Abstract

A new diagnostic scheme is presented for ball bearing localized faults, which utilizes preprocessed time domain features based pattern recognition (PR). Vibration data is acquired from faulty bearings using a test rig, and the features are extracted from the data segments that are preprocessed prior to use in the fault classification process. The preprocessing involves smoothing of the features, which reduces the undesired impact of noise and vibration randomness on the PR process, and thus enhances the diagnostic accuracy. The results are compared with a similar scheme in terms of minimum features requirement to achieve an optimum classification accuracy, and the feature processing based proposed scheme provides better results.

keywords: Fault Diagnosis, Vibration Analysis, Feature Processing, Pattern Recognition.

1 Introduction

Detection of ball bearing’s localized faults is challenging because of their very low amplitudes in vibration signals as compared to that of joint machinery sources. Thus, the application of conventional frequency analysis becomes somewhat limited, and the characteristic frequencies of bearing faults cannot be found in spectra of raw signals [1]. Thus, most of the existing fault detection methods involve a certain preprocessing of raw vibration data to facilitate the detection of the appropriate frequencies. PR methods are also used to classify the bearing faults to enable automatic processing of data [2]. However, noise often misleads the statistical classifiers during their training phase [3]. A lots of PR based schemes are developed for ball bearing fault diagnosis, which utilize time domain statistical features extracted from raw vibration data [4–7]. However, the classification accuracy is effected due to noise and vibration randomness. Therefore, achieving an optimum classification accuracy using minimal set of features has been a challenge for the researchers.
Preprocessing of extracted features before incorporating classifier has not been reported yet up to best of my knowledge. This research introduces a procedure for processing the time domain statistical features prior to classification process. A machine fault simulator (MFS) is used to generate acceleration signals from the bearings having different kind of localized faults. The data is validated and transformed into a number of segments, from which the prominent features are extracted. Each feature is processed separately before forming the instances for supervised learning and testing of classifier. Support vector machine (SVM) is used mainly for fault classification along with other classifiers to better judge the effect of feature processing. The results obtained from the proposed scheme are compared with that of similar work presented by V. Sugumaran et al. [6], and the performance of the proposed method is found better.

Section 2 describes the experimental set up to acquire data and its validation process. The proposed diagnostic scheme is elaborated in Section 3. Section 4 discusses the findings of the research along with the comparison. Finally, the conclusions are drawn in Section 5.

2 Experimental Setup

The MFS from SpectraQuest Inc. was used to generate signals from faulty bearings, where the out-board bearing was under test. An ICP piezoelectric accelerometer of sensitivity 10.2 mV/ms$^{-2}$ was mounted at the top of bearing housing. The bearing model ER-12K was used with a healthy shaft of 3/4 inch diameter. The outer race of the bearing was stationary, whereas the inner race was rotating. A 5kg loader was placed in the middle of the shaft, as shown in Figure 1.

![Figure 1: Schematic of machine fault simulator](image)

A set of four bearings was used having different localized faults, which include inner race fault (IR), outer race fault (OR), ball fault (BL), and mixture of the above faults (MX). Vibration data of 10 seconds was acquired at steady state motor speed of 1000 RPM (16.67 Hz). A 24 bit dynamic signal analyzer NI PCI-4472 was used along with NI LabVIEW software to acquire data at 60K samples/sec.
Table 1: Bearing fault frequencies (Hz)

| Speed | FTF  | BPFI | BPFO | BSF  |
|-------|------|------|------|------|
| 16.67 | 6.36 | 82.46| 50.87| 33.20|

Table 1 shows fault frequencies of the bearing, i.e. fundamental train frequency (FTF), ball pass frequency for Inner Race (BPFI), ball pass frequency for outer race (BPFO) and ball spin frequency (BSF), which are calculated using the formulae below:

\[
FTF = \frac{f}{2} \left(1 - \frac{d}{P_d} \times \cos\beta\right) \tag{1}
\]

\[
BPFI = \frac{N_b f}{2} \left(1 + \frac{d}{P_d} \times \cos\beta\right) \tag{2}
\]

\[
BPFO = \frac{N_b f}{2} \left(1 - \frac{d}{P_d} \times \cos\beta\right) \tag{3}
\]

\[
BSF = \frac{N_b f}{2} \left(1 - \left(\frac{d}{P_d}\right)^2 \times \cos^2\beta\right) \tag{4}
\]

Where \( f \) is the driving frequency, \( N_b \) is the number of balls in the bearing, \( d \) is the ball diameter, \( P_d \) is the pitch diameter and \( \beta \) is the ball’s contact angle.

(a) Enveloped Spectrum of IR fault

(b) Enveloped Spectrum of OR fault

(c) Enveloped Spectrum of BL fault

(d) Enveloped Spectrum of MX fault

Figure 2: Enveloped spectra of bearing faults

The envelope analysis was performed to validate the data set, which has been the benchmark method over many years [1]. During the process, appropriate bands were selected using the fast kurtogram method proposed by Antoni [8], implementing the eight-level kurtogram with the provision of fast decimated
filter-bank tree and classic kurtosis. Figure 2(a) shows the enveloped spectrum of IR fault, in which the harmonics of BPFI are present along with the sidebands of shaft speed. Figure 2(b) shows the first harmonic of BPFO for OR fault and BL fault is evident from the Figure 2(c), in which twice the BSF is appeared with the multiple side-bands of FTF. The Figure 2(d) shows the enveloped spectrum of MX fault, in which FTF and BSF are dominating. Hence, the data set contains all the required information related to ball bearing faults.

