Porosity and fluid discrimination from prestack seismic data using multiple vintage volumes

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Abstract

We develop and apply a reservoir characterization workflow for porosity, lithology and saturation estimation from the integration of prestack seismic data, well logs and core data. An important step of workflow is seismic data preconditioning to increase signal-to-noise ratio and vertical resolution of input data. Our results show that the uncertainty associated with saturation estimates is very large, making it only adequate as a semi-quantitative fluid indicator. When applied to different vintage data volumes, the workflow serves as a reservoir monitoring tool. We find time-lapse production effects which are consistent with production and conventional 4D data interpretation.

Introduction

The main goal in reservoir characterization is to define heterogeneities in terms of the important reservoir properties, such as porosity, lithology, fluid content, as well as reservoir compartmentalization. Few approaches have been proposed for jointly estimating reservoir properties, including Mukerji et al. (2001) and Eidsvik et al. (2004). These authors employ different statistical approaches for lithology and fluid discrimination, using indicator variables to represent lithological types and saturation states (water/oil). The spatial variability is either incorporated using geostatistics (Mukerji et al., 2001) or Markovian models (Eidsvik et al., 2004). Eidsvik et al. (2004) work with prestack data in their formulation. The high computational cost involved in a Markov Chain Monte Carlo (MCMC) simulation may represent a limitation.

Despite of the qualitative nature of the resulting fluid content predictions, these represent a remarkable improvement in the quality of hydrocarbon detection. This is verified as the new methodologies are able to incorporate larger amounts of information from well data, rock physics and seismics.

The main difficulty involved in fluid discrimination from seismic data is due to usually low sensibility of the seismic response to fluid saturation contrasts, which usually is further complicated by the ambiguity associated with clay volume and porosity. This partly explains an apparently higher degree of success in monitoring saturation effects using time lapse data (see e.g., Brevik, 1999; Tura & Lumley, 1999). In 4 D seismic analysis, anomalies are directly interpreted as reflecting changes in the dynamic properties of fluid saturations and pressure due to production. Of course, more complex cases need to account for other effects such as changes in porosity (compaction), stress (fracturing), temperature (steam injection) and composition (chemical/biological stimulation).

Bachrach (2006) present a stochastic formulation for porosity and saturation estimation from elastic seismic attributes, using empirical prior distribution and likelihood function, and MCMC sampling. The author shows that uncertainty associated with inferences about saturation is much larger than that associated with porosity. Considering current technology, an attempt to further improve fluid saturation predictions from conventional 3 D seismic data must rely on the quality of the lithology and calibrated rock-physics models. Here we develop a comprehensive workflow following a model-based data inversion perspective, given by the Bayesian method of inference. The workflow includes key steps which are the seismic data preconditioning and inferences at well-log and core data scales.

Our approach is based on the fact that elastic attributes have different sensitivity levels with regard to changes in porosity, lithology and fluid saturation. We first make inferences about lithofacies, followed by joint porosity and saturation inference, using rock-physics models which are best appropriate for each facies. The Bayesian formulation closely follows Loures and Moraes (2006) and da Costa et al. (2008), who use simplifying assumptions leading to posterior distributions available in closed form.

Method

Consider the usual representation of the subsurface discretized in a number of cubic cells, having uniform values for its properties, such as porosity (ϕ), lithology and water saturation (S_w). The goal is to obtain a detailed description the reservoir by making inferences about these properties from prestack seismic and well data. We also rely on additional information, given by interpreted seismic horizon, lithology and saturation at well locations.

The input data consist of prestack seismic data that has been processed with relative amplitude preservation to yield a set of common reflection or image gathers (CRPs), and well-log and core data. Prior to inversion the input data go through a series of data analysis steps, which are aimed on: i) quantifying and improve the seismic quality and sensitivity with respect to changes in effective

