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ANN based evaluation of performance of wavelet transform for condition monitoring of rolling element bearing

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Abstract

Bearings are one of the critical components in rotating machines and the majority of the failure arises from the defective bearings. Bearing failure leads to failure of a machine and unpredicted productivity loss for production facilities. Hence, bearing fault detection and diagnosis is an integral part of the preventive maintenance procedures. In this paper vibration signals for three conditions of a deep groove ball bearing Normal (N), defect on inner race (IR) and defect on outer race (OR) were acquired from a customized bearing test rig, under one load and two speed conditions. Discrete Wavelet Transform (DWT) has been used for vibration signal analysis. The statistical features extracted from the dominant wavelet coefficients are used as inputs to ANN classifier to evaluate its performance. The vibration signals have also been denoised using a new thresholding scheme. A comparison of ANN performance is made based on raw vibration data and denoised data. The ANN performance has been found to be comparatively higher when denoised signals were used as inputs to the classifier. Also various mother wavelet functions (Db8, Db4, Db44 and Sym10) were used to analyze the denoised vibration signals and their performance has been evaluated using the ANN classifiers.

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Keywords: Rolling element bearing; Discrete Wavelet Transform; Artificial Neural Network.

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1. Introduction

Early fault detection, diagnosis and classification are important topics in the engineering arena. Proper condition monitoring and fault detection methods will result in improved safety, reliability and reduction of manufacturing cost. Bearings are one of the most important and frequently encountered components in rotating machinery. The components of bearing are the outer ring, rolling element, cage and inner ring. Different methods are used for detection and diagnosis of bearing defects. They are vibration and acoustic measurement, temperature measurement and wear analysis. Among these vibration signature analysis is the one which is widely used as it provides important information about anomalies formed in the internal structure of the bearing [1].

Common techniques used in vibration signal analysis include time and frequency domain analyses. Statistical information of the time domain signal can be used as trend parameters. They can provide information such as the energy level of the vibration signals and the shape of the amplitude probability distributions. High energy level of the vibration signal measured by the RMS values may indicate severely damaged components, while spikiness of the signal measured by higher order moments of the probability distribution function indicates incipient defects. Many frequency analysis methods have been used for fault diagnostics, among which the FFT is one of the most widely used and well-established method. Frequency based techniques, however are not suitable for the analysis of non-stationary signals that are generally related to machinery defects. Nonstationary or transient signals can be analyzed by applying time–frequency domain techniques, as they use both time and frequency domain information allowing for the investigation of transient features, such as impacts.

A number of time–frequency domain techniques have been proposed including the short-time Fourier transform (STFT), the Wigner-Ville distribution (WVD), and the wavelet transform (WT). Wavelet theory has become one of the emerging and fast-evolving mathematical and signal processing tool for its many distinct merits. Wavelet analysis is capable of revealing aspects of data that other signal analysis techniques miss, like trends, breakdown points and discontinuities in higher derivatives. Furthermore, because it affords a different view of data than those presented by traditional techniques, wavelet analysis can often compress or denoise a signal without appreciable degradation. It is a relatively new signal processing technique, which can be used effectively in condition monitoring applications [2]. The WT is used to represent all possible types of transients in vibration signals generated by faults in a bearing. WT can be classified as Continuous Wavelet Transform (CWT), Discrete Wavelet Transform (DWT), and Wavelet Packet Transform (WPT).

