Multiscale reservoir geological modeling
and advanced geostatistics

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ABSTRACT

This presentation will discuss new methodologies and workflows developed to generate geological models 1) that look more realistic geologically speaking and 2) that respect the well and seismic data characterizing the studied area. Accounting simultaneously for these two constraints is challenging as they behave the opposite way. The more realistic the geological model, the more difficult the integration of data.

A first powerful approach is based upon the non-stationary plurigaussian simulation method. In this case, the available seismic data make it possible to compute the 3D probability distributions of facies proportions, which are then used to truncate the Gaussian functions.

A second method is rooted in the Bayesian sequential simulation. Recent developments have been proposed to extend this method to media including distinct facies. We suggest an improved variant to better account for the resolution differences between sonic logs and seismic data. This yields a more robust framework to integrate seismic data.

A third innovative approach reconciles geostatistical multipoint simulation with texture synthesis principles. Geostatistical multipoint methods provide models, which better reproduce complex geological features. However, they still call for significant computation times. On the other hand, texture synthesis has been developed for computer graphics: it can help reduce computation time, but it does not account for data. We then envision a hybrid multiscale algorithm with improved computation performances and yet able to respect data.

INTRODUCTION

Numerical geological modeling classically uses different geostatistical techniques, which face two conflicting objectives: to make the model more geological from a descriptive point of view and to make it consistent with all available data. As is well known, the more realistic the model, the more difficult the integration of data. Methods can be
ranked from pixel-based (Sequential Gaussian, Truncated Gaussian, Sequential Bayesian Simulations) to Object- or Process-based models. The former make data conditioning easy, but do not provide enough flexibility to reproduce geological objects like channels. The latter result in models that better reproduce geological concepts, but data conditioning is then challenging.

Many works have been dealing with the impact of geological heterogeneities on fluid flow. Various methodologies have been developed to integrate seismic data into geological models and to converge towards more realistic images of the subsurface geological complexity (Moulière et al., 1997; Yao and Journel, 1998; Doligez et al., 2007; Emery, 2008; Le Ravalec and Da Veiga, 2011). Within this framework, issues related to scale or resolution differences between well log data and seismic data have to be taken into account (Yao and Journel, 1998; Gilbert and Joseph, 2000). Many approaches are based upon the integration of 2D seismic map(s) and use the cross-covariances computed between geological and seismic properties (Behrens et al., 1996).

Exploratory efforts are ongoing at IFPEN about the development of geostatistical methods to simulate models respecting constraints originating from seismic or from genetic modeling to obtain more realistic geological distributions of heterogeneities. This paper focuses on three specific methods and workflows developed to generate geological models with an improved geological flavor and that respect the well and seismic data characterizing the studied area.

The first approach is the plurigaussian simulation. It uses a variogram and is thus restricted to the analysis of two-point statistics. Despite this inherent limitation, the extension to a non-stationary context through the computation of the 3D probability distributions of facies proportions offers numerous possibilities to use conceptual geological data and seismic derived information, qualitatively or quantitatively, depending on data.

The second method is based on the Bayesian sequential simulation (Doyen et al., 1997), with a proposed improved variant to better account for resolution differences between sonic logs and seismic data.

The third innovative approach reconciles the well-known geostatistical multipoint simulation concepts with texture synthesis that has been developed in computer graphics. An hybrid multiscale multipoint algorithm is then presented with better computation performances and yet able to respect data.

This exploratory project is still on development. Its final objective aims to test and evaluate these alternative approaches so that guidelines can be suggested for modeling.

**NON-STATIONARY PLURIGAUSSIAN WORKFLOW**

The principles behind the truncated Gaussian simulation method have been published in several reference papers (Journel and Isaaks, 1984; Matheron et al., 1987; Galli and Beucher, 1997). The extension to plurigaussian simulations (Armstrong et al., 2011) provides greater flexibility to simulate more realistic geological environments. Two three-dimensional Gaussian fields of values (correlated or not) are generated and truncated using a 3D distribution of facies proportions to end up with a 3D distribution of geological facies.

The truncated Plurigaussian model is defined 1/ by the matrices of covariances and cross-covariances, which fully define the model of the Gaussian functions (zero mean and unit variance) and 2/ by the method used to transform the set of Gaussian functions into a unique direct facies function.

This is done using a partition (truncation rule) of the plane defined by the two Gaussian random functions, depending 1/ on the geological characteristics of the field (the truncation rule is used as facies substitution diagram to reproduce the sequential and spatial organization of the sedimentary facies) and 2/ on the facies proportions, which may vary over the whole domain. The 3D distribution of proportions (also called matrix of proportions), used in the case of proportions varying vertically and laterally, is estimated from local proportions known at wells. It can integrate other sources of information, qualitative or quantitative depending on the correlations between facies proportions at wells and additional external constraint (derived from seismic or geological data).

