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Intelligent Diagnosis Method for Ball Bearing faults Using Time-Domain Features and Neural Network

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Abstract

Vibration signals resulting from rolling element bearing defects, present a rich content of physical information, the appropriate analysis of which can lead to the clear identification of the nature of the fault. The bearing characteristic frequencies (BCF) contain very little energy, and are usually overwhelmed by noise and higher levels of macro-structural vibrations. They are difficult to find in their frequency spectra when using the common technique of fast fourier transforms (FFT). Therefore, Envelope Detection (ED) has always been used with FFT to identify faults occurring at the BCF. In this paper procedure presents for fault diagnosis of rolling element bearings through artificial neural network (ANN). The characteristic features of time-domain vibration signals of the rotating machinery with normal and defective bearings have been used as inputs to the ANN consisting of input, hidden and output layers. The features are obtained from envelope analysis of the signals. The input layer consists of nodes, one each for root mean square, skewness, kurtosis, standard deviation and combinative feature which called 'comb' of the envelope spectrum of the vibration signals. The results show the effectiveness of the ANN in diagnosis of the machine condition. The proposed procedure requires only a few features extracted from the measured vibration data either directly or with simple preprocessing. The reduced number of inputs leads to faster training requiring far less iterations making the procedure suitable for on-line condition monitoring and diagnostics of machines. Also results show that 'comb' feature is better than other features, because the distance between classes increases considerably with this feature from envelop analysis.

Keywords: envelope; artificial neural network; on-line condition monitoring; bearings.

1. Introduction

Rolling element bearings are widely used in various types of machines ranging from simple electric fans to complex manufacturing facilities. Bearing faults, in fact, are a common cause of machinery failures. Therefore, an effective bearing fault diagnostic technique is critically needed for a wide array of industries for early detection of bearing defects so as to prevent machinery performance degradation and malfunction. Several methods have been proposed in the literature for bearing fault detection. To inspect raw vibration signals, a wide variety of techniques have been introduced that may be categorized into two main groups: classic signal processing and intelligent systems. To make mention of a few, FFT, Wigner-Ville distribution, wavelet are classic signal processing methods [1]-[3]. ANN-based and SVM could be classified as intelligent systems [4]-[6]. Currently, industrial applications of intelligent monitoring systems have been increased by the progress of intelligent systems. Rafiee et al. are applied new wavelet selection method and studied 324 mother wavelet and results shows that db44 has most similar shape across both gear and bearing vibration signals but it is not the proper function for all wavelet-based processing [7]. Kankar et al. have presented two wavelet selection criteria Maximum Energy to Shannon Entropy ratio and Maximum Relative Wavelet Energy to select an appropriate wavelet for feature extraction. They fed four statistical features as input to SVM, ANN, SOM classifiers [8]. Envelope Detection (ED), capable of processing stationary and non-stationary signals, was used for feature extraction [9].

In this paper a methodology is proposed for fault detection. The features are obtained from envelope analysis of the signals are fed as input to artificial neural network (ANN).The input layer consists of nodes, one each for root mean square, skewness, kurtosis, standard deviation and combinative feature which called 'comb' of the envelope spectrum of the vibration signals. The results show the effectiveness of the ANN in diagnosis of the machine condition. The proposed procedure requires only a few features extracted from the measured vibration data either directly or with simple pre-processing. The reduced number of inputs leads to faster training requiring far less iterations making the procedure suitable for on-line condition monitoring and diagnostics of machines. Also results show that 'comb' feature is better than other features, because the distance between classes increases considerably with this feature from envelop analysis.

2. Theory of Ann

2.1 Review of machine learning techniques

Machine learning is an approach of using examples (data) to synthesize programs. In the particular case when the examples are input/output pairs, it is called supervised learning. In a case, where there are no output values and the learning task is to gain some understanding of the process that generated the data, this type of learning is said to be unsupervised. In the present study, the back propagation (BP) algorithm is considered. Pattern recognition and classification using machine learning techniques are described here [10].

