Spatially coupled lithology/fluid inversion from real seismic data and well observations

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Abstract

Lithology/fluid inversion based on prestack seismic data and well observations from a gas reservoir offshore Norway is made in a Bayesian setting. The prior profile Markov random field model captures general reservoir characteristics. The likelihood model is inferred from basic seismic theory and observations in the well. An approximate posterior model is defined, and it is simulated from by the recursive upward-downward algorithm. Both lithology/fluid realization and prediction look trustworthy, and reflect general reservoir experience and information provided by the data. The lithology/fluid inversion is also evaluated by cross-validation in a well.

Introduction

The objective of the study is on inversion of lithology/fluid (LF) classes from prestack seismic data and well observations in a reservoir offshore Norway. The study is made in a 2D cross-section of the reservoir, but extensions into 3D are feasible in the current framework. The inversion is defined in a Bayesian setting, with a prior model containing information about the LF characteristics and a likelihood model linking the observed data to these characteristics. The complete solution is the posterior model from which realizations can be generated and the most probable configuration with associated uncertainty measures can be identified. The full study is presented in the paper Ulvmoen et al. (2009).

Model Inference

The target zone is a sandstone reservoir offshore Norway, where both seismic prestack data d^s for the incidence angles $\theta = (10^\circ, 21^\circ, 36^\circ)$, Figure 1, and well data d^w, Figure 2, are available. The inversion window is within the upper and lower solid lines which are parallel to BCU, see Figure 1, and the seismic data in the target zone are aligned to these lines such that a rectangular field is inverted. The target zone is divided into vertical profiles discretized downward in time t, and lateral horizons with discretization corresponding to the seismic survey positions in x.

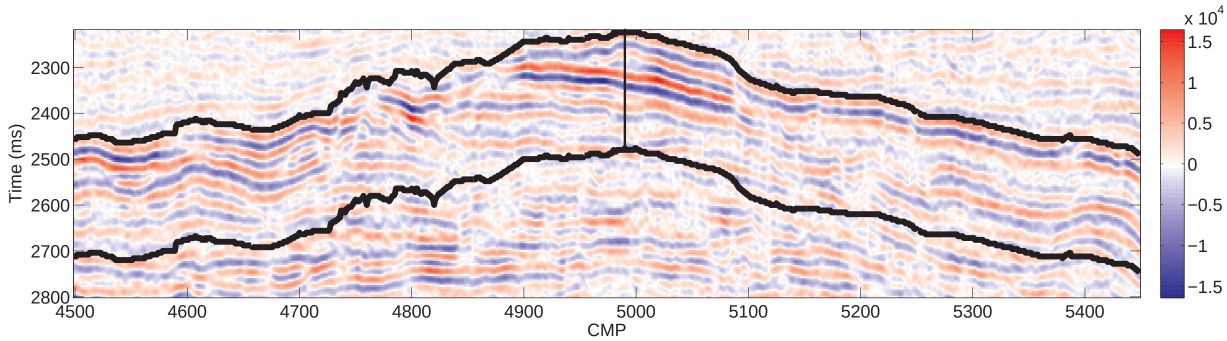

***Figure 1**: Stack of seismic data for angles $\theta = (10^\circ, 21^\circ, 36^\circ)$. Time window in inversion between black lines. Well location marked as vertical line.*

The complete set of LF classes is denoted by $\pi : \{\pi_{x,t};\ \text{all } (x,t)\}$ with $\pi_{x,t}$ being the LF class in lattice node (x,t). The well contains observations of gas-saturated sandstone, brine-saturated sandstone, shale, and source rock, such that $\pi_{x.t} \in \{$ SG, SB, SH, SR $\}$. The LF characteristics π are the focus of the study.

The inversion is defined in a Bayesian setting where the complete solution is the posterior model defined by

$$p\left(\pi \mid d^w, d^s\right) = const \times p\left(d^w \mid \pi\right) p\left(d^s \mid \pi\right) p\left(\pi\right) \tag{1.1}$$

where $p(d^w \mid \pi)$ is a likelihood for the well data, $p(d^s \mid \pi)$ is a likelihood for the seismic data and $p(\pi)$ is the prior model. Elastic material properties are included in the model by rewriting the likelihood for the seismic data as

$$p(d^s \mid \pi) = \int \dots \int p(d^s \mid m)\, p(m \mid \pi)\, p(\pi)\ dm \tag{1.2}$$

where $p(d^s \mid m)$ is a seismic likelihood model and $p(m \mid \pi)$ is a rock-physics likelihood model. We use the three elastic material properties P-wave velocity, S-wave velocity and density in the study, and denote the logarithm of these by $m : \{m_{x,t};\ \text{all } (x,t)\}$.

