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4D seismic inversion in the Brazilian pre-salt: Deep Learning vs. FWI

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Introduction

The growing application of Machine Learning (ML) in geophysics has opened new perspectives for addressing complex challenges and, in some cases, replacing traditional techniques. In the context of seismic inversion, ML offers promising alternatives, especially in complex environments such as pre-salt reservoirs. This study compares the accuracy and the computational cost of applying Deep Learning (DL) methodologies for time-lapse seismic inversion using Ocean Bottom Node (OBN) data with a standard inversion methodology. A Convolutional Neural Network (CNN) was used to perform the DL inversion to predict subsurface velocity changes, while a Full Wave Inversion Double Difference (FWIDD) was used for the standard inversion. The dataset was designed to represent realistic geological features, with a focus on a specific target area where the neural network could effectively learn to estimate velocity anomalies. We assess the differences in terms of accuracy and computational efficiency. CNN predictions are evaluated using the Mean Squared Error (MSE) and the Index of Structural Similarity (SSIM).

Method

Based on a pre-salt velocity model, baseline and monitor synthetic datasets were generated using OBN acquisition with a single-shot configuration. The monitor seismograms were created by introducing a significant number of random Gaussian perturbations within a specific window, simulating realistic subsurface changes. The neural network was trained using input data constructed from the 4D difference between the monitor and baseline seismograms, with the target being the corresponding velocity model. Of the total dataset, 80% was used for training and 20% for testing. The final output of the network corresponds to a seismic inversion result for a single shot. Additionally, a conventional FWIDD was performed using the same acquisition geometry and the same velocity model for a direct comparison between the two approaches.

Results and Conclusions

The neural network achieved good inversion performance according to the MSE and SSIM metrics. It is noteworthy that this inversion was obtained by training the network with a single baseline shot and multiple monitor shots, which were generated with the same geometry as the baseline shot but propagated through different anomalies inserted in the baseline velocity model. Compared to the FWIDD method, executed with the same parameters, the DL inversion showed higher resolution, which is expected since standard FWI relies on the illumination provided by multiple shot positions and is thus directly dependent on the number of shots supplied to the FWI. A key advantage of the DL approach is its computational efficiency: FWI takes 50 minutes to complete 100 iterations, while the DL model, once trained in 5 minutes for 1000 epochs, can produce velocity model predictions in seconds. We conclude that the CNN is capable of inverting velocity anomalies within a known target area, which is a realistic scenario since the location of the reservoir is known from the baseline image. Specifically, the network learns the shape, location, and velocity anomalies in the ranges for which the different anomalies were designed. The next step will be to challenge the network with different types of anomalies that it has not seen during training, to evaluate whether it can generalize its predictions and accurately infer position and unknown velocity anomalies. As expected, when more shot locations are used FWI results improve significantly. In contrast, the improvement of the DL inversion with additional shot locations depends on how the network was trained: in this case it was trained shot by shot. As future work, the network could be trained using different shot positions as channels.