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Reconstruction of 3D porous media using multiple-point statistics based on a 3D training image

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ABSTRACT

To date many methods of constructing porous media have been proposed. Among them, the multiple-point statistics (MPS) method has a unique advantage in reconstructing 3D pore space because it can reproduce pore space of long-range connectivity. The Single Normal Equation Simulation (SNESIM) is one of most commonly used algorithms of MPS. In the SNESIM algorithm, the selection of training image is vital because it contains the basic pore structure patterns. In the previous reconstructions of 3D porous media using SNESIM, a 2D slice was usually employed as the training image. However, it is difficult for a 2D slice to contain complex 3D pore space geometry and topology patterns. In this paper, a 3D training image is used in order to provide more realistic 3D pore structure features. Besides, a multi-grid search template is applied for the purpose of capturing the pore structures of different scales and speeding up the reconstruction process. Two sandstone cores are taken as test examples and the 3D porous media are reconstructed. The two-point correlation function, pore network structure parameters and absolute permeability are applied as the evaluation indexes to validate the accuracy of the reconstructed models. The comparison result shows that the reconstructed models are in good agreement with the real model obtained by X-ray computed tomography scanning in the pore throat geometry and topology and transport property, which justifies the reliability of the proposed method.

1. Introduction

Porous media modeling—pore-scale imaging and modeling is becoming more and more popular for engineers of both petroleum and environment fields to predict the macroscopic transport properties and understand the displacement processes (Blunt et al., 2013; Wang et al., 2007; Chen and Zhou, 2017; Chen and Yao, 2017; Chen et al., 2016; Abdelfatah et al., 2017; Alizadeh et al., 2014; An et al., 2016a; Kakouei et al., 2017; Vaz et al., 2016). As a result, a new technique, digital rock analysis, has been developed not only for understanding the visualization of pore structures and mineral spatial arrangement (Chen and Zhou, 2017; Liu et al., 2016), but also for predicting various petrophysical properties and studying transport processes, such as transport of electricity, acoustic wave and multiphase flow in porous medium (Van der Land et al., 2013; Wang and Chen, 2007; Arabjamaloei and Ruth, 2016; An et al., 2016b; Nooruddin and Blunt, 2016; Qajar and Arns, 2016; Liu et al., 2017). In essence, these transport properties are governed by the types of grains, the morphology and topology of the pore space, arrangements between the grains and pore space and the conditions of transport process (Okabe and Blunt, 2005; Tahmasebi and Sahimi, 2012). The premise of predicting these properties and understanding these transport processes is to build an accurate 3D pore space.

With the innovation of experimental instruments and the breakthrough of new theories, scholars have put forward many methods to construct the porous media. So far, the methods of modeling porous media are divided into two main groups, namely, experiment technology methods and statistical methods. The former applies experimental instruments to photograph or scan the rock sample to obtain a large number of 2D images, then uses the software to build a 3D rock model by stacking these 2D slices. For this approach, X-ray computed tomography (Blunt et al., 2013, An et al., 2016a), focused ion beams (Hemes, et al., 2015; Kim et al., 2012) and laser scanning confocal microscopy (Minsky, 2011; Paddock, 2000) are common tools. Although the X-ray computed tomography scanning method and focused ion beams can establish an accurate 3D digital core model, they are so expensive and time-consuming (Hajizadeh et al., 2011). Statistical

