User centric noise source ranking

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Summary

User centric noise source ranking is proposed as an extension to the conventional machinery noise ranking methodology. It focuses on the improvement of the machinery operator and additional personnel working conditions. Similar to the conventional noise ranking methodology, the partial noise sources are identified and their joint effect is evaluated. In the user centric noise ranking, the location where the combined noise effect is evaluated is the user or operator position. The operator may be inside a cabin, or directly exposed to the noise. Additionally, the noise data is analysed with psychoacoustic methods to obtain the noise annoyance for the experienced noise. This approach has been evaluated with acquired data from hard rock mining equipment working in real conditions. As an additional requirements, user centric noise source ranking also limits the used component analysis methods and ways to acquire the noise data, and some signal source separation methods do not work properly. Psychoacoustic analysis methods employed require acquisition of sound pressure as a time series, and this limits the available algorithms. This creates new demands for the data acquisition and analysis methods, but the possible benefits will outweigh them.

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1. Introduction

User centric noise source ranking is proposed as an extension to the conventional machinery noise ranking methodology [1]–[3]. It focuses on the improvement of the machinery operator and additional personnel working conditions. Similar to the conventional noise ranking methodology, the partial noise sources are identified and their joint effect is evaluated. Such work has been carried out in our earlier research in a simple form [4]. Now we have expanded this work towards more systematic approach than earlier.

As with the conventional noise control, the connection to the underlying vibration and noise generation mechanics are recognised, and appropriate measures to decrease the noise effects on the operator are carried out. They include the effects on the noise sources, transmission path, and the receiving person.

The most important way to reduce the noise effects on the user or operator is to change the properties of the noise source. The difference here compared to the conventional noise source ranking and noise abatement methods is the way to monitor the results: the situation directly at the operator is observed and changes are made corresponding to this.

The secondary level to affect is the noise transmission path. Again, the methods are same as with the conventional noise control, and only the way to monitor the results differs.

Finally, the last part of the noise propagation chain is the operator and operator's PPE (personal protection equipment). Also this part of the protection is evaluated by the user experience.

User centric noise source ranking limits the used component analysis methods and ways to acquire the noise data. This is because psychoacoustic analysis methods require acquisition of sound pressure as a time series. This creates new demands for the data acquisition methods, as well as signal source separation algorithms because many frequency domain methods may not be utilised.

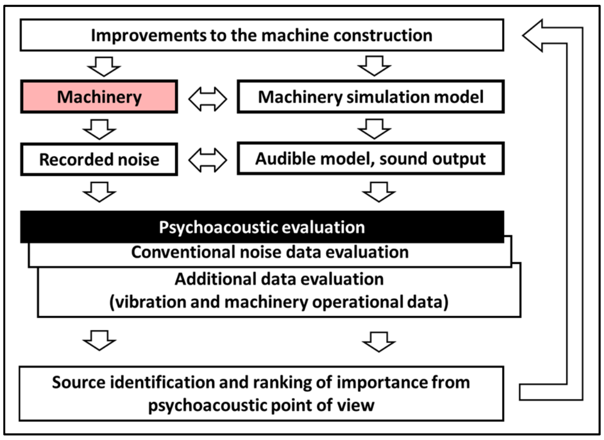

Figure 1. The psychoacoustic ranking and machinery improvement cycle.

2. Psychoacoustic evaluation principle

The Figure 1 illustrates the idea of the psychoacoustic ranking cycle to improve the machinery noise conditions. At the very center of matters is the machinery itself. Derived from this machinery and also in parallel to it is the machinery simulation model, including geometry and other possible parameters for mechanics, noise, thermal conditions, electronics and control systems, to mention a few.

The noise data is possible to acquire either from a real machinery, if it already exists, or from a simulation model. We have used a specific tool called Audible Modeling Platform for this purpose [5]–[7].

