Condition Monitoring using Wavelet Transform and Fuzzy Logic by Vibration Signals

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Abstract: Gearboxes are widely applied in power transmission lines, so their health monitoring has a great impact in industrial applications. In the present study, vibration signals of Pride gearbox in different conditions, namely, healthy, broken first gear, broken second gear and bearing fault are collected by a vibration sensor. Discrete wavelet transform (DWT) is applied to process the signals. In order to identify the various conditions of the gearbox, fuzzy logic technique is used in decision-making stage. The results indicate that this method allow identification at a 96.25% level of efficiency. Therefore, the proposed approach can be reliably applied to gearbox fault detection.

[Maryam Nassser and Masoud Mohammadi. **Condition Monitoring using Wavelet Transform and Fuzzy Logic by Vibration Signals.** *Life Sci J* 2012;9(4):5680-5685] (ISSN:1097-8135). http://www.lifesciencesite.com. 846
Keywords: Intelligent fault diagnosis, J48 algorithm, Fuzzy inference system, Gearbox

1. Introduction

Gearboxes are widely used in industrial applications. An unexpected failure of the gearbox may cause significant economic losses. Tooth breakage is the most serious failure for a gearbox. Fault diagnosis of gearboxes is of crucial importance and has been studied for several decades. In modern industry, fault diagnosis plays an important role in accident prevention, human safety, maintenance, decision-making, and cost minimization. It is, therefore, very important to find early fault symptoms from gearboxes [1]. Usually, vibration signals are acquired from accelerometers mounted on the outer surface of a bearing housing. The signals consist of vibrations from the meshing gears, shafts, bearings, and other components. The useful information is corrupted and it is difficult to diagnose a gearbox from such vibration signals [2]. Processing the vibration signals usually was doing in tree domain that called: Time domain, Frequency domain and Time-Scale domain. A common technique in Time-Scale domain is wavelet analysis. Wavelet analysis is the best way for processing the non-stationary signals such as vibration signals of gearboxes. Discrete wavelet analysis is faster in calculations than continues wavelet analysis [3]. During the last few years, wavelet transform has been used for gearbox diagnosis [4,5]. The publications in the field of condition monitoring via vibrations are quite versatile. Selecting a few and focusing on advanced signal processing techniques the works of Wang and Mcfadden [10,11] must be mentioned, that utilized time-frequency analysis techniques and showed that the spectrogram has advantages over Wigner–Ville distribution for the analysis of vibration signals for the early detection of damage in gears. The same authors have also employed the wavelet transform [12,13] to analyze the local features of vibration signals and showed that unlike the time-frequency distribution, which incorporates a constant time and frequency resolution, the wavelet transform can accommodate simultaneously both the large and small scales in a signal, enabling the detection of both distributed and local faults. Baydar and Ball [14,15] have proposed the instantaneous power spectrum and have shown that it is capable in detecting local tooth faults in standard industrial helical gearboxes. The propagation of local faults was identified by monitoring variations in the features of the power spectrum distribution. The same authors have also applied the Wigner–Ville distribution [16] as well as the wavelet transform [17] on vibration and acoustic signals for the same purpose. Samanta [18] investigated three types of artificial neural networks: a multi-layer perceptron (MLP), radial basis function network (RBF) and probabilistic neural network (PNN), and applied genetic algorithm (GA) for the fault detection of a two-stage gear reduction unit. However, it was pointed out that the retraining of the ANN-based approaches may be required for a changed machine condition with different load. Other contribution to this area include the papers by Chen and Wang [19], Staszewski et al. [20], Paya et al. [21], Yang et al. [22], Mechefske [23], and Yen and Lin [24], among others.

2. Material and methods

2.1 Experimental works and data acquisition

For this work, at first a test bed was built to mount the gearbox and electromotor on it. The 2KW electromotor was used to drive power to the gearbox using a coupling power transmission. The input shaft of gearbox was drove by the electromotor and its speed was controlled by an inverter. The experiment setup is shown in figure 1.

Four classes were classified in this work, namely, healthy gearbox 'H', broken first gear 'B-F-G', broken second gear 'B-S-G' and bearing fault 'B-F' that each class considers a type of fault as a most common fault of gearbox. The vibration signals were collected by a vibration sensor (figure 1).