2.2 Supervised Learning

Artificial neural network is an interconnected group of artificial neurons. These neurons use a mathematical or computational model for information processing. ANN is an adaptive system that changes its structure based on information that flows through the network [10]. A single neuron consists of synapses, adder and activation function. Bias is an external parameter of neural network. Model of a neuron can be represented by following mathematical model.

$$y_k = \phi(\sum_{i=1}^{p} w_{ki} x_i + w_{k0}) . \tag{1}$$

Input vector comprises of 'p' inputs multiplied by their respective synaptic weights, and sum off all weighted inputs. A threshold (bias) is used with constant input. Activation function converts general output into a limited range of output. Intelligence of neural network lies in the weights between neurons. BP algorithm is used as learning algorithm for calculating synaptic weights.

3. Signal processing task

3.1 Experimental setup and data acquisition

The bearing vibration signal of four types of bearing conditions were extracted from Case Western Reserve University bearing test data center [11]. The ball bearings used in the experiment are installed in a motor driven mechanical system as shown in fig. 1.

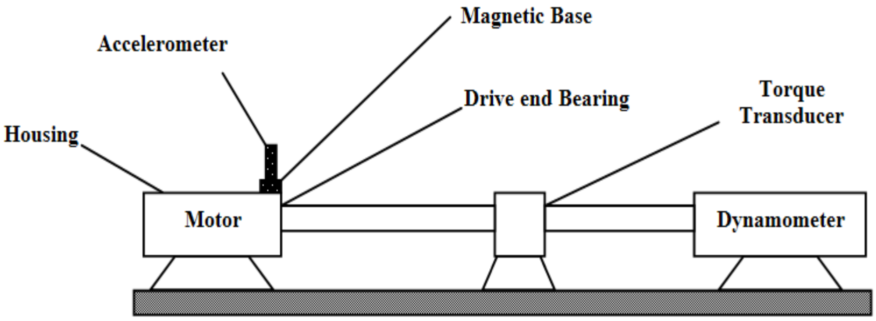

Figure 1. **Schematic of Experiment System.**

The test stand is made up of a 2 hp Reliance Electric motor, a torque transducer-encoder, a dynamometer, and control electronics. Vibration signals from the bearings were acquired using an accelerometer that was attached to motor housing at the drive end of the motor with a magnetic base.

Single point faults with diameter 0.007 inches were introduced separately at inner race, ball, and outer race of the drive end and bearings, using electro-discharge machining. The motor speed and load is 1797 rpm and 2 hp respectively. The bearing vibration signals for normal condition and three fault conditions were collected using a 16 DAT recorder with a sampling frequency of 12,000 Hz and were post-processed in a matlab environment.

Each vibration signal condition was cut into 30 samples with the length 3,600 points. Then, the first 20 samples of each vibration signal condition were used to training and modeling, and the rest were kept for testing the ANNs. Also raw signals of each defect for one sample (3,600 points) are shown in fig. 2.

3.2 Envelope detection (ED)

The faulty features can be detected by Hilbert envelope spectrum analysis of raw signal in time-domain. The high-frequency vibration amplitude of operating bearings with local faults was modulated by pulse force. In order to obtain the fault characteristic, the vibration signals of rolling element bearings need to demodulate. Defining a series x(t) of raw signal, we can have its Hilbert transform as

$$H[x(t)] = \frac{1}{\pi}\int_{-\infty}^{+\infty} \frac{x(t)}{t-\tau} d\tau \ . \qquad (2)$$

Then the Hilbert envelope spectrum can be given as

$$h[s] = \int_{-\infty}^{+\infty} \sqrt{x^2(t) + H^2[x(t)]} d\tau \ . \qquad (3)$$

Fig. 3 showed the Hilbert envelope spectrum analysis of raw signal of the most salient with different operating conditions.

3.3 Feature extraction based envelope

Root mean square (RMS) value, crest factor, kurtosis, skewness, standard deviation, etc., are most commonly used statistical measures used for fault diagnosis of rolling element bearings. Statistical moments like kurtosis, skewness and standard deviation are descriptors of the shape of the amplitude distribution of vibration data collected from a bearing, and have some advantages over traditional time and frequency analysis, such as its lower sensitivity to the variations of load and speed, the analysis of the condition monitoring results is easy and convenient, and no precious history of the bearing life is required for assessing the bearing condition. When selecting certain

