Joint inversion of marine seismic AVA and CSEM data using statistical rock-physics models and Markov random fields

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Summary

Joint inversion of seismic AVA and CSEM data needs rock-physics models to link seismic attributes to electrical properties. Ideally, we can develop physical-based models (e.g., Gassmann's equation and Archie's law) from nearby borehole logs to connect them through reservoir parameters (e.g., porosity and water saturation). However, in the exploration stage, this could be very difficult because information available are typically insufficient for choosing suitable rock-physics models and for obtaining reliable estimates of their associated parameters. The unsuitable rock-physics models and the inaccuracy of their subsequent estimates of model parameters may result in very misleading inversion results. However, it is fairly easy to derive statistical-based relationship (e.g., covariance matrix and regression equations) among seismic and electrical attributes from distant borehole logs. The statistical-based relations may improve estimates of both seismic and electrical properties even with uncertainty. We test such a hypothesis in this study by developing a Bayesian model for joint inversion of seismic AVA and CSEM data. We estimate seismic P- and S-wave velocity, density, electrical resistivity, and lithotypes (shale, brine sand, or oil sand) as functions of depth by conditioning to seismic AVA and CSEM data. The spatial dependences of those quantities are carried out by lithotypes through Markov random fields. We demonstrate the effectiveness of the developed model using a 2D synthetic model and derived datasets that has been developed to closely mimic field conditions. We use borehole logs at two different locations (one with and the other without reservoir) to obtain statistical rock-physics relations; we invert seismic AVA and CSEM data at a third location with reservoir using the derived rock-physics models. Comparison of the inversion results shows the developed Bayesian model is effective and combination of seismic AVA and CSEM data improves estimates of geophysical attributes. The developed model can be extended to incorporate estimates of reservoir parameters (e.g., porosity and fluid saturation).

Introduction

Joint inversion of seismic AVA and CSEM data has been demonstrated to be beneficial for reservoir parameter estimation (Hoversten et al., 2006; Chen et al., 2007) because they provide complementary information on reservoir parameters. This estimation requires rock-physics models to connect seismic attributes to electrical conductivity, which are often derived from suitable nearby borehole logs in practice. First, an appropriate family of rock-physics models is chosen and then those parameters associated with the rock-physics models are estimated by fitting them to the selected borehole logs. However, in the exploration stage, the derivation of detailed rock-physics models could be very difficult due to the lack of nearby wells. However, we can often find logging data at more distant locations where parameter covariance- or regression-based relations can be derived sufficiently. The statistical-based relationship, with associated uncertainty, may improve estimates of seismic and electrical properties (thus reservoir parameters) even though they are less precise than physical-based rock-physics models.

In this study, we develop a Bayesian method based on statistical rock-physics models derived from borehole logs to jointly invert seismic AVA and CSEM data. We apply the developed stochastic model to a synthetic dataset generated from a 2D synthetic model that closely mimics field conditions. We use borehole logs at two different locations, one with and the other without reservoir, to obtain statistical rock-physics relations. We invert seismic AVA and CSEM data at a third location with reservoir using the derived statistical rock-physics models and compare the inversion results to demonstrate the effectiveness of the developed method. This is an ongoing research and the developed model will be extended to incorporate estimates of reservoir parameters later. Section 2 describes the Bayesian model and Markov chain Monte Carlo (MCMC) sampling strategies and Section 3 shows some results of the synthetic study.

Method

Bayesian Model

We develop a Bayesian model for a layered reservoir as done by Hoversten et al. (2006) and Chen et al. (2007) to estimate seismic P-wave velocity ($\mathbf{V}_p$), S-wave velocity ($\mathbf{V}_s$), density ($\boldsymbol{\rho}$), electrical resistivity ($\mathbf{r}$), and lithotypes ($\mathbf{L}$) as functions of depth. The main difference of this study from the one given by Chen et al. (2007) lies in the use of statistical rock-physics models and Markov random fields for lithotypes. Similar to the model given by Chen et al. (2007), we add several layers above and below the reservoir to account for uncertainty in selecting the time window for

seismic AVA data inversion. For those layers, we invert for elastic bulk modulus $\mathbf{K}$, shear modulus $\boldsymbol{\mu}$, and density $\boldsymbol{\rho}_0$. Seismic P- and S-wave velocity and density in the layers can be calculated directly from their corresponding bulk and shear moduli and density. Because resistivity in the seawater and in the overburden and bedrock affects estimates of reservoir parameters, we also consider these as unknown parameters in this model and denoted by the vector $\mathbf{r}_0$.

