887. Fault diagnosis of antifriction bearings through sound signals using support vector machine

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Abstract. Bearings constitute a crucial part of machinery that need to be continuously monitored. Major breakdowns can be prevented if bearing defects are identified at the earlier stage. Sound signals of the bearings can be used to continuously monitor bearing life. This paper uses sound signals acquired in bearings under healthy and simulated faulty conditions for the purpose of fault diagnosis through machine learning approach. The statistical features were extracted from the sound signals. Significantly important features were selected using J48 decision tree algorithm. Support Vector Machine (SVM) is used as a classifier. The selected features were given as inputs for the c-SVM and ν-SVM (nu – SVM) model of SVM and their classification accuracies were compared.

Keywords: bearing fault diagnosis, decision tree algorithm, feature selection, machine learning approach, Support Vector Machine.

1. Introduction

Antifriction bearings are one of the common rotating machine element used in almost all industries. There are many failure mechanisms that may trigger bearing damage including mechanical damage, crack damage, wear damage, lubricant deficiency, corrosion and plastic deformation. Whenever any bearing defect occurs, it leads to machinery shutdown to avoid catastrophic damages and thereby incurs substantial time and economical losses. Vibration signals monitoring and analysis is one of the main technologies used to predict defects in antifriction bearings [1]. Smalley et al [2] investigated an air crash and reported the crash was caused by bearing failure resulting from damage to the bearing balls. Mohamadi et al [3] employed time domain analysis, vibration spectrum analysis to identify different defects in bearings. Heng et al [4] investigated the application of sound pressure and vibration signals to detect defects in rolling element bearings using statistical parameter estimation method. The well-established statistical parameters such as crest factor and the distribution of moments including kurtosis and skewness, as well as other parameters obtained from beta distribution functions were utilized in this study. Results revealed that kurtosis and crest factor from both sound and vibration signals provide better diagnostic information than the beta function parameters. Ramroop et al [5] carried a comparative study of conventional vibration and acoustic monitoring techniques to diagnose defects in industrial multistage gearbox, operating under healthy and faulty conditions. This study concluded with a series of empirically derived best practice guidelines for implementation of acoustic condition monitoring and to assist researchers in subsequent interpretation of gearbox sound acoustics. Diagnosis of ball bearings using Artificial Neural networks was done by Subrahmanyam et al [6]. Feed forward neural network was used by Liu et al [7] for the recognition of different states of roller bearings by feeding various parameters obtained by processing vibration acceleration signals as inputs to the neural network which decides the bearing condition. Chiou et al [8] used vibration signatures in the ultrasonic frequency range (beyond 100 kHz) to train a neural network in order to identify the condition of needle bearings. Bearing faults using FFT method was investigated by Zhenyu et al [9] based on vibration and current measurements. The vibration-based fault diagnosis of a rotor bearing system using artificial neural network and support vector machine was studied by Pavan et al [10] including experimental comparison of the effectiveness of ANNs and SVM approaches. Saravanan et al [11] extracted vibration signals from rotating parts of machineries to assess the condition of operating machine and studied the effectiveness of wavelet-based features for fault diagnosis of a gear box using ANN and proximal support vector machines (PSVM). Saravanan et al [12] have shown the effectiveness of wavelet-based features for fault diagnosis using SVM and PSVM. Many researchers reported usage of vibrations signals in condition monitoring of bearings. But only several papers discussed exploitation of sound signals for the fault diagnosis of bearings. In this paper, a novel attempt is made with the utilization of sound signals for the purpose of fault detection of bearings by using SVM. By comparing the signals of a bearing running in normal and faulty conditions, the detection of faults becomes possible. The faults considered in the present study are inner race fault and outer race fault. Descriptive statistical features like mean, median, kurtosis etc. were used. The effect of a number of features was studied and subsequently important features were selected using J48 decision tree algorithm. With the selected statistical features, classification was carried out using Support Vector Machine and the results with discussions are presented.

2. Experimental setup and procedure

Fig. 1 illustrates block diagram of the experimental setup. Experiments were carried out on four sets of bearings (SKF R7 NB 62) of motor pump. The motor is operated at a normal speed of 1200 rpm. Rolling bearing element generally consists of two rings, which are called the outer race way and the inner race way with a set of rolling elements rotating in the tracks. New healthy bearing is fixed on the test rig and dimensions of the new bearing is given in Table 1. The three test conditions investigated are (1) healthy bearings (2) inner race fault and (3) outer race fault. The bearing faults are simulated using Electric Discharge Machining (EDM) to introduce ‘pits’ in the inner and outer races of bearings. The diameter and depth of the cylindrical pit is approximately 0.7 mm.