Thanks to its flexibility and the large panel of possibilities to account for additional geological or seismic data, this method is now widely applied in petroleum industry
building geological models. It has been used for handling various applications and geological environments of which a highly fractured Iranian carbonate reservoir (de Galard et al., 2005), a cretaceous turbidite environment (Albertao et al., 2005), the distribution of diagenetic properties in a siliciclastic reservoir (Pontiggia et al., 2010). Plurigaussian simulations have been also used in the mining industry for modeling deposits (Fontaine and Beucher, 2006; Carrasco et al., 2007; Rondon, 2009 among others), as well as in hydrogeology and environmental sciences (Mariethoz et al., 2009; Cherubini et al., 2009).

There are indeed numerous techniques to integrate geological or seismic information into the distribution of facies proportions (Doligez et al., 1999a, 1999b, 2007, 2013; Dubrule 2003; Doyen 2007). The basic approach entails the use of well data and local vertical proportion curves (VPCs) calculated at wells to estimate facies proportions throughout the entire field without any other constraint. This is traditionally performed with ordinary kriging.

A bit more refined technique calls for additional information. This may be a two-dimensional map of paleogeographic environments, which delineates regions with very specific VPCs (Figure 1-a). These ones are computed from the wells included in the target regions. The final grid of facies proportions is obtained by kriging the local VPCs within each area, and with a possible smoothing between the areas (Labourdette et al., 2005; Hamon et al., 2014, Figure 1-b).

Figure 1: a) map of paleoenvironment for the studied unit; b) matrix of proportions constrained with the map 1-a as background; c - d/ two levels in the reservoir with simulated geological facies using the matrix of proportions.

The impact of the non-stationarity of facies proportions is illustrated by the two horizontal cross-sections extracted from the final resulting simulation in Figure 1-c & d (Hamon et al., 2014).
Lithoseismic interpretation may provide 2D or 3D grids of seismic facies (or packages of reflectors with similar seismic characteristics). In this case, a statistical pattern recognition approach based on discriminant analysis techniques, and supervised with training samples or not is performed on selected seismic attributes data. A second possibility to get the grid of geological facies proportions constrained by seismic consists in using the map of seismic facies as a background to identify the areas associated to a given seismic facies. The following step is dedicated to the computation of the VPCs from the wells belonging to the defined regions. At this stage, each seismic facies is related to the vertical sequence of geological facies within each region. The 3D grid of proportions is then estimated by kriging. It is considered for each level of the grid and each facies in each region (Beucher et al., 1999, Doligez et al., 1999a).

Other techniques call for the definition of facies proportions throughout the reservoir and the use of a 2D or 3D constraint given in terms of proportions. This additional information is expressed as a 2D map or a 3D grid populated with mean lithofacies thickness or proportions. They can be derived either from stratigraphic modeling (Doligez et al., 1999b) or from statistical calibration using seismic attributes when a correlation exists between some reservoir properties (for instance between impedance and porosity). The resulting 2D map or 3D grid is used as a constraint to estimate VPCs. The idea behind is to write the kriging system with an aggregation constraint relative to the sum of facies proportions in each cell of the proportion grid (Moulière et al., 1997).

Another original example of integration and specific workflow to compute the 3D grid of facies proportions for plurigaussian simulation was published by Nivlet et al. (2007) and Lerat et al. (2007) to take the most from seismic data of exceptional quality. The 3D grid of facies proportions was directly computed from the 3D high resolution seismic data accounting for scale differences between seismic and well data in several steps: 1/ an electrofacies analysis led to the definition of seven geological facies from well logs data; 2/ a second supervised electrofacies analysis based upon well impedance logs permitted to correctly discriminate six geological facies. Therefore, two of the original facies were merged into an “heterolothic facies”. This emphasized that geological facies could be discriminated from Ip and Is well logs; 3/ upscaling of the available well logs informed with the six geological facies to go to the seismic scale, keeping the most probable electrofacies; 4/ definition of the seismic facies grid, supervised by a training database of 5x5 traces extracted from areas surrounding well positions; 5/ geological calibration of the seismic facies grid as a proportion matrix based upon the computation of the geological facies proportions within each seismic facies. Last, the truncated Gaussian method was applied to generate realizations constrained to well data and geological facies proportions. The simulation of multiple realizations made it possible to evaluate the uncertainty in the spatial distribution of facies.

