



Birnie, C., Chambers, K., Angus, D., & Stork, A. (2016). Effect of noise on microseismic event detection and imaging using ICOVA statistical noise modelling method. In SEG Technical Program Expanded Abstracts 2016. (pp. 2622-2626). (SEG Technical Program Expanded Abstracts 2016). Society of Exploration Geophysicists, Tulsa, USA. DOI: 10.1190/segam2016-13858910.1

Peer reviewed version

Link to published version (if available):  
[10.1190/segam2016-13858910.1](https://doi.org/10.1190/segam2016-13858910.1)

[Link to publication record in Explore Bristol Research](#)  
PDF-document

## University of Bristol - Explore Bristol Research

### General rights

This document is made available in accordance with publisher policies. Please cite only the published version using the reference above. Full terms of use are available:  
<http://www.bristol.ac.uk/pure/about/ebr-terms.html>

# Effect of noise on microseismic event detection and imaging procedures using ICOVA statistical noise modelling method

Claire Birnie, University of Leeds, Kit Chambers, Nanometrics Inc., Doug Angus, University of Leeds, Anna L. Stork, University of Bristol

## Summary

Despite the evidence that noise does not conform to the White Gaussian Noise (WGN) assumption, the robustness of new processing and imaging algorithms are still tested with WGN. This paper presents an alternative noise modelling method, based on multivariate statistics, to generate realistic noise for incorporation in synthetic datasets. The realistic noise model captures the complex nature of noise arising from multiple sources and the varying signal-to-noise (SNR) observed at the different stations across the array. This complex noise structure results in microseismic events being detected at lower SNR than would be implied using a WGN model. It also successfully re-creates smearing of energy during imaging of microseismic events at low SNRs. This modelling method provides an opportunity to test the robustness of new algorithms under realistic noise conditions prior to recording data in the field.

## Introduction

Synthetic microseismic datasets are commonly used to test the sensitivity/robustness of imaging algorithms to noise, providing a confidence limit onto the conditions under which an algorithm can be used to accurately identify an event and its properties such as fracture location, orientation and length. To provide a closer representation to recorded seismic data, noise is commonly added to synthetic microseismic datasets.

Despite the evidence that noise does not conform to the WGN assumption, the robustness of new processing (e.g. Zhang et al., 2015) and imaging (e.g. Trojanowski and Eisner, 2015) algorithms are still commonly tested using WGN. Since this is not a representation of realistic noise, it becomes unclear as to how an algorithm will handle noise from a field dataset, leading to uncertainty in the accuracy of identified events and their derived properties. Other modelling methods include using distributed surface sources as demonstrated by Dean et al. (2015), or convolving a sample of recorded noise with broadband white noise as proposed by Pearce and Barley (1977). Chambers et al. (2010) directly incorporate a sample of recorded noise into the computed dataset, commonly referred to as creating a semi-synthetic dataset. The first method fails to capture the complex combination of meteorological, geological and geographical effects on noise (Dean et al. 2015) while the latter two methods

require noise to be collected prior to modelling therefore making them of little use where noise data is unavailable.

This study introduces a novel modelling method to create realistic noise models to be incorporated into the production of synthetic microseismic datasets. Comparing synthetic datasets with WGN, modelled realistic noise and recorded noise, this paper investigates the extent to which the noise models imitate recorded noise focusing on signal to noise ratio (SNR) across the array and the effect of noise on microseismic event detection and imaging procedures.

## Method

The modelling method used in this paper is an extension of multivariate normal modelling that uses the covariance matrix to recreate multidimensional structures in the data. Our Isolated COVariance-based (ICOVA) modelling method requires individual noise types to be identified and uses multiple realisations of each noise type to compute a mean vector,  $\mu$ , and a covariance matrix,  $C$ , which form the basis of the noise model. The modelling workflow is illustrated in Figure 1,

