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LOCAL FAULT DETECTION OF ROLLING ELEMENT BEARING COMPONENTS BY SPECTROGRAM CLUSTERING WITH SEMI-BINARY NMF

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Abstract

Information extraction is a very important problem nowadays. In diagnostics, it is particularly useful when one desires to isolate information about machine damage from a measured diagnostic signal. The method presented in this paper utilizes the idea that is based on a very important topic in numerical algebra, which is nonnegative matrix factorization. When applied to the matrix of multidimensional representation of the measured data, it can extract very useful information about the events which occur in the signal and are not recognizable otherwise. In the presented methodology, we use the algorithm called Semi-Binary Nonnegative Matrix Factorization (SB-NMF), and apply it to a time-frequency representation of the real-life vibration signal measured on faulty bearing operating in a belt conveyor driving station. Detected impulses of local damage are clearly identifiable. Performance of the algorithm is very satisfying in terms of time efficiency and output signal quality.

Keywords: vibration data, time-frequency analysis, nonnegative matrix factorization, local damage detection

WYKRYWANIE USZKODZEŃ LOKALNYCH ELEMENTÓW ŁOŻYSK TOCZNYCH POPRZEZ KLASTERYZACJĘ SPEKTROGRAMU ZA POMOCĄ PÓŁBINARNEJ NIEUJEMNEJ FAKTORYZACJI MACIERZY

Streszczenie

Ekstrakcja informacji jest aktualnym kierunkiem badań. Jest ona szczególnie użyteczna, kiedy próbuje się wyizolować informację na temat uszkodzenia maszyny z zarejestrowanego sygnału diagnostycznego. Metoda zaprezentowana w niniejszej pracy bazuje na bardzo ważnym zagadnieniu algebry numerycznej, jakim jest nieujemna faktoryzacja macierzy. Kiedy jest ona zastosowana do analizy macierzy będącej wielowymiarową reprezentacją sygnału wejściowego, może wyizolować informację istotną z punktu widzenia procesów zachodzących w sygnale, a która nie jest rozpoznawalna w inny sposób. Przedstawiona metodologia korzysta z algorytmu znanego jako półbinarna nieujemna faktoryzacja macierzy, zastosowanego do reprezentacji czasowo-częstotliwościowej rzeczywistego sygnału drganiowego, zmierzonego na uszkodzonym łożysku pracującym w stacji napędowej przenośnika taśmowego. Wykryte impulsy związane z uszkodzeniem lokalnym zostały wyraźnie zidentyfikowane. Działanie algorytmu jest satysfakcjonujące w kwestii wydajności obliczeniowej oraz jakości otrzymanego wyniku.

Słowa kluczowe: dane drganiowe, analiza czasowo – częstotliwościowa, nieujemna faktoryzacja macierzy, wykrywanie uszkodzeń lokalnych

1. INTRODUCTION

Detection and diagnostics of fault in rotating machines is an open subject for a long time. For this type of analysis a vibration signal is still the most frequent medium. Local damage in rotating machinery is a form of change in machine condition that causes cyclic, impulsive and non-stationary contribution in a machine vibration response. One can find some reviews of gears and bearings diagnostics in the literature 789. In the vibration signal acquired from such machines, most of the time one will not be able to notice any improper behavior going on. Impulsive disturbances in time domain are in many cases buried in the signal among other vibration sources produced by the operating machine 1011 121718. It is often necessary to incorporate multidimensional representations of the information being carried, as well as efficient methods for their analysis. In many cases, time-frequency representation of the signal is much easier to analyze and interpret, because short impulsive excitation manifests itself as wideband disturbance in the spectrum. In this paper, we utilize multidimensionality of time-frequency representation of the measured vibration signal, in combination with Nonnegative Matrix Factorization (NMF) method for information extraction 1236. The investigated data is a vibration acceleration of the damaged bearing operating within a driving station of the belt conveyor. NMF algorithm will be performed on the spectrogram of the considered signal. The presented method uses a certain matrix factorization algorithm as a way to perform clustering of individual spectra to extract information of impulsive signal behavior.

It should be noted that so called AI methods, especially artificial neural networks, are frequently used in diagnostics, mainly for bearing data classification 131415. Regarding those, it is worth mentioning that NMF could be applied to whole spectra as well as extracted features.

