Bearing and Gear Fault Detection Using Artificial Neural Networks

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Abstract

Rotating machinery plays an important role in industrial applications. When these machines recently are getting more complicated, fault diagnosis techniques have become more and more significant. In order to keep the machine performing at its best, one of the principal tools for the diagnosis of rotating machinery problems is the vibration analysis, which can be used to extract the fault features and then identify the fault patterns. In addition, there is a demand for techniques that can make decision on the running health of the machine automatically and reliably. Artificial intelligent techniques have been successfully applied to automated detection and diagnosis of machine conditions. They largely increase the reliability of fault detection and diagnosis systems. Accordingly, the aim of this paper is to apply a feed-forward efficient neural network to classify a large number of vibration signals acquired from rotating machinery in different states: normal, good gear but faulty bearing, good bearing but faulty gear and faulty gear and bearing. The parameters given to the neural networks have been extracted from the power spectral density of the signals. The main impact of this neural network is to generate answers that give the combined state of gears and bearings simultaneously whereas most of previous neural networks have focalized mainly on gears or on bearings alone.

1 Introduction

Rotating machinery, as one of the most common types of mechanical equipment, plays an important role in industrial applications [1, 2]. When these machines recently are getting more complicated, precise and expensive, fault diagnosis techniques for them have become more and more significant [3].

Most of the used machinery operates by means of bearings, gears and other rotating parts which may frequently develop faults. These faults may cause the machine to break down and decrease its level of performance [4]. In order to keep the machine performing at its best and avoid personal casualties and economical loss, different methods of fault diagnosis have been developed and used effectively to detect and localize the machine faults in the specified element at an early stage. One of the principal tools for diagnosing rotating machinery problems is the vibration analysis [5, 6]. Through the use of some processing techniques of vibration signals, it is possible to obtain vital diagnosis information. These techniques are used to extract the fault features and then identify the fault patterns; many conventional methods such as Fourier analysis and time-domain analysis are studied in the recent researches and executed in many applications [3].

However, many techniques available presently require a good deal of expertise to apply them successfully. Simpler approaches are needed which allow relatively unskilled operators to make reliable decisions without a diagnosis specialist to examine data and diagnose problems. Therefore, there is a demand for techniques that can make decision on the running health of the machine automatically and reliably [7, 8, 9]. Artificial intelligent techniques, such as artificial neural networks (ANNs) and fuzzy logic, etc., have been successfully applied to automated detection and diagnosis of machine conditions. They largely increase the reliability of fault detection and diagnosis systems.

Accordingly, in our application, we used a great deal of data composed of a large number of vibration signals acquired from rotating machinery in different states: normal, good gear but faulty bearing, good bearing but faulty gear and faulty gear and bearing.

Among multiple techniques we have chosen the Frequency analysis, based on the Fourier transform as a tool for the vibration signal processing. We decided to extract multiple power spectral density parameters from the vibration signals.

After extracting all the parameters for all the signals, we aimed to develop a way to determine if these signals are acquired from a faulty or normal machine, and to localize the fault by determining the faulty element (bearing or gear). Due to their capability of learning and their capacity of classification and generalization, the ANNs are considered an ideal solution for this fault detection and classification. So we have conceived Feed Forward Neural Networks that take the power spectral density parameters as an input and generate answers that give the state of the machine, whether it's at a normal state or having a defected bearing or defected gear or both at the same time.

As a result we have conceived a method to diagnose a rotating machine by detecting the fault and localizing it using simple spectral parameters with feed forward artificial neural networks.

In this paper we will first present the used signals in this application, and then define the parameters extracted from these signals. In addition we will give a brief explanation on the feed forward neural networks used and finally we will present the results.

2 Database used in the Study

2.1 Signals Acquisition

The data used in our study was captured during a thesis at the University of New South Wales in Australia. In fact, four channels of data were recorded by the Sony DAT recorder. The first channel was dedicated for the accelerometer signal, which was placed above the bearing under test. The two other channels were acquiring signals from encoders from the first and second shafts. The fourth channel was for the tachometer signal obtained from the encoder on the first shaft. In our study we have used the accelerometer signals only. Since errors can take place either in bearing elements or in gears, the acquisition of signals was done in four different cases:

- ✓ Good Gear and Good Bearing
- ✓ Good Gear and Faulty Bearing
- ✓ Faulty Gear and Good Bearing
- ✓ Faulty Gear and Faulty Bearing

In addition, the bearing defection can be either a ball defection or inner race defection or outer race defection, which leads us to eight different cases instead of four. In each case there are about thirteen signal acquired for a different shaft speed and a different load, speeds were 3Hz, 6Hz or 10 Hz, and loads were 25Nm, 50Nm, 75Nm or 100Nm.

