Petro-elastic and lithology-fluid inversion from seismic data – state-of-the-art and new opportunities

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Summary

During the last couple of decades, there have been great advances in seismic inversion and lithology/fluid prediction. In the last few years, we have seen breakthroughs in integration of seismic methods, rock physics, spatial statistics and reservoir geology, allowing for more robust and realistic predictions of reservoir parameters from seismic data. The greatest advances have been made in academia and at research centers; now is the time to implement recent technologies into the workflows of the oil industry, in order to reduce exploration risk in frontier areas and boost oil recovery in existing fields. In this presentation, we give an overview of major breakthroughs in the last decade, and we suggest further extensions on how to integrate seismic inversion, rock physics, spatial statistics and geological knowledge during seismic reservoir prediction. In particular, we demonstrate that the uncertainties in lithology/fluids predictions can be reduced if geological trends are included as constraints in the inversion model. The lithology/fluid classification is constrained by depth trends and a Markov random field prior model for spatial coupling of the discrete lithology/fluids classes. A Bayesian method then combines seismic data, well observations, and prior information to predict lithology/fluid classes with associated uncertainties. The inversion approach is evaluated on a real case from the North Sea. The prior Markov random field makes it possible to identify complex structures in the lithology/fluid characteristics, by improving spatial continuity laterally. Furthermore, the posterior estimates of lithologies and fluids are used to constrain the estimation of continuous reservoir parameters like porosity. By honoring spatial continuity and vertical transitions in lithologies and fluids, we obtain sharper porosity sections and unravel details in the data not detectable from more conventional inversion algorithms. Our results also show better match with well log porosities than direct estimates of porosities from elastic parameters.
Introduction

Seismic inversion of elastic rock properties has during the last two decades become an integral part of the exploration workflow in the oil industry, as a complimentary technique to conventional seismic interpretation. The state of the art of seismic elastic inversion is to do simultaneous inversion of pre-stack data, using an optimization algorithm that minimize the error between a synthetic forward model and real data, by iteratively updating the elastic parameters of a stratigraphic earth model. Using rock physics models, the elastic parameters can be further translated into reservoir (lithology and fluid) parameters. The seismic inversion procedure poses many challenges and associated uncertainties, including non-uniqueness, noise in the data, resolution limitations, simplified modelling assumptions, etc. There are also uncertainties associated with the rock physics translation of elastic properties to reservoir parameters. Several authors have provided workflows that honor some of these uncertainties, for instance by doing Monte-Carlo simulations of rock physics input parameters (e.g., Mukerji et al., 2001), or by including spatial dependencies in the estimated reservoir parameters (e.g., Eidsvik et al., 2004; Gonzales et al., 2008). Nevertheless, there has been surprisingly little focus on implementing workflows that quantifies uncertainties during seismic inversion in the oil industry. In this study, we apply a Bayesian approach that integrates seismic data, well observations, and prior information to predict lithology/fluid classes with associated uncertainties. The classification of lithology and fluid parameters is constrained by rock physics depth trends and a Markov random field prior model. Finally, we predict porosities constrained by the posterior estimates of lithologies/Fluids. We demonstrate this approach on a North Sea turbidite oil and gas field of Paleocene age.

Model

The main objective of the current study is to classify lithology/fluids $\pi$ from seismic elastic inversion data taking into account rock physics relations and spatial dependencies in the reservoir parameters. The variables considered are both discrete (lithology and fluid) and continuous (porosity). The lithologies are classified as sand or shale, while the fluids are gas, oil, or brine. The classification of lithology and fluids is further used to constrain the porosity prediction. The observations are denoted $\mathbf{o} = [\mathbf{d}, \mathbf{o}_w]$, where the vectors $\mathbf{d}$ and $\mathbf{o}_w$ are seismic prestack data and well observations, respectively. The global forward model parameters, which are assumed not to vary spatially, are represented by $\mathbf{\theta} = [\lambda, \mathbf{s}, \mathbf{\Sigma}_m, \mathbf{\Sigma}_d]$, that includes parameters for porosity depth trend $\lambda$, convolution wavelets $\mathbf{s}$, rock physics model error covariance matrix $\mathbf{\Sigma}_m$, and seismic model and observation error covariance matrix $\mathbf{\Sigma}_d$. The inversion is solved in a Bayesian framework; hence assessment of the posterior model $p(\mathbf{\pi} | \mathbf{o})$ is the objective of this study

