Application of non-Gaussian-based stochastic methods for local damage detection in mining machines

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Agenda

- Introduction and motivation
- The classical approach for local damage detection
- New methods for local damage detection
- Results for simulated signals
- Results for real signal
- Summary

Introduction and motivation

- The local damage detection is one of the most common issues raised in the literature of condition monitoring.
- There are at least two reasons for this type of problems. Firstly, the detection of such damages in the real world can be very difficult due to the low signal-to-noise ratio and the specific characteristics of the informative signal.
- Secondly, the amplitude of the vibration associated with the damage is much lower than the amplitude of signals received during normal operation of the machine.
- Vibration analysis seems to be the most effective approach in this problem.

Introduction and motivation

- Local damages cause the appearance of the impulsive signal.
- Due to the rotating shafts in the machine, this signal should be cyclic.
- In simple cases, these impulses may be observed in the time domain. In such cases, the classical methods allow the detection of local damages. The next step after damage detection is to assign it to a specific machine elements based on the so-called frequency characteristic.
- The motivation for using more advanced methods in local damage detection for industrial machines is detection of damage at early stage of development and the fact that the impulses in the time domain are unobservable.

Introduction and motivation

- In these cases, the cyclic impulses can be hardly noticeable and there is a need to separate the signal of interest from the noise coming from different sources.
- The most reasonable approach in this case is to design a filter which enables the separation of the signal of interest.
- The particular attention should be paid to filters based on the characteristics of the analyzed data. The filter can be defined by its impulse response in the time domain or as the frequency characteristics.
- In the second case design of the filter is based on the information that the frequencies are informative (so called informative frequency bands, IFB), and which are noninformative (filtration should remove them).

Introduction and motivation

Figure: The exemplary crushing machine in the copper ore mine.

Introduction and motivation

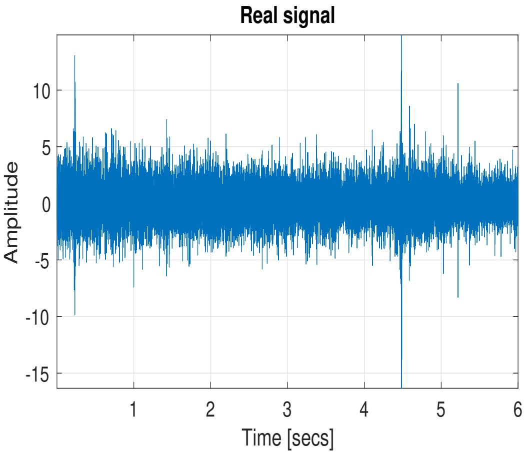

Figure: The real vibration signal from the crushing machine.

Introduction and motivation

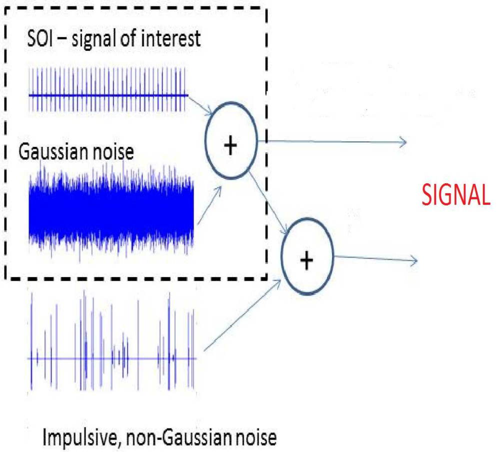

Figure: The schematic model of the signal.

The classical approach for local damage detection

The raw signal is transformed into time-frequency map (spectrogram). Spectrogram is a square of the absolute value of the short-time Fourier transform (STFT).

For the discrete vector of observations $x_1, x_2, ..., x_N$, time $t \in T$ and frequency$f \in F$ the STFT takes the form:

$$STFT(t, f) = \sum_{k=0}^{N-1} x_k w(t-k) e^{2j\pi fk/N}. \tag{1}$$

- The interpretation of the STFT$-$based map is intuitive – it describes energy flow in time for some narrow frequency band i.e. sub-signal.
- Any statistic that is applied to the spectrogram that indicates the informative bands is called informative frequency band (IFB) selector.

