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Implementing discrete wavelet transform and artificial neural networks for acoustic condition monitoring of gearbox

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ABSTRACT

In present research, acoustic signals from gearbox of Massey Ferguson 285 are used for fault diagnosis of gears. Worn tooth face gear and broken tooth gear are studied as two common faults in gear-sets. Signal processing on acquired acoustic signals are done using wavelet transform. Decomposition is made using discrete wavelet transform (DWT) in four levels and using Db4 mother wavelet. Desired information from DWT decomposition is provided by applying some functions on DWT outputs. The investigated data set is fed into feed forward back-propagation neural network to classify the gears status. Two layer networks are trained and tested with separate data sets and using variable hidden layer neurons count. Results show that 100% performance is gained by a network with two neurons in hidden layer.

Introduction

Reliability has always been an important aspect in the assessment of industrial products. By development of technology, cost of time-based preventive maintenance increased thus, new approaches in maintenance such as condition-based maintenance (CBM) developed[1]. Machine condition monitoring has long been accepted as one of the most effective and cost-efficient approaches to avoid catastrophic failures of machines[2]. Precise and high accuracy assessment of machinery condition results in fewer stoppages and better product quality and reduce maintenance costs for plants. Thus, they can optimize workforce and implement more efficient operations[3].

Rotating machineries are used considerably utilized in the manufacturing of industrial products. Gearboxes as a key rotating motion transmission component, plays a critical role in industrial applications. Therefore, attracts research interests in condition monitoring and fault diagnosis of this equipment. Importance of gears and bearings in condition monitoring of the machine is undeniable, thus, processing and analysis of acoustic and vibration signals of the gearbox gears and bearings is the common way of extracting reliable representative of the gearbox condition [4,5,6].

Many signal processing techniques have been used for fault diagnosis, so far. Among this time, FFT is widely used in fault detection purpose. Unfortunately, FFT based techniques can not result in proper results for non-stationary signals, and by spotting that these non-stationary behaviors which could be created by environmental causes, contain reach information about machine faults. Therefor, it is important to analyze the non-stationary signals. Due to disadvantages of FFT analysis, Time-Frequency analysis methods are the most popular techniques for processing non-stationary signals. Some of common time-frequency methods are Wigner-Ville distribution (WVD), Short Fourier Transform (STFT) and Wavelet Transform (WT).

Artificial intelligent systems are widely and successfully used for classification and fault diagnosis. These techniques such as Artificial Neural Networks (ANN) and Fuzzy logic are developed to mimic humans in decision-making and recognition. Due to this development, these AI methods are investigated in several researches. Kong and Chan used a combined method for fault diagnosis of triplex pump based on wavelet transform, fuzzy logic and neural networks[7]. In 2009, Chang et al, implemented probability neural networks for machinery fault classification[8]. In 2010, Jian-Da Wu and Jian-Ji Chan, identified faulted gear in a gear-set by using two types of neural networks[9]. Omid, 2010, used Fuzzy logic for a sorting and classification purpose[10].

In present study, acoustic signals of MF285 gearbox are decomposed by discrete wavelet (Db4) in fourth level. Twenty-five functions are applied into approximation and details coefficient for data mining. Processed data are fed into neural networks with different topologies where this variation are made by using several neurons count in hidden layer.

Experimental Setup

The experimental setup consists of a Massey Ferguson 285 gearbox mounted on a test bed and 4kW two-pole three-phase electromotor that provides drive power using belt transmission. The three-speed transmission gearbox has 1st, 2nd, 3rd and reverse crash type gears and no synchro-meshed gears included. Three states of health are studied for first gear. Following states are faults classes that are initialized on instances of gears: "Worn" tooth face and "Broken" states Broken state is prepared by removing over 50% of tooth body and Worn class by wearing tip of tooth head.

Every single instance of gears is mounted inside gearbox and its acoustic emission signals acquired while gearbox operating in target gear.

Data Acquisition

Three different condition gears are installed inside the gearbox simultaneously and system is set to drive on 1300 RPM.

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Acoustic emitted signals of gears in every condition are recorded by a dynamic microphone which is placed perpendicularly afront of tail side of the gearbox while facing the biggest original orifice of the body. Using this origin, sharper and non-decayed acoustic data is gained and the need of removing gearbox bonnet is solved. These signals are transferred into Macintosh computer by an M-Audio Fast Track USB interface and recorded with 44.1 kHz sampling rate and 24-bit depth.

