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Bearing damage assessment using Jensen-Rényi Divergence based on EEMD

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ABSTRACT

An Ensemble Empirical Mode Decomposition (EEMD) and Jensen Rényi divergence (JRD) based methodology is proposed for the degradation assessment of rolling element bearings using vibration data. The EEMD decomposes vibration signals into a set of intrinsic mode functions (IMFs). A systematic methodology to select IMFs that are sensitive and closely related to the fault is proposed in the paper. The change in probability distribution of the energies of the sensitive IMFs is measured through JRD which acts as a damage identification parameter. Evaluation of JRD with sensitive IMFs makes it largely unaffected by change/fluctuations in operating conditions. Further, an algorithm based on Chebyshev's inequality is applied to JRD to identify exact points of change in bearing health and remove outliers. The identified change points are investigated for fault classification as possible locations where specific defect initiation could have taken place. For fault classification, two new parameters are proposed: 'α value' and Probable Fault Index, which together classify the fault. To standardize the degradation process, a Confidence Value parameter is proposed to quantify the bearing degradation value in a range of zero to unity. A simulation study is first carried out to demonstrate the robustness of the proposed JRD parameter under variable operating conditions of load and speed. The proposed methodology is then validated on experimental data (seeded defect data and accelerated bearing life test data). The first validation on two different vibration datasets (inner/outer) obtained from seeded defect experiments demonstrate the effectiveness of JRD parameter in detecting a change in health state as the severity of fault changes. The second validation is on two accelerated life tests. The results demonstrate the proposed approach as a potential tool for bearing performance degradation assessment.

1. Introduction

Rolling element bearing forms an integral and vital part of any modern rotating machinery. Over a period of time due to variety of reasons faults may develop in them that may cause overheating, friction torque, increased clearance leading to drop in performance and if undetected can cause breakdown. Based on vibration data, a number of signal processing techniques in time domain, frequency domain and time-frequency domain have been proposed in the past for an early and accurate fault detection [1]. However, the traditional methods can have some drawbacks and limitations that hinder the development of a robust online bearing

Abbreviations: BDF, Ball Defect Frequency; CV, Confidence Value; EMD, Empirical Mode decomposition; EEMD, Ensemble Empirical Mode Decomposition; FFT, Fast Fourier Transform; IMFs, Intrinsic Mode Function; IRDF, Inner Race Defect Frequency; JRD, Jensen-Rényi divergence; ORDF, Outer Race Defect Frequency; PFI, Probable Fault Index; SNR, Signal to Noise Ratio; WPD, Wavelet Packet Decomposition

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Nomenclature

a	Scaling parameter to evaluate confidence value
$a(t)$	Envelope signal
A_m	Amplitude of the mth harmonic of rotational speed in healthy signal
$c_i(t)$	ith IMF of a signal
d_o	Magnitude of the impulse or amplitude level of defect
$d(t)$	Impulse function
$D_{JR_\alpha^\omega}$	Jensen-Rényi divergence
E	Total signal energy
E_i	Energy of ith IMF
f	Frequency
f_{inner}	Characteristic inner race defect frequency
f_{outer}	Characteristic outer race defect frequency
f_s	Shaft rotational frequency
$H[.]$	Hilbert transform of a signal
K	Number of standard deviations to be considered in Chebyshev's inequality
M	Number of points to be considered to evaluate mean for removing outlier in Z-statistics
$n(t)$	White Gaussian Noise
p	Probability distribution
p_i	percent of energy of ith IMF
q_{inner}	Applied load on the shaft in case of inner race defect
q_{mean}	Applied mean radial load on the shaft
q_{outer}	Applied load on the shaft in case of outer race defect
$q_o(t)$	Applied radial load on the shaft
$q_{unbalance}$	Unbalance force on the shaft
q_v	Random variation of the load
Q	Consecutive data points to be considered to declare change in health of a bearing in Z-statistics
$r_n(t)$	Residual function of EEMD
$R(r,k)$	Time deviation from the expected period of impulse repetition
$R_\alpha(p)$	Rényi entropy
T_d	reciprocal of corresponding bearing defect frequency
T_{do}	Modified T_d to account for speed variation
$x(t)$	vibration signal in time domain
$x_H(t)$	simulated healthy vibration signal in time domain
$z(t)$	analytic signal
α	Rényi entropy exponent
α value	parameter extracted from EEMD envelope spectrum of IMF
β_n	Sensitivity index of IMFs
$\delta(t)$	Dirac delta function
ε	load distribution factor
σ	Standard Deviation
μ	Mean of a distribution
ψ_n	Pearson's correlation coefficient between original signal and nth IMF
$\pi_1, \pi_2 \ldots .\pi_n$	weights assigned to distributions in Jensen-Rényi divergence
$\theta_{\max}$	angle limiting the load zone

degradation assessment tool. For example, in practice whenever data is acquired over the entire life span of a bearing, the signals are usually exposed to interference by the effect of background noise, presence of outliers, unexpected variation in operating parameters such as load variation and speed fluctuation. It can become challenging to accurately assess the bearing health status over its lifetime and timely forewarning of failure. The accurate estimation of current health status may reduce economic losses, decrease production downtime and improve efficiency.

Many researchers have attempted to address this problem in the past. Enough literature on variety of fault features is available in the field of bearing degradation assessment. Different features are sensitive to different faults and degradation severity [2]. Statistical moments such as RMS and kurtosis have been frequently used in many works as features for machine health condition monitoring [3,4]. Qiu et al. [5] and Peter et al. [6] showed that the sensitivity of the RMS feature, in terms of identifying an incipient defect, is very low. Gebraeel et al. [7] chose the average of the amplitudes of the defective frequency and its first six harmonics, as the degradation index over the full cycle life of a bearing. However, it is difficult to detect and track the weak signals at an early stage using only time domain and frequency domain parameters [8].

Qiu et al. [5] developed a robust degradation assessment method based on optimal wavelet filter and self-organizing map (SOM). Huang et al. [9] further predicted the degradation condition using SOM and back propagation neural network on the basis of the methodology given by Qiu et al. [5]. Pan et al. [10] proposed a methodology for bearing performance assessment based on an improved wavelet packet-support vector data description. Suggesting further improvements in the past work, Pan et al. [2] proposed a new health assessment index based on lifting wavelet packet decomposition and fuzzy c-means. Pan et al. [11] proposed spectral entropy as a health index and the results of both simulations and experiments showed that spectral entropy effectively reflects the bearing degradation process. Yu [12,13] proposed dimension reduction and feature extraction approach based on locally preserving projections for bearing degradation assessment, and further quantified the performance of bearings by the integration of the exponential weighted moving average statistic and the negative log likelihood probability based on Gaussian mixture model. He proposed a hybrid-learning-based feature selection method for fault diagnosis and machine health assessment [14]. Mi et al. [15] proposed a method to achieve multi-step bearing degradation prediction based on an improved back propagation neural network model using features extracted by principle component analysis. Wang [16] trained the features extracted from Empirical Mode Decomposition (EMD) using SVM and further used Mahalanobis distance as a fault indicator. Li et al. [17] used autoregressive model to separate the original vibration signal into random parts and deterministic parts and used the energy ratio between the random parts and the original signal as a fault indicator. Hong et al. [18] combined wavelet packet and EMD for feature extraction and derived a confidence value through SOM to assess bearing health states. Shakya et al. [19] applied Chebyshev's inequality to the Mahalanobis distance for online monitoring and damage stage detection for naturally progressing defect. Ali et al. [20] combined traditional statistical features and EMD energy entropy and estimated the degradation condition with the back propagation neural