# Signal processing techniques for local damage detection in gears and bearings in presence of non-Gaussian noise - a stochastic perspective

*A keynote for CMMNO Conference in China (2021)*


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**Faculty of Pure and Applied Mathematics**
**The Hugo Steinhaus Center for Stochastic Processes**


HR EXCELLENCE IN RESEARCH

Wrocław University of Science and Technology

# Highlights

We will present recent developments related to signal processing for local damage detection in bearings and gearboxes with focus on heavy duty mining mechanical systems. We will address following issues :

**Why local damage?** - still hot topic for condition monitoring community.

**State of the art** - focus on heavy duty industry perspective.

**Challenges** - T-V Load/speed conditions, non-Gaussian noise, multiple damage, mixture of various sources, poor SNR.

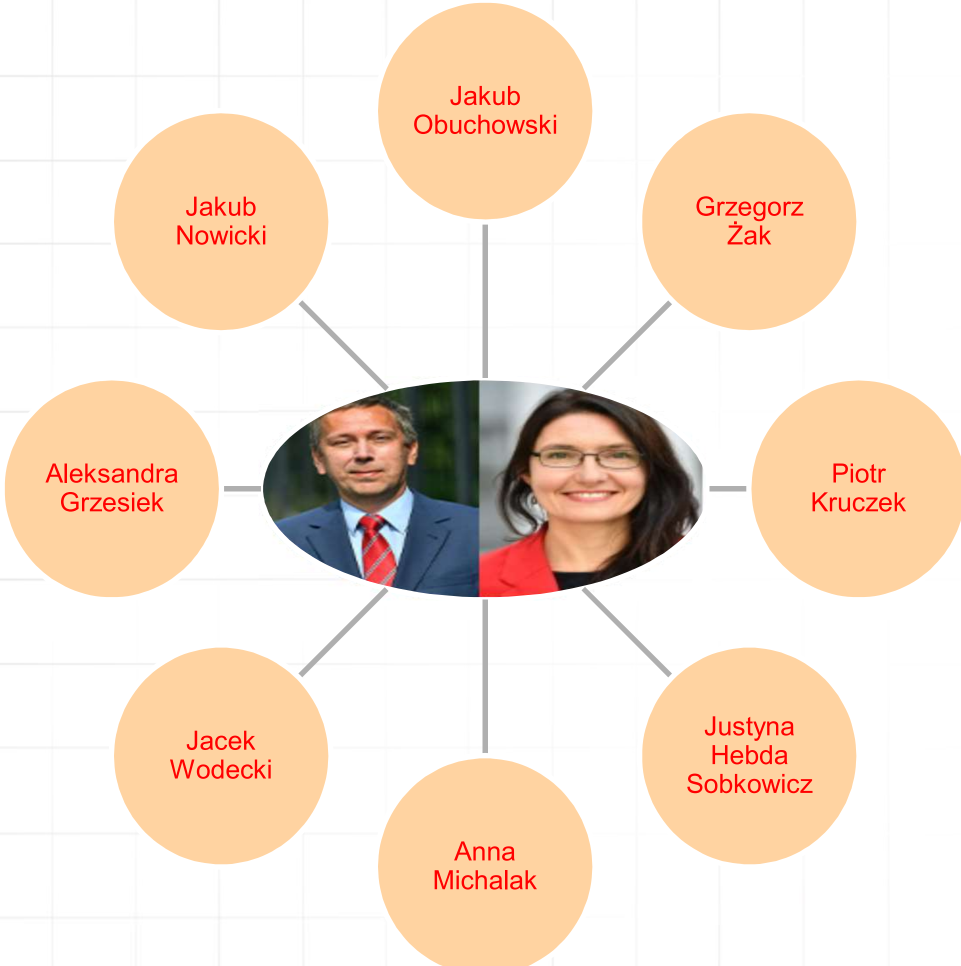
**Recent solutions** – cyclo-stationary analysis in presence of non-Gaussian noise, optimal filter design for SOI extraction, source separation, de-noising.

**Methods** - alternative dependence measures, robust statistics, statistical modelling, stochastic processes, Non-Negative Matrix Factorisation.

**Future** - inspection robots, acoustic signals.

Each approach presented in the talk will touch **objects**, their specific **design** and **operational** factors, **math background** for proposed solutions and finally **results** obtained for real data from **industry**.

# Our vision: Basic science with Engineering applications



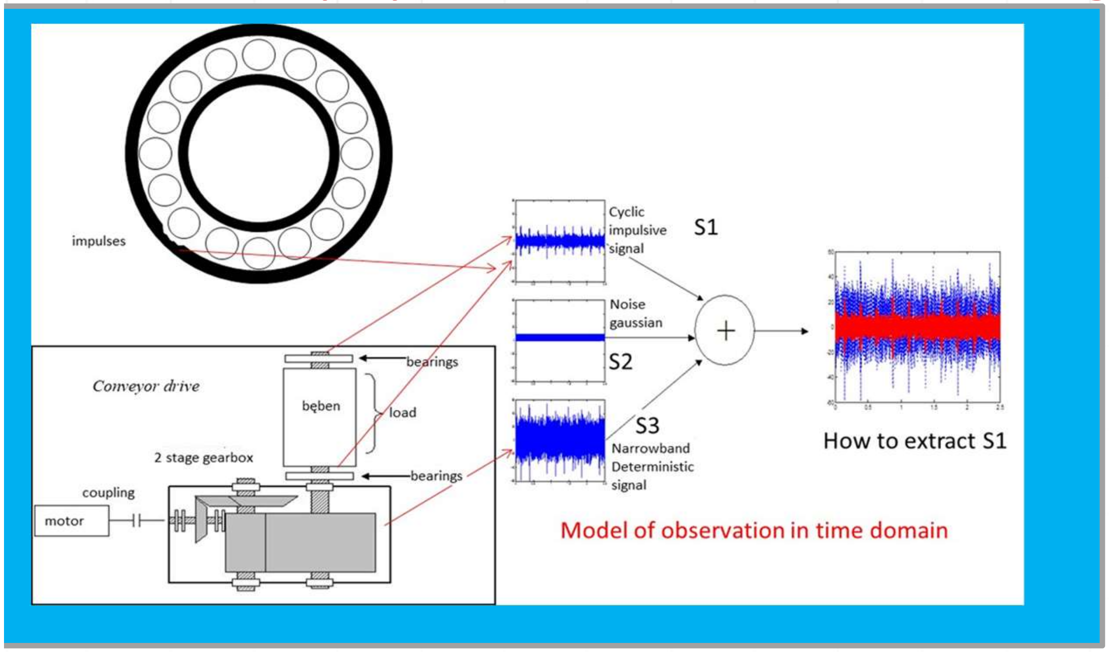

- Use math to solve engineering problem
- Observe Engineers to find a problem

## key issues in Condition Monitoring of local damage in gears/bearings

- Understand the object, its design, technological process, sources of vibration, physical model of observed signal
- Use appropriate mathematical tools to analyse signal structure
- Describe (model) the signal in language of stochastic processes
- Extract features – impulsiveness and/or periodicity
- Filter design, SOI extraction, sources separation

key issues in Condition Monitoring of local damage in gears/bearings

Understand the object, its design, technological process, sources of vibration, physical model of observed signal



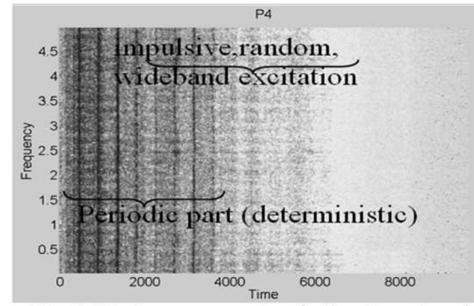
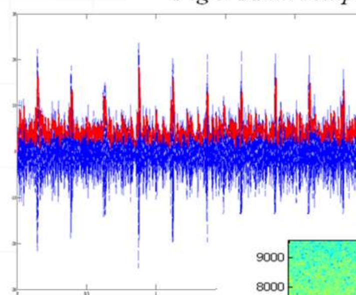
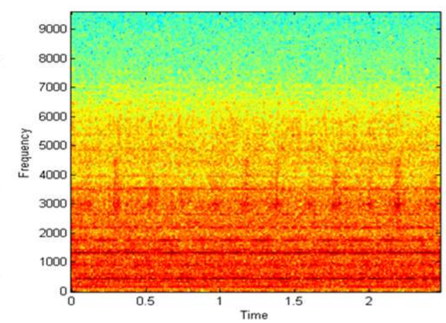
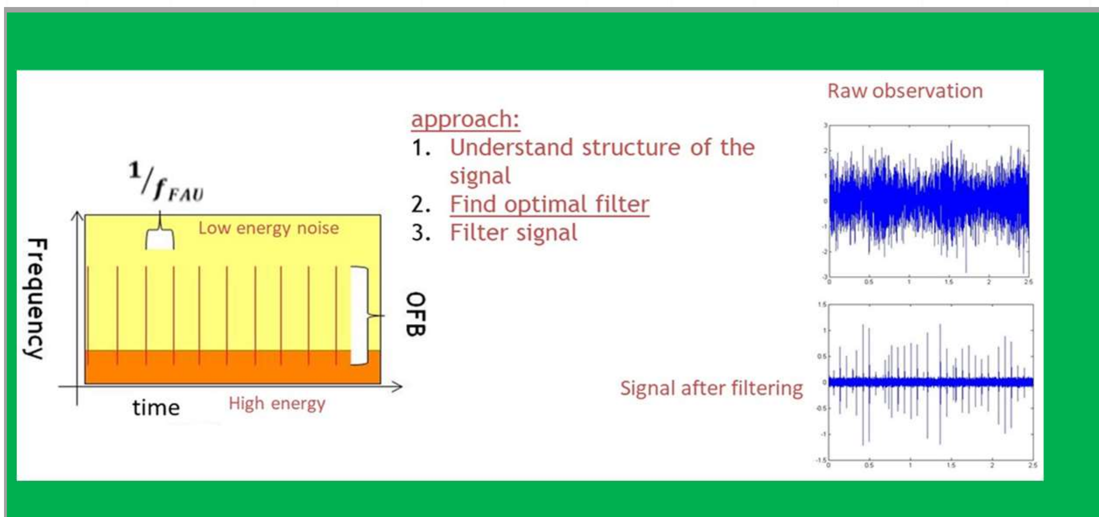




*Fig 3 Main components of vibration signal*



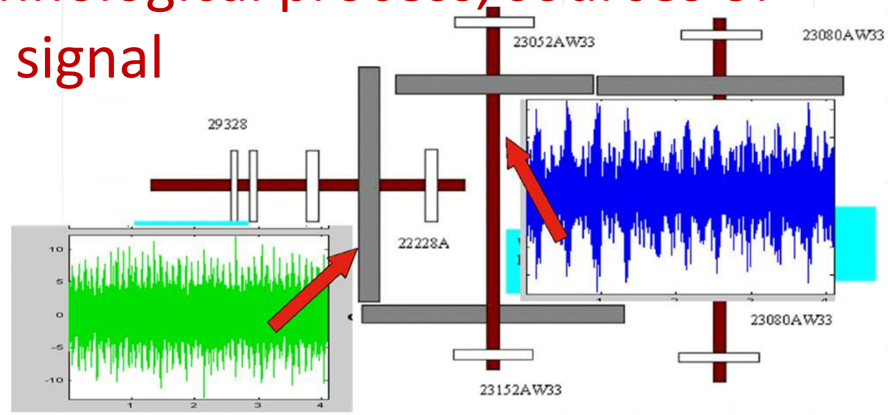



Impulsive,
periodic (cyclic),
modulated AM/PM/FM,
Non-stationary,
cyclostationary
Non-Gaussian

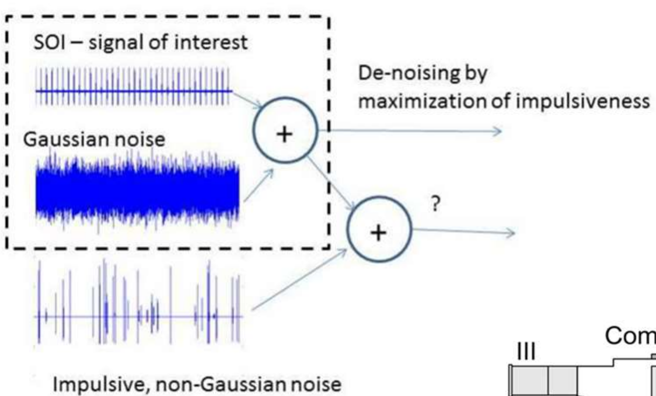
key issues in Condition Monitoring of local damage in gears/bearings

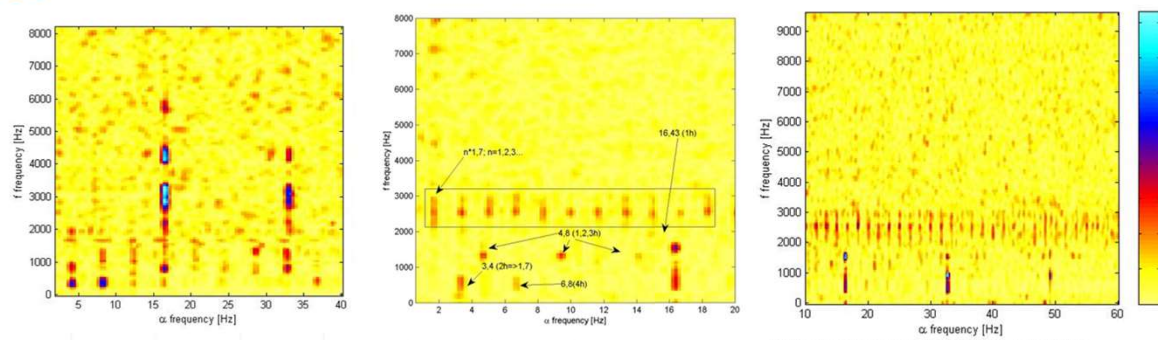
Understand the object, its design, technological process, sources of vibration, physical model of observed signal

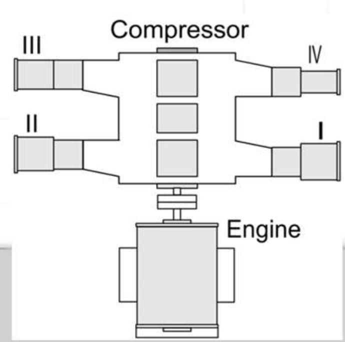


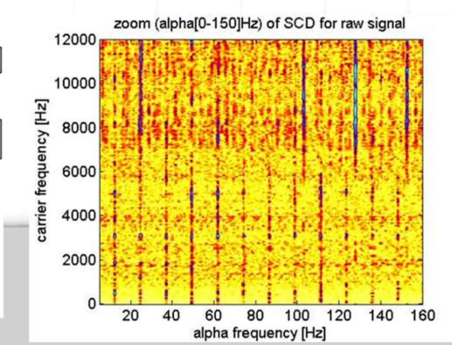

- **Kurtosis (impulsiveness) based filter optimization**
- **Demodulation**
- **Envelope Spectrum**