The vibration sensor is connected to the amplifier and signal acquisition unit (figure 1). The vibration signal in digital form is fed to the computer through a USB port. The software 'SpectraPro-4' that accompanies the signal conditioning unit is used for recording the signals directly in the computer's secondary memory. The frequency of the data acquisition was 40966 Hz, with 16386 sample data and giving a measured time of 0.4 s. The data were acquired from gearbox in four mentioned states. The working level of gearbox speed was 3500 rpm.

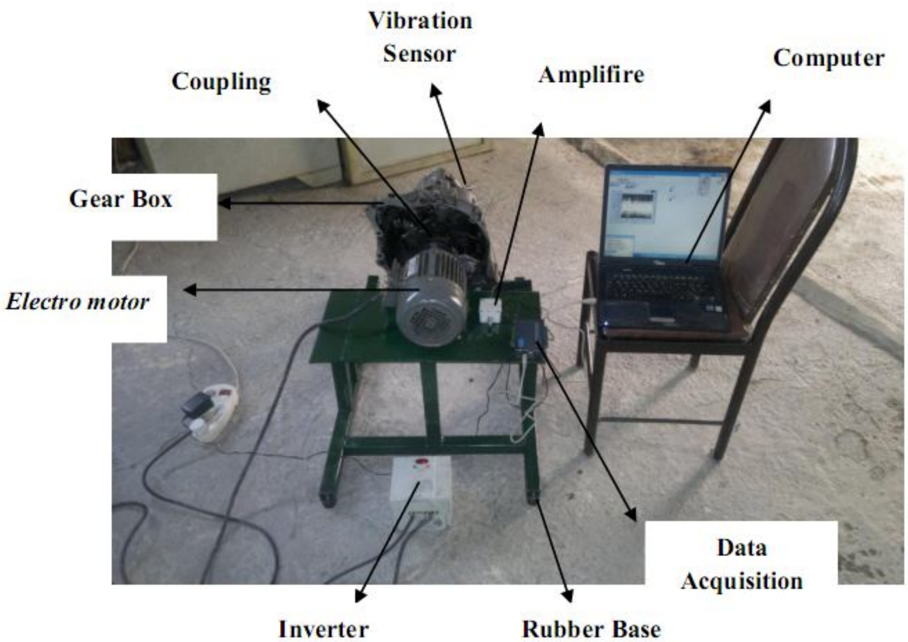


Figure 1, Experimental set up

2.2 Signal Processing and Feature extraction

In recent articles, advanced non-parametric approaches have been considered for signal processing such as wavelets, Fast Fourier Transform (FFT), short time Fourier transform (STFT) [25, 26]. In this study wavelet transform signal processing technique was employed to transfer the vibration signals from time domain to time-frequency domain. After transferring data the measured data were used to obtain the most significant features by feature extraction. The accuracy of feature extraction is of great importance since it directly affects the final diagnosis results. In this paper, the feature extraction using descriptive statistics on the time-frequency domain data were used. Research works have reported the use of this method [27]. For more information about used features, see [27, 28]

2.3 Feature selection and classification model extraction

A 'divide-and-conquer' approach to the problem of learning from a set of independent instances leads naturally to a style of representation called a decision tree. A decision tree is a tree based knowledge representation methodology used to represent classification rules. A standard tree induced with c5.0 (or possibly ID3 or c4.5) 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 one attribute. The occurrence of an attribute in a tree provides the information about the importance of the associated attribute. In a decision tree, the top node is the best node for classification. The other features in the nodes of a decision tree appear in descending order of importance.

It is to be stressed here that only features that contribute to the classification appear in the decision tree and others do not. Features that have less discriminating capability can be consciously discarded by deciding on the threshold. This concept is made use of for selecting good features.

