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Time-Lapse Machine Learning Seismic inversion with elastic seismic data

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Introduction

In this study, we conduct a Machine Learning (ML)-based inversion utilizing the elastic components of seismic acquisition. The objective of the inversion is to estimate time-lapse velocity variations within the reservoir region. In fact, the elastic components are usually available in ocean bottom node acquisition, but they are heavily time consuming in seismic inversion. In this way, a low cost ML inversion using elastic components holds considerable relevance for the petroleum industry. The problem we focus on in this work is the time-lapse inversion. The primary datasets employed consist of the elastic velocity components from baseline and monitor surveys, with their difference attributed to velocity anomalies induced by hydrocarbon displacement resulting from reservoir production.

Method

To perform the elastic inversion, a synthetically generated training dataset was developed. This seismic database was constructed by simulating reservoirs with varying velocity anomalies modeling with help of a Gaussian distribution. The baseline model consists of a 2D velocity profile representative of the Brazilian pre-salt geology, specifically within the Santos Basin, Brazil. The acquisition geometry comprises one hundred shots and a single ocean bottom node. For each synthetic reservoir, the corresponding seismic data was generated through forward modeling of elastic wave propagation. The synthetic reservoir models were randomly partitioned into two subsets: a training set (80%) and a testing set (20%). The ML architecture is designed to accept a seismic data input, while the output corresponds to the usual P-wave velocity anomaly. The ML technique consists of a convolutional Neural Network with four layers. We tested three input data: (a) the three-component elastic seismograms, (b) the P-wave seismogram and (c) a proxy of the Vp/Vs ratio produced from the elastic componentsWe notice that the higher volume of input data in the first case compared to items (b) and (c) is associated with larger computational cost (time and memory).

Results and Conclusions

Our simulations demonstrate strong agreement between the true reservoir anomalies and those inverted via the ML approach for the three cases. We tested the performance of the inversion with noise added to the seismic data with acceptable results. A comparison between the inversion with the three elastic data components (a) and the P-wave (b) shows the superiority of the elastic inversion. A second comparison between the elastic components (a) and the Vp/Vs ratio (c) reveals that the Vp/Vs ratio produces the best anomaly inversion. Moreover, the Vp/Vs ratio has low computational cost compared to the inversion with all elastic components. Finally, we emphasize that the elastic ML inversion implemented in this study is specifically focused on the reservoir zone, indicating that our methodology constitutes a target-oriented inversion.