To increase the number of elements in each case (or class) we divided each signal into 4 segments, thus we have a minimum of 52 signals representing each case.

The classification of bearing defection was done in previous work by using feed forward neural networks with a high performance [10]. Plus, once any element of a bearing was defected the entire bearing will be replaced, thus we don't need to determine the defected element in the bearing. Consequently, the classification we aimed to do was to determine whether the gear or the bearing was defected or not and the signals of each class were chosen randomly from the subclasses.

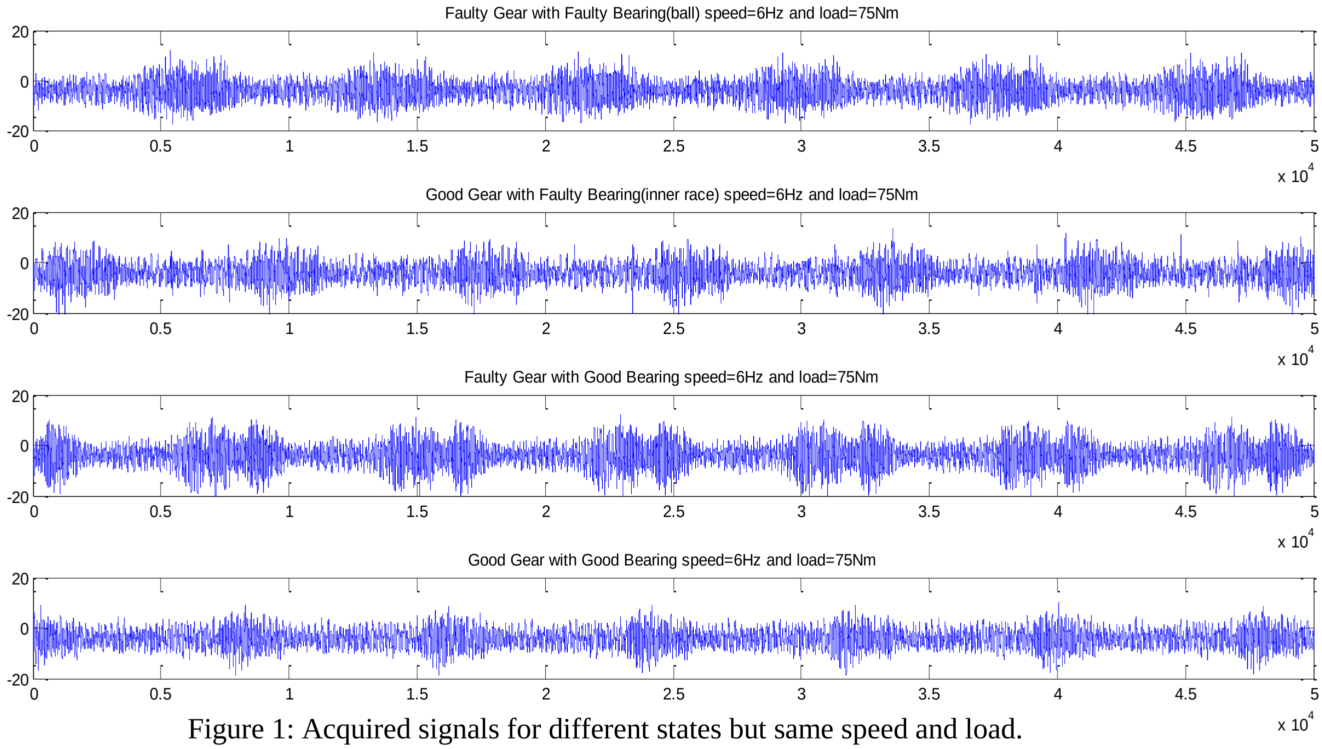

Figure 1: Acquired signals for different states but same speed and load.

2.2 Features Extraction

According to the set of signals already prsented, each bearing and gear state is represented by a set of vibration signals. These signals must be processed in order to be replaced by a vector of parameters to simplify the classification procedure. So, we had to choose some features that can include the most important information contained in the signal and then extract them in order to prepare the matrices of learning and testing for the neural networks.