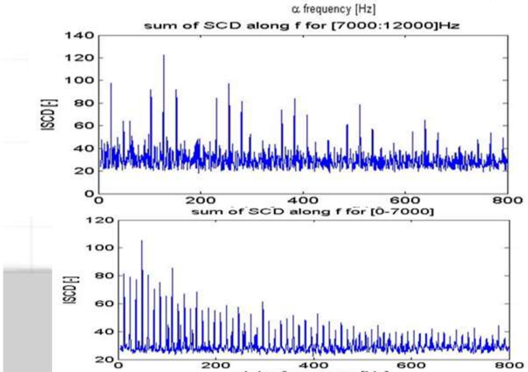
Multiple modulations, cyclostationary analysis



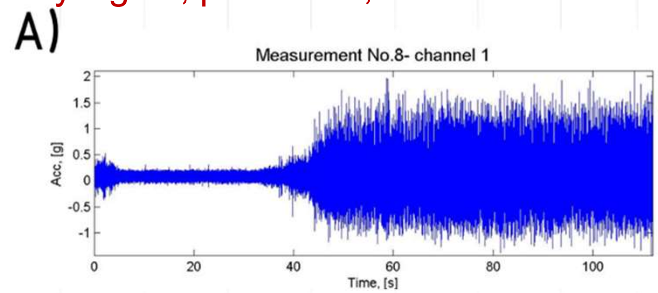



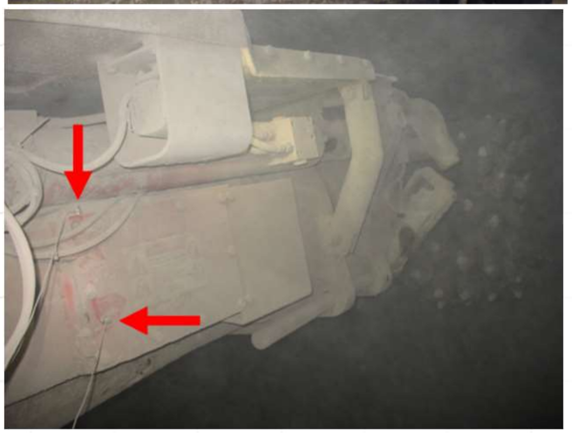



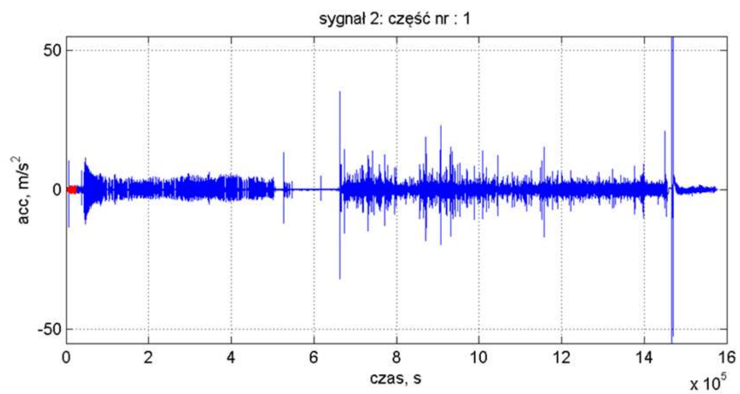
# Understand the object, its design, technological process, sources of vibration, physical model of observed signal

Highly nonstationary signal, poor SNR, nonGaussian noise, T-V load

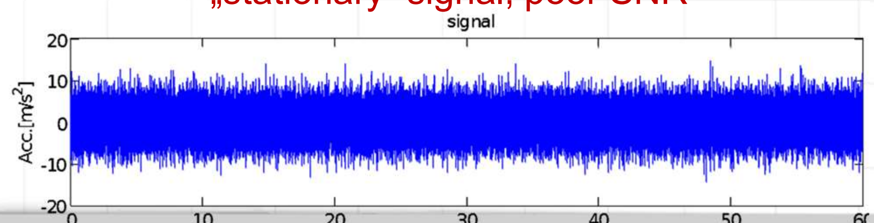


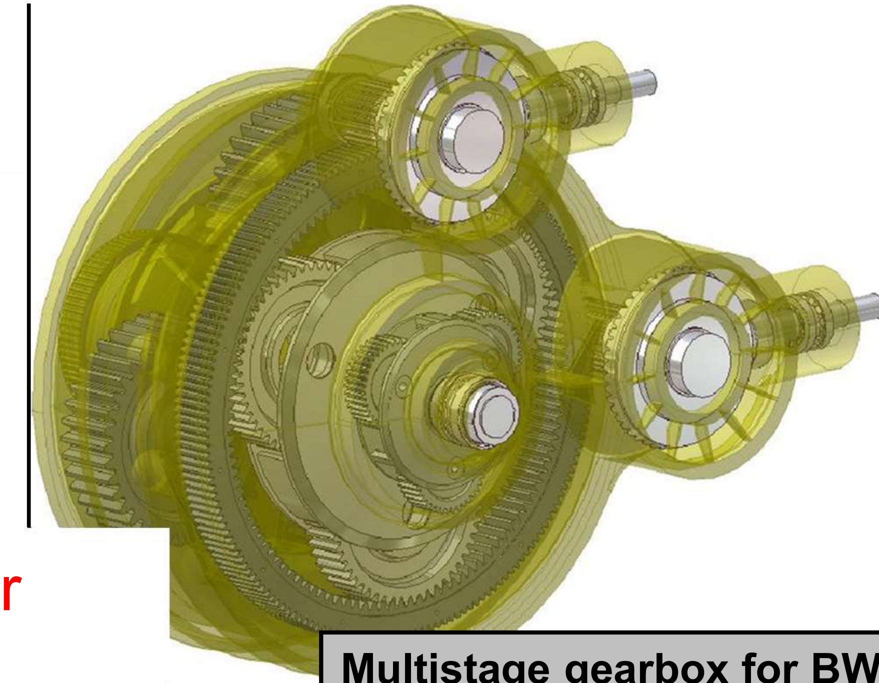



Highly nonstationary signal, poor SNR, nonGaussian noise

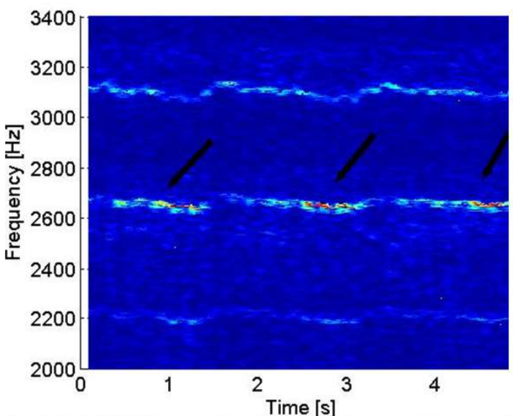



„stationary" signal, poor SNR

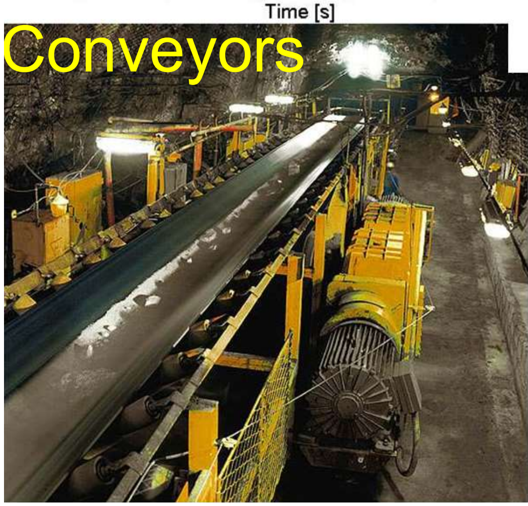


**Multistage gearbox for BWE**
- **power – 2 x 500 kW,**
- **input speed – 987 rpm,**
- **output speed – 4,28 rpm,**
- **total ratio i = 230,3644,**
- **weigth ~ 35 000 kg.**









**Recent solutions** – cyclostationary analysis in presence of non-Gaussian noise, optimal filter design for SOI extraction, source separation, de-noising.

Signal of Interest is impulsive and cyclic (periodic)

- In presence of Gaussian noise – kurtosis based approaches are great to detect impulsive component in noisy observation!
- However, there are also other statistics that could be used. They could be better in some cases!

- Cyclostationarity detection is based on autocovariance measure
- In case of non-Gaussian noise – it should NOT be used!
- **Alternative measures** are needed!

- Signal of Interest is impulsive and cyclic (periodic) => why not use these properties together? (concept of **Extended Infogram**)

# Use cases presentation

**Robust statistics, statistical modelling, stochastic processes** for non-Gaussian signal processing (band selection, filtering, cycle detection)

**Measures of dependences** for band selection and filter design for SOI extraction in presence of non-Gaussian noise – bearings damage detection in crusher

**Novel cyclo-stationary analysis** in presence of non-Gaussian noise – bearings damage detection in crusher

**Non-Negative Matrix Factorisation** for source separation

**Fusion of time and frequency domains** – Concept of Extended Infogram for impulsive signals

# Use cases presentation

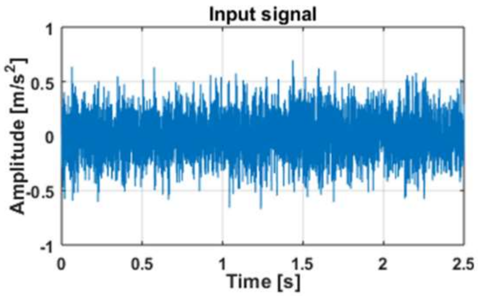
**Robust statistics, statistical modelling, stochastic processes** for non-Gaussian signal processing (band selection, filtering, cycle detection)

**J Obuchowski, A Wyłomańska, R Zimroz**
Selection of informative frequency band in local damage detection in rotating machinery
Mechanical Systems and Signal Processing 48 (1-2), 138-152
**A Wyłomańska, G Żak, P Kruczek, R Zimroz** Application of tempered stable distribution for selection of optimal frequency band in gearbox local damage detection Applied Acoustics 128, 14-22

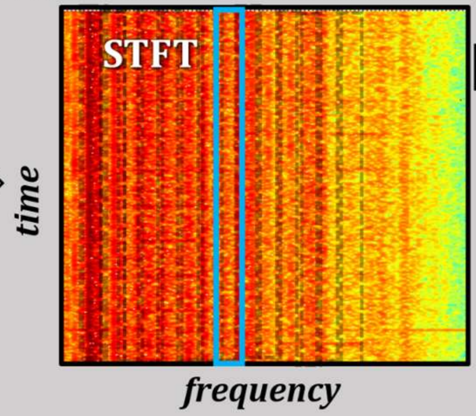
**G Żak, A Wyłomańska, R Zimroz**
Periodically impulsive behavior detection in noisy observation based on generalized fractional order dependency map Applied Acoustics 144, 31-39
**G Żak, M Teuerle, A Wyłomańska, R Zimroz**
Measures of dependence for-stable distributed processes and its application to diagnostics of local damage in presence of impulsive noise Shock and Vibration 2017

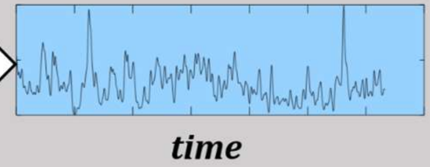
**G Żak, A Wyłomańska, R Zimroz**
Local damage detection method based on distribution distances applied to time-frequency map of vibration signal IEEE Transactions on Industry Applications 54 (5), 4091-4103

# Use appropriate mathematical tools to analyse signal structure

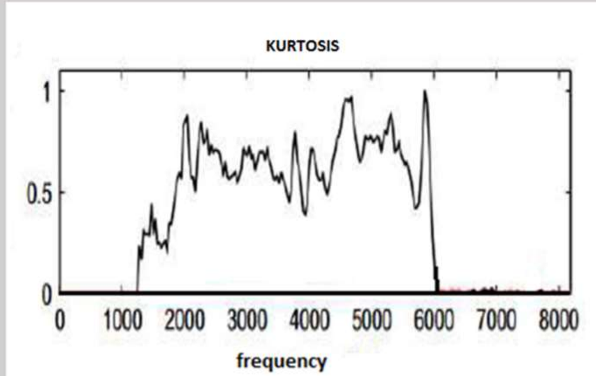



RAW INPUT SIGNAL




KURTOSIS(f)




**Kolmogorov-Smirnov statistics**

$$KSS(f) = sup_x\,|ECDF(f,x) - \Phi(f,x)|$$

**Cramer-von Misses statistics**

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

**Anderson-Darling statistics = CVM with $\phi$=1.**

**IFB selector based on QQplot**

**JB statistics**

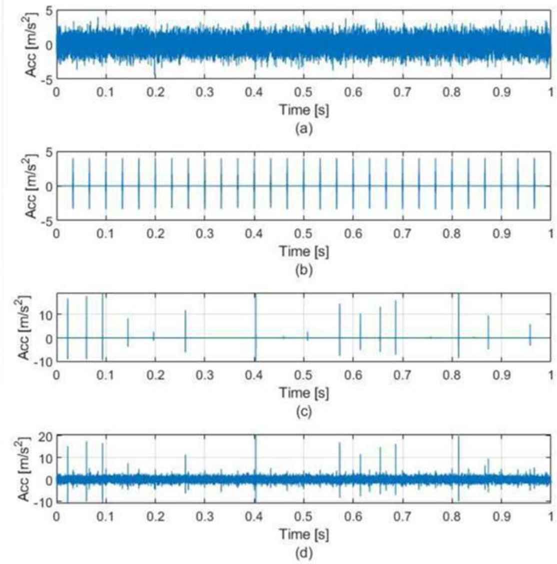
**Local maxima- based selector**

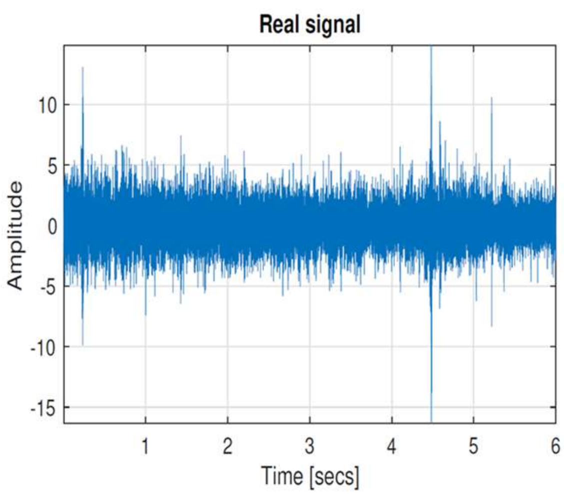
**…**

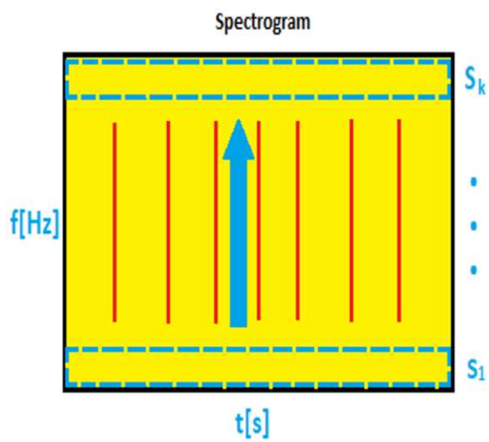
NOT APPROPRIATE FOR NON-GAUSSIAN NOISE!