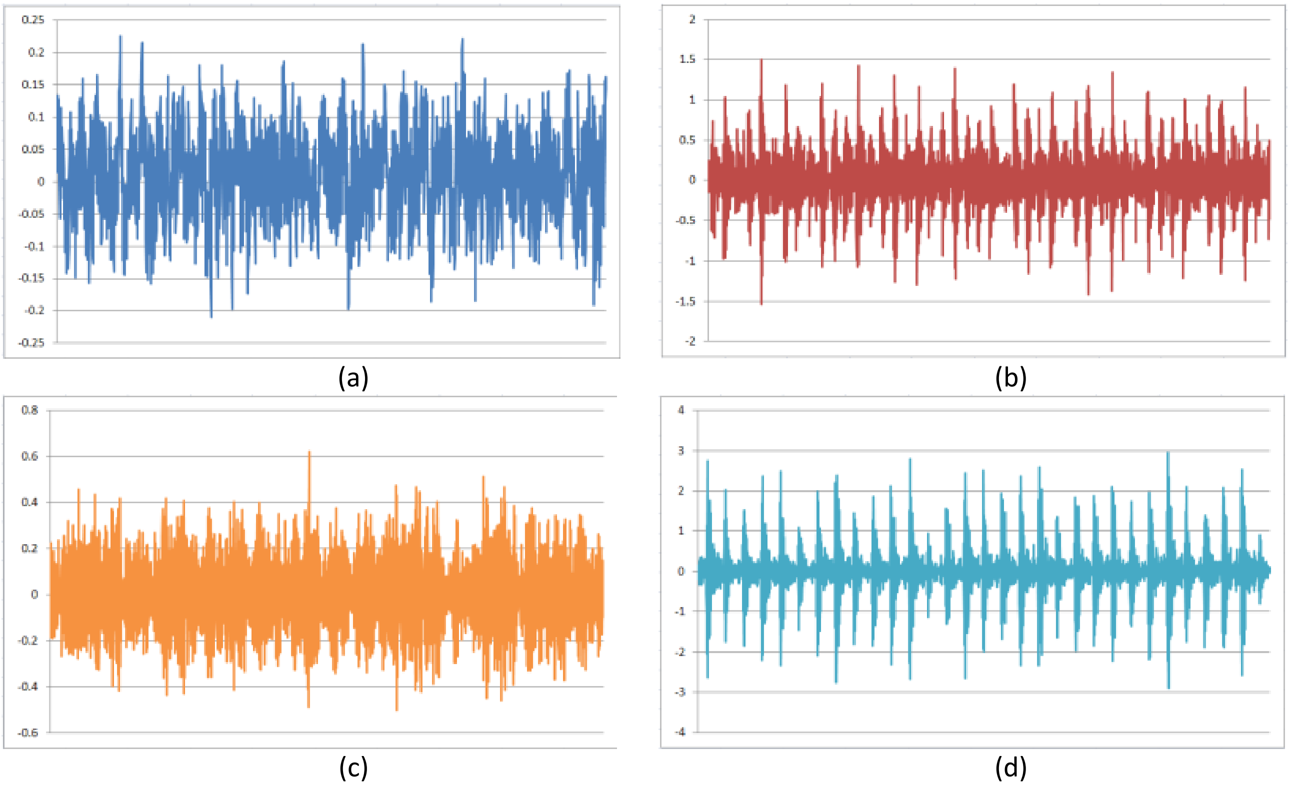

Figure 2. **Vibration signals acquired from four states of bearing. (a) Normal bearings (NB), (b) Outer race fault (ORF), (c) Inner race fault (IRF), (d) Ball fault (BF).**

normalized statistical moments to monitor the bearing condition, we usually need to consider two most essential characteristics, i.e. sensitivity and robustness. By rectifying the signal, Honarvar and Martin compared the third moment, skewness, of the rectified data to kurtosis, and found that this third moment has better characteristics than kurtosis [10]. In present paper, author's use statistical moments like RMS, kurtosis, skewness, standard deviation and *Comb* as features to effectively indicate early faults occurring in rolling element bearing. These statistical features are briefly described as follows.

