Neurocomputing 110 (2013) 9–17

Contents lists available at SciVerse ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom

Fault diagnosis of rolling element bearing using cyclic autocorrelation and wavelet transform

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ARTICLE INFO

Article history:
Received 13 October 2011
Received in revised form
15 November 2012
Accepted 17 November 2012
Communicated by J. Zhang
Available online 9 February 2013

Keywords:
Cyclostationarity
Cyclic autocorrelation
Energy to Shannon Entropy ratio
Wavelets
Support vector machine (SVM)
Artificial neural network (ANN)
Self-organizing maps (SOM)

ABSTRACT

Fault diagnosis of bearings under localized defects is essential in the design of high performance rotor bearing system. Traditionally, fault diagnosis of rolling element bearings is carried out performed by the use of signal processing methods, which assume statistically stationary signal features. This paper presents a feature-recognition system for rolling element bearings fault diagnosis, which utilizes cyclic autocorrelation of raw vibration signals. Cyclostationary analysis of non-stationary signals clearly indicates the appearance of several distinct modulating frequencies. The coefficients of wavelet transform are calculated using six different base wavelets, after calculating cyclic autocorrelation of vibration signals. The base wavelet that maximizes the Energy to Shannon Entropy ratio is selected to extract statistical features from wavelet coefficients. Finally, a comparative study is carried out with the calculated statistical features as input to soft computing techniques. Three soft computing techniques are used for faults classifications, out of which two are supervised techniques i.e. Support vector machine, Artificial Neural Network and other one is an unsupervised technique i.e. Self-Organizing Maps. The Complex Gaussian wavelet is selected based on maximum Energy to Shannon Entropy ratio. The results show that the support vector machine identifies the fault categories of rolling element bearing more accurately and has a better diagnosis performance.

1. Introduction

Rolling element bearings are used in a wide variety of rotating machineries from small hand-held devices to heavy duty industrial systems and are primary cause of breakdowns in these machines. Condition monitoring of rolling element bearings using vibration signature analysis is most commonly used to prevent breakdowns in machinery. To analyze vibration signals, different techniques such as time, frequency and time-frequency domain are extensively used. Most methods used for fault diagnosis of rolling element bearings consider the signal statistical properties as stationary like demodulation or enveloping method. The complex and non-stationary vibration signals with a large amount of noise make the bearing defects very difficult to detect by conventional methods. During last few years, vibration signals obtained from rotating machines are modeled as cyclostationary. Cyclostationary analysis assumes periodically time-varying statistics [1,2]. Various application areas of cyclostationary analysis in mechanical engineering include gears [2–5], rolling element bearings [6–9], IC engines [10,11] etc. Antoni et al. [12] have proposed a methodology to model rotating machine signals as cyclostationary processes.

The wavelet transform method has been proposed by some researchers [13–19] to extract very weak signals for which FFT becomes futile. Their property of being localized in time (space) as well as scale (frequency) makes them useful for non-stationary signals. This provides a time-scale map of a signal, enabling the extraction of features that vary in time. The adaptive time–frequency resolution makes it superior vis-à-vis FFT. The effectiveness of wavelet-based features for fault diagnosis of gears using support vector machines (SVM) and proximal support vector machines (PSVM) has been revealed by Saravanan et al. [13]. Rafiee et al. [14] have proposed a technique for selecting mother wavelet function using an intelligent fault diagnosis system. The type of gear failures of a complex gearbox system are identified using genetic algorithm and artificial neural networks.

Kankar et al. [15–17] have paper presented a methodology for fault diagnosis of ball bearings having localized defects on the various bearing components using wavelet-based feature extraction. In present paper, fault diagnosis methodology presented earlier [17] is further extended by considering signal as cyclostationary in nature which is more realistic. A feature-recognition

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http://dx.doi.org/10.1016/j.neucom.2012.11.012