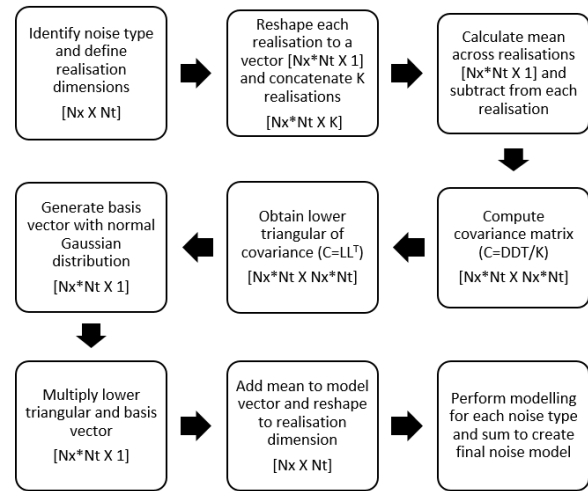


Figure 1: ICOVA Modelling workflow

where the lower triangular of the covariance matrix is obtained using a Cholesky decomposition. The final noise model of a realization of a noise type is generated by,

$$\mathbf{d} = \mathbf{L}\mathbf{b} + \boldsymbol{\mu} \quad (1)$$

## Effect of noise on microseismic event detection and imaging

where  $\mathbf{b}$  is a random basis vector with a normal Gaussian distribution and  $\boldsymbol{\mu}$  is the mean vector obtained from the recorded noise realisations.

Once the desired noise model is generated it is superimposed on synthetic waveform data. Two other synthetic datasets have been created for comparison – a synthetic with WGN, and a semi-synthetic with recorded noise superimposed on synthetic waveform data. The waveform data is scaled to provide the desired array SNR. The following analysis is performed on all three synthetic datasets.

As a first port-of-call, SNR is calculated for the full array and for each station within a 0.2 second time window proceeding the first break. The SNR is calculated using

$$\text{SNR} = S_{\text{RMS}} / N_{\text{RMS}} \quad (2)$$

where  $S_{\text{RMS}}$  and  $N_{\text{RMS}}$  are the root mean squares of the amplitudes of the signal and noise, respectively, over the defined time window. The SNR analysis was performed on the raw data whilst the event detection and location investigation is performed on the data after a 10-60Hz bandpass was applied.

To investigate the effect of noise on automated event detection, the ratio between the Short Term Average (STA) recorded amplitudes and the Long Term Average (LTA) amplitudes is calculated over a sliding window, similar to that used by Stork et al. (2014). The window lengths and event threshold were determined based on the STA/LTA results calculated on the semi-synthetic dataset and a minimum of 5 stations must observe the event before the trigger will occur.

We also investigate detection and location in the image domain. Imaging was performed using a conventional diffraction stack imaging procedure (Zhebel et al., 2011). As the source is explosive, there is no need for a correction for moment tensor in this case. However, the technique can also be applied in situations where correction for the source mechanism is required.

### Data

The ‘noise’ data used in this study was recorded on a permanent surface array at the Aquistore CO<sub>2</sub> storage site in Saskatchewan, Canada. An initial noise analysis was performed by Birnie et al. (2015) which identified and classified different noise signals present in the data. The noise types modelled in this paper are the previously identified stationary and pseudo-non-stationary noise signals.

The waveform data is generated using E3D (Larsen and Harris, 1993) and aims to imitate a microseismic event

occurring at the reservoir level of the Aquistore CO<sub>2</sub> storage site. The modelled event is an explosive source below the middle of the N-S/E-W cross-shaped array at a depth of 3140m, where the subsurface is modelled as a 16-layer, laterally homogeneous, isotropic medium with properties as described by Roach et al. (2015).

### Results

The noise modelling results are given in the Figure 2. Comparing the noise modelling results of ICOVA (a,d) and WGN (b,e) with the recorded noise (c,f), it is clear that in both the time and frequency domain ICOVA provides a much closer representation of recorded noise. The ICOVA model also observes the change in noise types at ~60 seconds. Two seconds of data around the event arrival are given in Figure 2g-i for each synthetic dataset.

Figure 3a+b, illustrate the results from the SNR investigation for the N-S and E-W receiver profiles respectively. All synthetics have an array SNR of one however it is clear that the individual stations’ SNR varies greatly across the array, in part due to the increased noise level around the center of the array. This variation is captured on the ICOVA synthetic dataset however is not observed on the WGN synthetic dataset. The SNR of the ICOVA data does not fully match the Semi-Synthetic due to the fact that the modelling method aims to recreate the statistical properties of the noise and not identically replicate the recorded noise.

