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Bayesian approach for seismic inversion and facies classification using IP and VP/VS parametrization

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Abstract Summary

We present a Bayesian framework for seismic inversion and facies classification using a novel AVO formulation based on P-impedance and P-to-S-wave velocity ratio, which are the key properties commonly used for facies classification. Assuming a Gaussian prior distribution and a linearized convolutional model, the method derives elastic properties via Bayesian linearized AVO inversion and estimates facies through Bayesian classification with Gaussian likelihoods. The methodology is validated on a synthetic case based on the F3 block from the North Sea.

Introduction

Seismic inversion plays a crucial role in the oil and gas industry by transforming seismic amplitudes into quantitative subsurface properties. Among its applications, facies characterization stands out as a critical process for identifying and mapping lithological and petrophysical variations within reservoirs. Incorporating seismic data into facies classification significantly improves the precision of reservoir characterization, enabling more effective exploration and production strategies. In this work, we discuss a Bayesian framework for seismic inversion and facies classification. The method uses a new AVO formulation in terms of P-impedance and P to S-wave velocity ratio, a domain space commonly used for facies classification

Method

Recently, a new AVO formulation was proposed by Figueiredo and Grana (2025). The equation defines the reflection coefficients of P-waves in terms of an average value of ${V_S^2}/{V_P^2}$, and the differences of P-impedance and velocity ratio between two adjacent layers of a geological sequence:

$$R(\theta) \approx \left[\frac{1}{2} - \frac{18}{5}\frac{V_S^2}{V_P^2}\sin^2\theta + \frac{2}{5}\tan^2\theta\right]\frac{\Delta I_P}{I_P} + \left[4\frac{V_S^2}{V_P^2}\sin^2\theta\right]\frac{\Delta {V_P}/{V_S}}{{V_P}/{V_S}}. \tag{1}$$

This equation was successfully integrated to the Bayesian Linearized AVO inversion framework for facies classification (Grana et al., 2025). Defining the unknown elastics attributes along a seismic trace as the model vector $\boldsymbol{m} = [\ln(\boldsymbol{I}_P)\ln({\boldsymbol{V}_P}/{\boldsymbol{V}_S})]^T$. The prior model of $\boldsymbol{m}$ is assumed to be a multivariate Gaussian distribution with prior mean $\boldsymbol{\mu}_m$ and covariance matrix $\boldsymbol{\Sigma_m}$. The prior mean is assumed to include the low frequency models of the elastic attributes. and the prior covariance matrix accounts for spatial correlation Buland and Omre (2003).

As show by Grana et al. (2025), the convolutional seismic model based on Equation 1 can be represented by the linear operation $\boldsymbol{d} = \boldsymbol{G}\boldsymbol{m} + \boldsymbol{e}_d$, where $\boldsymbol{d}$ is the observed data defined by a number of angle-stacked seismic data stacked in a single vector, and $\boldsymbol{e}_d$ is the error term. Since the forward model is linear and the prior is Gaussian, the posterior distribution of the logarithm of the elastic properties $\boldsymbol{m}$ conditioned to the seismic data $\boldsymbol{d}$ can be analytically obtained. The posterior is a Gaussian distribution with mean and covariance matrix given by

$$\boldsymbol{\mu}_{m|d} = \boldsymbol{\mu}_m + \boldsymbol{\Sigma}_m \boldsymbol{G}^T \left(\boldsymbol{G}\boldsymbol{\Sigma}_m \boldsymbol{G}^T + \boldsymbol{\Sigma}_d \right)^{-1} (\boldsymbol{d} - \boldsymbol{G}\boldsymbol{\mu}_m) \tag{2}$$

and

$$\boldsymbol{\Sigma}_{m|d} = \boldsymbol{\Sigma}_m - \boldsymbol{\Sigma}_m \boldsymbol{G}^T \left(\boldsymbol{G}\boldsymbol{\Sigma}_m \boldsymbol{G}^T + \boldsymbol{\Sigma}_d \right)^{-1} \boldsymbol{G}\boldsymbol{\Sigma}_m. \tag{3}$$

Equation 2 provides the maximum a posteriori (MAP) solution of the logarithm of the elastic properties. To obtain the MAP solution of the properties P-impedance $\boldsymbol{I}_p$ and velocity ratio $\boldsymbol{V}_P/\boldsymbol{V}_S$, we compute the transformation $\exp(\boldsymbol{\mu}_{m|d} + \frac{1}{2} diag(\boldsymbol{\Sigma}_{m|d}))$.