Wrocław University of Science and Technology

# Signal processing perspective




$S_1 = \{ |STFT(t_1,f_1)|, |STFT(t_2,f_1)|, \dots, |STFT(t_l,f_1)| \}$

$S_2 = \{ |STFT(t_1,f_2)|, |STFT(t_2,f_2)|, \dots, |STFT(t_l,f_2)| \}$

$\vdots$

$S_k = \{ |STFT(t_1,f_k)|, |STFT(t_2,f_k)|, \dots, |STFT(t_l,f_k)| \}$

# New approaches – α-stable distribution –based methods

- The class of $\alpha$ – 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 $\alpha$ – distribution simplifies to the Gaussian distribution with some parameters $\mu, \sigma$. If the $\alpha$ tends to 0 then the examined distribution becomes more impulsive (the values of the outliers significantly increase).

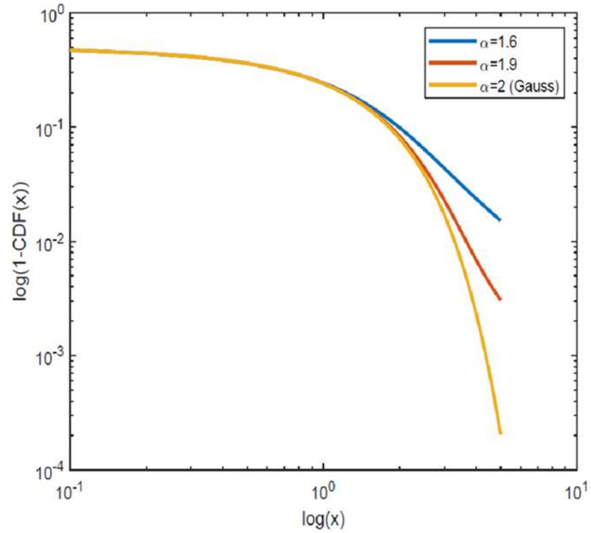
# New approaches – α-stable distribution –based methods

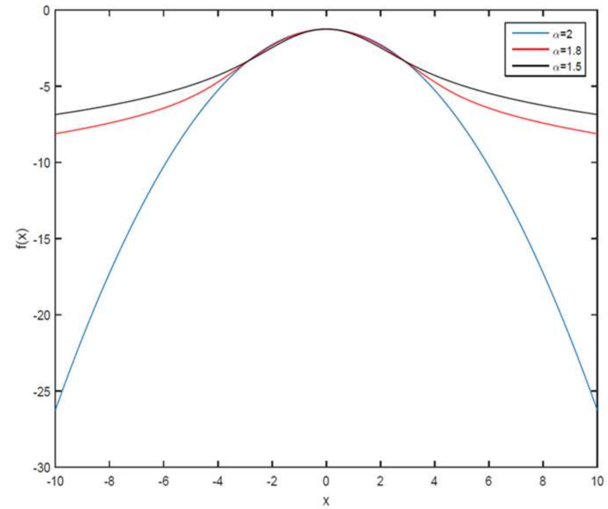
The $\alpha$ – stable distribution is defined by the characteristic function, which is as follows:

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

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

# New approaches – α-stable distribution –based methods




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

**ALPHA SELECTOR=2-α**

# Use cases presentation

**Robust statistics, statistical modelling, stochastic processes** for non-Gaussian signal processing (band selection, filtering, cycle detection)

## conditional variance statistics
## for informative band selection

**J Hebda-Sobkowicz, R Zimroz, M Pitera, A Wyłomańska**
Informative frequency band selection in the presence of non-Gaussian noise–a novel approach based on the conditional variance statistic with application to bearing fault diagnosis
Mechanical Systems and Signal Processing 145, 106971

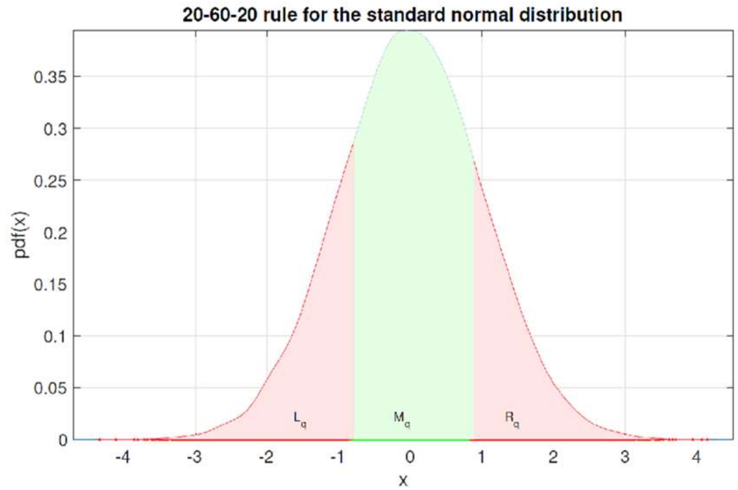



Figure 1: Pdf of the standard normal distribution with marked partitions corresponding to the 20-60-20 rule.

$$N := \frac{1}{\rho}\left(\frac{\hat{\sigma}^2_{L_q} - \hat{\sigma}^2_{M_q}}{\hat{\sigma}^2} + \frac{\hat{\sigma}^2_{R_q} - \hat{\sigma}^2_{M_q}}{\hat{\sigma}^2}\right)\sqrt{n},$$

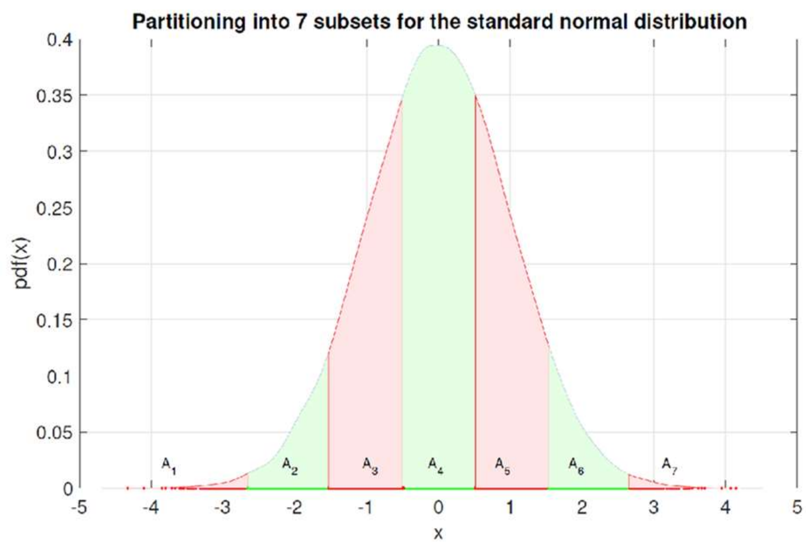



Figure 3: Pdf function of the standard normal distribution with a marked partition (7 subsets).

$$N_2 := \left(\frac{\hat{\sigma}^2_{A_3} - \hat{\sigma}^2_{A_4}}{\hat{\sigma}} + \frac{\hat{\sigma}^2_{A_5} - \hat{\sigma}^2_{A_4}}{\hat{\sigma}}\right)^2\sqrt{n},$$

# New approaches – conditional variance statistics -based methods

- 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 approaches – conditional variance statistics -based methods

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

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

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 $\sigma_{A_i}$ in the given set $A_i$. The main property of divisions $A_i$ is that their variances are equal.

## New approaches – conditional variance statistics -based methods

Assuming the Gaussian distribution the following equation is fulfilled:

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

- 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.

# Selected results – new IFB selectors

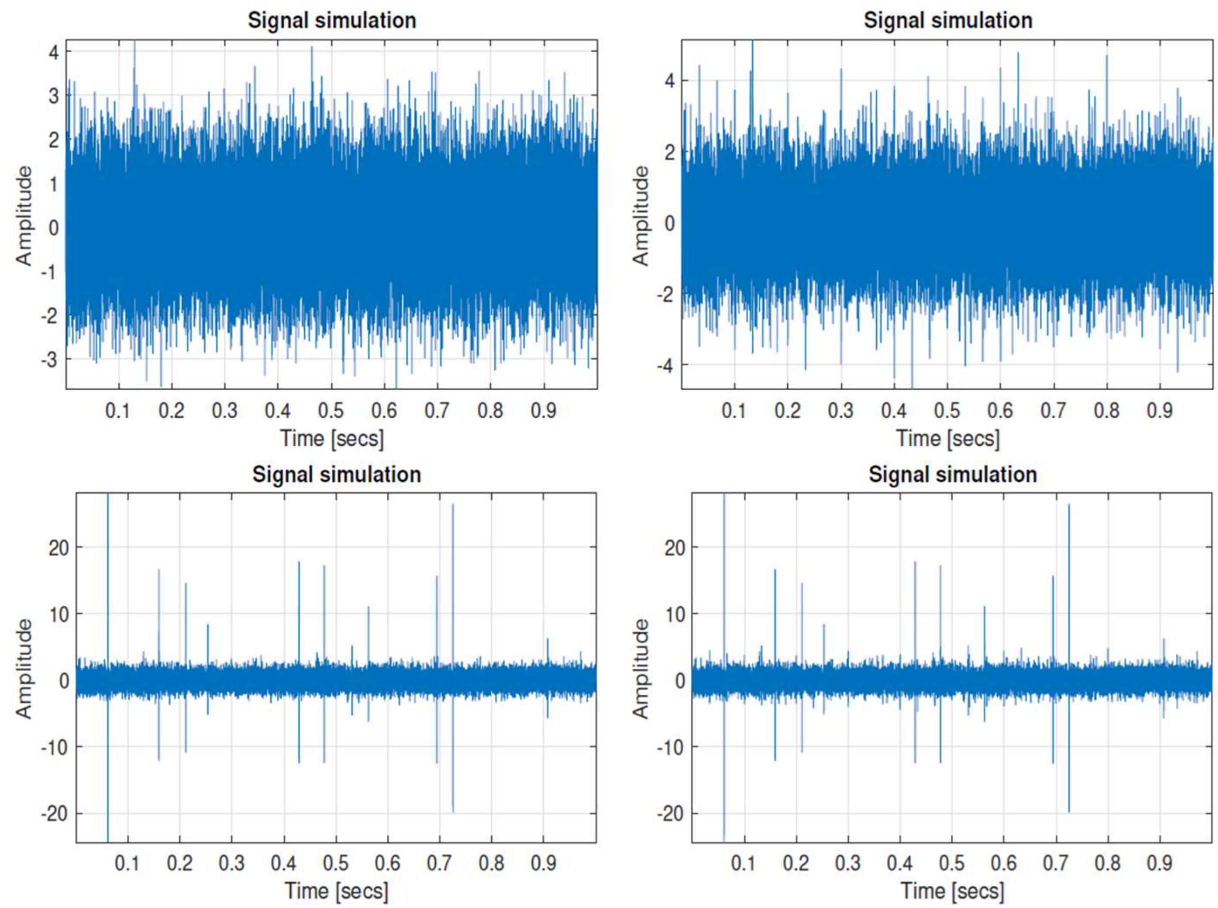



Figure: Simulated signals: s1- Gaussian noise, s2- Gaussian noise with cyclic impulses, s3- non-Gaussian noise, s4- non-Gaussian noise with cyclic impulses.

# Selected results – new IFB selectors

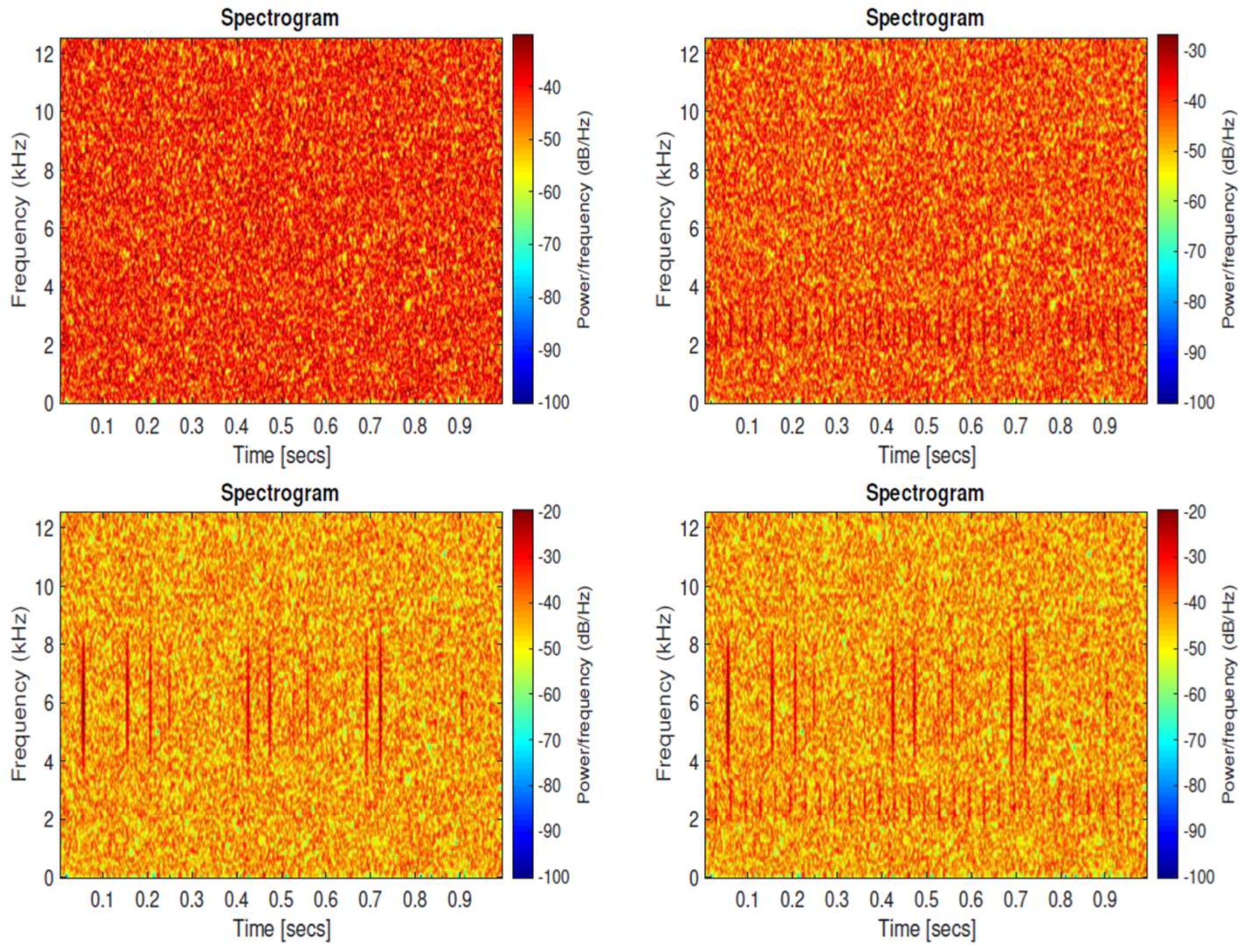



Figure: Spectrograms of the simulated signals: s1- Gaussian noise, s2- Gaussian noise with cyclic impulses, s3- non-Gaussian noise, s4- non-Gaussian noise with cyclic impulses.

