Risk Reduction in Gas Reservoir Exploration Using Joint Seismic-EM Inversion

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A method for identification of gas saturation in deep ocean oil-gas reservoirs, which combines data obtained from seismic with electromagnetic surveys, is presented. Researchers from the University of California, Berkeley, and Lawrence Berkeley National Lab test their ideas using synthetic and real-life data from the Troll Gas Province in the North Sea and prove the potential for significant exploration risk reduction.

The prediction of reservoir parameters such as gas or oil saturation or both from geophysical data is the goal of most geophysical surveys performed in the context of hydrocarbon exploration and production. Interpretation of geophysical data is rarely a trivial task, but is particularly challenging in the case of gas exploration.

Current seismic imaging technology cannot accurately discriminate between economic and non-economic concentrations of gas. This is primarily because of the insensitivity of acoustic (V_p) and shear (V_s) wave velocities to gas saturation. According to Gassmann's equations, a gas sand with 1% gas saturation can have the same V_p/V_s as a commercial accumulation of gas.

In recent years, the focus of oil-related geophysical exploration has been on using time-lapse seismic data for predicting changes in pressure and fluid saturation. Predictions of changes in pore pressure can be done when there is only oil saturation (S_o) and water saturation (S_w). The presence of gas complicates the problem by introducing a third independent variable, the gas saturation (S_g). In the case of a reservoir with an oil-water-gas mix, the determination of gas saturation is inherently non-unique.
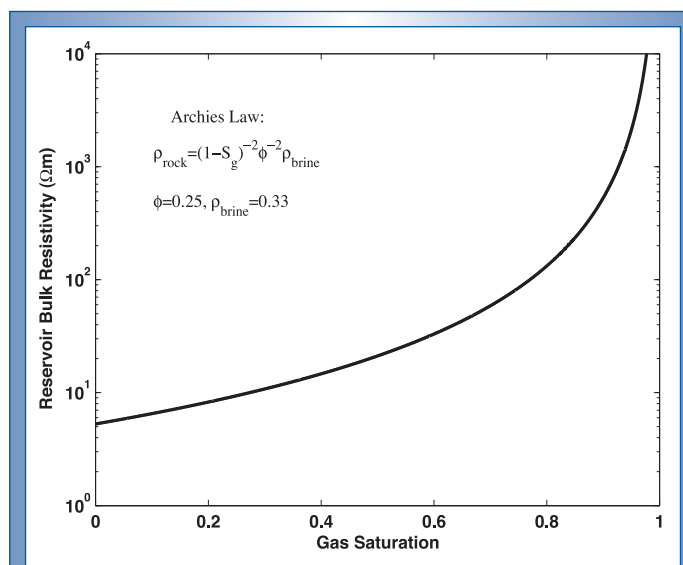

Figure 1. Reservoir bulk resistivity as a function of gas saturation (S_g). Porosity = 25%

Archies Law:

$$\rho_{rock} = (1-S_g)^{-2}\phi^{-2}\rho_{brine}$$

$$\phi = 0.25, \rho_{brine} = 0.33$$

Seismic technology can provide two critical pieces of information needed for the ultimate estimation of gas saturation: the physical location of the reservoir unit, to within a few percent of the true values; and the porosity of the reservoir unit.

In contrast to the insensitivity of seismic attributes such as V_p/V_s, AVO slope and intercept or acoustic-shear impedance to gas saturation, the electrical resistivity of reservoir rocks is highly sensitive to S_g, through the link to water saturation. This sensitivity can be seen using Archie's law, which has been demonstrated to accurately describe the electrical resistivity of sedimentary rocks. Figure 1

shows the bulk resistivity (R_{bulk}) as a function of $S_g = (1-S_w)$ for a reservoir having 25% porosity and brine salinity of 0.07 ppm. The relationship between R_{bulk} and S_g has the advantage of displaying the steepest slope in rock bulk resistivity R_{bulk} in the S_g range from 0.5 to 1.0, where the division between economic and non-economic S_g usually occurs.