The classical approach for local damage detection

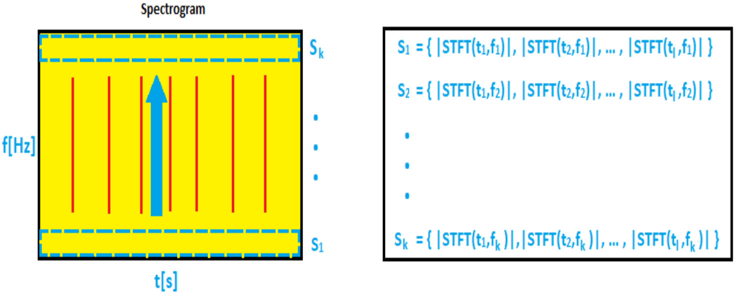

Figure: Sub-signals extraction for each frequency bin from the STFT matrix.

The classical approach for local damage detection

The kurtosis statistic is the most known impulsive measure in the probability and statistical theory. It gives the knowledge about the non-Gaussianity of the signal (for the Gaussian distribution the statistic is equal to 0) or in other words about the impulsiveness of the signal. The kurtosis for the vector $x = (x_1, x_2, ..., x_N)$ is defined as follows:

$$\hat{K}(x) = \frac{\frac{1}{N}\sum_{i=1}^{N}(x_i - \overline{x})^4}{\left(\frac{1}{N}\sum_{i=1}^{N}(x_i - \overline{x})^2\right)^2} - 3, \qquad (2)$$

where $\overline{x}$ is the sample mean and N is the sample length.

- It is the most frequent used sparsity index in the diagnosis of bearing faults.
- In the classical approach, the kurtosis is applied not to the raw signal, but to its time-frequency representation (spectrogram). Thus the selector is called spectral kurtosis.

The simulated signals

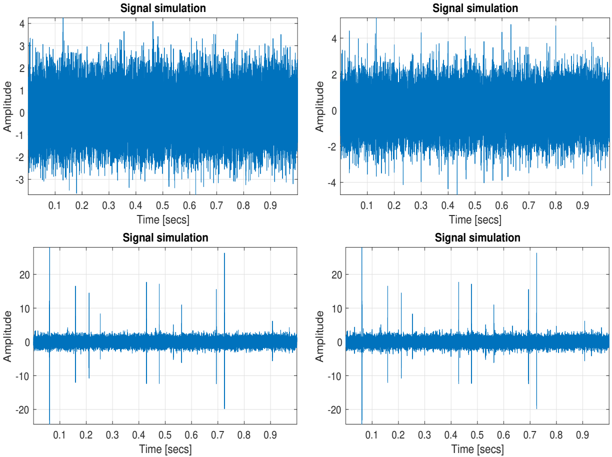

Figure: Simulated signals: s1- Gaussian noise, s2- Gaussian noise with cyclic impulses, s3- non-Gaussian noise, s4- non-Gaussian noise with cyclic impulses.

The simulated signals

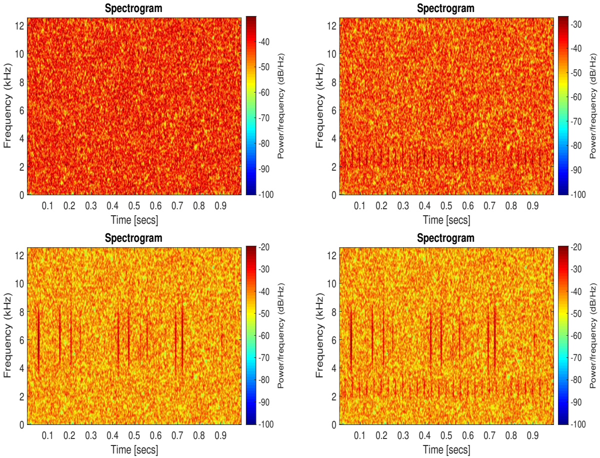

Figure: Spectrograms of the simulated signals: s1- Gaussian noise, s2- Gaussian noise with cyclic impulses, s3- non-Gaussian noise, s4- non-Gaussian noise with cyclic impulses.