# Selected results – new IFB selectors

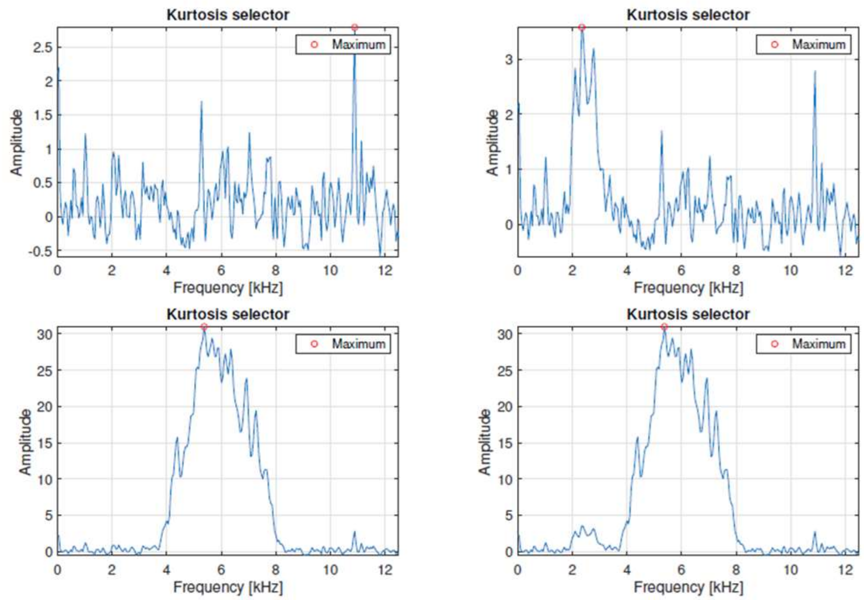



Figure: Spectral kurtosis for simulated signals: s1- Gaussian noise, s2- Gaussian noise with cyclic impulses, s3- non-Gaussian noise, s4- non-Gaussian noise with cyclic impulses.

# Selected results – new IFB selectors

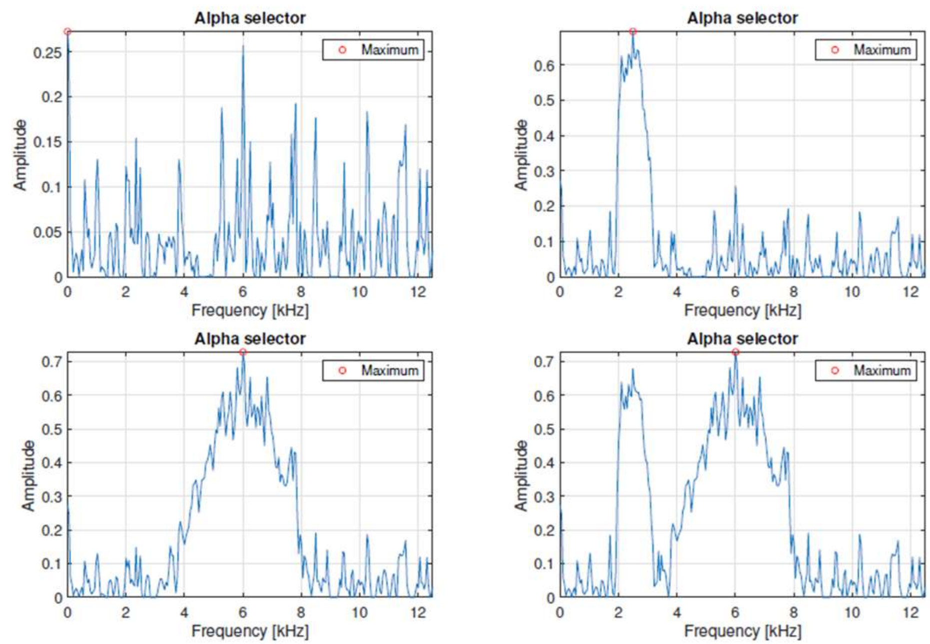



Figure: Alpha selector for simulated signals: s1- Gaussian noise, s2- Gaussian noise with cyclic impulses, s3- non-Gaussian noise, s4- non-Gaussian noise with cyclic impulses.

# Selected results – new IFB selectors

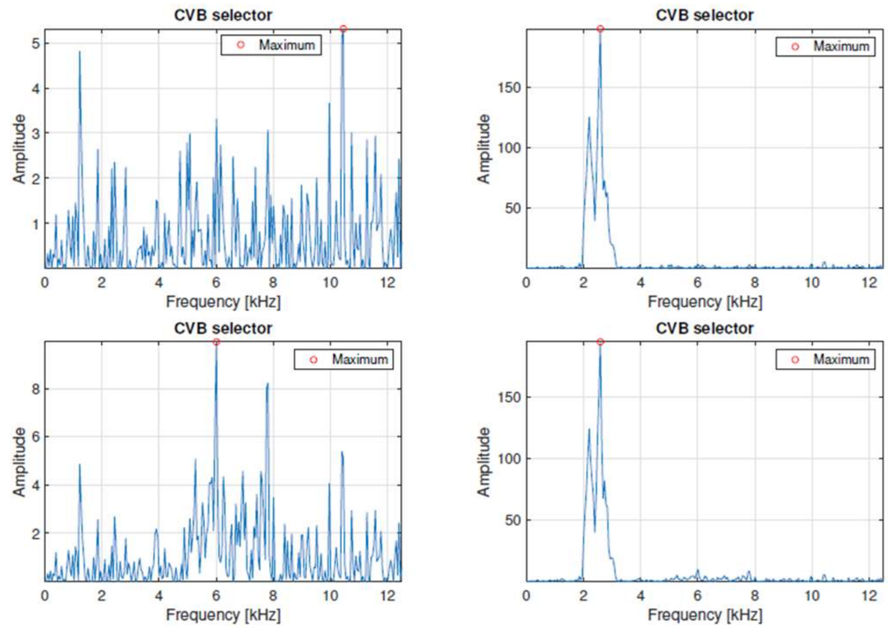



Figure: CVB selector for simulated signals: s1- Gaussian noise, s2- Gaussian noise with cyclic impulses, s3- non-Gaussian noise, s4- non-Gaussian noise with cyclic impulses.

# Selected results – new IFB selectors

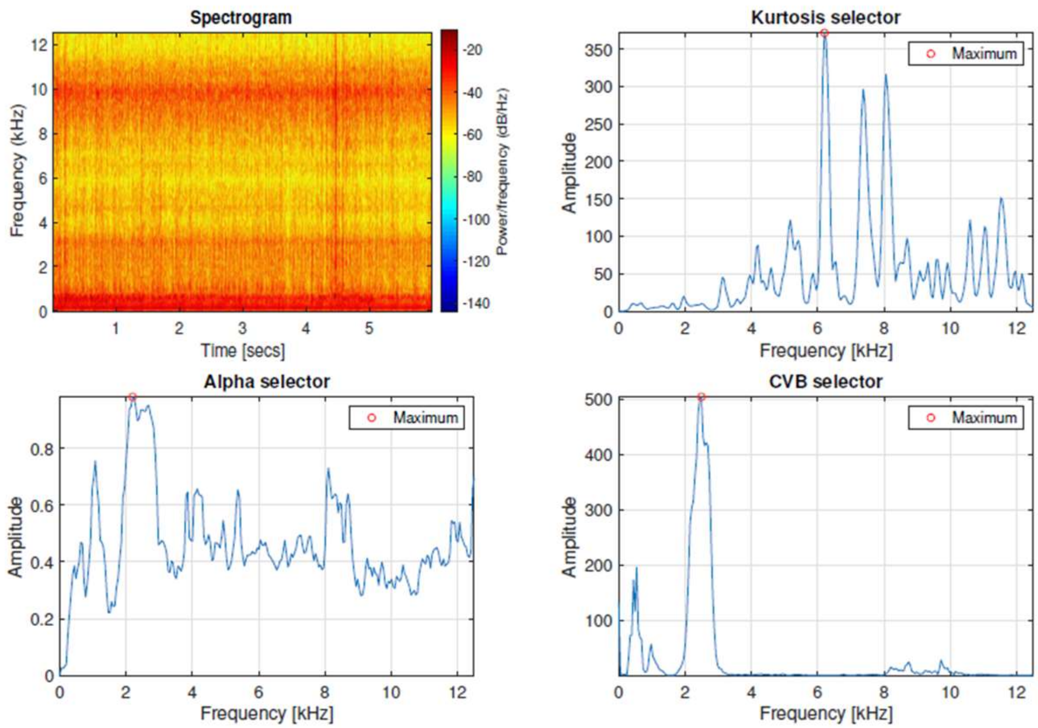



Figure: Results for real signal from crushing machine.

# Selected results – new IFB selectors

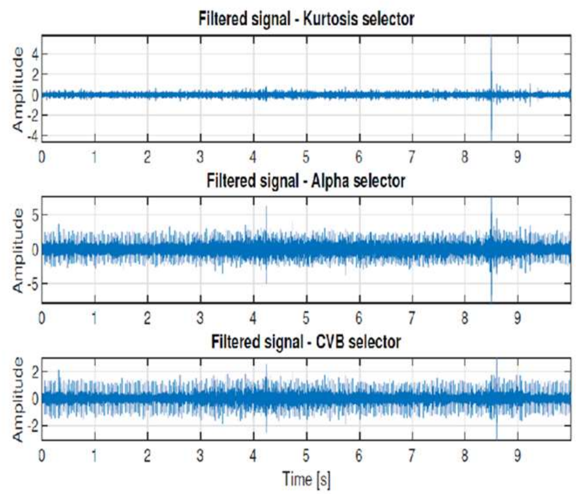



Figure: The results of the copper ore crusher's signal filtration perf by three different selectors.

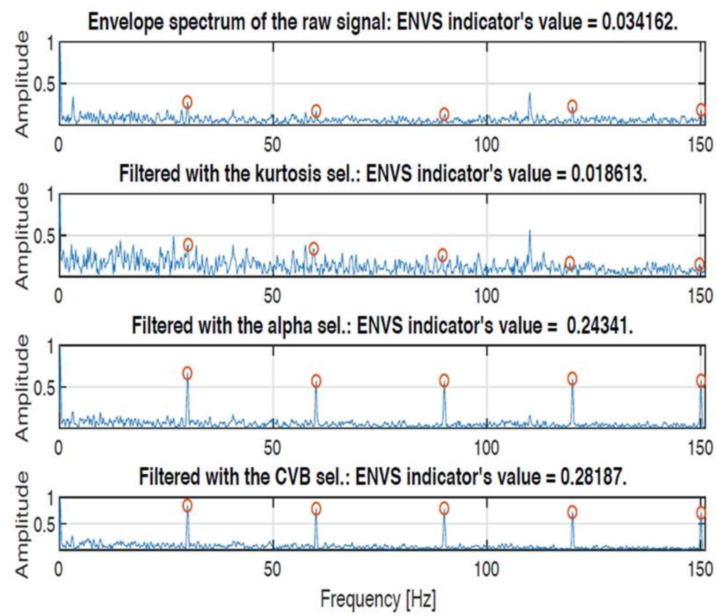
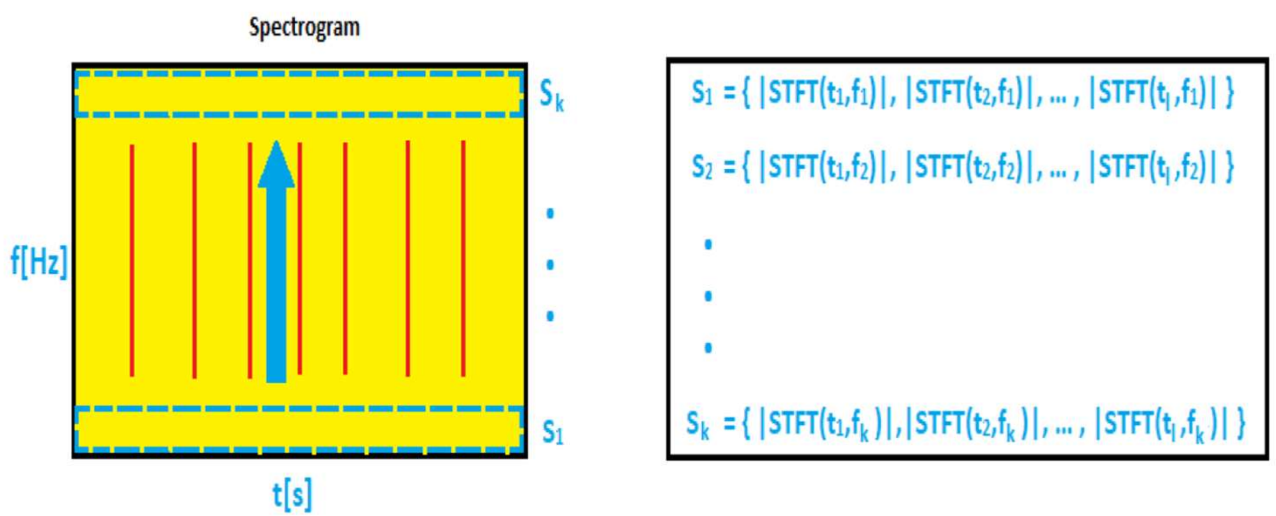



Figure: The envelope spectrum for filtered signals.

