Heavy-tailed-based approach in application to local damage detection in mining machines

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OPMO - Operation monitoring of mineral crushing machinery

Cooperation

- Faculty of Geoengineering, Mining and Geology, WUST
- KGHM
- KGHM Cuprum R&D Center

KGHM Polska Miedz

- KGHM extracts and processes natural resources. The company possesses a geographically diversified portfolio of mining projects. It owns production plants on three continents - in Europe, South and North America.
- Polish copper deposits - one of the biggest in the world - are exploited by three underground mines: "Lubin", "Polkowice-Sieroszowice" and "Rudna".
- On the other side of the ocean, KGHM owns six mines: Robinson, Carlota(USA), McCreedy West, Morrison(Canada) and Franke and Sierra Gorda(Chile). Apart from copper, these mines also produce molybdenum, nickel, gold, palladium and platinum.
- KGHM ranks among the world's best producers of silver and copper.

Agenda

- Introduction
- Motivation
- The classical approach
- The extension of the classical approach
- New selectors of IFB
- Heavy-tailed-based approach
- Conclusions

- Problem of the local damage detection is a crucial task in modern condition monitoring.
- Vibration analysis seems to be the most effective approach in this problem.
- Most of the classical methods rely on being tested in laboratories in the isolated test stands.
- In case of the real world data, there are outer sources of the noise (for instance nearby machines).
- Such noise can affect shape of the signal and increase the level of difficulty in finding information about the fault.

Introduction

- One can define problem of the fault detection as a finding cyclic (due to the rotating shafts in the machine) impulses in the signal.
- In simple cases, impulses related to damage 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

- 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).

Motivation

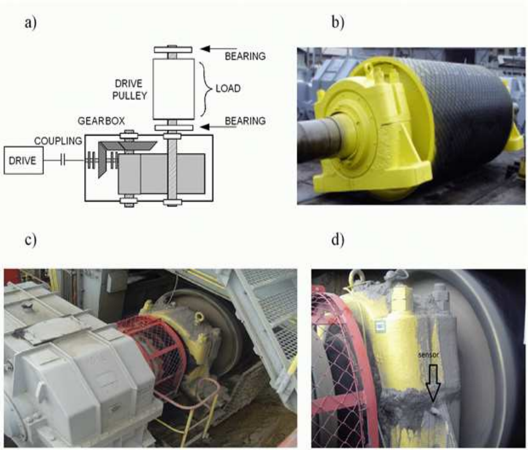

Figure: Diagnosed object A: a) Scheme, b) Pulley with bearing housing mounted on shaft, c) View on joint of output shaft in gearbox with pulley, d) View on sensor location on pulley.

Motivation

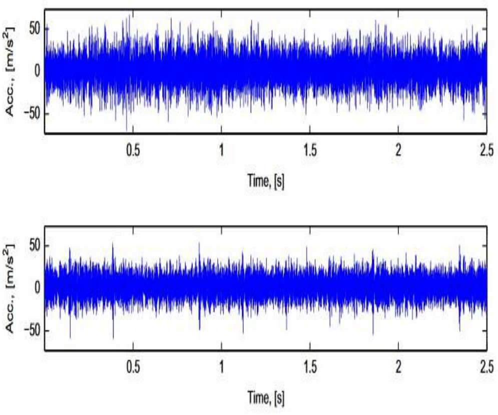

Figure: Raw vibration signal from healthy (top panel) and faulty (bottom panel) gearbox. Note barely visible impulses related to the fault frequency (bottom panel).

Motivation

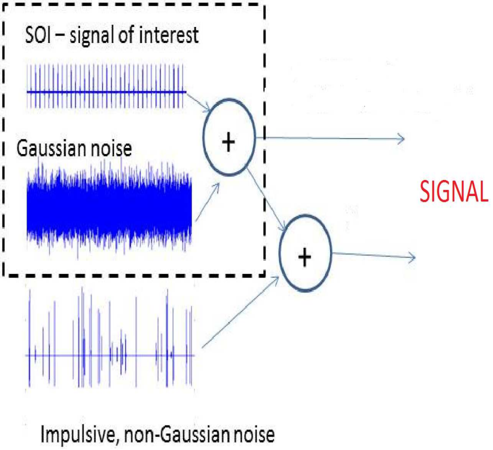

Figure: The schematic model of the signal.

