_j) = K(x_i, x_j) = e^{-q\|x_i - x_j\|^2}, \tag{5}$$

with width parameter q. Now the Wolfe dual form is written as:

$$W = \sum_j K(x_j, x_j)\alpha_j - \sum_{i,j}\alpha_i\alpha_j K(x_i, x_j) \tag{6}$$

In view of (2), (4) we have:

$$R^2(x) = K(x,x) - 2\sum_j K(x_j, x)\alpha_j + \sum_{i,j}\alpha_i\alpha_j K(x_i, x_j) \tag{7}$$

In the view of (7) when the radius R (x_i) is equal to R, x_i is support vector. Therefore, support vectors (SVs) lie on the sphere ($0< \alpha_j <C$), bounded support vectors (BSVs) are outside the sphere ($\alpha_j=C$), and other points are inside the sphere ($\alpha_j=0$).

D. Corrosion pitting detection method

The basic procedure of the proposed method is shown in Fig. 1.

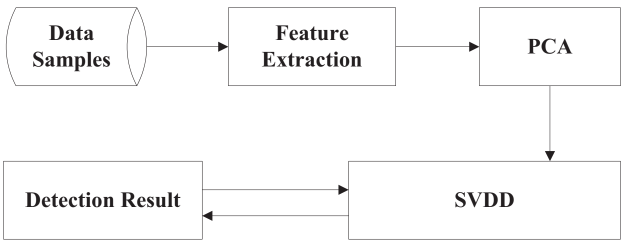


Fig. 1. Flowchart of the method procedure

There are three steps:

(1) Feature extraction utilizes some statistical method to generate useful features from the original vibrant signals. In this paper, we use input sets with 13 features in Table Ⅰ.

(2) We choose a dimensionality reduction method with PCA in this paper.

(3) We employ the SVDD algorithm for corrosion pitting damage detection.

III. RESULT AND DISCUSSION

The experimental data set includes 224 samples with 13 features. In this study, PCA is developed Version 4.0 in MATLAB. The cumulative contribution rate of all principle components are shown in Table Ⅱ.

TABLE II. CONTRIBUTION RATE OF PRINCIPLE COMPONENTS

Principle components	Contribution	Cumulative contribution
1	0.621	0.621
2	0.109	0.73
3	0.073	0.803
4	0.055	0.858
5	0.046	0.904
6	0.047	0.951
7	0.021	0.972
8	0.009	0.981
9	0.01	0.991
10	0.004	0.995
11	0.003	0.998
12	0.001	0.999
13	0.001	1

From Table Ⅱ, the first six principal components were selected based on containment of 95.1% of the total variability. The partial data for vibrant signals using PCA are shown in Table Ⅲ.

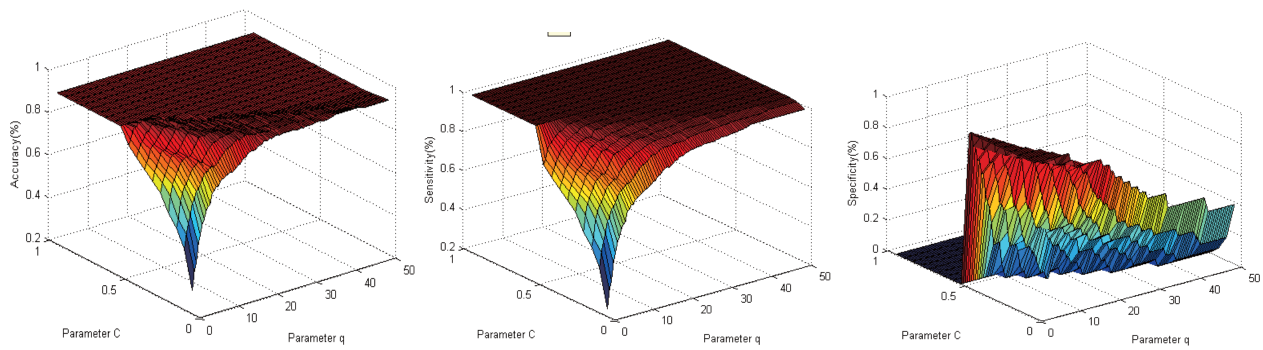
The width of Gaussian kernel function and the penalty constant need to be optimised in SVDD. There is no systematic methodology for the optimisation of the two parameters [14].