The vibration signals need to be subjected to various signal processing techniques like low pass filtering, high pass filtering and band pass filtering technique to remove noise from the raw acquired vibration signals and improve the signal to noise ratio [3]. Purushotham et al. [4] have applied the DWT towards the detection of localized bearing defects. The vibration signals were decomposed up to 4 levels using “Db2” mother wavelet. The complex cepstral coefficients of wavelet transformed time windows at Mel-frequency scales constituted the features that trained Hidden Markov Models for the fault detection and classification. Z. K. Peng et al. [2] have reviewed the application of wavelet transform in machine condition monitoring and fault diagnostics. S. Prabhakar et al. [5] have shown the effectiveness of DWT technique over FFT technique in the single and multiple fault diagnosis of REB. Rujiang Hao et al. [6] proposed a novel morphological undecimated wavelet (MUDW) decomposition scheme for fault diagnostics of rolling element bearings. OMAR JOSÉ LARA CASTRO et al. [7] presented an automatic fault classification technique based on Discrete Wavelet Transform (DWT) and three different Neural Networks, Multilayer Perceptron (MLP), Radial basis Function (RBF) and Probabilistic Neural Networks (PNN). They showed with their experiments, that probabilistic neural network yielded best results and it is superior to traditional methods in classifying the fault characteristics of bearing. J. Rafiee et al. [8] proposed automatic feature extraction system for gear and bearing fault diagnosis using wavelet-based signal processing. In their work they studied 324 mother wavelets, and results showed that Daubechies 44 (Db44) had the most similar shape across both gear and bearing vibration signals.

In recent years ANNs have gained considerable interest in engineering field as problem solving tools. The fundamental element is a neuron which has multiple inputs and multiple outputs [9]. ANN’s have the advantages of superior learning, noise suppression and parallel computation abilities. However, successful implementation of an ANN based monitoring system strongly depends on proper selection of the type of network structure and amount of training data, which are not always available [10]. Zarei [11] has proposed to improve diagnostic
abilities of an ANN applied to a four-condition bearing classification using time domain features as the ANN’s input. Castejon et al. [12] proposed a new methodology for data collected from a quasi-real industrial machine. Multiresolution analysis (MRA) was used to extract interesting features in the signal. The performance was evaluated by ANN classifier. Bo Li et al. [13] used neural networks to detect common bearing defects from motor vibration data. The results showed that neural network is an effective tool in detecting various motor bearing faults through the measurement and interpretation of motor bearing vibration signals. Ruqiang Yan et al. [14] presented an efficient approach to machine condition monitoring and health diagnosis, based on the Discrete Harmonic Wavelet Packet Transform (DHWPT). Vibration signals measured from a bearing test bed were decomposed into a number of frequency sub-bands and key features associated with each sub-band were selected, based on the Fisher’s linear discriminant criterion. The key features were then used as inputs to a neural network classifier for assessing the system’s health status. Khalid F. Al-Raheem et al. [15] proposed Laplace-wavelet transforms combined with an ANN for rolling bearing fault detection and classification. They optimized wavelet shape parameters and the ANN parameters using a genetic algorithm (GA) to enhance the feature extraction and classification process. To increase the classification procedure speed and effectiveness, the extracted features of the dominant wavelet scales were used to generate the neural network input vectors which yielded good results. In this paper, Wavelet Transform (WT) is used to analyse the vibration signals acquired from deep groove ball bearing under three conditions namely N, IR and OR. By application of DWT, the raw vibration signals of the bearing are decomposed into several frequency levels. Features have been extracted from dominant wavelet coefficients (detailed cD2) and are used as inputs to the ANN classifier to evaluate the performance of the classifier. The energy values of the DWT coefficients are higher in second level and hence considered as the dominant wavelet coefficients. Also the vibration signals were subjected to denoising based on Modified soft thresholding (MST) scheme to evaluate the performance of the ANN classifier. Various mother wavelet functions (Db8, Db4, Db44 and Sym10) were used to analyse the denoised vibration signals and their performance have been evaluated using the ANN classifiers.

2. Experimental test rig and data collection

The bearing test rig mainly consists of a shaft of diameter 32mm which is supported between bearings. The shaft is driven by an induction motor with variable speed controller. The drive motor and the bearing test rig are driven through a timer belt and pulley arrangement. The speed ratio for this timer pulley arrangement is 2.25. The test rig allows the shaft to be run at different speeds (rpm) under variable radial loads. The motor speed can be varied from 0 to 1400 rpm. A photographic view of customized test rig used for extracting bearing vibration signals is shown in Fig. 1. In this present study, a 6205 bearing is mounted at one end of the shaft on which tests are conducted. Radial load on the test bearing is applied through a hydraulic loading arrangement.