The classical approach for local damage detection

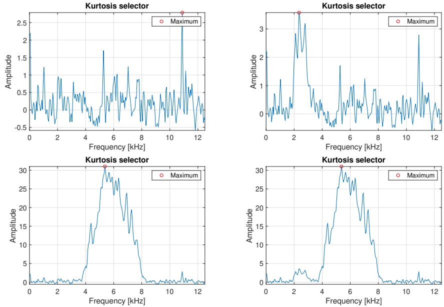

Figure: Spectral kurtosis for simulated signals: s1- Gaussian noise, s2- Gaussian noise with cyclic impulses, s3- non-Gaussian noise, s4- non-Gaussian noise with cyclic impulses.

New methods for local damage detection - the Alpha selector

- The class of α – stable distributions is known as an extension of the classical Gaussian distribution.
- One of the distribution's parameters is the stability index $\alpha \in (0, 2]$, which indicates the distance from the Gaussian distribution.
- This parameter indicates how impulsive is the distribution.
- For the $\alpha = 2$ the α – distribution simplifies to the Gaussian distribution with some parameters μ, σ. If the α tends to 0 then the examined distribution becomes more impulsive (the values of the outliers significantly increase).

The new methods for local damage detection - the Alpha selector

The $\alpha-$stable distribution is defined by the characteristic function, which is as follows:

$$\mathbb{E}[\exp i\theta X] = \phi_X(\theta) = \begin{cases} e^{-\sigma^\alpha|\theta|^\alpha\{1-i\beta\mathrm{sign}(\theta)\tan(\pi\alpha/2)\}+i\mu\theta}, & \alpha \neq 1, \\ e^{-\sigma|\theta|\{1+i\beta\mathrm{sign}(\theta)\frac{2}{\pi}\log(|\theta|\}+i\mu\theta}, & \alpha = 1. \end{cases}$$

The parameters $\sigma > 0$, $\beta \in [-1, 1]$, and $\mu \in \mathbb{R}$ are the scale, skeweness and shift parameters respectively.

New methods for local damage detection - the Alpha selector

To estimate the parameter α from the $\alpha-$stable distribution one can use the following definition, adapted from the McCulloch method:

$$\hat{\alpha}(x) = \psi(\hat{v}_\alpha, \hat{v}_\beta),\ \hat{v}_\alpha = \frac{\hat{x}_{.95} - \hat{x}_{.05}}{\hat{x}_{.75} - \hat{x}_{.25}},\ \hat{v}_\beta = \frac{\hat{x}_{.95} - \hat{x}_{.05} - 2\hat{x}_{.5}}{\hat{x}_{.95} - \hat{x}_{.05}}, \quad (3)$$

where $\hat{x_q}$ is the sample quantile of order q based on the vector $x = (x_1, \ldots, x_N)$.

- The Alpha selector has been defined as $2 - \hat{\alpha}$ and applied to the spectral frequency f_i: $\hat{\alpha}(f_i)$ after time-frequency signal decomposition (spectrogram).
- If the amplitude of the impulses in the examined data distribution increase then the $\hat{\alpha}$ parameter tends to 0 and Alpha selector increases.

The Alpha selector for local damage detection

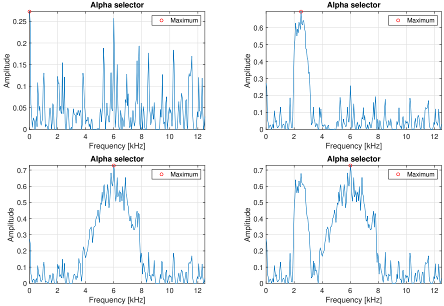

Figure: Alpha selector for simulated signals: s1- Gaussian noise, s2- Gaussian noise with cyclic impulses, s3- non-Gaussian noise, s4- non-Gaussian noise with cyclic impulses.

New methods for local damage detection - the CVB selector

- The conditional variance statistic originates from the statistical phenomenon commonly referred to as 20/60/20 Rule.
- It bases on the conditional variance measurement.
- This rule says that if the population is divided into three groups, according to some arbitrary reference criterion (e.g. 20% of the smallest, 60% of the middle and 20% of the largest values), this particular relationship often means some kind of balance.