Figure 3c details the number of receivers (at different array SNRs) that observe an event in the STA/LTA investigation. The synthetic with WGN does not trigger 5 or more traces until a SNR of 1.5. Both the semi-synthetic and the synthetic with the ICOVA noise begin triggering by a SNR of 1 and both datasets show an increasing trend with the number of stations triggered and the array SNR. This is likely due to the uneven SNR distribution observed across the array therefore stations which individually have a higher SNR are likely to trigger before stations in noisier sections of the array.

The N-S receiver slice of the imaging results are illustrated in Figure 4. Due to the array design all images display a diffraction smile. While both the ICOVA and WGN datasets perform similarly to the semi-synthetic at SNRs of 1 and above, at lower SNRs the recorded noise starts to contaminate the image resulting in energy being smeared across the image (Figure 4i). This smearing is not observed on the data with WGN due to the random nature of the noise however it is observed on the ICOVA dataset which maintains the spatio-temporal structure of the noise signals from which it was modelled.

## Effect of noise on microseismic event detection and imaging

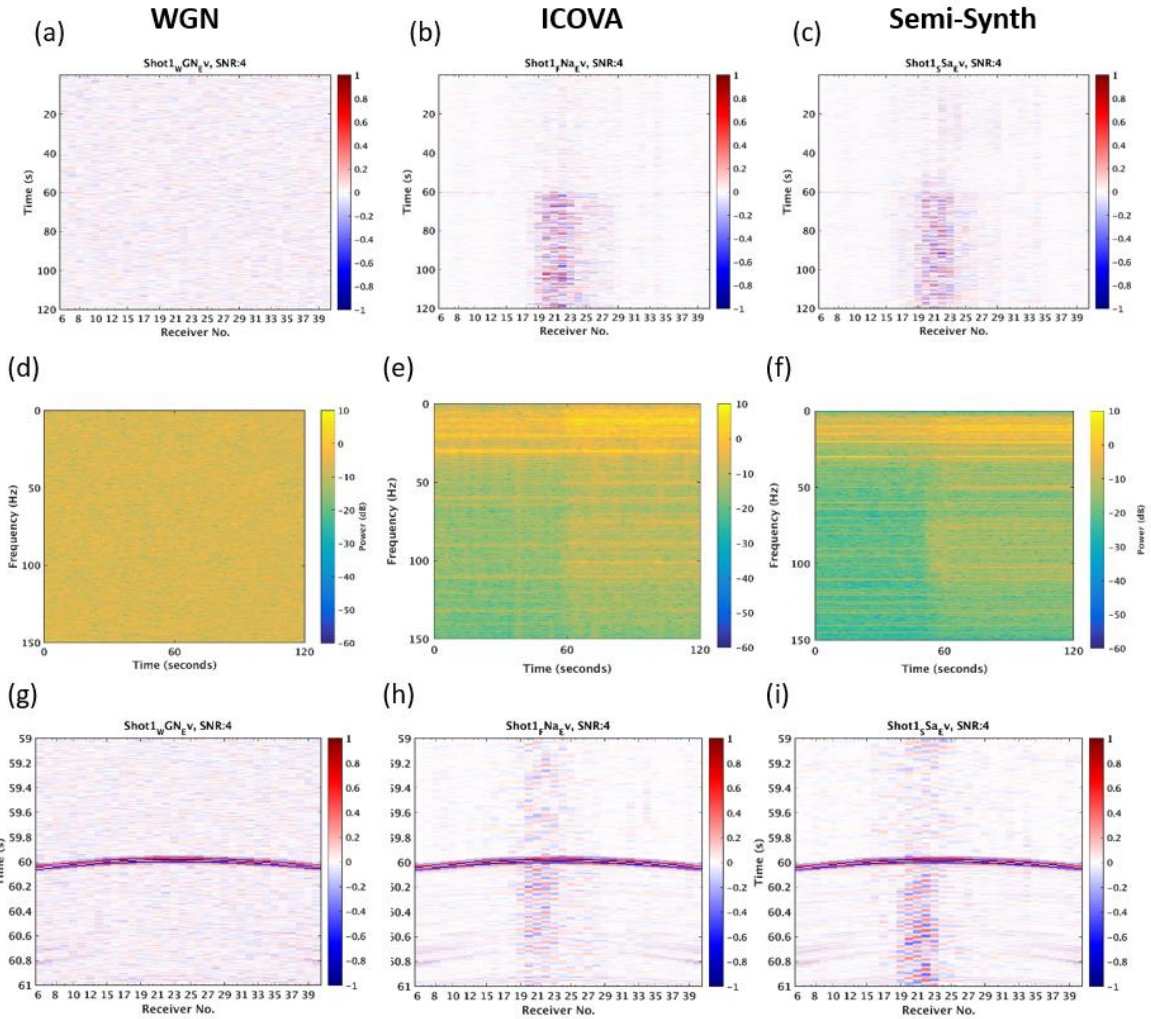


Figure 2: 2 minutes of data in time (row 1) and frequency (row 2) for WGN (column 1), ICOVA noise (column 2), and recorded noise (column 3). Final row illustrates 2 seconds in which the first arrival from a synthetic microseismic event is observed at an array SNR=4.

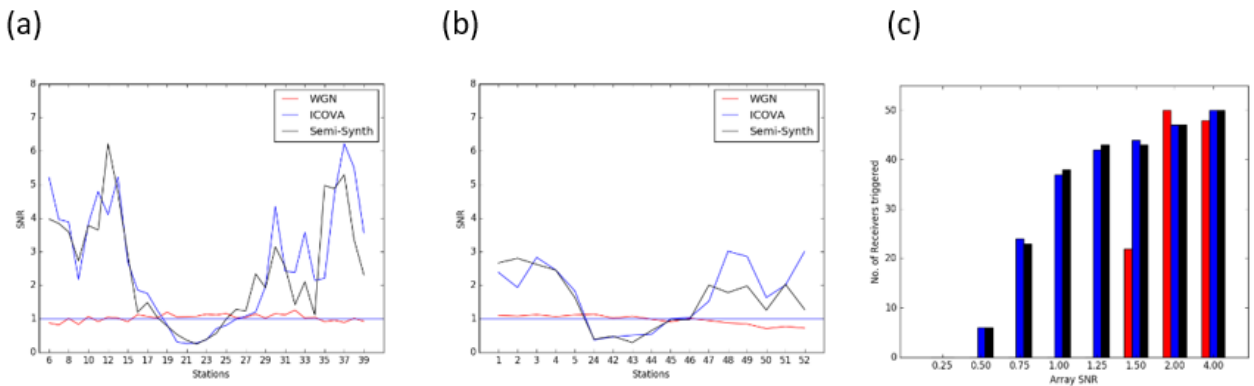


Figure 3: Individual stations' signal-to-noise ratio across (a) N-S profile and (b) E-W profile, and (c) STALTA results detailing the number of stations triggered at different array SNRs. Red illustrates WGN, blue illustrates ICOVA noise and black illustrates recorded noise.

## Effect of noise on microseismic event detection and imaging

### Conclusions

This paper introduced a noise modelling method to generate realistic noise models that replicate the complex spatio-temporal structures observed in recorded noise. Unsurprisingly, in all the analyses performed in this study, WGN failed to imitate recorded noise, particularly at low SNRs. The ICOVA modelling method better represented the noise signals in both the time and frequency domain, the varying SNR across the array, and the effect of noise on event detection and imaging procedures. Providing a closer comparison to recorded noise means that the synthetic dataset using noise modelled with the ICOVA method provides a better opportunity to investigate the effect of noise on processing and imaging algorithms.

An additional benefit of the ICOVA modelling method is that once noise types have been identified then their modelling parameters,  $\mathbf{L}$  and  $\boldsymbol{\mu}$ , can be saved for future models therefore removing the requirement for the full noise identification and modelling procedure to be repeated.

Due to the requirement of multiple realisations of a noise type prior to modelling with the ICOVA method, this study has not included rare, non-stationary signals observed in the data, such as passing cars. Alternative methods for modelling such noise signals include using a linear prediction filter method which can model non-stationary signals and then be combined with other noise models created using the ICOVA method. Future work will aim to identify additional noise types and analyse the effect they have on event detection and imaging algorithms.

