1 Introduction

In petrophysical inversion from logging data the tool response is modeled by a system of equations linking the volumetric composition of the rock to its physical properties. This technique has been successfully applied in reservoir evaluation using nuclear, acoustic, and electrical log data. Temperature logging, on the other hand, has played only a minor role in this scheme. We present an inversion algorithm that is able to invert simultaneously temperature logs and other wireline logs. The forward model incorporates variable layering and inclusion of shoulder effects for various tools. A Bayesian approach is used with a regularisation to solve the inverse problem. The Bayesian method offers the opportunity to use a-priori information and utilise information on the uncertainties in data and parameters in the inversion.

2 Forward Model and Inverse Method

To compute the theoretical log response a number of constituents and their log responses is defined. The depth profile is then divided into a number of layers. Each layer is assigned a volume fraction of the previously defined components with the sum of the fractional volumes equal to one (Figure 1). The thickness of the layers can vary according to the geology encountered. A natural choice for the thickness is the sampling interval of the wireline logs, or a multiple of it for noise suppression. A log response is computed for each layer. For acoustic logs an arithmetic average is used. For nuclear logs an arithmetic average and a geometric average for thermal conductivity is used.

![Figure 1: Geometry of the lithologic model.](image)

A response equation computing the log response from the layer responses is associated with each log type. Figure 2 shows how the effective log response is derived. A weighted average of the sampled layers is used for sonic logs. For nuclear logs an exponential decay model is used and for the temperature the steady-state heat conduction equation is solved.

![Figure 2: Schematic of the tool response geometry used in the forward model. From left to right: Sonic, nuclear, and nuclear tools.](image)

For the inverse scheme we use a Bayesian approach. We seek a model to minimize the nonlinear functional

\[ \min \left\{ \frac{1}{2} \left( y - A x \right)^T R^{-1} \left( y - A x \right) + \frac{1}{2} \left( x - x_0 \right)^T \Sigma^{-1} \left( x - x_0 \right) \right\} \]

where \( y \) is the measured data, \( A \) is the forward operator, and \( x \) is the model parameter. \( \Sigma \) is the input covariance matrix and \( R \) is the data covariance matrix.

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3 Synthetic Example

We use a synthetic example to test the algorithm. The forward model (shown in Figure 3 left panel) is used to compute a synthetic data set for a 100 m long section. The section consists of sand (yellow) with layers of carbonate (blue) and shale (grey). The data is fed into the inversion scheme after adding normal noise to the synthetic data set. Parameters of the forward model are shown in table 1. The input model is reproduced with a standard deviation of 0.03. (Figure 4)

![Figure 3: Synthetic Model and Fit. Outer left: Input model that has been used to compute the synthetic data set. Inner left: Inverted model. Centre: Components have been used, these can be identified as shale (grey), carbonate (blue), and sand (yellow). Middle to outer right panels: Input data and computed data. GR = gamma ray; \( \Delta t \) = acoustic slowness; \( T \) = temperature. Green lines: Original data, computed from the synthetic model. Blue lines: Synthetic data with noise added. Red Lines: Data computed from the inverted model.](image)

![Figure 4: Histogram of differences in volume content. It can be seen that the majority of the data is within ±0.05 of the input values. The standard deviation is 0.03.](image)

![Figure 5: Inversion results from a borehole in the German Molasse Basin. GR = gamma ray; \( \Delta t \) = acoustic slowness; \( T \) = temperature gradient; \( \rho_b \) = bulk density.](image)

4 Field data from the Molasse Basin

Figure 5 shows results for a borehole from the Northern Alpine Molasse Basin in Germany. The sequence consists of Tertiary Flysch (marlstones and shaly sandstones) up to 1060 m. Below follow Upper Jurassic limestones and marlstones. The temperature data was corrected for paleoclimatic effects, and environmental corrections were applied to the wireline data. The agreement between inverted and measured data is generally very good. Major deviations in the interval 1150 – 1200 are probably due to groundwater flow in the Karst regions of the Upper Jurassic.

5 Summary — Outlook

We present an inversion approach which can be used to develop geologic models for boreholes that can explain consistently wireline logging together with temperature data. The algorithm is flexible and can be adapted to suit specific needs. The method is an important step toward a joint modeling of thermal processes. Right now the paleoclimatic correction has to be subtracted before the inversion. In the future, we will incorporate a model for paleoclimate inversion to model these processes simultaneously. A similar approach will be taken for heat advection by groundwater flow. Certain configurations for groundwater flow (e.g. [3]) will be incorporated.

References