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Probabilistic Estimation of Reservoir Parameters Using the Complementary Nature of Seismic and mCSEM Data

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Summary

Considering the steadily declining prices in the oil and gas industry, nowadays, the requirement for geophysical information becomes more important in order to get the most out of available reservoirs. Electromagnetic measurements could complement seismic data where it lacks information. The EM response to fluid fill complements the resolving power of seismic data. In the current study, we use a probabilistic method to estimate reservoir parameters individually and jointly through two simplistic, synthetic, 2D reservoir models which can be considered as the geometrical limits of water-oil-contacts in oil and gas fields. We demonstrate a constructive contribution of the measurements with different physical natures in the estimation of reservoir parameters.

Introduction

To address the inherent non-uniqueness of seismic inverse problems, to complement seismic data where it lacks information, and to take advantage of information obtained from other physical data, an individual inverse problem may be reformulated as a joint one to find the solution satisfying both physical measurements (van Leeuwen, 2017). As the complementary source of information to seismic data for reservoir parameter estimation and monitoring, marine Controlled-Source Electromagnetic (mCSEM) data seems an ideal candidate. mCSEM is considered the most significant method of exploring the subsurface after the development of 3D reflection seismology (Constable and Srnka, 2007) and is able to properly include low-frequency information of the Earth, where low-acoustic-impedance interfaces result in poor illumination (Mukerji et al., 2009). Note that this complementary nature is not one-sided, meaning that seismic data can also be of help to the limited spatial resolution of mCSEM data.

Although geophysical inverse problems are conventionally treated in deterministic ways, prone to be trapped in local minima and often uninformed about uncertainties, probabilistic methods can be considered as more appropriate methods towards inverse problems (Tarantola, 2005). A particular difficulty for the probabilistic view is the model space which is remarkably huge. As a consequence, the search for the solution takes quite a few computer resources as well as a significant amount of time making the searching process computationally expensive. Probabilistic approaches, therefore, have been on hold for a long time. However, today, enjoying the increasing power of CPUs, GPUs, and clusters, distributing the computational burden of large-scale problems, and specially for reservoir parameter estimation problems, where more constraints are available and can be placed, the probabilistic view sounds compelling.

This paper is inspired by two previous papers by Fliedner et al. (2011) as well as Trainor-Guitton and Hoversten (2012). In this study, after a brief description with regard to the theory and methodology used to produce results, we will investigate the complementary nature of seismic and mCSEM data in a probabilistic framework through two simplistic, synthetic, 2D cases which are common in oil and gas fields.

Theory and Methodology

In the following, we follow the notation and argumentation of Tarantola (2005). Form the probabilistic point of view, a geophysical inverse problem, due to uncertainties in the physical theory, observations, and prior knowledge, involves three states of information corresponding to three probability density functions (pdfs): observational, theoretical, and prior information pdfs. The conjunction of two different states of information, the prior information pdf (ρ) and theoretical information pdf (θ), is denoted by the equation below,

$$\zeta(\mathbf{d},\mathbf{m}) = k\,\frac{\rho(\mathbf{d},\mathbf{m})\,\theta(\mathbf{d},\mathbf{m})}{\mu(\mathbf{d},\mathbf{m})}, \tag{1}$$

where k is a normalization factor and $\mu(\mathbf{d},\mathbf{m})$ is called the homogenous probability density function. The updated state of information in the model space or, equivalently, the solution to inverse problems in the model space, is determined by the integral below over the data space,

$$\zeta_{\mathrm{M}}(\mathbf{m}) = \int_{\mathfrak{D}-space} \zeta(\mathbf{d},\mathbf{m})\,d\mathbf{d} = k\,\rho_{\mathrm{M}}(\mathbf{m}) \int_{\mathfrak{D}-space} \frac{\rho_{\mathrm{D}}(\mathbf{d})\theta(\mathbf{d}|\mathbf{m})}{\mu_{\mathrm{D}}(\mathbf{d})}\,d\mathbf{d} = k\,\rho_{\mathrm{M}}(\mathbf{m})\,L(\mathbf{m}), \tag{2}$$