3 Fault Diagnostic Scheme

The proposed diagnostic scheme consists of five steps, which are elaborated by the schematic in Figure 3. At first step, vibration data was acquired from faulty bearings. Data was segmented at the second step, where the features were extracted from each segment of every signal.

At third step, the features were processed using moving average (MA) filter. The smoother features were then utilized to formulate instances at the fourth step, which were fed into the classifier at final step to recognize the type of fault. The following subsections explain the steps.

3.1 Data Segmentation and Feature Extraction

Vibration data of every faulty signal was divided into 40 segments, and eleven time domain statistical features were extracted from each of the segment. Thus, every signal formulated a set of eleven features containing values of the respective fault. In this way, each feature in the set contained values equal to the number of segments.
Table 2: Time domain statistical features

| Feature                      | Formula                                                                 |
|------------------------------|-------------------------------------------------------------------------|
| RMS                          | \( \left( \frac{1}{N} \sum_{i=1}^{N} [X(i)]^2 \right)^{\frac{1}{2}} \) |
| Mean                         | \( \frac{1}{N} \sum_{i=1}^{N} X(i) \)                                 |
| St. Deviation                | \( \sigma = \left( \frac{1}{N} \sum_{i=1}^{N} (X(i) - \mu)^2 \right)^{\frac{1}{2}} \) |
| Variance                     | \( \frac{1}{N} \sum_{i=1}^{N} (X(i) - \mu)^2 \)                        |
| Skewness                     | \( \frac{1}{N} \sum_{i=1}^{N} \left( \frac{X(i) - \mu}{\sigma} \right)^3 \) |
| Kurtosis                     | \( \frac{\text{RMS}}{\text{RMS}} \)                                    |
| Crest Factor                 | \( \frac{\text{max}(|X|)}{\sum_{i=1}^{N} |X(i)|} \)                     |
| Impulse Factor               | \( \frac{\text{RMS}}{\sum_{i=1}^{N} |X(i)|} \)                         |
| Shape Factor                 | \( \text{median} \left( \frac{1}{N+1} \right) \)                        |
| Range                        | \( \text{max}(X) - \text{min}(X) \)                                      |

The relations used to extract the features are given in Table 2, where \( X \) is the sequence of data samples obtained by digitizing time domain continuous signal, \( X(i) \) is the amplitude of the \( i^{th} \) sample and \( N \) is the total number of samples in the sequence.

3.2 Feature Processing

The features were processed separately to smooth out their values, prior to formulate them into instances for the classification process. Outliers present in a feature may influence the accuracy of a classifier considerably due to the overlapping of its values extracted from different faulty signals. The concept of central tendency (CT) was utilized for smoothing the feature values. The CT attempts to describe a set of data with a single value, where mean, median, mode and range are its valid measures [9]. However, each measure can be more advantageous under different conditions. For instance, Figure 4(a) elaborates the median scores of kurtosis feature extracted for every fault, whereas Figure 4(b) shows the raw elements of the feature having random distribution.

Figure 4: Kurtosis feature extracted from every faulty signal, Graph legends of the faults are common for the rest of relevant graphs.
This research used mean, which is the frequently used measure. The MA filter was implemented with a fixed window of specified number of elements to smooth out the features by suppressing possible outliers. Algorithm 1 illustrates the listing of the MA filter.

Algorithm 1 Listing of MA filter

| Input: | $f_{raw} = \text{feature}, \text{segments} = 40, \text{win} = 10$ |
|--------|---------------------------------------------------------------|
| Output: | $f_{smooth}$                                                |
|        | $\text{length} = \text{win}$                                |
| for i = 1 → (segments − win) do |
|        | portion = $f_{raw}(i, \text{length})$                        |
|        | $f_{smooth}(i) = \text{Mean}(\text{portion})$               |
| end for|

3.3 Data Preparation and Fault Classification

After processing all the features through MA filter separately, they were transformed into the instances by including fault class labels at the 12th column, i.e. $\text{features} + 1$. The evenly poised instances of every class were mixed up randomly prior to feed into classifier to prevent from possible biasing. Total $\text{faults} \times (\text{segments} − \text{win})$ instances (120 instances) were fed to the classifier, where $\text{faults}$ are the number of fault classes. Primarily, the SVM classifier was employed, whereas bayesNet, decision tree and decision table were used to compare the results. Multi-class classification with 10-folds cross validation method was used with the default settings in Weka software.

4 Results and Discussion

The MA smoothing filter was employed for processing the time domain statistical features, prior to use in the PR based fault classification process. As a result, the proposed systematic data processing scheme has shown excellent results.

