Feature-level fusion based on wavelet transform and Artificial Neural Network for fault diagnosis of planetary gearbox using acoustic and vibration signals

Meghdad Khazaee, Hojat Ahmadi, Mahmoud Omid, Ashkan Moosavian

Abstract: in recent years, cause of requiring further reliability and accessibility of the machines, condition monitoring using multi information resources and fusion data resulted rather using one resource has become widely used. In this article, an intelligent system is proposed for fault diagnosis and classification of planetary gearboxes based on fusion the acoustic and vibration data at feature level and using artificial neural network (ANN) classifier. First, acoustic and vibration data of the planetary gearbox was simultaneously collected in four conditions: 1. healthy, 2. Worn, 3. Cracked, and 4. Broken. Gained signals were transmitted from time domain to time-frequency domain by wavelet transform. Then, 30 statistic features were extracted from each one to be used as the classifier input. Artificial neural network was applied as the classifier. The first classification of the faults was based on the extracted features from each sensor where classification accuracy for each acoustic and vibration data was respectively about %88.4 and %86.9. The classification accuracy using fused features was gained as %98.6 indicating the efficiency of proposed method for fault diagnosis the planetary gearbox. Also, %10 accuracy increase gained through using data fusion method clearly put it that using the method can significantly enhance the quality and accuracy of fault diagnosis and as a result condition monitoring of the machineries.

Keywords: Feature level fusion, Fault diagnosis, Planetary gearbox, Artificial Neural Network, Wavelet transform.

1. Introduction

Today and with the advances in technology, industrial machinery become increasingly complicated and at the same time more sensitive and require further attention; since their fault and failure might lead to overwhelming costs (1). Accordingly, reliability, accessibility and lower failure and service time of the machines are of great importance in industrial applications. In the same regard, condition monitoring is widely considered as an effective and efficient method for increasing factors such as reliability, health and optimized performance of machineries (2). Furthermore, a wide range of studies are conducted regarding condition monitoring and fault diagnosis of machineries and many articles have been published in recent years (1). Condition monitoring is defined as fault diagnosis and maintaining the machines while they are working (3). Generally, condition monitoring is based on regular data recording of dynamic features of the machines and comparing them to their intact or normal state. In classical condition monitoring, fault diagnosis is usually based on either vibration data or acoustic data (1, 4). Many methods are introduced and conducted for one-sensor condition monitoring and based on one type data either vibrations (5, 6) or acoustic (7) and using one classifier such as support vector machine (8), artificial neural network (ANN) (6), fuzzy logic (9). But studies show that using only one sensor includes many limitations in detecting delicate faults and specific applications in condition monitoring. The matter emphasizes on using multi data resources and data fusion (1).
Gears are the commonest rotary machines widely used in power transmission lines and industrial applications. So, their fault diagnosis is of great significance in preventing from bigger fractures and failure of the machineries. The increasing significance has drawn many researchers to condition monitoring of gearboxes (3, 4, 5).

Planetary gearbox is among the most conventional gearboxes widely considered for their wide range of gear ratios and in particular in helicopters and heavy machineries. Low weight and small room in power transmission lines are their most significant advantages. These gearboxes are generally composed of three parts: 1- sun gear 2- ring gear 3- planet gears. Fig1 displays the general structure of planetary gearbox and the estate of relationship between its components.

![Fig1. Planetary gearbox and its components](image)

In this study, one of the varieties of planetary gears, namely, MF285 tractor final drive was used. Final drive is the last component of power transmission system of all tractors located between differentials and wheels and its function is to increase torque on the wheels and decrease the speed. Fig2 represents general type of tractors power transmission lines and place of final drive in them.

In this work, to fault diagnosis of planetary gearbox of MF 285 tractor’s final drive, vibration and acoustic data was simultaneously collected by two sensor. Collected signals were transmitted from time domain to time-frequency domain using wavelet analysis. Then, statistical features of each signal was extracted and used as the artificial neural network (ANN) classifier input. The above steps were conducted for each sensor’s data separately and also for their fused features.
2. Experimental setup

The experimental setup to collect dataset consists of MF285 final drive, 3kW two-pole three phase electromotor that provides drive power using a coupling. A Test-bed was designed to mount gearbox, electromotor, transmission equipment and four shock absorbers under Bases to cancel out vibrations. The planetary gearbox coupled to the electromotor that was initially run under normal operating conditions and its speed at 300RPM was controlled by an inverter. Fig3 illustrates the experimental setup and equipment that was used in this study.
The faults were manually created on gears. Four common states examined on the gears were: 1. Healthy gear, 2. Broken ring gear, 3. Cracked ring gear, and 4. Planet gear with worn tooth face. Fig4 shows four classes that classified in this study.

