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Machine Learning Time-lapse velocity inversion: Super-Network versus Modular Networks strategies

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Introduction

Time-lapse velocity inversion using Machine Learning (ML) has been attracting a lot of attention in seismic exploration, both in academia and industry. The ML techniques provide a computationally efficient alternative to physical-based methods known for its high computational cost. An important issue of ML techniques is deciding how many models will be trained on which portions of the training dataset. In this work we compare two ML strategies: a single super-network versus many small modular networks. In our case, the super network employs the totality of the seismic data to perform the inversion. In opposition, the small network modular strategy consists in performing the seismic inversion using separately each shot and combine them by averaging the results.

Method

In the time lapse inversion, we modeled two synthetic acquisitions: baseline and monitor. The production-related velocity anomaly in the reservoir is modeled as a Gaussian-like function in space, centered at the middle of the reservoir zone. The baseline consists in a realistic velocity model typical of the Brazilian pre-salt. The seismic data set was obtained by propagating an acoustic wave. The acquisition geometry is the following: 200 sources at 8 m depth and 10 ocean bottom nodes sparsely distributed along the ocean floor. In our study we make use of the reciprocity principle by interchanging nodes with shots for computational efficiency. The supernetwork is fed with all shots to produce the inversion, whereas in the modular strategy one network is trained on each shot gather, and their predictions are then aggregated to produce the final estimate of velocity changes.

Results and Conclusions

The advantage of modular networks inversion consists in separately analyzing the contribution of each node and comparing the results with illumination data obtained from ray tracing. In addition, the neural network size is smaller and the computational time is shorter. On the other hand, the super network inversion produces a more accurate result since it can, in principle, deal with interference patterns among the nodes and deliver better results than average nodes. However, using large data sets in the input model impacts the computational cost and needs an enlarged data training. The accuracy of both strategies are compared computing the inversion error and also the computational time and memory.