![Fig. 1 Photograph of the bearing test rig.](image)

Two accelerometers were mounted on the housing of the test bearing. The accelerometer is connected to signal conditioning amplifier and finally to Data Acquisition system (DAQ) hardware installed in a computer through connecting cables. After allowing initial running of the bearing for some time, the acceleration signals from the transducer mounted on the test bearing is fed to the amplifier and the data is acquired using Data Acquisition
board. A customized LAB VIEW (vi) program was prepared which collected the signals at specified sampling rate and stored in the computer as a .txt file. For each experiment, a separate .txt file was created which was used for further analysis.

The signal was subjected to the DWT and decomposed into four levels using Daubechies 8 mother wavelet function using MATLAB program. According to Nyquist’s rule, the maximum frequency of the vibration signal was set to be 24 kHz because the sampling frequency is 48 kHz [4].

In this work, acceleration signals at a sampling rate of 48000 samples per second were collected for 5.08 seconds. Signals were collected for three conditions - under a radial load of 1.7 kN and shaft speeds of 356 rpm and 622 rpm. Signals collected from accelerometer-X (vertical) were considered for analysis in this paper as the accelerometer signal acquired in Y- direction (horizontal) was found to be not very sensitive to bearing condition. Each trial of experiment resulted in a data vector of size 250000 x 1. Hence for one load, two speed conditions and three bearing conditions (Normal, IR defect, and OR defect), six such data vectors were generated (two for each bearing condition).

3. Discrete wavelet transform

The wavelet transform is a tool that cuts up data, functions or operators into different frequency components, and then studies each component with a resolution matched to its scale. The use of wavelet transform is appropriate since it gives the information about the signal both in frequency and time domains. The basic step of decomposition of the WT is shown in Fig. 2. In the decomposition step the discrete signal is convolved with a low pass filter L and a high pass filter H, resulting in two vectors cA1 and cD1. The elements of these vector cA1 are called Approximate Coefficients and the elements of the vector cD1 are called Detailed Coefficients. The symbol \( \downarrow 2 \) denotes down sampling, i.e., omitting the odd indexed elements of the filtered signal, so that the number of the coefficients produced by the basic step is approximately the same as the number of elements in the discrete signal ‘s’. An important property of this step is: \( s = cA1 + cD1 \) [4].

The continuous wavelet transform (CWT) of \( f(t) \) is defined as

\[
CWT(a, b) = \int_{-\infty}^{+\infty} f(t) \psi_{a,b}(t) dt.
\]

where

\[
\psi_{a,b}(t) = \frac{1}{\sqrt{a}} \psi \left( \frac{t - b}{a} \right), a, b \in R; a \neq 0
\]

where \( \psi_{a,b}(t) \) denotes the mother wavelet. The parameter ‘a’ represents the scale index, which is a reciprocal of frequency. The parameter ‘b’ indicates the time shifting (or translation).

\[ \text{Fig. 2 Basic step of decomposition of the wavelet transform} \]

The DWT is derived from the discretization of CWT \( (a, b) \) given by

\[
DWT(j, k) = \frac{1}{\sqrt{2^j}} \int_{-\infty}^{+\infty} f(t) \psi \left( \frac{t - 2^j k}{2^j} \right)
\]

where \( a \) and \( b \) are replaced by \( 2^j \) and \( 2^j k \).
The expressions for computing signal Energy and Kurtosis is given in (3) and (4) respectively:

\[ E = \sum_{i=1}^{n} x_i^2 \]  

(3)

where \( E \) is the energy of the signal \( x \) and \( n \) is the length of the signal.

\[ K_j = \frac{1}{n_j} \sum_{i=1}^{n_j} \left( \frac{d_j(i) - \mu_j}{\sigma_j} \right)^4 \]  

(4)

where \( K_j \) is kurtosis for level \( j \), \( d_j(i) \) is the \( i^{\text{th}} \) detail coefficient \( (i = 1 \text{ to } n_j) \), \( n_j \) is the number of detail coefficients in level \( j \), \( \mu_j \) and \( \sigma_j \) are mean and standard deviation respectively.