![Fig4. Different conditions of gears that classified in this research. a) Healthy, b) Broken ring gear, c) cracked ring gear, d) planet gear with worn tooth face](image)

Then vibration signal of each class was captured from the experimental testing with an accelerometer type VMI 102 that set horizontally on surface of final drive. Acoustic emitted signals of gears in every condition are recorded by The AKG microphone Model C 417 with frequency range between 20Hz-20 KHz which is placed perpendicularly affront of tail side of the gearbox while facing the biggest original orifice of the body. And finally Easy-Viber used as Data acquisition that was an interface between PC and sensor.

3. Signal processing

Although acoustic and vibration data carry significant and useful data about the machine conditions, they include not only fault signals but they carry all components signals. Presence of the noises in time domain signals faces fault detection with challenges (10). Removing this problem requires the signals to transmit from time domain to frequency or time-frequency domain so that besides removing noise, it allows useful data collection. There a variety of methods for signals processing among which Wavelet analysis, Fast Fourier Transform (FFT), Short Time Fourier Transform (STFT) and etc can be mentioned. Fast Fourier Transform is one of the commonest signal processing methods widely used in condition monitoring. The FFT technique transfers the signals from time domain to frequency domain. However, the method has no good performance in unstable and non-stationary conditions and also do not represent time features of the signals well (7, 10).

Wavelet transform is capable of providing the time and frequency information simultaneously, hence giving a time-frequency representation of the signal. Wavelet analysis reveal aspects of data that other signal processing techniques miss, aspects like trends, breakdown points, discontinuities in higher derivatives, and self-similarity. This series of
functions, that usually called mother wavelets, have different frequencies to deal with transient signals in different time intervals. In present study, wavelet transform was used for transmitting data from time domain to time-frequency domain. Thereby, it is possible to collect time and frequency data of any position in a signal and have better performance in extracting the features and classification the faults. Continues wavelet transform (CWT) decomposes signal in both domain and frequency domains simultaneously, CWT is defined as

$$\text{CWT}(a, \tau) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t) \psi^* \left( \frac{t - \tau}{a} \right) dt$$

(1)

where \(a\), \(\tau\) and \(\psi\) and are the scale parameter, translation parameter and mother wavelet, respectively, and \(\psi^*\) is the complex conjugate of \(\psi\). Computation of wavelet coefficients at every conceivable scale takes lots of calculations and work, and result in huge and awful amount of data. Thus, using dyadic scale and positions, makes analysis more efficient and accurate, this procedure is called discrete wavelet transform (DWT). DWT which is the discrete form of CWT is expressed as:

$$\text{DWT}(a, \tau) = \frac{1}{\sqrt{2^j}} \int_{-\infty}^{\infty} x(t) \psi^* \left( \frac{t - 2^j k}{2^j} \right) dt$$

(2)

Where \(a\) and \(\tau\) represent \(2^j\) and \(2^j k\). The DWT analysis is done by passing the raw signal through a series of high and low pass frequency filters. Each level of decomposition consist of one high-pass and one low-pass filter, thus, the raw signal is decomposed into two parts, high frequency bands (Details \((D_j)\)) and low frequency bands (Approximation \((A_j)\)). In next level of decomposition, Approximation signal of previous level is applied as input of decomposition and high and low frequency bands will be separated, and this process is done till reach of desired decomposition level. The original signal can be defined as (7).

$$x(t) = A_j + \sum_{j=1}^{J} D_j$$

(3)

Where \(A_j\) and \(D_j\) are approximation and detail of the signal at level \(j^{th}\), respectively. In other words, this signal is the composition of \(j^{th}\) level details and last level approximations wavelet coefficients.

Processing of the signals was conducted using wavelet transform toolbox in MATLAB Software. Fig 5 shows an example of acoustic signals in time domain. The wavelet decompositions of acoustic signals of each four classes under study were shown in Fig 6. Also the time domain and time-frequency domain of vibration signals was shown in Fig 7 and Fig 8 respectively.
**Fig 5.** Time domain of acoustic signals a) Healthy, b) planet gear with worn tooth face, c) Broken ring gear, d) cracked ring gear

**Fig 6.** Time wavelet decompositions of acoustic signals a) Healthy, b) planet gear with worn tooth face, c) Broken ring gear, d) cracked ring gear
Fig 7. Time domain of vibration signals a) Healthy, b) planet gear with worn tooth face, c) Broken ring gear, d) cracked ring gear

![Time domain of vibration signals](image)

Fig 8. Wavelet decompositions of vibration signals a) Healthy, b) planet gear with worn tooth face, c) Broken ring gear, d) cracked ring gear

![Wavelet decompositions of vibration signals](image)
4. Feature extraction

Wavelet coefficients could not directly use as inputs of classifier and a post process stage is needed to prepare data for classifier (7). The procedure of extracting useful information from raw signals is the so-called feature extraction (2). Processed signals contain a large set of data for each sample therefore some functions are used to reduce feature vectors. In current study 30 features from the coefficient of wavelet was extracted such as mean, standard deviation, kurtosis, skewness and etc in approximation and details. Mathematical formulas of some important feature are shown in Table 1. The extracted features were employed to feed the ANN classifier for fault detection and classification.

