Copenhagen '12

A014

Uncertainty Analysis of Velocity to Resistivity Transforms for Near Field Exploration

D. Werthmüller* (University of Edinburgh), A.M. Ziolkowski (University of Edinburgh) & D.A. Wright (University of Edinburgh)

SUMMARY

Joint analysis of seismic and electromagnetic data is difficult because the data sets lack a common physical parameter, and rock physics is usually applied to link the two methods via porosity. However, rock physics parameters are not well known in near field exploration, and estimates are likely to have large errors associated with them. In this work, we use the Gassmann equation to link velocity to porosity, and the self-similar model to link porosity to resistivity. We calculate a simple depth-trend from the data, and estimate the uncertainty of our model. We apply our methodology to well logs from the North Sea. We show that the background resistivities of a field can be modelled by (1) calibrating the rock physics model on a well log from an adjacent field (including a depth-trend), and (2) calculating the corresponding uncertainty. This method is a useful tool for joint analysis of seismic and electromagnetic data.

Introduction

Joint analysis of seismic and electromagnetic data are a particular focus with the commercialization of marine Controlled-Source EM (CSEM) methods in the last decade. A possible approach to combine these data is to obtain resistivity estimates from seismic data. This usually involves rock physics as a link, as there is no common physical parameter (Ziolkowski and Engelmark, 2009). There are two steps: first, to transform velocity to porosity and, second, to transform porosity to resistivity. Carcione et al. (2007) presented an extensive overview of cross-property relations specific to seismic and electromagnetic data. Engelmark (2010) emphasizes the importance of background (shale) modelling for EM inversions, and the depth-dependence of rock physics models. However, any rock physics model has an extrinsic uncertainty from the parameters, and an intrinsic uncertainty from the model. Chen and Dickens (2009) present a strategy to calculate these uncertainties.

We combine these methods, rock physics modelling, depth-trend, and uncertainty analysis, and apply our methodology to well data from the North Sea Harding Field (Beckly et al., 2003), where a successful electromagnetic repeatability experiment was carried out, Ziolkowski et al. (2010).

First, we explain our chosen rock physics model and the applied depth trend. We then show the result of the uncertainty analysis, and apply our method to a near field exploration scenario.

Rock Physics Model

Elastic and electromagnetic waves share no physical parameters and have very different spatial resolution (e.g. Ziolkowski and Engelmark, 2009). This fundamental obstacle to combining these two types of data is usually tackled in two steps: first, velocities are transformed into porosities and, second, porosities are transformed into resistivities. Carcione et al. (2007) give an extensive overview of cross-property relations between elastic and electromagnetic waves. These and more rock physics models are presented in Mavko et al. (2009), and all equations in this section can be found in that book.

We use a Gassmann-based relation for the transformation from velocity to resistivity,

$$v = \sqrt{\frac{K_G + 4G_m/3}{(1-\phi)\delta_s + \phi\delta_f}}\,, \tag{1}$$

where δ_s and δ_f are the density of the solid and the fluid fraction respectively, and ϕ is porosity. The Gassmann bulk modulus K_G is given by

$$K_G = \frac{K_s - K_m + \phi K_m(K_s/K_f - 1)}{1 - \phi - K_m/K_s + \phi K_s/K_f}\,, \tag{2}$$

where K_s and K_f are the bulk moduli of the solid and the fluid fraction respectively. The dry bulk and shear moduli, K_m and G_m, are calculated using Krief's relations,

$$K_m = K_s(1-\phi)^{3/(1-\phi)}\,, \quad G_m = G_s(1-\phi)^{3/(1-\phi)}\,, \tag{3}$$

where G_s is the shear modulus of the solid fraction. This model must be solved iteratively to yield porosity ϕ for a given P-wave velocity v.

For the transformation from porosity ϕ to resistivity ρ, we use the self-similar model,

$$\rho = \left(\frac{\rho - \rho_s}{\rho_f - \rho_s}\right)^m \rho_f \phi^{-m}\,, \tag{4}$$

where ρ_s and ρ_f are the resistivities of the solid and the fluid fraction respectively, and m is the cementation exponent.

Figure 1a shows the two models for porosities $\phi \leq 45$ %, with $K_s = 20$ GPa, $K_f = 2.25$ GPa, $G_s =$ 15 GPa, $\delta_s = 2.67$ g/cm^3, $\delta_f = 1.03$ g/cm^3, $\rho_s = 10$ Ωm, $\rho_f = 0.17$ Ωm, and $m = 2$. The application to the full extent of the available logs of Well 9/23b-7 is shown in Figure 1b. The model was fitted to the well data in a thick shale layer around 1.4 km depth. The result shows a good fit around 1.4 km, but in shallower parts the resistivities are too low (resembling more the sandstone layers). It obviously does not predict the resistivities where hydrocarbons are present. The logs v^s, ρ^s are smoothed with a Hanning window over 320 log-samples (≈ 48.8 m). The smoothing is justified by the expected resolution of our CSEM data.