Fig. 3 and Fig. 4 shows frequency bandwidths of approximation and detailed coefficients of wavelet decomposition and the energy of detailed coefficient (cD2) for different bearing conditions respectively.

Fig. 3 Discrete wavelet decomposition of bearing vibration signal.  

Fig. 4 Energy of detail coefficient cD2 for different bearing conditions.

Detailed coefficients of the DWT contain high-frequency noise components along with some of the characteristic information of the machine fault [11]. Suitable compression or suppression of these components would remove the noise. Suppressed detail coefficients can then be used to reconstruct the original signal along with approximation coefficients by using Inverse Wavelet Transform (IWT), which would be free of noise. It is clear from the Fig. 4 that cD2 coefficient is having the highest energy when compared to other coefficients. Hence in this paper, statistical features were extracted from this dominant wavelet coefficient.

4. Wavelet based denoising

Wavelet based de-noising is a very interesting and important application of wavelets in the processing of signals from condition monitoring. It is very widely adopted in many studies, as it is ideal to extract hidden
diagnostic information and enhance the impulsive components of complex, non-stationary signals with strong background noise. Wavelet thresholding is based on the idea that the energy of the signal is concentrated in a few wavelet coefficients, while the energy of noise spreads throughout all the resulting wavelet coefficients. Similarity between the mother wavelet and the signal to be analysed plays a very important role, making it possible for the signal energy to concentrate in a fewer coefficients and thus it’s choice is critical in the efficiency of the de-noising task [18]. The wavelet based denoising has been able to overcome the limitations of most of the conventional denoising methods. Suppose that a signal of interest $f$ has been corrupted by noise, so that we observe a signal $g$:

$$g(n) = f(n) + \sigma z(n)$$  \hspace{1cm} (5)$$

where $z(n)$ is unit-variance, zero-mean Gaussian white noise. Denoising is a way to recover $f(n)$ from the samples of $g(n)$ as properly as possible [19].

The problem of the strong noise components masking the weak characteristic signals has always posed challenges to the condition monitoring expert. Hence researchers have proposed and tried several wavelet based denoising schemes aiming to denoise the signal so as to increase signal to noise ratio and reduce the root mean square error. Denoising is used for different purposes like image denoising, signal analysis etc. Wavelet based denoising consists of three steps (i) Decomposition of raw signal using Wavelet Transform (WT) to get approximation and detailed coefficients (ii) Suppressing the detailed coefficients by selecting a threshold value and by applying a suitable thresholding rule (iii) Reconstruct the signal by applying inverse WT to original approximation coefficients and suppressed detailed coefficients to get the denoised signal.

Vijay et al. [17] compared Conventional Soft Thresholding (CST) and Modified Soft Thresholding (MST) schemes and inferred that MST is superior when compared to CST. This is due to the fact that MST is continuous, easily differentiable, statistically very reliable and robust. In MST, suppression of the detailed coefficient $y(x)$ is done by the equation (6)

$$y(x) = x \times \frac{1 - e^{-\frac{x^2}{\lambda^2}}}{1 + e^{-\frac{x^2}{\lambda^2}}}$$  \hspace{1cm} (6)$$

where, $\lambda$ is a constant and MST scheme depends on the proper selection of this constant. Hence in this paper raw vibration signals were denoised by MST scheme.

![Raw Normal](image1)

![Denoised Normal](image2)

Fig. 5 (A) Plots of raw and 5(B) MST denoised vibration signals for normal bearing, bearing with IR and OR defect.

Fig. 5(A) shows the raw vibration signal for three conditions of bearing and Fig. 5(B) shows denoised signal using MST scheme. From the plot it is clear that MST denoised signals will effectively represent the bearing conditions with reduced noise.

The signal energy and kurtosis values for the raw and denoised vibration signal for three conditions of bearing are shown in the table1.
Table 1 Energy and Kurtosis values of raw and denoised vibration signals.

