V022 STOCHASTIC INVERSION

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Introduction

In addition to traditional models, geostatistics offers a variety of methods to build a stochastic model of the reservoir. Geostatistics offers interpolation techniques that account for the spatial relationship of variables. Some advantages of stochastic modelling are:

- The impact of uncertainty on the models can be assessed.
- Spatial heterogeneity as described by distributions, variograms and cross-variograms is modelled statistically correct.
- Complex information can be incorporated.

The basics of geostatistics are described by Journel et al (1978). Geostatistical algorithms are outlined by Deutsch et al (1992).

Seismic data in geostatistics

In this paper we limit ourselves geostatistical methods that are derived from the sequential simulation class of algorithms. Grid nodes are modelled one by one by estimating a conditional local probability density function (PDF). The grid node is simulated by randomly drawing a value from the PDF.

The uncertainty of the models can be decreased by including seismic data in the sequential simulation. Different techniques have been developed for using seismic data:

- Seismic data can be related to the interpolation statistically by means of a cross-variogram in Sequential Gaussian Co-Simulation or as a trend in Sequential Gaussian Simulation with external drift (SGCS or SGS with external drift, Deutsch et al, 1992).
- A deterministic forward model (e.g. convolution) can be used in combination with Sequential Gaussian Simulation. Only those realizations that have a good seismic/synthetic fit are accepted (Inverse SGS, Haas et al, 1994).
- Seismic data can be included in Bayesian form. The local PDF of seismic data is derived from cross-plots (Bayesian SGS, Doyen et al, 1996).
- Lithology can be interpolated using trend from seismic data with Sequential Indicator Simulation with trend (SIS with trend, Bakke et al, 1996).
- Lithotypes can be modelled with object based Boolean techniques. Each object is interpolated with Sequential Gaussian Simulation. Objects are accepted or rejected using a simple cross-plot relation with seismic (combined Boolean modeling & SGS, Tjolsen et al, 1995).

Figure 1 and Figure 2 show the distribution of porosity well log data in sands and shales respectively. Sand/shale logs are used for classification. From the distributions it can be seen that a lot can be said for describing the local and spatial statistics of reservoir properties within each lithotype independently (as is done in the latter approach of combined Boolean modelling & SGS). We propose a geostatistical interpolation of reservoir properties based on Sequential Gaussian Co-Simulation that models seismic data deterministically using convolution and that handles the statistics within each lithotype separately. The lithotypes are modelled simultaneously with Sequential Indicator Simulation (inverse combined SGCS & SIS).

Sequential Gaussian simulation

The basis of our method is the Sequential Gaussian Simulation algorithm (SGS). In SGS the probability function is assumed to be normal. In SGCS different reservoir properties that are spatially correlated can be simulated simultaneously. Variables that have a non-normal distribution can be transformed before simulation to approximate the Gaussian normal distribution. When the mean of the PDF is selected instead of drawing a random value, the Kriging and co-Kriging interpolations are obtained. In SIS no assumption is made about the shape of the PDF,

which is estimated by directly estimating the probability of being below a series of thresholds or by directly estimating the probability of being within a set of discrete classes (Isaaks et al, 1989).

The flow diagram of SGS is outlined in Figure 3. The flow diagrams of SGCS and SIS are similar. In SGCS the PDF of the primary data to be interpolated is also conditioned to a densely sampled secondary data set. In SIS the conditional local probabilities for each lithotype or for each threshold are computed instead of the PDF.

Stratigraphic framework

Joseph et al (1996) present an algorithm for stratigraphic geostatistical interpolation. Thibaut et al (1996) use a stratigraphic framework for inverse SGS.

Our sequential simulation is done in a series of dependent (fault blocks) or independent (otherwise) 3D grids. Each 3D grid describes one stratigraphic sequence of our model. The 3D grids are transformed such that the lateral grid planes align with the stratification in each sequence and the lateral grid locations align with the seismic grid. The vertical and lateral anisotropic variogram distances will be measured relative of these stratigraphic grids.

The relations between the sequences are described by a stratigraphic framework. The framework handles relations such as conformable, onlap, offlap, fault, truncation, channel and reef.