$$p(\mathbf{\pi}, \mathbf{\theta} | \mathbf{o}) = \text{const} \times p(\mathbf{o} | \mathbf{\pi}, \mathbf{\theta}) p(\mathbf{\pi}, \mathbf{\theta}),$$

where $p(\cdot)$ is the generic term for probability mass function or probability density function, $p(\mathbf{o} | \mathbf{\pi}, \mathbf{\theta})$ is the likelihood and $p(\mathbf{\pi}, \mathbf{\theta})$. The posterior model is estimated by a McMC algorithm.

The likelihood consists of a rock physics likelihood model that relates the lithology/fluid classes and the seismic elastic properties, and a seismic likelihood model that relates the seismic elastic parameters and the seismic observations. Dry rock properties are determined using heuristic rock physics models for unconsolidated sands, cemented sandstones (Avseth et al., 2005), and shales (Holt and Fjær, 2003), respectively. Fluid effects are calculated by Gassmann’s relations, see Mavko et al. (2009). The likelihood model is based on a convolutional model and a linearized weak contrast approximation of the Zoeppritz equation, see Buland and Omre (2003). The prior model for the lithology/fluids $\mathbf{\pi}$ is a Markov random field which provides spatial continuity and fluid sorting (Ulvmoen and Omre, 2010). The full model is presented in Rimstad and Omre (2010).
Field example

The studied field is in the North Sea and represents a Paleocene-age turbidite system. The burial depth is around 2 km corresponding to a temperature of circa 70°C. This is where we expect a transition from mechanical to chemical compaction, and quartz-rich sands become cemented with quartz cement. Chemical compaction results in significant stiffening of the rock frame, which again has a large effect on fluid sensitivity. It can be difficult to predict the correct pore fluid without taking into account these geological changes. Hence, a correct local rock physics depth trend is crucial for the seismic inversion results. Figure 1-4 displays the results from the inversion. We have used different models to illustrate the effects of spatially coupled lithology/fluid classes and rock physics depth trends. In Figure 1 and 2 we see that the Markov random field provides spatial continuity in the lithology/fluid predictions, and the rock physics depth trends give better predictions. In Figure 3 and 4 we see that the predictions with lithology/fluid classes give sharper contrasts. Performing porosity prediction constrained by lithology classes shows improved match with well log observations compared to direct porosity prediction from elastic parameters without spatial dependencies (Figure 4).

Conclusions

A Bayesian lithology/fluid inversion approach based on pre-stack seismic data and well observations is presented. The model includes rock physics depth trends and a spatially coupled prior model for the lithology/fluid characteristics. Moreover, uncertainties in global model parameters are included. The inversion approach is evaluated on a real case from the North Sea. The prior Markov random field makes it possible to identify complex structures in the lithology/fluid characteristics, by improving spatial continuity laterally. Furthermore, the posterior estimates of lithologies and fluids are used to constrain the estimation of continuous reservoir parameters like porosity. By honoring spatial continuity and vertical transitions in lithologies and fluids, we obtain sharper porosity sections and unravel details in the data not detected by more conventional inversion algorithms. Our results also show better match with well log porosities than direct estimates of porosities from elastic parameters.

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References


Figure 1: Posterior model. 50% iso-probability plots for sand with gas (red) and sand with oil (green): (a) with depth trends and spatial couplings, (b) without depth trends and with spatial couplings, and (c) with depth trends and without spatial couplings.

Figure 2: Well cross-validation: (a) with depth trends and spatial couplings, (b) without depth trends and with spatial couplings, and (c) with depth trends and without spatial couplings.
Figure 3: Posterior elastic properties and porosity. To the left: inversion with lithology/fluid classes, to the right without lithology/fluid classes.

Figure 4: Porosity prediction and well logs. Solid red is the posterior mean with red dashed 2 standard deviation prediction interval for posterior with lithology/fluid classes, cyan is posterior mean without lithology/fluid classes. Solid black is the well log and dashed black is the posterior mean depth trend for shale and sand.