MADRID
inter.noise 2019
June 16 - 19
NOISE CONTROL FOR A BETTER ENVIRONMENT

Machinery noise source identification with deep learning

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ABSTRACT

Machinery noise is produced by several noise sources. Our study focuses on hard rock mining machinery in harsh conditions. In such machinery, there are several independent and inter-dependent noise sources. They include cutting, airflow, drilling, and auxiliary devices such as hydraulics. In this study, we isolate the most annoying or harmful noise sources. This is done by automatic ranking of the noise sources.

For the automatic ranking of the noise sources, we have tried deep learning, independent component analysis, and principal component analysis. Deep learning has produced the best results. It is used widely in detection of noise sources, but it has not been commonly applied to machinery noise source detection.

The results show the possibility to separate the noise sources, if adequately long datasets without excessive random and impulsive components are available. A priori information about the individual noise sources improves the capabilities of the deep learning method, as well. The challenge is to use real-world datasets with slightly corrupted contents successfully and with adequate accuracy to improve the machinery noise properties.

Keywords: Noise sources, Noise ranking, Deep learning

I-INCE Classification of Subject Numbers: 11, 74, 79

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1. INTRODUCTION

Machine noise source identification and ranking is widely used methodology to determine the most important sound sources in a machinery [1]–[3]. Similar methods have long been used in machinery fault detection by vibration [4]. An expansion of this methodology is user-centric noise ranking, where the criteria for the most important noise sources is not only the sound pressure level, but how a person experiences the noise. User centric noise ranking has been carried out in our earlier research in a simple form [5]. Now we have expanded this work towards more systematic approach than earlier [6].

Several methods of source identification and component analysis may be used, and they are critical for the successful identification of the noise sources and their contributions. The target for the noise source ranking is to find out the most important noise sources, and to be able to improve the noise conditions according to this information. So, the connection of the identified noise sources to real machinery parts and machinery operations is important.

To establish such connection it is important to have correct evaluation criteria. When the importance of the noise sources is ranked to an order, it is possible to make changes to either the model or a real machinery, or both. The signal source identification is related to the sound and vibration analysis of machine design. The measured signal are linear and non-linear combination of several, mixed source signals. The aim of source separation is to estimate original source signals from the measurements so that contribution of different sources in specific location can be estimated.

2. METHODS

There are several methods to identify individual machinery noise sources. They include Independent Component Analysis (ICA) [7], [8], Principal Component Analysis (PCA) [9], and various other Deep Learning (DL) categories [10]. Both ICA and PCA belong to Blind Source Separation (BSS) methods, meaning that there is no prior information about the generating process of the system. Both sources and transfer functions are unknown. An extensive review of BSS methods has been presented by Comon & Jutten [11].

We used a deep mining equipment as a test case for the source separation methodology. The target was hard rock mining equipment working in real conditions. Noise, user-centric vibration and machinery data was acquired simultaneously. For the test case 6 separate signal sources were considered and separation of them from an unknown signal was studied.

The signals included 2 conditions for hydraulic pumps, cutter motors, conveyor belt, drilling compressor, and a dust exhaust system. Some of those signals were measured in different location and process state, so the total amount of classes is 11. In Figure 1 signals for the hydraulic pump and the cutter motor are presented. Both signals have clearly their own typical fingerprints, and periodic components. However, there is relatively large temporal variation in the signals, as well as impulse noise in case of the cutter motor signals, which make the classification challenging.

