Comput Geosci (2012) 16:779–797
DOI 10.1007/s10596-012-9287-1

ORIGINAL PAPER

Multiple-point geostatistical modeling based on the cross-correlation functions

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Received: 11 June 2011 / Accepted: 10 February 2012 / Published online: 8 March 2012

Abstract An important issue in reservoir modeling is accurate generation of complex structures. The problem is difficult because the connectivity of the flow paths must be preserved. Multiple-point geostatistics is one of the most effective methods that can model the spatial patterns of geological structures, which is based on an informative geological training image that contains the variability, connectivity, and structural properties of a reservoir. Several pixel- and pattern-based methods have been developed in the past. In particular, pattern-based algorithms have become popular due to their ability for honoring the connectivity and geological features of a reservoir. But a shortcoming of such methods is that they require a massive data base, which make them highly memory- and CPU-intensive. In this paper, we propose a novel methodology for which there is no need to construct pattern data base and small data event. A new function for the similarity of the generated pattern and the training image, based on a cross-correlation (CC) function, is proposed that can be used with both categorical and continuous training images. We combine the CC function with an overlap strategy and a new approach, adaptive recursive template splitting along a raster path, in order to develop an algorithm, which we call cross-correlation simulation (CCSIM), for generation of the realizations of a reservoir with accurate conditioning and continuity. The performance of CCSIM is tested for a variety of training images. The results, when compared with those of the previous methods, indicate significant improvement in the CPU and memory requirements.

Keywords Multiple-point geostatistics · Cross-correlation · Training image · Conditional simulation · Adaptive recursive template splitting

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1 Introduction

A most important problem in modeling of large-scale porous media, such as oil reservoirs, and simulation of fluid flow therein is the identification of the flow paths that consist of the zones with significant permeabilities and are distributed in the interwell regions. Kriging [39, 63] has been used for many years for extrapolating the existing data to the interwell regions. But because kriging produces permeability and porosity fields that are excessively smooth [29, 39, 44, 63], it is not an effective tool for modeling of the interwell regions of highly heterogeneous reservoirs. Therefore, methods based on stochastic or geostatistical simulation have been developed to overcome the problems associated with the smoothness problem [39, 40, 44, 52, 63]. Such methods generate many realizations of a reservoir that can reproduce the broad heterogeneity and spatial uncertainty in the properties of the reservoir, indicated by the existing data for the reservoir [7, 63]. Due to such a distinct advantage, geostatistical simulations are used frequently in mining, reservoir modeling, and hydrogeology. In general, such methods are classified into three main groups:

In one group are object-based simulation methods that consist of marked point process [46] and the Boolean method in which the reservoir is represented as a collection of independent stochastic objects whose geometries are based on a specific statistical distribution [19, 30, 35, 64].

Pixel-based methods belong to the second group. They are based on defining an array of points or pixels in a regular grid [11, 18, 27], with the pixels representing various properties of a reservoir.

Such methods as conditional simulations via the LU decomposition of the covariance matrix [16], sequential Gaussian simulation [21], frequency-domain simulation [4, 12], simulated annealing [17, 31, 63], and the genetic algorithm (for a review, see [63]) are in the last group. The latter two methods are optimization techniques that determine the most plausible realization of a reservoir, given some data.

Each of such methods has some advantages, as well as limitations. For example, object-based simulations are accurate in reproducing geological features, but they are CPU-intensive and encounter difficulty when one tries to condition the model to dense hard (quantitative) data and integrate them with soft (qualitative) data. Pixel-based simulations work on one pixel at a time and, thus, are accurate for data conditioning, but because they use variograms that represent two-point statistics, they cannot capture complex and curvilinear features and thus fail when the models that they generate are used in the simulation of flow and transport problems in reservoirs. In addition, they are usually slow.

The aforementioned shortcomings have led to the development of a more accurate method, based on multiple-point statistics (MPS) [29, 41, 65], which is an accurate algorithm for addressing some of the problems. The essence of the MPS method is to use useful features of both the variogram-based and object-based algorithms by using a tool—a training image (TI) of the system—that is the analog of variogram/covariance models in geostatistical models that utilize two-point statistics. In other words, TI is the conceptual information that depicts the subsurface heterogeneity and/or a prior numerical geological feature that mainly represents the spatial continuity, patterns, and distribution of the available features in a reservoir. It is then used for computing multiple-point properties of the system. Therefore, because the MPS method considers more than two points at a time, one may expect the complex facies in a reservoir to be reproduced more accurately.

However, the original MPS algorithm proposed by Guardiano and Srivastava [29] was impractical because to condition each new data event, the method had to scan the TI anew, and consequently, it was extremely CPU demanding. Note that we use the terminology of “data event” because during the simulations, the data change as the MPS algorithm progresses. Strebelle [68] proposed an alternative method—single normal equation simulation (SNESIM)—by using a search tree structure that is an efficient method of accessing high-dimensional data that can overcome the problem associated with the original MPS method [49, 59]. By using a search tree, the TI is scanned once, and all the replicas of the patterns are stored. Therefore, it is possible to apply SNESIM to 3D reservoirs [1, 10, 32, 33, 49, 69] and hydrogeological modeling [13, 25, 37, 60, 61]. However, SNESIM also suffers from intensive memory and CPU requirements, when used in the simulation of large 3D reservoirs. In addition, SNESIM is impractical for continuous TI and co-simulation (see below). One can improve SNESIM by several method; we will briefly describe such methods shortly.

Several methods have been proposed for reproducing the continuity of a TI by incorporating the multiple-point information, but they still have many limitations. For example, when one uses the simulated annealing method, one can generate a realization of a reservoir based on the previously extracted TI and some inferred MPS that are imposed as constraints and must be honored [17, 24]. Other iterative methods, such as Markov random fields [73], artificial neural networks [8, 9], and directional Metropolis–Hastings algorithm [14, 74, 75], and methods that belong to the Markov chain family, such as the Gibbs sampler [50] and mesh models [46], have been proposed, but most of them are highly CPU demanding and their convergence to the solution is slow. Other ideas, such as the integration of MPS with traditional simulation, e.g., indicator probabilities [55, 56] using the texture synthesis that is borrowed from computer vision field [15, 58], have also been studied. Dimitrakopoulos et al. [20] used spatial cumulants for modeling complex non-Gaussian and nonlinear phenomena and asserted that the method can generate nonlinear patterns and connectivity of highly permeable zones. Generally speaking, most of such works tried to capture the essential features of such systems by using a considerable amount of data.