### Acknowledgements

We would like to thank the Petroleum Technology Research Centre (PTRC) for access to Aquistore Data. CB is funded by the NERC Open CASE studentship NE/L009226/1 and Pinnacle-Halliburton. This research was partially funded by the EPSRC Geological Storage consortium DiSECCS (EP/K035878/1) and EPSRC Early Career Fellowship (EP/K021869/1) held by DA and the EPSRC.

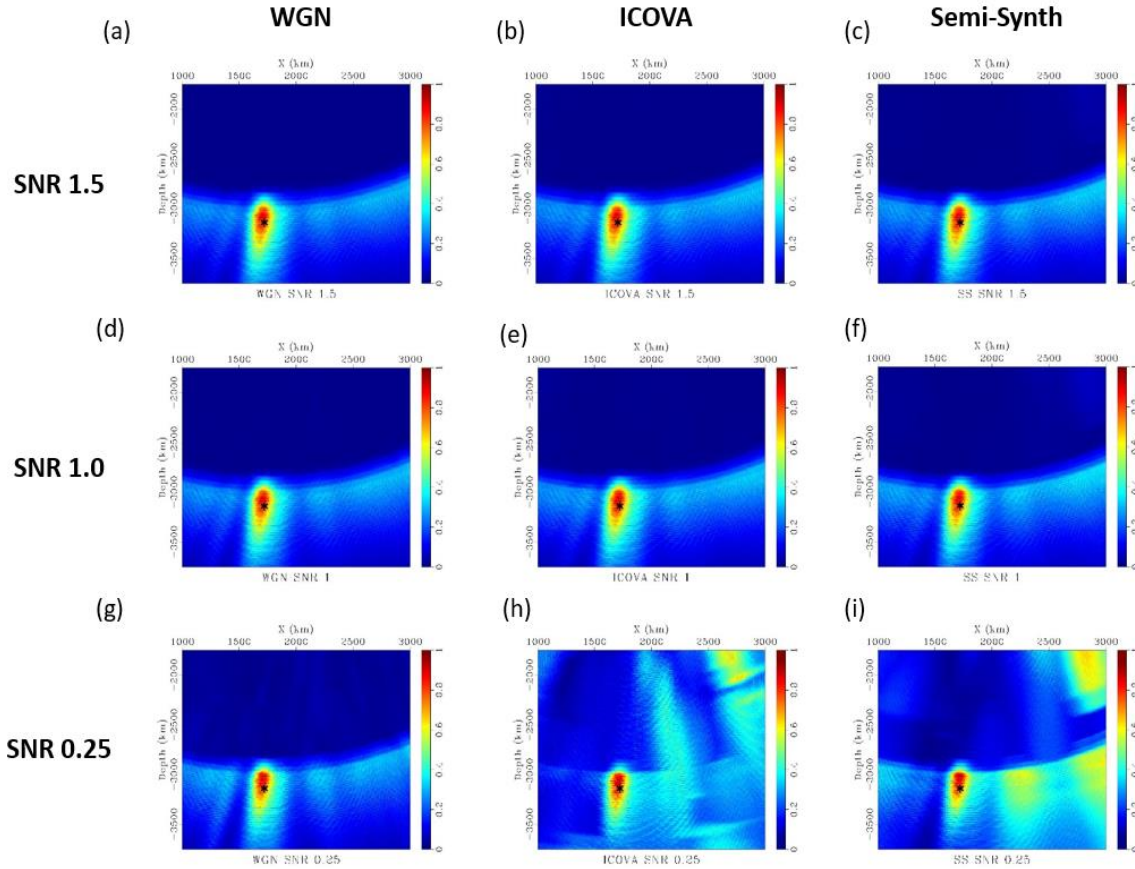


Figure 4: Slice of diffraction stack imaging results for N-S receiver profiles of synthetic datasets with WGN (column 1), ICOVA noise model (column 2) and recorded noise (column 3) at array signal-to-noise ratios of 1.5 (row 1), 1 (row 2), and 0.25 (row 3). The black star indicates the true source location and all images have been normalised.