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Entropy measures for early detection of bearing faults

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HIGHLIGHTS

- We study 12 entropy-based features for monitoring and detection of bearing faults.
- The proposed methodology is tested on two real bearing vibration signal datasets.
- Entropy is shown to be a valuable tool for early detection of anomalies in bearings.

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ABSTRACT

This paper investigates the performance of the 12 entropy-based features for the monitoring and detection of bearing faults. These entropy measures were proposed both in time, frequency and time–frequency domain. Probability mass function (PMF) was extracted from the time waveforms using four different methods: (i) via power spectral density, (ii) via ordinal pattern distribution, (iii) via wavelet packet tree and iv) ensemble empirical mode decomposition. Three different entropy measures were used in the article: (i) Shannon entropy, (ii) Rényi entropy and (iii) Jensen–Rényi divergence. A new bearing produces a vibration time series characterised by random noise without prominent periodic content. As soon as a fault develops, impulses are produced, what excites structural resonances generating a train of impulse responses. As defect grows, it becomes a distributed fault, and then no sharp impulses are generated but rather an amplitude modulated random noise signal. The proposed methodology has been applied to detect bearing faults by the analysis of two real bearing datasets, from run-to-failure experiments. Three bearings that presented different defects in the test (inner race fault, rolling elements fault and outer race fault) were analysed to validate the performance of the entropy-based features. The modified Z-score has been implemented and used as an index to detect changes of the entropy features. The results clearly demonstrate that the proposed approach represents a valuable non-parametric tool for early detection of anomalies in bearings vibration signals.

1. Introduction

Machinery faults generate specific frequency components which can be recorded from sensors installed in a machine to capture anomalous behaviour. The standard procedure to monitor the performance of mechanical components is to analyse

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its corresponding time series, aiming to detect anomalies in its behaviour. The monitoring of a real machine component is not easy and becomes problematic mainly because of (i) load variation, (ii) speed fluctuations and (iii) background noise. Therefore, the direct analysis of the time series by the use of conventional statistical measures, such as mean, root mean square, standard deviation, kurtosis and skewness is not always useful due to the complexity of the signal [1].

Due to the periodic behaviour of the time series coming from rotating machine components, the usual procedure is to transform the signal from time to frequency domain by the application of Fast Fourier Transform (FFT), analyse the most significant peaks in the frequency spectrum and, finally, correlate those peaks with the fault frequencies.

Sometimes, machinery behaviour is non-stationary imposing some difficulties on the use of the FFT procedure. In order to complement FFT when dealing with non-periodic signals, other methods have been proposed, such as the use of information theory based features [2], Fisher Information [3,4], wavelets [5,6], neural networks [7] and many others.

Bearings are one of the most used components in general machinery, and their monitoring is very challenging due to the aforementioned effects. In general, the cost of a bearing is irrelevant compared to the total machine cost, but a simple failure in a bearing component can evolve and cause collateral and catastrophic failures, damaging the whole machine.

Therefore, it is of utmost importance to understand how bearing failures appear and progress, and how they may be identified efficiently as early as possible to allow sufficient time to carry out all the necessary maintenance actions with anticipation.

This work focuses on the evaluation of four different quantifiers based on the entropy, power spectrum entropy (PSE), permutation entropy (PE), wavelet entropy (WE) and ensemble empirical mode decomposition entropy (EEMDE), and one divergence-based quantifier, Jensen–Rényi divergence (JRD). These quantifiers were then applied to real bearing data of a run-to-failure measurement. A similar work has been carried out by Kowalsky et al. [8], who analysed two different approaches for the extraction of the probability mass function (PMF): histograms and Bandt–Pompe methodology and applied the method to the logistic map and a physical model.

The first step of the proposed methodology is the extraction of the PMFs from the time waveforms, and it is presented in Section 2 together with the features used to quantify the bearing status and also the methodology to detect the fault. In Section 3 the data used in the article is characterised. The results and discussions of the application of the proposed approach to the bearing vibration data are presented in Section 4 and, finally, the conclusions are drawn in Section 5.

2. Methodology

In order to calculate the entropy of a given time waveform, it is necessary to obtain its corresponding PMF which characterises the signal at any given moment. In this work we have selected four different PMF extraction methods, studied and identified as adequate for the characterisation of bearing vibration signals. The selected PMF extraction methods characterise the signals in the frequency domain (PSE), time domain (PE), and also in the time–frequency domain (WE and EEMDE).

Entropy quantifies the level of uncertainty of a given time series. Once the PMF of a given time waveform is calculated, one should proceed with the entropy calculation. Here we evaluate two different entropy measures: non-parametric Shannon entropy, and parametric Rényi entropy.

Divergence is a measure of relative distance between a given set of PMFs. For the present, JRD has been used as a potential feature to characterise bearing faults.

The main idea is that when a bearing is healthy, it will produce low amplitude random vibration with a uniform-like PMF and as the fault occurs and progresses some PMF component will be prevalent with a higher probability of occurrence. Thus, for a uniform distribution, entropy measures approach their maximum values (maximum uncertainty), and divergence will approach its minimum value, while for the periodic-like PMF, entropy measures will present the minimum values (minimum uncertainty) and divergence its maximum value.

2.1. Shannon and Rényi entropy

The Shannon entropy [9], defined for a given PMF, $p\left(k\right), k = 1, \ldots, N$, associated with a time series, $x\left(t\right)$, is given by

$$S\left(p\right) = -\sum_{k=1}^{N} p\left(k\right) \log\left(p\left(k\right)\right), \tag{1}$$

where N is the number of bins.

Shannon entropy is a non-parametric measure, and it is well known that it does not have significant sensitivity when dealing with noisy data. For this reason, Rényi entropy [10] has been chosen as another potential entropy measure, given that the α parameter allows specifying where the focus on the PMF lies. For the cases where the focus is on the tail of the PMFs, α should be small and when the focus is on the bulk of probability α must be close to 1 and, in which case Rényi entropy tends to Shannon,

$$R_{\alpha}\left(p\right) = -\frac{1}{1-\alpha} log \sum_{k=1}^{N} p\left(k\right)^{\alpha}. \tag{2}$$