In this research, the J48 algorithm (A WEKA implementation of c4.5 Algorithm) was used to construct decision trees [27]. Input to the algorithm was the set of statistical features extracted from vibration signatures. The data sets of the features for each condition have 70 samples. In each operating condition, two-thirds of samples are employed for the training process and the remaining samples for testing purposes. The detailed descriptions of those data sets are given in Table 2. Based on the output of the J48 algorithm, various statistical parameters are selected for the various conditions of the gearbox. Selected statistical features are used as membership functions and the values appearing between various nodes in the decision tree are used for generating the fuzzy rules to classify the various conditions of the gearbox under study.

Table 2 Descriptions of data sets in each condition

Label of classification	Number of training samples	Number of testing samples
Healthy Gearbox 'H'	50	20
Broken First Gear 'B-F-G'	50	20
Broken Second Gear 'B-S-G'	50	20
Bearing Fault 'B-F'	50	20

2.4 Fault diagnosis using fuzzy inference system

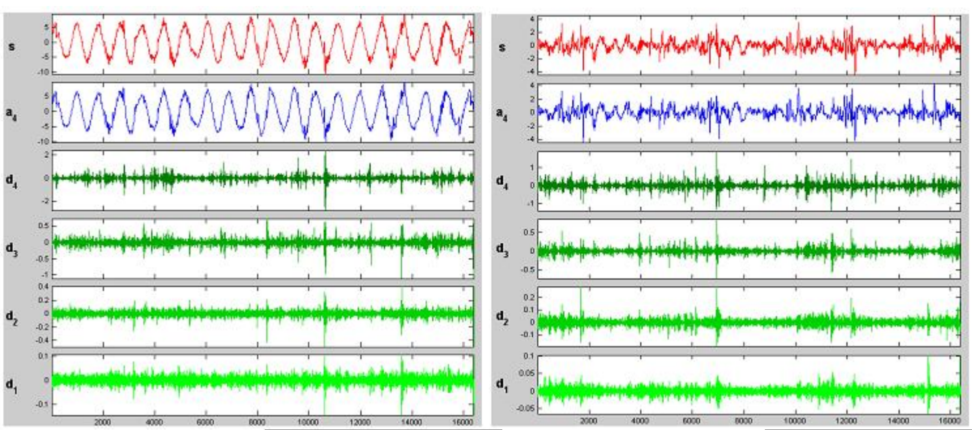
Fuzzy logic makes use of the knowledge of experts through its transformation into linguistic terms. Fuzzy logic is a rule-based system that successfully combines fuzzy set theory with the inference capability of human beings. As rules, linguistic terms are used and are modelled through membership functions that represent simulation of the comprehension of an expert. Membership functions give the scaled value of definite number values that are defined by linguistic labels. Rules are defined such as IF (condition) THEN (result). The conditions and results are linguistic terms that represent the input and output variables, respectively. The rule base of the fuzzy logic classifier consists of many rules. A rule base is used to obtain a definite output value according to the input value [27].

After defining membership functions and generating the 'if-then' rules by J48 algorithm, the next step is to build the fuzzy inference engine. The fuzzy toolbox available in MATLAB (version: 2011a) was used for building the fuzzy inference engine. Each rule was taken at a time and using membership functions and fuzzy operators the rules were entered [27].