<table>
<thead>
<tr>
<th>Sl. No</th>
<th>Bearing condition</th>
<th>$E_{raw}$</th>
<th>$E_{Denoised}$</th>
<th>$K_{raw}$</th>
<th>$K_{Denoised}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Normal</td>
<td>79.429</td>
<td>70.482</td>
<td>3.5950</td>
<td>3.069</td>
</tr>
<tr>
<td>2</td>
<td>Inner Race</td>
<td>193.22</td>
<td>161.04</td>
<td>5.6482</td>
<td>6.7073</td>
</tr>
<tr>
<td>3</td>
<td>Outer Race</td>
<td>796.25</td>
<td>219.408</td>
<td>57.93</td>
<td>430.68</td>
</tr>
</tbody>
</table>

It is clear that kurtosis and energy values for denoised vibration signals are less when compared to raw vibration signals for normal bearing. Also the values of Energy and Kurtosis are high for bearing with IR defect and OR defect when compared to normal bearing for both raw and denoised vibration signals and can be used as an indicator to detect the presence of defects in bearings.

5. Feature extraction

Vibration signal data (250000 \times 1) has been divided into 25 non-overlapping bins with each bin having 10000 data. Features are extracted under two conditions: (a) without denoising (b) with denoising. Seventeen (17) features are extracted from the dominant wavelet coefficient (cD2). This formed a single pattern [16]. Hence, for three conditions of bearing, one load and two speed conditions, a total of 150 patterns (25\times6) are extracted. The feature set matrix consisted of 17 features \times150 patterns. Each feature value is normalized, by dividing each element of the feature by the feature maxima, so as to obtain values between 0 and 1. The patterns of the matrix are thoroughly mixed, out of which 120 patterns (80\%) were used in training data set and the remaining 30 (20\%) patterns in test data set.

6. ANN classifier

An ANN is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. An ANN can be configured for a specific application, such as pattern recognition or data classification, through learning process [7]. Neural Network application consists of two stages: Training stage and testing stage. The network is trained with input data, and then it is tested.

A Multilayer Perceptron (MLP) is a feed forward neural network model that maps sets of input data onto a set of appropriate output. It is a modification of the standard linear perceptron using three or more layers of neurons (nodes) with nonlinear activation functions. Hence, it is more powerful than the perceptron as it can distinguish data that is nonlinearly separable. The basic structure of MLP neural network is shown in Fig. 6. The network consists of an input and an output layer with one or more hidden layers of nonlinearly-activating nodes. Each node in one layer connects with a certain weight to every other node in the following layer. The number of neurons in the input layer is same as number of input features. The network is trained using different algorithms such as Resilient back propagation algorithm (trainrp), Scaled conjugate gradient algorithm (trainscg), Levenberg-Marquardt algorithm (trainlm) etc. [7, 20].

In this work, a binary scheme of classification is used to define the bearing condition at the output of the classifier, namely N (1 0 0), IR (0 1 0), and OR defect (0 0 1) to denote three conditions of the bearing. Only one hidden layer with different numbers of neurons in hidden layer, $n_h = 5, 10, 15, 20, 25, 30, 35, 40, 45$ and $50$ are used. The sigmoid activation function is used in the hidden and the output layer. A mean square error of $10^{-4}$, a minimum gradient of $10^{-10}$, and maximum number of epochs of 1000 are used. The training process would stop if any one of these conditions is met. The initial weights and biases of the network are fixed randomly. The MLPNN has been implemented by using the MATLAB Neural Network Toolbox [21]. The MLPNN has been trained using these training algorithms in this work namely trainbfg, trainscg, and trainlm.
7. Results

The performance of the ANN classifier for raw and denoised vibration signal for different algorithms is shown in table 2 and table 3. The prediction accuracy of the MLP network is based on mean square error (MSE) which is given by equation (7) [21]

\[ \text{MSE} = \frac{1}{Q} \sum_{i=1}^{Q} (y^{(i)} - t^{(i)})^2 \]  

(7)

\( y^{(i)} \) is network output, \( t^{(i)} \) is desired output and \( Q \) is the number of training patterns (input-output pairs). For each input pair, the output of the network \( y^{(i)} \) is compared with the desired output \( t^{(i)} \) by computing the error given by equation (8)

\[ e = y^{(i)} - t^{(i)} \]  

(8)

If the network output value is ±10% of the desired output value then it is correctly classified otherwise it is misclassified.