Kurtosis: A statistical measure used to describe the distribution of observed data around the mean. Kurtosis is defined as the degree to which a statistical frequency curve is peaked.

$$Kurtosis = \left\{ \frac{n(n+1)}{(n-1)(n-2)(n-3)} \sum \left(\frac{x_i - \bar{x}}{s} \right)^4 \right\} - \frac{3(n-1)^2}{(n-2)(n-3)}. \tag{4}$$

Skewness: Skewness characterizes the degree of asymmetry of distribution around its mean. Skewness can be negative or positive.

$$Skewness = \frac{n}{(n-1)(n-2)} \sum \left(\frac{x_i - \bar{x}}{s} \right)^3. \tag{5}$$

Standard deviation: Standard deviation is measure of energy content in the vibration signal

$$Std = \sqrt{\frac{n\sum x^2 - \left(\sum x\right)^2}{n\left(n-1\right)}} . \tag{6}$$

Comb: Combinative feature is measure of combine of signal power (RMS) and Statistical distribution (Std) content in the vibration signal

$$Comb = \exp(Std)^{\frac{Std}{RMS}} . \tag{7}$$

which RMS is root mean square of the signal.

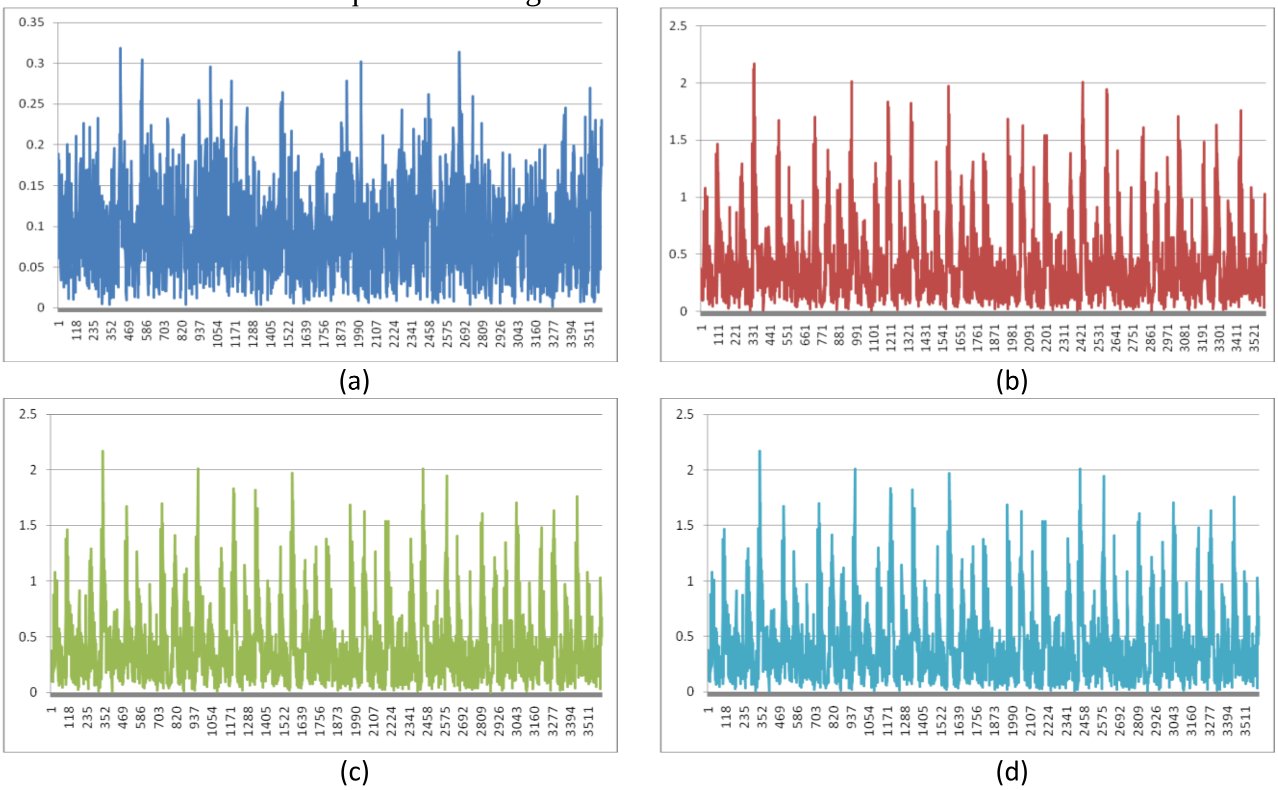

Figure 2. **Envelope analysis of raw signal in four conditions. (a) Normal bearings (NB), (b) Outer race fault (ORF), (c) Inner race fault (IRF), (d) Ball fault (BF).**