3. Results and discussion

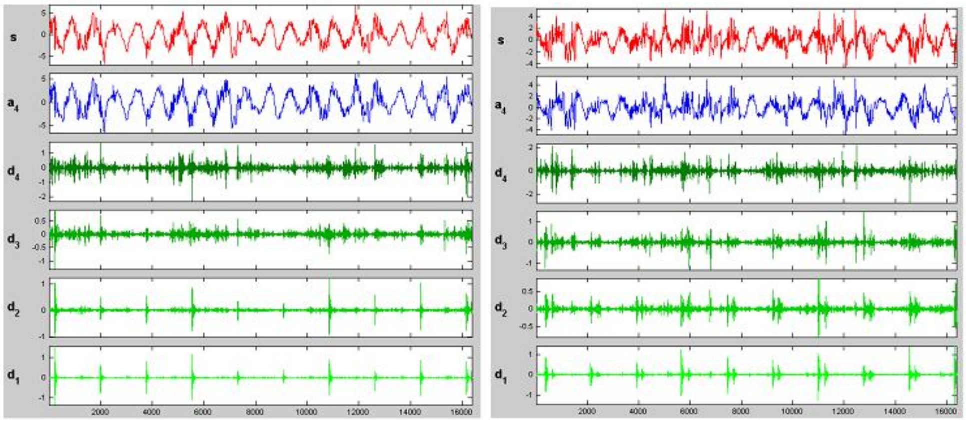
3.1 vibration signals

Figure 2 shows graphs of vibration signal in time-frequency domain for 3500 rpm rotational speed. Results show that graphs of various conditions of gearbox are different but fault diagnosis of gearbox is difficult using a spectrum of vibration signals alone. Therefore it is necessary to utilize an automatic signal classification system in order to increase accuracy and reduce errors caused by subjective human judgement.



Health

Bearing Fault



Broken First Gear Broken Second Gear

Figure 2, Graphs of vibration signal in time-frequency domain for 3500 rpm rotational speed

3.2 Decision trees

The outcomes of the J48 algorithm are shown in Figure 3. Decision trees show the relation between features and the condition of the gearbox. Tracing a branch from the root node leads to a condition of the gearbox and decoding the information available in a branch in the form of the 'if-then' statement gives the rules for classification using fuzzy for various conditions of gearbox. Hence, the usefulness of the decision tree in forming the rules for fuzzy classification is established. The top node of the decision tree is the best node for classification. The other features appear in the nodes of the decision tree in descending order of importance. It is to be stressed here that only features that contribute to the classification appear in the decision tree and others do not. The level of contribution is not the same and all statistical features are not equally important. The level of contribution by an individual feature is given by a statistical measure within the parenthesis in the decision tree. The first number in the parenthesis indicates the number of data points that can be classified using that feature set. The second number indicates the number of samples against this action. If the first number is very small compared to the total number of samples, then the corresponding features can be considered as outliers and hence ignored. Features that have less discriminating capability can be consciously discarded by deciding on the threshold. This concept is used in selecting good features. The algorithm identifies the good features for the purpose of classification from the given training data set and thus reduces the domain knowledge required to select good features for the pattern classification problem.

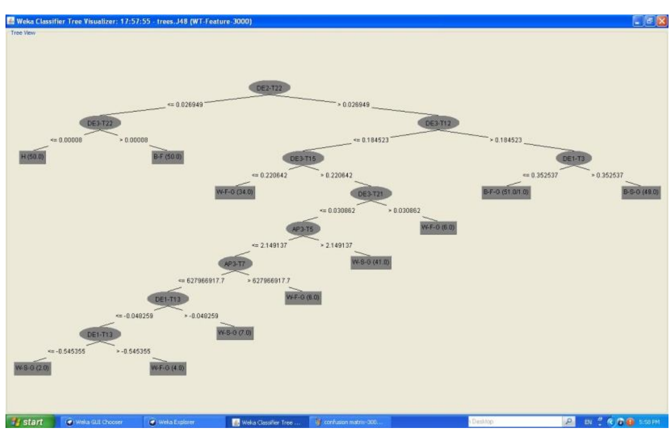


Figure 3, Decision tree for 3500 rpm rotational speed

3.3 Fuzzy rules

Rules designed for 3500 r/min condition

1. If (DE2-T22 is not MF-DE2-T22) and (DE3-T22 is MF-DE3-T22) then (output1 is B-F) (1)
2. If (DE2-T22 is not MF-DE2-T22) and (DE3-T22 is not MF-DE3-T22) then (output1 is H) (1)