where L is the model likelihood function. In the case of negligible theoretical uncertainties, which is the case for the most practical inverse problems in geophysics, we have, $\theta(\mathbf{d}\,|\,\mathbf{m}) = \delta(\mathbf{d} - \mathrm{g}(\mathbf{m}))$, where $\mathbf{g}$ is the forward modeling operator, and in the case of a linear data space, we have, $\mu_{\mathrm{D}}(\mathbf{d}) = \text{const.}$ As a result, equation (2) is simplified to,

$$\zeta_{\mathrm{M}}(\mathbf{m}) = \text{const. } \rho_{\mathrm{M}}(\mathbf{m})\,\rho_{\mathrm{D}}(\mathbf{g}(\mathbf{m})). \tag{3}$$

In general, while having a full description of the posterior is impractical due to the corresponding cost, sampling the posterior seems practical. Stochastic sampling methods such as importance sampling, rejection sampling, sequential importance sampling, sampling-importance resampling, and Markov Chain Monte Carlo are among the popular ones.

In this probabilistic joint inversion of seismic and mCSEM data, as the number of uncertain reservoir parameters intended is two for each type of physical information, we use two 2D posterior pdfs to represent the complementary nature of both physical information. Accordingly, we just use the concept of stochasticity for sampling the 2D posterior pdfs rather than the above-mentioned stochastic sampling methods. In order to update the 2D posterior pdfs, we follow two steps:

(1) Generate an ensemble of the prior model for the first type of physical information (EM) uniformly. Then, generate an ensemble of the prior model for the second type of physical information (seismic) via a cross-property relation.

Different geophysical domains can be linked to each other at a petrophysical level. The petrophysical link can be explained by cross properties between the geophysical properties such as compressional wave velocity (Vp) and conductivity (σ) on the one hand, and the porosity and saturation of reservoir fluids on the other, with the aid of theoretical/empirical rock-physics models (Dell'Aversana, 2014). In this study, we use a synthetic cross-property relation between Vp and σ to connect them directly in a way while the σ contrast at the oil-water contact (OWC) is remarkable, the Vp contrast is poor, which is the case for the most OWCs. The synthetic cross-property relation used in this study is $\mathrm{Vp} = 64\ln(\sigma) + 2449$.

(2) Compute the likelihood function for the generated prior models in step (1). Then, update the posterior pdfs of both physical properties by the multiplication of priors and likelihoods.

For the seismic forward modeling, we use 2D full wavefield modeling (Berkhout, 2014a). For the EM forward modeling, we use a multigrid solver for 3D electromagnetic diffusion (Mulder, 2006). Both modeling parts are conducted in the frequency domain and run in parallel.

