Journal of Applied Geophysics 147 (2017) 68–80

Contents lists available at ScienceDirect

Journal of Applied Geophysics

journal homepage: www.elsevier.com/locate/jappgeo

Bayesian inversion of seismic and electromagnetic data for marine gas reservoir characterization using multi-chain Markov chain Monte Carlo sampling

Huiying Ren [a,*], Jaideep Ray [b], Zhangshuan Hou [a], Maoyi Huang [a], Jie Bao [a], Laura Swiler [c]

[a] Pacific Northwest National Laboratory, Richland, WA, USA
[b] Sandia National Laboratories, Livermore, CA, USA
[c] Sandia National Laboratories, Albuquerque, NM, USA

ARTICLE INFO

Article history:
Received 19 September 2016
Received in revised form 28 June 2017
Accepted 10 October 2017
Available online 17 October 2017

Keywords:
Seismic Amplitude Versus Angle
Controlled-Source Electromagnetic
Joint inversion
Bayesian
Multi-chain Markov-chain Monte Carlo

ABSTRACT

In this study we developed an efficient Bayesian inversion framework for interpreting marine seismic Amplitude Versus Angle and Controlled-Source Electromagnetic data for marine reservoir characterization. The framework uses a multi-chain Markov-chain Monte Carlo sampler, which is a hybrid of DiffeRential Evolution Adaptive Metropolis and Adaptive Metropolis samplers. The inversion framework is tested by estimating reservoir-fluid saturations and porosity based on marine seismic and Controlled-Source Electromagnetic data. The multi-chain Markov-chain Monte Carlo is scalable in terms of the number of chains, and is useful for computationally demanding Bayesian model calibration in scientific and engineering problems. As a demonstration, the approach is used to efficiently and accurately estimate the porosity and saturations in a representative layered synthetic reservoir. The results indicate that the seismic Amplitude Versus Angle and Controlled-Source Electromagnetic joint inversion provides better estimation of reservoir saturations than the seismic Amplitude Versus Angle only inversion, especially for the parameters in deep layers. The performance of the inversion approach for various levels of noise in observational data was evaluated — reasonable estimates can be obtained with noise levels up to 25%. Sampling efficiency due to the use of multiple chains was also checked and was found to have almost linear scalability.

1. Introduction

Successful marine gas reservoir characterization requires accurate estimation of reservoir properties such as porosity and fluid/gas saturations, and the quantification of errors/uncertainties in these estimates. Controlled-Source Electromagnetic (CSEM) data are known to be sensitive to the presence of hydrocarbons — as shown in Archie's law (Archie, 1942), the electrical resistivity of reservoir rocks is highly sensitive to gas saturation through the link to water saturation. Such a dependence of bulk resistivity on gas saturation makes it possible to discriminate between economic and non-economic gas saturations. However, the CSEM data are insensitive to geological structural details, which makes standalone CSEM inversion challenging to interpret. Seismic data, on the other hand, provide detailed structural information and can help resolve rock properties such as porosity, but cannot distinguish fluid properties given the inadequate contrast in density and seismic velocities. Since seismic velocity and density have low sensitivity to variations in gas saturation (Castagna and Backus, 1993; Dębski and Tarantola, 1995; Plessix and Bork, 2000), both fluid and pressure changes have approximately the same degree of impact on the seismic Amplitude Versus Angle (AVA) data according to Gassmann's equations (Gassmann, 1951). The two types of data (seismic AVA and CSEM) can therefore be used as supplementary information to each other to provide adequate constraints on reservoir properties. There have been successful applications of joint inversion of seismic AVA and CSEM data for characterizing marine reservoirs (e.g., Aki and Richards, 1980; Chen et al., 2007; Du and MacGregor, 2010; Fliedner et al., 2011; Hou et al., 2006; Lang and Grana, 2015).

