Analysis of the vibro-acoustic data from test rig - comparison of acoustic and vibrational methods

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Abstract.
Detection of damage is a significant issue in providing efficiency and safety in industrial processes. In underground mining much research effort is made for developing an automatic system of diagnosing the machinery using robots. One of the major groups of equipment utilized and maintained in the mines is rotating machinery. Local damage occurring in such machines commonly have a cyclostationary character in short term as any change in their characteristics is expected to repeat periodically. In most cases they can be easily detected based on vibration signals measured with contact sensors (accelerometers). However if mobile robots such as UAV (unmanned aerial vehicles) are planned to be used, remote measurement is firmly preferred. In this paper we compare vibroacoustic detection with a novel approach based on analysing an acoustic signal recorded by a microphone.

1. State of the art
Failure in rotating systems can cause significant financial loses so it is really important to identify faults before they will be appear in devices. Many researchers are focused to expand or develop a method to detect damage before it cause serious loss. Rolling bearing is an important part of rotating systems and has significant effect on their reliability. Therefore, in recent years, fault detection of bearings has been the subject of many articles and thesis.

The most popular methods for fault detection of bearing include detection based on vibration signal which has been the subject of many researches [1, 2, 3, 4, 5, 6]. Conventional defects on the bearing usually begin when a rolling element cross over a faulty area localised on the inner or outer race of a bearing. Subsequently mechanical shockwaves are produced due to this small collision that has happened. Also this shockwaves can excite the natural frequencies of the system. This process happen every time when any bearing part has contact with the crash area. And the rate of this event can be calculated by conventional formulas that are defined based on various type of fault in the bearing. More information of this process, including the set of four basic characteristic fault frequencies defined for any bearing, can be found in literature [7]. The vibration-based methods can be used easily to detect fault in bearings. However, in this approach, the vibration sensors (measuring acceleration, velocity, or displacement) should be placed very near to or directly on the bearing cage.

Utilizing acoustic signals is another method used for fault detection in some literature, e.g. [8, 9]. Analysis based on acoustic signal has significant advantages. The installation for measuring sound is simple and the microphones can be placed anywhere near the target motor.
On the other hand analyzing the acoustic signals may be problematic. As the microphone records a mixture of sounds from the environment, the main problem is the environmental noise. Therefore it is really necessary to utilize advance signal processing to extract the signal of interest. Adam Glowacz and Zygfryd Glowacz [8] introduced a technique for detection of 3 phase induction motors bearing fault. The proposed technique was based on recognition of acoustic signals and demonstrated that they have good potential to be used for fault detection of such kind of motors. D.P.Jena and S.N.Panigrahi [10] designed a passive acoustic filter for elimination of noise effect from the signal. They used a genetic algorithm to optimize the band pass filter parameters and illustrated that the proposed methodology can increase reliability of fault detection.

Another reason for using remote sensors such like microphones recording acoustic signals is that they can be easily acquired using the unmanned aerial vehicles (UAV). UAVs, commonly known as drones, are widely used in the industry. In this paper we focus particularly on the diagnostics for the underground mining plants. From this point of view, the possibility of penetrating hard-to-reach places and taking the risk instead of human is extremely beneficial. One of the potential applications for UAV is predictive maintenance by carrying microphones and other signals to inspect all of the machines. Using such a system of automated diagnostics would be much easier to maintain than locating separate sensors for every single part like a bearing, gearbox or idler that is needed to be diagnosed and collect all the data. A problem that arises is the drone’s ego-noise produced by its rotors and engines. This additional component, present in any sound recorded by the microphone located on a drone, cannot be removed entirely. Therefore there is need for complex signal analysis methods extracting hidden informative part of a signal. UAV noise has been widely investigated [11, 12, 13].

Many techniques aiming at optimal informative frequency band selection [14, 15, 16] and signal decomposition [2, 17, 18, 19, 20] have been developed. They have big potential for the issues of preprocessing, denoising, segmentation and feature extraction preceding the proper analysis.

2. Analysis method
The purpose of this paper was to compare the inference from acoustic measurement compared with the vibration measurement using the same methods of analysis. We have made a preliminary study that aimed at proving that using both kinds of measurement may provide satisfactory results.