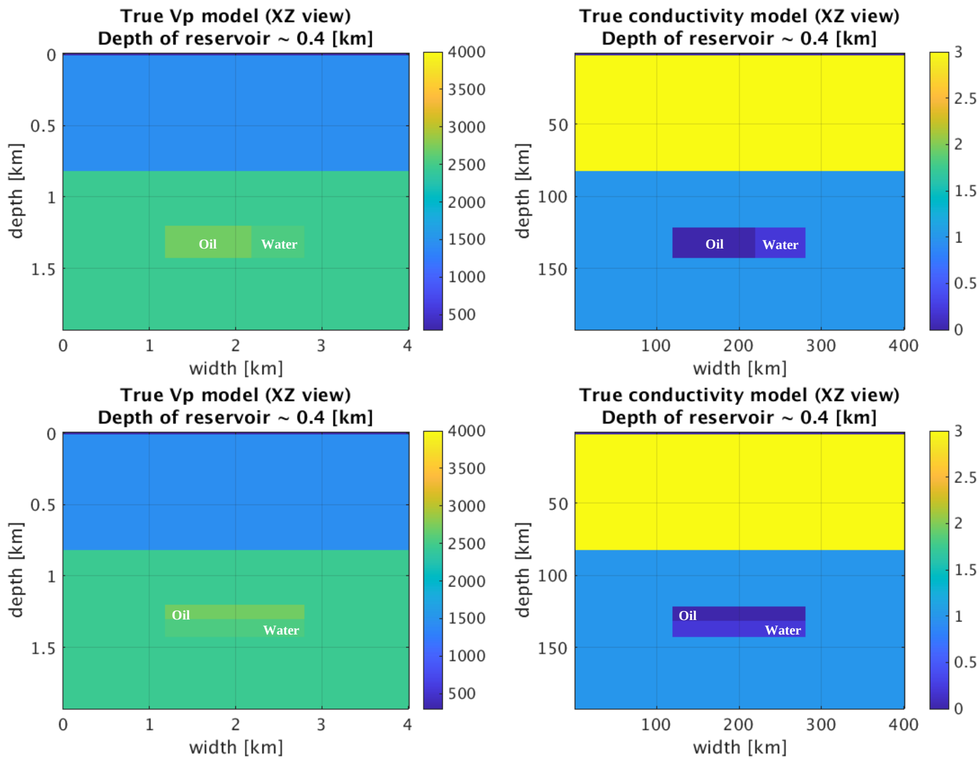

Figure 1 *The top row represents the true reservoir models used for the first numerical experiment, where the OWC is vertical, and the bottom row represents the true reservoir models for the second numerical experiment with a horizontal OWC.*

Numerical Experiments

We use two simplified reservoir models where the OWC is vertical and horizontal, respectively. In Figure 1, the true models for both numerical experiments are shown. In both experiments, to generate Vp priors, we assume that all grid points of the oil-bearing part of the reservoir have identical Vp values, which is the case for the true models as well. Similarly, we make the same assumption for the water-bearing part of the reservoirs. In addition, subsurface structures and all geophysical parameters within the prior models are considered known except the Vp and σ values within the oil and water-bearing parts of the reservoirs. The OWC is also considered known here. Thus, the only parameters to be estimated are Vp and σ within the oil and water-bearing parts of the reservoirs. We assume that we have Gaussian observational information and uniform prior information meaning that posteriors are proportional to likelihoods. Seismic data, observed and synthetics, is produced using 8 frequency components and includes only primaries. mCSEM data, observed and synthetics, is produced using only 1 frequency component. Both observed seismic and mCSEM data are noise-free

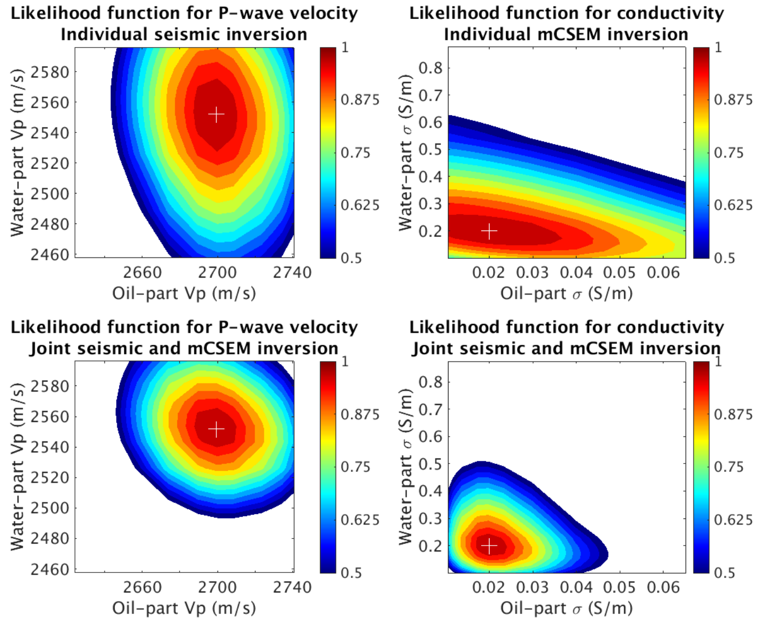

Figure 2 *The top row represents the 2D individual likelihood functions for the first numerical experiment, where OWC is vertical, and the bottom row represents the joint ones. White plus signs denote the truth.*

