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On the generation of geometry-independent noise models for microseismic monitoring purposes

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As a result of the world-wide interest in carbon storage and geothermal energy production, increased emphasis is nowadays placed on the development of reliable microseismic monitoring techniques for hazard monitoring related to fluid movement and reactivation of faults. In the process of developing and benchmarking these techniques, the incorporation of realistic noise into synthetic datasets is of vital importance to predict their effectiveness once deployed in the real world. Similarly, the recent widespread use of Machine Learning in seismological applications calls for the creation of synthetic seismic datasets that are indistinguishable from the field data to which they will be applied.

Noise generation procedures can be split into two categories: model-based and data-driven. The distributed surface sources approach is the most common method in the first category: however, it is well-known that this fails to capture the complexity of recorded noise (Dean et al., 2015). Pearce and Barley (1977)'s convolutional approach offers a data-driven procedure that has the ability to accurately capture the frequency content of noise however imposes that noise must be stationary. Birnie et al. (2016)'s covariance-based approach removes the stationarity requirement accurately capturing spatio-temporal characterisations of noise, however, like all other data-driven approaches it is constrained to the survey geometry in which the noise data has been collected.

In this work, we propose an extension of the covariance-based noise modelling workflow that aims to generate a noise model over a user-defined geometry. The extended workflow comprises of two steps: the first step is responsible for the characterisation of the recorded noise field and the generation of multiple realisations with the same statistical properties, constrained to the original acquisition geometry. Gaussian Process Regression (GPR) is subsequently applied over each time slice of the noise model transforming the model into the desired geometry.

The workflow is initially validated on synthetically generated noise with a user-defined input covariance matrix. This allows us to prove that the noise statistics (i.e., covariance and variogram) can be kept almost identical between the noise extracted from the synthetic dataset and the various steps of the noise model procedure. The workflow is further applied to the openly available ToC2ME passive dataset from Alberta, Canada consisting of 69 geophones arranged in a pseudo-random pattern. The noise is modelled and transformed into a 56-sensor, gridded array, which is shown to a very close resemblance to the recorded noise field.

Whilst the importance of using realistic noise in synthetic datasets for benchmarking algorithms or training ML solutions cannot be overstated, the ability to transform such noise models into arbitrary receiver geometries opens up a host of new opportunities in the area of survey design. We argue that by coupling the noise generation and monitoring algorithms, the placement of sensors can be optimized based on the expected microseismic signatures as well as the surrounding noise behaviour. This could be of particular interest for geothermal and CO_2 storage sites where processing plants are likely to be in close proximity to the permanent monitoring stations.