3. If (DE2-T22 is MF-DE2-T22) and (DE3-T12 is MF-DE3-T12) and (DE1-T3 is MF-DE1-T3) then (output1 is B-S-G) (1)
4. If (DE2-T22 is MF-DE2-T22) and (DE3-T12 is MF-DE3-T12) and (DE1-T3 is not MF-DE1-T3) then (output1 is B-F-G) (1)
5. If (DE2-T22 is MF-DE2-T22) and (DE3-T12 is not MF-DE3-T12) and (DE3-T15 is not MF-DE3-T15) then (output1 is B-F-G) (1)
6. If (DE2-T22 is MF-DE2-T22) and (DE3-T12 is not MF-DE3-T12) and (DE3-T15 is MF-DE3-T15) and (DE3-T21 is DE3-T21) then (output1 is B-F-G) (1)
7. If (DE2-T22 is MF-DE2-T22) and (DE3-T12 is not MF-DE3-T12) and (DE3-T15 is MF-DE3-T15) and (DE3-T21 is not DE3-T21) and (AP3-T5 is MF-AP3-T5) then (output1 is B-S-G) (1)
8. If (DE2-T22 is MF-DE2-T22) and (DE3-T12 is not MF-DE3-T12) and (DE3-T15 is MF-DE3-T15) and (DE3-T21 is not DE3-T21) and (AP3-T5 is not MF-AP3-T5) and (AP3-T7 is MF-AP3-T7) then (output1 is B-F-G) (1)
9. If (DE2-T22 is MF-DE2-T22) and (DE3-T12 is not MF-DE3-T12) and (DE3-T15 is MF-DE3-T15) and (DE3-T21 is not DE3-T21) and (AP3-T5 is not MF-AP3-T5) and (AP3-T7 is not MF-AP3-T7) and (DE1-T13-1 is MF1-FE1-T13) then (output1 is B-S-G) (1)
10. If (DE2-T22 is MF-DE2-T22) and (DE3-T12 is not MF-DE3-T12) and (DE3-T15 is MF-DE3-T15) and (DE3-T21 is not DE3-T21) and (AP3-T5 is not MF-AP3-T5) and (AP3-T7 is not MF-AP3-T7) and (DE1-T13-1 is not MF1-FE1-T13) and (DE1-T13-2 is MF2-FE1-T13) then (output1 is B-F-G) (1)
11. If (DE2-T22 is MF-DE2-T22) and (DE3-T12 is not MF-DE3-T12) and (DE3-T15 is MF-DE3-T15) and (DE3-T21 is not DE3-T21) and (AP3-T5 is not MF-AP3-T5) and (AP3-T7 is not MF-AP3-T7) and (DE1-T13-1 is not MF1-FE1-T13) and (DE1-T13-2 is not MF2-FE1-T13) then (output1 is B-S-G) (1)

3.4 System accuracy

In each condition of gearbox, 20 samples were used for testing the final model. The confusion matrix for each condition is given in Table 3. The performance of the classifier can be checked by computing the statistical parameters such as sensitivity, specificity and total classification accuracy defined by:

Sensitivity: number of true positive decisions/number of actually positive cases.

Specificity: number of true negative decisions/number of actually negative cases.

Total classification accuracy: number of correct decisions/total number of cases.

The values of statistical parameters are given in Table 4. Results show that the total classification accuracy for 3500 rpm conditions are 96.25%.

Table 3. Confusion matrices for tow working speeds of gearbox

Condition	B-F	B-C	B-P	H
B-F	19	0	1	0
B-C	0	19	1	0
B-P	0	0	20	0
H	0	1	0	19

Table 4. The value of statistical parameters

Data sets label	Sensitivity (%)	Specificity (%)	Total classification accuracy (%)
B-F	95	98.33	96.25
B-C	95	98.33	
B-P	100	100	
H	95	98.33	

4. Conclusions

A combined classification tree (J48 algorithm) and fuzzy inference system (FIS) have been presented to perform fault diagnosis of a gearbox. The implementation of J48-FIS based classifier requires two consecutive steps. Firstly, the J48 algorithm is utilized to select the relevant features in the data set obtained from feature extraction part. The output of the J48 algorithm is a decision tree that is employed to produce the crisp if-then rule and membership function sets. Secondly, the structure of the FIS classifier is defined based on the obtained rules, which were fuzzified in order to avoid classification surface discontinuity. The classification results and statistical measures are then used for evaluating the J48-FIS model. The total classification accuracy for 3500 rpm conditions was 96.25%. The results indicate that the proposed J48-FIS model can be used in diagnosing gearbox faults. Finally In order to simplify condition monitoring, produced fuzzy inference engines were transmitted to the SIMULINK of MATLAB that the operator can easily detect the condition of gearbox with mentioned accuracy.

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