Depth Trend

All parameters of the rock physics model are a function of, amongst other things, pressure and temperature, and hence, to a first order approximation, a function of depth. Engelmark (2010) showed that the change of brine resistivity with changing temperature is likely to be the major influence. We apply a simple linear relationship,

$$\rho_f = \frac{1}{a + b(4 + 30d)} , \tag{5}$$

where d is depth (km), and a and b are empirically fitted constants from the well data. The red line in Figure 1b shows the result of the Gassmann/self-similar model with a depth-trend, where $a = 0.52$ and $b = 0.12$, derived from the calibration to two shale sections around 0.8 and 1.4 km depth. The result is a good fit to all shale sections of the log, resistivities that are too high for sandstone sections and too low where hydrocarbons are present.

Uncertainty Analysis

Chen and Dickens (2009) describe a methodology to account for the uncertainties related to rock physics parameters and the rock physics model itself. They describe the rock physics model as gamma distribution in a Bayesian framework, with a defined error E, and the rock physics parameters as distributions,

$$f(x|\theta) = \frac{\beta^\alpha x^{\alpha-1}}{\Gamma(\alpha)} \exp(-\beta x) , \tag{6}$$

where θ is a vector containing all model parameter distributions, $\alpha = 1/\mathrm{E}^2$, and $\beta = (\alpha - 1)/\rho_m$. Here, ρ_m is one realization of the rock physics model (Equations 1–4) with a random set of model parameters. To get the probability density function (pdf) of the whole range of possible parameters, one has to

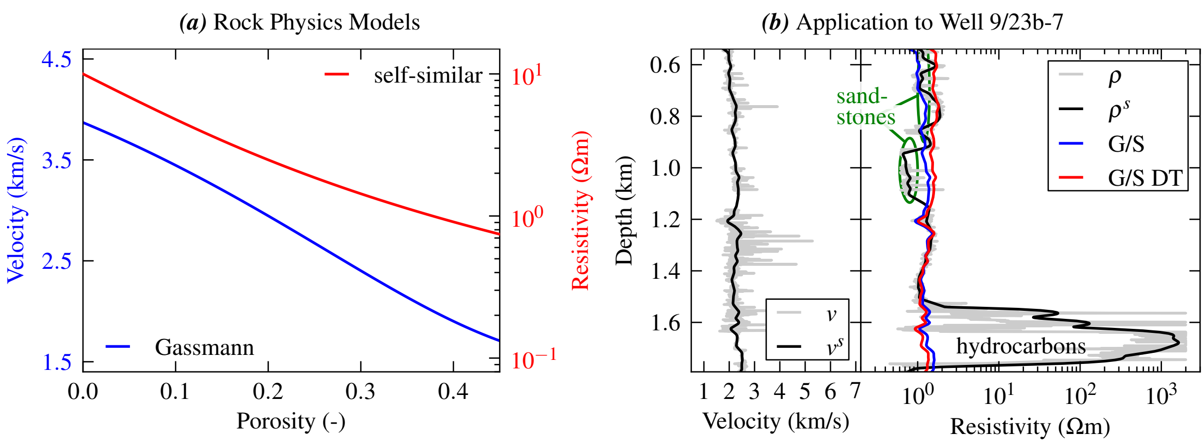

Figure 1: *(a) Gassmann and self-similar model for porosities $\phi \leq 45$ %, parameters given in the text. (b) Application of the Gassmann/self-similar model to Well 9/23b-7. v, ρ are the logs, and v^s, ρ^s are the smoothed logs.* G/S *is the Gassmann/self-similar model, and* G/S DT *is the model with a depth-trend.*

integrate over all values,

$$f(x) = \int f(x|\theta)f(\theta)d\theta \,, \tag{7}$$

for this we used a Markov Chain Monte Carlo sampler, as suggested by the authors. However, our approach differs in that we describe *all* fixed input parameters as uniform distribution around the defined value with an error $E = 5\ \%$, and we define the distribution of the velocity *from the data themselves*, as shown in Figure 2a. The distribution is defined as the difference between the log values and the values of the smoothed log, $v(z) - v^s(z)$. The pdf of this data distribution is then found by either a Gaussian with the corresponding standard deviation, or a kernel density estimation, here with a Gaussian kernel.