The general approach applied in this paper is based on time-frequency analysis. A decomposition of the signals provided by calculating short-time Fourier transform (STFT) [21] is given by the equation

\[ STFT(t, f) = \sum_{k=0}^{N-1} w_{t-k} x_k e^{-j2\pifk/N}. \] (1)

It is plotted on spectrogram and investigated in terms of cyclic change of its characteristic. A repeated pattern observed in specific frequency band is an evidence of occurring amplitude modulation. In analogy to telecommunications the analytic signal of the modulated signal \( y(t) \) may be described as follows [22]:

\[ y(t) = x(t)m(t), \] (2)

where \( x(t) \) is the carrier signal and \( m(t) \) is the modulating signal.

In fault detection the carrier signal may be associated with the signals emitted by the bearing during normal work. If there is a fault in some part of a bearing there appear a modulation component \( m(t) \). If all its frequency components are below the frequency band of the carrier,
then it can be effectively detected using envelope analysis methods [7]. We process both the th\e vibration and acoustic signals based on this assumption.

To separate the impact of the modulating signal we calculate the envelope (instantaneous amplitude) of the measured modulated signal being the absolute value of its analytic signal:

$$\hat{m}(t) = y_{env}(t) = \sqrt{y^2(t) + y_H^2(t)}, \quad (3)$$

where $y_H(t)$ is the Hilbert transform of $y(t)$.

In this way the modulating signal associated with faults is estimated. To get the analytic signal we apply a standard Matlab function based on the calculation of the inverse FFT (Fast Fourier Transform) of the one-side spectrum (note that also other methods have been developed [23]). The modulating frequencies are supposed to be exposed by calculating the power spectrum of the envelope signal (FFT of squared $\hat{m}(t)$), excluding the constant (0 frequency component).

We used a simple high-pass filter to extract the informative part of the frequency band of the raw signals and observe the impact of this preprocessing step (envelope spectrum is then calculated again). The cutoff frequency is chosen based on the observation of the visible patterns in the spectrogram and on the assumption that all three of the examined informative signals may reveal the same modulating frequency (which is a frequency associated with fault). The overall scheme of the performed analysis was depicted in Fig. 1.

![Figure 1: Diagram depicting the analysis method that was used.](image)

The main workflow is marked with the solid lines whereas the auxiliary inference and workflow is marked with the dashed lines. Boxes contain names of the numeric operations that we perform and the input/output data are placed outside the boxes.

3. Experiment
A test rig (presented in Fig. 2a) containing a rotary engine was analyzed. Accelerometers KISTLER Model 8702B500 were stacked in horizontal (orthogonally to the axis of rotation) and
vertical direction to two bearings with sampling rate 50k sample per second. A microphone (Fig. 2b) was located in the proximity of a currently measured element. Above the test rig a quadrotor UAV unit (Fig. 2c) was steered manually to hover in addition the acoustic data is collected with 50k sample per second.

(a) Test rig examined in the experiment.

(b) Brüel & Kjær 4189-A-021 microphone with with 2671 type preamplifier.

(c) DJI Mavic Mini quadrotor drone.

Figure 2

The left bearing was intentionally damaged (and the right bearing not). The analysis of the acquired data presented in the next section was focused on the signals collected from the damaged bearing.

4. Results
First part of the analysis is focused on the data without UAV’s contribution to background noise. The raw data containing signals from accelerometers located along horizontal axis (VibH) and
vertical axis (VibV) and the recorded sound pressure (Mic) are presented at Fig. 3a. As it can be noted vertical vibrations have a strong cyclic impulsive component. Spectrograms were generated for all three signals (Fig. 4a). Time-frequency decomposition of the horizontal vibrations exposes impulses having the same periodicity. Impulsive component is also visible on the spectrogram of the acoustic signal. Amplitude modulation of the vibro-acoustic signals was investigated by calculating envelope of the signal and transforming it to frequency domain. Resulting envelope spectra are showed on Fig 5a. The frequency of the periodic repetition of the impulses can be estimated based on the envelope spectrum of the vertical vibrations signal. To make results more informative (especially for the acoustic signal) a high-pass filter was applied to the raw signals (Fig. 3b and Fig. 4b) based on the observation that cyclic changes of magnitude are present primarily in the high frequency band on the spectrograms. Envelope spectra calculated for the filtered signals (Fig. 5b) distinctly expose modulation of the signals with impulsive periodic components. Modulating frequency may be estimated based on all three sources of data.