The means of estimating R_{bulk} have recently become available through the use of electromagnetic (EM) sounding systems. Recently, attention has been focused on the use of controlled-source electromagnetic (CSEM) systems in direct detection/mapping of hydrocarbon. A marine CSEM system consists of a ship-towed electric dipole source and a number of seafloor deployed recording instruments capable of recording orthogonal electric fields. During the past few years, a number of contractors have begun offering marine CSEM data on a commercial basis.

The relative strengths of seismic and CSEM technologies suggest they can complement each other. Combining the two types of data should improve fluid saturation estimates in a joint inversion, since they provide different and complementary images of the geology. This is not a new idea, and studies along this line were reported, such as Hoversten et al.,

2003. This article develops a new systematic approach for application and illustrates the benefits of joint amplitude vs. angle (AVA) and CSEM inversion for estimating gas saturation and porosity.

A strategy for marine natural gas exploration

Several challenges need to be addressed before joint AVA-CSEM inversion can become routine: (a) different types of data, as well as data obtained from different sources, are characterized by different error levels, which are not always known prior to the inversion. Thus, methods are needed for modeling such errors with minimum bias, while assigning proper weight to the different data; (b) deterministic inversion – one which assumes unknown parameters can be uniquely defined – is in general an ill-posed mathematical problem because of non-uniqueness and instability of the inverse problem. This in turn suggests that inversion formulated in a stochastic framework – one which views the unknown parameters as random variables, in a statistical sense – may be more robust than traditional deterministic approaches, and must be formulated rigorously; and (c) prior information is available, in many cases, to constrain the inversion in reservoirs. Such data may be available, for example, from geologically similar formations, but its incorporation into stochastic inversion requires answering questions such as what relative weight the prior information should be assigned compared with direct measurements, and what would be a rational approach for incorporating prior information into a stochastic framework for inversion.

Data used for inversion

Seismic data used for this study are the pre-stacked seismic time series at several incident angles along depth, typically representing two-way travel times. After appropriate seismic processing, including amplitude recovery, we will assume the seismic attenuations in the earth

above the target interval (the overburden) have been accounted for and can be neglected in the seismic modeling. We can choose to invert seismic V_p and V_s and density in the zones outside the reservoir, and invert gas saturation and porosity within the reservoir.

Marine EM data used in this study include the amplitudes and phases of the recorded electrical field from many receivers on the seafloor. The EM amplitudes and phases, along with the applied current and transmitter locations, are recorded as time series, which are then averaged to produce in-phase and out-of-phase electric field. Those data are the responses to the electrical conductivity in the space that includes seawater, overburden above the gas reservoir, gas reservoir and bedrock below the reservoir.

Inversion approach

Designating the inversion target parameters as random variables offers a rational way of modeling the uncertainty because of measurement errors, data scarcity and spatial variability. We represent the inversion target parameters by a vector m the composition of which can change between reservoirs, but in general it contains saturation of various layers, porosities, resistivities, etc. To account for parameter uncertainty, m is viewed as a realization of a random vector M which is characterized by a p-variate probability distribution function (pdf), $f(m)$, where p is the number of parameters in M. Our inversion approach is based on Bayes' Theorem

$$f(m) \propto f(d^*|m,I)\,f(m|I),$$

that identifies $f(m)$, known as the posterior (or a-posteriori) pdf, as a function proportional to the product of a prior (or a-priori) pdf, $f(m|I)$, and a likelihood function, $f(d^*|m,I)$. The symbols to the right of the vertical bar denote information, given or assumed. The prior pdf, $f(m|I)$, summarizes, in a statistical form, the information available on the parameters vector M prior to the EM and seismic surveys. It represents the probability of M to assume the set of values m, given prior informa-

tion I, consisting of information such as expertise gained in other parts of the reservoir, relevant borehole information, as well as information and expertise borrowed from other, geologically-similar formations. There can be many physically plausible combinations to m, and $f(m|I)$ assigns to each of them a different probability according to how realistic or unrealistic it is, in light of I. This opens the door for subjectivity, which can be detrimental. One of the challenges in using priors is minimizing the subjectivity associated with its formulation. Our approach is to select the prior pdf that minimizes the subjectivity using entropy-based measures of information. We refer to this approach as minimum relative entropy (MRE). The likelihood function, $f(d^*|m,I)$, represents the probability of observing the data vector, d^*, which includes data obtained from the EM and seismic survey, given m and I. It provides the means for updating the prior pdf with new information gleaned from d^*. The likelihood function maps the prior into the posterior pdf: it assigns larger probabilities to those m that make observing d^* more probable, and smaller probabilities to those m that make observing d^* less probable.

