Multiple-Point Geostatistics: from Theory to Practice

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Abstract The limitations of variogram-based simulation programs to model complex, yet fairly common, geological elements, e.g. sinuous channels, have been recognized for a long time. In applications involving flow simulation, such as hydrocarbon reservoir modeling, variogram-based methods typically generate high entropy models that commonly misrepresent the heterogeneity and connectivity of the actual field under study, and thus may provide incorrect flow performance predictions. Several solutions have been proposed to go beyond two-point statistics to be able to reproduce geologically realistic patterns. Because limited sample data makes the inference of multiple-point statistics extremely challenging, the idea of using an external source, namely a training image that describes the expected subsurface geology, has been a very attractive solution. However, important issues need be addressed to make that idea practical. The first fundamental question is: where to find training images, or how to generate them? This paper explains why unconditional object-based modeling is a simple but comprehensive approach to build training images. Because training images are conceptual, objects do not need to be conditioned to actual data, thus complex facies geobodies as well as complex interactions among facies can be implemented and simulated without dealing with traditional data conditioning limitations of object-based modeling. The selection of appropriate training images and their consistency with actual data are also discussed in this paper. The next question is about handling non-stationarity: how to impose spatial variations of facies proportions or facies geobody geometries? Considering the training image as a (stationary) collection of patterns, and then imposing external constraints such as variable azimuth fields and facies probability cubes, has proven to be a very effective workflow. Finally, an overview of tools, lessons learned and best practices to make multiple-point statistics simulation time-efficient is provided, and illustrated with various reservoir modeling case studies.

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Introduction

Most geological environments, especially clastic environments, are characterized by the successive deposition of elements, or geobodies, through time. These elements are traditionally grouped into classes, commonly named “depositional facies”, based on their lithology, geometry, physical properties, and biological structure. For example, the typical depositional facies that characterize a fluvial environment are high permeability sand channels, bordered by medium range permeability levies and splays, in a low permeability shale matrix.

Reservoir heterogeneity, and consequently flow performance, is primarily controlled by the spatial distribution of depositional facies. Thus, whenever depositional facies can be characterized, they should be modeled first, and then populated using their corresponding specific porosity and permeability distributions. However, this best practice is still not widely adopted by reservoir modelers. The main reason is that techniques traditionally used to model depositional facies suffer from important limitations:

- In variogram-based techniques, for example sequential indicator simulation, or SIS [2], facies models can be conditioned to well, seismic, and production data. But these models are unable to capture the long-range continuity and/or sinuosity of facies geobodies, such as channels [8]. As a result, they misrepresent reservoir connectivity, and provide poor reservoir performance forecasting.
- In object-based simulation methods [4, 6, 11], in contrast to variogram-based techniques, simulating relatively realistic facies architecture is possible, but data conditioning, either hard well data or exhaustive secondary data, is a well-known critical limitation.

For the last ten years, an alternative facies modeling approach has emerged: Multiple-Point Statistics or MPS. The idea is to combine the ability to reproduce “shapes” of object-based techniques with the speed and easy data-conditioning of variogram-based techniques. For that, MPS needs to infer and reproduce multiple-point statistics moments way beyond the traditional two-point statistics variogram. Because reservoir data are too sparse to infer such high-order statistics, Guardiano and Srivastava [3] proposed the use of a training image, i.e. a three-dimensional numerical conceptual representation of the facies thought to be present in the reservoir to be modeled. Their MPS simulation implementation is the same as Sequential Indicator Simulation, except that the variogram is replaced with a training image, and kriging is replaced with the following process to estimate local conditional facies probabilities:

1. Look for the n conditioning data (original well data or previously simulated cell values) closest to the grid node $\mathbf{u}$ to be simulated. These conditioning data form a data event d_n that is fully characterized by its geometrical configuration (the data locations relative to $\mathbf{u}$), and its data values (the facies at the data locations).

2. Scan the training image to find all training replicates of d_n (same geometric configuration and same data values as d_n). For each replicate, record the facies value at the central location of the training replicate. By central location, we mean the grid node corresponding to the same relative location as $\mathbf{u}$ in the data event d_n.
3. The estimated conditional probability of each facies at $\mathbf{u}$ is computed as the proportion of training d_n replicates that have this facies at their central locations.