Frequency analysis has become a fundamental tool for vibration signal processing. It is based on the Fourrier Transform that allows the passage from time domain to frequency domain. This transformation allows knowing the variation of power of the signal with the frequency f. Thus, it can detect the presence of a bearing or gear defection generating a periodic shock at a determined frequency [11]. Consequently, we decided to extract the power spectral density parameters from the vibration signals we already have. Before the extraction, we divided each signal into 4 segments to have enough elements representing each class (bearing and gear state). Then, we extracted the parameters of the power spectral density (PSD) listed below (every parameter with its formula):

1. Power of the Signal:

$$M_r = 2\int_0^{\infty} f^r S_x(f)df \qquad (1)$$

2. Mean Frequency: MPF=M1/M0

$$M_r = 2\int_0^{\infty} f^r S_x(f)df \qquad (2)$$

3. Skewness :

$$CD = \frac{M_3^{\;*}}{\sqrt{M_2^{\;3*}}} \qquad (3)$$

$$Mr^* = 2\int_0^{\infty} (f - MPF)^r S_x(f)df$$

4. Kurtosis:

$$CA = \frac{M_4^{\,*}}{M_2^{\,2*}} \tag{4}$$

5. Median Frequency:

$$\int_0^{Fmed} S_x(f)df = \int_{Fmed}^{F\max} S_x(f)df \tag{5}$$

6. Relative energy by frequency band (10 values)

$$W_n = \frac{\int_{f_{n-1}}^{f_n} S_x(f)df}{M_0} \tag{6}$$

$$fn = \frac{n}{N} f_{\max} \qquad \text{and} \quad 1 < \mathrm{n} < \mathrm{N}$$

7. Deciles (8 values):

$$\int_{f_{p-1}}^{f_p} S_x(f)df = k\int_0^{F\max} S_x(f)df \tag{7}$$

$$0 < k \leq 1$$

8. Spectral Entropy:

$$H = -\int_0^{f_{\max}} S_x(f)\ln[S_x(f)]df \tag{8}$$

9. Peak Frequency: where the PSD reaches its maximum value [12].

Finally we have as a result a vector with 25 parameters representing the bearing and gear state. This bearing may be in one of 4 states: Normal bearing and normal gear, normal gear but defected bearing,defected gear but normal bearing and defected gear and bearing . To determine their state we have to pass these parameters to the final process: Neural Network Classification.

3 Neural Network Classification

3.1 Importance of Neural Networks

In fact, the diagnosis decision remains in the classification issue, many methods of classification are used nowadays in machine monitoring in order to detect faults early and prevent from big losses. These methods include: Applications of Support Vector Machine, application of fuzzy sets, Artificial Neural Networks and too many other methods.

Neural networks have emerged as an important tool for classification. The recent vast research activities in neural classification have established that neural networks are a promising alternative to various conventional classification methods. The advantage of neural networks lies in the following theoretical aspects. First, neural networks are data driven self-adaptive methods in that they can adjust themselves to the data without any explicit specification of functional or distributional form for the underlying model. Second, they are universal functional approximators in that neural networks can approximate any function with arbitrary accuracy [13]. Since any classification procedure seeks a functional relationship between the group membership and the attributes of the object, accurate identification of this underlying function is doubtlessly important. Third, neural networks are nonlinear models, which makes them flexible in modeling real world complex relationships. Finally, neural networks are able to estimate the posterior probabilities, which provides the basis for establishing classification rule and performing statistical analysis [14]. On the other hand, the effectiveness of neural network classification has been tested empirically. Neural networks have been successfully applied to a variety of real world classification tasks in industry, business and science [15].Thus, we used the Artificial Neural Networks (ANN) due to their capability of learning and generalization which makes them ideal for fault detection and error classification [16].

3.2 Feed Forward Neural Networks

The role of ANN is to take the already extracted parameters as inputs and give the class that the corresponding vector belongs to as an output.

