# Robust unsupervised 5D seismic data reconstruction on an irregular grid

*Ji Li[1*], Dawei Liu[2], Mauricio Sacchi[2], and Daniel Trad[1]*
*[1]Department of Earth, Energy and Environment, University of Calgary*
*[2]Department of Physics, University of Alberta*

## ABSTRACT

Seismic data reconstruction in five dimensions (5D) has become a central focus in seismic data processing, addressing challenges posed by irregular sampling due to physical and budgetary constraints. Most traditional high-dimensional reconstruction methods commonly utilize the fast Fourier transform (FFT), requiring regular grids and preliminary 4D binning before 5D interpolation. Notably, this binning process can compromise the continuity of the seismic wavefield, leading to a loss of fidelity in the reconstructed data. Discrete Fourier transform (DFT) (Duijndam et al., 1999; Xu et al., 2005) and non-equidistant FFT (Duijndam and Schonewille, 1999;Keiner et al., 2009) can honor original irregular coordinates. However, when using the exact locations of the original coordinates, these methods become computationally expensive.

We introduce an unsupervised deep-learning methodology to learn a continuous function across sampled points in seismic data, facilitating reconstruction on both regular and irregular grids. The network comprises a multilayer perceptron (MLP) with linear layers and element-wise periodic activation functions. It excels at mapping input coordinates to corresponding seismic data amplitudes without relying on external training sets. The network's intrinsic low-frequency bias is crucial in prioritizing acquiring self-similar features over high-frequency, incoherent ones during training. This implicit regularization mitigates incoherent noise in seismic data, including random and erratic components.

The proposed unsupervised reconstruction method is based on the implicit neural representation (INR), consisting of an MLP with an element-wise sinusoidal activation function. In the proposed method, the training input consists of each data point's 5D coordinates (one temporal coordinate and four spatial coordinates). In contrast, the training target is the amplitude at the corresponding coordinate. Subsequently, the trained model can predict the seismic data at a desired regular coordinate.

Figure 1 presents the reconstruction outcomes for comparing three different approaches. Subfigure (a) is the binned data on a regular grid. Subfigure (b) is the reconstruction result for the binned data using a frequently used traditional POCS method (Projection onto Convex Sets) (Abma and Kabir, 2006; Gao et al., 2013). Subfigure (c) contains the reconstruction results for the binned data using the proposed INR method. Subfigure (d) is the reconstruction result of the proposed INR method that applies directly to the original unbinned data. Comparing the results, the proposed robust INR method utilizing binned spatial coordinates yields results akin to POCS but with noticeably reduced noise levels. Additionally, when employing the original unbinned spatial coordinates in the robust INR method, some faint events (between 0 to 0.6s) are successfully reconstructed, particularly evident in the upper portion of this example. However, these events were either not captured by POCS and robust INR from the binned data or appeared less distinct in the reconstructed results. These results emphasize our approach's sophisticated capabilities and highlight the superiority of irregular reconstruction over the regular method.

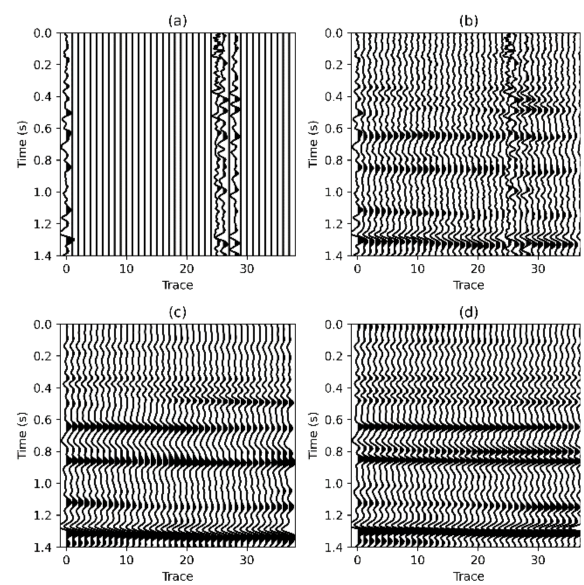


Figure 1: Reconstructed field seismic data. (a) Original data after binning, (b) POCS result based on binning data, (c) Robust INR with binned data, and (d) Robust INR with original irregular coordinates.

**Acknowledgements**

The first author expresses gratitude to the CREWES industrial sponsors, NSERC (Natural Science and Engineering Research Council of Canada), through the grant CRDPJ 543578-19. The second author thanks to the all the sponsors for the SAIG group.