Joint stochastic inversion of pre-stack seismic data and well logs for high-resolution reservoir delineation and improved production forecast

Omar J. Varela, Carlos Torres-Verdín, and Mrinal K. Sen. The U. of Texas at Austin*

Abstract

Integrated reservoir characterization makes use of different varieties of data to construct detailed spatial distributions of petrophysical and fluid parameters. The benefit of data integration is the generation of consistent and accurate reservoir models that can be used for reservoir optimization, surveillance, and management. This paper describes a novel strategy for the static and dynamic characterization of hydrocarbon reservoirs based on the extensive use of 3D pre-stack seismic data, wireline logs, core data, geological information, and time records of fluid production measurements. A stochastic simulation procedure is used to extrapolate petrophysical variables laterally away from wells subject to honoring the existing 3D pre-stack seismic data. This procedure yields high-resolution estimates of inter-well petrophysical parameters (and of bulk density, compressional-, and shear-wave velocities as a by-product) associated with pre-stack seismic data. A numerical study in two dimensions is performed to evaluate the estimation algorithm applied to pre-stack seismic data, as well as to assess different strategies for the direct estimation of petrophysical properties related to elastic parameters. The same numerical study is used to quantify consistency of the estimated reservoir parameters with the time record of fluid production measurements. The inversion algorithm is CPU intensive and is based on a global optimization technique. Examples of applications show that the inversion algorithm lends itself to accurate estimation of petrophysical properties, such as porosity, that honor both the pre-stack seismic data and the well logs. Depending on the number of wells and the distance between them, the inversion algorithm can produce estimates of inter-well petrophysical properties with a resolution midway between that of seismic data and well logs. Models generated with this inversion scheme yield highly accurate predictions of reservoir dynamic behavior when compared to predictions performed with standard geostatistical techniques.

Introduction

Accurate and efficient reservoir management requires geological models amenable to numerical simulation of multiphase fluid-flow. These models are used to match production history data, if available, and to assess potential production schemes in light of time-dependent economic value of assets. Reservoir characterization allows one to build cellular spatial distributions of properties described by measurable petrophysical or geological parameters from different types of measurements such as seismic data, well logs, and ancillary information (e.g., stratigraphy). The main focus of this paper is to describe a novel algorithm to generate inter-well petrophysical properties that makes optimal use of the high-resolution of well logs and the lateral resolution of 3D pre-stack seismic data.

Statistical modeling techniques, such as kriging, are widely used for data interpolation. The same techniques are at the heart of geostatistical methods used to simulate reservoir properties that honor the well-log data and a-priori measures of spatial continuity. Seismic data are sensitive to the entire reservoir and hence provide a realistic means to fill the spatial gap between sparse well locations. Amplitude variations of 3D seismic data have been traditionally used to delineate flow-units and in general to infer the geometrical properties of reservoirs (Brown, 1999). More recent approaches make use of seismic attributes to guide, correlate, or constrain the estimation of inter-well parameters. The quantitative use of seismic amplitude variations offers a powerful tool to guide the simulation of inter-well reservoir properties. This approach is referred in the literature to as geostatistical seismic inversion (Haas and Dubrule, 1994) and makes use of post-stack seismic data to constrain the geostatistical simulation of inter-well reservoir properties. Improvements and applications of this approach can be found in the technical literature (Torres-Verdín et al. 1999; Grijalba et al., 2000). The inversion algorithm presented in this paper is stochastic in nature, makes use of 3D pre-stack seismic data, and assumes the existence of quantitative relationships between petrophysical and elastic parameters. Well-log data are necessary to determine whether these relationships can be assumed of a deterministic or a stochastic nature. Spatial distributions of reservoir properties between existing wells are obtained by joint stochastic inversion of 3D pre-stack seismic data and well logs. The inversion is performed using a global optimization technique in which simulations of inter-well properties are obtained and subjected to an acceptance test that guaranties a reduction in the global misfit between the measured pre-stack seismic data and their numerical simulation. To the best of our knowledge, no such an algorithm has been reported in the open technical literature. The proposed algorithm is tested on a synthetic reservoir model. Static and dynamic results are compared between those associated with a benchmark reference model, models constructed with standard geostatistical techniques, and the models obtained with the proposed algorithm.