When we have either simulated or recorded data we can carry out psychoacoustic evaluation of the noise, shown also in detail in Figure 2. The psychoacoustic evaluation consists of 2 main paths: listening tests and calculation of the values directly. From listening tests it is possible to have direct sound quality and annoyance results. From the individual, calculated psychoacoustic metrics it is necessary to make a combination metrics describing the total effect of the noise. Such combination metrics may be generated with a ready-made combination equation, such as Unbiased Annoyance [8], or it may be formulated by the results of the listening tests for each individual case. The combination metrics make it possible to compare different cases and rank their effects in a certain order.

In addition to the psychoacoustic evaluation, noise data is analysed using conventional metrics and visualisation methods, including sound levels and spectrograms. Also, other relevant measurement results are combined with the psychoacoustic evaluation and conventional noise analysis. They may include vibration and machinery operational data, usually acquired from the internal CAN-bus or similar [9]. This gives an enhanced insight of the machinery noise, especially experienced by the users and operators. Several methods of source identification and component analysis may be used at this stage, and they are critical for the successful identification of the noise sources and their contributions. Their functionality is a topic for another study, and this issue has been discussed at the latter part of this paper.

The target for the psychoacoustic noise source ranking is to find out the most important and annoying noise sources from the user or operator point of view, and to be able to improve the noise situation according to this information. So, the connection of the identified noise sources to real machinery parts and machinery operations is vitally important, to gain benefits of this evaluation.

To establish such connection it is important to have correct evaluation criteria. In case of the psychoacoustic ranking the evaluation criteria are directly linked to the human experienced noise at certain locations. 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.

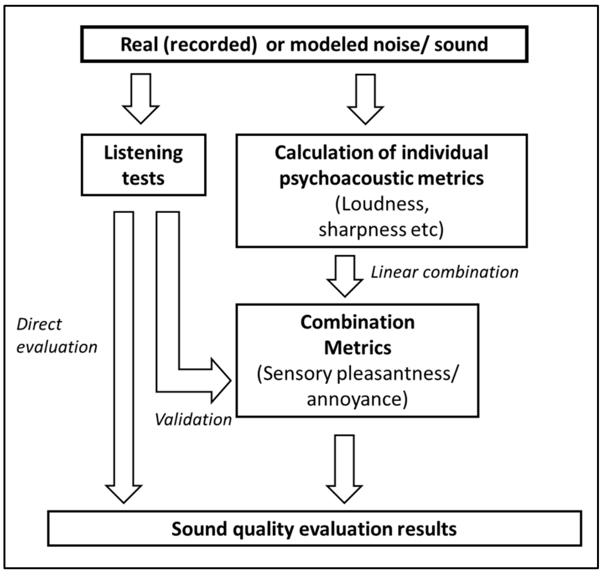

Figure 2. The psychoacoustic evaluation procedure.

The fastest loop to evaluate the changes, albeit in somewhat inaccurate way is to change the simulation model or directly the parameters of an audible model. Such parameters may simply include the static relative volumes of partial noise sources. Or, they may be more elaborated and also change in the time or frequency domain. This may already give enough information how the machinery should be developed further.
Based on this information, it is possible to make actual changes to the machinery in refined way, utilising this a priori information of the noise sources and their contributions to the total noise.

3. Typical source data and the evaluation results

This approach has been under evaluation with acquired data from hard rock mining equipment working in real conditions. Noise, user-centric vibration and machinery data was acquired simultaneously. The noise data was analysed with psychoacoustic methods to obtain the noise annoyance for the experienced noise. The primary psychoacoustic parameter at the first stage has been loudness, and it has been compared to more conventional metrics.