The classical approach

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:

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

One of the most known selector used to determining of the informative frequency band is the spectral kurtosis (SK) defined as follows:

$$SK(f) = \#T \frac{\sum_{t \in T} |STFT(t,f)|^4}{(\sum_{t \in T} |STFT(t,f)|^2)^2} - 2, \tag{2}$$

where $\#T$ denotes the number of elements of the set T, i.e. number of time points for which STFT is calculated.

The classical approach

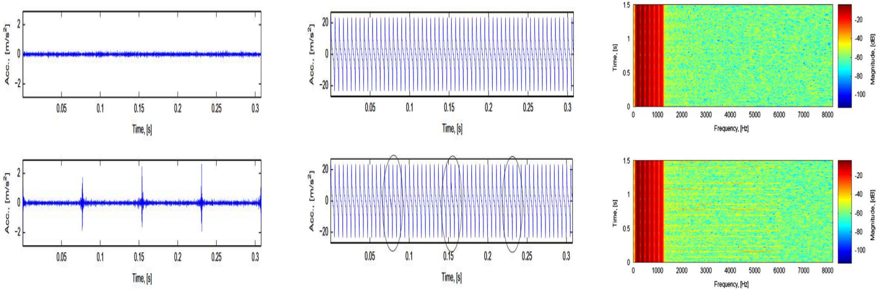

Figure: The signal of noise of simulated signal (left panels), simulated signal (middle panels) and the spectrograms (right panels) from healthy (top panels) and faulty (bottom panels) machine.

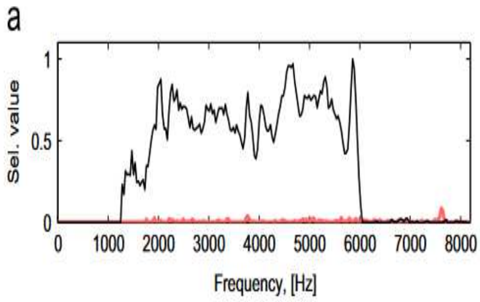

Figure: The selector *SK* calculated for simulated vibration signal from faulty (thin black lines) and healthy (thick red lines) rotating machine.

The classical approach

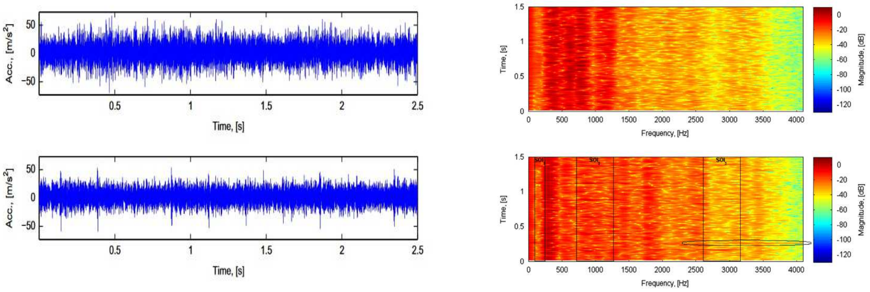

Figure: The real signal from healthy and unhealthy gearbox (left panels) and corresponding spectrograms.

The classical approach

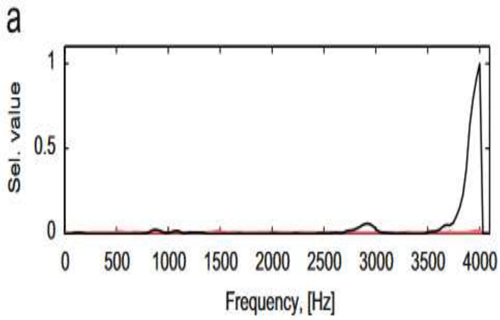

Figure: The selector *SK* calculated for real vibration signal from faulty (thin black lines) and healthy (thick red lines) rotating machine.

The extension of the classical approach

- The SK selector is very useful for IFB selection in easy cases.
- There is need to introduce the more advanced methods which can be useful also for more complicated signals.
- Idea: the sub-signals corresponding to noninformative FB have distribution which is closer to Gaussian one than the sub-signals from IFB (impulsive nature).
- New selectors - distance between empirical distribution of corresponding sub-signals and the classical Gaussian distribution.