Let matrix $\mathbf{R}$ represent seismic AVA data, which are the explicit functions of seismic P- and S-wave velocity and density within the reservoir and the implicit functions of elastic properties (i.e., $\mathbf{K}$, $\boldsymbol{\mu}$, and $\boldsymbol{\rho}$) in the zones outside the reservoir. Let matrix $\mathbf{E}$ represent CSEM data, which are the functions of reservoir resistivity $\mathbf{r}$ and resistivity $\mathbf{r}_0$ in the seawater, overburden, and bedrock. Since seismic AVA and CSEM data are two different types of geophysical measurements, it is reasonable to assume that their measurement errors are independent of each other. Consequently, we obtain the following Bayesian model:

$$\begin{aligned} & f(\mathbf{V}_p,\mathbf{V}_s,\boldsymbol{\rho},\mathbf{K},\boldsymbol{\mu},\boldsymbol{\rho}_0,\mathbf{r},\mathbf{r}_0,\mathbf{L}\mid\mathbf{R},\mathbf{E}) \\ & \quad \propto f(\mathbf{R}\mid\mathbf{V}_p,\mathbf{V}_s,\boldsymbol{\rho},\mathbf{K},\boldsymbol{\mu},\boldsymbol{\rho}_0)f(\mathbf{E}\mid\mathbf{r},\mathbf{r}_0) \\ & \quad f(\mathbf{V}_p,\mathbf{V}_s,\boldsymbol{\rho},\mathbf{r}\mid\mathbf{L})f(\mathbf{L}) \\ & \quad f(\mathbf{K},\boldsymbol{\mu},\boldsymbol{\rho}_0,\mathbf{r}_0) \end{aligned} \tag{1}$$

Equation 1 defines a joint posterior probability distribution function of all unknown parameters, which is known up to a normalizing constant. The first and second terms on the right side of the equation are the likelihood functions of seismic AVA and CSEM data, respectively; they are the same as those used by Chen et al. (2007) and Chen and Dickens (2009). The third term on the right side of the equation is the statistical rock-physics model derived from borehole logs for given lithotypes. The fourth term is the prior probability distribution of lithotypes given as a Markov random field. The last term on the right side of the equation is the prior distribution of the unknown variables outside the reservoir. We use the same prior distribution as done by Chen et al. (2007). Because the current study is built on our previous work, we only show the differences in the following. Please refer to Chen et al. (2007) and Chen and Dickens (2009) for more detail.

Statistical Rock-physics Model

We derive rock-physics models from remote borehole logs. Let i and j be indices at two different reservoir layers. We assume that the joint conditional probability distribution given lithotypes at layer i is independent of that given lithotypes at layer j. This is justified from analysis of real logs. As a result, we can write the statistical rock-physical model as:

$$f(\mathbf{V}_p,\mathbf{V}_s,\boldsymbol{\rho},\mathbf{r}\mid\mathbf{L}) = \prod_{i=1}^{m} f(V_{pi},V_{si},\rho_i,r_i\mid L_i), \tag{2}$$

where V_{pi}, V_{si}, ρ_i, r_i, and L_i are seismic P-wave velocity, S-wave velocity, density, electrical resistivity, and lithotype at layer i. The statistical model is problem-specific.

Markov Random Fields

We use the first-order Markov random field to simulate the spatial dependence of lithotypes as done by Eidsvik et al. (2004). Although in this study, we only estimate seismic and electrical parameters along a 1D profile, the developed model can be extended to 2D cross-sections. The Markov random model is Ising and Potts model. As shown by Higdon (1998), we can write the joint lithotypes distribution as:

$$f(\mathbf{L}) \propto \exp\left\{\sum_{i\sim j}\beta \mathrm{Ind}[L_i = L_j]\right\}, \tag{3}$$

where $\mathrm{Ind}[\cdot]$ is an indicator function, which takes the value of 1 if $L_i = L_j$ and the value of 0 otherwise. Parameter β is a measure of the spatial dependence and will be jointly estimated in the inversion. Sampling from such a joint distribution typically suffers from low convergence using traditional Gibbs or Metropolis-Hasting methods. In this study, we use the Swendsen-Wang algorithm (Swendsen and Wang, 1987), which was designed specially to treat such slow convergence for the model.