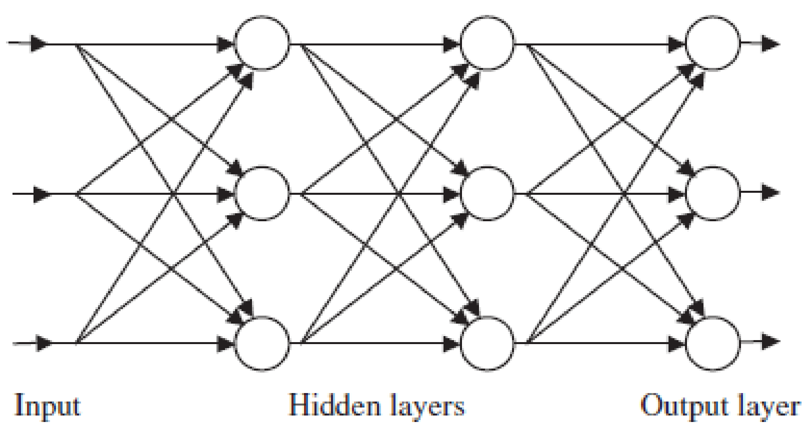

Figure 2: Feed Forward Neural Network with Multiple Hidden Layers.

The type of ANNs we used is multilayer feedforward networks, these networks are mostly used for classification because of their simplicity and their capacity of learning. In fact, they are used in many decision making situations especially diagnosis. In [18], multilayer feedforward neural networks are used in medical diagnosis study profiting of the classification capability of these artificial networks.

In our application, we used three neural networks: the first neural network has to determine whether the bearing was defected or not without giving any detail about the gear. According to the answer, the second or the third network is chosen. The second network determines the state of the gear (whether it is defected or not) knowing that the bearing is good (according to the answer of the first network). On the other hand, the third network determines the state of the gear knowing that the bearing is defected. Figure three shows how the classification is accomplished by the three neural networks.

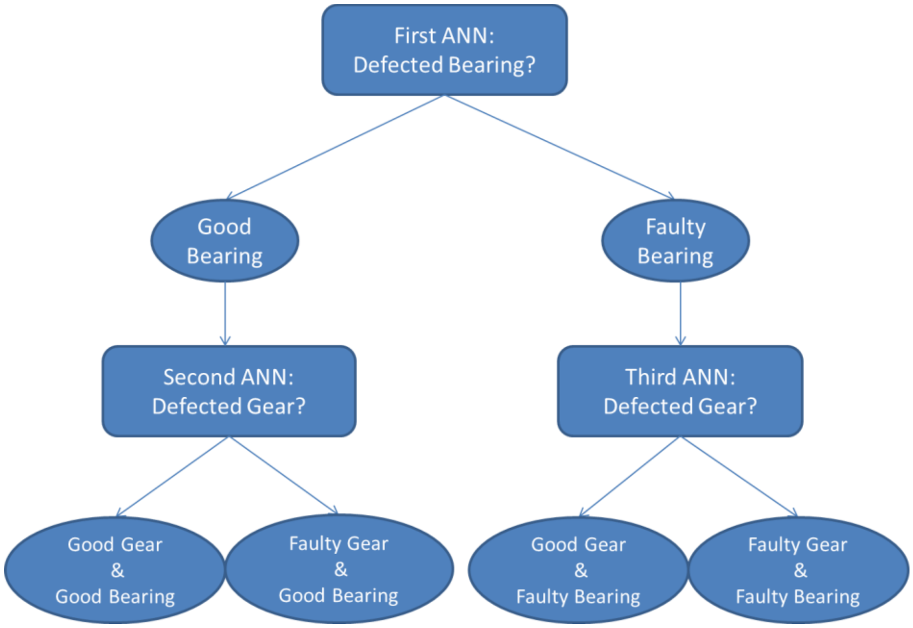

Figure 3: how the decision is made by the three neural networks.

3.3 Data Preparation and Neural Networks Conception

In order to prepare the learning phase and the testing phase for neural networks, each vibration signal is divided into 4 segments in order to have a greater number of elements in each class (or bearingand gear state) as mentioned before. After segmentation, signals are processed to extract their PSD parameters (whose number is 25) to obtain, instead of signals, vectors representing the elements of each class. To create the learning matrix and the test matrix for each network, we randomly select vectors from each class and add them to the corresponding matrix.