Based on the inverted results of P-impedance and velocity ratio, the facies can be estimated using the Bayesian facies classification. We define the vector of elastic properties at a given position of the cube as $(I_P, V_P/V_S)$, and we aim to estimate the conditional probability of the facies f, defined as $p(f \mid I_P, V_P/V_S)$, and the corresponding most likely facies model $\hat{f}$.

The assessment of $p(f \mid I_P, \frac{V_P}{V_S})$ can be done using Bayes' theorem by:

$$p(f = k \mid I_P, V_P/V_S) \propto p\,(I_P, V_P/V_S \mid f = k)\, p(f = k) \tag{4}$$

for $k = 1, \ldots, F$, where F is the number of facies (Grana et al., 2021).

The term $p(f = k)$ is the prior model representing the prior knowledge about the facies distribution (i.e., the facies proportions or probability trends). The term $p\,(I_P, V_P/V_S \mid f = k)$ is the likelihood function that links the elastic properties to the facies. In this work, we considered the likelihood function as Gaussian distributions. Therefore, in practice, the likelihood represents a bivariate Gaussian distribution of I_P and V_P/V_S for each facies k, which can be computed based on the well logs. After computing the posterior probabilities $p(f \mid I_P, V_P/V_S)$ for all facies and each point of the cube, the most likely facies model is obtained by identifying the facies with the maximum probability.

Results

We validate the methodology to a synthetic case constructed based on the real dataset of the F3 block, which is located in the Dutch sector of the North Sea. We focus on the time interval that consists of deposits of a large fluviodeltaic system belonging to the Miocene, Pliocene, and Pleistocene. The test dataset consist of four wells and three angle-stacked seismic data with incident angles of 8^o, 18^o and 28^o. The well logs includes a facies description where five facies are identified: coarse sand, medium sand, fine sand, shaly sand and shale. In this section, all the results are shown in an arbitrary line passing through the four wells for visual quality evaluation.

For each angle-stack, a zero-phase wavelet was estimated based on the seismic vertical autocorrelation. The low frequency models were computed by applying a high-pass filtering of $10Hz$ to the interpolated models, which were obtained by interpolating the well logs in a stratigraphic grid defined based on 5 horizons . Applying Equation 2 we obtain the inverted MAP solutions for P-impedance and velocity ratio. The inverted properties are shown in Figure 1. Then, based on the well logs of the two elastic properties and lithology, the conditional distribution of the properties for each facies in computed. Figure 2 shows the cross plot of P-impedance I_P versus velocity ratio V_P/V_S with the well logs and each bi-variate Gaussian distribution $p\,(I_P, V_P/V_S \mid f)$, color coded by facies. In our application we consider all the facies equiprobable, that is $p(f) = 0.2$ for all the five facies. With these distributions defined, we apply the facies classification for the entire cube of P-impedance and velocity ratio. The most likely facies model is shown in Figure 3.

In both Figures 1 and 3 the corresponding well logs are shown in the same color scale for visual quality evaluation of the results. By comparing the inverted properties and the estimated most likely facies to the well logs, we can see that the methodology is able to retrieve the reference properties with good accuracy.

