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Cyclic sources extraction from complex multiple-component vibration signal via periodically time varying filter

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Abstract: The problem of local damage detection is widely discussed in the literature. There are many methods which can be applied, however there is still a need for new techniques addressing specific diagnostic issues. In particular, the case of complex multiple-component vibration signal is a challenging problem. In this paper we focus on such a problem related to a gearbox operating in industrial conditions. Our method consists of several stages. First we transform signal to time-frequency domain using spectrogram. Then for each frequency bin we apply a novel procedure which indicates location of cyclic impulses in given time series. This algorithm is based on the periodically distributed local maxima detection and quantification of their significance. Such procedure requires a priori known fault frequency. If the machine might reveal multiple fault, the procedure has to be calculated separately for each fault frequency. A time-varying filter is designed using the indicated local maxima comprised in the score matrix. Then, signals representing each fault frequency are obtained using inverse short-time Fourier transform algorithm. The method is illustrated with application to simulated and real data from complex mining machine - heavy duty gearbox.

1. Introduction

Fault detection on early stage can prevent the machinery from unexpected breakdowns. Furthermore, it gives a possibility to schedule the repair for the most convenient time. Thus, the machine performance can be enhanced in terms of availability and reliability. It has been already described by many authors that damage diagnosis based on vibration signal analysis can provide satisfactory results [1–5]. The signal acquired on the machine often consists of many components related to different machine elements. Moreover, the environment in which the machine is located influences the data as well. It is especially important in case of the mining industry, where machines work in harsh conditions [4,6,7]. In such case the standard fault detection methods might not perform properly. In order to overcome this issue a source extraction method can be applied taking into account specific characteristics of external sources. In [8] the kernel independent component analysis (ICA) was used to extract the fault-related component of the gearbox vibration signal. Another approach to involve ICA in condition monitoring is presented in [9] where its combination with kurtogram is proved as a reliable method for source identification. Once the data from several channels (sensors) is available, the principal component analysis can be applied to provide more comprehensive information than from a single sensor [10]. In order to assess condition of the rotating machine one can also extract features related to its condition and detect anomalies instead of making a decision upon the entire signal [11]. Furthermore, signals from complex machines are mixture of several sources. For instance, planetary gearbox consists of many components assembled in a compact form. Therefore, vibration signal from such machine requires advance processing tools [12–14]. An interesting approach was introduced in [15], namely the logarithm is applied in order to stabilize the variance. It provides the new log-envelope procedure for signal analysis. In case of the highly impulsive contamination of the vibration signal one can extract signal related to damage via cancelation of the impulses, which are not related to the damage (are not cyclic). As a result the signal with more visible and easier to detect cyclic impulses is obtained. In [16] the authors presented the method for cancelation based on the regime switching model. Blind extraction of source signal related to damage might be also performed by blind deconvolution methods

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e.g. minimum entropy deconvolution, maximum correlated kurtosis deconvolution etc. [17–21]. Moreover, it was shown in [22] that α-stable distribution can be applied to extract the signal of interest. Furthermore, the filter based on the α-stable distribution for signal enhacment can be designed [23]. On the other hand, in case of the early stages of the damage the tempered stable distribution is suitable [24]. The sources in a vibration signal from rotating machine might be also considered as cyclostationary. The procedure for extraction of second-order cyclostationary sources is illustrated in [25]. The described method requires to predefine the fault frequencies. Another cyclostationary source extraction algorithm is presented in [26], where a subspace decomposition of the signal using periodic statistics is investigated. In [27] authors illustrate the application of the discrete-random extraction to the non-stationary signal. In case of local damage the fault component reveals in the signal as a periodic pulse train, contrary to non-cyclic impulsive noise that might arise due to specific operation of a machine. This property has been already used for damage detection in [28].

In this article we propose a novel method for source separation which is based on a periodically time varying filter. An example of application of periodically correlated structure to the real data is PAR time series. In [29] the method was applied to the data from the energy marked. Moreover, in [30] the spectral properties of the PARMA sequences were analyzed. Filter coefficients are cyclic and the filter design reflects the periodic nature of impulses related to damage. In the first step the signal is represented in time-frequency domain. Then data in each frequency bin is considered as time series and local maxima with given time axis range are indicated. Each local maximum is assigned with a value proportional to the number of equally spaced local maxima indicated by the previous step. The requested time interval between these local maxima is related to the investigated fault frequency. Finally, the obtained two dimensional score values are considered as the time-varying filter with cyclic coefficients. Different fault frequencies will result in a different filter design. The performance of proposed algorithm is tested on the simulated and real data recorded on a heavy-duty gearbox operating in an underground mine.

The paper is organized as follows. Section 2 describes the methodology, including details of the filter design. In Section 3 application to simulated data is discussed. Application to real data is presented in Section 4. Section 5 summarizes the results of this work and draws conclusions.