The extension of the classical approach

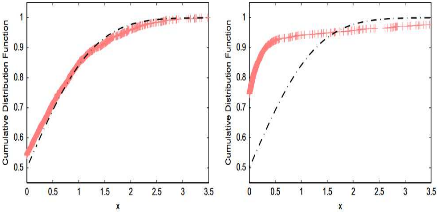

Figure: The empirical and theoretical (Gaussian) cumulative distribution functions for exemplary sub-signals from machine in good condition (left panel) and damaged one (right panel). The black dashed line represents the reference cumulative distribution function of Gaussian distribution.

New selectors of IFB

The new selectors are statistics based on the distance between empirical cumulative distribution function corresponding to sub-signal corresponding to given frequency and theoretical one for Gaussian distribution. One of the selector which is based on this property is the Kolmogorov-Smirnov (KS) statistic, which for given frequency f is defined as follows:

$$KSS(f) = sup_x \left| ECDF(f,x) - \Phi(f,x) \right|, \tag{3}$$

where $\Phi(f,\cdot)$ is the cumulative distribution function for Gaussian distribution with parameters estimated from sub-signal corresponding to frequency f and $ECDF$ is its empirical cumulative distribution function.

The next analyzed selector is the Anderson-Darling (AD) statistic, that belongs to the family of statistics of Cramer-von Mises defined as follows:

$$Q(f) = \#T \int_{-\infty}^{\infty} \left(ECDF\left(f, x\right) - \Phi\left(f, x\right)\right)^{2} \phi\left(x\right) dx, \tag{4}$$

where $\phi(x)$ appropriate weight function. For $\phi(x) = [\Phi(f, x)(1 - \Phi(f, x))]^{-1}$ the above equation defines the AD statistic. For $\phi(x) = 1$, the statistic (4) is called Cramer-von Mises (CVM) statistic.

Last selector measures the distance between empirical and theoretical (Gaussian) distribution on the QQplot.

New selectors of IFB

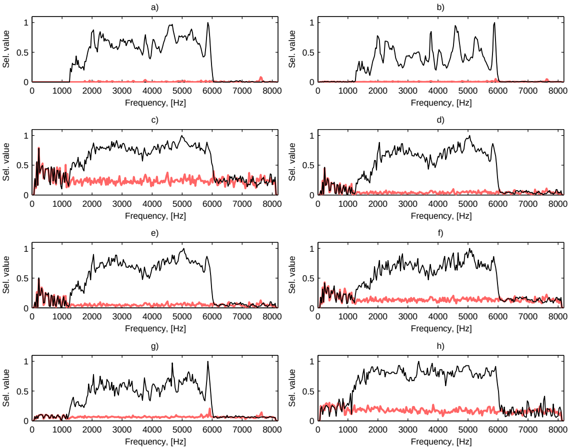

Figure: The new selectors calculated for simulated vibration signal from faulty and healthy rotating machine: *SK* (a), *JB* (b), *KSS* (c), *CVM* (d), *AD* (e), H_{aver} (f), H_{max} (g) and *LM* (h).

New selectors of IFB

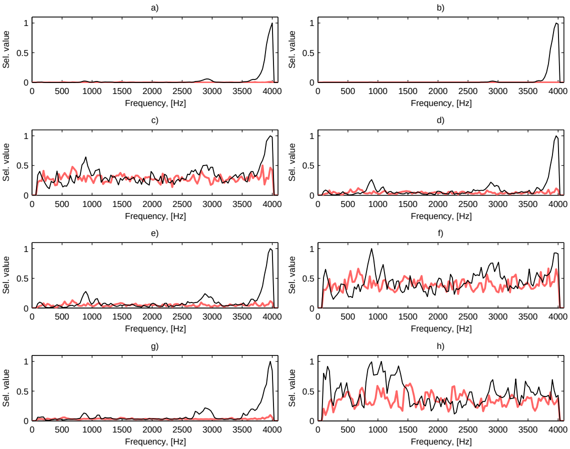

Figure: Selectors calculated for real vibration signal from faulty and healthy gearbox: *SK* (a), *JB* (b), *KSS* (c), *CVM* (d), *AD* (e), H_{aver} (f), H_{max} (g) and *LM* (h).

Heavy-tailed-based approach

- Instead of calculating statistics it is proposed to model sub-signals from time-frequency map.
- There is need to select the universal distribution appropriate for IFB and noninformative FB.
- Idea: application of heavy-tailed class of distribution which is the generalisation of the Gaussian one. Proposition: the $\alpha-$stable distribution.