The local and spatial statistics of each sequence may differ. Different distributions, variograms and cross-variograms may be assigned to each sequence. Sequences can be coupled for interpolation over fault boundaries.

Stochastic inversion

In stochastic inversion we not only try to satisfy the statistical constraints:

- Spatial heterogeneity as described by distributions, variograms and cross-variograms must be modelled statistically correct.
- The simulation must reproduce the input well data

We also want to satisfy seismic constraints:

- The interpolated models should have a good fit to the seismic data.

The synthetic data are computed from impedance that is directly or indirectly derived from the reservoir properties that are simulated. Convolution is used to model the synthetic data.

Different optimization algorithms can be used to combine the seismic constraints with the simulation algorithm, e.g. steepest descent or simulated annealing. Deutsch (1992) gives applications of simulated annealing geostatistics.

In our scheme, reservoir properties and lithotypes are interpolated simultaneously. Doing the lithotype and reservoir property interpolation would result in an underestimate of the uncertainty involved in the lithotype realizations. Inversion gives a handle for doing the SIS and SGS realizations simultaneously, the seismic fit criterion can be used to discriminate between solutions. Without the inversion seismic fit criterion it would make no sense to do simultaneous SIS and SGS, sequential simulation geostatistics does not give a theoretical framework to connect lithotype and reservoir property outcomes.

Our scheme poses no limitation on the method employed for the reservoir property interpolation, e.g. we could use co-simulation or indicator simulation with trend as well as simple simulation.

Example

We will apply inverse SGCS and inverse combined SGCS & SIS on a North Sea data case. The results will be compared to using only SGCS and SIS.

Figure 4 and Figure 5 show the result of 20 realizations of two methods that both use seismic data in the interpolation, the sonic is averaged over all realizations within the reservoir. In SGCS the seismic data is linked statistically to the interpolated reservoir property with a cross-variogram, in inverse SGS the seismic data is linked deterministically with convolution. Although both methods use seismic data, the results are clearly different. Figure 6 and Figure 7 show the uncertainties of the final ensemble of realizations. The plots show one random line of the 3D uncertainty volume, the line is approximately parallel to three of the well tracks that are shown in overlay. The dark colors correspond to low uncertainty, the light colors to high uncertainty. The uncertainties are minimum at the well tracks and slowly increase moving away from the wells. In general, the uncertainties for the inverse deterministic simulation are much smaller than for the statistic co-simulation.

By including both seismic and lithology data in the interpolation of the reservoir parameters, the solution space will be decreased even more, resulting in more accuracy.

Figure 8 and Figure 9 show the sonic values for 10 to 90 % cumulative probabilities extracted from the 20 SGCS and inverse SGS realizations for the random line. These plots also show that the uncertainty near the three wells is minimum, increases moving away from the wells and is much smaller for the inverse method.

Conclusions

Sequential simulation techniques give us a better grasp of the uncertainties involved in data interpolation. We can increase the confidence in the interpolation result by using other available data in the interpolation. We presented a method that assumes a deterministic relation between the reservoir properties to interpolate and seismic data (convolution). Compared to methods that assume a statistical relation to seismic data, the uncertainty contained in the solution space can be decreased considerably. The quality of the interpolation is improved by describing the interpolation grids with a stratigraphic framework and by simultaneous modeling of lithology and reservoir properties in an inverse combined SGCS & SIS approach. The advantage of sequential simulation over non-geostatistical inversion methods is that we obtain a range of equiprobable solutions which give a good description of the uncertainty in our results.

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Figure 1 Distribution porosity in sands.

Figure 2 Distribution porosity in shales.

Figure 3 Flow diagram of SGS.

MEAN SONIC CO-SIMULATION

Figure 4 Mean sonic SGCS.

MEAN SONIC INVERSE SIMULATION

Figure 5 Mean sonic inverse SGS.

Figure 6 Uncertainty sonic SGCS.

Figure 7 Uncertainty sonic inverse SGS.

PROBABILITY 10-90 % SONIC SGCS

Figure 8 Sonic 10/90 % cumulative probability SGCS.

PROBABILITY 10-90 % SONIC INVERSE SGS

Figure 9 Sonic 10/90 % cumulative probability inverse SGS.