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Fault diagnosis of roller bearing using fuzzy classifier and histogram features with focus on automatic rule learning

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ABSTRACT

Roller bearing is one of the most widely used elements in rotary machines. Condition monitoring of such elements is conceived as pattern recognition problem. Pattern recognition has three main phases: feature extraction, feature selection and feature classification. Histogram features can be used for fault diagnosis of roller bearing. This paper presents the use of decision tree for selecting best few histogram features (bin ranges) that will discriminate the fault conditions of the bearing from given train samples. These features are extracted from vibration signals. A rule set is formed from the extracted features and fed to a fuzzy classifier. The rule set necessary for building the fuzzy classifier is obtained largely by intuition and domain knowledge. This paper also presents the usage of decision tree to generate the rules automatically from the feature set. The vibration signal from a piezoelectric transducer is captured for the following conditions – good bearing, bearing with inner race fault, bearing with outer race fault, and inner and outer race fault. The histogram features were extracted and good features that discriminate the different fault conditions of the bearing were selected using decision tree. The rule set for fuzzy classifier is obtained by once using the decision tree again. A fuzzy classifier is built and tested with representative data. The results are found to be encouraging.

1. Introduction

Machine condition monitoring system can be seen as a decision support tool, which is capable of identifying the failure of a machine and which also predicts failure from its symptoms (Wang, 1989). In most machinery, bearing is one of the essential components; it directly influences the operation of the whole machinery. Faulty bearings cause the majority of the problems in the rotary machinery (Winder & Littmann, 1976). Localized defect is the main failure mode of rolling element bearings. Localized defect is dislodging of a sizable piece of contact surface during operation as a result of fatigue cracking under cyclic contact stress in the bearing metal (James Li & Wu, 1989). Vibration and Acoustic Emission (AE) signals are widely used in condition monitoring of rotating machines. The fault detection is possible by comparing the signals of a machine running in normal and faulty conditions. The faults considered in the present study are inner race fault, outer race fault and inner and outer race fault.

Artificial Neural Network (ANN), Support Vector Machine (SVM) and fuzzy classifier are widely used as classification tool and reported in literature (Burgess, 1998; Jack & Nandi, 2000a; Nandi, 2000; Samanta & Al-Baulshi, 2003; Samanta, Al-Baulshi, & Al-Araimi, 2003; Shi, Xu, & Xu, 1988). Among them, ANN has limitations on generalization of the results in models that can over fit the data (Samanta et al., 2003). SVM has high classification accuracy and good generalization capabilities for crisp data (Burgess, 1998; Jack & Nandi, 2000a; Shi et al., 1988). In the problem at hand, the nature of the fault itself is fuzzy in nature. Fuzzy classifier models the physical problem under study more closely. Moreover, the computation time involved in fuzzy classifier is less compared to ANN and SVM. Hence, fuzzy classifier is used for classification. The flow chart of the fault diagnostic system is shown in Fig. 1.

2. Experimental studies

Referring to Fig. 1, the fault simulator with sensor and data acquisition is discussed in the following topics under experimental setup and experimental procedure respectively.

2.1. Experimental setup

A variable speed DC motor (0.5 hp) with speed up to 3000 rpm is the basic drive. A short shaft of 30 mm diameter is attached to the shaft of the motor through a flexible coupling; this is to

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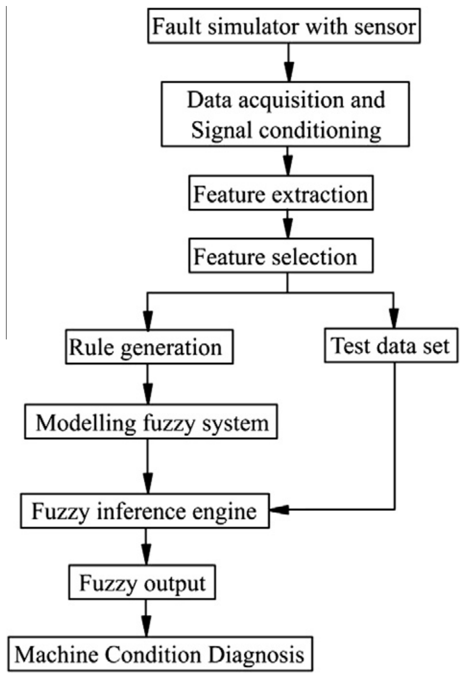

Fig. 1. Flowchart of fault diagnosis system.

minimize effects of misalignment and transmission of vibration from the motor. The shaft is supported at its ends by two roller bearings. The one that is closer to the motor is a brand new bearing (assumed to be free from defects). The bearing at the farther end is the bearing under test; provision is also made to change it easily. The sensor is to be mounted on top of the bearing housing. The selected area is made flat and smooth to ensure effective coupling.

