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Time-lapse seismic inversion of two reservoir anomalies with deep learning using sparse OBN geometries

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Introduction.

Seismic time-lapse (4D) monitoring is a powerful technique for tracking subsurface changes related to fluid flow, pressure variation, and reservoir compaction over time. However, the high cost and logistical complexity of dense Ocean Bottom Node (OBN) acquisitions pose significant challenges, particularly in offshore environments. Motivated by recent advances, we explore the use of sparse acquisition geometries combined with Machine Learning (ML) techniques as a viable alternative for wavefield inversion. Specifically, we apply a convolutional neural network to perform seismic inversion using 2D synthetic data acquired through extremely sparse OBN configurations.

Our study focuses on more complex scenarios by introducing two reservoir anomalies within a well-defined target region. Each model contains two Gaussian-shaped anomalies, arranged either horizontally apart or vertically stacked. This setup is intended to evaluate the ML ability to identify and reconstruct spatially complex perturbations, better reflecting the variability found in realistic geological environments.

Method and/or Theory

This study was conducted using synthetic seismic data to test and validate a convolutional neural network for time-lapse inversion in a well-defined target region. The data were generated through a baseline acquisition and 1000 subsequent monitoring acquisitions per receiver, simulated in a realistic 2D P-wave velocity model—20 km wide and 7.5 km deep. Seismic sources were evenly distributed along a 20 km line at 8 meters depth, spaced every 50 meters to ensure repeatability. Thirteen Ocean Bottom Nodes (OBNs) were positioned 2 km below the water surface, uniformly spaced at 1.5 km intervals from 1 km to 19 km along the acquisition line. The source wavelet was a Ricker with peak energy at 5 Hz and a maximum bandwidth of 15 Hz.

The standard procedure involves generating seismic data for a baseline and several monitor acquisitions, simulating temporal reservoir evolution. The neural network receives as input the difference between monitor and baseline data, and outputs the corresponding velocity perturbation. Each scenario includes two simultaneous anomalies, modeled as Gaussian perturbations, located within the target region. Their spatial configurations were varied, either horizontally separated or vertically stacked, to better represent plausible subsurface reservoir conditions. The Mean Squared Error (MSE) metric is used to quantify how closely the predicted anomalies match the true ones.

Results and Conclusions

Overall, the method proved robust and reliable for time-lapse wavefield inversion under varying anomaly configurations. Despite higher errors in complex cases, the results are physically consistent and highlight the neural network’s capacity to generalize across diverse geophysical scenarios, offering a promising direction for ML-based seismic monitoring. The ultimate goal is to evaluate the generalization capability of ML-based inversion methods in challenging scenarios, laying the groundwork for future application to real geollogical data.