Although joint inversion of seismic AVA and CSEM data can provide better estimates of gas saturation and porosity than inversion of individual data sets (Chen et al., 2004; Chen et al., 2007; Hou et al., 2006), the integration of two types of data can be challenging due to the high dimensionality of the unknown parameter space. Consequently, parameter estimates and their uncertainties may vary significantly given the choice of inversion approaches (e.g., deterministic versus stochastic), designs of objective and likelihood functions and the transformation and weighting of observational data.

* Corresponding author at: Pacific Northwest National Laboratory, PO Box 999, Richland, WA 99352, USA.
E-mail address: Huiying.Ren@pnnl.gov (H. Ren).

https://doi.org/10.1016/j.jappgeo.2017.10.004
0926-9851/

In typical geophysical characterization, the existence of noise and the inadequacy (e.g., spatial and temporal coverage and resolution) of the data imply that the problem is ill constrained and therefore, geophysical characterization is a good target for statistical inference. Since there is usually an infinite number of models that can fit the data, it is useful to employ stochastic approaches (e.g., Bayesian), where unknowns are inferred in the form of a posterior probability density function (PDF), thus automatically quantifying the uncertainty in the estimates of the unknowns. The estimation problem is posed as a statistical inverse problem, which provides an expression for the posterior density (alternatively, the joint PDF of the unknowns of interest). The PDF is realized by drawing samples using a method such as Markov chain Monte Carlo (MCMC). MCMC (Liang et al., 2011) methods describe a random walk in the parameter space. Each step in the walk is evaluated by running a forward model to gauge the quality of a new parameter proposal (alternatively, a proposed step in the random walk). Most proposed steps are rejected, making MCMC very expensive, since a sufficient number of samples need to be taken to recover the PDF. To reduce computational time, multi-chain (i.e., parallel) MCMC methods have been developed. Our MCMC procedure starts with 4 chains running DREAM (DiffeRential Evolution Adaptive Metropolis; Vrugt et al., 2009). When a sufficient number of samples have been collected by DREAM to make a useful proposal distribution, the MCMC method transitions to a parallel (4 chains) AM (Adaptive Metropolis; Haario et al., 2006), implemented in a manner identical to Solonen's method (Solonen et al., 2012).

In our paper, we considered a five-layer reservoir model, similar to the synthetic model setup in (Hou et al., 2006), to demonstrate the accuracy and efficiency of the newly developed multi-chain MCMC-Bayesian approach. The unknowns include gas saturation and porosity in each layer in the reservoir. We also investigated the performance of the proposed approach under different levels of noise in both seismic AVA and CSEM observational data, and evaluated the efficiency and scalability of the multi-chain MCMC.

The paper is organized as follows. Section 2 introduces the methodology, followed by the results and discussions in Section 3. Concluding remarks are presented in Section 4.

2. Methodology

2.1. Seismic AVA and CSEM modeling

In seismic modeling, the reservoir variables of interest are porosity (φ), water ($\mathbf{S_w}$) and gas saturation ($\mathbf{S_g}$) within the reservoir. The Zoeppritz equation (Aki and Richards, 1980) was used to model the angle-dependent reflectivity, which is convolved with the compressional wave reflection coefficient to form the calculated seismic AVA responses (Shuey, 1985). ρ, V_p and V_s (density, compressional and shear wave velocities) of the reservoir are calculated from water and gas saturation and porosity using a rock-physics model as described by Dvorkin and Nur (1996) and Hoversten et al. (2003). The model parameters are adopted from Chen et al. (2007). The bulk and shear moduli and density are assumed known, and in practice can be obtained from nearby well logs or can be included in the unknown parameters to be inverted.

CSEM data are the amplitude and phases of the recorded electrical field as a function of frequency and transmitter-receiver offsets. This data is gathered at 21 receivers located on the seafloor. CSEM data are the responses to the electrical conductivity of the entire half-space, which includes the seawater ($\boldsymbol{\sigma_s}$), the overburden ($\boldsymbol{\sigma_o}$) above the reservoir, the reservoir and the bedrock beneath the reservoir. For the EM forward model, we applied an integral-equation solution for the electric field from an electric-dipole source within a layered medium (Ward and Hohmann, 1988). The sensitivity of electrical resistivity of reservoir rocks linked to water saturation can be modeled by Archie's law (Archie, 1942).