In Figure 3 a typical measurement and its analysis is presented. The horizontal axis is the time, and there are several analysis plots. The upper analysis plot is the spectrogram of the noise. This gives a temporal overview of the noise. This is important in separating the noisiest parts in the work cycles, and pinpoint to them instead of observing the mean values for the whole period of machinery operation.
The middle analysis screen shows the Loudness [10] as a psychoacoustic parameter and compares it with the more conventional A-weighted sound pressure level with fast time-weighting, L_{paF}. In this case these 2 metrics do not differ considerably, but in some cases the differences may be important from the observer point of view. Finally, at the lowest screen there are vibration values related to the operator conditions.
Continuing from this the next steps include calculation of other relevant psychoacoustic parameters and combination metrics, possible listening tests, and source separation and ranking. This may be carried out with several ways of component analysis.

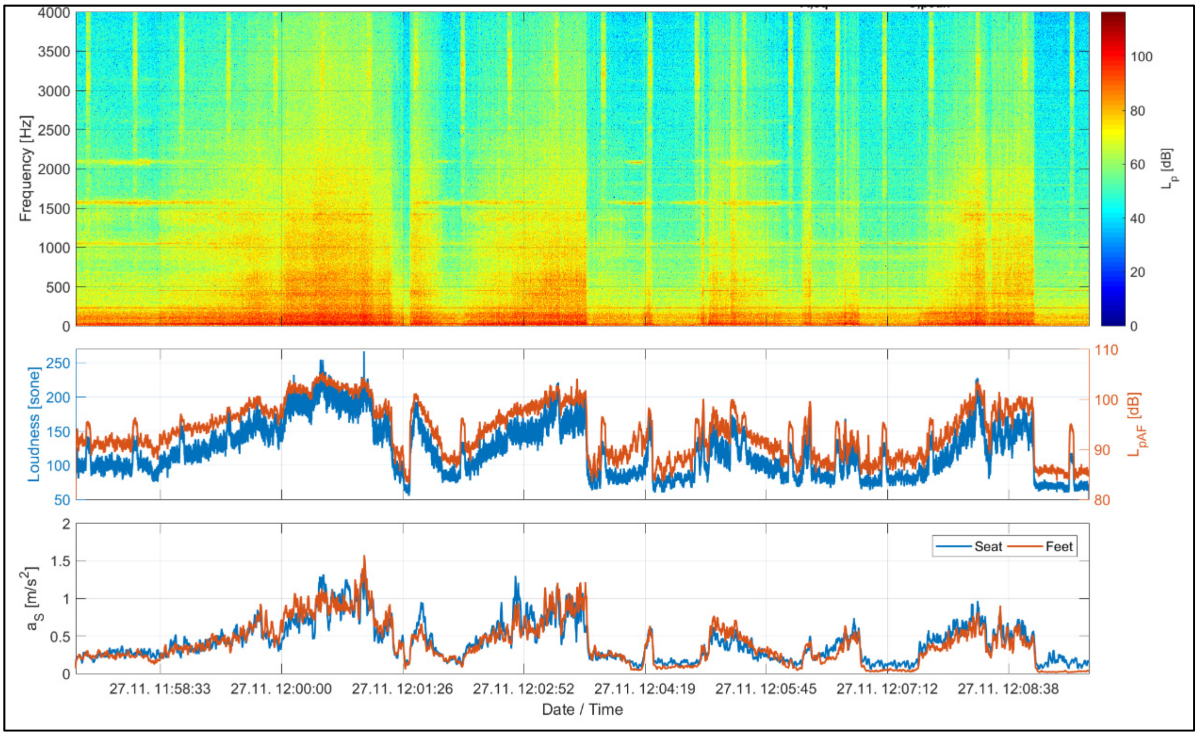

Figure 3. A long excerpt of several machinery noise components.

5. Component analysis

Typical example of Signal Source Separation is “Cocktail party problem” [11]. There are several persons speaking simultaneously and the listener must recognize the speaker and follow his or her speech. A simplified case can be solved with statistical procedures, but in practice, it is a difficult problem for digital signal processing.

The signal source separation 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.

