Orthogonal nonnegative matrix factorization as informative frequency band selector

Mateusz GABOR[1], Rafał ZDUNEK[1], Radosław Zimroz[1]
Agnieszka WYŁOMAŃSKA[1*]

[1]Wroclaw University of Science and Technology, Wybrzeze Wyspianskiego 27
50-370 Wroclaw, Poland

Abstract

One of the most common representations of acquired vibration signals from a faulty machine is the time-frequency representation in the form of a spectrogram matrix. Because the magnitude part of the spectrogram matrix consists only of non-negative elements, it can be decomposed using non-negative matrix factorization (NMF) into a base matrix and weight matrix, which represent the frequency and time content of the signal, respectively. The frequency features of the base matrix can be used as filters to detect local damage in bearings by filtering the original signal with these filters. However, classical NMF provides filters that cover all frequency bands with different amplitudes. Unfortunately, such filters cover both informative and non-informative frequency bands, the second ones correspond to the noise. To solve this problem, the NMF can be enhanced by using orthogonal non-negative matrix factorization (ONMF), which imposes orthogonality constraints onto the NMF model. The orthogonality constrained applied to NMF improves the quality of clustering properties of NMF, which corresponds to better detecting of informative frequency bands. Additionally, the orthogonality constraints make the decomposition more sparse, which translates into zero amplitude at the non-informative frequency band related to the noise. Hence, using ONMF we can obtain a more selective filter which filters out only the most relevant information from the signal. The ONMF works for both signals with Gaussian and non-Gaussian noises. The analyzed signals come from a test rig with faulty bearings (Gaussian noise) and belt conveyor (non-Gaussian noise).

1 Introduction

Machine defect detection typically employs non-stationary signal processing with time-frequency representations (TFRs). The spectrogram is one of the most fundamental, well-known, and understandable representations of signals. A spectrogram can be used to quickly identify important and non-informative frequency bands in a specific context (fault detection in this case). However, non-negative matrix factorization (NMF) has already been employed in condition monitoring when the spectrogram is regarded as a non-negative matrix. It enables us to locate a reliable source of information, to obtain a suitable time profile, or to locate spectral content within a certain frequency range. By multiplying the frequency profile by the observed signal in the frequency domain, the signal of interest (SOI) can be easily extracted by using it as a filter characteristic. A selective filter characteristic, or the pass-band for the SOI-related frequencies and the stop-band for other frequencies, is necessary for such a method. The SOI should be impulsive, cyclic, and have a higher signal-to-noise ratio (SNR) than the raw signal after filtering.

The primary goal of this work is to show an effective method for bearing fault detection in a vibration/acoustic signal. Pre-filtering the original, unprocessed signal will improve the SNR and help reach the target. Practically, there are some frequency bands where diagnostic data (i.e., an instructive component of the raw signal) are found, but their precise location is unknown. By creating an optimal frequency band (OFB) selector with the orthogonal version of NMF (ONMF), where orthogonality constraints are enforced on the frequency profiles, we present a fault detection method to address the filtration problem. The ONMF version

*The work of MG, RZ and AW is supported by National Center of Science under Sheng2 project No. UMO-2021/40/Q/ST8/00024.

proposed by Asteris [1] served as the inspiration for the stochastic sampled ONMF algorithm (SS-ONMF) [2] that we applied in this work, which is more stable for initialization by changing the selection rule of subspace exploration.

2 Proposed methodology

Observed signal $y(t)$ is assumed to be a superposition of three components: $s(t)$ is periodic impulsive signal of interest (SOI), $d(t)$ is disturbing non-Gaussian (impulsive) signal, and $n(t)$ is disturbing zero-mean Gaussian noise (mostly colored noise) . Thus:

$$y(t) = s(t) + d(t) + n(t). \tag{1}$$

Let $Y \in \mathbb{R}_+^{I \times T}$ be a discretized version of spectrogram of the input signal $y(t)$. Assuming the orthogonality conditions for any pair of frequency profiles, i.e., $w_s^T w_d = 0$, $w_s^T w_n = 0$, and $w_d^T w_n = 0$, spectrogram Y of model (1) can be rewritten by the ONMF model:

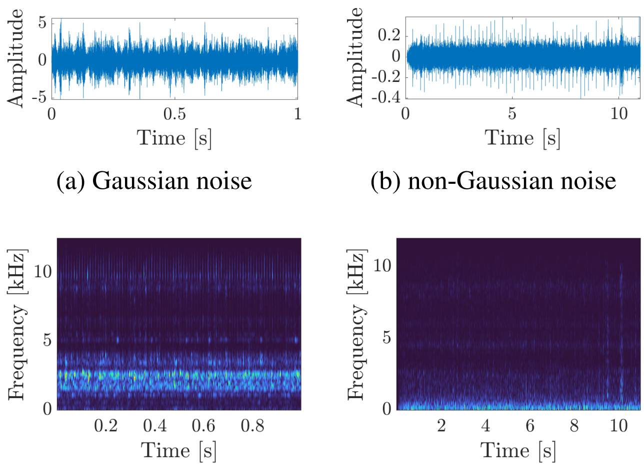
$$Y \quad = \quad WH^T, \quad \text{where} \quad W^T W = I_R, W = [w_s, w_d, w_n] \in \mathbb{R}_+^{I \times R},\ H \in \mathbb{R}_+^{T \times R}, \tag{2}$$

where $I_R \in \mathbb{R}^{R \times R}$ is an identity matrix, and $R = 3$ for the discussed case.

3 Experiments

The mixed signal of sources (the SOI plus noisy components) is used as experimental input. This signal is converted into a spectrogram and then decomposed using the SS-ONMF method into W and H matrices. In order to filter the original signal, the matrix W consists of R OFB selectors. There are five steps in this process: 1) spectrogram calculation of the diagnostic signal; 2) factorization of the spectrogram; 3) band selection; 4) original signal filtering; 5) assessment of impulsiveness (by kurtosis) or periodicity (estimation of the envelope-based spectral indicator (ENVSI)). The SS-ONMF is compared with the following competitive methods: NMF with multiplicative updates (NMF-MU), orthogonal NMF through subspace exploration (ONMFS), and infogram. The $[6, 15]$ range of ranks was tested for the NMF-based algorithms and 100 Monte Carlo trials were performed for NMF methods, because of the non-convexity of NMF algorithms.

In the experiments, we evaluated two real signals. The first signal is a vibration signal with Gaussian noise from the test rig. The second signal is an acoustic signal from a belt conveyor. The signals and their spectrograms are presented in Figure 1.



(a) Gaussian noise (b) non-Gaussian noise

(c) Gaussian noise (d) non-Gaussian noise

Figure 1: Recorded real vibration signal with Gaussian noise (a), its spectrogram (c) and real acoustic signal with non-Gaussian noise (b), its spectrogram (d).

Figure 2 demonstrates that while NMF-MU and SS-ONMF produce similar OFBs, SS-ONMF has the least amount of spectral leakage. As a result, the kurtosis is highest for the filtered signals using SS-ONMF. It is the result of both the orthogonality constraints and the improved stability of SS-ONMF in comparison to ONMFS.