# Classical approaches

- Approach based on the second order cyclostationarity (analysis of autocovariance function, Cyclic Spectral Coherence, cyclostationarity indicators, etc.).
- Application of the measures of impulsiveness to the signal in time-frequency representation (Spectral Kurtosis, selectors based on the statistics used for Gaussian distribution testing, other IFB selectors).
- ……



# Use cases presentation

**Novel cyclo-stationary analysis** in presence of non-Gaussian noise – bearings damage detection in crusher

**P Kruczek, R Zimroz, A Wyłomańska**
How to detect the cyclostationarity in heavy-tailed distributed signals
Signal Processing 172, 107514

**P Kruczek, R Zimroz, J Antoni, A Wyłomańska**
Generalized spectral coherence for cyclostationary signals with α-stable distribution
Mechanical Systems and Signal Processing 159, 107737

# Selected results – alternative dependency measures for heavy-tailed distributed signals

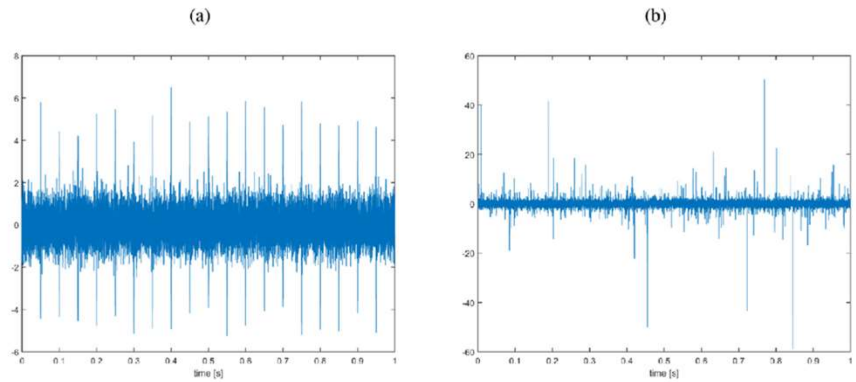
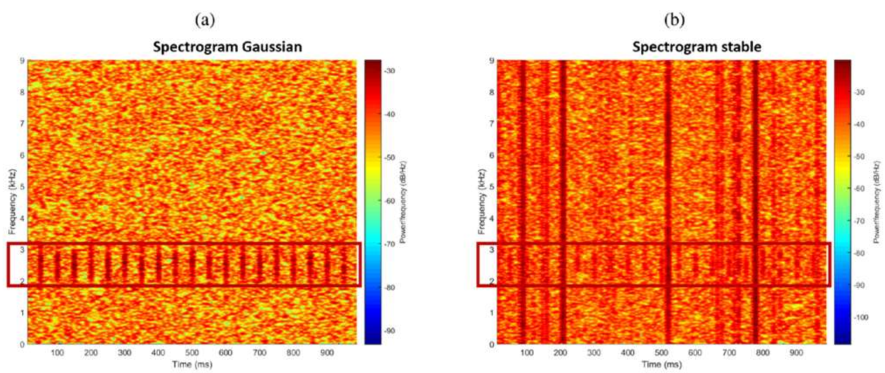
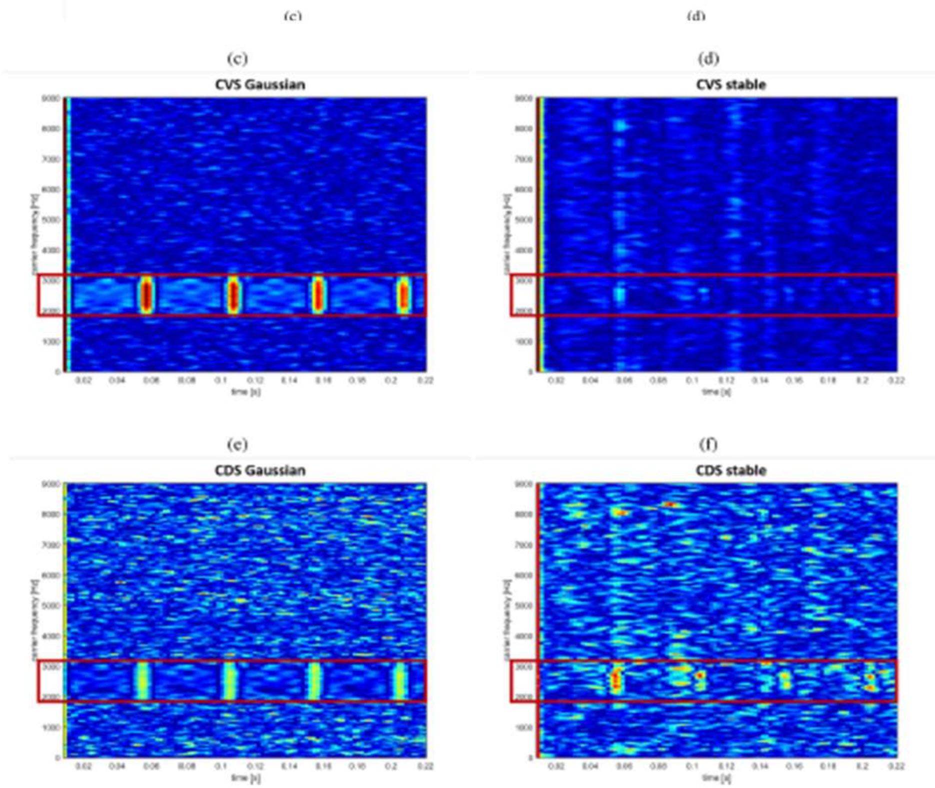



Fig. 4. The exemplary simulated signal without $S\alpha S$ noise (a) and with $S\alpha S$ noise (b). Because the amplitude for signal with $S\alpha S$ noise is much higher, the presented signals have different scale on the y axis.




g. 5. The spectrogram of simulated signal without $S\alpha S$ noise (a) nad with $S\alpha S$ noise (b). The CVS map of simulated signal without $S\alpha S$ noise (c) nad with $S\alpha S$ noise (d). ie CDS map of simulated signal without $S\alpha S$ noise (e) nad with $S\alpha S$ noise (f).



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# Selected results – alternative dependency measures for heavy-tailed distributed signals

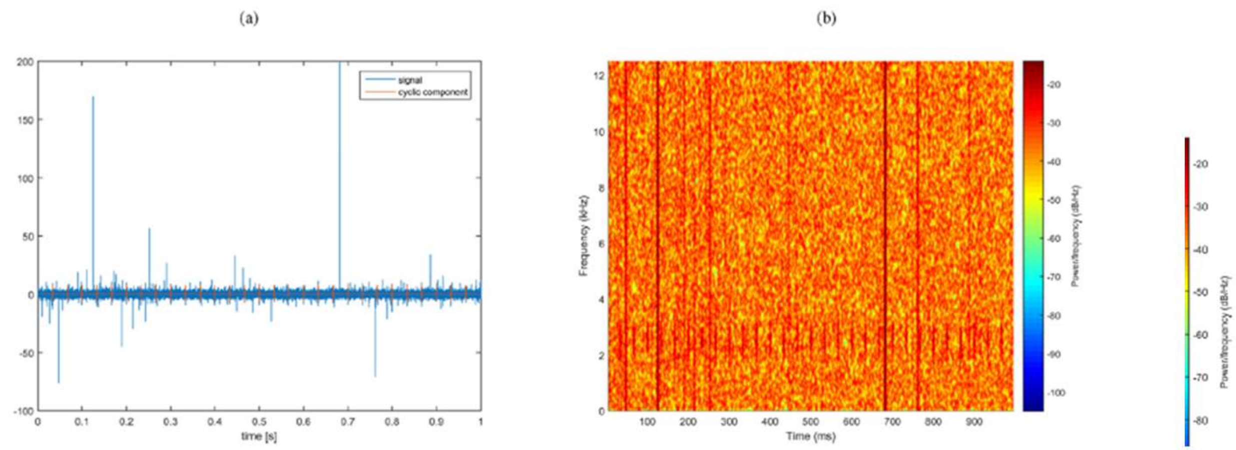
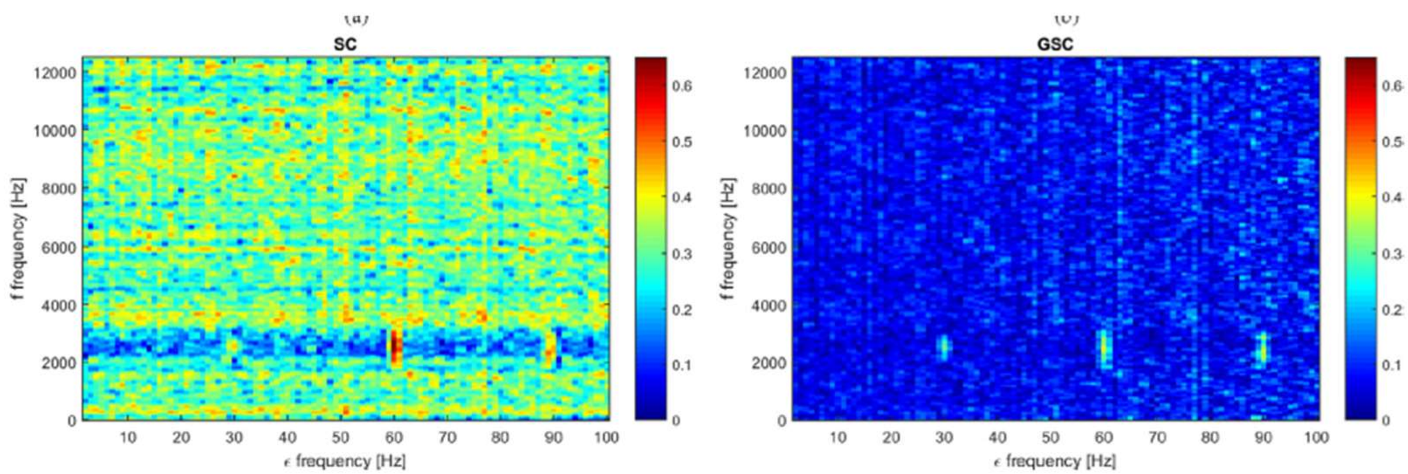



**Fig. 1.** The exemplary simulated signal (a) and its spectrogram (b).



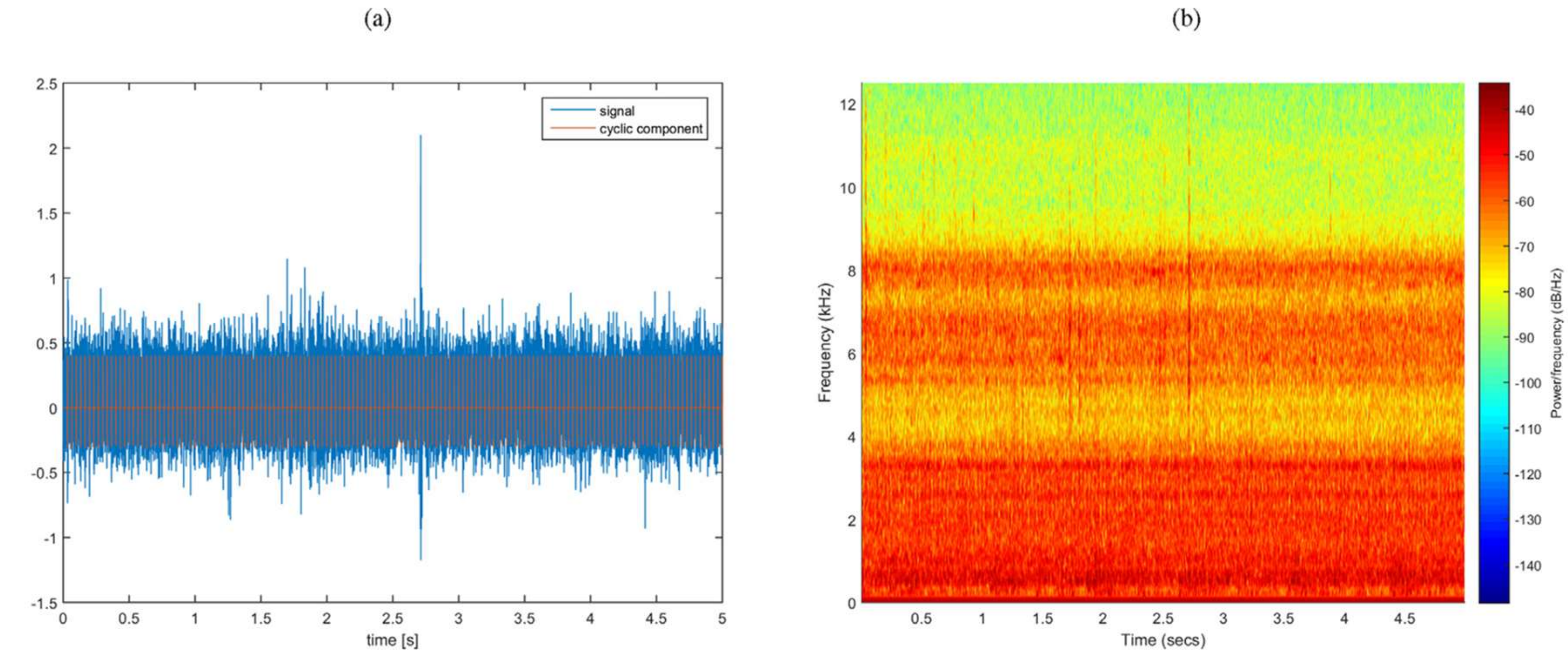



**Fig. 8.** The vibration signal from crusher machine with added cyclic impulses (a) and its spectrogram (b).

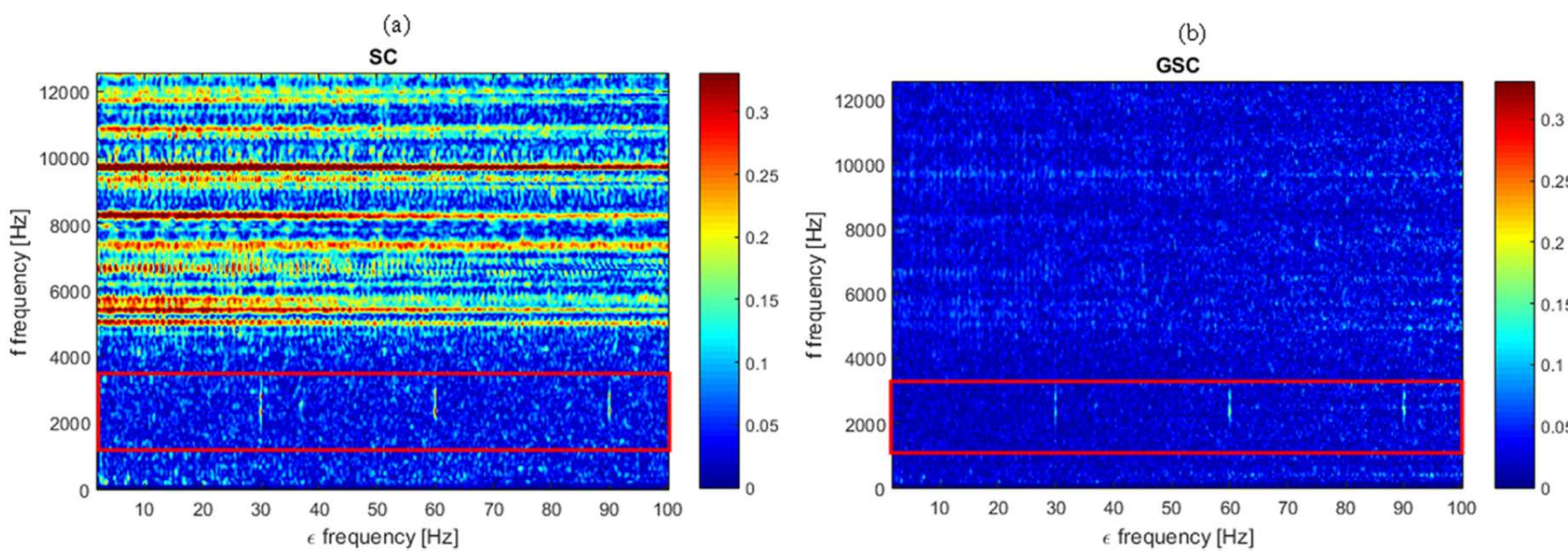



**Fig. 9.** The SC (a) and GSC (b) maps for the signal from Fig. 8a.

# Use cases presentation

**Measures of dependences** for band selection and filter design for SOI extraction in presence of non-Gaussian noise – bearings damage detection in crusher