**Bayesian sequential simulation**

The Bayesian sequential simulation (BSS) method was originally introduced by Doyen and Boer (1996) for the interpolation and extrapolation of data. Its purpose is the simulation of several realizations of a given primary variable conditionally to intensive measurements of a secondary variable throughout the model space. The main BSS components are recapped below. A first step consists in building the joint probability density function (pdf) between the two variables of interest given collocated measurements. This joint probability is assumed to be spatially invariant. It can be estimated from the cloud plot using the nonparametric kernel density estimation method. The second step focuses on the simulation process. A grid block is randomly selected in the discretized model space for which the value of the primary variable is unknown. Then, the prior pdf is derived from simple kriging given the measured values or the values simulated previously for the primary variable. The value of the secondary variable attributed to the current grid block is used to identify a 1-D slice through the joint pdf. This yields the likelihood function. The product of the prior pdf and the likelihood function then gives the posterior pdf. Last, a value is drawn from this pdf and attributed to the current grid block. Repeating this simulation step until populating the entire grid yields a realization of the primary variable. This algorithm was improved by Dubreuil-Boiclair et al. (2011) who proposed to use a Gaussian Mixture Model (GMM) to approximate the likelihood function at each iteration. The combination of several normal distributions makes it possible to reproduce multimodal behaviors.
We investigate the potential of BSS to model spatial porosity variations in a sub-domain of the Marble Falls in the south of the Fort Worth Basin, Texas. The early Pennsylvanian Marble Falls formation is a fractured carbonate reservoir. It is about 100m thick and lies right above the Barnett shales. The studied area is roughly 1.13 km² and centered at a well, called well 1 (Figure 2).

The data used include high-resolution log and low-resolution seismic data (Figure 3): the porosity and P-wave impedances estimated from logs at well 1, and a cube of seismic P-wave impedances derived from the inversion of seismic data acquired in 2005 and 2006 (Adelinet et al., 2013). For simplicity, we focus on the slice extracted from the impedance cube for time 670 ms.

In a first study, we applied BSS following the workflow described by Dubreuil-Boiclair et al. (2011). The log data provided the joint pdf between P impedances and porosities. Then, we generated a porosity realization conditionally to the seismic P impedances. The log P impedances used to establish the joint pdf and the seismic P impedances that provide the spatial constraint were considered the same way despite the resolution difference. The joint pdf, as well as the subsequent likelihoods, were approximated by a GMM with two Gaussian densities (Figure 4-a). An example of porosity realization simulated with this process is displayed in Figure 5-a. Its distribution is compared to the distribution of porosity data in Figure 5-c. A divergence is pointed out: the simulated realization does not properly reflect the significant occurrence of small porosity values. This is actually related to the fact that we equally treated seismic and log impedances. The simulation process is driven by the seismic impedances and the joint pdf between porosity and impedances is based upon logs. There are less large impedance values for seismic than for logs. On the other hand, large impedances and low porosities characterize the first family of the GMM. Therefore, the contribution of this first family is lessened, which results in less low porosity values.
Figure 4: a/ scatter plot of porosity and log impedances superposed to the GMM imprint (with 2 kernels)  
b/ scatter plot of log and seismic impedances superposed to the Gaussian density imprint.

Figure 5: a/ porosity realizations simulated from basic BSS,  
b/ porosity realizations simulated from double BSS,  
c/ distribution of porosity data (red) compared with distribution of the simulated porosity values 5-a  
d/ distribution of porosity data (red) compared with distribution of the simulated porosity values for 5-b.
To avoid this pitfall and to account for resolution differences between seismic and logs, we developed an improved modeling workflow calling twice for BSS as suggested by Ruggeri et al. (2013). The first call is used to simulate a log impedance field conditionally to seismic impedances. At this stage, the simulation grid is a sub gridded version of the original seismic. Each grid block was split into 5\times5 grid blocks. The second call to BSS aims to simulate a porosity field conditionally to the log impedance field obtained right before. A second joint pdf is then required to relate log and seismic impedances (Figure 4-b). This one was modeled by a single Gaussian density. We performed a few tests to investigate the potential of the double BSS approach. A randomly drawn porosity realization is depicted in Figure 5-b with its distribution in Figure 5-d. Clearly, there is now a better agreement between this distribution and the one calculated from the porosity data. The proposed workflow leads to more reliable porosity realizations.