By means of our empirical results, we use the constraints $0.125<q<50$ and $0<C<1$. In the iteration process, 100 homogeneous points was selected in the constraint domain of the width of Gaussian kernel function, and 20 points of the penalty constant. And in step of iteration, the first five sum value of accuracy, sensitivity and specificity was shown in Table Ⅳ, and Fig. 2 shows the diagnostic results from the SVDD model. As shown in Fig. 2, our method gives effective results. From

Table 4, we find maximises the sum value (sum=2.7643) when q=3.4848 and C=0.2631.

TABLE III. PART OF THE 6-D DATA SET USING PCA

ID	P1	P2	P3	P4	P5	P6	Label
1	-0.15305	0.433098	0.317692	0.060431	0.089407	0.09854	1
2	1.789488	-1.10677	0.502186	-0.6107	0.45429	-0.17943	1
3	-0.25483	-0.02178	0.158976	0.061178	0.03267	0.127365	1
4	1.994177	0.304993	-0.62112	-0.23202	-1.11194	-0.08021	1
5	-0.12846	0.206226	0.252837	0.100375	0.310396	0.009204	1
......							
220	2.351393	-1.07385	-0.46091	0.117521	-0.73665	-0.22418	-1
221	2.569474	-0.25612	-0.1007	-0.12758	-0.9986	-0.28898	-1
222	1.367059	0.829412	0.457739	-1.02471	-0.72377	0.35493	-1
223	0.892897	-0.09581	0.269373	0.210348	-0.11851	-0.18574	-1
224	2.218714	0.646739	0.285279	0.756803	-0.81038	-0.60158	-1



(a) (b) (c)

Fig. 2. Accuracy, sensitivity, and specificity as functions of the parameters in SVDD: (a) Accuracy of SVDD models with different values of parameter q and C. (b) Sensitivity of SVDD models with different values of parameter q and C. (c) Specificity of SVDD models with different values of parameter q and C.

TABLE IV. FIRST FIVE SUM FOR ACCURACY, SENSITIVITY AND SPECIFICITY

q	C	Accuracy	Sensitivity	Specificity	Sum
3.4848	0.2631	0.9285	0.9311	0.9047	2.7643
5.2335	0.3157	0.9241	0.9261	0.9047	2.7549
8.7245	0.3684	0.9062	0.9064	0.9047	2.7173
17.3628	0.4211	0.8794	0.8768	0.9047	2.6609
17.3628	0.4736	0.9107	0.9211	0.8095	2.6413

We also conducted experiments for the same data set using SVDD, ANN, and SVM. Table Ⅴ lists the results for these four classification methods. A ten-fold cross-validation technique was used for SVM. The ANN architecture is composed of 30 neurons in hidden layer. Accuracy may always be the most significant performance criterion in the pattern recognition literature [1-5, 15].

TABLE V. COMPARISON OF THE METHODS FOR THE SAME DATA SET

Method	Accuracy	Sensitivity	Specificity
PCA+SVDD	92.85%	93.11%	90.47%
SVDD	86.2%	87.45%	85.85%
ANN	73.43%	71%	76.34%
SVM	80.62%	70%	85.43%

As shown in TableⅤ, SVDD with PCA can increase the accuracy to 92.85%, sensitivity to 93.11%, and specificity to 90.47%. The proposed method does significantly improve the accuracy compared with plain SVDD without PCA, it does also outperform the later in terms of the sensitivity and specificity. The SVDD is dominant on imbalanced datasets in this paper because the ANN and SVM are clearly inferior to the first two methods from Table 5.

IV. CONCLUSION

In this study, we introduce a dimensionality reduction and one-class method for an imbalanced dataset obtained from vibrant signals in time domain. The dataset include 203 healthy samples and 21 fault samples with corrosion pitting on the raceways and ball in rolling bearings. This method is remarkably effective in separating normal and abnormal types. Our results confirm that the proposed method shows its superior performance for diagnosing corrosion pitting fault in contrast to conventional two class methods, yields excellent accuracy, sensitivity and specificity, and should be thus well-suited for corrosion pitting detection on the raceways and ball in rolling bearings.

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