**J Nowicki, J Hebda-Sobkowicz, R Zimroz, A Wyłomańska**
Dependency measures for the diagnosis of local faults in application to the heavy-tailed vibration signal
Applied Acoustics 178, 107974
**J Nowicki, J Hebda-Sobkowicz, R Zimroz, A Wylomanska**
Local Defect Detection in Bearings in the Presence of Heavy-Tailed Noise and Spectral Overlapping of Informative and Non-Informative Impulses
Sensors 20 (22), 6444
**J Hebda-Sobkowicz, R Zimroz, A Wyłomańska**
Selection of the Informative Frequency Band in a Bearing Fault Diagnosis in the Presence of Non-Gaussian Noise—Comparison of Recently Developed Methods
Applied Sciences 10 (8), 2657

# Selected results – alternative dependency measures for heavy-tailed distributed signals

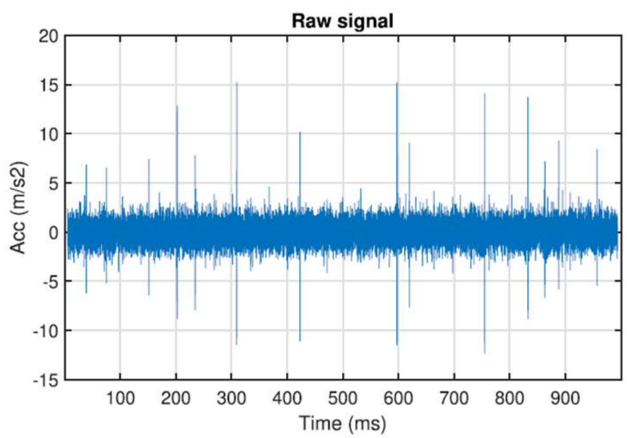
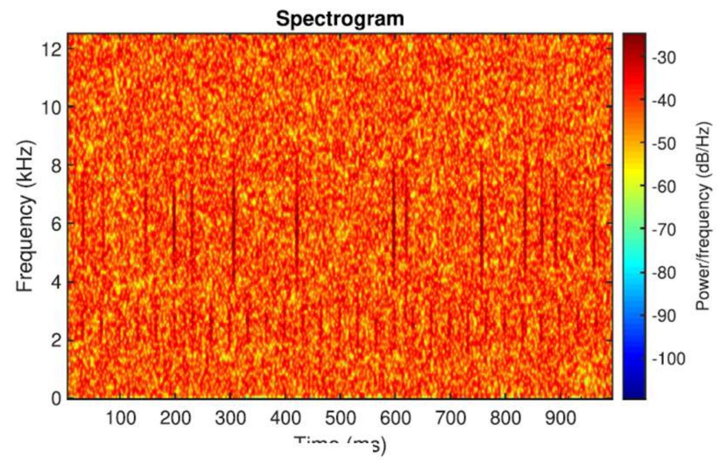



**Fig. 5.** Simulated signal

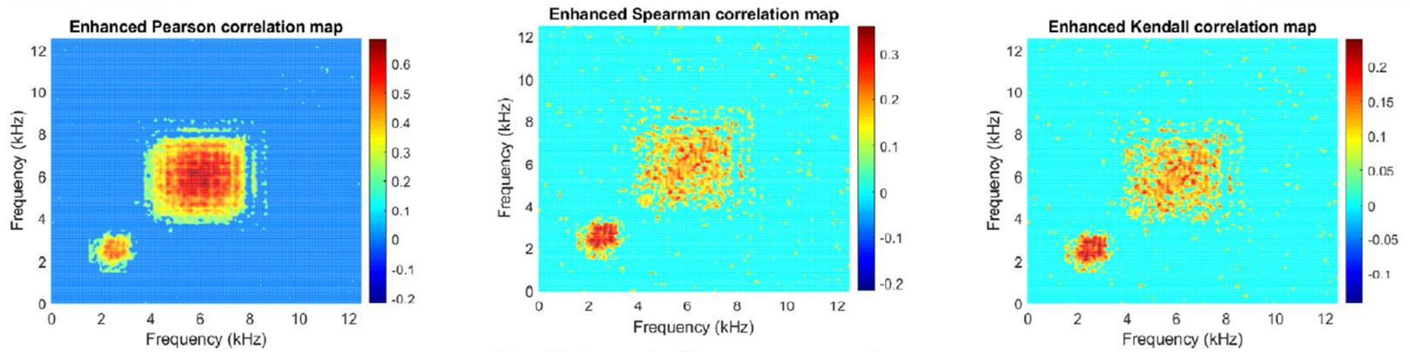



he simulated signal $x$.

**Dependency map**

$$
\begin{matrix}
m(s_1,s_1), m(s_1,s_2), & \cdots & , m(s_1,s_l) \\
m(s_2,s_1), m(s_2,s_2), & \cdots & , m(s_2,s_l) \\
\vdots & & \\
m(s_k,s_1), m(s_k,s_2), & \cdots & , m(s_k,s_l)
\end{matrix}
$$

# Selected results – alternative dependency measures for heavy-tailed distributed signals

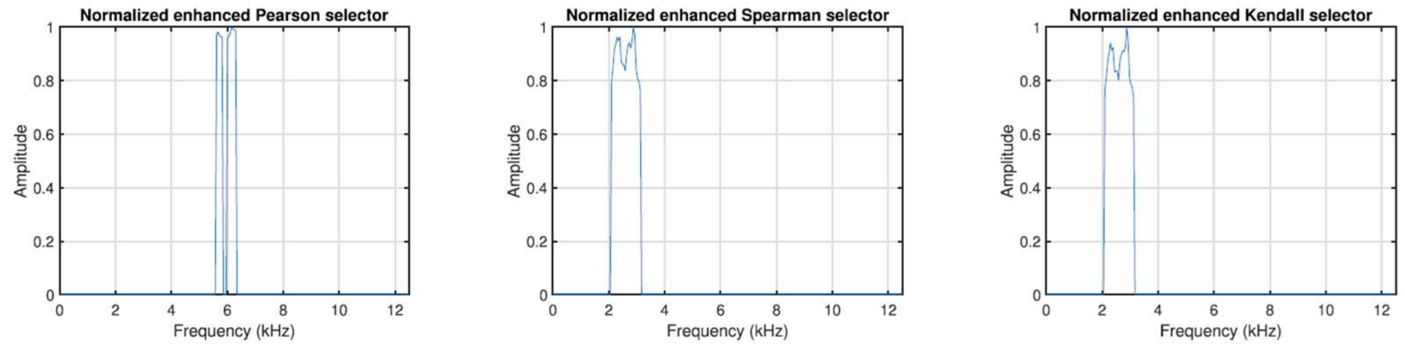



(a) Enhanced Pearson correlation map.

(b) Enhanced Spearman correlation map.

(c) Enhanced Kendall correlation map.

**Fig.** Enhanced correlation maps for the simulated data.



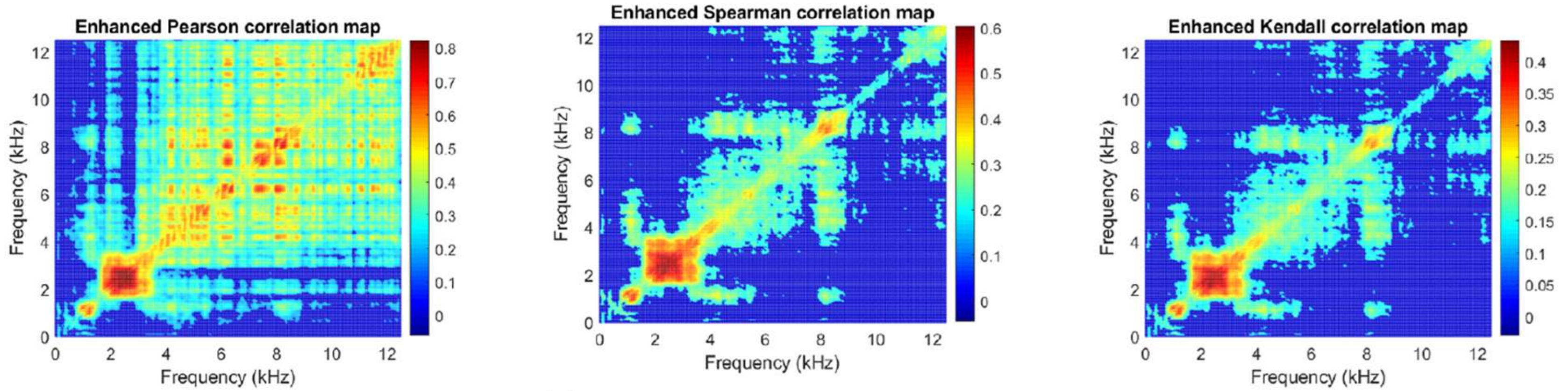

(a) Normalized enhanced Pearson selector.

(b) Normalized enhanced Spearman selector.

(c) Normalized enhanced Kendall selector.

**Fig.** Normalized enhanced IFB selectors for the simulated data.

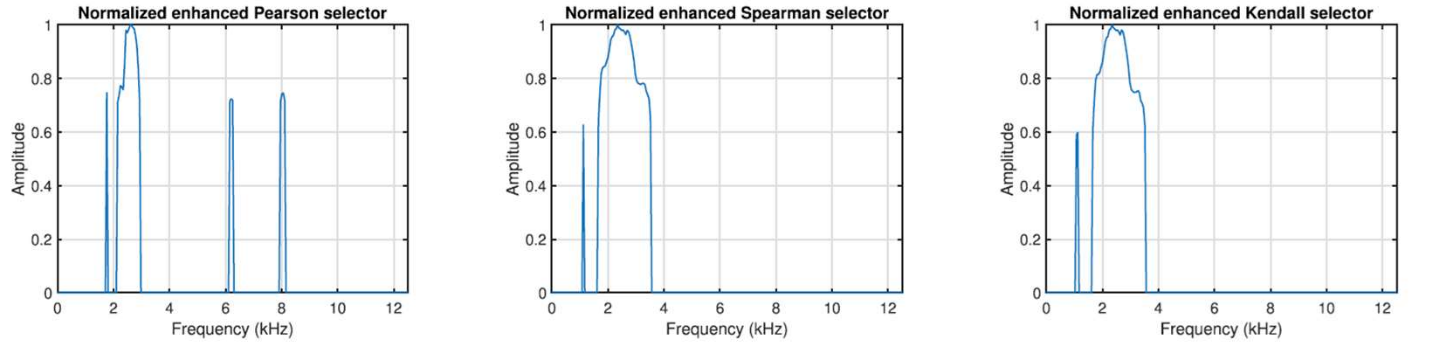
# Selected results – alternative dependency measures for heavy-tailed distributed signals




(a) Enhanced Pearson correlation map. (b) Enhanced Spearman correlation map. (c) Enhanced Kendall correlation map.

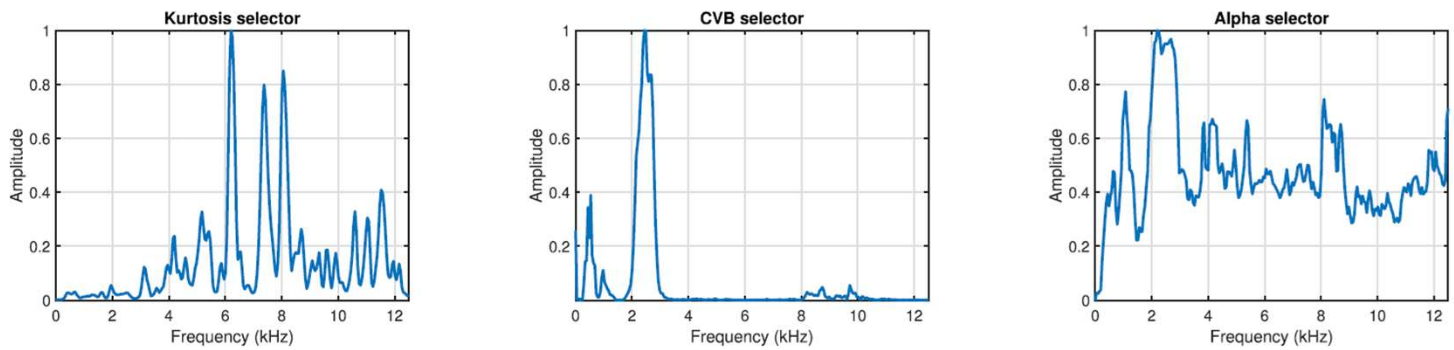
**Fig.** Enhanced correlation maps for industrial data.

# Selected results – comparison




(a) Normalized enhanced Pearson selector. (b) Normalized enhanced Spearman selector. (c) Normalized enhanced Kendall selector.

**Fig.** Normalized enhanced selectors for the industrial data.




(a) (b) (c)

**Fig.** Results of the informative frequency band selection for three different known methods for the real data from the bearing of the crushing machine: (a) Kurtosis selector (a) CVB selector (a) Alpha selector.