Application I. Synthetic data

To illustrate the performances of the individual and combined inversion of seismic and EM data, we constructed a simple model (Figure 2) from which we generated the synthetic seismic and EM datasets, assuming the rock properties to be known. The gas saturation values (S_g) and porosities (ϕ) of the layers are shown from top to bottom, in Table 1.

The synthetic AVA is sampled 80 times at

Table 1. The gas saturation values and porosities of the layers from top to bottom

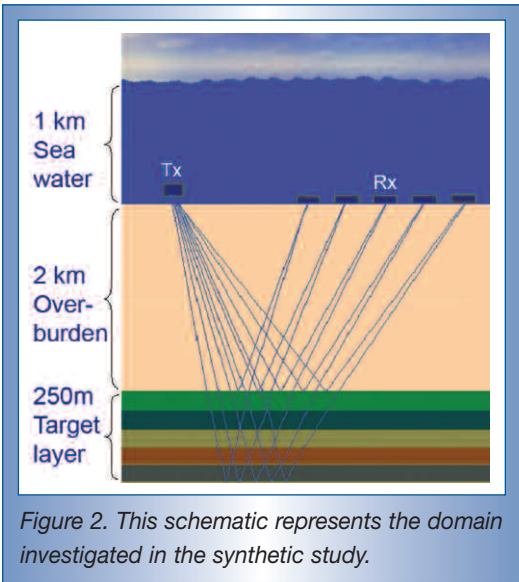| Target Layer	S_g	ϕ
1	0.10	0.15
2	0.95	0.25
3	0.40	0.15
4	0.90	0.10
5	0.10	0.05

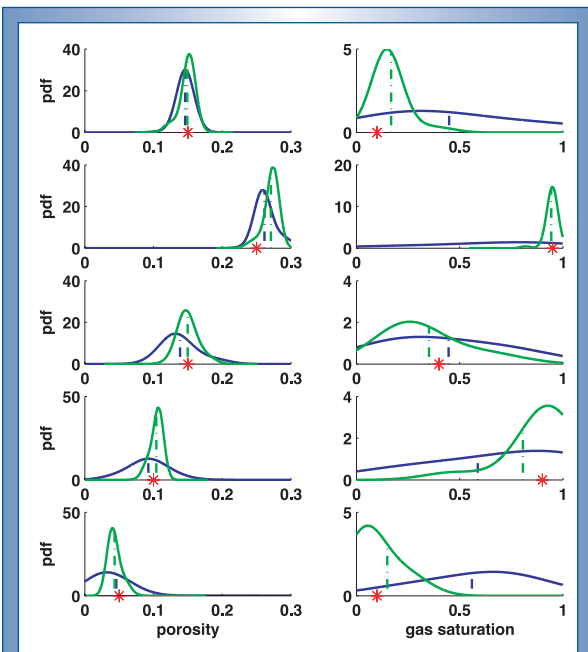Figure 2. This schematic represents the domain investigated in the synthetic study.

Figure 3. This graph shows the estimated porosity and gas saturation using seismic data only inversion (blue lines) and joint inversion (green lines). The true values are represented by red star symbols, and the solid lines represent the posterior probability distribution function obtained from inversion. The dash-dotted lines represent the posterior means.

2ms for five incident angles. The synthetic EM data includes the amplitude and phase of the measured electric field at frequencies 0.25 Hz, 0.75 Hz and 1.25 Hz, for 15 source-receiver offsets. Gaussian random noise was added starting with 10% noise for the first

angle and increasing up to 30% for the far angle. Similarly, 10% Gaussian noise was added to the electric fields at the near offsets, increasing to 30% for the maximum offset.

Figure 3 (blue lines) shows the results from a seismic-only inversion. The results are given in the form of the pdfs of the target statistics. The mode of a pdf is the most likely estimate, and the mean of the distribution is another acceptable estimate. When an estimate is accompanied by a widely spread pdf, there is only limited confidence in it. On the other hand, narrower pdfs, with well-defined modes, indicate high confidence in the estimates. Figure 3 (blue lines) shows that porosity estimates are quite accurate, with the associated uncertainty increasing with depth. The gas saturation estimates, on the other hand, are poor, as expected.