Signal Processing

Generally, the acoustic and vibration machinery signals can be implemented for fault classification of rotary systems. Several signal processing techniques are developed during recent years to analyze these raw signals in time or frequency domains. Wavelet transform is a conventional time-frequency domain signal analyzer that uses oscillating functions as window functions. This series of functions, that usually called mother wavelets, have different frequencies to deal with transient signals in different time intervals[9]. Wavelet is useful for the transient nature of non-stationary signal[11]. Continues wavelet transform (CWT) decomposes signal in both domain and frequency domains simultaneously, CWT is defined as:

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

In CWT, a and t represent the scale and translation parameters, ψ represents mother wavelet and ψ^{*} is the complex conjugate of ψ [12]. Calculation 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) [13]. On the other hand, DWT is the discrete form of CWT.

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

Where a and t represent 2_j and 2_{jk}, respectively. 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 lower-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 used 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 is follow:

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

Where A_j and D_j approximation and detail of the signal at level J^{th} respectively. Fourth member of discrete wavelets Daubechies family (Db4) is selected as mother wavelet and decomposition is done in four levels.

Feature Extraction

Wavelet coefficients could not directly used as inputs of classifier and a post process stage is needed to prepare data for classifier. This process is usually called feature extraction. Many researches declared the use of wavelet transform for feature extraction from raw signals. This could be described by the nature of wavelets where it could extract significant time-frequency information from signals, which could be called feature extraction especially for energy feature that has a specific value. But coefficients are arrays and feeding the huge amount of data into classifier makes the classification more complex and significantly decrease correct classification ratio. To avoid this disadvantage, the feature extraction stage, takes out significant parameters of the wavelet coefficients remarkably reduce data set size. Investigated data from this stage is adequate for classification. Based on this theory, 25 different functions applied to approximation and detail signals which most of theme are simple statistical parameters. Additionally energy feature of wavelet decomposition for all levels is used as another extracted feature. By gathering all features together 130 features constitute input vectors.

Where A_j and D_j approximation and detail of the signal at level J^{th} respectively. Fourth member of discrete wavelets Daubechies family (Db4) is selected as mother wavelet and decomposition is done in four levels. This process is done on every sample. Figure 2 shows decomposition of one sample.

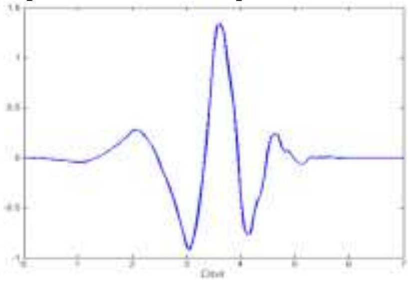

Figure 1. Db4 mother wavelet

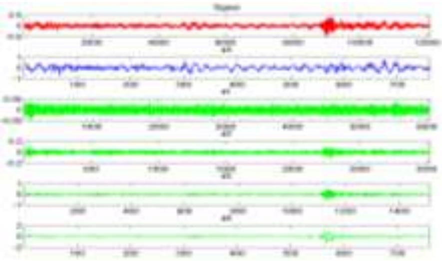

Figure 2. Four level Decomposition

Neural Network

Fault diagnosis in current study is done using two layers feed forward back-propagation networks. Outputs layer of all networks consist of three neurons, this is due to defining output in data set as three columns matrix having 0-1 digits to define desired class. This means 0-1-0 output is related to second class. Using this output method turns classification to a pattern recognition problem and based on previous studies, in pattern recognition problems, Resilient Back-propagation (RP-trainrp) training algorithm has the best performance in comparison to the other training methods in both case of time-memory consumption and mean square error of training. Input layer neurons are defined by features count. The most important layer of networks is middle layer (hidden 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. This set of nine networks generated by training with train set and simultaneously simulated by test sets. Using test sets has the advantage of preparing a real decision condition for generated classifier to perform a performance exam with new arrival data.

Simulation results of test data set show that, every nine structure of neural networks gained 100% performance. This shows that using enough and correct features could will result in strong inputs for classifier and increase the performance of it. Gaining maximum performance makes network structure the indicator for selecting the best network. Based on this theory the most simple network structure with only two neurons in hidden layer and 130x2x3 structure is the best network.

Discussion

Current paper shows that acoustic signals could be reliable for condition monitoring of rotary systems like gearbox. The technique presented in current paper could be used for classification in more classes and for other equipment. same performance of different networks shows that quality of classifier input vectors is more important than it's structure.

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