In Blind Source Separation (BSS) there is no a priori information about the generating process of the system. Both sources and transfer functions are unknown. Typical methods of BSS include Principal Components Analysis [12], Independent Component Analysis [13], [14], Dependent Component Analysis [15], Stationary Subspace Analysis [16], Common Spatial Pattern [17], Factor analysis [18], Multivariate correlation analysis [19] and Partial least squares regression [20]. An extensive review of BSS can be found in [21], and an overview in Table .

If there is information about the source signals or the mixing process, there are some more methods to apply. This case is usually called simply source separation. The methods which can exploit the knowledge of the system, are Linear Discriminant Analysis [22], some pattern recognition and classification methods and supervised machine learning algorithms. Common features used in supervised learning of audio voice signals are pitch and Mel Frequency Cepstrum Coefficients (MFCC).

Principal components analysis (PCA) is extensively used in data analysis and image processing. This is caused by the fact that its computation is relatively simple and it is not too complicated to understand.

The main aim of using PCA in the analysis is to reveal internal structure of the system from which the data has been measured. Using the information it is possible reduce the dimension of the measured data. That will decrease the redundancy of data and filter some noise from the dataset.

Independent component analysis (ICA) is also a statistical technique. It is related to PCA, but it is more effective algorithm to reveal internal sources particularly in cases where PCA fails completely. The system model is very similar to PCA: the measured data is generated by an unknown linear mixing system, where sources, also called latent variables, are unknown. They are assumed to be nongaussian and mutually independent. ICA decomposes multivariate data into independent components.

The benefit of ICA is that the signal may remain in the time domain format and thus it is compatible with the most psychoacoustic analysis methods.

Several approaches have been proposed for the solution of the source separation problem. PCA and ICA are the most successful approaches but they work well in cases where no delays or echoes are present. In practical situations, performance of these methods is therefore very limited and more advanced methods are needed.

Table I. Typical Blind Source Separation methods.

Method	Notes	Results
PCA	Information from second order statistics, Gaussian signals Scaling sensitive, not removing higher order dependence - only correlation	Orthogonal directions that represent maximum variance
ICA	High order statistics, Non-Gaussian signals, perfect Gaussian sources cannot be separated, can only separate linearly mixed sources, all signals are equally important, cannot determine the variance of independent components	Space where signals are maximally independent Directions of space not orthogonal
DCA	Extension of ICA	Separate signals into sets which are dependent on signals within their own set
SSA	Estimate the inverse mixing separating the stationary from non-stationary	Separate signals into stationary and non-stationary components
CSP	Windowed version of PCA	Windowed directions

6. Test case for Independent Component Analysis

To find out the performance of a basic ICA algorithm in machinery acoustics a test case was created. The performance was evaluated with artificial test signals, resembling machinery noise. The objective was to separate 2 components that were emitted by 2 sources and measured by 2 sensors. The simulated setup is illustrated in Figure 4. For source 1, noise components for 3 different cases were created (Tables Table and Table). The idea of the noise components was to mimic the detection of 2 sources with 2 microphones. The source 1 had time-variable components whereas the source 2 was time-invariant. Also, low-amplitude white noise was also added to both sources to reduce the signal-to-noise ratio as in the real conditions.

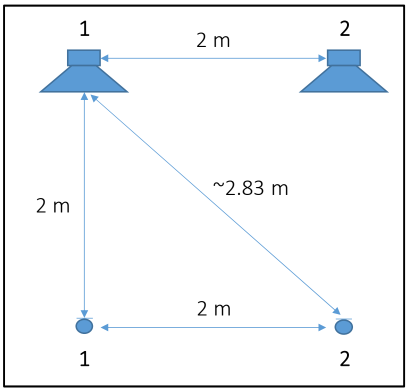

Figure 4. Test setup for ICA.

Table II. Source 1 noise components.

Case	Main Components frequency [Hz]			Modulation	
	1	2	3	Type	Modulation depth
1	100	200	300	-	-
2	100	200	300	Amplitude 4 Hz	50 %
3	100	200	300	Frequency 0.1 Hz	± 10 Hz

Table III. Source 2 noise components.

