

Local Probabilistic Inversion of seismic AVO data

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Introduction

Within the discipline of seismic reservoir characterisation, there is an ever-present ambition to improve the accuracy and detail in the analysis of the seismic data. At the same time, reservoir related decision-making and risk analysis also requires an increasingly degree of assessment of the uncertainties associated with any interpretations and statements based on the seismic data.

This process is constantly evolving and is quite often an integration process, where data and information at different scales from different domains are integrated to deliver an improved level of information of the reservoir and the subsurface. As the data comes with different levels of certainty, and as the models of the governing physics between the domains are only approximate, this integration process becomes relatively complex. The integration may be performed by a team of experts using qualitative criteria, yet it, or at least a part of it, may also be formulated as an inverse problem, see for instance [Bosch et al. 2010] for an overview.

The following will present an integration example, where information from standard processed seismic amplitude versus offset (AVO) data are integrated with information from a range of other domains. The approach will here be applied to the well-known exercise of interpreting surfaces from seismic data of key geologic and reservoir interfaces, which can be challenging at and below seismic resolution limits. So rather than interpreting surfaces of key reservoir interfaces, they will be estimated as a result of integration of data and information from different domains such as well logs, seismic data and geology.

Method

Motivated by the above observations, the problem can be formulated as a Bayesian inference problem, see for instance [Tarantola 2005].

$$\sigma(\boldsymbol{m}) = c \,\rho(\boldsymbol{m}) L(\boldsymbol{d}_{\boldsymbol{obs}} - \boldsymbol{g}(\boldsymbol{m})) \qquad \text{Eq 1}$$

Where *m* represents the subsurface model parameter configuration. In this context, information about *m* is described by a probability density function (pdf). In the initial state of the inference, that is prior to the seismic data experiment the information is described by the prior pdf, ρ . This is updated with the information from the seismic AVO data via the likelihood function L, which measures, in terms of probability, the misfit between forward modelled g(m) and measured seismic AVO data, d_{obs} . c is a normalising constant, and the posterior pdf, σ , constitutes the updated state of inference of our subsurface model parameters. Generally, the posterior pdf cannot be evaluated analytically, and hence one must resort to a sampling based approximation.

For the current problem, surfaces are defined as transitions from subsets of facies, and hence the model parameters, **m**, constitute a seismic grid of categorical variables. The prior pdf will be defined by a set of rules for sampling from it, as this is much more general and flexible compared to specifying a closed form of it. The likelihood, L, contains, in addition to a seismic noise model, the combination of a statistical rock physics model from facies to elastic property domain, and a seismic convolutional AVO forward model from elastic properties to the seismic angle-stack domain. As such, the solution to this problem can be considered a direct or one-step inversion for facies using seismic AVO data.

Markov chain Monte Carlo sampling methods [Tarantola 2005] can be demonstrated to provide an ensemble of samples, which will converge on the posterior pdf no matter how complex the prior pdf and likelihood function are. However, efficiency is very problem dependent and may be difficult to



achieve. In addition, required sampling density in a high dimensional model space (such as a standard sized seismic volume) means that these methods in general are computationally demanding and time consuming.

Short of compute power and time, a number of approximations can be made in the context of seismic AVO data and rock physics in order to make the inference problem computationally feasible. Surfaces of interfaces, defined as facies transitions, are (vertically) of short range or local by nature, and hence the point-wise marginal posterior or the joint posterior in a small volume are much more relevant compared to the long range correlations of the joint posterior distribution. Additionally, at a given point in the seismic grid, the rock physics model response of a facies can be assumed localised to a small region at and around the point, and the associated seismic convolutional response is limited to a wavelet length above and below the point thus ignoring wave propagation effects outside convolutional modelling of primary reflections. If the prior information is also limited to short range correlations only, the high dimensional inference problem can be split into a number of low dimensional problems, which can be approximately resolved by a weighted Monte Carlo method, see [Jullum et al. 2016] for details. Here is a conceptual outline:

- 1. Sample a large number N of local region sized facies realisations from the prior pdf.
- 2. Set up the local likelihood approximate function for each facies sample.
- 3. At a given point, **p**, in the seismic grid, extract the observed seismic AVO data, $d_{obs,p}$ in a local region with **p** as center.
- 4. For each facies sample, the local likelihood function with $d_{obs,p}$ as input is evaluated and provides a weight, v_p .
- 5. Normalise the weights, v_p, yielding normalised weights, w_p.
- 6. For each facies sample, identify the center value, f_p and pair it with w_p .