2. METHODOLOGY

A general outline of the algorithm is presented in Fig. 1. First, an input signal is transformed into a time-frequency representation (spectrogram). The spectrogram is a square absolute value of the short-time Fourier transform (STFT) defined as follows 20:

$$STFT(t,f)=\sum_{k=0}^{N-1}x_k w(t-k)e^{-j2\pi fk/N},$$

where $w(t\text{-}\tau)$ is a shifted window and x_k is the input signal. In the next step, we use the Semi-Binary NMF (SB-NMF) algorithm to group spectra vectors across all timestamps of the spectrogram. One of matrices produced by NMF carries information about the timestamp occurrence within clusters, which allows to construct so-called "partial output spectrograms". They are matrices of zeros with appropriate spectra vectors distributed amongst them.

As a result of this step we obtain J partial spectrograms where J is predefined number of clusters. The inverse short-time Fourier transform (ISTFT) is performed on all of them 21, and the one of maximum kurtosis is selected for further processing.

At this point obtained selected signal reveals presence at correct timestamps of impulses occurrence, but those areas do not look like impulses yet. To extract correct form of the impulses, highpass filtration is required. It gets rid of low-frequency high-energy frequency components and preserves impulse present in a wide band of the spectrum.

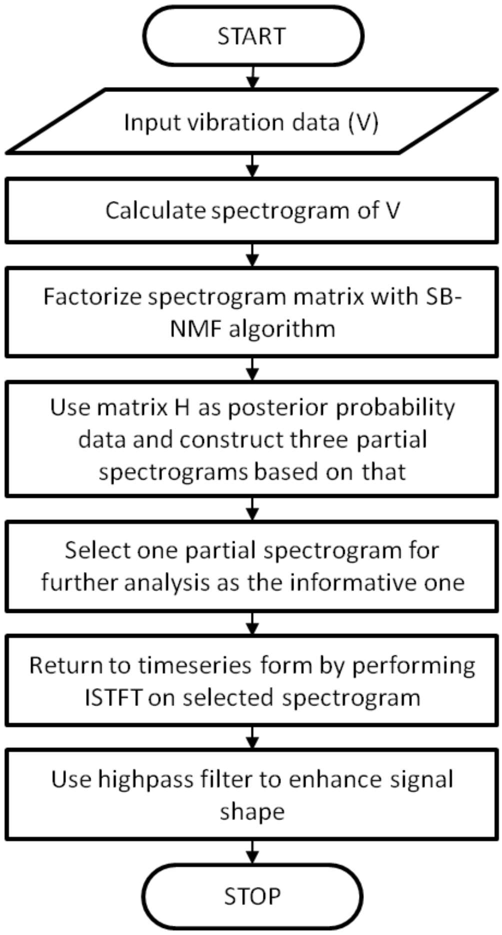

Fig. 1. Procedure flowchart

2.1. Semi-Binary NMF

Let $Y=[\,y_1,\ldots,\,y_T\,]\in \mathbb{R}_+^{I\times T}$ denote the spectrogram, where I is the number of frequency bins, and T is the number of timestamps. The spectra vectors $\{y_t\}$ can be grouped according to their frequency profile similarity, which can be performed in many ways. Since all the vectors are nonnegative and could be sparse, a good choice seems to be the usage of NMF. There are several NMF-based techniques that can be applied for clustering problems, e.g. convex-NMF, spectral clustering with NMF, probabilistic NMF, projective NMF, kernel NMF 234. Assuming the vectors $\{y_t\}$ form K disjoint clusters, this task can be achieved with the semi-binary NMF that is intended for hard-clustering of nonnegative data. The theoretical foundations for this algorithm have been given in 1. In this method, the data can be represented by the following model:

$$Y=AX, \qquad (1)$$

where $A\in \mathbb{R}_+^{I\times J}$ contains the centroids, and $X\in \mathbb{R}_+^{J\times T}$ has such a property that: $\forall t, \exists j: x_{jt}=1$ and $x_{st}=0$ for $s\neq j$. Hence, if $J<T$, X is a binary and row-orthogonal matrix. Motivated by the properties of A and X, we assume the factor A is

estimated by solving the Nonnegatively constrained Least-Square (NNLS) problem:

$$\min_{A} \frac{1}{2} || Y - AX ||_F^2, \quad \text{s.t.} \quad A \geq 0, \tag{2}$$

and the factor X by minimization of

$$F_X(X) = \sum_{t=1}^{T} \sum_{i=1}^{I} \psi\left([y_t - A x_t]_i\right), \tag{3}$$

subject to the binary and orthogonality constraints. To enforce a binary solution, we expressed $\psi(\xi)$ by a logistic regression function, i.e. $\psi(\xi) = \beta^2 \ln\cosh\left(\frac{\xi}{\beta}\right)$ with the parameter β .