Methodology for reservoir characterization

Construction of a reference model. A synthetic model representing a fluvial depositional environment was constructed to perform the numerical experiments described in this paper. Such a model was designed to assess seismic resolution in the presence of wavelet tuning. It consists of two sands in a background shale. The upper sand is water filled whereas the lower sand is oil-saturated. A mechanical compaction trend is taken into account in this subsurface model. Petrophysical properties such as porosity were populated into the reservoir using stochastic algorithms with a prescribed degree of spatial correlation. Initial fluid distributions in the oil-saturated sand were calculated by means of correlations. Both determination of elastic properties and numerical simulation of pre-production pre-stack seismic data were performed following the methodology described by Varela (2003). A Ricker wavelet (central frequency of 35 Hz) was used in both simulation and inversion of pre-stack seismic data. Ten percent, zero-mean, random Gaussian noise was added to the pre-stack seismic data in an effort to replicate acquisition and processing errors. Ten pre-stack seismic offsets per CDP gather were considered in this study.

Figure 1 shows a cross-section of the simulated pre-stack seismic data across the center of the subsurface model described above. This cross-section is considered the reference model (single true distribution of petrophysical and elastic properties), has 71 CPD gathers (~23 m between CDPs and time sampling interval of 2 ms), and is used to perform the numerical experiments reported in this paper. Two wells were located along this cross-section. Panel (a) in this figure shows both the well locations and the first (nearest) offset seismic trace whereas panel (b) shows the last (farthest) offset seismic trace.

Geostatistical modeling. Geostatistical simulation techniques are commonly used in the construction of 3D distributions of reservoir properties. Kriging is a deterministic interpolation method that allows the inclusion of secondary variables (i.e., cokriging) and additional constraints. This technique is used to generate models that honor well log data and yield a smooth spatial distribution of properties, thereby dismissing local detail in place of a good average. If each known point in an interpolation process is considered to have a local probability distribution function (PDF), then the outcome of the kriging interpolation is still unique but this solution (i.e., field of local PDFs) allows the generation of multiple realizations. Such a geostatistical approach is used in this paper to generate initial distributions of reservoir properties for the proposed inversion algorithm as well as for comparison purposes. Generation of multiple realizations allows the assessment of uncertainty of the spatial distribution of properties and of their associated effects on dynamic predictions of reservoir behavior.

Seismic inversion. The physical process of reflection, transmission, and mode conversion of plane waves at a horizontal boundary as a function of angle has been extensively applied in seismic prospecting (Aki and Richards, 2002). Estimation of elastic parameters such as compressional-wave acoustic impedance or compressional-(v_p), shear-wave velocity (v_s), and bulk density (ρ_b) of rock formations can be accomplished by means of inversion of post- or pre-stack seismic data, respectively. These results are usually related to petrophysical properties through an empirical correlation. A significant amount of work is currently underway to estimate quantitative indicators of fluid and lithology from 3D pre-stack seismic data. The inversion algorithm described in this paper yields estimates of petrophysical properties in one step. Moreover these estimates honor both multiple-offsets of pre-stack seismic data and existing well log data.

Proposed joint stochastic inversion algorithm. The estimation of inter-well petrophysical parameters (and elastic parameter as a by-product) from pre-stack seismic data, well logs, and geological description and interpretation, is cast into a global optimization problem. Different factors such as optimization technique, selection of an objective function, selection of an initial model, sampling strategy, and smoothing criterion, among others, contribute to the resolution of the results and to the efficiency of the inversion algorithm. Varela et al. (2003) performed a detailed assessment of 1D stochastic inversion of pre-stack seismic data to quantify the influence of all of the above-mentioned inversion parameters. Based on those results, the pre-stack stochastic inversion algorithm described in this paper makes use of a very fast simulated annealing as a global optimization technique. It also makes use of the reflectivity method (Kennett, 1983) to simulate pre-stack seismic data. The inversion algorithm also enforces a harmonic objective function (see Appendix A), initial models constrained by well information, a sampling strategy from local PDFs, and a global target property histogram. Different random seeds are used to generate multiple realizations. If the purpose of the inversion is to estimate elastic properties, the initial models of these properties are drawn from local PDFs that are calculated at each point using a kriging estimator on the well log data. On the other hand, if the objective of the inversion is to estimate a petrophysical property (and elastic parameters as a by-product), the initial model of such a property is drawn from local PDFs that are calculated at each point using a kriging estimator on the well log data. Perturbations of properties are performed directly in the petrophysical domain through a random walk in space and time. Because the pre-stack stochastic inversion operates on elastic parameters, a joint PDF is used to establish a quantitative link between the petrophysical and elastic properties.