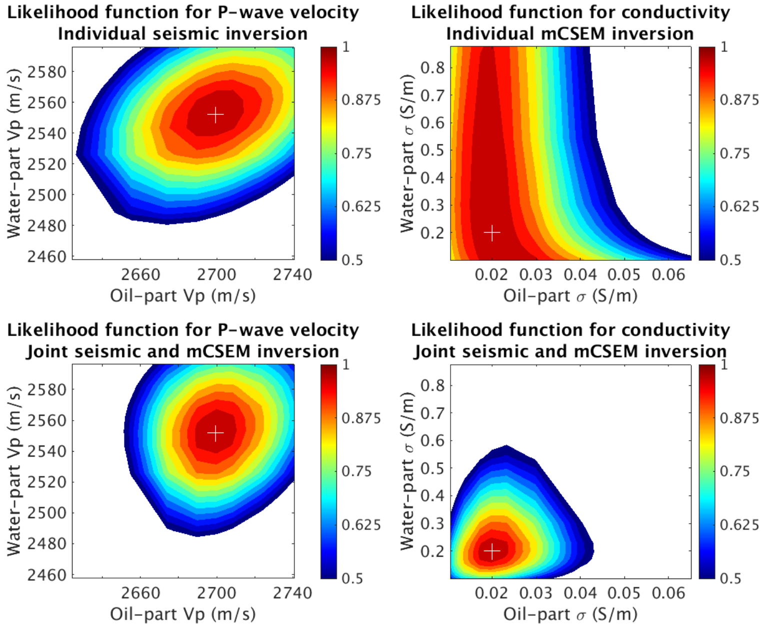

Figure 3 *The top row represents the 2D individual likelihood functions for the second numerical experiment, where the OWC is horizontal, and the bottom row represents the joint ones. White plus signs denote the truth.*

In Figure 2, the calculated likelihood function for the first numerical experiment, where the OWC is vertical, is shown. In Figure 3, the likelihood function for the second numerical experiment, where the OWC is horizontal, is represented.

The first numerical experiment with a vertical OWC demonstrates that while for the seismic inversion alone, the probability is more spread out over the water-part Vp axis, for the mCSEM inversion alone, the opposite is true (Figure 2, top row). However, when the measurements with different physical natures are used jointly, the different sensitivities of the measurements make a constructive contribution such that a more balanced probability distribution is obtained from the joint likelihood function for Vp (Figure 2, bottom-left). Both joint likelihood functions (Figure 2, bottom row) show a reduced-width probability distribution over both axes.

The second numerical experiment with a horizontal OWC confirms that seismic inversion alone provides us with a more balanced probability distribution in comparison to the vertical OWC experiment, and the mCSEM inversion alone is not fruitful in retrieving an informative likelihood function for σ (Figure 3, top row). The joint likelihood function for σ (Figure 3, bottom-right) confirms that there is again a constructive contribution of the measurements with different physical natures such that the weakly-informative likelihood function resulting from the individual mCSEM inversion turns into an informative one. Both joint likelihood functions (Figure 3, bottom row) show a reduced-width probability distribution over both axes.

Conclusions

The experiments with multi-physics measurements in two different configurations of oil and water-bearing layers, the geometrical limits of a realistic OWC, in a probabilistic framework illustrate the complementary nature of seismic and mCSEM data. A Bayesian estimation methodology that multiplies a prior distribution with the likelihood of the observations given the prior model, has the potential to estimate conductivity and compressional wave velocity from observed seismic and EM responses. While initial tests using noise-free observations from a synthetic truth give promising results, further experiments are required to explore the use of this method in a more realistic setting with a not purely vertical or horizontal OWC.

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