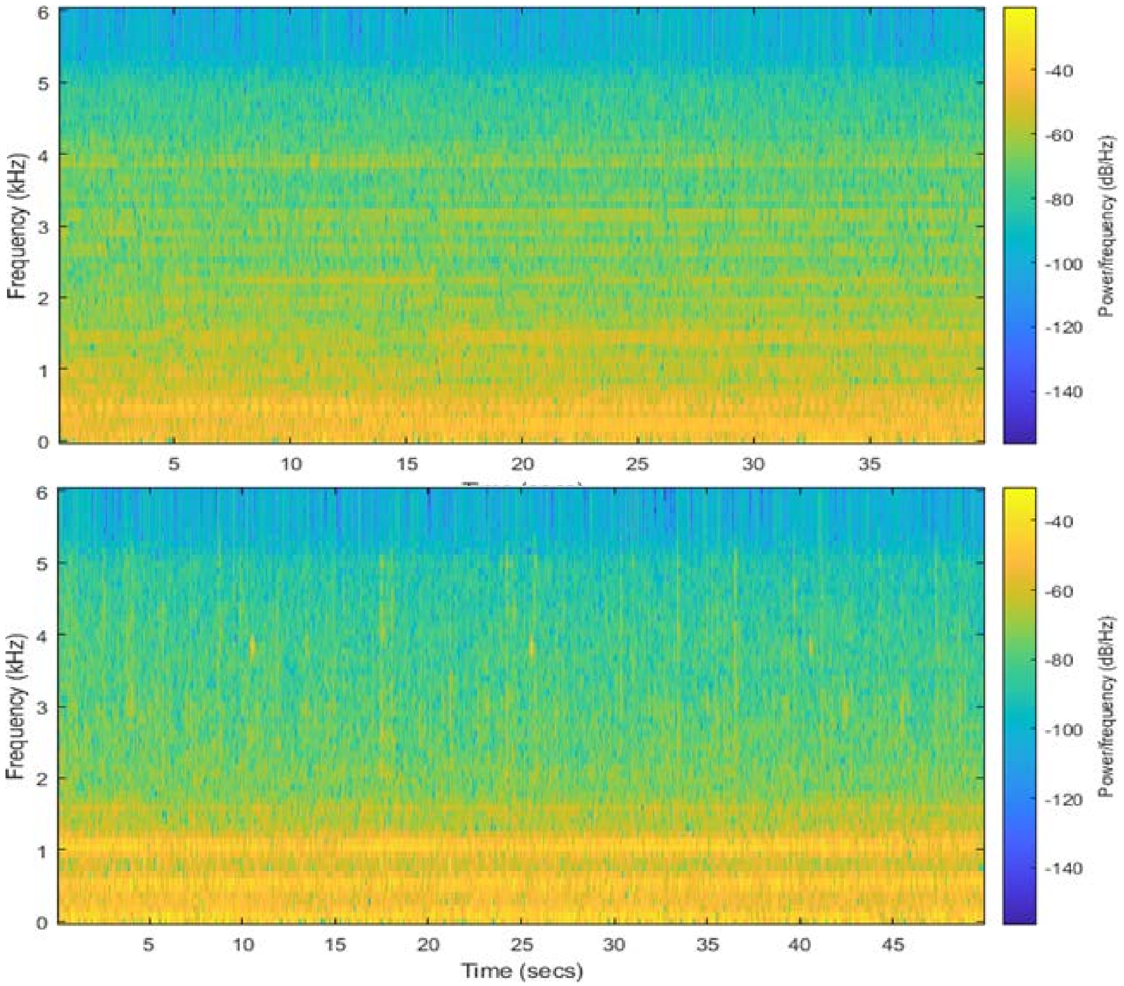

Figure 1. The spectrograms of the hydraulic pump (upper figure) and cutter motor (lower figure) signals, measured separately.

First, the acquired noise data was used and analysed using ICA methodology [6]. The lesson learned was if you want to use ICA, signals could not be desynced but only linearly mixed. In practise, the real-life phase shift and delay are problematic for ICA. In theory, ICA is a good algorithm, but in reality it performed poorly. ICA method cannot identify uniquely neither correct the ordering of the source signals. Similar issues were probable also with PCA.

Instead, we looked at the other DL methods. They included K-means by unsupervised clustering [12] and Neural Networks by supervised classification [13]. Sampling frequency was decimated to 12 kHz, and initial classification was done from AR spectrum with fixed order 30 and 257 values. The problem was that the signals are not stationary. If the training set is short, it is possible that it contains anomaly. If it is long, it is possible that it does not make proper generalization of the signal. In order to solve those problems a multilayer model was trained.