$\alpha-$stable distribution

- Stable laws - also called $\alpha-$stable, stable Paretian or Lévy stable were introduced by Lévy in 1925.
- The $\alpha-$stable distribution requires four parameters for complete description: index of stability $\alpha \in (0, 2]$ (also call the tail index), a skewness parameter $\beta \in [-1, 1]$, a scale parameter $\sigma > 0$ and a location parameter $\mu \in R$.
- The tail exponent α determines the rate at which the tails of the distribution taper off.
- When $\alpha = 2$ the stable distribution is a Gaussian one with mean μ and variance 2 (in this case β is unimportant).

$\alpha-$stable distribution

- When $\alpha < 2$, the variance is infinite and the tails are asymptotically equivalent to Pareto law, i.e. they exhibit power law behavior:

$$\lim_{x\to\infty} x^{\alpha} P(X > x) = C_{\alpha}, \quad \lim_{x\to\infty} x^{\alpha} P(X < -x) = C_{\alpha}.$$

- When $\alpha > 1$, the mean of the distribution exists and is equal to μ.
- The *pth* moment of stable random variable is finite iff $p < \alpha$.
- If $\beta < 0$, then the distribution is skewed to the left, if $\beta > 0$ - to the right. For $\beta = 0$ we have the symmetric (around μ) distribution. In case of $\beta = 0$ and $\mu = 0$ we denote it as SαS.

$\alpha-$stable distribution

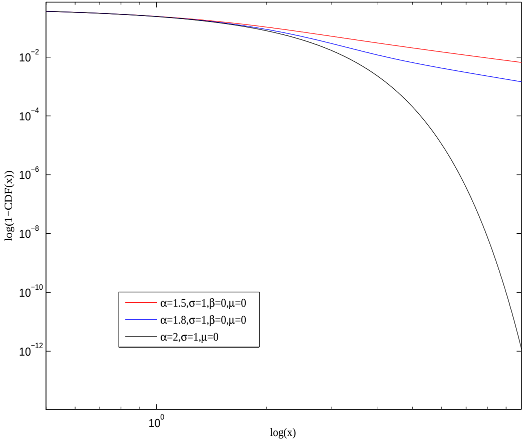

Figure: Right tails of SαS cumulative distributions functions (CDFs) on a double logarithmic scale.

$\alpha-$stable distribution

Due to the lack of closed form formulas for densities for all but three distributions (Gaussian, Lévy and Cauchy) the stable distribution in conventional way is described by the characteristic function $\phi(t)$ - the inverse Fourier transform of the pdf:

$$log \phi(t) = \begin{cases} -\sigma^{\alpha}|t|^{\alpha}\{1 - i\beta sign(t) tan \pi\alpha/2\} + i\mu t & \text{for } \alpha \neq 1 \\ -\sigma|t|\{1 + i\beta sign(t)\frac{2}{\pi} log(|t|\} + i\mu t & \text{for } \alpha = 1 \end{cases} \quad (5)$$

$\alpha-$stable distribution - estimation

- Tail exponent estimation, Hill (1975)
- Quantile estimation, McCulloch (1986)
- Regression-type method, Koutrouvelis (1980)
- Maximum likelihood method, new version - Mittnik et al. (1999).
- And many others....

$\alpha-$stable distribution approach

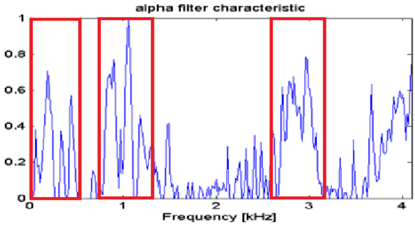

Figure: The $\alpha-$stable based selector calculated for real vibration signal from faulty rotating machine.

$\alpha-$stable distribution approach

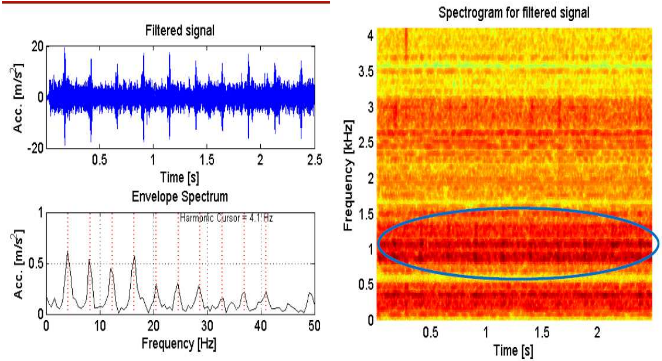

Figure: The filtered real signal, its envelope spectrum and spectrogram (faulty machine).