# Use cases presentation

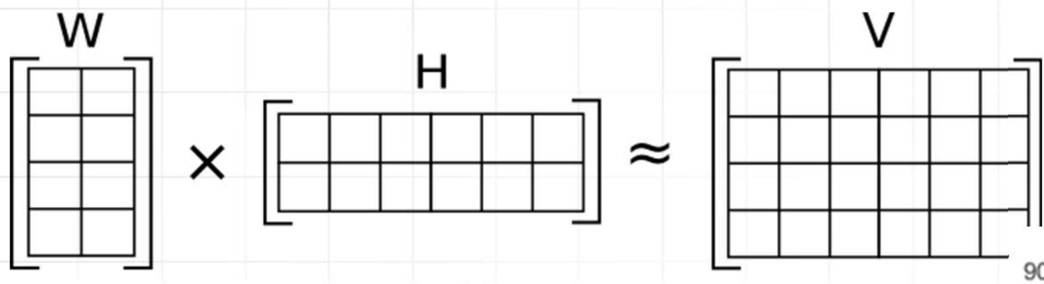
**Non-Negative Matrix Factorisation** for source separation

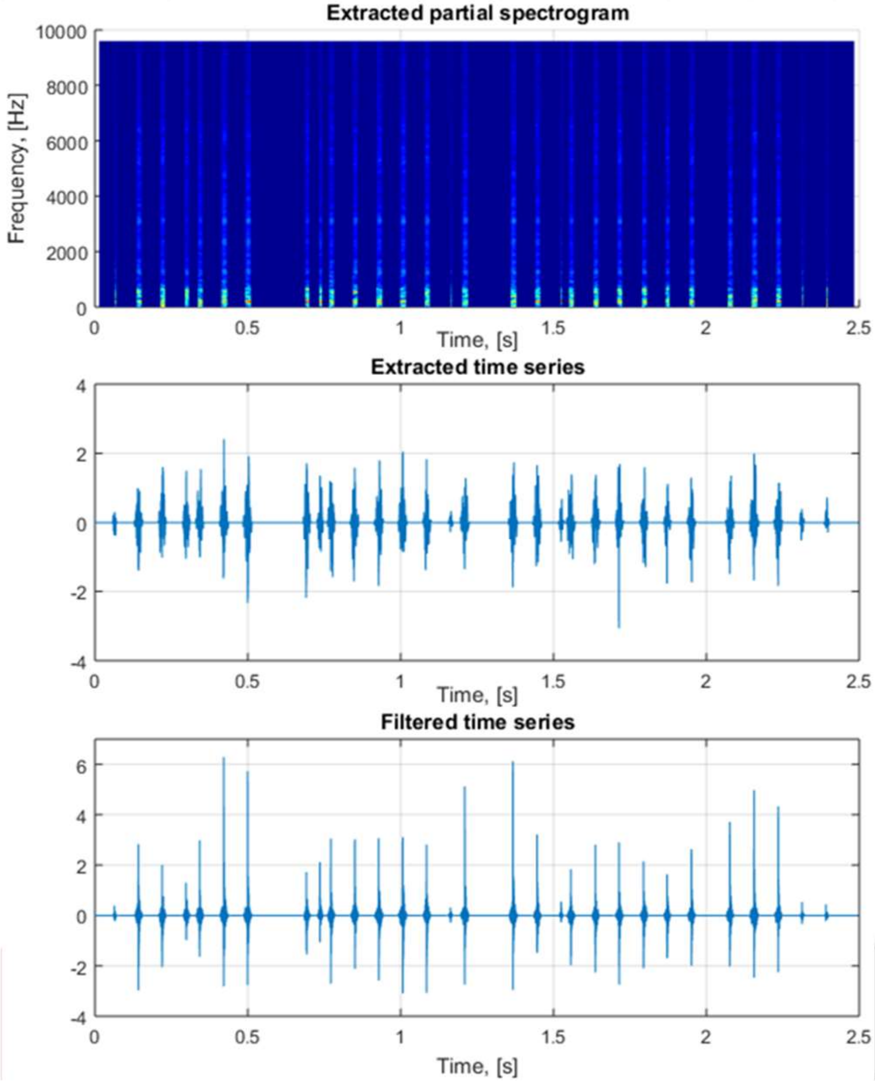
**J Wodecki, A Michalak, R Zimroz, T Barszcz, A Wyłomańska**
Impulsive source separation using combination of Nonnegative Matrix Factorization of bi-frequency map, spatial denoising and Monte Carlo simulation
Mechanical Systems and Signal Processing 127, 89-101

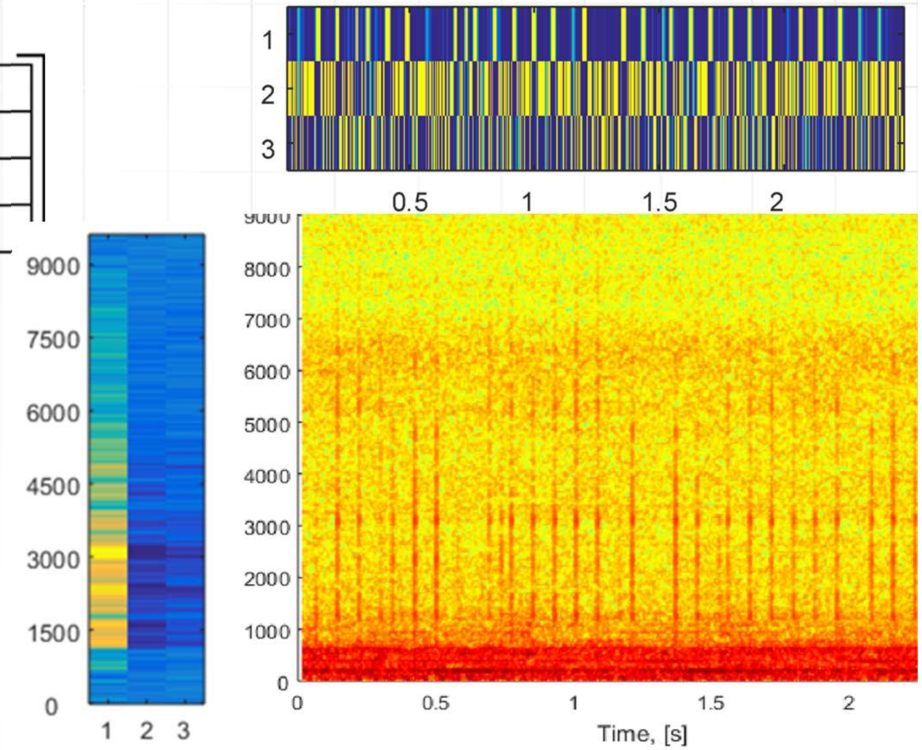
**J Wodecki, P Kruczek, A Bartkowiak, R Zimroz, A Wyłomańska**
Novel method of informative frequency band selection for vibration signal using Nonnegative Matrix Factorization of spectrogram matrix
Mechanical Systems and Signal Processing 130, 585-596

**J Wodecki, A Michalak, R Zimroz, A Wyłomańska**
Separation of multiple local-damage-related components from vibration data using Nonnegative Matrix Factorization and multichannel data Fusion
Mechanical Systems and Signal Processing 145, 106954

# What is NMF

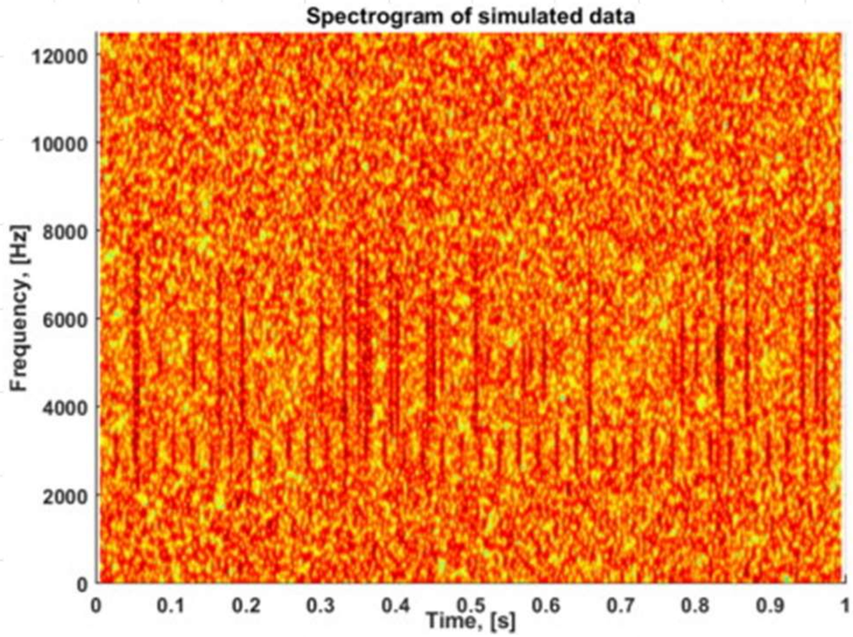


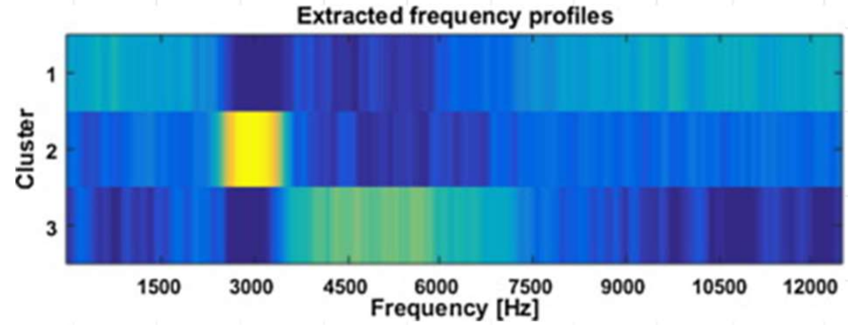




Spectrogram as non-neg. matrix

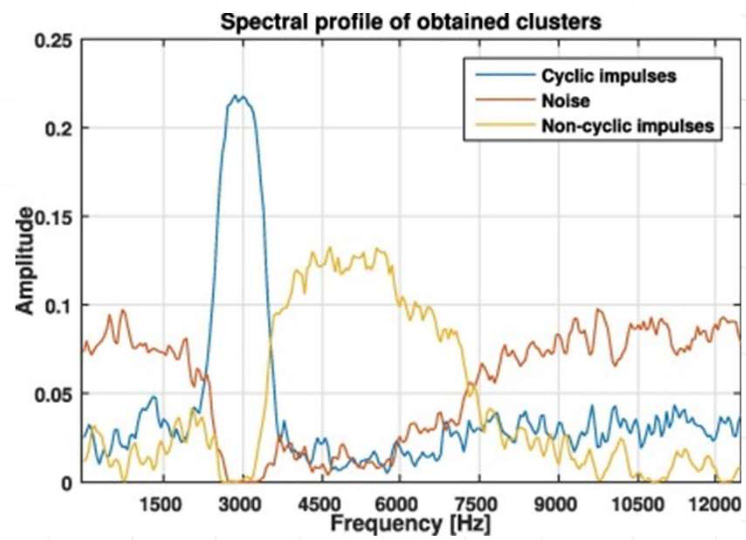
**Non-negative matrix factorization** (**NMF** or **NNMF**), also **non-negative matrix approximation** is a group of algorithms in multivariate analysis and linear algebra where a matrix **V** is factorized into (usually) two matrices **W** and **H**, with the property that all three matrices have no negative elements



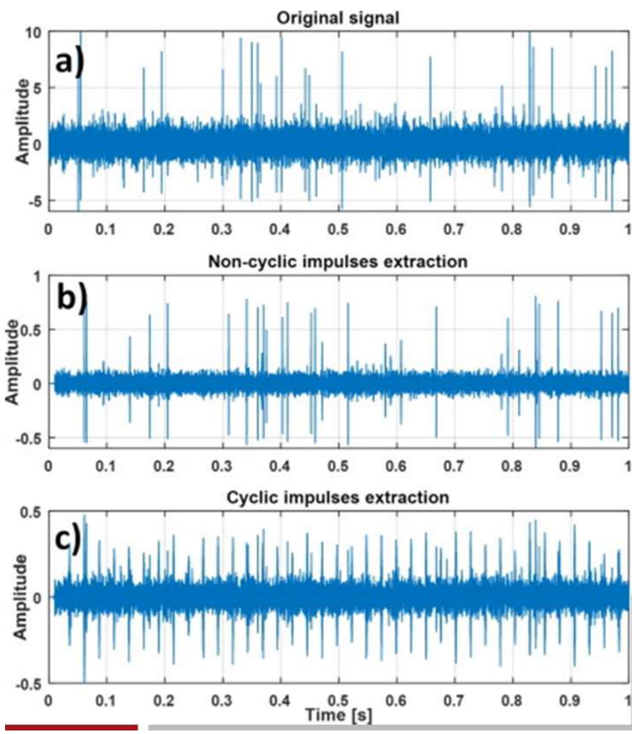




Matrix W containing r = 3 IFB selectors obtained by NMF from simulated data.

Each column vector of **W** is considered as averaged spectral density and can be used as filter characteristic (also named *selector*).




Spectral profiles (selectors) of obtained clusters for simulated signal




Results of filtration for simulated signal: a) original signal, b) non-cyclic impulses, c) cyclic impulses.

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# Use cases presentation

**Fusion of time and frequency domains** – Concept of Extended Infogram for impulsive signals

**Original Idea:**
J Antoni
The infogram: Entropic evidence of the signature of repetitive transients
Mechanical Systems and Signal Processing 74, 73-94

**Enhancement**
Justyna Hebda-Sobkowicz, Radoslaw Zimroz, Agnieszka Wylomanska, Jerome Antoni

Infogram performance analysis and its enhancement for bearings diagnostics in presence of non-Gaussian noise

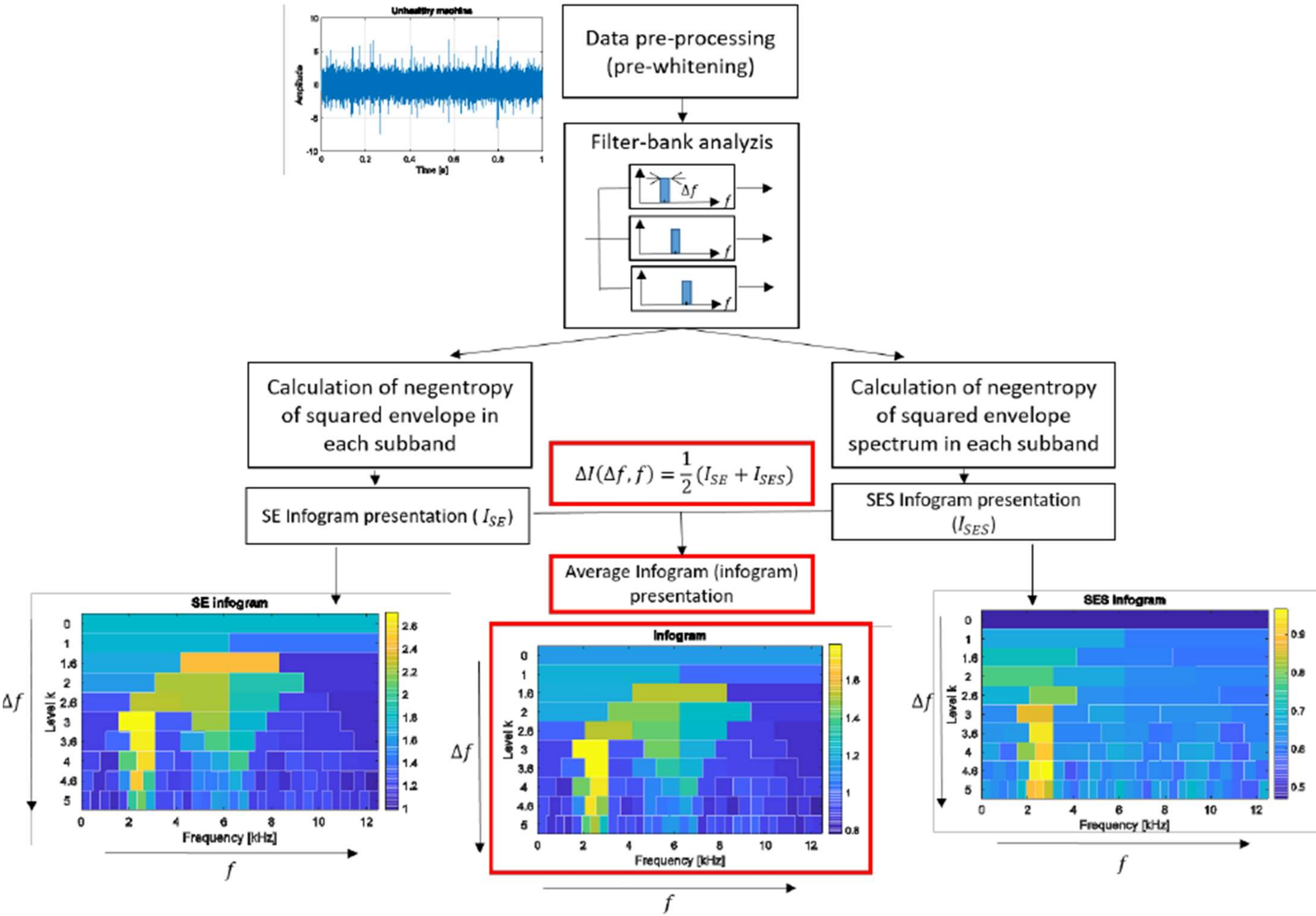


Figure 3: The flowchart of the algorithm for computing the infogram.