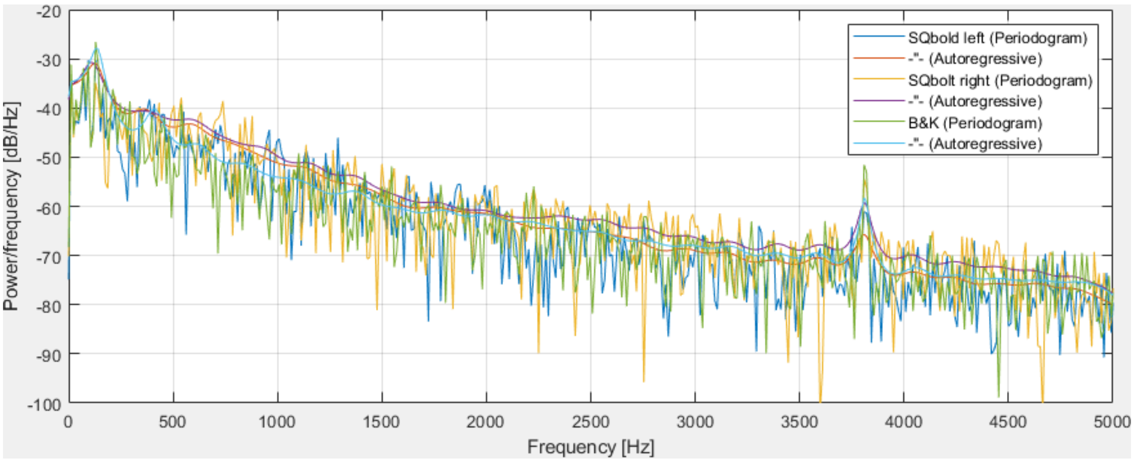

Figure 2. Examples of spectra using FFT-periodogram and autoregressive method.

3. RESULTS

Spectral estimates of a sound pressure signal using FFT based periodogram and autoregressive (AR) method are shown in Figure 2. Since there are more dispersion with periodogram than in AR method, the smoother AR spectra was chosen to the training. The partial set was used in the analysis. It was selected to be the most representative time domain part of the signals.

Some achieved results are in Figures 3 - 5. The lengths of the learning samples are 100, 200 and 400, respectively. With 100 and 200 samples the classification is satisfactory but still not very good. When the amount of classification samples is increased to 400 samples (Figure 5) the results are good, and there are only 1 % of incorrect classification results.

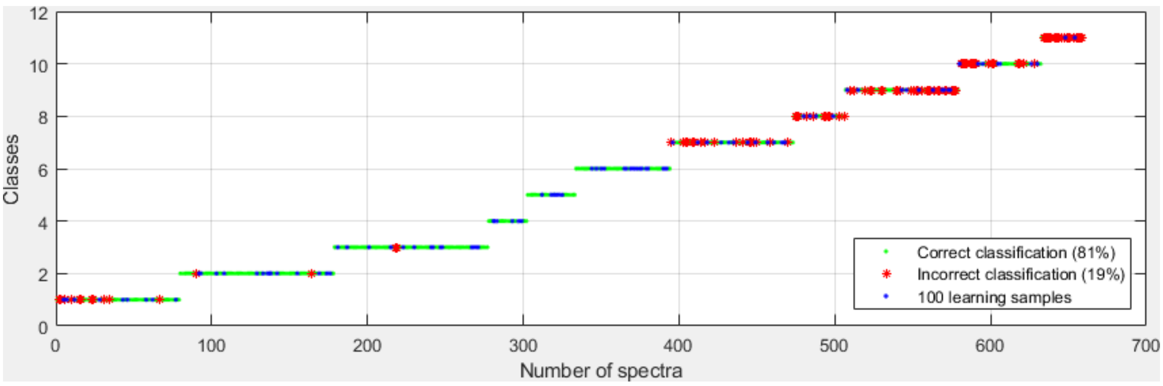

Figure 3.Classification results with 100 learning samples.