A piezoelectric accelerometer (Dytran model) is mounted on the flat surface using direct adhesive mounting technique. The accelerometer is connected to the signal-conditioning unit (DACTRAN FFT analyzer), where the signal goes through the charge amplifier and an Analogue-to-Digital converter (ADC). The vibration signal in digital form is fed to the computer through an USB port. The software RT Pro-series that accompanies the signal-conditioning unit is used for recording the signals directly in the computer's secondary memory. The signal is then read from the memory and replayed and processed to extract different features.

2.2. Experimental procedure

In the present study, four SKF30206 roller bearings were used. One was a brand new bearing and was assumed to be free from defects. In the other three roller bearings, defects were created using EDM in order to keep the size of the defect under control. The size of inner race defect is 0.525 mm wide and 0.827 mm deep and that of outer race defect is 0.652 mm wide and 0.981 mm deep.

The size of the defects is slightly bigger than one can encounter in a practical situation; however, it is in-line with work reported in literature (Yang, Mathew, & Ma, 2005). Before installing, each bearing was properly lubricated with grease.

The vibration signal from the piezoelectric pickup mounted on the test bearing was taken, after allowing initial running of the bearing for sometime. The sampling frequency was 12000 Hz and sample length was 8192 for all speeds and all conditions. The sample length was chosen arbitrarily. However, the following points were considered: Statistical measures are more meaningful when the number of samples is more. On the other hand, as the number of samples increases, the computation time increases. To strike a balance, sample length of around 10000 was chosen. In some feature extraction techniques, which will be used with the same data, the number of samples is to be 2^n. The nearest 2^n to 10000 is 8192, hence it was taken as sample length. Many trials were taken at the set speed and vibration signal was stored in the data file. The experiment was performed at 700 rpm.

Fig. 2 shows the time domain signals taken from bearings from different conditions. They show time domain plots of vibration acceleration of a normal bearing (without any fault), bearing with inner race defect, bearing with outer race defect and bearing with both inner race and outer race defects respectively.

3. Feature extraction

Vibration signals obtained corresponding to good and faulty bearing conditions are used in determining the faults. If the time domain (sampled) signal is to be used directly as inputs, the number of samples has to be constant for a given sampling rate. But, the number of samples is a function of speed. Hence cannot be used directly as inputs to classifier. Some features have to be extracted prior to classification.

Fig. 2 shows the time domain plot of vibration signals and corresponding histogram plots are shown in Fig. 3. Observing the magnitude of the signal, it is found that the range varies from class to class. A better plot to show the range variation is the histogram plot.

The information derived from a histogram plot can be used as features in the fault diagnosis. A representative sample from each bearing condition (class) is taken and the histogram is plotted. The selection of bin involves two criteria:

(a) The bin range should accommodate the amplitude range of signals obtained from all conditions of bearings analyzed. Bin range is the range of values considered for plotting histogram. It is from minimum value to maximum value. The minimum and maximum values for a particular condition of the bearing may be small and for another condition large. The bin range selected should accommodate all conditions.

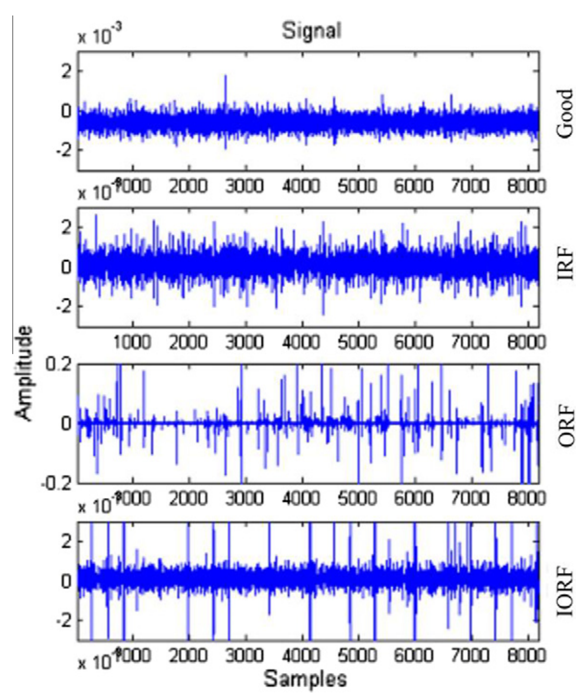

Fig. 2. Time domain plots of signals.