Extreme value statistics for vibration spectra outlier detection

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Abstract

The issue of detecting abnormal vibrations from spectra is tackled in this article, when little is known about the mechanical behavior of the system, or the fault pattern. To do so, an original algorithm relying on the statistics of the maximum of log-periodograms is introduced. Receiver Operator Characteristic (ROC) curves are built and show good performance with bearing deterioration even when little wear is present.

Keywords: fault detection, vibration, rotating machine, bearing, periodogram, maximum, excess, generalized pareto, probabilistic model

1. Introduction

A new algorithm based on Extreme Value Statistics is introduced, to deal with the issue of condition monitoring for rotating machine. The machine rotation speed is supposed constant, and no mechanical model is available.

First, a probabilistic model of a healthy signal is built using a small learning set and the density of an excess value of log-periodograms (see [1]). Secondly, new signals will be compared with this model so as to detect unusual behavior, in the spirit of novelty detection [2]. The performance of the algorithm is evaluated thanks to ROC curves (Receiver Operating Characteristics [3, 3.4]).

Section 2 links our work to related articles in various fields, sec. 3 describes the algorithm, which results are summarized in sec. 4. Sec. 5 concludes this article and discusses its perspectives.

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2. Related work

In Vibratory Health monitoring [4], many methods focus on specific faults, such as rotor/stator contact [5], rotor unbalance, blade defects [6], bearing [7] and gearings defects [8]. However, unexpected problems can occur, whose fault patterns are unknown.

Several authors propose to build a model of normality, for example with neural networks such as Self-Organizing Maps [9, 10, 11]. This approach is sometimes termed *generative*, in contrast with a *discriminative* one [12].

Probabilistic models [2] may also depict normal behavior. For example, a Bayesian approach to normality modelling in jet engine health monitoring has been developped [13, 14, 15]. The authors show that using Extreme Value Theory to model the maxima of order amplitudes increases the robustness of the detection procedure.

So far, these works address the case of a restricted number of shaft order amplitudes, and not the whole periodogram. In sections 3 we discuss an algorithm that belong to the probabilistic generative approach to novelty detection, in the case of vibrations monitoring in the spectral domain where the dimensionality of data is high.

3. Peak-over-threshold statistics for fault detection

The aim of this algorithm is to make the most of EVT in novelty detection -as spearheaded by Tarassenko, Clifton and co-workers [16]- but in the high-dimensional context of vibratory log-periodograms. In these works, the pdf of the maximum of a given statistics is considered instead of the pdf of the statistics itself (e.g. the scalar energy of the first order of the low-pressure shaft of an aircraft engine). The parameters of this pdf are learnt thanks to Bayesian inference, before running a statistical test.

Our case is different because we deal with large vectors (the log-periodograms) rather than scalar or low-dimensional vectors [17]. We propose to use excess-value statistics instead of maximum statistics: given a vector threshold, i.e. an upper limit for the spectra, we claim that monitoring all peaks that go beyond this threshold can solve the problem. This step stems from well-known fault detection algorithms in vibration monitoring [4, 4.2], where a mask is built using healthy vibration data. However, this procedure lacked a probabilistic translation so far.

To do so, EVT provides us with the necessary tools, since it models the probability of the excess value $P(X \mid X > t)$. Under mild conditions on the pdf of X, if t is large enough then $P(X \mid X > t)$ can be approximated by the Generalized Pareto distribution [1, 5.3.1]:

$$F(x) \;=\; 1 - \left(1 + \frac{\gamma x}{\sigma}\right)^{-\frac{1}{\gamma}} \tag{1}$$

where γ is the shape and σ the scale, and both need to be estimated from measurements.

The fault detection algorithm may then be written:

1. select a subset of the learning dataset, made of N log-periodograms of length F. For each frequency f we compute the max of the log-periodograms across the subset. A real vector $m = [m_1, \ldots, m_f, \ldots m_F]$ is obtained, the *mask*.
2. spot excesses over the mask in the rest of the learning dataset. Only excess values $Y = X_f - m_f \mid X > m_f$ are recorded, regardless of the frequency for which they occur. They consitute a sample of scalar excesses $\{Y_i\}_{i \leq I}$, and serve as inputs to the parameter estimation of the Generalized Pareto distribution.
3. a detection threshold t is set from standard probabilistic considerations, and enables the definition of a decision rule: any excess Y over the threshold t is considered as a fault.

The last two steps of the procedure are repeated when new uncategorized data are tested: excesses Y over the mask are first computed, then compared to t. Fig. 1 summarizes the algorithm

4. Dataset and results

The IMS bearing dataset [18] is a publicly available[1] set of vibration signals. Four bearings are installed on a shaft that rotates at a constant speed of 2000 rpm. Progressive degradations are recorded over a month from 8 accelerometers as the designed life time of the bearings is exceeded.

Log-periodograms with length $T = 8092$ are displayed by Fig. 2 at the beginning and at the end of the test, when a bearing is damaged.