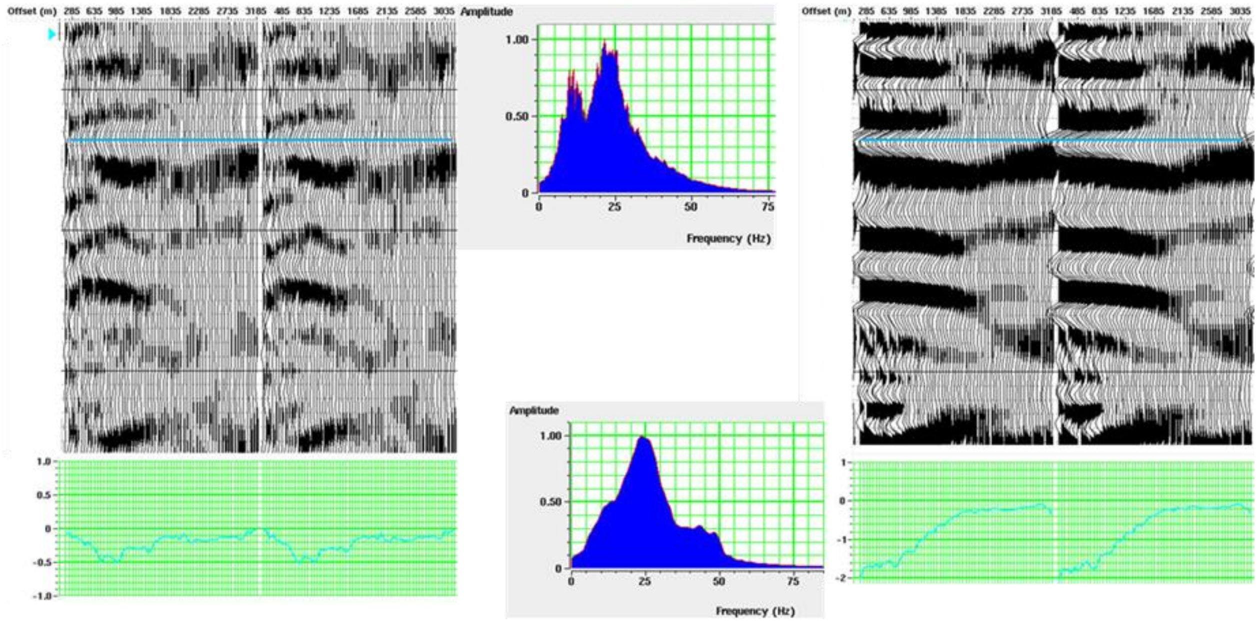

Figure 1: prestack data panels before (left) and after (right) seismic data preconditioning, displaying two adjacents CRP gathers (top), AVO picks (bottom) relative to top reservoir (blue line) and corresponding amplitude spectra (center).

porosity and saturation, and ii) calibrating the rock-physics and probabilistic models relating reservoir properties and elastic attributes. After that, the main part of the workflow consists of an AVO inversion followed by a petrophysical inference which yields a collection of marginal posterior distributions for facies, porosity and saturation, in each cell of the reservoir. The complete workflow sequence is summarized below.

Well-log and core data analysis

The well data provide invaluable information for more accurate definition of reservoir properties and production effects. In this part of the workflow, a variety of well information is brought together for model calibration and the computation of the seismic attribute response to fluid and pressure substitution through the following set of steps:

• well-log data correction, regularization and crossplotting, followed by Bayesian network (BN) modeling using well-log data derived eletrofacies and P-impedance (IP) and S-impedance (IS);

• joint effective porosity and saturation inference using gamma ray, neutron porosity, density and resistivity logs, following the work by da Costa et al. (2008);

• facies dependent calibration of velocity models with respect to changes in effective porosity and saturation.

During the first step of the analysis, BN modeling follows the work of Braga and Loures (2005). The intermediate step, consisting of a joint porosity and saturation inference, is aimed on the conciliation of porosity and saturation logs to be used in the following step of calibration of the velocity models. This final step consists of estimating fluid, matrix and frame elastic properties required by rock-physics model such as Gassmann´s equations, which are used for the inference of reservoir properties.

Seismic data analysis

This part of the workflow is designed to access the quality of the seismic data, especially with respect to the amplitude preservation aspect of the data processing workflow, and to establish the seismic sensitivity for the changes in saturation and pressure due to reservoir production by performing

• a conventional amplitude interpretation of seismic horizons and well-to-seismic tie;

• synthetic data modeling using well-log derived attributes (VP, VS and density), before and after fluid and pressure substitutions;

• AVO analysis to check for the consistency of seismic amplitudes and characterize observed AVO signatures.

Seismic data preconditioning

Prior to inversion seismic data is submitted though a series of process to increase S/N ratio and vertical resolution. Figure 1 shows the result of data preconditioning on CRP gathers, AVO signature corresponding to top reservoir and amplitude spectrum. Note how the AVO anomaly after preconditioning (right) recovered its characteristic class III shape, which could not be observed on the original data (left) due to noise contamination of the near offset traces. The main preconditioning workflow steps are: radon multiple suppression, noise filtering by curvelet transform, inverse Q filtering, followed by a final pass of a noise filter (either cuvelet or radon filtering). Figure 2 shows the result of data preconditioning on stacked data.