One major advantage of this implementation is that, as in any pixel-based sequential simulation method, in contrast to object-based methods, well data are honored exactly. In addition, by capturing multiple-point statistics from the training image through the estimation of facies probabilities conditional to multiple-point data events, the MPS model reproduces training image patterns. However, the repetitive scanning of the training image to estimate facies probabilities is extremely time-consuming. To help solve this issue, Strebelle [9] introduced a dynamic data structure named search tree to store, prior to the simulation, all the conditional probability distributions that could be inferred from the training image. He also developed a multiple-grid simulation approach that consists in simulating increasingly finer nested grids to capture training image patterns at various scales. In this multiple-grid approach, the conditioning data search neighborhood is defined by a template that only consists of nodes from the nested grid currently simulated. One search tree is built per data template, or per nested grid.

Although Strebelle's algorithm SNESIM was the first practical implementation of MPS simulation, several challenges needed to be addressed:

- The training image is the core of MPS simulation. But where should modelers look for training images, or how can they generate them?
- The training image can be described as a collection of facies geobody patterns that MPS simulation reproduces while honoring conditioning well data. How can modelers control the local geometry and the spatial distribution of these patterns away from areas strongly influenced by well data?
- Can MPS simulation time and memory requirements decrease while at the same time improving training pattern reproduction quality?

Training Images

The training image is the main new concept introduced in Multiple-Point Geostatistics. It can be defined as a 3D numerical rendering of the interpreted reservoir geology. This training image should represent the full range of possible dimensions and shapes of the facies geobodies thought to be present in the subsurface, as well as the possible associations among those facies geobodies. The training image is a purely conceptual geological model; it contains no absolute (only relative) spatial information; it is not conditioned to any hard or soft data.

Properly digitized photographs of outcrops or sketches hand-drawn by a geologist were initially proposed as potential training images of the facies geobodies to be modeled in the MPS simulation. However, they would provide only 2D map view or cross-section information about the 3D facies elements to be modeled. Combining such 2D training images to infer the 3D multiple-point statistics moments needed in MPS simulation is an ill-posed exercise, and simplistic hypotheses have had limited success [7, 8]. The most straightforward way to obtain 3D training images actually consists in generating unconditional realizations using an object-based program. Object-based models, freed from all conditioning constraints, are indeed extremely fast and easy to build:

1. First, the user provides a description of each depositional facies: map view and cross-section shape; length, width, thickness and orientation distributions; and, if relevant, sinuosity amplitude and wavelength distributions. Such information can be derived from well log data and good quality seismic data, or can be retrieved from reservoir data bases.
2. Then the user needs to specify erosion rules and relative lateral and vertical positioning constraints, typically derived from core data analysis and analogs.

Figure 1 displays a representative horizontal and vertical cross-section of a 3D training image generated using an unconditional object-based method as described above, based on sketches hand-drawn by a geologist, and geometric parameters derived from a reservoir data base.