Figure 3: Vibrations and sound recorded from the left bearing of the test rig without contribution of UAV noise - signals.
Next part of the research concerned analogous measurement performed in the presence of the noise generated by a hovering UAV (Fig. 6a). As we expected the impulsive local damage component is harder to examine based on time-frequency decomposition (Fig. 7a) of the acoustic signal in these background conditions. Envelope spectra of the raw signals (Fig. 8a) give similar result as in the former case of no drone noise. We again apply a high-pass filter (see filtered signals on Fig. 6b) based on the same observation as before. Despite the lower signal-to-noise ratio presence of some source of amplitude modulation in high frequency band may be observed on the spectrograms (Fig. 7b). Filtering allow us to estimate the frequency of the modulation even in the case of the acoustic signal though the first peak of the spectrum is covered up by the noise (Fig. 8b).
Figure 6: Vibrations and sound recorded from the left bearing of the test rig mixed with UAV noise - signals.

Figure 7: Vibrations and sound recorded from the left bearing of the test rig mixed with UAV noise - spectrograms.
Comparing Fig. 5b and Fig. 8b plots obtained for the vibrations show similar waveforms as the they were in the case of the previous study. It is because these can be treated approximately as the new realisations of the same processes. The impact of the noise characteristics is qualitatively greater in the case of the sound recorded by the microphone decreasing signal-to-noise ratio but using a filter we have effectively reduced it.

By comparing the envelope spectrum of the vibration signal with an acoustic signal, it is clearly noticeable from the plots that several harmonic spectra are the same. The fundamental frequency was estimated to 91.5 Hz. For comparison a repeated pattern of its harmonics was marked with red dashed line on Fig. 5b and Fig. 8b. We can conclude that the potential of using acoustic signal as a valuable source of information for fault detection has been positively validated.

5. Conclusion
This work presented a methodology used for fault detection of a bearing in a steady-state mode by collecting acoustic signal in two different kinds of background conditions. A measurement of two vibrational and one acoustic signal was performed on a test rig without an additional source of noise and then repeated in the presence of a hovering drone. All signals were analyzed using spectrograms and envelope spectra. To select the part of the signal containing information about the fault, high-pass filtering was applied. It proved as well to be sufficient for eliminating the noise effect in the case of the sound signal recorded in the vicinity of the quadrotor drone. The results demonstrated that diagnostics of the rotating machinery is achievable by means of the acoustic signal analysis. The results compared to the vibration based approach clearly correspond as we compared the plots of envelope spectra. It assures their reliability although no precise measure was applied. The results obtained from each of the three signals are consistent as the only peaks that appear in the envelope spectra are formed in a pattern of harmonics, i.e. the primary modulation frequency and its multiplies.

Using acoustic signals for diagnostics is highly beneficial. They fall under the category of non-destructive methods, which do not create any harm to the engine performance during its operation. Sound measurements can be used to detect the fault of numerous systems in harsh environment such as underground mines. However to benefit from such a measurement more care is needed than in the case of vibrational sensing. Raw sound record usually has low signal to
noise ratio so it must be processed to obtain useful information. It is necessary to use advanced acoustic signal processing methods to eliminate noise effects.

There is still a big challenge in automation and improvement of the measurement and analysis causing a need for more research on this subject in the future.

Acknowledgments
This activity has received funding from European Institute of Innovation and Technology (EIT), a body of the European Union, under the Horizon 2020, the EU Framework Programme for Research and Innovation. This work is supported by EIT RawMaterials GmbH under Framework Partnership Agreement No. 19018 (Autonomous Monitoring and Control System for Mining Plants - AMICOS).

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