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Bayesian seismic inversion based on rock-physics prior modeling for the joint estimation of acoustic impedance, porosity and lithofacies

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A B S T R A C T

We propose a Bayesian approach for seismic inversion to estimate acoustic impedance, porosity and lithofacies within the reservoir conditioned to post-stack seismic and well data. The link between elastic and petrophysical properties is given by a joint prior distribution for the logarithm of impedance and porosity, based on a rock-physics model. The well conditioning is performed through a background model obtained by well log interpolation. Two different approaches are presented: in the first approach, the prior is defined by a single Gaussian distribution, whereas in the second approach it is defined by a Gaussian mixture to represent the well data multimodal distribution and link the Gaussian components to different geological lithofacies. The forward model is based on a linearized convolutional model. For the single Gaussian case, we obtain an analytical expression for the posterior distribution, resulting in a fast algorithm to compute the solution of the inverse problem, i.e. the posterior distribution of acoustic impedance and porosity as well as the facies probability given the observed data. For the Gaussian mixture prior, it is not possible to obtain the distributions analytically, hence we propose a Gibbs algorithm to perform the posterior sampling and obtain several reservoir model realizations, allowing an uncertainty analysis of the estimated properties and lithofacies. Both methodologies are applied to a real seismic dataset with three wells to obtain 3D models of acoustic impedance, porosity and lithofacies. The methodologies are validated through a blind well test and compared to a standard Bayesian inversion approach. Using the probability of the reservoir lithofacies, we also compute a 3D isosurface probability model of the main oil reservoir in the studied field.

1. Introduction

From a mathematical point of view, the estimation of reservoir properties from seismic data is an inverse problem. The goal of inverse modeling is to predict model variables from a parameterized physical system from observable data,

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assuming theoretical relations between observable and unobservable parameters, as well as prior information [40]. Seismic inversion is an important step in the process of modeling and characterization of oil and gas reservoirs, because it allows estimating the elastic properties of rocks from seismic data [12,37]. Elastic properties are related to petrophysical properties such as porosity and fluid saturation [4,25] that are the main variables in formation evaluation for the quantification of the hydrocarbon volume within the reservoir. Typically, seismic data are measured according to a regular geometry, for example seismic traces are measured at several locations every 25 m along orthogonal directions (namely inline and crossline) and the dataset includes the measurements of seismic traveltime and seismic amplitudes. Well measurements are generally used in reservoir characterization as a validation of the inversion results. Furthermore, well data provide direct measurements of rock and fluid properties in the borehole, as well as prior information for the wavelet estimation [11] and rock-physics model calibration [17]. Generally well measurements include measurements of elastic and petrophysical properties such as P- and S-wave velocity, density, porosity, and fluid saturation. The rock-physics model provides a relation between the petrophysical properties and the elastic properties. It is usually given by a set of equations that can be obtained by a simple fitting of well data or by a more complex theoretical relation [13,17,25]. The distribution of rock and fluid properties in the subsurface depends on the rock type, namely the lithofacies. In our work, a lithofacies (or simply facies) is defined as a geobody with specific physical and geological characteristics related to the sedimentological and depositional conditions [34].

The main challenge in seismic inversion is the limited bandwidth of seismic data and consequently the non-uniqueness of the solution, particularly outside of this band. Thus, it is possible to find different values of the model parameters that are compatible with the measured data. Besides, the presence of noise in the data and errors associated to the modeling process affect the accuracy of the inversion results [38]. These factors motivate the development of stochastic inversion methods, that can generate several configurations, or stochastic realizations, of subsurface properties with higher resolution than the input seismic data, providing a quantification of the uncertainty and a set of solutions with different scenarios of the reservoir model [8]. Stochastic optimization methods, such as simulated annealing, genetic algorithms or particle swarm optimization, have been proposed to solve geophysical inverse problems [9,22,27]. These methods are based on optimization procedures and are strongly dependent on computational resources. More efficient techniques based on stochastic Bayesian formulations using Monte Carlo methods have been proposed in recent publications for the estimation of the posterior distribution of reservoir properties conditioned to geophysical data [4,7,17,35,36]. For linearized forward models and under the assumption of Gaussian distribution of the model parameters and observation errors, the posterior distribution can be analytically computed, leading to very fast algorithms [6,11]. Monte Carlo methods estimate a probability distribution by numerical random sampling following some criteria. It was firstly introduced by [26] to simulate a liquid in equilibrium with its gas phase, originating the class of simulations called Metropolis algorithms. The methodology was generalized by [19], and posteriorly [15] presented a special case of the Metropolis–Hasting algorithm called Gibbs Sampler. These methods have been largely applied in physics, chemistry, biology and mathematics [28] in the last decades. The use of Monte Carlo methods for inverse problems in geophysics was introduced by [20] and [31], as a methodology to estimate the probability distribution over the model parameter space [7,10,17,33,35,40]. Differently from other stochastic optimization techniques and Approximate Bayesian Computation algorithms, in Markov chain Monte Carlo methods, the likelihood function is explicitly computed, allowing the exact estimation of the posterior distribution and a correct quantification of the model uncertainty.

In this work, we propose a Bayesian seismic inversion based on a rock-physics relation that accounts for the statistical correlation between porosity and the natural logarithm of acoustic impedance. The rock-physics model is embedded in the joint prior multivariate normal distribution of both properties. This assumption, together with the linearized convolutional model and the Gaussian assumption for the errors, enables us to obtain the analytical expression for the conditional distributions of the model parameters given the observed seismic data. We propose two approaches to obtain the acoustic impedance, porosity and facies within the reservoir conditioned to the seismic data and the well data. The first approach is based on a single Gaussian prior distribution, where the posterior distribution for impedance and porosity as well as the probability of facies given these properties is analytically derived, and hence calculated with a small computational cost (Method 1 – Analytical). In the second method, we propose a Gaussian mixture model for the prior distribution, and we introduce a Gibbs algorithm to sample the joint posterior distribution for impedance, porosity and facies (Method 2 – Monte Carlo).

2. Methodology

In this section, we present the seismic forward modeling, the rock-physics model for the prior, and the background prior model, which are common elements for both proposed inversion methods. We then introduce the analytical formulation for Method 1 and the statistical sampling algorithm for Method 2.

2.1. Seismic model

A seismic dataset includes the measurements of seismic amplitudes for a given time interval during wave propagation at a set of spatial locations regularly distributed over a surface area corresponding to the subsurface reservoir region. Assuming