2. Methodology

The proposed methodology consists of six main steps. In the first one the vibration signal $x(t)$ is converted into the time-frequency domain. In this paper we propose to use the spectrogram, which is based on the short-time Fourier transform, although other decompositions might be beneficial as well. The formula for spectrogram is presented in Eq. (1):

$$\mathbf{Spec}(t,f) = |STFT(t,f)|^2 = \left|\sum_{m=0}^{K-1} w(t-m)x(m)e^{-2i\pi fm/K}\right|^2, \qquad (1)$$

where $w(\cdot)$ is a W-long window function, $t = 1,\ldots,N$ is a time point, f is a frequency bin and $K \geqslant M$ is the number of points in which the Fourier Transform is calculated. Given the time-frequency representation of the data, time series related to each frequency bin are examined for having cyclic properties. Periodic amplitude modulation, shared by several frequency bins, might be a signature of local damage. It starts with spectrogram-based decomposition of the signal on subbands with following parameters: N_w - window length, Ov - overlap (percentage of overlapping windows), fs - sampling frequency and $NFFT$ - the number of FFT points. In the next step the analyzed fault frequency has to be set. In case of testing several different fault frequencies the following operation have to be repeated for each fault frequency separately. Thus, the proposed methodology allows to extract separate sources related to different modulation frequencies. On the other hand, indicators of the informative frequency band, e.g. spectral kurtosis, infogram, protrugram etc. would indicate both carrier frequency bands as containing information about local damage [31–34]. As a result, signals related to each fault frequency would not be separated.

In the following step for each frequency bin in the time series $\mathbf{Spec}(:,f)$ local maxima are found. The crucial parameter in this step is the range in which the maximum is founded. Low range leads to large number of local maxima unrelated to local damage. On the other hand, wide range could result in some significant fault signatures omitted. Therefore, we propose to relate the range with considered fault frequency, i.e. $r = \left\lfloor \frac{2}{3}\frac{fs}{f_f N_w(1-O_v)} \right\rfloor$. Such r translates the period related to fault frequency into the spectrogram time axis. The factor $\frac{2}{3}$ is responsible for slight reduction of the range, since subsequent fault-related local maxima might occur on the boundary of the period $1/f_f$. The binary function that indicates if the time point t_i reveals the local maximum might be defined as:

$$M(t_i,f) = \begin{cases} 1, & \text{if } \mathbf{Spec}(t_i,f) = \max\limits_{i-r\leqslant k\leqslant i+r}\{\mathbf{Spec}(t_k,f)\} \\ 0, & \text{otherwise.} \end{cases}$$

Thereafter each subband in M is considered separately. Given f, a score, which quantifies periodicity, is assigned to each t_i. It evaluates the average of M values at time points $(\ldots,t_i-2T,t_i-T,t_i,t_i+T,t_i+2T,\ldots)$, namely:

$$score(t_i,f) = \frac{\sum_{1\leqslant t_i+kT\leqslant \lfloor N/T\rfloor} M(t_i+kT,f)}{\lfloor N/T\rfloor},$$

where $T = \left\lfloor \frac{fs}{f_f N_w(1-O_v)} \right\rfloor$ is the fault-related period (in samples) and $k \in \mathbb{Z}$. The score matrix indicates the average number of local maxima in time points spaced by T. Thus, it might be considered as a time-varying filter with periodic coefficients, since $score(t_i,f) = score(t_i+kT,f)$.

In order to return to the time domain the STFT is multiplied element-wise by the score matrix. Then, the inverse short-time Fourier transform algorithm is applied to such STFT with modified amplitudes and filtered signal $y(t)$ might be further analyzed [35]:

$$y(t) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} STFT_x(t,f)score(t,f)e^{2\pi ift}dtdf.$$

The numerical computation of the inverse short-time Fourier transform can be applied with weighted Overlap-add method [36]. As the result both the filtered and raw signals are of the same length. Amplitude of $y(t)$ reflects not only presence of periodic local maxima in raw signal spectrogram but also real amplitudes related to them. Thus, the proposed method takes into account presence of periodic amplitude modulation in each subband separately, and the corresponding energy. It is worth mentioning that in case of real signal, which is cyclostationary of order 2 (CS2), $y(t)$ is also CS2. Therefore, the standard envelope based method can be applied. On the other hand, proposed filtration provide the signal, which contain only the cyclic components, thus the proper harmonics should be more visible in the envelope spectrum. In Fig. 1 the flowchart of the proposed algorithm is presented.

Clearly, real signals might consist of two sources with different modulation frequencies, which are observed in different carrier frequencies. In most of such cases the algorithm is expected to separate signal sources appropriately. The problem might occur once the first modulation frequency is the multiple of the second and