<table>
<thead>
<tr>
<th>Feature Description</th>
<th>Formula</th>
<th>Feature Description</th>
<th>Formula</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean value</td>
<td>[ \bar{x} = \frac{\sum_{i=1}^{n} x_i}{n} ]</td>
<td>Third central moment</td>
<td>[ \frac{\sum_{i=1}^{n} (x_i - \bar{x})^3}{n} ]</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>[ \sqrt{\frac{1}{n} \sum_{i=1}^{n} (x_i - \bar{x})^2} ]</td>
<td>Forth central moment</td>
<td>[ \frac{\sum_{i=1}^{n} (x_i - \bar{x})^4}{n} ]</td>
</tr>
<tr>
<td>Root mean square</td>
<td>[ \sqrt{\frac{\sum_{i=1}^{n} (x_i)^2}{n}} ]</td>
<td>Kurtosis</td>
<td>[ \frac{\frac{1}{n} \sum_{i=1}^{n} (x_i - \bar{x})^4}{\left(\frac{1}{n} \sum_{i=1}^{n} (x_i - \bar{x})^2 \right)^2} - 3 ]</td>
</tr>
<tr>
<td>Variance</td>
<td>[ \frac{\sum_{i=1}^{n} (x_i - \bar{x})^2}{n} ]</td>
<td>Crest factor</td>
<td>[ \frac{x_{peak}}{x_{RMS}} ]</td>
</tr>
<tr>
<td>Skewness</td>
<td>[ \frac{\frac{1}{n} \sum_{i=1}^{n} (x_i - \bar{x})^3}{\left(\frac{1}{n} \sum_{i=1}^{n} (x_i - \bar{x})^2 \right)^{3/2}} ]</td>
<td>FM4</td>
<td>[ \frac{n \sum_{i=1}^{n} (x_i - \bar{x})^4}{\left(\sum_{i=1}^{n} (x_i - \bar{x})^2 \right)^2} ]</td>
</tr>
</tbody>
</table>

5. Artificial Neural Network (ANN)

Artificial neural network (ANN) is one of the most widely used artificial intelligence methods in condition monitoring and fault diagnosis (7), and also it was used for classification the different conditions of gears in this study. Outlet layer of all networks included four neurons, since it was defined as a 1-row-4- column matrix with 0-1 digits to define desired class. This means 0-1-0-0 and 0-0-1-0 outputs respectively is related to second and third classes of the quartet classes. Nevertheless, the most important layer in designing neural network is the hidden layer (middle layer) that should be defined by settings. In current research, networks with ‘tansig’ transfer function and ‘mse’ performance function and variable count, between 2 and 10, are used to gain the best classification results. To meet the best network performance, the number of middle layers were tested among which the best results gained with 10 neurons of the middle layer. In designing, a neuron was assigned to each extracted feature and since there were 30 features extracted, for the sake of one sensory fault diagnosis, network input had 30 neurons. Finally, regarding the explanations, optimal neural network structure designed in this study was 30*10*4.
After fusion the extracted features, a larger group of 60 features composed. Now, it was required the networks designs to change and since each feature had an input neuron, the optimal neural network structure designed was 60*10*4.

6. Feature level data fusion

Till recent years, using one data source (e.g., an acoustic or vibration sensor) was enough to supply industrial needs including condition monitoring and fault diagnosis. But for complex machinery, one sensor does not possess data collection capacity and required accuracy for condition monitoring and fault diagnosis the equipment. Accordingly, for the sake of further accuracy, we need data fusion methods (2). Data fusion is the method addresses the estate of fusion data from different sources toward the best decision making. In recent years, data fusion has attracted a wide attention for its wide applications in military and non-military, robotic, intelligent condition monitoring and etc industries (12).

Data fusion is conducted at three levels:

1- Data (signal) level fusion: here, different information sources data are directly fused and then integrative signal features are extracted to determine the input of each class. The method is used for reinforcing fault signal against noise signal. Data level fusion has many limitations including the necessity for the same data type for fusion the signals (1, 13, 14).

2- Feature fusion: at this level, first, the features of each sensor data’s are separately extracted and then the features are all fused into a more complete group to use as a classifier input to gain a better accuracy (1, 14).