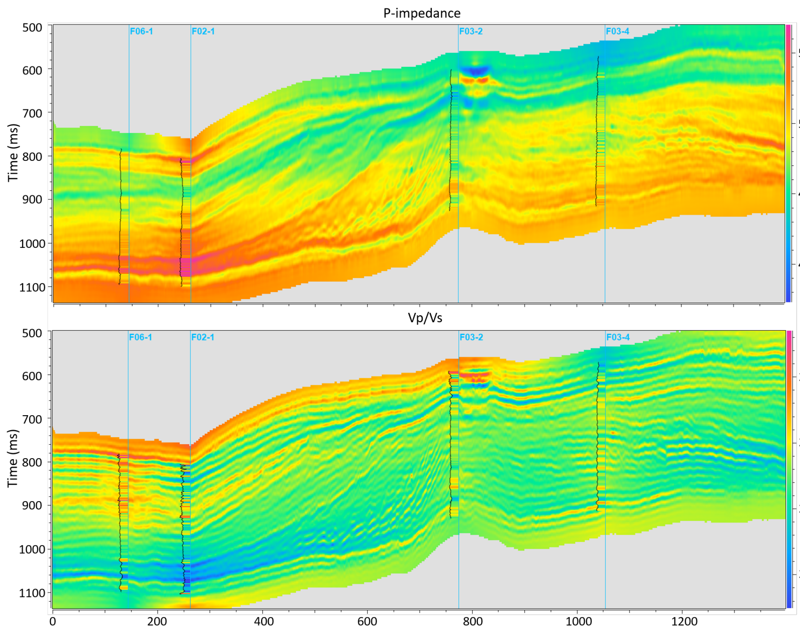

Figure 1: Inverted elastic properties: P-impedance on the top and P to S-wave velocity ratio on the bottom. In both images the corresponding well logs are shown in the same color scale.

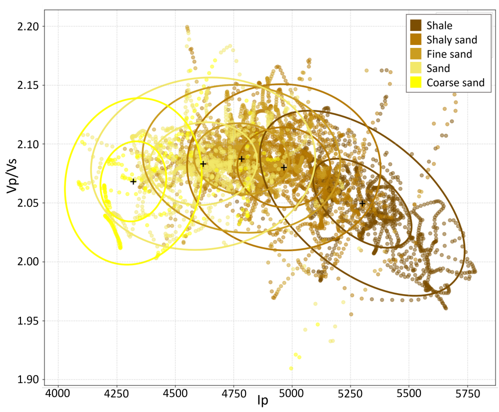

Figure 2: Cross-plot of P-impedance versus P to S-wavelet velocity ratio: the points are the well logs and the level curves represents the distribution of the properties conditioned on each facies.

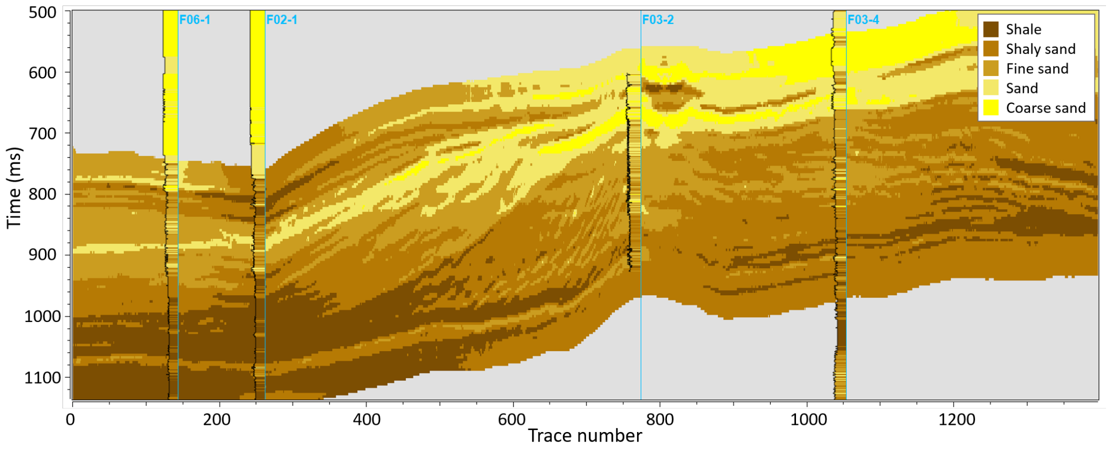

Figure 3: Estimated most likely facies model in comparison to the facies well logs as reference.

Conclusions

We discuss a Bayesian framework for seismic inversion and facies classification, utilizing a novel AVO formulation based on P-impedance and P-to-S-wave velocity ratio, a domain space widely utilized for facies classification. We validate the method in a realistic synthetic case based on the F3 block dataset from the North Sea. Results demonstrate that the approach accurately retrieves elastic properties and facies distributions, providing a robust tool for enhanced reservoir characterization.

Acknowledgments

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