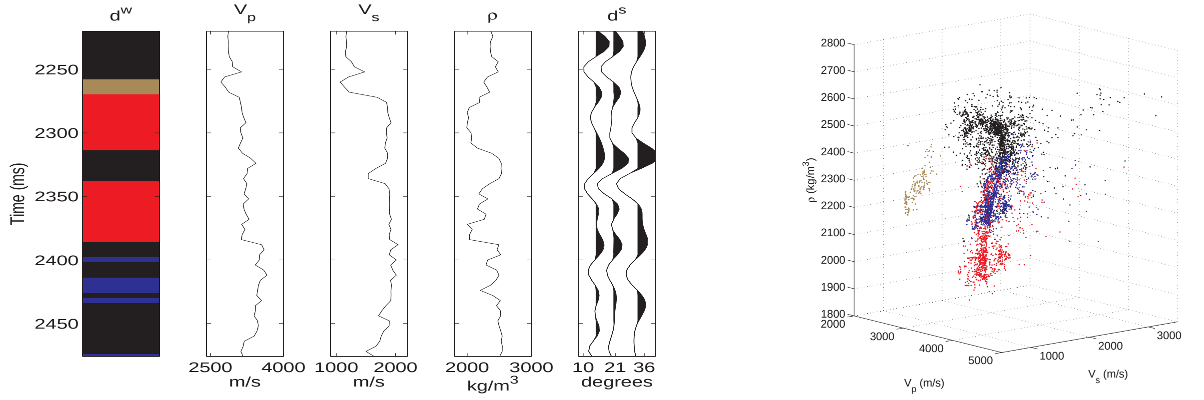

***Figure 2**: Well observations of LF classes, elastic material properties P-wave velocity (V_p), S-wave velocity (V_s), and density (ρ), and seismic data in well location; and elastic material properties given SG (red), SB (blue), SH (black) and SR (brown) from locationwise observations in well.*

Likelihood Model

The well likelihood model $p(d^w \mid \pi)$ contains locationwise observations of LF classes in the well profile, see Figure 2, and it is defined in the well location only.

The seismic likelihood model $p(d^s \mid m)$ is defined as the ratio of the Gaussian posterior $p_*(m \mid d^s)$ over the Gaussian prior $p_*(m)$ in linearized Zoeppritz inversion, see Buland and Omre (2003). It is then approximated like in Larsen et al. (2006) by only using the diagonal elements of the corresponding covariance matrices, such that the approximate seismic likelihood model is given as

$$\tilde{p}(d^s \mid m) = const \times \prod_{x,t} \frac{p_*(m_{x,t} \mid d^s)}{p_*(m_{x,t})}. \tag{1.3}$$

The rock-physics likelihood model $p(m \mid \pi)$ is defined by locationwise observations of $[m_{x,t} \mid \pi_{x,t}]$ in the well, see Figure 2.

By using the likelihood models defined above one observes that it factorizes, and the approximated likelihood model for the seismic data in Expression (1.2) is rephrased as

$$l(d^s \mid \pi) = \prod_{x,t} \iiint \frac{p_*(m_{x,t} \mid d^s)}{p_*(m_{x,t})} \, p(m_{x,t} \mid \pi_{x,t}) \, dm_{x,t} \tag{1.4}$$

where the integral is of dimension three and numerically tractable.

Prior Model

The prior model for the LF variables should capture their general characteristics, and must be based on general reservoir experience. The lithologies are created by sedimentary processes; hence they are expected to appear as thin, elongated units. The fluids will at an initial state be horizontally continuous and gravitationally segregated, which entails that brine cannot be immediately above gas. These characteristics should be captured by the prior model. We let the prior be defined as a profile Markov random field model, where each vertical LF profile π_x only is dependent on the neighbouring profiles given all the LF classes in the target zone. Further, we let the vertical profiles follow Markov chain models upward through the target zone, where the upward transition probabilities are dependent on the node immediately below in addition to the nodes in the lateral neighbourhood $\partial(x)$ around x. This Markov chain model is given by

$$p(\pi_x \mid \pi_{-x}) = \prod_t p(\pi_{x,t} \mid \pi_{x,t+1}, \pi_{y,t}; y \in \partial(x)); \text{ all } x, \tag{1.5}$$

defined by a set of transition matrices. The profile Markov random field definition captures the general characteristics described above. Experience from similar reservoir environments tells that the lithologies and fluids occur in different proportions in various layers of the reservoir. We let the expected proportions of the LF classes vary in the target zone by defining a gas/brine contact between 2380 ms and 2460 ms such that the probability of gas is higher above and the probability of brine higher below the contact. This is done by shifting probabilities in the transition matrices. Similarly, probabilities are shifted between shale and source rock at different reservoir zones below BCU.

Posterior Model

The approximate posterior model $\tilde{p}(\pi \mid d^w, d^s)$ is fully defined by the prior and likelihood models above. It is written in full conditional form

$$\tilde{p}(\pi_x \mid \pi_{-x}, d^w, d^s) = const \times \prod_t p(d^w_{x,t} \mid \pi_{x,t}) l(d^s \mid \pi_{x,t}) p(\pi_{x,t} \mid \pi_{x,t+1}, \pi_{y,t}; y \in \partial(x)); \text{ all } x. \qquad (1.6)$$

The recursive upward-downward algorithm defined in Larsen et al. (2006) is used to simulate exactly from this conditional posterior model vertically in each profile. Laterally, a block Gibbs simulation algorithm is used as the profile Markov random field is defined by the complete set of conditional posteriors. The simulation algorithm converges within 500 updates of each profile in the target zone.