Nomenclature

b	Bias or threshold
$C_{n,i}$	i^{th} wavelet coefficient of n^{th} scale
$E(n)$	Energy of n^{th} scale
$E[]$	Expected value
$f(t)$	Signal
f'	Mean value of population
n	Scale number
$R_f(t,\tau)$	Autocorrelation function
$R_f^{\alpha}(t,\tau)$	Cyclic autocorrelation function
$S_{entropy}(n)$	Shannon Entropy of n^{th} scale
$W(\lambda)$	Lagrange function
w_{jk}	Synaptic weight between hidden and output layer
x_{pi}	i^{th} input of the p^{th} input vector
y_k	Output of k^{th} neuron
α	Cyclic frequency
λ_i	Lagrange multipliers
σ_x	Standard deviation
τ	Time lag
ξ_i	The distance between the margin and the examples x_i that lying on the wrong side of the margin
ω_{bpfi}	Ball passage frequency on the inner race
ω_{bpfo}	Ball passage frequency on the outer race
ω_{bsf}	Ball spin frequency
ω_{cage}	Cage frequency
ω_{in}	Rotational frequency of inner race
$\|w\|^{-2}$	Geometrical margin $\zeta(n)$
$\zeta(n)$	Energy to Shannon Entropy ratio of n^{th} scale

system is presented for rolling element bearings fault diagnosis, which utilizes cyclic autocorrelation and wavelet coefficients. Cyclic auto-correlated vibration signals (CAVS) are obtained for healthy and faulty bearing conditions from raw vibration signals. The signals obtained using cyclic autocorrelation are divided into 2^7 sub-signals i.e. 128 scales in seventh level of decomposition, which converted the complex vibration signals into simplified signals with more resolution in time and frequency domains. Six different wavelets are considered each with 128 scales, first three from real valued (Meyer, Coiflet5 and Symlet2) and the other three from complex valued (complex Gaussian, complex Morlet and Shannon). In order to select the best base wavelet for rolling element bearings fault diagnosis, Energy to Shannon Entropy ratio for each wavelet is calculated. Then statistical features are calculated from wavelet coefficients and fed as input along with degree of cyclostationary, loader condition and rotor speed to soft computing techniques i.e. Artificial Neural Network (ANN), SVM and Self-Organizing maps (SOM). The diagnosis results validate the effectiveness of the proposed approach.

2. Review of soft computing techniques

Soft computing is an approach of using examples (data) to synthesize programs. In the present study, the two supervised soft computing techniques are considered i.e. ANN and SVM. Pattern recognition and classification using soft computing techniques are described here [20,21].

2.1. Artificial neural network

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 [20].

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

$$y_k = \varphi\left(\sum_{i=1}^{p} w_{ki}x_i + w_{k0}\right) \tag{1}$$

Input vector comprising 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 output into a limited range output. Intelligence of neural network lies in the weights between neurons. Back Propagation (BP) algorithm is most widely used as learning algorithm for calculating synaptic weights.

2.2. Support vector machine

SVM is a supervised machine learning method based on the statistical learning theory. It is a useful method for classification and regression in small-sample cases such as fault diagnosis. In this method, a boundary is placed between the two different classes and orientates it in such way that the margin is maximized, which results in least generalization error. The nearest data points that used to define the margin are called *Support Vectors*. This is implemented by reducing it to a convex optimization problem: minimizing a quadratic function under linear inequality constraints [21]. A training sample set $\{(x_i,y_i)\}$; $i=1$ to N is considered, where N is total number of samples. The hyperplane $f(x)=0$ that separates the given data can be obtained as a solution to the following optimization problem

$$\text{Minimize } \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{N}\xi_i \tag{2}$$

$$\text{Subject to } \begin{cases} y_i(w^T x_i + b) \geq 1 - \xi_i \\ \xi_i \geq 0, \quad i = 1,\ 2,\ \ldots,\ N \end{cases} \tag{3}$$

where C is a constant representing error penalty. Rewriting the above optimization problem in terms of Lagrange multipliers, leads to the problem

$$\text{Maximize } W(\lambda) = \sum_{i=1}^{N}\lambda_i - \frac{1}{2}\sum_{i,j=1}^{N} y_i y_j \lambda_i \lambda_j (x_i.x_j) \tag{4}$$

$$\text{Subject to } \begin{cases} 0 \leq \lambda_i \leq C \\ \sum_{i=1}^{N}\lambda_i y_i = 0, \quad i = 1,\ 2,\ \ldots,\ N \end{cases} \tag{5}$$

The Sequential Minimal Optimization (SMO) algorithm gives an efficient way of solving the dual problem arising from the derivation of the SVM. SMO decomposes the overall quadratic programming problem into quadratic programming sub-problems.

2.3. Self-organizing maps (SOM)

Self-organizing maps are special class of ANN and are based on competitive learning. In self-organizing maps, the neurons are placed at the nodes of a lattice that is usually one or two dimensional. The neurons become selectively tuned to various input patterns or classes of input patterns in the course of a