Table 2 MLP performance on raw vibration signal for different training algorithms.

<table>
<thead>
<tr>
<th>Train algorithm</th>
<th>Epochs</th>
<th>No. Neurons</th>
<th>Error</th>
<th>Accuracy on training data (%)</th>
<th>Accuracy on test data (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>trainbfg</td>
<td>1000</td>
<td>10</td>
<td>0.0054</td>
<td>99.17</td>
<td>86.67</td>
</tr>
<tr>
<td>trainscg</td>
<td>1000</td>
<td>5</td>
<td>0.0072</td>
<td>90.83</td>
<td>60.00</td>
</tr>
<tr>
<td>trainlm</td>
<td>78</td>
<td>5</td>
<td>0.0001</td>
<td>100</td>
<td>83.33</td>
</tr>
</tbody>
</table>

Table 3 MLP performance on denoised vibration signal for different training algorithms.

<table>
<thead>
<tr>
<th>Train algorithm</th>
<th>Epochs</th>
<th>No. Neurons</th>
<th>Error</th>
<th>Accuracy on training data (%)</th>
<th>Accuracy on test data (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>trainbfg</td>
<td>1000</td>
<td>10</td>
<td>0.0054</td>
<td>97.50</td>
<td>93.33</td>
</tr>
<tr>
<td>trainscg</td>
<td>86</td>
<td>15</td>
<td>0.0001</td>
<td>95.83</td>
<td>73.33</td>
</tr>
<tr>
<td>trainlm</td>
<td>86</td>
<td>15</td>
<td>0.0001</td>
<td>100</td>
<td>66.67</td>
</tr>
</tbody>
</table>

Fig. 7 (a) and (b) shows the variation in the accuracy on the test data for different training algorithms with the number of neurons in the hidden layer for raw and denoised vibration signals.
In another study various mother wavelet functions (Db8, Db4, Db44 and Sym10) were used to analyse the denoised vibration signals and their performance has been evaluated using the ANN classifiers. Fig. 9 shows the variation in the accuracy on test data for different training algorithms with the mother wavelet functions.

8. Discussions

The number of neurons, MSE and accuracy on test data are the parameters based on which ANN performance is evaluated. From table 2, it is clear that trainbfg gives the best possible performance with 86.67% accuracy on test data for raw bearing vibration signals when compared to other algorithms. The ANN performance improves considerably when denoised bearing vibration signals were used which is evident from the table 3 with the accuracy on test data as high as 93.33% for trainbfg algorithm. In Fig. 7(a), for different number of neurons in the hidden layer, the accuracy is definitely higher for trainbfg algorithm, when compared to other algorithms. Also in Fig. 7(b), a similar kind of behaviour is observed for denoised vibration signals, but the gap, with respect to other training algorithms is much lesser here, when compared to raw vibration signals. In both the cases, the overall trend that is evident is that as the number of neurons in the hidden layer increases, the accuracy on test data decreases.

From the Fig. 8 it is clear that Db4 provides optimum performance with regard to accuracy on test data with 96.67% for trainbfg algorithm. Hence it is obvious that performance of the ANN classifier improves significantly by varying the mother wavelets for wavelet transformation of the denoised vibration signals and there is considerable improvement in the performance of the classifier when Db4 is used.
9. Conclusion

In this study, vibration signals are decomposed by DWT and features are extracted from the dominant wavelet coefficient for three conditions of bearing namely Normal, defect on Inner Race and defect on Outer Race. The features obtained from raw and denoised vibration signals are used as inputs to the ANN classifier to evaluate its performance. The results showed that ANN performance improved considerably when denoised vibration signals are used when compared to the raw vibration signals. Also when the mother wavelet functions (like Db8, Db44, Db4 and Sym10) were varied to evaluate the performance of the classifier, it has been found that Db4 gives the highest possible performance. Thus it is found that ANN classifier can be effectively used to evaluate the performance of WT for analysing bearing vibration signals.

References