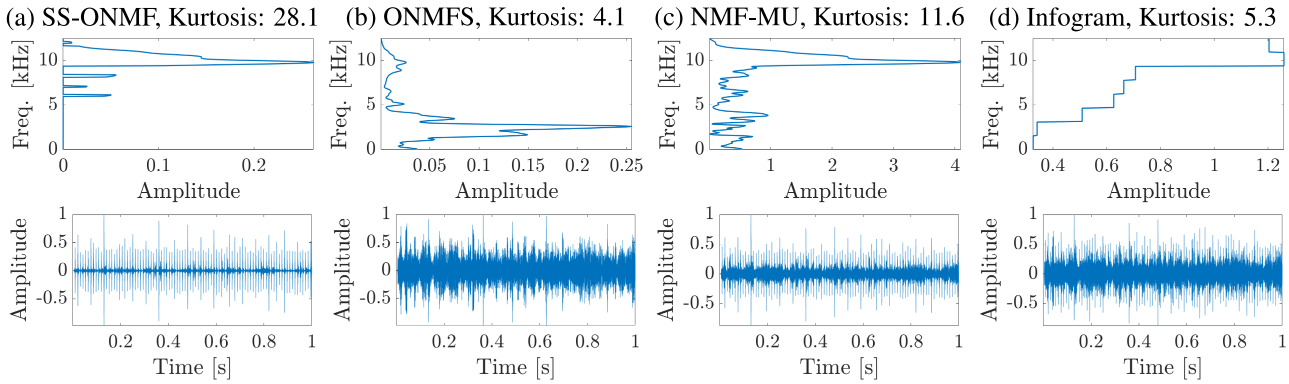


Figure 2: Exemplary filters and real Gaussian noisy signals filtered with analyzed methods.

The performance of the considered methods for filtering the acoustic signal with non-Gaussian disturbances can be observed in Figure 3. In such a situation, the signal cannot be evaluated using kurtosis, because of non-Gaussian impulses that occur. Hence, the filtered spectra were evaluated using the ENVSI measure. As can be seen, SS-ONMF offers the most accurate filter (zero values are between 5-12 kHz and 0-3.5 kHz), which points directly at an informative frequency band. The filtered signals obtained with ONMFS and NMF-MU are significantly noisier than SS-ONMF. When comparing all of the methods, SS-ONMF provides the highest ENVSI for the analysis of the envelope spectra.

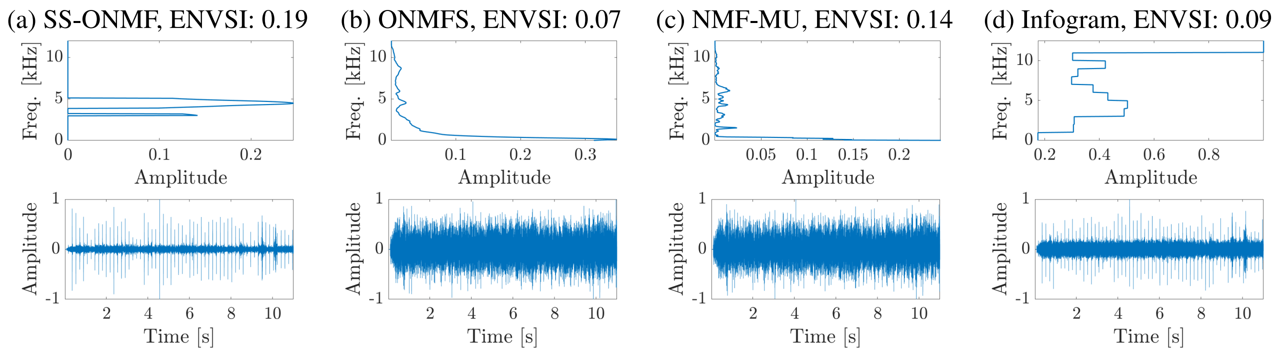


Figure 3: Exemplary filters and real non-Gaussian noisy signals filtered with analyzed methods.

4 Conclusions

An innovative method for vibration/acoustic flaw identification in rolling element bearings has been used in this work. It is based on spectrogram factorization with an ONMF for the detection of filter characteristics. The results made clear how crucial orthogonality constraints are to generate a highly selective filter characteristic that only encompasses the useful frequency region. The characteristic values are primarily zeros outside of the band. he proposed approach provides better results than the state-of-the-art methods for signals with both Gaussian and non-Gaussian noise.

References

[1] M. Asteris, D. Papailiopoulos, A. Dimakis, *Orthogonal nmf through subspace exploration*, Advances in Neural Information Processing Systems (NeurIPS), 2015.

[2] M. Gabor, R. Zdunek, R. Zimroz, A. Wyłomańska, *Bearing damage detection with orthogonal and non-negative low-rank feature extraction*, under review to IEEE TII, 2023.