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3D Circular geometry Time-lapse Velocity Inversion Using Supervised CNNs

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Introduction

Time-lapse seismic is a crucial technique for monitoring dynamic subsurface changes and optimizing hydrocarbon production by providing insights into fluid movements and reservoir performance over time. In this study, we focus on 3D time-lapse acquisition using sparse ocean bottom nodes arranged in a circular geometry of shot points. The reservoir region contains velocity changes characterized by both softening and hardening anomalies. The primary goal of this work is to invert these velocity changes from seismic data using Machine Learning (ML) techniques. Specifically, we seek to recover velocity anomalies in targeted areas by applying supervised learning with convolutional neural networks (CNNs) to the seismic data.

Method

We use a baseline velocity model based on a real Brazilian complex pre-salt reservoir environment. The monitor velocity models are obtained synthetically by introducing a couple of random Gaussian perturbations, simulating non-trivial realistic subsurface changes. Thereafter, the seismic acquisitions dataset is generated by propagating an acoustic wave. The CNN is trained using input data constructed from the 4D difference between the monitor and the baseline pre-stack seismograms, with the CNN target being the corresponding anomaly velocity model. From the total dataset, 80% is used for training the ML and 20% for testing the methodology. The ML predictions are evaluated using the Mean Squared Error (MSE), and the Index of Structural Similarity (SSIM). We also tested the methodology adding some noise in the seismic data.

Results and Conclusions

We achieved highly accurate and precise predictions of the disturbances inside the targeted region, with the benefit of using only a fraction of the computational resources needed by conventional techniques. This method also proved efficient at compiling and utilizing the information from multiple shots showing good MSE and SSIM statistics. The main conclusion of this study is that the ML is capable of inverting, in a low noise scenario, non-trivial velocity 3D anomalies within the target area. The next step in our research consists in adding non repeatability effects to test the methodology.