Results obtained after augmenting the seismic data with EM synthetic data are shown as green lines in Figure 3. The joint inversion provides better estimates of gas saturation at all layers. Although the uncertainty levels for the bottom layers are still not small, the modes of the pdfs are close to the true values, thus all gas-rich or water-rich layers are well identified through the maximum likelihood estimates. As stated above, up to 30% noise is introduced into both measurements and forward model responses, and large predictive bounds are not unexpected.

Application II. Troll field study

In this section, we apply our MRE-based Bayesian approach to the Troll field site in the North Sea. At the study site, hydrocarbon-filled sands occur at a depth of about 1,400m below sea level. The well log from a nearby

borehole shows a predominantly oil zone between 1,544.5-m and 1,557.5-m depth. The Bayesian model for this application was developed based on the geometry shown in Figure 4. We divided the reservoir into 16 layers, each of which having a thickness of 20m. The unknowns are S_w, S_g, S_o, and ϕ for each of these target layers. For seismic AVA data inversion, we also consider V_p, V_s and bulk density ρ at each of the five layers above and the one layer below the reservoir as unknowns, with each layer having a thickness of 20m. For the EM data inversion, we divided the reservoir overburden (including seawater) into 13 layers, based on resistivity logs from a nearby well, and considered the electrical conductivity of each layer as unknown.

In practice, information on the reservoir parameters is available, for example, in the form of bounds and/or expectation values (prior means), which can be obtained from the site geology or from other sites explored in this province. With only information about the bounds, the priors assume uniform distributions. Given information about the bounds as well as the prior means, the priors take the form of truncated exponential distributions, based on MRE theory.

We performed inversions using seismic AVA data and EM data individually, as well as a joint inversion using both types of data. The results shown (figures 5 and 6) are for AVA-only and joint AVA-EM respectively, using truncated exponential priors.

By comparing the results from seismic only inversion (Figure 5) to the joint inversion (Figure 6), we can see that the joint inversion improved the predictions of the target parameters, leading to much narrower predictive intervals, especially for the gas saturation estimates at the bottom layers. The predictions obtained for the water and oil saturations are closer to the well log observations.

Compared with the results generated using uniform priors, the predictive intervals of almost all the target parameters are narrower, and the estimated posterior modes are
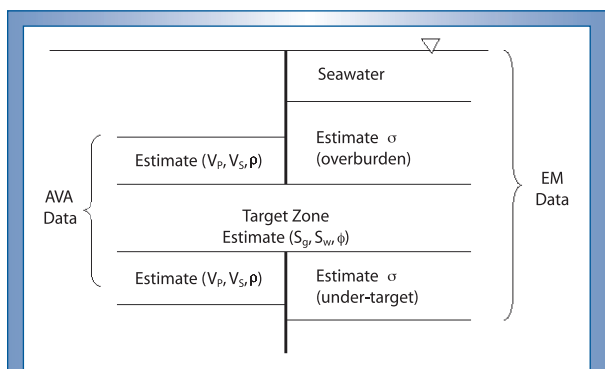
Figure 4. This schematic map shows the inversion domain.

closer to the well-log values. These results are expected, since more information is included when using bounds and means priors compared with the case where only uniform bounds are available.

The seismic and EM observations and the model responses calculated using the posterior modes of the parameters from joint inversion are plotted in figures 7 and 8, respectively. The figures show that the model responses match the observations well.

Discussion and conclusions

We proposed here an MRE-Bayesian approach for joint seismic and EM inversion. Our results using synthetic data indicate that joint inversion based on seismic and EM data improves our capability to identify and confirm the locations of gas-rich layers. Incorporation of EM data in the inversion is useful in improving predicted gas saturations. The approach is also applied to field data at Troll field in the North Sea. Results show the benefits of including EM data with seismic data in the inversion. Compared with any individual inversion using seismic or EM data, the

joint inversion gives predictions that are generally closer to well logs and yields narrower predictive intervals.