Synthetic Study

We apply the developed Bayesian model to a synthetic dataset extracted from an elaborately designed 2D model that closely simulates real field conditions. Both seismic AVA and CSEM synthetic data were generated using 2D finite difference and finite element forward models respectively. For the purpose of this study, we assume that we have logs at two different locations (CDP-1135 and CDP-1520), one with oil reservoirs (CDP-1520) but the other without (CDP-1135). We use information at the two locations to derive statistical rock-physics models and invert seismic AVA and EM data at the third location (CDP-766) with presence of oil reservoirs.

Borehole Logs and Statistical Rock-physics Models

We develop rock-physics models from borehole logs at CDP-1135 and CDP-1520. Figure 1 shows seismic velocity, density, shale content, and electrical resistivity as functions of depth from borehole logs at CDP-1520. An oil reservoir

presents at the depth interval between 1800m and 1900m. Based on the borehole data, we define the following three lithotypes: (1) shale (shale content is greater than 0.6), (2) brine sand (shale content is less than 0.6 and water saturation is greater than 0.9), and (3) oil sand (shale content is less than 0.6 and water saturation is less than 0.9). The choice of the cutoff values for the definitions of lithotypes will be problem specific. Figure 2(a-c) shows seismic P-wave and S-wave velocity and resistivity as functions of density and lithotypes; Figure 2(d) shows density as a function of depth and lithotypes. According to the cross-correlation, we can develop the following statistical models:

$$f(V_{pi}, V_{si}, \rho_i, r_i \mid L_i) = f(V_{pi} \mid \rho_i, L_i) f(V_{si} \mid \rho_i, L_i) \times f(r_i \mid \rho_i, L_i) f(\rho_i \mid z, L_i). \quad (4)$$

From Equation (4), we can see that depth dependence of seismic velocity and resistivity is carried out by density and the spatial correlation of those quantities is carried out by lithotypes.

Effects of Statistical Rock-physics Prior Models

We first investigate the effects of statistical rock-physics models on the estimated geophysical attributes by inverting synthetic 1D seismic data. Figure 3 compares the inversion results with their corresponding true values (black curves with circles) without using statistical prior models. Figure 4 shows similar results but with the use of statistical rock-physics prior models. Table 1 shows the RMS of differences between the true values and the medians and averaged width of 95% predictive intervals for above two cases. From those figures and table, we can see that the use of statistical rock-physical models improves the estimates of seismic attributes significantly, especially for density estimation. Another benefit of using statistical rock-physical models is that we can also directly estimate the probability of being oil sand.

Estimation of oil sand

Since the primary goal of exploration is to identify the presence of oil sand, we compare the estimated oil sand with the true values at CDP-766 using synthetic 1D convolution seismic data and 2D EM data. Figure 5(a) shows the true lithotypes as a function of depth, where values 0, 1, and 2 represent shale, brine sand, and oil sand, respectively. Figure 5(b) shows 6000 realizations of lithotypes, where red color represents oil sand. We can see that the inversion correctly identifies the presence and location of the major oil reservoir. Figure 6 shows similar results but using the synthetic 2D elastic seismic data and 2D EM data. We can see that given the difference between the 2D models for generating seismic and EM data and 1D convolution seismic and 1D layered EM models for inversion and given various sources of uncertainty, we can still correctly estimate the presence of oil sand.

Conclusions

We developed a Bayesian method based on statistical rock-physics models and Markov random fields. Synthetic case studies show that the developed model is effective for joint inversion of seismic and EM data and the use of statistical rock-physics models improve the inversion results. However, improvements are needed for addressing unpleasant features showing in the estimates of the shallow part between depth 2100-2200m in Figures 5 and 6.