Numerical experiments

Three different types of experiments were performed to validate the proposed inversion algorithm: (a) pre-stack stochastic inversion resolution, (b) static, and (c) dynamic reservoir characterization.

Spatial resolution of pre-stack stochastic inversion. A number of experiments were performed to evaluate the resolution of the pre-stack stochastic inversion algorithm when used to estimate compressional-wave velocity, shear-wave velocity, and bulk density. Figure 2 shows cross-sections of the mean of inverted compressional- and shear-wave velocities and bulk density for ten independent realizations. All ten realizations have the same global similarity in data space. These cross-sections identify the background shale and oil-saturated sand. Global correlation coefficients (r^2) were calculated between initial and actual values of elastic properties ($r^2_{vp} = 0.25$, $r^2_{vs} = 0.68$, and $r^2_{\rho b} = 0.64$, respectively) and between mean values of inverted and actual values of elastic properties ($r^2_{vp} = 0.67$, $r^2_{vs} = 0.98$, and $r^2_{\rho b} = 0.98$, respectively). Further analysis of these inversion results shows that the estimated elastic properties of the sand exhibit more variability than the elastic properties of shales. Compressional-wave velocity in the oil saturated sand exhibits the most variability as per standard deviation calculations. Compressional-wave velocity also exhibits the lowest global correlation coefficient compared to those of the remaining elastic properties. This low value for compressional-wave velocity is due to (a) the large boundary constraints used in the inversion, (b) small contrast in velocity between the oil-saturated sand and background shale, and (c) the effect of a non-optimal seismic signal-to-noise ratio.

Static reservoir characterization. Figure 3 shows a cross-section of the mean of ten independent realizations of inverted porosity distributions. Realizations obtained with the proposed algorithm exhibit the same global similarity in data space. When calculating the global correlation coefficient between the mean of porosity (mean of ten realizations) and the actual porosity, an average value of 0.96 was obtained for the proposed inversion algorithm whereas an average value of 0.54 was obtained for the initial models. Further analysis of the inversion results show that because the proposed algorithm honors the multiple offsets of pre-stack seismic data, the variability of porosity is smaller than that of initial models. Values of porosity estimated within the sand exhibit more variability than those estimated within the shale background.

Dynamic reservoir characterization. Quantifying the impact of spatial distributions of reservoir properties on production is used for the appraisal of reservoir uncertainty. A simple injection/production scheme was designed to compare the dynamic results of the static model shown in Figure 3. The same production, fluid, and rock properties and constraints were applied to the fluid production scheme. The permeability field was determined using a simple porosity-permeability transformation. Figure 4 shows a cross-plot of the cumulative oil recovery as a function of time for the reference case, initial model, and proposed inversion algorithm. Results shown in this figure represent a global dynamic response and clearly indicate that more accurate predictions are obtained from reservoir models generated with the proposed inversion algorithm.

Conclusions

Estimation of petrophysical properties (and elastic properties as a by-product) from 3D pre-stack seismic data and well logs provides reservoir property distributions that honor not only the well logs but also the multiple offsets of pre-stack seismic data. The inversion algorithm described in this paper yields estimates of inter-well petrophysical properties with a resolution midway between that of seismic data and well logs. Using seismic data to fill the spatial gap between wells can reduce the uncertainty in the petrophysical property models being estimated and their associated dynamic predictions. The stochastic nature of the algorithm also allows the assessment of reservoir property uncertainty and of their associated effect on dynamic behavior. This approach can significantly shorten the reservoir appraisal cycle and provide more flexibility to quantitatively evaluate different conceptual geological models and production schemes.

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Appendix A. Objective function

The following harmonic objective function is adopted from the work of Sen and Stoffa (1995) to quantify the misfit in data space:

$$\left\| e_f \right\|_h = \frac{1}{N_{CDP}} \sum_{j=1}^{N_{CDP}} \left\{ \frac{1}{N_{off}} \sum_{i=1}^{Noff} \left[\alpha_i \left(A / (B + C) \right) \right] \right\}, \textit{ where}$$

$$A = 2 \sum_{1}^{Nf} S(x,f)^{data} S^*(x,f)^{est}, \; B = \left(\sum_{1}^{Nf} S(x,f)^{data} S^*(x,f)^{data} \right)^{1/2},$$

$$\textit{and} \;\; C = \left(\sum_{1}^{Nf} S(x,f)^{est} S^*(x,f)^{est} \right)^{1/2}.$$

In the above equation, x is position, f is frequency, N_{CDP} is number of CDP gathers, N_{off} is number of source-receiver offsets, α is offset weight factor, N_f is the number of frequencies in each trace for a given offset, $[S(x,t)]^{est}$ is synthetic and $[S(x,t)]^{data}$ is measured pre-stack seismic data, and the superscript (*) is used to designate the conjugate operator.