Reservoir property inference

This is the core of the workflow, where the seismic data is used to make inferences about porosity, lithology and saturation, in three steps:

• AVO inversion to generate elastic attributes (IP and IS), using linearized amplitude inversion, based on a Zoeppritz type approximation, followed by a non linear zero-offset reflectivity inversion (Oliveira et al., 2008);

• seismic facies classification from elastic attributes and Bayesian networks trained using well-log data;

• petrophysical inference of porosity and saturation from elastic attributes and facies classification, with the appropriate rock-physics model selected using the facies information.

Bayesian formulation

The above workflow includes several inference procedures for porosity and saturation, beginning at well-log scale. We closely follow the formulation described in Loures and Moraes (2006) and adaptations by da Costa et al. (2008). These authors give a closed form expression for the joint posterior distribution for porosity and saturation, at a given cell of the reservoir, as given by

$$p(\phi, S_w \mid \mathbf{d}_1, \mathbf{d}_2, \chi) \propto \prod_{i=1}^{2} \left\{ [\mathbf{d}_i - \mathbf{f}_i(\phi, S_w)]^T [\mathbf{d}_i - \mathbf{f}_i(\phi, S_w)] \right\}^{-\frac{N_i}{2}}, \quad \text{for} \quad 0 \le \phi \le 0.4 \quad \text{and} \quad 0 \le S_w \le 1, \tag{1}$$

where $\mathbf{d}_i = 1, 2$ represent the data (i.e., vectors of seismic impedances: IP, for $i = 1$, and IS, for $i = 2$) and $\mathbf{f}_i = 1, 2$ represent computed P and S impedances, as vector valued functions constructed on the basis of rock-physics equations (da Costa et al., 2008). The main simplifying assumptions involved in the derivation of equation (1) lead to a constant prior distribution about porosity and saturation, uncorrelated data with unknown variances, and a normal distribution for the errors. By marginalizing the resulting distribution with respect to data variances, one can obtain the posterior distribution in the form of equation (1). Amongst the inferences that can be addressed to the marginal posterior distribution, we use the mode and the width of a 0.95 probability interval. Such inferences can be used, respectively, as the estimate and an uncertainty measure.

Application to a Campos Basin reservoir

The porosity, lithology and saturation inference workflow is applied to a siliciclastic reservoir from Campos Basin, Brazil. Ida et al. (2002) present the development history of the field, including descriptions of the seismic data coverage and the main geological aspects of the field. There are 4 reservoir compartments, which are: 2 from Cretaceous, 1 Eocene, 1 Oligocene. We focus our work on the upper Cretaceous reservoir level, composed by sandstones from amalgamated and divergent channel system environments. Well-log analysts have identified 4 eletrofacies, consisting of clean sandstone, shaly sandstone, cemented shale and shale.

Top reservoir can be identified as a negative amplitude event due to lower impedance sands with respect to overlaying shales. The preliminary data analysis for calibrating rock-physics models relied on a complete suite of logs from several wells, core and fluid data, and formation tests (WFT). Core data consist of mineralogical composition, porosity, density, permeability and sonic responses from pressure sensitivity testing.

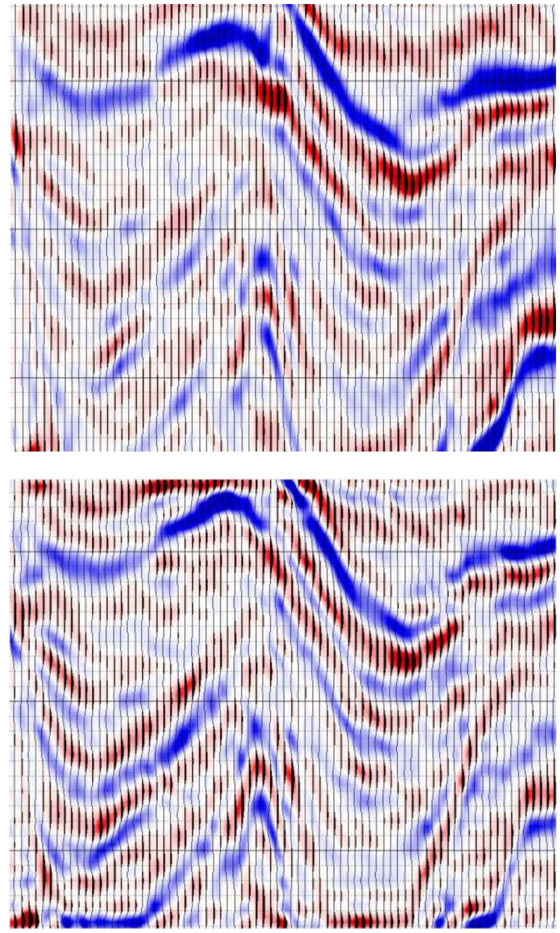

Figure 2: stacked data before (top) and after (bottom) applying the preconditioning workflow