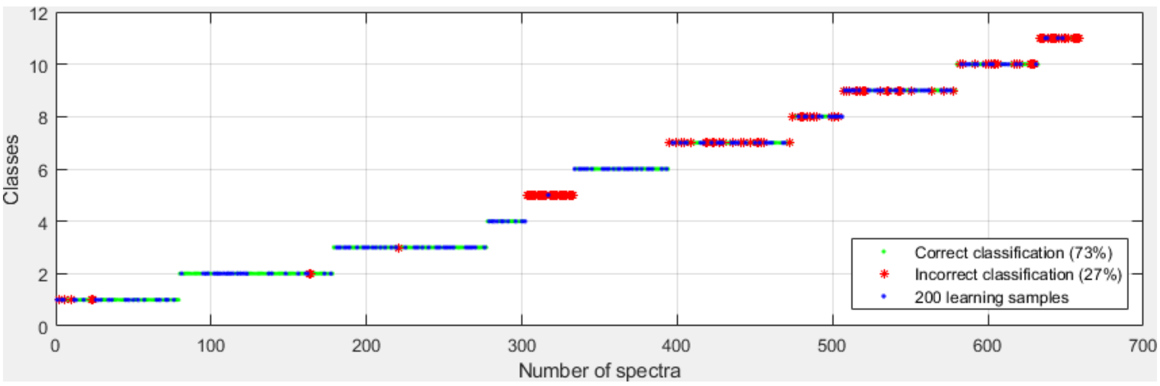

Figure 4.Classification results with 200 learning samples.

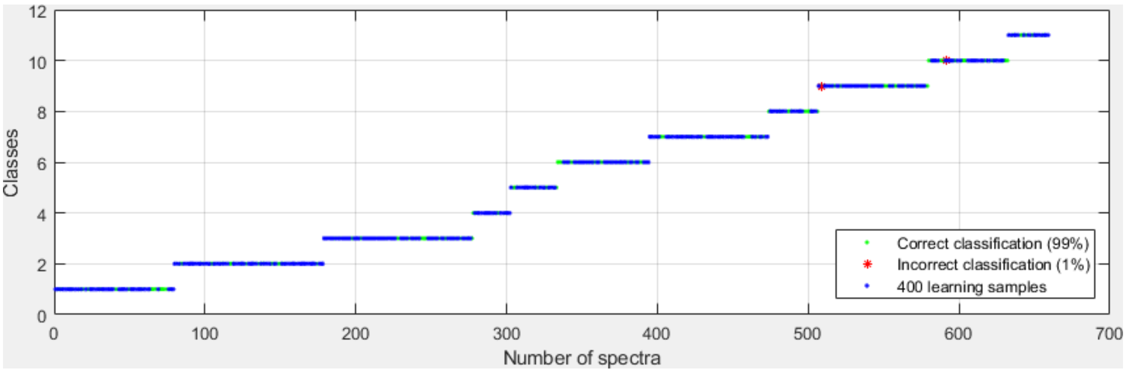

Figure 5.Classification results with 400 learning samples.

4. CONCLUSIONS

The results show the possibility to separate the noise sources, if adequately long time-invariant datasets without excessive random and impulsive components are available. In practise, the need for a relatively long training and test sets to achieve good enough accuracy may be challenging due to the time-variant nature of the signals as well as sporadic impulsive signals in mining environment. However, with careful selection of the training it seems to be possible to achieve reliable identification.

The challenge and the target for the further studies is to use real-world datasets with slightly corrupted contents successfully and with adequate accuracy for improving the machinery noise properties.

5. ACKNOWLEDGEMENTS

The work was carried out in RockVader - Smart Hard Rock Mining System project (project number 16136) which has received funding from European Union’s EIT RawMaterials initiative. Special acknowledgements to Sandvik Austria for arrangements of the measurement possibilities and coordination of the RockVader project.

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