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FAULT DETECTION WITH MACHINE LEARNING OF VIBRATION SIGNALS

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ABSTRACT

Ball bearings faults are one of the main causes of breakdown of rotating machines. Thus, detection and diagnosis of mechanical faults in ball bearings is very crucial for the reliable operation. This study is focused on fault diagnosis of ball bearings using artificial neural network (ANN) and support vector machine (SVM). A test rig of high speed rotor supported on rolling bearings is used. The vibration response are obtained and analyzed for the various defects of ball bearings. The specific defects are considered as crack in outer race, inner race with rough surface and corrosion pitting in balls. Statistical methods are used to extract features and to reduce the dimensionality of original vibration features. A comparative experimental study of the effectiveness of ANN and SVM is carried out. The results show that the machine learning algorithms mentioned above can be used for automated diagnosis of bearing faults. It is also observed that the severe (chaotic) vibrations occur under bearings with rough inner race surface and ball with corrosion pitting

INTRODUCTION

Condition monitoring of rotating machinery helps in early detection of faults and anticipation of problems in time, so as to prevent complete failure. Bearing vibration can generate noise and degrade the quality of a product line. Severe vibrations of bearings can even cause the entire system to function incorrectly and that results in downtime for the system and economic loss to the customer. Rolling bearings defects may be categorized as point or local defects and distributed defects. The vibrations are generated by geometrical imperfections on the individual bearing components and these imperfections are caused by irregularities during the manufacturing process as well as wear and tear. The various distributed defects are surface roughness, waviness, misaligned races, and off-size rolling elements. The local defects include cracks, corrosion pitting, brinnelling and spalls on the rolling surfaces. McFadden and Smith (1985, 1984) have developed the models for vibration produced by a single and multiple point defects on the inner race of the rolling element bearing under radial load based on high-frequency resonance technique.

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Prabhakar, Mohanty, and Sekhar (2002) have considered single and multiple point defects on inner race, outer race and the combination faults and used discrete wavelet transform (DWT) to detect these faults on bearings. Kankar, Harsha, Pradeep, and Sharma Satish (2009) have applied response surface methodology (RSM), to investigate the effects of various defects on the non-linear vibrations of rotor bearing system. Various artificial intelligent (AI) techniques such as hidden Markov models (HMM) (Li, Wu, He, & Fulei, 2005), artificial neural networks (ANN) (Vyas & Satishkumar, 2001) and support vector machines (SVM) (Widodo & Yang, 2007; Yuan & Chu, 2007) have been used in the fault diagnosis of machines. Zhitong, Jiazhong, Hongpingn, Guoguang, and Ritchie (2003) have carried out fault detection of induction motor using SVM technique for detecting broken rotor bars. In their experiment, induction motor was experimented with no fault, one broken bar, two broken bars and three broken bars. They used stator current to obtain the signal and calculated the frequency spectrum for fault detection. Samanta (2004) has compared the performance of gear fault detection using ANN and SVM. The time-domain vibration signal of a rotating machine with normal and defective gears were processed for feature extraction. The results compare the effectiveness of both types of classifiers without and with GA-based selection of features and the classifier parameters. The main difference between ANNs and SVMs is in the principle of risk minimization (RM) (Gunn, 1998). In case of SVMs, structural risk minimization (SRM) principle is used for minimizing an upper bound on the expected risk whereas in ANNs, traditional empirical risk minimization (ERM) is used for minimizing the error on the training data. This paper is mainly focused on bearing fault classification using two machine learning methods ANN and SVM as both can work with non-linear classifications. Vibration data are collected by piezoelectric accelerometers as a time domain signals for the healthy bearing and bearing with different faults. Defects are considered as crack in outer race, inner race with rough surface and corrosion pitting in balls. The signals obtained are processed for machine condition diagnosis as shown in the flow chart Fig. 1. Features are extracted from the time domain signal by statistical method. These features are fed to a supervised attribute filter that can be used to select features. Selected features with the known output are used for training and testing of ANN and SVM

SUPPORT VECTOR MACHINE

Support vector machine (SVM) is a

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supervised machine learning method based on the statistical learning theory. It is a useful method for classification and regression in small-sample cases such as fault diagnosis. Pattern recognition and classification using SVM is described in brief (Cristianini & Shawe-Taylor, 2000). A simple case of two classes is considered, which can be separated by a linear classifier. Fig. 2 shows triangles and squares stand for these two classes of sample points. Hyper plane H is one of the separation planes that separate two classes. H1 and H2 (shown by dashed lines) are the planes those are parallel to H and pass through the sample points closest to H in these two classes. Margin is the distance between H1 and H2. The SVM tries to place a linear boundary between the two different classes H1 and H2, and orientate it in such a way that the margin is maximized, which results in least generalization error. The nearest data points that used to define the margin are called support vectors.