After preliminary data analysis, we performed the reservoir property inference part of the workflow, as described above. Figure 3 represents the main steps of the workflow. Note the last part, which is the joint porosity and saturation inference from elastic attributes (IP and IS) and facies classification. The outputs consist of 4 volumes presented by the sections displayed on the figure, which are from top to bottom, porosity modes, the length of 0.95 probability interval for porosity, saturation modes and the length of 0.95 probability interval for saturation. Notice that the uncertainty associated with saturation is very large. Consequently, it is not reliable to consider the actual saturation value, but to use it in connection to the posterior distribution as a semi-quantitative fluid indicator.

The workflow was applied on two conventional 3D streamer data, respectively acquired during the years of 1984 (before production) and 1999 (after production). The data has been reprocessed by PETROBRAS for crossequalizing the amplitudes with a postack-analysis objective. A qualitative analysis of resulting saturation maps, for a weakly coupled inversion (using only a common background impedance model), show water movement which is consistent with production and 4D amplitude interpretation. A final analysis indicates that the results can be improved by increasing coupling between the two inversions. This can be done by using baseline impedances as initial model and a constant porosity model for the inversion of the monitor survey.

Conclusions

The proposed workflow is developed from an inference perspective, in which all variables of the problem are set by a data fitting procedure. This includes rock-physics model coefficients and calibration logs, such as effective porosity and saturation. This is beneficial in the following aspects:

i. gives better control of the porosity type, i.e., total versus effective porosity;

ii. provides better assessment of the uncertainty involved in each step of the workflow;

iii. opens the possibility for handling large uncertainties associated with the saturation, in connection with the posterior distribution, as a variety of semi-quantitative fluid indicators.

The methodology can be exploited as a reservoir monitoring tool if applied to multiple vintage data sets. However care must be taken to avoid interpreting spurious differences when comparing different inversion results.

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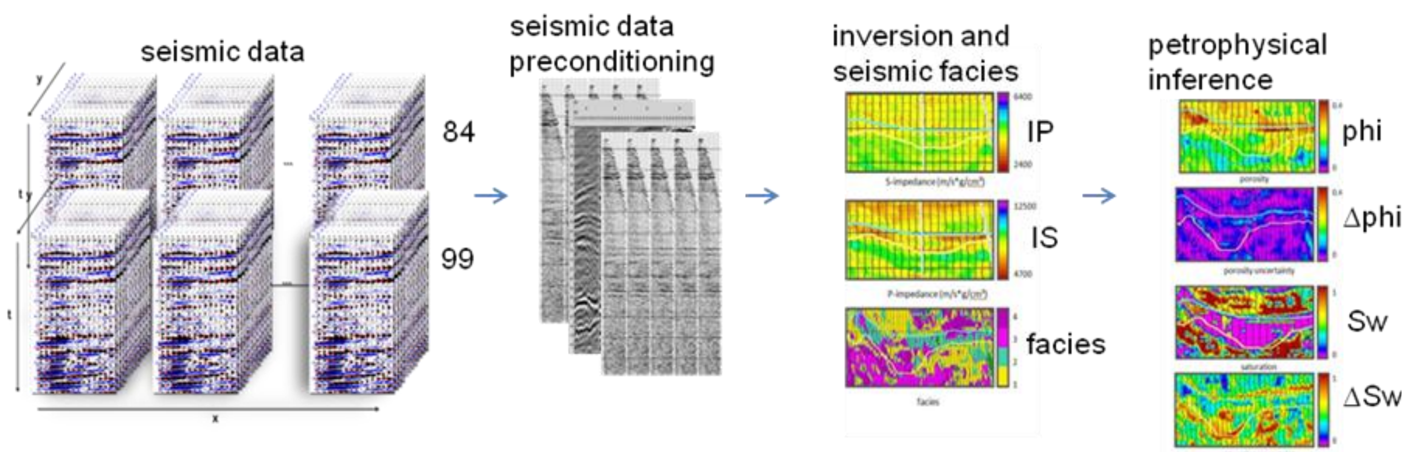

Figure 3: schematic representation of the main steps of the workflow represented by input prestack data vintages 99 and 84, seismic data preconditioning, P and S impedance inversion followed by seismic facies determination and petrophysical inference for porosity and fluid saturation.