**Multiscale multipoint simulation**

Multiple-Point Statistics (MPS) simulation was introduced as an alternate answer to the quest of more realism into geological models (Guardiano and Srivastava, 1993). It belongs to the class of sequential non-parametric pixel-based methods, but departs from the techniques presented in the above sections as spatial variability is inferred from multiple-point statistics instead of two-point statistics. Heterogeneity is no longer characterized by a variogram, but by a training image that is viewed as a conceptual model of the expected heterogeneity. Multiple-point statistics are then inferred from the training image and integrated into the simulation process. MPS simulation yields realizations that reflect the knowledge of the objects present in the geological formation while still respecting measurements at wells and auxiliary information like seismic. On the other hand, the last decade also saw the emergence of texture synthesis techniques (Efros and Leung, 1999; Wei and Levoy, 2000) in computer graphics. These techniques aim to produce large digital images from small digital sample images by taking advantage of its structural content. Although designed for different applications, MPS simulation and texture synthesis techniques clearly share common ideas. To date, MPS simulation is still tackling performance issues. Referring to texture synthesis may help design adequate strategies (Arpat and Caers, 2007; Straubhaar et al., 2011; Tahmasebi et al., 2014): the training image can be considered as a database of patterns instead of being used from estimating probabilities, grid blocks can be populated patch by patch instead of one by one, the path followed to visit the entire grid can be regular instead of random, the database can be organized to simplify its exploration, it can be also partially and not fully investigated when looking for an appropriate pattern. The interested reader can refer to Hu and Chugunova (2008) and Mariethoz and Lefebvre (2014) for comprehensive reviews. Following the same ideas, Gardet and Le Ravalec (2014) developed a multiscale multipoint algorithm. For simplicity, we restrict our attention to two scales: the fine scale given by the training image and an intermediate coarse scale. A preliminary step consists in constructing a coarse training image by coarsening the original training image. Then, a multiscale database is created from the concatenation of the patterns extracted from both the fine and coarse training images. The simulation process involves two successive steps. First, a realization is simulated at the coarse scale using the information provided by the coarse training image. This is extremely fast and the resulting coarse realization is viewed as secondary information in the following step. Second, a realization is simulated at the fine scale conditionally to the realization already simulated at the coarse scale. This is performed using the information saved in the multiscale database. The multiscale capability makes it possible to capture large-scale objects with smaller templates, which induces a significant decrease in the computational overburden.

Three examples are presented hereafter. Two-dimensional cases were preferred for illustrative purposes only, but the above multiscale multipoint algorithm is also able to handle three-dimensional simulation. The training image of the first example (Figure 6-a) was extracted from a satellite image. It shows a fraction of the Ganges delta with a network of large and small channels. The coarsening process based upon the arithmetic mean provided the coarse training image in Figure 6-b. An interesting feature is the disappearance of the smallest channels. We then moved to the first simulation step and got the coarse realization in Figure 6-c. This one reproduces pretty well the channels described by the coarse training image. As expected, there are only large channels. Then, this coarse realization is used to constrain the simulation of the realization at the fine scale (Figure 6-d).
Figure 6: a/ Fine scale training image, b/ coarse scale training image, c/ Coarse realization. Coarse grids for both the training image and the realization: 66×66 pixels, d/ Fine realization. Fine grids for both the training image and the realization: 200×200 pixels.

The large channels of the coarse realization are still visible on the fine realization, but details were added all around. We finally obtain a network of small and large channels that looks like the one represented in the fine training image.

The two following examples focus on fractured media. The first one involves a training image created by mapping fracture traces in a marble formation from the Germencik field, Turkey (Jafari and Babadagli, 2010). The resulting network is very complex and well connected. It comprises large fractures with a prevailing diagonal orientation. There are also many smaller fractures characterized by T intersections (Figure 7-a). A realization simulated at the fine scale is displayed in Figure 7-b. It shows a fracture network very similar in appearance to the one portrayed by the training image. The last example corresponds to systematic joints. The training image, inspired by the Bloemendaal reservoir model (Verscheure et al., 2012), exhibits 2 families of small and large sub parallel joints (Figure 8-a). Again, the resemblance between the simulated realizations (Figure 8-b) and the training image is good.
Conclusion

The three methods and algorithms presented in this paper can be used to generate geological models respecting high resolution well data and low resolution seismic data. The techniques considered to handle the required constraints are different, but the final objective is the same: to obtain a
result realistic enough in terms of properties and heterogeneity distribution for fluid flow simulations. Each approach has its own strong and weak points.

The non-stationary Plurigaussian method yields great flexibility and a large panel of possibilities to account for various geological or seismic data in the computation of the matrix of facies proportions. On the other hand, the use of this method and workflow implies the construction of a geological facies model before focusing on the simulation of petrophysical properties distribution. This can be viewed as a benefit since it provides an additional control on the result, or as a supplementary contribution to the global uncertainties.

The Bayesian Sequential Simulation and proposed variations have also the great advantage of flexibility and simplicity in their implementations. The link between well and seismic data is only introduced through probability laws. However, the lack of geological control in the final results can be considered as a weakness of this family of approaches

The proposed multiscale multipoint method is promising in terms of geological realism: the simulated realizations can reproduce very complex structures. However, the various tests performed still stress the need for improved computation performances. In addition, the simulation of large objects remains a challenge.

The examples presented above illustrated that it is possible to generate realistic geological 3D models while integrating multiscale data. However, we may expect that in real field studies, the quality of the results will strongly depend on the available data, their quality, and the possible links between the primary fine scale and secondary coarse scale set of data. These relationships between data can be qualitative or quantitative, with more or less uncertainty to be taken into account.

References


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