Table 3: Fault classification accuracies (%) using SVM classifier, before and after processing of the features

| Classifier   | Before Processing | After Processing |
|--------------|-------------------|------------------|
| SVM          | 74.4              | 98.3             |
| BayesNet     | 68.1              | 99.2             |
| Decision Table | 68.8             | 94.2             |
| Decision Tree | 75.6              | 99.2             |

Table 3 shows a comparison of fault classification accuracies produced by
different classifiers before and after processing of the features using MA filter. The results illustrate a significant impact of the features preprocessing on the fault classification process.

Table 4: Confusion matrices using SVM classifier, before and after applying MA filter

|     | IR | OR | BL | MX |
|-----|----|----|----|----|
| (a) | 25 | 0  | 0  | 5  |
|     | 0  | 39 | 1  | 0  |
|     | 5  | 0  | 25 | 10 |
|     | 5  | 2  | 14 | 19 |

|     | IR | OR | BL | MX |
|-----|----|----|----|----|
| (b) | 29 | 0  | 0  | 1  |
|     | 0  | 30 | 0  | 0  |
|     | 0  | 0  | 30 | 0  |
|     | 1  | 0  | 0  | 29 |

The confusion matrix in Table 4(a) shows classification accuracy with raw features using SVM classifier, where almost every fault class is misclassified to some extent. The accuracy obtained against this matrix was 74.4%, whereas 98.3% classification accuracy was achieved by using the MA based features.

Impulse Factor (IF) feature processing is elaborated in Figure 5, where Figure 5(a) shows raw values of the IF extracted from every fault class. Overlapping among outlying values of different classes can be observed, which is the main reason of misclassification exhibited by the classifiers. Therefore, these outliers are suppressed through smoothing out the values of the features. Figure 5(b) electorates the effect of processing the raw feature by using MA filter with win=10. The outlying feature values are pulled towards the mean, which aid the classifiers in their training and decision making process.

![Figure 5: Graphs of Impulse Factor processing with MA filter](a) Raw values of IF feature (b) IF values after applying MA filter)

Diagnostic capability of every individual feature was observed in the model using SVM classifier. The classification accuracy of the scheme was observed using single smoother feature at a time. Table 5 compares the accuracies attained by the features, where MA based features produced higher accuracy.

V. Sugumaran et al. [6] investigated the effect of number of features on the ball bearing fault classification accuracy. Eleven time domain statistical features were used in the study, which include mean, standard error, median, standard
Table 5: SVM classification accuracies (%) produced by the features individually before and after processing

| Feature        | Raw | MA  |
|----------------|-----|-----|
| RMS            | 50.0| 65.8|
| Mean           | 56.7| 80.0|
| St. Deviation  | 50.8| 65.8|
| Variance       | 58.3| 65.8|
| Skewness       | 57.5| 77.5|
| Kurtosis       | 58.3| 90.0|
| Crest Factor   | 54.2| 89.1|
| Impulse Factor | 53.3| 85.8|
| Shape Factor   | 50.0| 68.3|
| Median         | 59.2| 88.3|
| Range          | 57.5| 89.1|

deviation, variance, skewness, skewness, range, minimum, maximum and sum, where as the SVM classifier was used to recognize the fault classes. Minimum seven statistical features were suggested to maintain an optimum classification accuracy in the diagnostic model, and the results were compared with that of proposed scheme using SVM classifier.

Table 6: Comparison of classification accuracies (%) with the existing scheme, in terms of number of features against different combination of fault classes

| Technique | Feature Type | Classifier | Features | Accuracy |
|-----------|--------------|------------|----------|----------|
| V. Sugumaran [6] | Statistical | SVM       | 7        | 89.1 99.1 100 |
| MFS Raw Features | Statistical | SVM       | 7        | 88.3 85.8 95.0 |
| MFS MA Features   | Statistical | SVM       | 3        | 100 100 100 |

A: Bearing in good condition Vs Bearing with faults; B: Bearing with inner race fault Vs Bearing with outer race fault and combination faults; C: Bearing with outer race fault Vs Bearing with combination faults

Table 6 shows the comparison of classification accuracies in terms of number of features used for different combinations of faults (A, B and C). The proposed systematic data processing diagnostic scheme produced very accurate results using three features only, for every combination of the faults. Note that the results were even less accurate than that of [6], when using seven raw features from MFS data with SVM classifier.
5 Conclusions

The significance of using preprocessed features in PR based fault classification process was investigated with the intent to diagnose ball bearing localized faults generated by MFS. Time domain statistical features were extracted from data segments to form a data set, which were processed by the MA filter prior to use into the fault classification process. Consequently significant enhancement was noticed in the classification accuracy of various classifiers. The smoothing filter suppressed the outlying values of the features, which reduced the undesired affect of randomness in vibration signals enabling the classifiers as better decision makers. The results of the proposed diagnostic scheme were compared with that of an existing scheme in terms of minimum number of features requirement to maintain an optimum classification accuracy. The comparison revealed that the CT based feature preprocessing produced more accurate results at lower computational cost.

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