New methods for local damage detection - the CVB selector

- It has been shown that for any population that can be described by a multidimensional normal vector, this fixed ratio leads to a global equilibrium state and we have:

$$\sigma_L^2 = \sigma_M^2 = \sigma_R^2,$$

$$\sigma_L^2 = Var(X|X < q_{0.2}),\ \sigma_M^2 = Var(X|q_{0.2} < X < q_{0.8})$$
$$\sigma_R^2 = Var(X|q_{0.8} < X).$$

- Based on the 20/60/20 rule the test for the Gaussianity was proposed, where the test statistic was defined as:

$$C_3 = \rho\sqrt{N}\left(\frac{\hat{\sigma}_L^2 - \hat{\sigma}_M^2}{\hat{\sigma}^2} + \frac{\hat{\sigma}_R^2 - \hat{\sigma}_M^2}{\hat{\sigma}^2}\right).$$

New methods for local damage detection - the CVB selector

The conditional variance statistic for the bearing fault diagnosis is defined as follows:

$$\hat{C}_7 := \left(\frac{\hat{\sigma}^2_{A_3} - \hat{\sigma}^2_{A_4}}{\hat{\sigma}^2} + \frac{\hat{\sigma}^2_{A_5} - \hat{\sigma}^2_{A_4}}{\hat{\sigma}^2} \right)^2 \sqrt{N}. \quad (4)$$

The lower index 7 in the statistic $C_7(\cdot)$ refers to the amount of the partitions A_i into which the distribution of the vector $x = (x_1, ..., x_N)$ has been divided. Whereas $\hat{\sigma}_{A_i}$ denotes the estimator of the standard deviation σ_{A_i} in the given set A_i. The main property of divisions A_i is that their variances are equal.

New methods for local damage detection - the CVB selector

More specifically, for partitioning on 7 subsets the estimators of A_i are defined as follows:

$$\begin{aligned}
\hat{A}_1 &:= (-\infty,\ \hat{x}_{.004}],\\
\hat{A}_2 &:= (\hat{x}_{.004},\ \hat{x}_{.062}],\\
\hat{A}_3 &:= (\hat{x}_{.062},\ \hat{x}_{.308}],\\
\hat{A}_4 &:= (\hat{x}_{.308},\ \hat{x}_{.692}],\\
\hat{A}_5 &:= (\hat{x}_{.692},\ \hat{x}_{.938}],\\
\hat{A}_6 &:= (\hat{x}_{.938},\ \hat{x}_{.996}]\\
\hat{A}_7 &:= (\hat{x}_{.996},\ \infty,)
\end{aligned}$$

where, $\hat{x}_q$ is the empirical quantile of order q calculated for vector $x_1, x_2, \cdots, x_N$.

New methods for local damage detection - the CVB selector

Assuming the Gaussian distribution the following equation is fulfilled:

$$\sigma^2_{A_1} = \sigma^2_{A_2} = \sigma^2_{A_3} = \sigma^2_{A_4} = \sigma^2_{A_5} = \sigma^2_{A_6} = \sigma^2_{A_7}. \qquad (5)$$

- The condition (5) creates a dispersion balance for the conditional populations and a different number of partitioning sets could be considered.
- After time-frequency signal decomposition the estimator $\hat{C}_7(\cdot)$ applied to the individual frequency band f_i: $\hat{C}_7(f_i)$ is called conditional variance-based selector (CVB selector).
- The CVB selector is able to distinguish occurring different impulses based on the distribution of their amplitudes.

New methods for local damage detection - the CVB selector

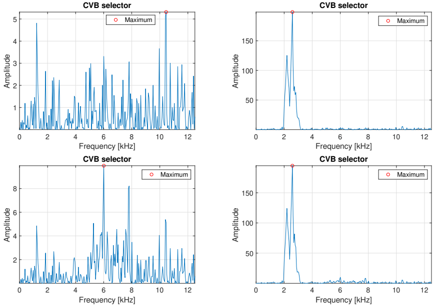

Figure: CVB selector for simulated signals: s1- Gaussian noise, s2- Gaussian noise with cyclic impulses, s3- non-Gaussian noise, s4- non-Gaussian noise with cyclic impulses.