$\alpha-$stable distribution approach

- The α parameter is considered as a measure of impulsiveness.
- There is need to recognize the cyclic nature of the signal.
- Idea: application of measures of dependence.
- By the assumption of $\alpha-$stable distribution the classical autocovariance does not exist.
- There are considered alternative measures of dependence: codifference and covariation.

Let X and Y be jointly SαS and let Γ be the spectral measure of the random vector (X, Y). If $\alpha < 2$ then the covariance is not defined and thus other measures of dependence have to be used. The most popular measures are: the **covariation** $CV(X, Y)$ of X on Y defined in the following way:

$$CV(X,Y) = \int_{S_2} s_1 s_2^{<\alpha-1>} \Gamma(d\mathbf{s}), \quad 1 < \alpha \leq 2, \tag{6}$$

where $\mathbf{s} = (s_1, s_2)$ and the signed power $z^{<p>}$ is given by $z^{<p>} = |z|^{p-1}\bar{z}$, and the **codifference** $CD(X, Y)$ of X on Y defined for $0 < \alpha \leq 2$:

$$CD(X,Y) = \ln E\exp\{i(X - Y)\} - \ln E\exp\{iX\} - \ln E\exp\{-iY\}. \tag{7}$$

$\alpha-$stable distribution approach

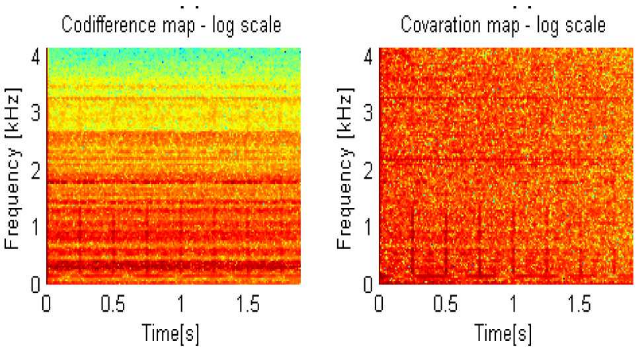

Figure: The codifference and covariation maps for real vibration signal.

$\alpha-$stable distribution approach

- We analyze the real world signal acquired from the two-stage gearbox. Data were acquired from the complex mechanical system working in mining environment. Signal length is equal to 2.5 s, frequency sampling is equal to 16384 Hz. Suspected fault frequency is equal to 16.5 Hz.
- Extraction of the IFB for this signal is quite difficult.
- There are two IFBs.
- Visible impulses are present in the IFB2 only
- Impulsive behavior that should be visible in IFB1 is masked by high energy of the other components.

$\alpha-$stable distribution approach

Fractional lower-order covariance for the stochastic process $\{X_t\}$ with $\alpha-$ stable distribution is defined as:

$$R_{XX}(k) = E[X_t^{<A>} X_{t-k}^{<B>}], \qquad 0 \leq A, B \leq \frac{\alpha}{2}$$

where α is index of stability of the α-distribution, $k = 0, \pm 1, \pm 2, \ldots$ and function:

$$a^{<p>} = |a|^p \mathrm{sign} a$$

The estimator of FLOC takes the form:

$$\widehat{R_{XX}(k)} = \frac{\sum_{n=L_1+1}^{L_2} |x(n)|^A |x(n+k)|^B sgn[x(n)x(n+1)]}{L_2 - L_1}$$

where

N is a number of observations

$L_1 = \max(0, -k)$

$L_2 = \min(N, N-k)$

$0 \leq A, B \leq \frac{\alpha}{2}$.

$\alpha-$stable distribution approach

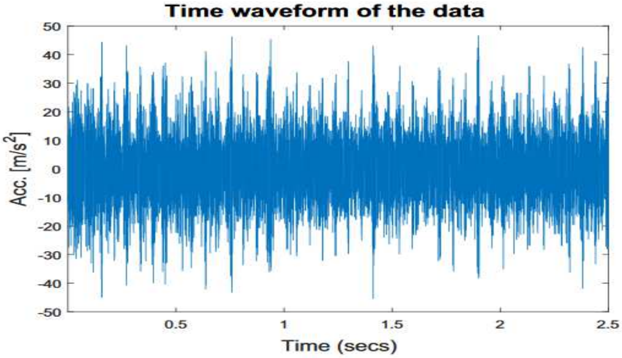

Figure: The waveform of the real signal.