The advantage of formulating the inverse problem in a stochastic framework is manifested in the statistics of the target parameters. Instead of the usual single-valued estimation provided by deterministic approaches, we obtain a probability distribution, which allows computing mean, mode and confidence intervals and is useful for a rational evaluation of uncertainty and risk. Moreover, the MRE-Bayesian framework improves estimation results when incorporating informative priors.

We made several important assumptions in the study. We assumed a one-dimensional layered model can represent the earth. This assumption may be inappropriate for high frequency EM datasets at large offsets, since higher frequency EM responses are more easily affected by three-dimensional structures

of the earth. For seismic data inversion, we assumed the effects of multiples and waveform spreading can be neglected. We also assumed the rock physics model parameters developed from the well logs nearby are true for our study site. These assumptions can be relaxed by increasing the complexity of the seismic and EM models. For example, we can use one-dimensional elastic seismic calculation with waveform spreading, mode-conversions and all multiples; or we can consider quasi-two-dimensional, two-dimensional or even three-dimensional forward models.

The limitations described above notwithstanding, we have shown that combining CSEM with seismic data through joint inversion significantly reduced the risk of making an error when trying to identify gas-rich layers. We continue to pursue this topic. For more information, please email *rubin@newton.berkeley.edu* ✧
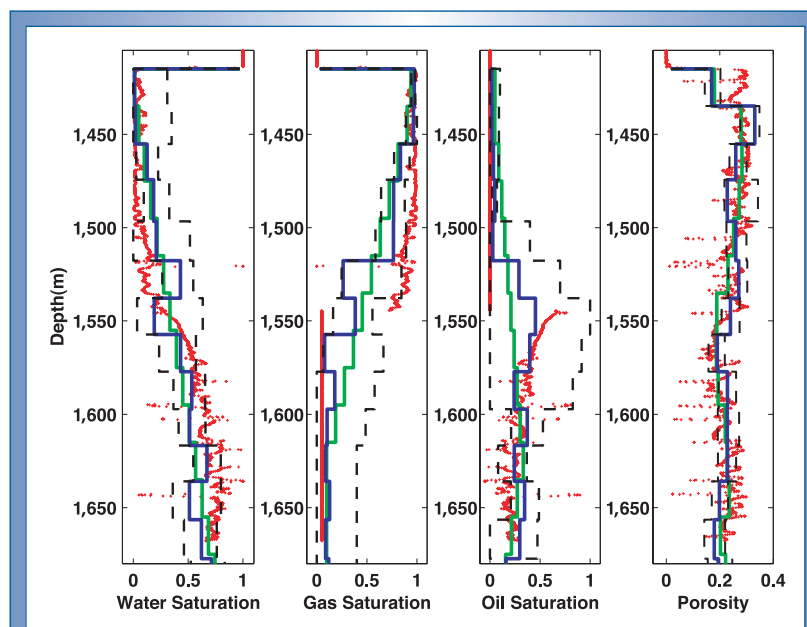
Figure 5. This graphic shows an inversion using only seismic data with information about prior means. Red crosses represent well log values, green lines are the prior means, blue lines are the estimated posterior modes, and black lines represent 99% predictive intervals.
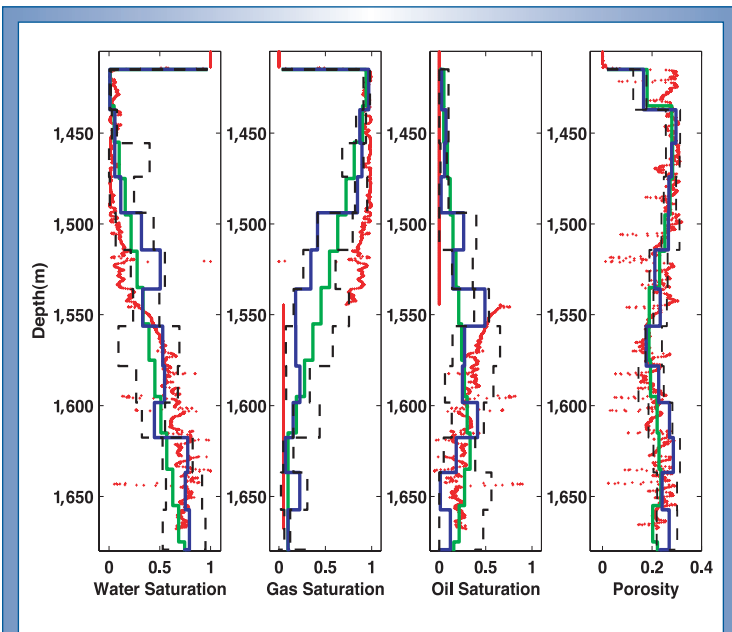
Figure 6. This graphic is a joint inversion using seismic and electromagnetic data, with information about prior means. Red crosses represent well log values, green lines represent the prior means, blue lines represent the estimated posterior modes, and black lines represent 99% predictive intervals.
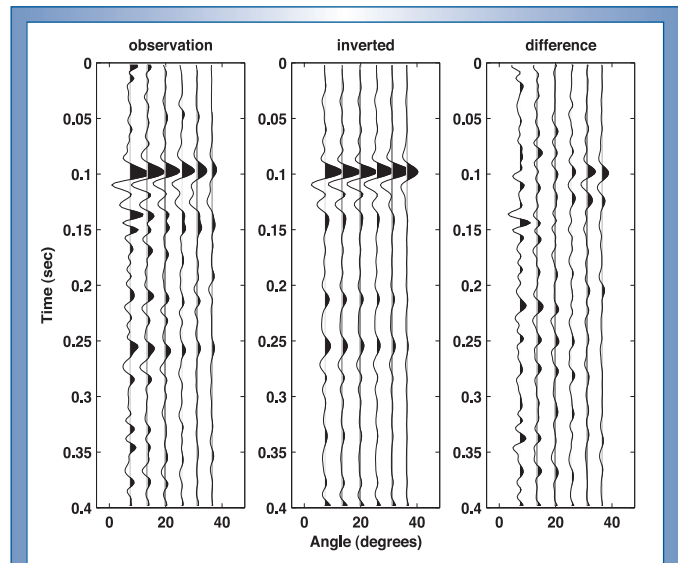