Table 1. Effects of input signals identification of machine condition with four feature based on Envelope Analysis using ANN (sets: Comb(1), Kurtosis(2), Skewness(3), Std(4))

Case no.	Feature set	Raw signal	Envelope
1	*1*	64.8%	98.4%
2	*2*	80.3%	75.6%
3	*3*	93.5%	86.1%
4	*4*	94.5%	81.65%
5	*1,2*	85.45%	68.3%
6	*1,3*	87.5%	60.2%
7	*1,4*	76.3%	78.2%
8	*2,3*	68.5%	86.7%
9	*2,4*	70.1%	76.4%
10	*3,4*	83.7%	79.7%
11	*1,2,3*	75.00%	73.3%
12	*1,2,4*	97.2%	99.9%
13	*1,3,4*	83.5%	96.5%
14	*2,3,4*	92.1%	87.3%
15	*1,2,3,4*	94.2%	96.2%

4. Results and discussion

The features which described in pervious section extracted raw time domain signal and envelop analysis used as inputs to the ANN and the results obtained are shown in Table 1. Total 15 set states according to Eq. (8) were considered.

$$\sum_{n=1,F=4}^{4} \frac{F!}{(F-n)!n!} = 15. \tag{8}$$

where 'F' is the number of features.

The training success for each was 100%. The results are shown that, case no.12 is appropriate feature set for fault diagnosis. Table I shows accuracy associated with each analysis for faults classification. The correctly classified using Envelope for ANN is 99.9%.

To show the efficiency of the selected features and the methodology, a comparison between the current work and some published literatures has been shown in Table 2.

Table 2. A compressive study between the present work and some recent publications.

	Refrences				
	Paya et al. [11]	Abbasion et al. [12]	Kankar et al. [8]	Rafee et al. [7]	Peresent work
Objects	Bearings and gears	Rolling element bearings	Rolling element bearings	Bearings and gears	Rolling element bearings
Defects considered	Defects on inner race of bearing and gear tooth irregularity	Bearing looseness, defects in rolling elements and bearing raceways	Spall in inner race, outer race,rolling element and combined component defects	For gear broken-tooth gear,slight-worn gear and medium-worn gear, For bearing defects, inner race fault ,ball fault , and cage fault	inner race fault ,ball fault , and outer race fault
Techniques used for vibration signature analysis	D4 wavelet	Meyer wavelet	Meyer, Coiflet5, Symlet2, Gaussian, complex Morlet and Shannon wavelets	324 mother wavelet, Haar, Daubechies, Symlet, Coiflet, Gaussian, Morlet, complex Morlet, Mexican hat, bio-orthogonal, reverse bio-orthogonal, Meyer, discrete approximation of Meyer, complex Gaussian, Shannon, and frequency B-spline wavelets	Envelope Analysis
Features considered	10 wavelet numbers indicating both time and frequency and their 10 corresponding amplitudes	Fundamental cage frequency (Fc), ball pass inner raceway frequency (FBPI), ball pass outer raceway frequency (FBPO) and ball rotational frequency (FB)	Statistical features namely, kurtosis, skewness and standard deviation from wavelet coefficients corresponding to scale maximizing Energy to Shannon entropy ratio or Relative Wavelet Energy	Statistical features namely, standard deviation, variance, kurtosis, and fourth central moment of continuous wavelet coefficients of synchronized vibration signals (CWC-SVS).	Statistical features namely, kurtosis, skewness, standard deviation,,RMS, innovative feature called 'comb'
Classifier used	Artificial neural networks	Support vector machine	Support vector machines, artificial neural networks, self-organizing maps	Artificial neural networks	Back propagation neural network
Classifier efficiencies	96%	100%	Best efficiency obtained using test set with Meyer wavelet and SVM – 98.6667%	NA	Best efficiency obtained using test set with BP – 99.9%

5. Conclusion

This study presents a methodology for detection of bearing faults by classifying them using back propagation (BP) ANN this methodology incorporates most appropriate features, which are extracted from Envelop analysis of raw vibration signals. Also innovative Feature is proposed. The results show the potential application of proposed methodology with machine learning techniques for the development of on-line fault diagnosis systems for machine condition.

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