In the first classification (first ANN) we have chosen randomly 26 vectors from each class for creating learning matrixes:

- Class of Good Bearing: it is composed of two subclasses faulty gear with good bearing and good gear with good bearing. We uniformly and randomly chose 13 vectors from each subclass to complete the learning matrix.
- Class of Faulty Bearing: it is composed of two subclasses faulty gear with faulty bearing and good gear with faulty bearing. But each subclass is also divided into 3 subclasses because the bearing defection can be either a ball defection or inner race defection or outer race defection. Thus we uniformly and randomly chose from each subclass 13 vectors with verifying that these vectors are chosen from the different three subclasses.

The testing matrix are chosen in the same way.

In the second classification (second ANN) learning matrix and testing matrix are composed each of 26 vectors where 13 are randomly chosen from the class of faulty gear with good bearing and the class of good gear with good bearing.

In the third classification (third ANN) learning matrix and testing matrix are created in the same way:

- Class of Good Gear (with faulty bearing): this class is composed of three subclasses, from each subclass 10 vectors are randomly chosen.

- Class of Faulty Gear(with faulty bearing): this class is also composed of three subclasses, from each subclass 10 vectors are randomly chosen.

So in this classification the matrix are composed of thirty vectors.

Thus, learning matrix and testing matrix in the first two classifications are composed of 26 vectors having 25 elements each. In the third classification learning and testing matrix are composed of 30 vectors with 25 elements each. The output of the three neural networks is either 0 or 1. In the three cases the faulty state is represented by 0 and the good state is represented by 1.

4 Results

The whole work was developped in MATLAB(2011), in fact the three ANNs where trained and simulated using the Neural Network Tools in MATLAB, the most important details of these ANNs are given in Table 1.

Network	Layer1	Layer 2	Layer 3	Layer 4	Layer 5	Performance
First	45	30	20	10	5	96%
Second	30	20	10	5	3	98%
Third	30	20	10	5	3	99%

Table 1: Details of all neural networks used for classification.

The performance mentioned in the last column is calculated by the formula (10).

$$per = \frac{ny_b}{ny_i} \times 100 \qquad (10)$$

ny_b= number of elements classified conveniently

ny_i= total number of elements to be classified [16].

In fact when testing the second ANN it give only one fault answer where it judged a good gear as faulty, which is a faulty alarm. In figure 4 we see the response of the ANN: where the first 26 vectors are correclty classified as faulty (which means corresponding to faulty gear) and the second 26 vectors are correctly classified as good (which means corresponding to good gear), but only one vector is wrongly classified to be faulty while it is good.

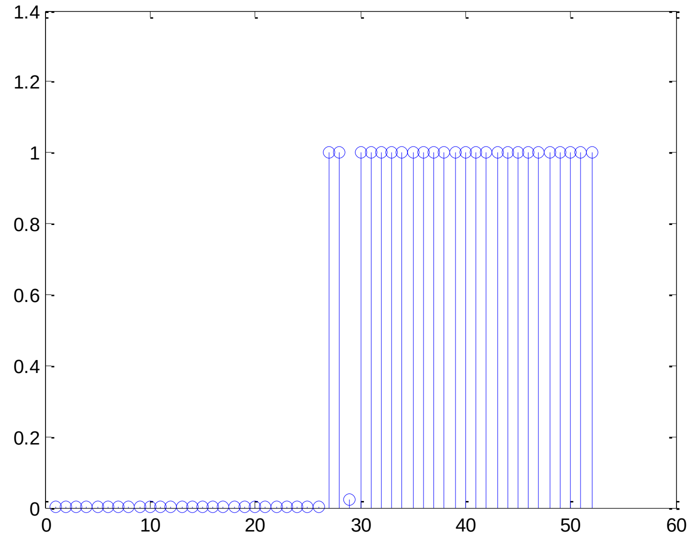

Figure 4: Second ANN response with only one fault answer within 52.

As a result we obtain a program that acquires a vibration signal from a bearing and a gear. Then, the program calculates the PSD (power spectral density) of the signal to deduce the 25 parameters. These parameters are treated by the neural networks to identify the state of the studied bearing and gear. Consequently, the defection is detected and localized in the same time.

5 Conclusion

We can deduce that Artificial Neural Networks simplify the bearing and gear fault diagnosis by detecting errors and specifying the faults position. This fact encourages us to do hardware verification for these results, and also program implementation on microcontrollers or DSP (Digital Signal Processor) to obtain new devices that can accomplish monitoring operations like fault detection and specification. But maybe this implementation conduct us to do some method to reduce the number of used parameters like Principal Component Analysis or Genetique Algorithm.

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