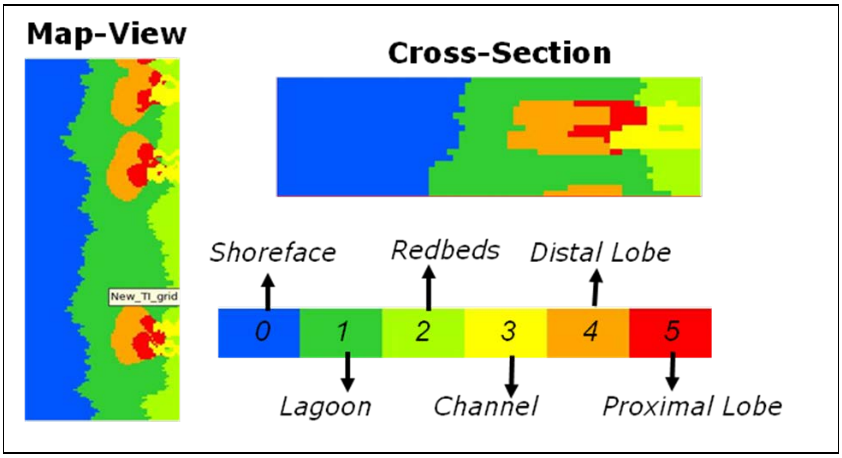

Figure 1 Example of fluvial-deltaic training image

One major challenge is for modelers to select or generate appropriate training images. Simple techniques have been proposed to check the consistency of training images with actual well data by comparing, for example, variograms (vertical variograms only in sparse well environments), or facies transition matrices. However, it is very likely that different training images corresponding to alternative geological scenarios would match the statistics from the same well data set. Training images very often represent a first-order uncertainty, and it is very important to account properly for that uncertainty by selecting or generating a suite of training images with variable connectivity and heterogeneity.

Simulation constraints

When MPS Simulation was originally developed, one important assumption underlying the inference of multiple-point statistics moments from the training image and their reproduction in the MPS model was the stationarity of the field under study: facies relative proportions, geometries, and associations were expected to be reasonably homogeneous over the field. In other words, any pattern from the training image could be reproduced anywhere in the MPS model as long as it could match local conditioning hard data. However, most actual reservoirs are not stationary. Stratigraphic and structural events, e.g. sea level cycles or faulting, lead to significant spatial variations of facies proportions (horizontal and vertical trends), and facies geobody geometry (orientation and size).

Such variations can be inferred from well and/or seismic data using statistical data analysis tools. For example:

- Facies proportion map and curves can be derived from well data by computing facies proportions layer-wise or column-wise in the reservoir stratigraphic grid. These constraints can be integrated in MPS models by expanding the use of the servosystem introduced by Strebelle in SNESIM [8] to match target facies proportions per layer or per column instead of globally.
- Variable azimuth maps can be estimated from seismic data by looking for local major directions of continuity. Local rotations of the training image can impose this constraint onto MPS models [10].
- Seismic data can be calibrated to well data to generate an exhaustive 3D facies probability cube, which can constrain the MPS simulation by using different data integration methods, for example the tau-model proposed by Journel [5].

In sparse well environments, facies proportion curves, proportion maps or probability cubes directly computed from actual reservoir data commonly need to be edited to correct potential bias due to preferential well locations and data sampling, and account for geological interpretation based on reservoir analogs. It is important, however, to check that the modified proportion constraints are still locally consistent with well data. Furthermore, as with training images, the uncertainty related to facies actual spatial distribution and continuity should be accounted for by generating alternative facies proportion and geometry constraints. For example, the impact of potential horizontal flow barriers can be evaluated by imposing high proportions of low permeability facies in particular grid layers through a vertical facies proportion curve constraint.

Figure 2 displays the facies proportion curves and facies proportion maps computed from 6 wells for a fluvial-deltaic reservoir mimicking a Chevron modeling study.

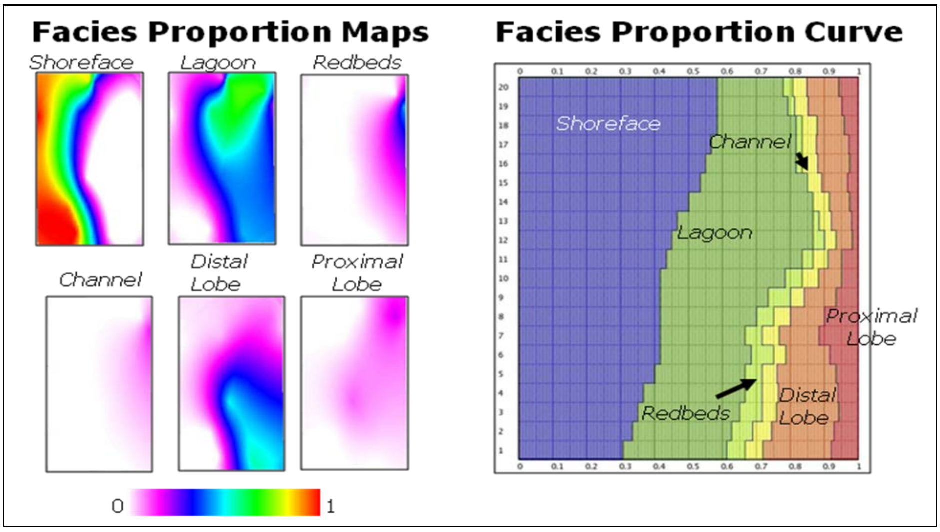

Figure 2 Example of facies proportion maps and curve computed from well data for a fluvial-deltaic reservoir.