Figure 7. The above graphic shows observed seismic amplitude vs. angle (AVA) gather (left panel), calculated AVA data from seismic only inversion (middle panel) and the difference between observed and calculated AVA data (right panel). Zero time corresponds to the top of the seismic inversion zone 100m above the reservoir. The top and base of the gas reservoir are at 0.1 seconds and 0.37 seconds.

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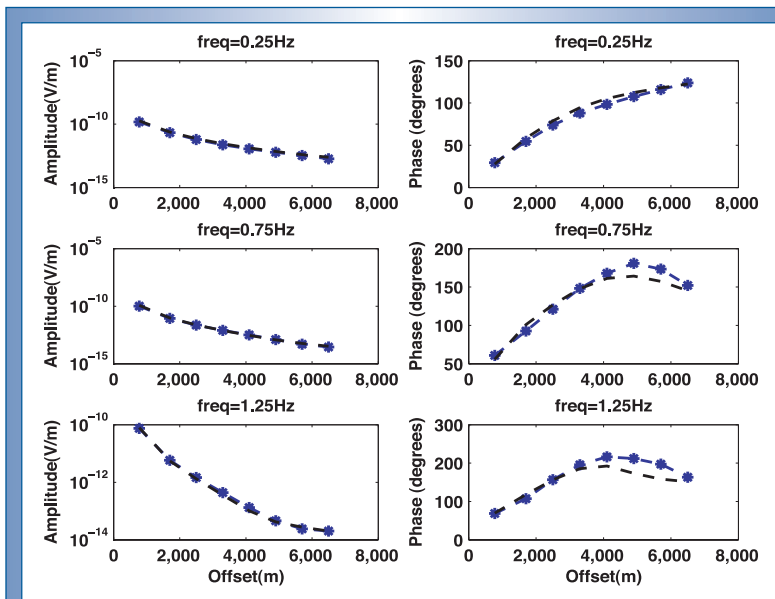
Figure 8. The above graphic shows observed controlled source electromagnetic data and calculated data from joint inversion. The blue lines represent the field data, black lines represent the calculated data.