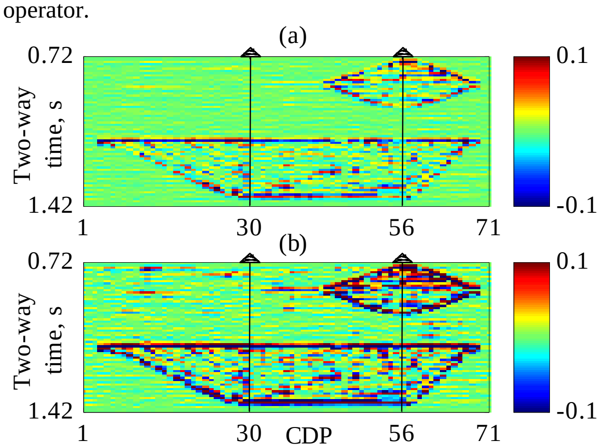

Figure 1. Graphical description of the subsurface model and well locations used to validate the inversion algorithm described in this paper. Panels (a) and (b) show the first (nearest) and last (farthest) traces of pre-stack seismic gathers, respectively.

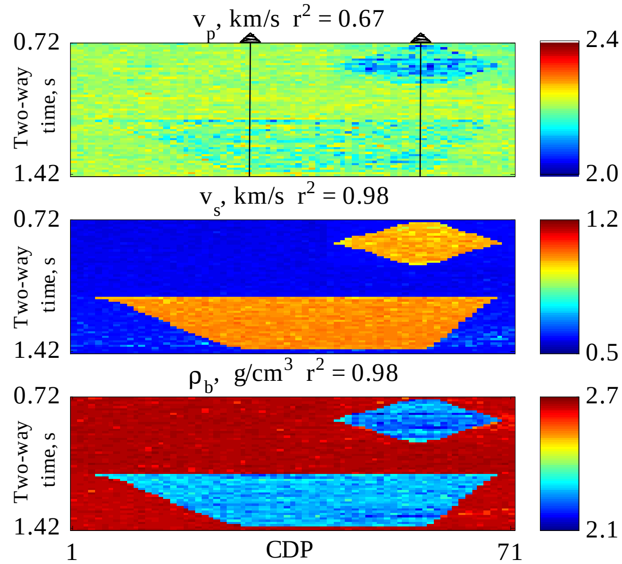

Figure 2. Cross-sections of the mean of inverted compressional-, shear-wave velocities, and bulk density for ten independent realizations obtained with the proposed inversion algorithm. Global correlation coefficients (r^2) are calculated with respect to the reference model of elastic properties.

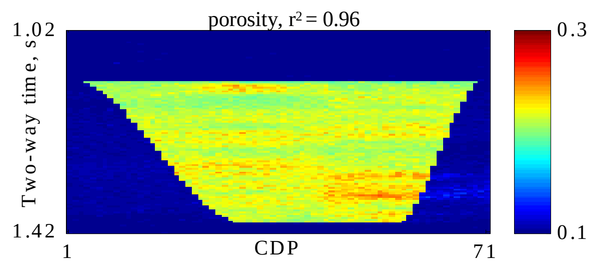

Figure 3. Comparison of static results. Cross-section of the mean of ten independent realizations of inverted porosity distributions obtained with the proposed inversion algorithm. Global correlation coefficients (r^2) are calculated with respect to the reference porosity model.

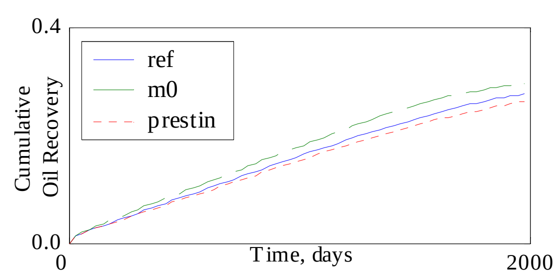

Figure 4. Comparison of dynamic results. Plot of cumulative oil recovery as a function of time for (a) the true or reference case (ref), (b) mean of initial models (m0), and (c) mean of proposed inversion algorithm (prestin).