Two datasets are built from the IMS recordings: one learning dataset, with 25 snapshots taken at the start of the recording session, while all bearings are healthy. Then, a test dataset is designed with 50 new recordings,

[1] `http://ti.arc.nasa.gov/tech/dash/pcoe/prognostic-data-repository/`

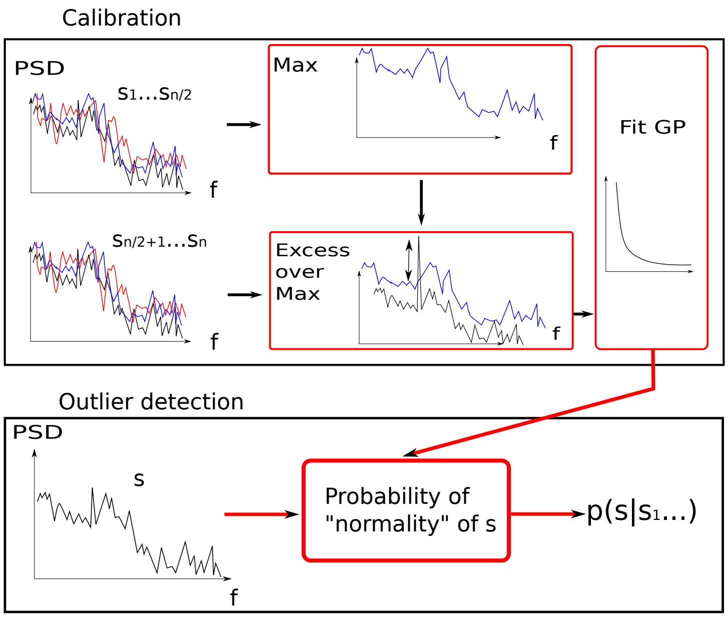

Figure 1: Peak-over-threshold detection algorithm.

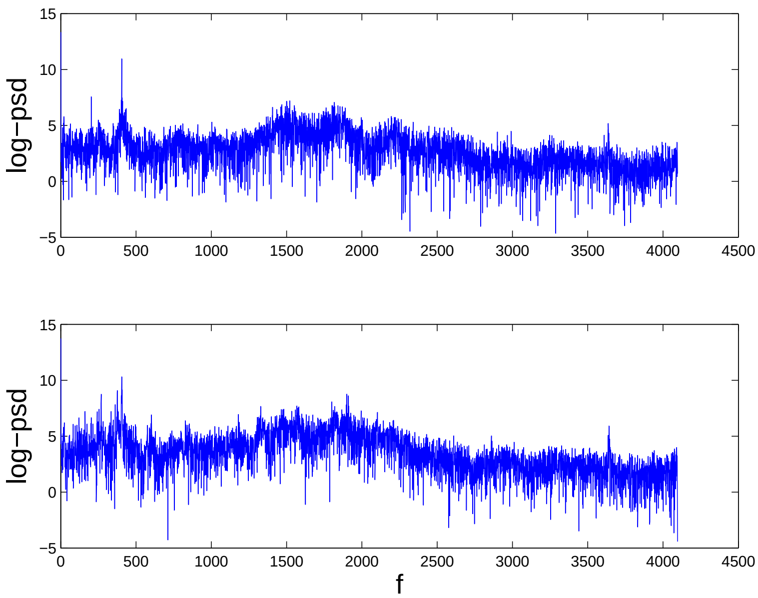

Figure 2: Log-periodogram of bearing vibrations (top) at the beginning of the test; (bottom) at the end of the test when a bearing is damaged.

25 taken at the start of the test and 25 after n days of operation when light damage appear. The higher n, the easier the detection task because of the fast degradation of the bearing.

4.1. Results

We first discuss the estimation of the parameters (σ, γ) of the probability of the excess value Y written in eq.(1). This estimation can be done with a frequentist [1, 5.3.2] of Bayesian [1, 11.5.3] point of view. Here we choose the frequentist approach, implemented in Matlab[2].

Fig. 3 shows a good accordance between the histogram of excesses Y defined in 3 and the fitted pdf. It is an important result that guarantees the quality of further processing steps. The estimated parameters[3] are $\gamma = -0.05$, $\sigma = 0.72$.

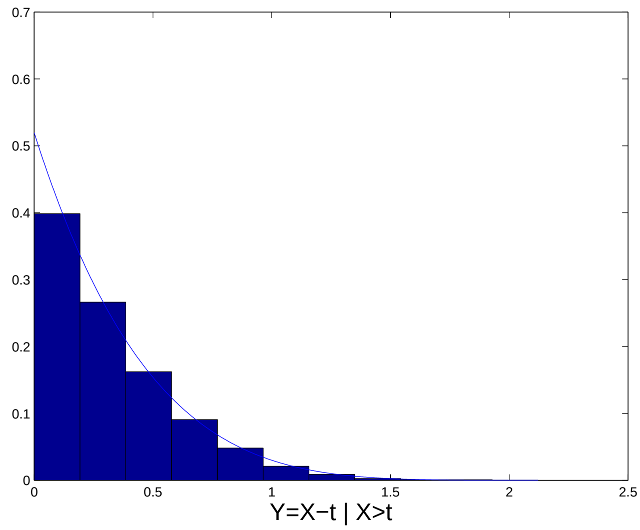

Figure 3: Histogram of excess values $Y = X - t|X > t$ and fitted Generalized Pareto pdf. Estimated parameters are: $\gamma = -0.05$, $\sigma = 0.72$