The problem (2) can be solved with any NNLS algorithm – we used the modified active-set method, originally introduced by Lawson and Hanson 5. The estimation of X is much more challenging due to the non-convexity of the constraints. In our approach, the factor X is estimated by maximizing the Gibbs–Boltzmann statistics 22 associated with the objective function in (3). Hence:

$$P_F(x_t) = \frac{\exp\left\{-\frac{1}{\tilde{T}} F(x_t)\right\}}{\sum_{x_t \in \{0,1\}^J} \exp\left\{-\frac{1}{\tilde{T}} F(x_t)\right\}}, \tag{4}$$

where $\tilde{T}$ is a temperature parameter controlling the ascent towards a global maximum of $P_F(x_t)$.

One can show that $\lim_{\tilde{T} \to 0} \langle x_t \rangle_{P_F} \to x_t^*$, where x_t^* is an exact solution.

Assuming the greedy search strategy for maximization of (4), we proposed the modified update rule for X:

$$X \leftarrow R./\left(e_J \otimes e_J^T R\right), \tag{5}$$

where $e_J = [1, \ldots, 1]^J \in \mathbb{R}^J$ is a vector of all ones, and the symbols ./ and $\otimes$ denote the component-wise division and Kronecker product, respectively. The elements of matrix $R = [\tilde{r}_{jt}] \in \mathbb{R}^{J \times T}$ are computed by the formulae:

$$\tilde{r}_{jt} = \exp\left\{-\frac{\tilde{\Psi}_{jt}}{\tilde{T}}\right\}, \tag{6}$$

where

$$\tilde{\Psi}_{jt} = \sum_{i=1}^{I} \psi(y_t - a_j). \tag{7}$$

The update rule (5) with (6) and (7) is computationally more efficient than in 2. The temperature schedule is motivated by simulated annealing methods, and set according to the exponential rule: $\tilde{T} = \bar{T} + T_0 \exp\{-\lambda s\}$, where $\bar{T}$ and λ are initial parameters, and s is the iterative step.

3. APPLICATION TO REAL DATA

Belt conveyor systems used in mining industry are very specific class of machines considering their structure, power and time-varying exploitation load 1618. Amount of installed drive units depends on the design of a particular application. There are several elements critical from the diagnostic point of view, such as gearbox, coupling, electric motor, drive pulley, non-drive pulley, idlers and belt itself. In this paper, we focus on rolling bearing of the drive pulley. In Fig. 2 time series of signal recorded on the faulty pulley bearing is presented, and Fig. 3 shows the spectrogram of the signal. This data has been already analyzed in recent papers, where several methods for local damage diagnostics have been proposed, see review in 18. The sampling frequency is equal to 19.2 kHz and the measurement is 2.5 seconds long. The spectrogram is obtained for the Hamming 512-sample length window with 450 overlapping samples and 512 FFT points. One can notice several wide-band excitations on the spectrogram at carrier frequency band 1-6 kHz that occur with the modulation frequency of 12.7 Hz (and its multiples). This stands for outer race local damage.

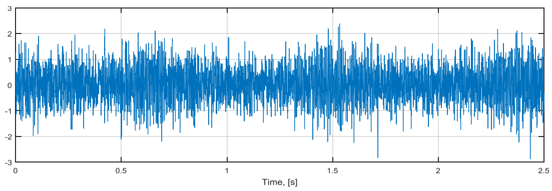

Fig. 2. Raw input signal

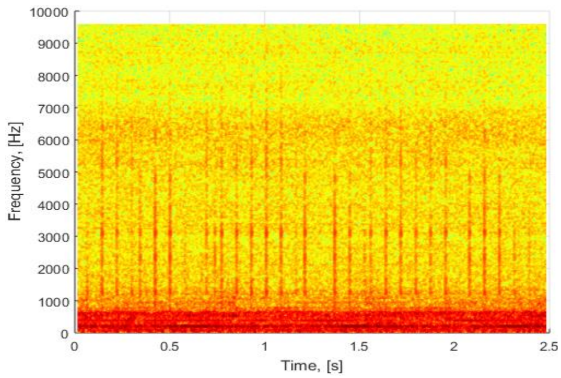

Fig. 3. Spectrogram of the input signal

As a next step, Semi-binary NMF algorithm groups the spectra into three clusters (see Fig. 4) and transform them back to time-series form using ISTFT. Third cluster is selected for further analysis based visual inspection (manually) or based on maximum kurtosis of obtained signals (automatically). The selected signal has zero value everywhere except for places where impulses occur (see Fig. 5 a). In those places ISTFT produced portion of the signal that comes from the spectrogram slices assigned to a particular place (typically 3-8 slices per impulse), and hence they carry information from the original signal (slightly suppressed by ISTFT windowing, see Fig. 6 a).