Figure 2b shows the outcome of the uncertainty analysis of the model in Figure 1a, together with the well log data between 1.2 and 1.5 km depth (high velocities in the well log data come from thin limestone layers). The black line shows the outcome of the rock physics model without uncertainty, the green line is the mode of the gamma distribution, and the red line shows where the probability of the gamma distribution is half the maximum value. The blue line indicates the location of the data shown in Figure 2c, an example of a pdf at velocity $v = 2.2$ km/s. Figure 2d is the same as Figure 1b, but with the result of the uncertainty analysis.

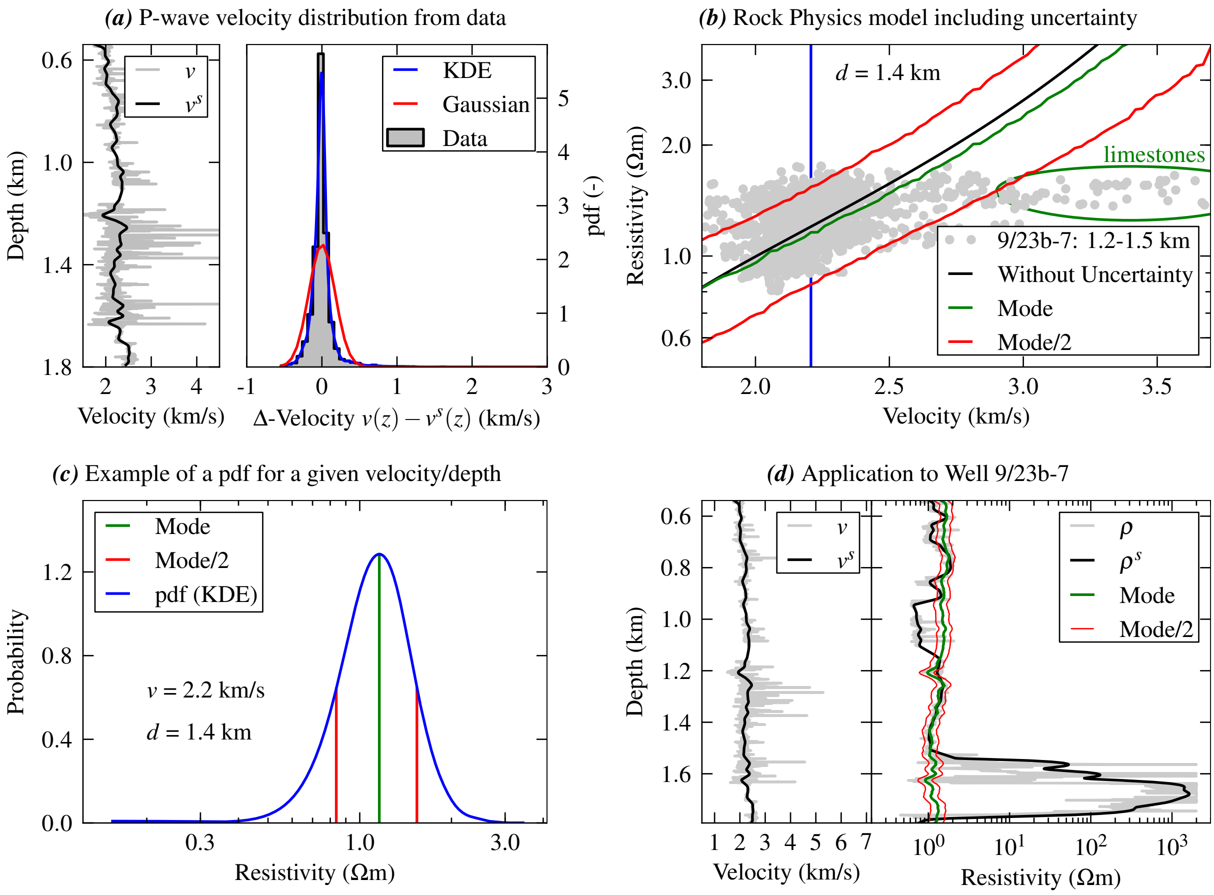

Figure 2: *(a) Estimation of P-wave velocity distribution from well log data, using a Gaussian Kernel Density Estimation, or simply a Gaussian. (b) Result of the uncertainty analysis, with well data from the calibration layer. (c) Example pdf for velocity $v = 2.2$ km/s at depth $d = 1.4$ km, corresponding to the blue line in (b). (d) Uncertainty applied to the well log.*

Near Field Exploration Simulation

We simulate a near field exploration situation, where we have knowledge from a nearby oilfield, and would like to extrapolate this knowledge to an exploration target. We calibrate our rock physics model with two shale sections around 0.8 and 1.4 km depth from Well 9/23b-8 from Harding South ($a = -1.292$ and $b = 0.189$ in Equation 5); the result is shown in the leftmost panel of Figure 3a. The same model is then applied to the wells of Harding Central, to test the robustness of the model. It shows that the model nicely predicts the resistivities of the shale sections.

