Direct non-stationary multiple-point modeling by distance-based pattern simulation

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Introduction

Most geostatistical techniques rely on some form of stationarity in their approach to creating model realizations. This assumption of stationarity is inherent to any statistical modeling technique. Often, random fields are decomposed into the sum of a trend component and a stationary stochastic component. Trends can be simple changes in mean, but can also consist of changes in affinity or angular direction variations or any other feature of the local spatial field. However, such decomposition limits the extent of real world spatial phenomena that can be modeled since not all phenomena can be easily decomposed in this fashion. Moreover, the modeler has the arduous task of modeling both trend and stochastic component.

In multiple-point geostatistics, the training image is central to the modeling of complex spatial distributions; however most techniques require the training image to model only the stationary component, which limits the application of such techniques to actual 3D applications. In this paper, we propose a new model for multiple-point geostatistical simulation that does not rely on any assumption of stationarity, nor decomposition and can directly create model realizations that depict the training image patterns, whatever their nature (trending or not). Our modeling approach relies on decomposing any 3D model into patterns and simulating these patterns directly, including whatever non-stationary element is present.

DISPAT: distance-based pattern modeling

Dispat (Honarkhah, 2011) builds further on the idea of *simpat* (Arpat, 2005) where instead of extracting and modeling statistics, one extract and models patterns from training images. *Dispat* solves the important remaining problem in *simpat* and that is of finding the most similar pattern to a data-event. The algorithm consists of two stages: 1) constructing a searchable pattern database and

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2) stochastic simulation. Stochastic simulation is much the same as other pattern-based codes such as *simpat*, *filtersim* (Zhang, 2006) and direct sampling (Mariethoz, 2009). One starts with an empty grid, gradually filling the grid with patterns extracted from the training image. At each grid-location, some previously simulated grid cells may be present (a data-event) and therefore a pattern that is similar (or at least compatible) with the current data-event must be found and pasted at that location. In *dispat* patterns are organized by means of a distance between any two patterns. The choice of distance depends on the type of patterns available in the training image. Distances allow for 1) dimensionality reduction using multi-dimensional scaling and 2) clustering of patterns into groups for quick searching. The CPU performance of *dispat*, its improved pattern reproduction and data conditioning are some of the attractions of this algorithm. Another appealing aspect is the direct non-stationary model generation.

Non-stationary simulation with DISPAT

Dispat relies on the calculation of distances between patterns and data event. Consider such a distance as d_{pat}. Consider now a training image such as in Figure 1, clearly the variation in such training image calls for non-stationary modeling and a different approach from the *dispat* algorithm described above. To account for the specific location-dependent nature of the pattern-variation, a second distance is introduced denoted as d_{loc}, which is the distance between the location in the simulation grid and the location where the pattern is extracted in the training image, then, a new distance is formulated as follows

$$d = (1-\omega)\frac{d_{pat}}{\|d_{pat}\|} + \omega\frac{d_{loc}}{\|d_{loc}\|}$$

Using this new distance, most similar patterns are searched in the pattern-database. In other words, one forces the algorithm to no longer pool all statistics/patterns over the entire grid, but only consider local patterns. The weight ω allows one to modulate between a stationary model and a fully non-stationary model, which in the limit is the training image itself.

Two methods for choosing ω are proposed:

1. Spatial self-similarity method (SSM): in this method patterns are ranked according to the their closeness from location **u** using a weighting function that decreases gradually to zero for further away patterns.
2. Automatic segmentation method (ASM): in this method the training image is automatically segmented into various regions using filters (Gabor filters in our case) and regions are used to determine the extent of the weighting function in the SSM.

Figure 1 provides an example of the SSM method for various weight choices, while Figure 2 shows the application of the ASM method. Figure 3 shows the application to a real world tidal-dominated reservoir.

