Predicting reservoir impedance changes in time-lapse ocean bottom node seismic with machine learning

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Abstract

Time-lapse seismic is an important tool to unveil reservoir property changes due to oil/gas production. Indeed, during the production life cycle of a reservoir, the displacement of water, oil and gas in the reservoir changes the impedance properties of the rocks, which can be captured in a seismic record. In this study, we propose using Machine Learning (ML) for the estimation of time-lapse impedance variation within the reservoir region from seismic data. To accomplish this task, we need an adequate training set that maps impedance in the reservoir region to the associated seismic data. In other words, we propose to invert the seismic data to obtain the acoustic impedance restricted to the reservoir region (target-oriented), using ML. We generated a synthetic seismic database by simulating reservoirs of varying impedances using a 2D velocity model, typical of the Brazilian pre-salt, located in Santos basin. To simulate the change in impedance caused by fluid substitution during production, we introduced an increase in impedance around the injector well. The impedance change around the well follows a 2D Laplacian probability density function (PDF), which has basically four parameters: maximum amplitude, decay rates in horizontal and vertical directions, and the inclination of the axis. To mimic a realistic scenario, the largest impedance change in the injector well is around 3% of the empirical velocity model and the horizontal and vertical parameters of the Laplacian PDF are compatible with reservoir dimensions. By properly sampling many combinations of the four parameters of the Laplacian PDF, we generate 1000 synthetic reservoirs. For each synthetic reservoir, the corresponding seismic data were obtained by numerically modeling the forward wave propagation with the 2D finite difference method, using the acoustic approximation. The main parameters of the numerical simulations are: time step of 2 ms, simulated time span of 10 s, grid cells size of 8 m. The acquisition geometry consists of 1 source and 49 receivers, the source is at 8-meter depth, and the receivers are spaced 400 meters apart from each other along the sea bottom, reproducing an OBN acquisition. The shot source employed was a Ricker wavelet with 8 Hz peak energy. The input of the ML is a subset of the seismogram (crop) corresponding to the reservoir region. The output of the ML is composed by variation in the impedance data on the region of the reservoir. We split the set of synthetic reservoirs into two subsets: training (70%) and testing (30%) sets. To test and quantify the accuracy of the ML inversion methodology, we compute the error between the predicted and the actual impedances. We point out that the ML inversion is restricted to the reservoir zone, i.e., a target-oriented inversion. Moreover, we intend to compare our results with FWI inversion. The preliminary results point to a satisfactory regression accuracy, but the results are strongly affected by the regression parameters employed in the ML method.