We assumed that the rock-physics models and Archie's law (which relate seismic velocity density and electrical conductivity) are given and exact. The pore pressure was also assumed to be constant. We also assume the effects of multiple reflections and waveform spreading can be neglected in seismic AVA data. The rock-physics model and Archie's law parameters used in our inversion are listed in Table 1.

2.2. Bayesian framework

We first explain the basic formulation of a Bayesian inverse problem and then adapt it for our problem. Consider a model $\mathbf{Y} = \mathcal{M}(\theta)$, which is driven by parameters θ. Consider, too, that we have observations $\mathbf{Y}^{(obs)} = \{y_j^{(obs)}\}$, $j = 1 \ldots M$, of $\mathbf{Y}$. So $\mathbf{Y}^{(obs)}$ is a vector of M observations. We seek to infer θ from $Y^{(obs)}$. We relate the model predictions to the observations using an error model, in our case, a Gaussian with zero mean

$$\mathbf{Y}^{(obs)} = \mathcal{M}(\theta) + \boldsymbol{\varepsilon}, \boldsymbol{\varepsilon} = \{\varepsilon_i\}, \varepsilon_i \sim \mathcal{N}\left(0, \sigma^2\right). \tag{1}$$

Here ε_i are the “errors” or the model-data mismatch. It is a composite of the measurement error and, in real-data inversion, the structural error. The structural error is the mismatch between observations and model predictions due to “missing physics” i.e., model approximations. Under this formulation, the likelihood of observing a single observation $y_j^{(obs)}$, for a given value of θ, is

$$\begin{aligned} f\left(y_j^{(obs)}\middle|\theta\right) &= \frac{1}{(2\pi)^{1/2}\sigma} \exp\left(-\frac{\varepsilon_j^2}{2\sigma^2}\right) \\ &= \frac{1}{(2\pi)^{1/2}\sigma} \exp\left(-\frac{\left(y_j^{(obs)} - \mathcal{M}^j(\theta)\right)^2}{2\sigma^2}\right) \end{aligned} \tag{2}$$

where $\mathcal{M}^j(\theta)$ is the jth component of the model prediction. Consequently, the likelihood $f(\mathbf{Y}^{(obs)}|\theta)$ of observing the data $\mathbf{Y}^{(obs)}$ for any given value of θ, is given by

$$f\left(\mathbf{Y}^{(obs)} \mid \theta\right) = \prod_j^M f\left(y_j^{(obs)}|\theta\right) = \frac{1}{(2\pi)^{\frac{M}{2}}\sigma^M} \exp\left[-\frac{\left\|\mathbf{Y}^{(\mathbf{obs})} - \mathcal{M}(\theta)\right\|_2^2}{2\sigma^2}\right] \tag{3}$$

where $\|\cdots\|_2$ is the L_2 norm. If one has two types of observations $\mathbf{Y}_1{}^{(obs)}$ and $\mathbf{Y}_2{}^{(obs)}$, of lengths M_1 and M_2, corresponding to two models driven

Table 1
The rock-physics model and Archie's law parameters used in the inversion.

Inversion domain (each layer)	Inversion domain thickness	50
	Pore pressure (GPa)	19.03
	Effective pressure (GPa)	5.84
	Temperature (°C)	55
Reservoir (rock-physics model parameters)	Grain shear pressure (GPa)	40.3278
	Grain Poisson ratio	0.05987
	Grain density (kg/m^3)	2759.64
	critical porosity	0.37
	Number of grain contacts	11.7766
	Oil API gravity	59
	Gas gravity	0.03625
Archie's law coefficients	Archie's law constant	0.46426
	Water saturation exponent	– 1.8646
	Porosity exponent	– 1.3855