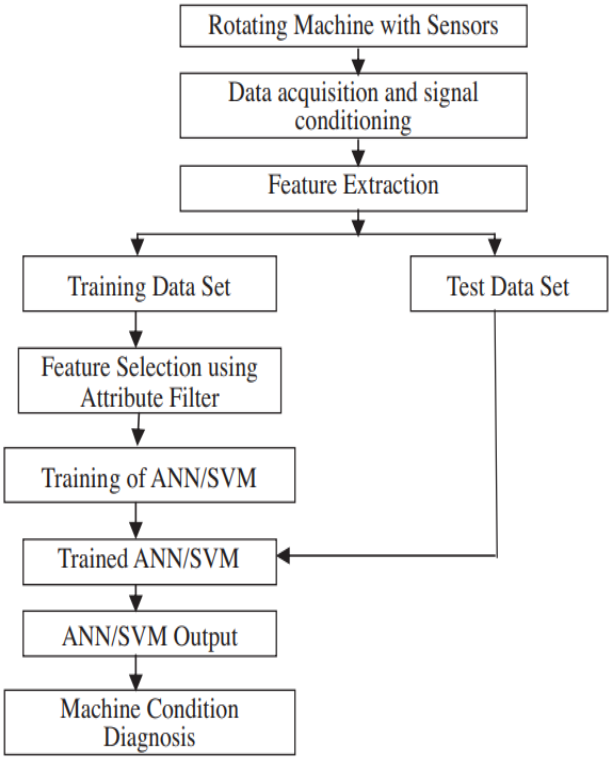

Fig: Flow chart of bearing health diagnosis

ARTIFICIAL NEURAL NETWORK

Artificial neural network (ANN) is an interconnected group of artificial neurons. These neurons use a mathematical or computational model for information processing. ANN is an adaptive system that changes its structure based on information that flows through the network (Zurada, 1999). A single neuron consists of synapses, adder and activation function. Bias is an external parameter of neural network. Model of a neuron shown in Fig. 3 can be represented by following mathematical model

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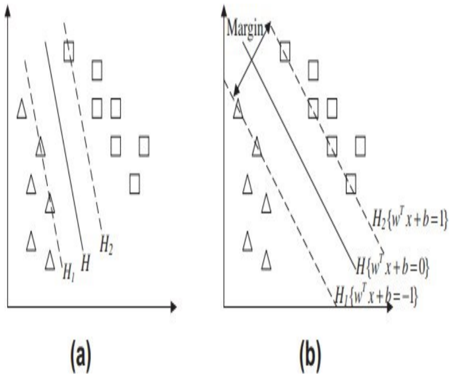

Fig: Hyperplane classifying two classes: (a) small margin and (b) large margin.

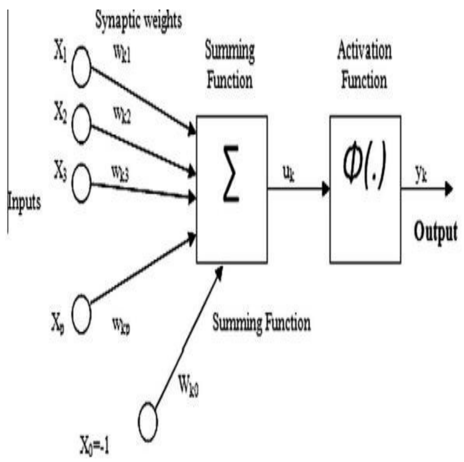

Fig: Model of a single non-linear neuron.

$$y_k = \phi\left(\sum_{i=1}^{p} w_{ki}x_i + w_{k0}\right)$$

Input vector comprising of 'p' inputs multiplied by their respective synaptic weights, and sum off all weighted inputs. A threshold (bias) is used with constant input. Activation function converts output into a limited range output

CONCLUSIONS This study presents a procedure for detection of bearing fault by classifying them using two machine learning methods, namely, ANNs and SVMs. Features are extracted from time-domain vibration signals using statistical techniques. Procedure incorporates most appropriate features selection by a filtering algorithm, which uses a density-based cluster to generate cluster membership values. The roles of different vibration signals, obtained with or without loader and at various speeds, are investigated. The time responses observed for different fault condition of bearing shows that severe (chaotic) vibrations occur under bearings with rough inner race surface and ball with corrosion pitting. The effect of combined defect has also significant on vibration of a rotor bearing system. It is also observed that the classification accuracy for SVM is better than of ANN. Both the machine learning methods give less accuracy to correctly predict the bearing condition with combined bearing component fault, though results obtained from SVM are slightly better, it may be because of small training data are taken for this study assuming that in practical situation less historical data is available. The results show the potential application of machine learning algorithm for developing a knowledge base system which can be useful for early diagnosis of defect for applying condition based maintenance to prevent catastrophic failure and reduce operating cost.

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