3- Decision level fusion: at this level, first, each information source data is independently analyzed by a classifier and then results of each classifier are fused. Also, this level of data fusion called “classifier fusion” (1, 14).

In fact, feature level and decision level are both two powerful and close methods working closely and sometimes overlap each other. However, in recent years, the latter has been a greater focus of the field researchers and in fact the former has not received enough attention (15). In this study, we address fusion the acoustic and vibration data at feature level, namely, first, acoustic and vibration signals features were extracted and separately used for fault diagnosis. Then, extracted features from both signals were fused and formed a larger group of features that used for classification respective faults. Fig 8 shows the structure of proposed method for feature fusion level of acoustic and vibration data aim to better classification the faults.
7. Results and discussion

In data collecting step, acoustic and vibration signal were simultaneously gathered via two separate sensors. Each one of four classes under study had 60 vibration and acoustic samples and, in sum, 480 samples. Each class data was divided into two parts: 45 samples (%75) out of each 60 samples of each class were selected fully randomly and applied for training ANN classifier and Other 15 samples were also used in testing classifier. Table 1 represent whole sample number with their classification for training and testing the classifier in both single sensor and fused dates.

30 statistical features of each signal in time-frequency domain were extracted. The two groups were separately extracted to use for analyzing artificial neural network for the accuracy of each to gain in each train and test of fault diagnosis system.

<table>
<thead>
<tr>
<th>classes</th>
<th>Train data</th>
<th>Test data</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Acoustic</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Healthy</td>
<td>45</td>
<td>15</td>
<td>240</td>
</tr>
<tr>
<td>Broken ring</td>
<td>45</td>
<td>15</td>
<td></td>
</tr>
<tr>
<td>Cracked ring</td>
<td>45</td>
<td>15</td>
<td></td>
</tr>
<tr>
<td>Planet worn</td>
<td>45</td>
<td>15</td>
<td></td>
</tr>
<tr>
<td>Vibration</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Healthy</td>
<td>45</td>
<td>15</td>
<td>240</td>
</tr>
<tr>
<td>Broken ring</td>
<td>45</td>
<td>15</td>
<td></td>
</tr>
<tr>
<td>Cracked ring</td>
<td>45</td>
<td>15</td>
<td></td>
</tr>
<tr>
<td>Planet worn</td>
<td>45</td>
<td>15</td>
<td></td>
</tr>
<tr>
<td>Fused data</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Healthy</td>
<td>90</td>
<td>30</td>
<td>480</td>
</tr>
<tr>
<td>Broken ring</td>
<td>90</td>
<td>30</td>
<td></td>
</tr>
<tr>
<td>Cracked ring</td>
<td>90</td>
<td>30</td>
<td></td>
</tr>
<tr>
<td>Planet worn</td>
<td>90</td>
<td>30</td>
<td></td>
</tr>
</tbody>
</table>

In single sensor condition monitoring, classification accuracy was gained %86.9 based on features extracted from vibration signals and using ANN classifier. Also, classification accuracy was gained %88.4 based on features extracted from acoustic signals indicating a relative superiority to vibration signals.

Then, the extracted features of both acoustic and vibration signals were fused and founded a comprehensive group of the features used for classification the faults. After fusion vibration...
and acoustic features gained via two different sensors, a comprehensive group of 60 fused features was transferred to classification and analysis center. Hence, system accuracy was gained as %99.2 for train data and %98.6 for test data. Results demonstrate high capability and appropriate quality of the introduced system in this article for condition monitoring and fault diagnosis of planetary gearbox. Furthermore, an increase more than %10 accuracy shows the strength of data fusion method in condition monitoring and fault diagnosis, and highlights the necessity of considering it in industrial activities more than ever before. Table 2 shows the whole gained results in this research.

Table 3. The all accuracies that gained in this research

<table>
<thead>
<tr>
<th>Classification Accuracy</th>
<th>Train (%)</th>
<th>Test (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Based on acoustic data</td>
<td>91.3</td>
<td>88.4</td>
</tr>
<tr>
<td>Based on vibration data</td>
<td>90.8</td>
<td>86.9</td>
</tr>
<tr>
<td>Based on data fusion</td>
<td>99.2</td>
<td>98.6</td>
</tr>
</tbody>
</table>

8. Conclusions

In this paper an intelligent system for fault detection and classification of planetary gearbox based on data fusion at feature level was proposed. The acoustic, vibration and fused features of these signals of gearbox were employed for this work. The classification accuracy based on acoustic and vibration signals was respectively 89.4% and 86.9%. Using fusion features of both of two signals the 98.6% accuracy was gained for test data that show the quality and ability of data fusion in intelligent fault detection and classification. Also, the Results show that using fused feature increases the accuracy more than 10%.

References


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