MPS Simulation

The introduction of the search tree was the technical breakthrough that made SNESIM the first practical implementation of MPS simulation. Further progress was made a few years ago to improve MPS simulation time by optimizing the data template used to store the MPS moments in the search tree. The idea came from the following observation: the greater the number of conditioning data in the search neighborhood defined by the data template used to build the search tree, the faster the computation of the associated facies probability distribution from the search tree. Thus, the solution was to design the data template such that it mostly consists of data locations corresponding to previously simulated nodes, i.e. nodes belonging to grids coarser than the grid currently simulated. Also, intermediary sub-grids were added to the traditional multiple-grid simulation approach to increase the relative proportion of previously simulated nodes in each nested grid.

These SNESIM implementation enhancements not only allowed decreasing MPS simulation time, but also helped reduce memory demand to build search trees. Alternative implementations of MPS simulation were proposed to tackle memory demand issues by classifying training patterns into a limited number of representative clusters, e.g. SIMPAT [1] or FILTERSIM [12], but those solutions were found at the expense of increased simulation time, and data conditioning issues.

Figure 3 displays a MPS model conditioned to 6 wells, using the training image of Figure 1, and the facies proportion constraints of Figure 2.

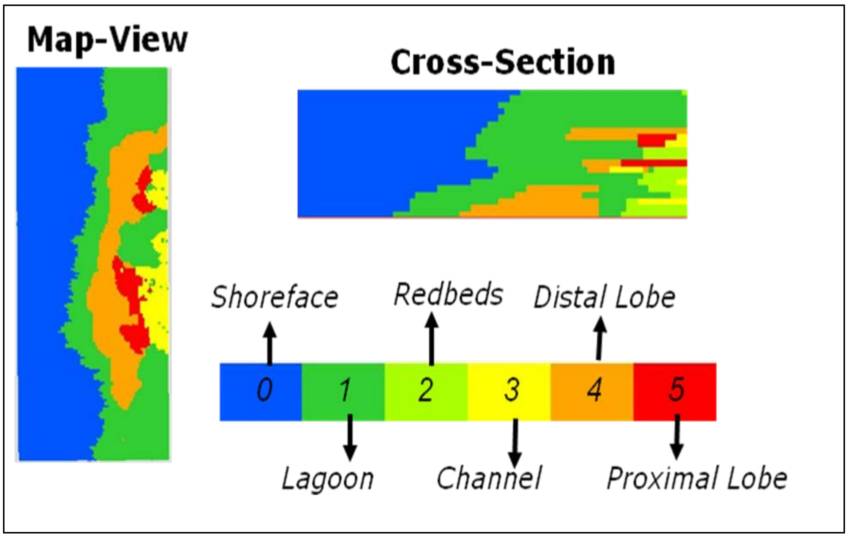

Figure 3 Example of MPS model simulated for fluvial-deltaic reservoir

Some fundamental questions remain however unanswered: What patterns or MPS moments do we want to extract and reproduce from the training image, and what training patterns are actually simulated in the MPS model? For example, in Figure 1, the training image displays fully connected channels while some simulated channels are disconnected in the corresponding MPS model shown in Figure 3. Provided that flow relevance studies confirm the importance of channel continuity, what MPS moments carry that information, and how can we ensure that those particular moments are properly reproduced in the MPS model?

Conclusions

For the last ten years, experience has shown that MPS simulation allows the generation of much more realistic geological models than traditional variogram-based techniques. MPS simulation captures connectivity and heterogeneity patterns that are essential for models to provide reasonable reservoir flow forecasting. In contrast to object-based techniques, MPS-based geological pattern reproduction is achieved without losing the critical ability of variogram-based methods to honor conditioning hard data exactly.

Great progress has been made to answer practical questions such as the generation and selection of training images, and the management of non-stationary features. More fundamental question such as filtering MPS moments extracted from the training image, and controlling the reproduction of those moments in MPS models still need to be addressed.

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