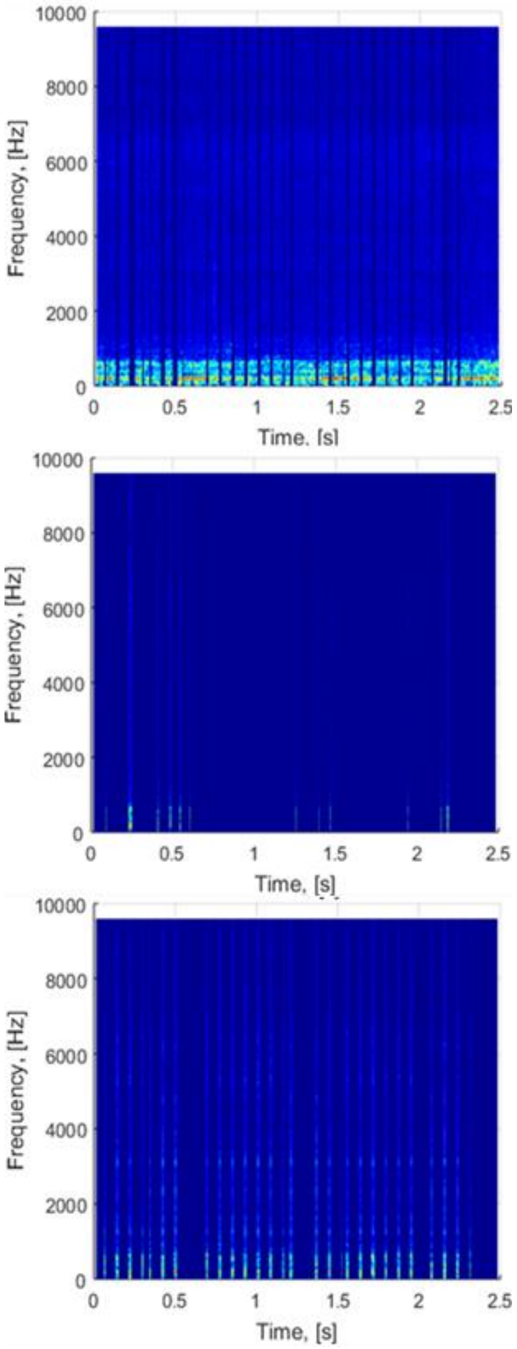

Fig. 4. Partial spectrograms constructed based on clustering results. Third spectrogram is selected for further analysis

The methodology is based on nonnegative matrix factorization of the spectrogram, but it should be mentioned that the algorithm can be applied to other multidimensional representations of the input signal. It operates according to the idea that some matrix factorization algorithms can be interpreted as multidimensional clustering tools with one of the output matrices being a posterior probability of item appearance in certain clusters.

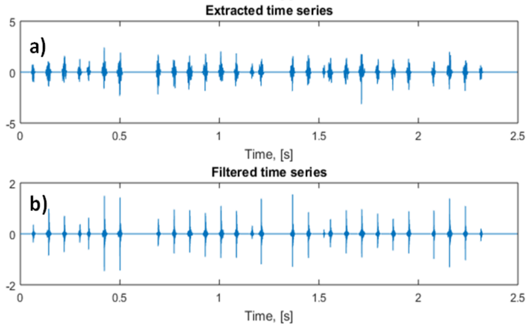

Fig. 5. Recovered time series: a) after ISTFT transformation from selected partial spectrogram, b) after further highpass filtration

To extract proper shape of the impulse we perform filtration of obtained signal with finite impulse response (FIR) highpass filter using the Kaiser window with the cutoff frequency equal to 1300 Hz (obtained as optimal for maximizing SNR value), the stopband attenuation of -15 dB (parameters optimized for the highest SNR). It removes low-frequency high-energy components from the signal, and retains the information about the actual impulse (see Fig. 6 b).