Results

Figure 3 contains a realization from the approximate posterior $\tilde{p}(\pi \mid d^w, d^s)$. The layers of lithology are elongated and thin, and the fluid gravity segregation is reproduced. The well observations are reproduced exactly, and they have lateral influence due to horizontal dependence in the prior model.

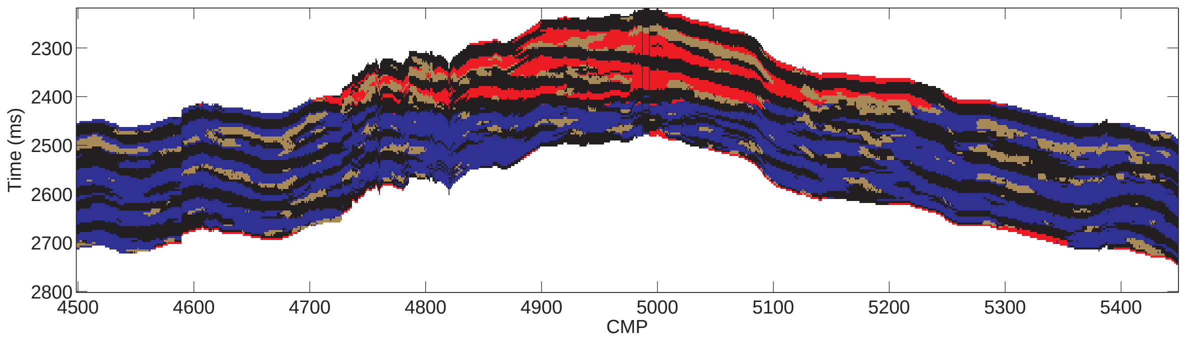

***Figure 3**: Realization of LF characteristics from approximate posterior $\tilde{p}(\pi \mid d^w, d^s)$ with SG (red), SB (blue), SH (black) and SR (brown).*

Figure 4 contains the locationwise most probable LF prediction. The prediction appears realistic as the fluid gravity segregation is reproduced, the layers of shale are thin with long lateral extensions, and the well information is an integral part of the solution. Due to exact observations in the well the prediction is more reliable in the near-well area than elsewhere. The prediction and simulation are very similar, indicating little uncertainty in the model.

Figure 5 contains cross-validation results for the LF prediction in the well profile. The LF classes observed in the well are displayed along the left axis, while the curves correspond to the marginal posterior probabilities based on seismic data only. The cross-validation results look very encouraging and provide credibility to the LF prediction in Figure 4.

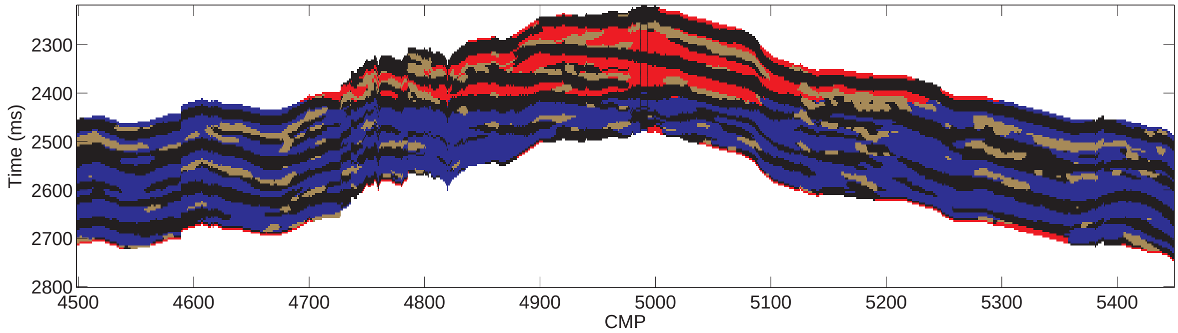

Figure 4: *Locationwise most probable LF characteristics prediction with SG (red), SB (blue), SH (black) and SR (brown).*

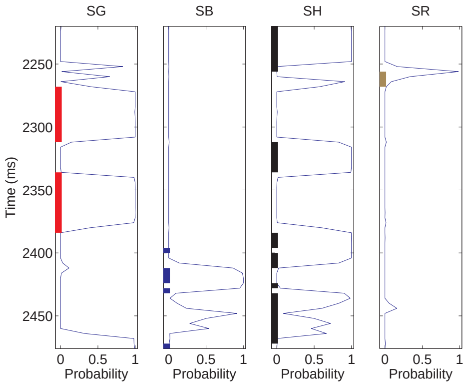

Figure 5: *Marginal approximate posterior in well profile based on seismic data only, with well observations* d^w *marked on respective axis.*

Conclusions

Lithology/fluid inversion is demonstrated by using real seismic data and well observations from a sandstone reservoir offshore Norway, and the results appear as reliable. Spatial coupling makes the well an integral part of the model, and it improves the resolution and realism in the solution. Extensions of the methodology to 3D are feasible as the simulation algorithm is recursive in 1D, and iterative only in 2D.

Acknowledgments

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