Acknowledgments

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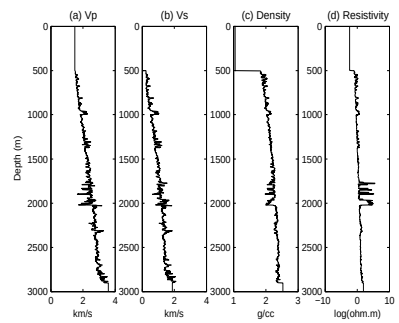

Figure 1: Borehole logs at CDP-1520 as functions of depth

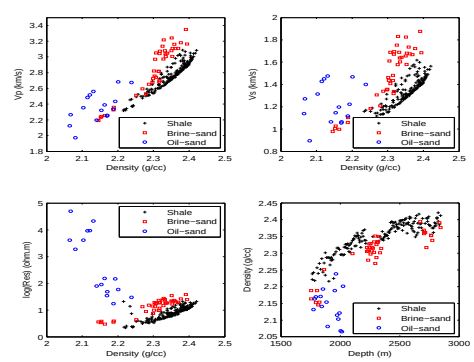

Figure 2: Cross-correlation among various seismic and electrical attributes, derived from borehole logs at CDP-1135 and CDP-1520.

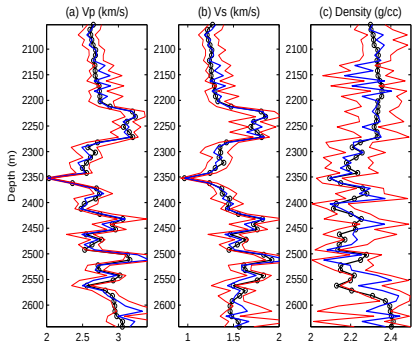

Figure 3: Estimated seismic attributes using synthetic data without using statistical rock-physics prior models.

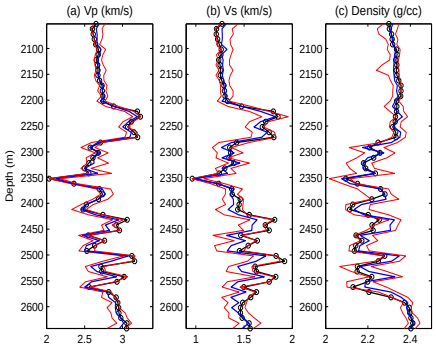

Figure 4: Estimated seismic attributes using synthetic data using statistical rock-physics prior models.

Table-1: Comparison between estimates of seismic attributes with and without statistical rock-physics models

Case	Attributes	Compared to true values (Errors: RMS)	Predictive intervals (Uncertainty: width)
No prior models	Vp	0.1054	0.2987
	Vs	0.0741	0.2482
	Density	0.0777	0.2128
Prior models	Vp	0.0794	0.1625
	Vs	0.0900	0.2054
	Density	0.0346	0.0896

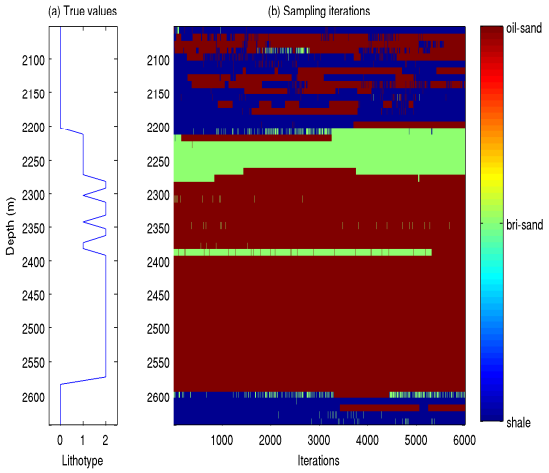

Figure 5: Comparison between the estimated lithotypes and the true lithotypes at CDP-766 using synthetic 1D convolution seismic data and 2D EM data.

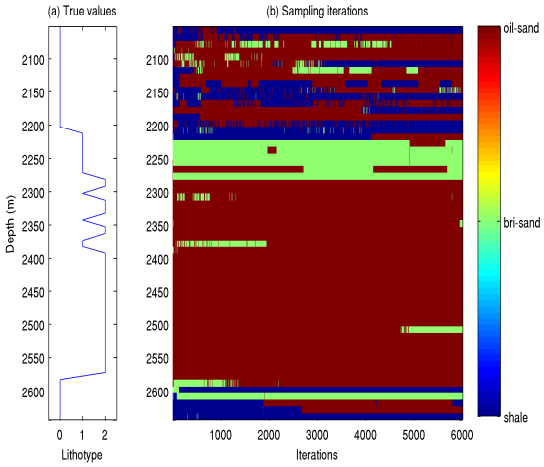

Figure 6: Comparison between the estimated seismic attributes and the true values at CDP-766 using synthetic 2D elastic seismic data and 2D EM data.

EDITED REFERENCES

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