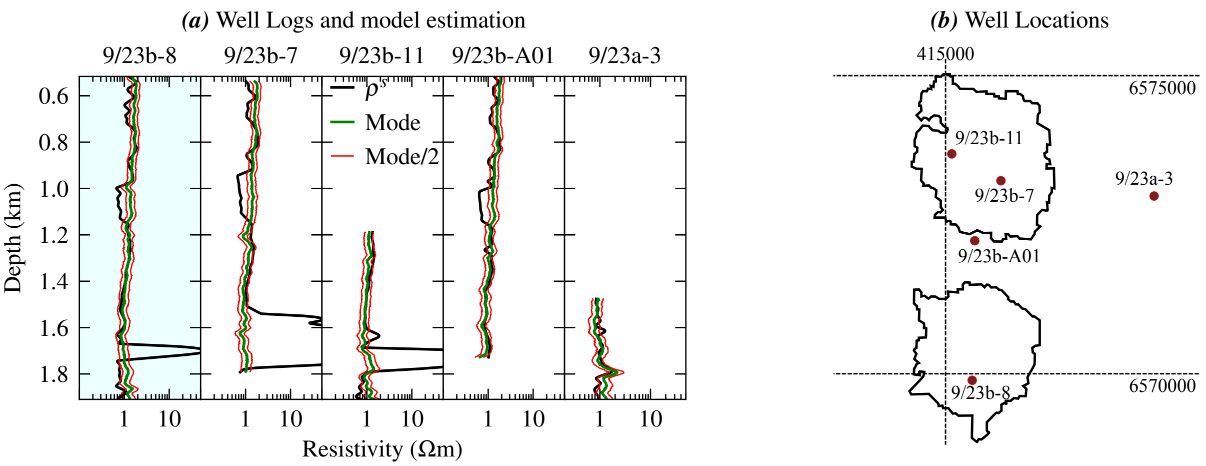

Figure 3: *(a) The model is calibrated with Well 9/23b-8 from Harding South within two shale layers around 0.8 and 1.4 km depth. The same parameters are applied to wells of Harding Central. (b) Location of the wells.*

Conclusions

Using well log data, we present an integrated approach for estimating background resistivities from seismic data, applying and extending known methods. The approach employs petrophysical cross-property relations, depth-trend estimation, and uncertainty analysis of both the data and the model. Our near field exploration example shows that this methodology yields a good estimate of background resistivities of an unknown field, and hence provides an excellent starting point for any CSEM inversion routine. Using a probability distribution instead of fixed values for the background model decreases the influence of unwanted bias that originates from the different physical properties of the seismic and EM methods.

Acknowledgements

We thank PGS for funding the research and the Harding partners, BP and Maersk, for permission to use the data.

References

Beckly, A.J., Nash, T., Pollard, R., Bruce, C., Freeman, P. and Page, G. [2003] The harding field, block 9/23b. In: Gluyas, J.G. and Hichens, H.M. (Eds.) *United Kingdom oil and gas fields commemorative millennium volume*. Geological Society Publishing House, Bath, vol. 20 of *Memoirs of the Geological Society of London*, 283–290, ISBN: 1-86239-089-4.

Carcione, J.M., Ursin, B. and Nordskag, J.I. [2007] Cross-property relations between electrical conductivity and the seismic velocity of rocks. *Geophysics*, **72**(5), E193–E204, DOI:10.1190/1.2762224.

Chen, J. and Dickens, T.A. [2009] Effects of uncertainty in rock-physics models on reservoir parameter estimation using seismic amplitude variation with angle and controlled-source electromagnetics data. *Geophysical Prospecting*, **57**(1), 61–74, DOI:10.1111/j.1365-2478.2008.00721.x.

Engelmark, F. [2010] Velocity to resistivity transform via porosity. *SEG Technical Program Expanded Abstracts*, **29**(1), 2501–2505, DOI:10.1190/1.3513358.

Mavko, G., Mukerji, T. and Dvorkin, J. [2009] *The Rock Physics Handbook*. Cambridge University Press Cambridge, ISBN: 978-0521861366.

Ziolkowski, A. and Engelmark, F. [2009] Use of seismic and EM data for exploration, appraisal and reservoir characterization. *CSPG CSEG SWLS Joint Convention Expanded Abstracts*, CSEG, 424–427, http://www.cseg.ca/conventions/abstracts/2009/2009abstracts/177.pdf.

Ziolkowski, A.M. et al. [2010] Multi-transient electromagnetic repeatability experiment over the North Sea Harding field. *Geophysical Prospecting*, **58**(6), 1159–1176, DOI:10.1111/j.1365-2478.2010.00882.x.