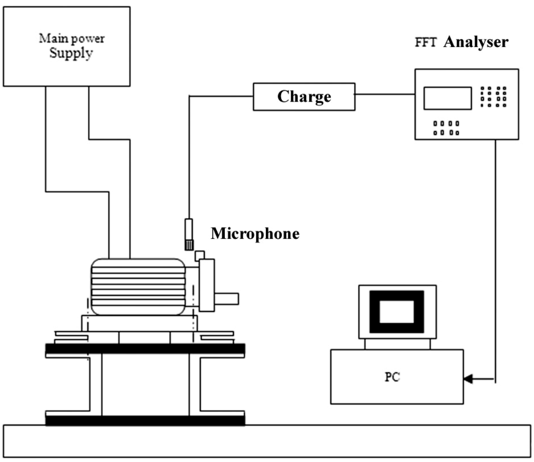

Fig. 1. Experimental setup

Bearing sound signals were acquired by mounting microphone and data acquisition. The healthy bearing is replaced by defective bearing and the signals are recorded for all the cases separately, under the same operating conditions.

Table 1. Dimensions of the bearing

Average diameter (mm)	14 mm
Ball diameter (mm)	4 mm
Number of rolling elements	7
Contact angle	0
Inner ring speed	0 rpm
Outer ring speed	1200 rpm
Healthy condition	33.3 Hz
Frequency of Inner race fault	149 Hz
Frequency of Outer race fault	84 Hz

3. Feature selection using decision tree

From the sound signals, descriptive statistical parameters such as mean, median, mode, kurtosis, skewness, standard error, standard deviation, minimum, maximum, sum, and range are computed to serve as features. They are named as 'statistical features' here. A decision tree consists of a number of branches, one root, a number of nodes and a number of leaves. One branch is a chain of nodes from root to a leaf and each node involves on attribute. The occurrence of an attribute in a tree provides the information about the importance of the associated attribute (Peng et al [13]). The formation of Decision Tree and feature selection is based on the procedures discussed by Hemantha et al [14].

4. Support vector machine

Support Vector Machine (SVM) is used as the classifier. It has emerged as a pattern classifier that can learn even from a small training data set for each class. The main idea of an SVM is to construct a hyper-plane as a decision surface in such a way that the separation between positive and negative examples (margin) is maximized. Fig. 2 shows the classification of a series of points for two different classes of data, class A+ (asterisk) and class A– (circles).

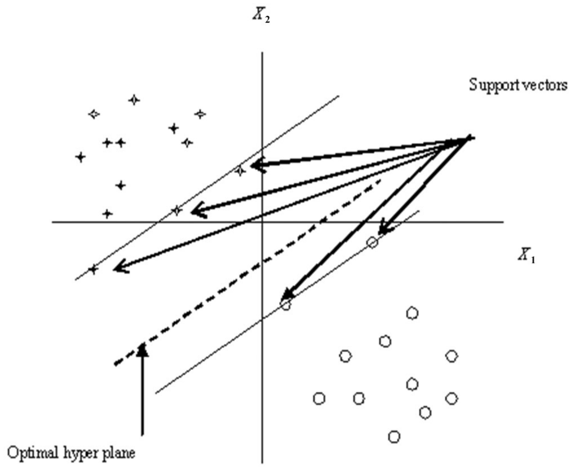

Fig. 2. Illustration of the idea of support vectors and optimal hyper plane

The notion that is central to the construction of the support vector learning algorithm is obtaining the inner-product kernel between the two separate support vectors (X_1 and X_2) drawn from the input space. Support vectors constitute a small subset of the training data extracted from the support learning algorithm. The separation between the hyper-plane and the closest data point is called the margin of separation. The goal of a support vector machine is to find a particular hyper-plane, which maximizes the margin of separation and also good classification efficiency. Under this condition the decision surface is referred to as optimal hyper-plane. C support vector and ν support vector classification has been done based on the procedures followed by Saimurugan et al [15].

5. Results and discussions

The sound signals were recorded for normal and faulty conditions of bearing. The faulty conditions considered in the present study are:

1. Inner race fault (IRF),
2. Outer race fault (ORF).

Totally 90 samples were collected; out of which 30 samples were from normal healthy condition. For inner race fault and outer race fault, 30 samples from each condition were collected. The statistical features explained in section 2 were treated as features and act as input to the algorithm. The corresponding status or condition (Healthy, IRF, and ORF) of the classified data will be the required output of the algorithm. This input and corresponding output together forms the dataset. The dataset is used with decision tree J48 algorithm for generating the decision tree for the purpose of feature selection and classification. The generated decision tree is shown in Fig. 3. The rectangles represent classes (condition of the bearing). In rectangle the information about the condition is given using abbreviations e. g. 'ORF'. Then within parenthesis, there are two numbers separated by a slash or one number. The first number (in case of two numbers) or the only number represents the number of data points that support the decision. Meaning, if one follows the rule (as described above 'if-then' rules) how many data points will be correctly classified is given as the first number. The second number (after slash) is optional and it represents the number of data points that is against the rule followed. Meaning, if one follows a rule, how many data points will be incorrectly classified is given as second number.