$\alpha-$stable distribution approach

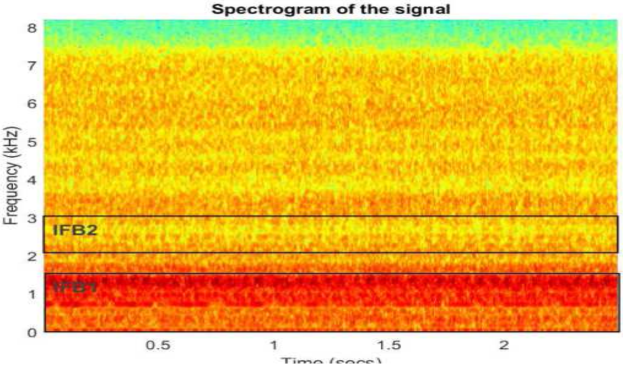

Figure: The spectrogram of the real signal.

$\alpha-$stable distribution approach

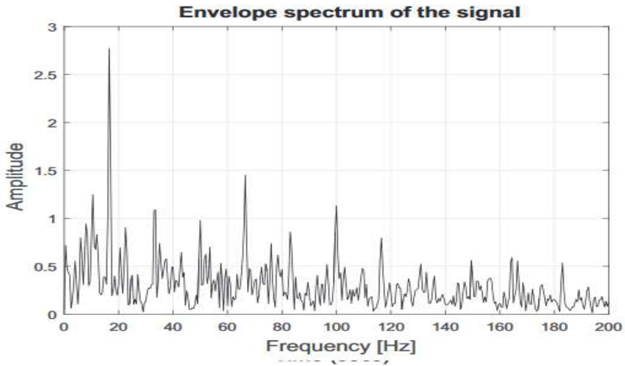

Figure: The envelope spectrum of the real signal.

$\alpha-$stable distribution approach

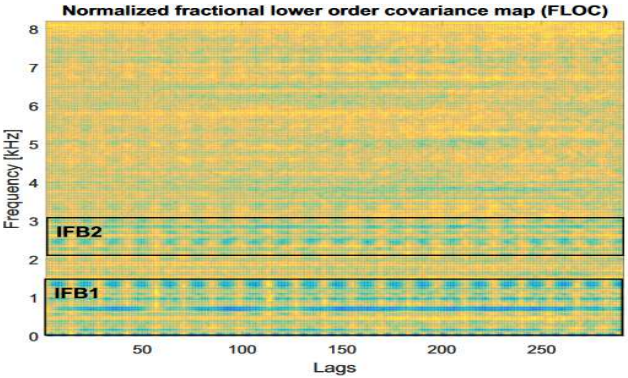

Figure: The normalized FLOC dependency map for the real signal.

$\alpha-$stable distribution approach

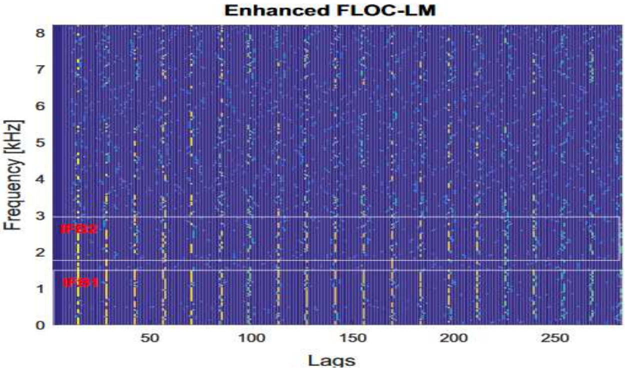

Figure: Local maxima method applied to the normalized FLOC dependency map for the real data.

Conclusions

- 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.
- The statistical and stochastic methods can be applied to adapt the methods previously used in the analysis of vibration signals.
- The proposed frequency band selection criteria have very good properties and can be an alternative to the widely used spectral kurtosis, and in some cases they give better results.

Conclusions

- The commonly used Gaussian distribution is insufficient to describe the data related to the mining machines, therefore it is necessary to use other distributions.
- The alternative for Gaussian-based approach is the $\alpha-$stable distribution approach (stability index as the measure of impulsiveness and the alternative measures of dependence as indicators of the cyclic nature of the vibration signal).
- The presented methods are applied to real mining machines diagnostics in KHGM Polska Miedz.

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Thank you for your attention!