Steps 3 to 6 are iterated through all the observed seismic data. At a given point in the seismic grid, the sum of the normalised weights for a given facies value is an approximation to the marginal posterior distribution. The accuracy and the computational cost of the method depend on N and the size of the local region around the point, \mathbf{p} . Using the estimated posterior marginal pdf and prior spatial information, if available, marginal posterior surface probabilities can readily be obtained.

Example

The following real data example illustrates the applicability of the outlined method and demonstrates the power of a probabilistic integration of information from different domains.

The seismic AVO data originates from a 3D land seismic survey data covering a producing oil field in Australia's Eromanga Basin. The field has produced more than 1 MMbbl from stacked Jurassic age reservoirs. The Birkhead Formation reservoir depositional model is described as a lacustrine and low energy fluvial environment, which manifests itself in sinuous stratigraphic traps. In most cases reservoir thickness is below seismic tuning and not easily mapped on NMO/stacked reflection seismic data. A complicating factor is the presence of overlying, laterally varying amounts of calcite, which can distort the seismic response. Industry standard optimisation based seismic AVO inversion has been used as a tool to reduce the uncertainty with varying amounts of success. The outlined direct estimation of surface probabilities was applied to assess whether it could improve mapping of the complex reservoir model across the area.

From regional wells, shale, brine sand, oil sand and calcite were identified as the primary facies belonging to a number of formations (Figure 1 left) resulting in 33 different facies defined in a 3D seismic volume. A priori probabilities for the surfaces of interest were defined from regional major interpreted surfaces and converted into prior facies probabilities assuming equal proportions of facies inside each formation. The a priori local spatial structure of the facies is assumed to be 1D and can be approximated by a vertical Markov process [Larsen et al. 2006] (Figure 1 top right). The estimated



transition probability matrix and the point-wise facies probabilities are the rules from which samples of the prior distribution are generated.

Well log elastic data are used as input to a statistical rock physics model (Figure 1 bottom right). Wavelets specific for each of 9 partial stacks are estimated, and together with an Aki & Richards AVO model and an uncorrelated noise model, they define a Gaussian seismic likelihood.



Figure 1 Left: Stratigraphic column for the study area. The interval of interest is Early Cretaceous to Middle Jurassic. Top right: Logarithm to the probability of thicknesses larger than a given thickness. The linear trend indicates that thicknesses are exponentially distributed in line with a vertical Markov spatial model. Bottom right: Cross-plot of seismic scale acoustic impedance versus vp/vs ratio well log data color-coded with defined facies, shale (green), brine sand (yellow), oil sand (red), calcite cemented sand (blue). Brightness in colour increases with depth of formation. Separation of the different facies indicates that the facies may be resolved by seismic AVO data.

Following the application of the method to the 9 partial stacks, the prior and posterior marginal facies probabilities are shown for a bin location near a well (Figure 2). The added information from the seismic AVO data is clear. A similar comparison for the defined surfaces interfaces is also shown. Note the consistency with the well formation tops.

Conclusions

Under reasonable assumptions, a high dimensional Bayesian inference problem involving seismic AVO data can be reduced to a number of local low dimensional inference problems. This enables an application of a general and flexible probabilistic framework for rigorous propagation of uncertainties as well as infusing prior knowledge from multiple domains for industry standard sized volumes. The applicability is tested on the local scale inference problem of estimating surfaces with uncertainties, here defined as transitions between subsets of facies. The example illustrates the methods ability to



provide robust surface estimates at and below seismic tuning due to the utilisation of statistical prior information.

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Figure 2 Evaluation at a well location. From left to right: Petro-physical logs, facies log, prior and posterior marginal facies proportions at the well location, mini-sections of prior and posterior surface marginal probabilities along a mini section around a well location and compared with well petro-physical data. The probabilities are summed for 4 selected surfaces for display. Facies colour-code is the same as in Figure 1 lower right. Note the resolution of the Top Namur, Top intra Namur shale and the Top Westbourne. Top Birkhead is only resolved to a limited degree.