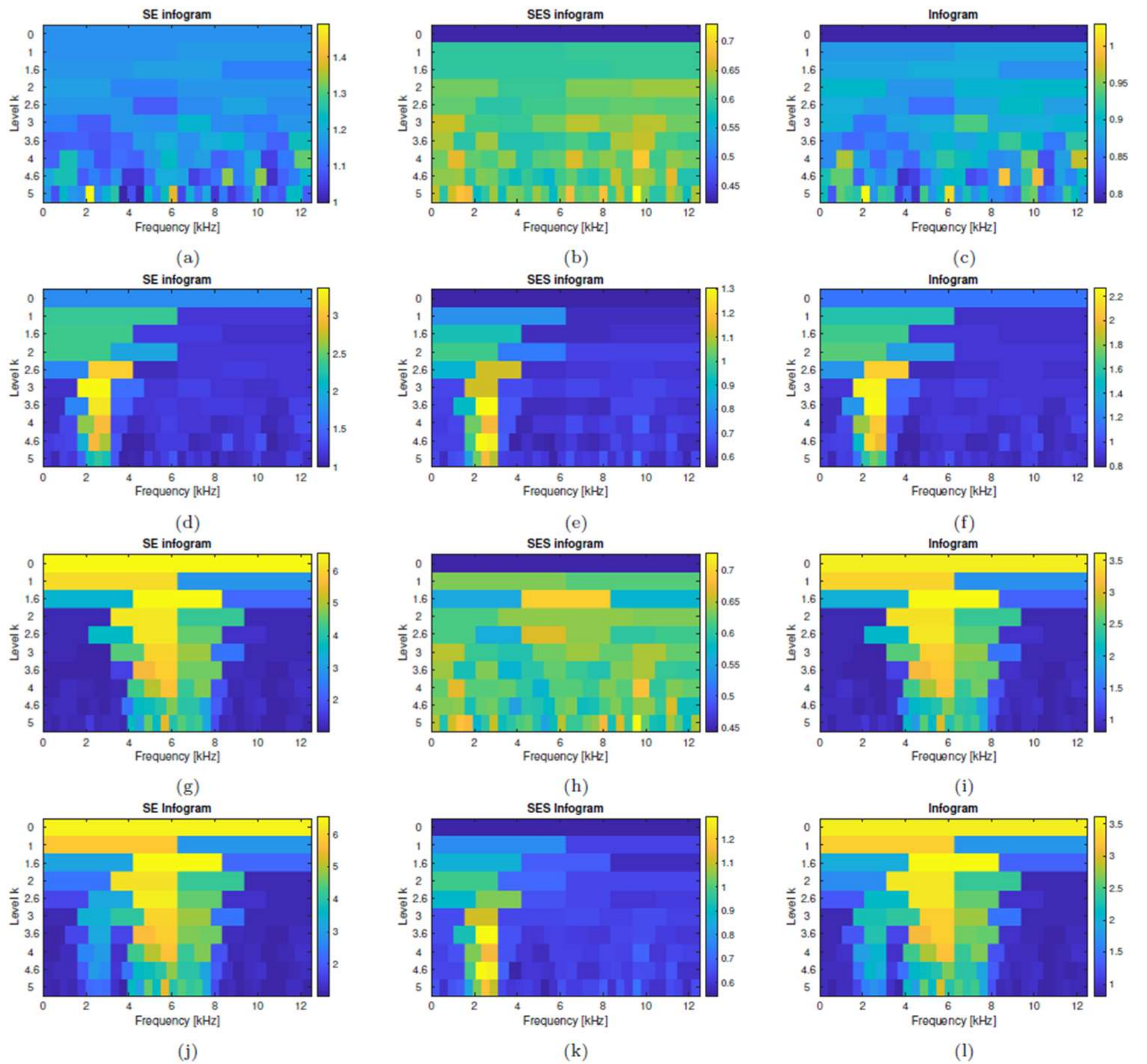


Figure 2: (a)-(c) Infogram and its SE/SES components for the simulated signal $s_1$ (Gaussian noise), (d)-(f) signal $s_2$ (Gaussian noise + barely visible SOI), (g)-(i) signal $s_3$ (Gaussian noise + non-cyclic-impulses), and (j)-(l) signal $s_4$ all components together.

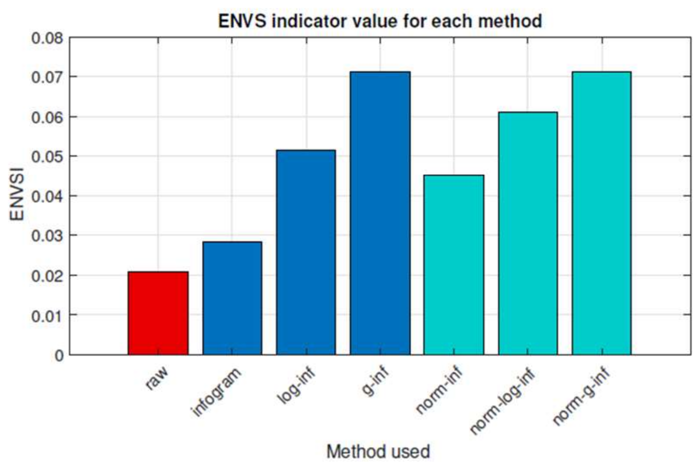


Figure 8: ENVS indicator value for each method.

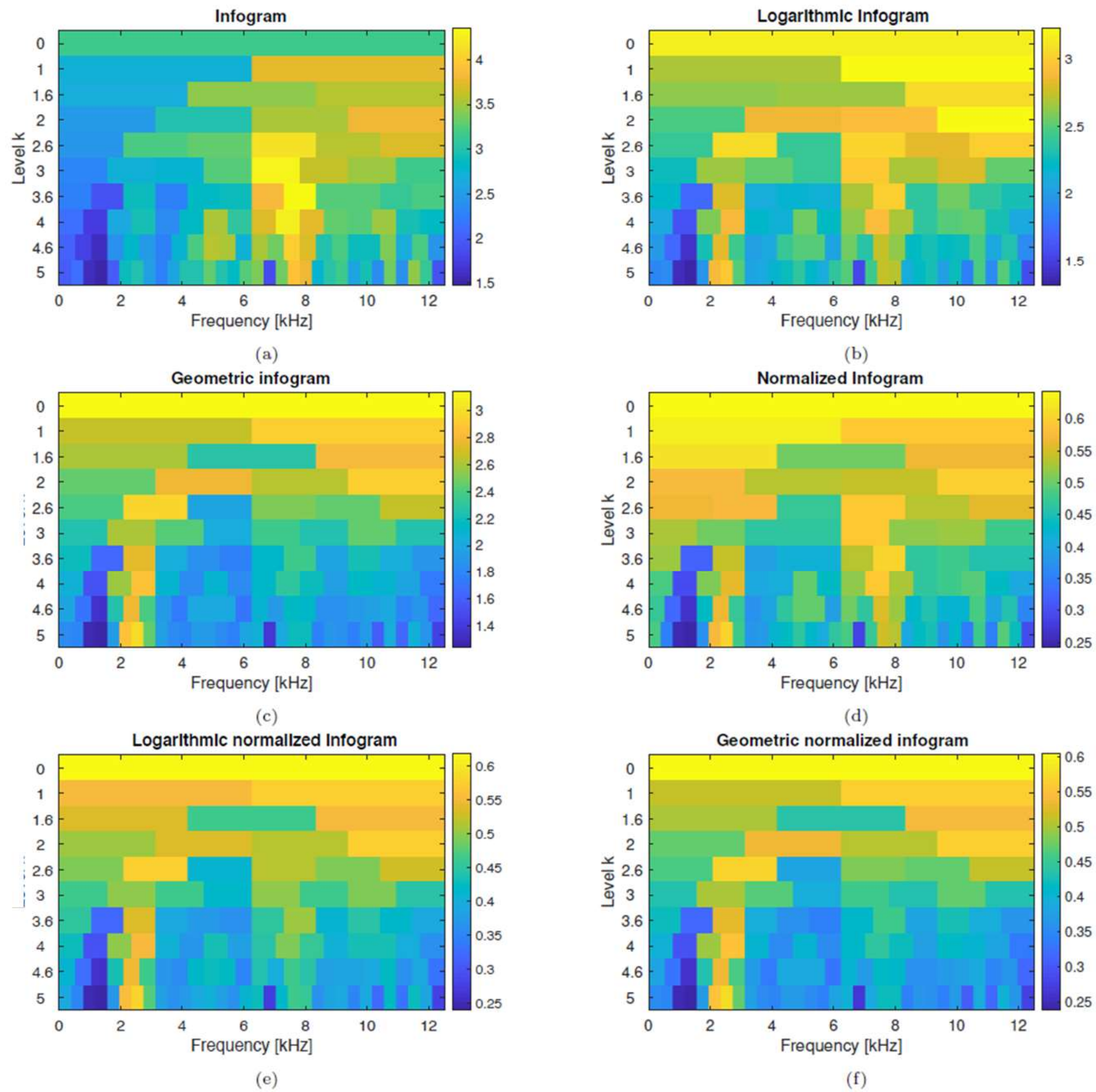


Figure 7: Summary of the results of the IFB selection by the averaged infogram (a) and its extended versions: log-infogram (b), g-infogram (c), norm-infogram (d), ln-norm-infogram (e), g-norm-infogram (f).

# Summary

- For years, mathematical methods have been used in various engineering applications.
- The inspiration for us was prof. Hugo Steinhaus, who believed that “There is no applied mathematics as a ready-made doctrine. It is created when mathematical thought comes into contact with the surrounding world ”.
- The ideas of prof. Steinhaus is continued by his students.
- In research conducted as part of the cooperation between Faculty of Pure and Applied Mathematics and Geoengineering, Mining and Geology (WUST) we prove that

✓ mathematics can be useful, and the development of new mathematical methods in CM enables the analysis of increasingly complex systems;

✓ interdisciplinary cooperation between two different fields is possible;

✓ such cooperation benefits both sides.

## Summary – condition monitoring perspective

- **industrial application** of condition monitoring strongly depends on several factors (machine design/complexity, fault type/size, operational condition and its variability, noninformative disturbances: character and level =>SNR)
- in mining mechanical systems one may meet many critical combination of these factors and it push us to work on **novel**, more **effective**, less complex, more **robust** etc techniques.
- one of the biggest challenge is related to **impulsive noise** related to **technological process** (cutting, sieving, crushing, compressing etc.), external conditions, multiple faults, other specific conditions, unexpected disturbances…
- We have found that most really powerful **methods** developed by famous researchers **don't work** for our data!
- We tried to **understand reasons** of that, we proposed **models** of signals and we developed **new approaches** for **informative band selection** based on **statistical parameters** other than famous **kurtosis**
- we realise that **some techniques cannot work** and it has serious **theoretical background** as assumptions required by many techniques used in applications are not fulfilled! Even if we are able to obtain some results, from scientific point of view the reliability of the result is difficult to estimate
- another great example is cyclostationary analysis - classical formula in case non-Gaussian noise will not provide results with poor SNR (SNR is not defined for non-Gaussian noise as it based on variance...)
- for our diagnostic data we need advanced **mathematical methods**, both application and definition of new theorems and estimation techniques...

## Summary – time series, stochastic processes ➔math perspective

- From math point of view, the CM is one of **challenging application** of mathematical theories.
- It is often related to applications of **robust statistics** or **alternative dependency measures, analysis and modelling of time series (especially with non-Gaussian distribution).**
- However, it has appeared, that it also could be **beneficial to maths** itself!
- Real world examples allowed to define **new class of problems.** One of the example is the new theory of non-Gaussian and non-stationary time series.
- **Theory of cyclostationary analysis** developed for **stochastic processes** with **non-Gaussian distribution** is currently a topic for 2 PhD @ Faculty of Pure and Applied Mathematics, WUST.
- Many MSc and Engineering thesis in math during last 9 years appeared at Faculty of Pure and Applied mathematics, WUST.
- Math students can see **real applications** of learned theories (statistics, time series analysis, stochastic modelling courses).
- Thanks to collaboration between Faculty of Maths and Faculty of Mining more than 80 papers have been published! Also in mathematical journals.
- 

# Where we are going?

- We continue the collaboration in the area of condition monitoring -  new methods dedicated for the non-stationary signals with non-Gaussian distributions.
- We work on both theoretical solutions as well as implementations (deploying monitoring systems with our methods)
- We are happy to collaborate with prof. Fulei Chu (Tsinghua University) – Chinese-Polish Sheng project on new methods of processing non-stationary signals with non-Gaussian characteristics has been submitted 2021.
- We are also interesting in diagnostic and prognostic approaches for condition monitoring systems of complex mechanical structures operating in the presence of non-Gaussian disturbances and variable operating conditions
- We are Editors of several special issues  - contact us if you want to submit an article!
- Interested in post-doc positions or Phd positions?
- We are open in research collaboration

Thank you for your attention!