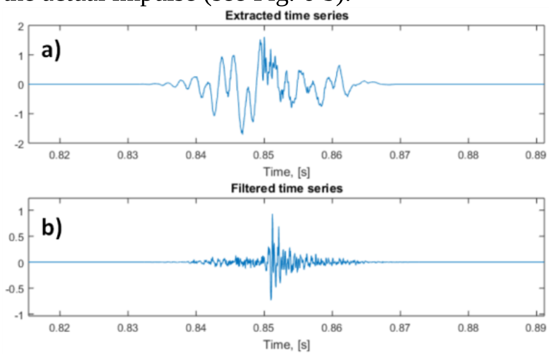

Fig. 6. Example of impulse shape before and after filtration

Obtained filtered signal contains detected impulses caused by local damage of the bearing (see Fig. 5 b). Further analysis of signal structure (e.g. spectral analysis) and correlating the results with the knowledge about the machine kinematics can provide information leading to identification of precise origin of the damage.

3.1. Comparison to Spectral Kurtosis

Spectral Kurtosis (SK) proposed by Antoni and Randall is one of the most popular and powerful approach to identify informative frequency band 7. We will use SK as a reference method to compare it with NMF-based approach. As SK is well known we will not provide details related to description of the method.

In Fig. 7 the normalized (3 is subtracted) kurtosis value distributed along frequency is presented for our signal. An informative band could be roughly identified between (0.05-0.3) of normalized frequency that gives informative frequency band c.a. (1000-6000) Hz. Fig. 7 was used as the basis for filter design, and final SK-based enhanced signal is presented in Fig. 8

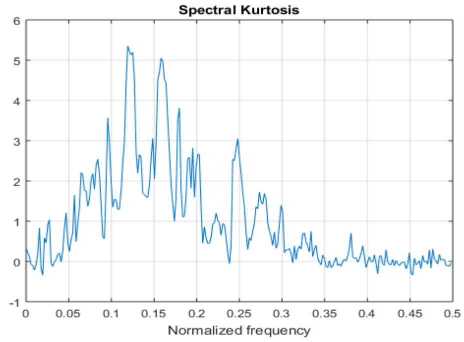

Fig. 7. Spectral Kurtosis (distribution of kurtosis along frequency bins)

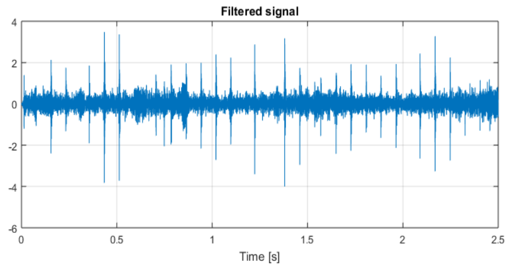

Fig. 8. Result of filtering using Spectral Kurtosis

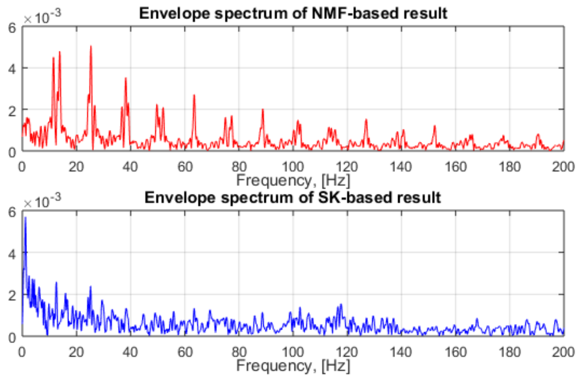

Fig. 9. Comparison of output signals' envelope spectra after SK filtration and after processing with our method

As it could be seen indeed one might notice impulsive nature of the signal, however some noise level is still present in the signal. For both enhancement techniques, the final form for diagnostic decision making is envelope spectrum. In Fig. 9 two envelope spectra estimated for signal presented in Fig. 5 b (NMF-based - red color) and in Fig. 8 (SK-based – blue color) are shown.

4. CONCLUSIONS

In this paper, we introduced a new approach to local damage detection in rotary machines based on impulsive acceleration signal. Investigated input data is a real-life vibration signal measured on faulty bearing in belt conveyor driving station.

Utilizing this idea, spectrogram slices along the timestamps for consecutive frequency bins can be treated as multidimensional points in feature frequency space, and the NMF-based algorithm assigns them to certain clusters. As a postprocessing step, highpass filtration is performed to clear and enhance the shape of actual impulses. By using this methodology the impulses hidden in the signal are extracted in a clearly visible and distinguishable way. The proposed algorithm is automatic and can be applied to other vibration signals as well.

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