Case	Main Components			White noise
	1	2	3	
1	120 Hz	240 Hz	360 Hz	x
2	120 Hz	240 Hz	360 Hz	x
3	120 Hz	240 Hz	360 Hz	x

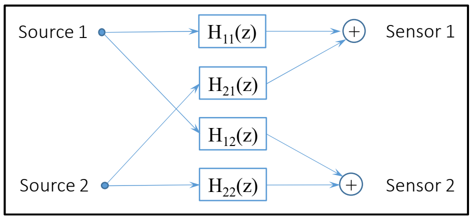

Figure 5. Simulation model.

Parallel to practical tests, a simulation model of the setup was created in Matlab (Figure 5). Transfer functions between the sources and sensors were approximated with delay lines. The transfer functions $H_{ij}(z)$ were modelled as FIR filters with constant magnitude and linear phase delay. Magnitude for H_{11} and H_{22} was equal to 1, whereas magnitude for H_{12} and H_{21} was 0.9, attenuating sound as a function of distance.

6.1. ICA simulation results

The simulations showed mixed results. ICA fails to separate the components when all the delays were different. Results with test case 2 are given in Figure 6. After ICA has been applied, the components are still mixed. Similar results were obtained with the other test signals.
Then all delays were set equal. Such a setup is achieved only when the sensors are located on opposite sides of the source line and all distances are equal. In this case, ICA works perfectly and the two components are fully separated. Results with test case 2 are shown in Figure 7.

6.2. Acoustical test results for ICA

The test setup shown in Figure 4 was also assembled with 2 loudspeakers and microphones. The test signals were fed to the loudspeakers and the signals acquired by the microphones were processed with ICA. As expected, results were similar to the ones with the simulation model containing non-equal delays. ICA was not able to separate the components (Figure 8).
As conclusion, the used ICA algorithm is extremely sensitive to phase delay variation of components. Therefore, this algorithm probably cannot be used in practice when the acoustic environment is complex and contains varying transfer delays from sources to measurement points. Improved algorithms taking into account the time-delayed signal should be used instead [23], [24].

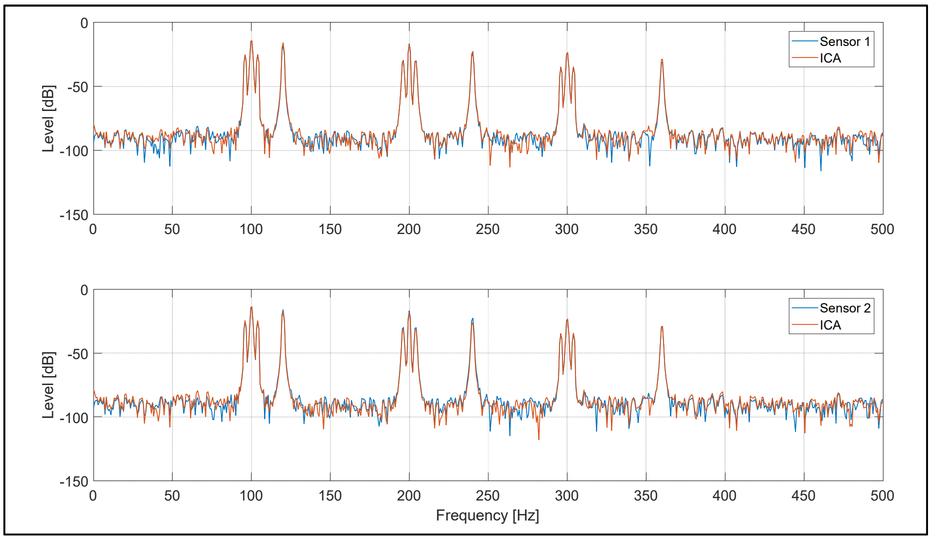

Figure 6. ICA test results with non-equal delays.