Secondly, we plot the ROC curve of the detection algorithm in Fig. 4, defined here as the empirical false negative rate (FNR) as a function of the empirical false positive rate (FPR). Both FPR and FNR are functions of the

[2] see the function gpfit in Statistics Toolbox.

[3] negative γ distributions are referred to as the class of "extremal Weibull" distributions in the EVT literature.

detection threshold t defined in sec. 3. There is a classical tradeoff between the two rates, in the sense that it is not possible to decrease arbitrarily the two rates simultaneously while moving t. Faulty data are recorded just $n = 2$ days after the beginning of the fatigue test, which explains why the ROC curve is close to the diagonal.

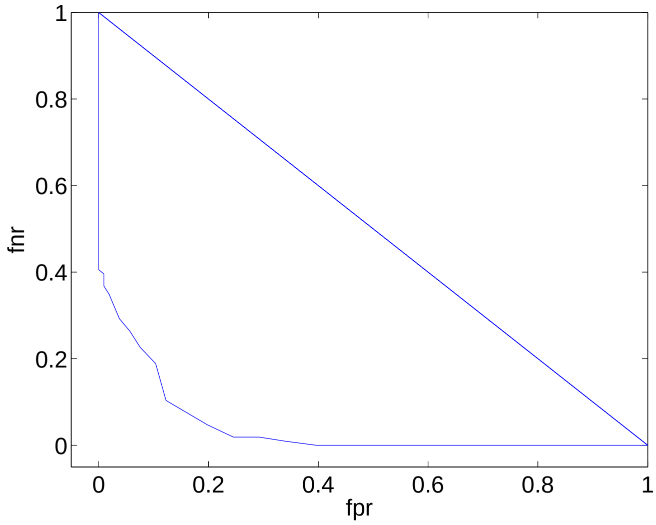

Figure 4: ROC curves. Faulty test data recorded after $n = 2$ days of operation.

Lastly we examine the behavior of both FNR and FPR with respect to the threshold t, to make explicit the dependence and show how it should be chosen so as to minimize both error rates. We expect that as t increases, the FPR should descrease, while the FNR should rise. Fig. 5 reveals first that this is the observed behavior, then that there is a single value of t close to 1.6 such that both error rates are minimized simultaneously. The obtained error rate -approximately 0.1- is high but is consistent with the fact that only 2 days have passed since the beginning of the fatigue test.

5. Conclusion and perspectives

Peak-over-threshold detection in the spectral domain is an original algorithm, inspired both by classical practice in Condition Health Monitoring and by Extreme Value Theory. In this article, its performance was examined in the context of vibratory condition monitoring.

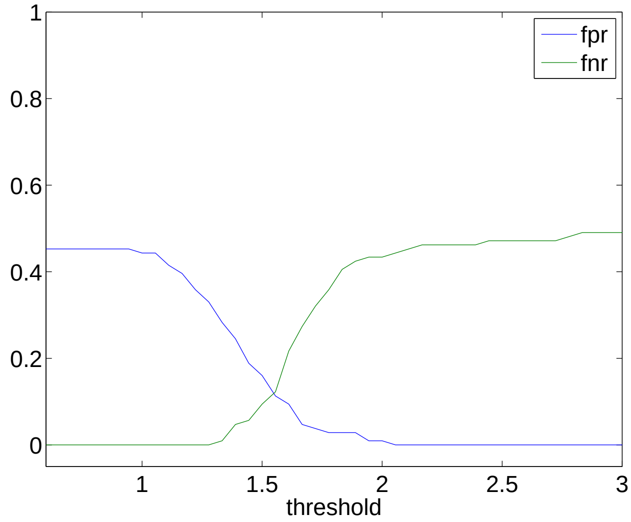

Figure 5: False Negative and False Positive Rates as functions of the threshold level t.

To reflect industrial constraints, it operates with a small learning dataset, at constant regime and with no mechanical model. Indeed, in the field of large and complex rotating machines such as turbofans, many defects can't be modelled nor anticipated, and records of faults are very rare.

Bearing fatigue test data were used in this article to assess detection performance. It is shown that the proposed generative model for excess-over-threshold fit the spectral data well, allowing us to build an efficient novelty detection algorithm. The Receiver Operator Characteristic (ROC) curve was computed thanks to annotated data, and exhibits good overall properties, even after a short delay after the beginning of the fatigue test.

In future works this algorithm will be compared to other state-of-the-art algorithms, and to our own previous contributions, such as Bayesian detection in the wavelet domain [19].

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