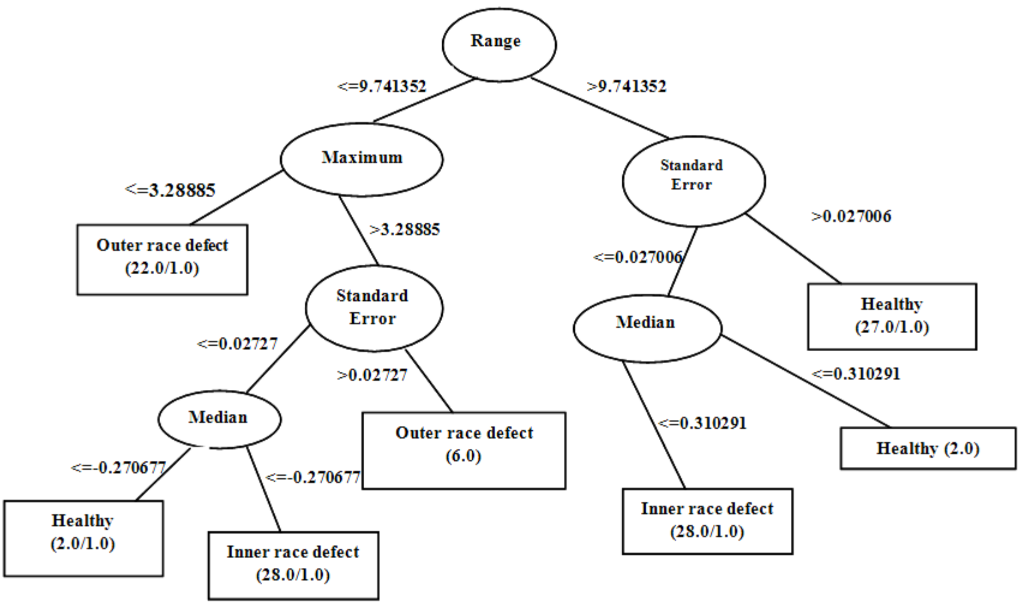

Fig. 3. Decision tree

5. 1 Feature extraction and selection

Twelve descriptive statistical features were extracted from the sound signals. Significant features are extracted using decision tree. Researchers have to extract all descriptive statistical features and then select the good ones. Here, decision tree was used for feature selection (Sugumaran et al [20]). The Decision tree algorithm (J48 algorithm) has been applied to the problem under discussion. In decision tree (Fig. 3), the feature that occurs first will be the root node and the same will be the best feature for classification. The other features in the tree are in the order of importance. In decision tree, only four features are present namely Range, Maximum, Standard Error and median in the order of importance. Table 2 shows the classification efficiency using c-SVM and ν-SVM with linear, Radial Basis Function (RBF) and Sigmoid kernel functions.

Table 2. SVM Performance

Kernel Function	c-SVM	ν-SVM
Linear	87.78 %	87.78 %
Radial Basis Function (RBF)	92.22 %	90 %
Sigmoid	86.67 %	86.67 %

Both c-SVM and ν-SVM models yielded approximately 88 % classification accuracy with linear kernel. With Radial Basis Function (RBF) as kernel function, c-SVM produced a classification accuracy of 92 % while the ν-SVM results in 90 % accuracy. Sigmoid kernel function results in an overall accuracy of 87 % with c-SVM and ν-SVM. Sample test result for ν-SVM with Radial Basis Function (RBF) is presented in the form of confusion matrix in Table 3.

Table 3. Confusion matrix

a	b	c	
27	1	2	a - Healthy
2	28	0	b - Inner Race fault
4	0	26	c - Outer Race fault

The diagonal elements in the confusion matrix show the number of correctly classified instances. For example in the first row, 27 instances are correctly classified as ‘Healthy’ while 1 instance is wrongly classified as ‘Inner Race fault’ and 2 instances as ‘Outer Race fault’. Thus the maximum accuracy is around 92 % for Radial basis function (RBF) c-SVM for the fault diagnosis of the bearing with sound signals.

6. Conclusion

Defect detection is one of the most crucial processes for the machine maintenance. Many researchers reported on fault diagnosis of bearings by using vibrations signals through various algorithms like J48, naive Bayes, etc. But here, the significant features were selected based on the decision tree from J48 algorithm and the selected features were classified by Support Vector Machine (c-SVM and ν-SVM). Based on the results obtained, one can conclude that radial basis function c-SVM classifier is a good candidate for the defect detection of bearing using sound signals.

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