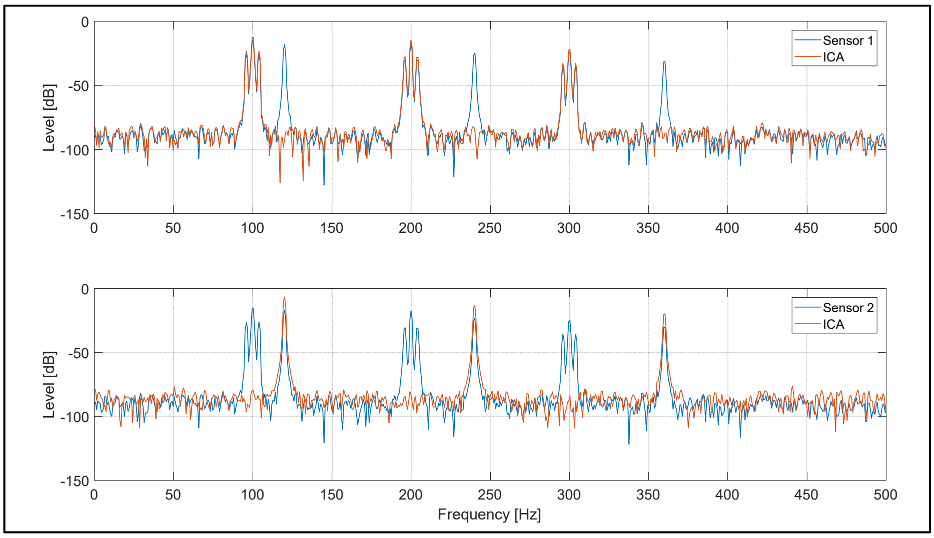

Figure 7. ICA test results with equal delays.

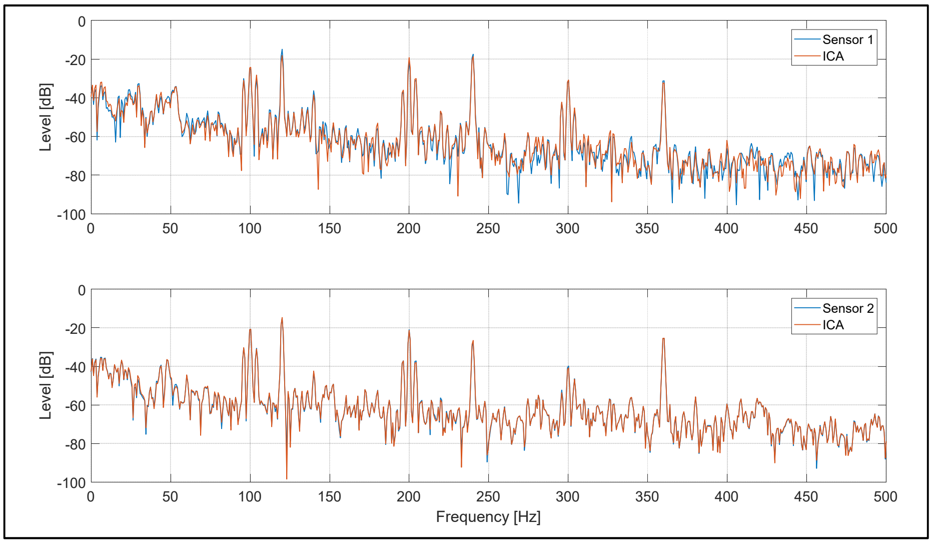

Figure 8. ICA test measurement results with loudspeakers and microphones.

7. Conclusions

The analysis shows that the user centric noise source ranking methodology will expand the conventional noise ranking possibilities, because it allows analysis that is more detailed, and effects the working conditions of the operators directly. There are, however, some issues with the component analysis and source separation, where further studies are needed to obtain best possible results related to this methodology.

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