Results for real signal

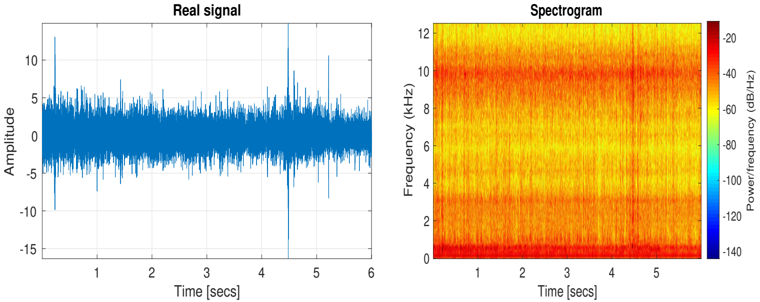

Figure: Real signal and its spectrogram.

Results for real signal

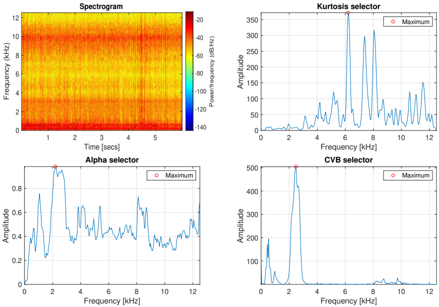

Figure: Results for real signal from crushing machine.

Results for real signal

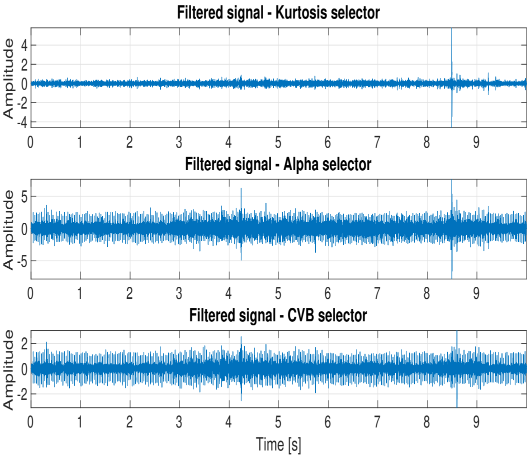

Figure: The results of the copper ore crusher's signal filtration performed by three different selectors.

Results for real signal

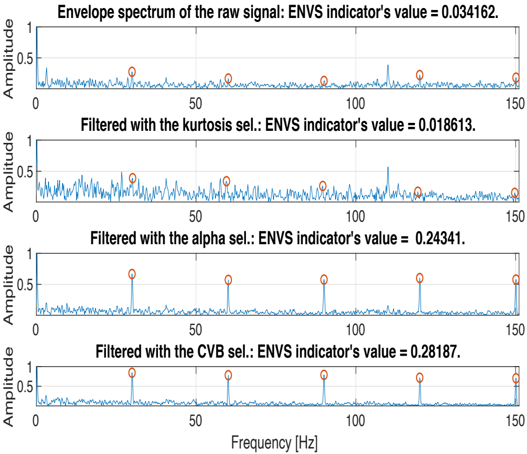

Figure: The envelope spectrum for filtered signals.

Summary

- The problem of local damage detection (especially in the early stage) in rotating machines is very important from the practical point of view.
- The most effective methods are based on the analysis of the vibration signals.
- The methods are based on two important properties of the signal: impulsiveness and cyclic behavior.

Summary

- We have presented the recently proposed techniques of the IFB selection for benchmark signals that imitate four different cases of the condition of the rotating component of the machine:
  1. the Gaussian White Noise, which corresponds to the vibration coming from bearing in the healthy condition,
  2. the Gaussian White Noise with cyclic impulses, which corresponds to the local damaged bearing,
  3. the non-Gaussian noise, which corresponds to the case without the local damage (for the machine in a good condition executed specific technological process e.g. crushing of the rock mass),
  4. the non-Gaussian noise with cyclic impulses, which correspond to the damaged bearing in presence of the impulsive noise, associated with the machine operation e.g. local fault of bearing in the crusher.

Summary

- In case of the good condition of the machine, we should expect the "flat" distribution of the selector for each technique, whereas for damaged cases one should find some frequency band with a higher value of "diagnostic feature" (selector) than for other frequencies.
- The real signal was also considered where the additional components may occur.
- Here we do not take into consideration the cyclic behavior of the signal, only its impulsiveness.
- In the last year the new results related to cyclic behavior of the signal in the presented of non-Gaussian noise were proposed.
- They are based on the consideration of the dependency measures of the signal under the assumption of the non-Gaussian distribution.

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Thank you for your attention!