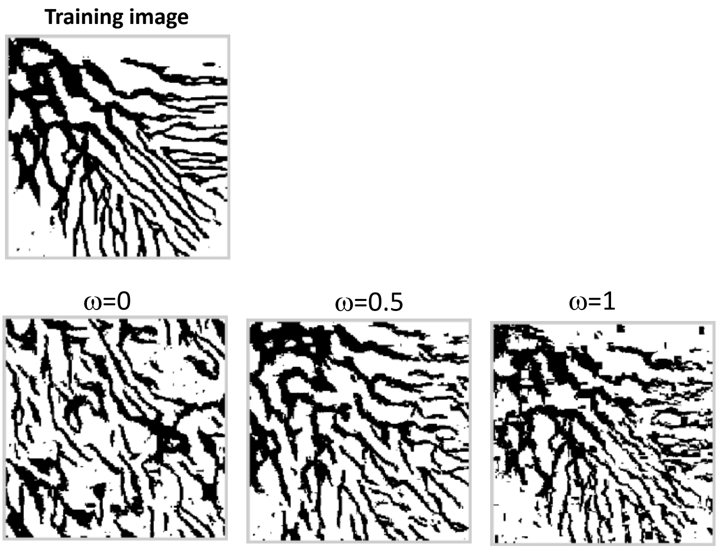

Figure 1: non-stationary training image and realizations for various choices of ω

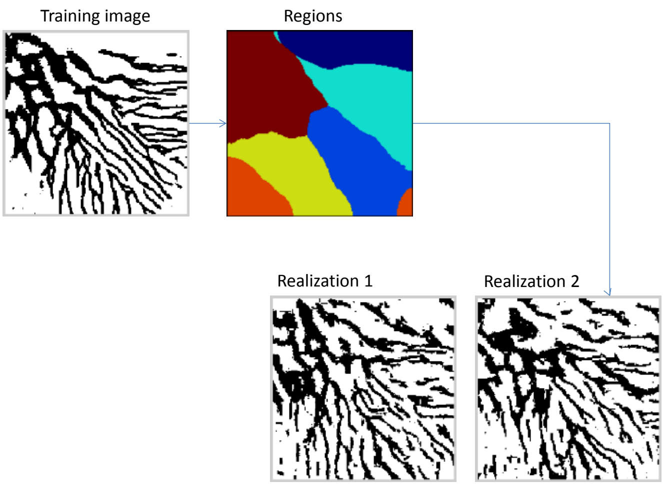

Figure 2: ASM: result of the automatic segmentation (discovery of non-stationary regions) and two realizations

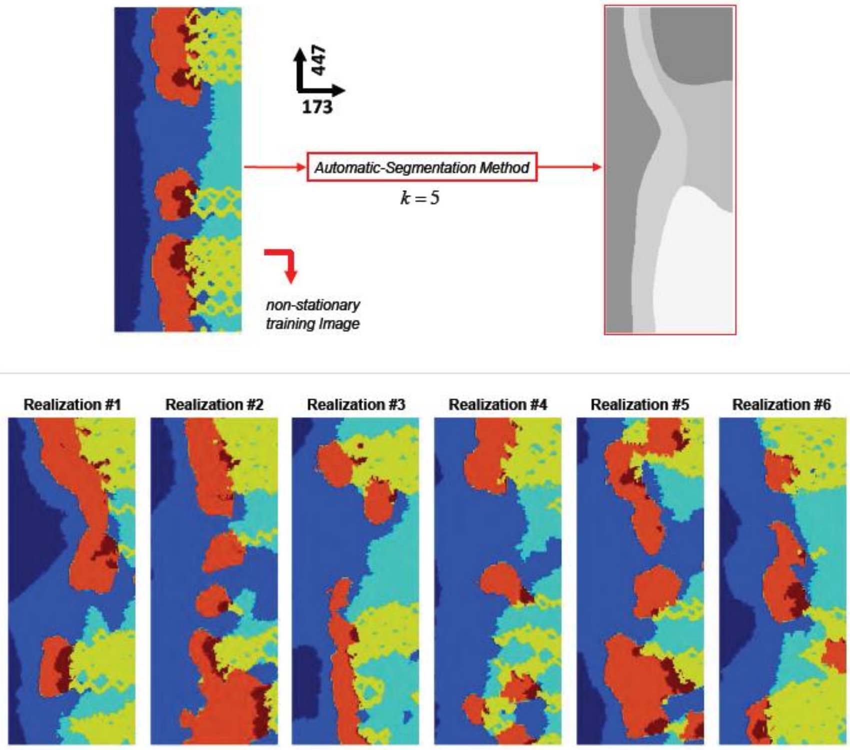

Figure 3: results of the ASM method for a tidal-dominated reservoir

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