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Machine Learning 4D seismic inversion of realistic changes in pre-salt reservoirs

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Introduction

Time-lapse seismic monitoring is a well-established technique for tracking changes in oil and gas reservoirs during production. As hydrocarbons are extracted and replaced by water or gas, reservoir parameters shift, altering the rock's elastic properties—such as bulk modulus and density—and consequently affecting P-velocitiy. These modifications result in measurable differences between successive seismic surveys. Given the direct relationship between wave velocity and subsurface physical properties, estimating velocity changes through time-lapse seismic inversion is a critical area of research in both industrial and academic settings. Of particular interest is *target-oriented* time-lapse velocity inversion, which focuses specifically on velocity variations within the reservoir zone, or the reservoir anomaly. However, conventional physics-based approaches to this problem are often computationally intensive, in this study we bypass this problem by using Machine Learning ML technique. Moreover, we simulate complex reservoir anomalies using superposition Gaussian distributions with random parameters. These realistic anomalies are used to test ML inversion methodology.

Method and/or Theory

Two acquisitions are considered, baseline and monitor. The main schema of the method is the following: a difference between seismic data from monitor and baseline is used as input to the ML, while the output of the ML consists in the difference between the monitor minus baseline velocities, the reservoir anomaly. In our simulations, the baseline velocity model comes from a typical pre-salt Brazilian field. The schema to create reservoir anomalies consists in adding over the baseline model a couple of superposed Gaussian distributions with random vertical and horizontal standard deviations, positions and maximal velocities. The modeled anomalies are representative of water or gas injection, in one or more wells, into single or multi-layer reservoirs.

For each anomaly seismic data is generated with the following acquisition geometry: 400 shots and 13 sparse ocean bottom nodes spaced by 800 m. The vertical dimension of the anomalies are around 70 m and the horizontal dimension varies from 100 m to 1000 m being formed by several horizontal Gaussians randomly distributed but with the same depth. The maximal velocity anomaly consists of 4% of the baseline velocity. To generate the seismic data we employ an acoustic propagator.

Results and Conclusions

In order to test the methodology, five thousand heterogeneous reservoir are produced with the corresponding seismic data, 80% of them are used to train the neural network and the rest for testing. After performing the inversion three main conclusions unfolded from the study: (a) the ML inversion archived errors below 5% in a small noise scenario, (b) a slight amount of noise can benefit the performance of a neural network**,** (c) the quality of the inversion is related with the strength of the anomalies, weak velocity perturbations in the media are not well captured by the ML.