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methods employ stochastic algorithms to generate stochastic models based on the little information from the slices. These methods include the truncated Gaussian random field (Quiblier, 1984; Ioannidis et al., 1997; Yeong and Torquato, 1998), simulated annealing (Talukdar and Torsaeter, 2002 ; Talukdar et al., 2004; Kainourgiakis et al. 2005; Ju et al. 2014), Markov chain Monte Carlo (Wu and Crawford, 2004; Wu et al., 2006), sequential indicator simulation (Keehm, 2003; Keehm et al., 2004), multiple-point statistics (Okabe and Blunt, 2004; Okabe and Blunt, 2005; Tahmasebi et al., 2012; Comunian et al., 2012; Xu et al., 2012; Hurley et al., 2015; Tahmasebi et al., 2015a; Tahmasebi et al., 2015b), phase-recovery algorithm (Fullwood et al., 2008; Hasanabadi et al., 2016a; Hasanabadi et al., 2016b) and process-based or grain method (Øren and Bakke, 2002; Øren and Bakke, 2003; Biswal et al., 2007; Thovert and Adler, 2011). Comparing with the former method, the latter not only has the merits of low cost and high efficiency, but it can also combine different scale information and reconstruct a larger model (Blunt et al., 2013). However, the truncated Gaussian random field, simulated annealing and sequential indicator simulation rely on the variogram to evaluate the correlation of two points of the geological variable. The variogram is difficult to precisely simulate the void space with complex geometry and topology, which tends to cause reconstruction of the pore space lacking of long-range connectivity (Hajizadeh et al., 2011; Tahmasebi and Sahimi, 2012; Tahmasebi et al., 2012). In 2002, Bakke and Øren put forward a new modeling technique based on the formation of sedimentary rock containing sedimentation, compaction and diagenesis processes (Øren and Bakke, 2002). But the process-based method assumes that all the particles are spheres, which is not real for the sedimentation of grains in that the shape of most grains is irregular when they are depositing. The method also only simulates several diageneses, such as quartz cement overgrowth and clays growth, so it is not suitable for simulating the rock of having undergone complex diageneses. The above disadvantages have contributed to the proposal of a more accurate method based on the multiple-point statistics (MPS) that can effectively address the aforementioned problems especially in the long-range connectivity (Deutsch, 1992; Strebelle, 2000; Strebelle, 2002; Okabe and Blunt, 2004; Okabe and Blunt, 2005; Tahmasebi et al., 2012; Comunian et al., 2012; Xu et al., 2012; Hurley et al., 2015).

MPS was first proposed by Deutsch (1992). To date MPS is divided into two major categories, iterative algorithms and noniterative algorithms (Strebelle, 2002). Iterative algorithms were extremely CPU demanding and seriously restricted the efficiency (Guardiano and Srivastava, 1993). Until 2000, Strebelle proposed the Single Normal Equation Simulation (SNESIM) algorithm that effectively overcomes the problem associated with the previous algorithm (Strebelle, 2000). SNESIM algorithm applies the search tree to record and store the conditional probability distribution of all data events acquired by scanning the training image, which needs to scan the training image only once in the simulation process and dramatically reduces the computational time needed.

MPS has been widely used in reservoir modeling (Srivastava, 1992; Liu, 2006; Boucher, 2009), especially in fluvial facies. In 2004, Okabe and Blunt reconstructed digital rock modeling using the MPS (Okabe and Blunt, 2004, 2005, 2007). They took a 2D image from 3D micro-CT data of the rock as the training image and rotated this image around each principal axis to generate 3D conditioning data. Then the preferred search template was used to scan the training image and a stochastic 3D digital rock was reconstructed. Comparing with the model established by the simulated annealing method, the curve fraction of percolating cells of the model gotten by MPS is in better agreement with the curve of the real model obtained by the X-ray computed tomography scanning, which verifies that MPS is better than the simulated annealing method in reproducing the pore space of long-range connectivity.

However, Okabe and Blunt assumed that the porous medium was explicitly isotropic in X, Y and Z directions, which is obviously unreal for the heterogeneous rock. Therefore, a novel idea was proposed to address the problem by generating a sequence of 2D slices and stacking these 2D slices. (Hajizadeh et al., 2011). Later, the cross-correlation simulation method was also presented to reconstruct anisotropic 3D digital rocks only using a single 2D thin section (Tahmasebi and Sahimi, 2012; Tahmasebi et al., 2015a, 2015b). Other scholars also reconstructed some 3D porous media based on a 2D training image (Comunian et al., 2012; Xu et al., 2012; Hurley et al., 2015). For these reconstructions, the training image is only one 2D slice. In fact, a 2D image cannot contain 3D pore-space structural features, for example the topology characteristic (Zhang, 2015). Different from the previous reconstruction of porous media using SNESIM algorithm, we will make use of a 3D training image built by X-ray computed tomography scanning taking the place of a 2D training image to supply the more accurate 3D pore structures in this paper. Two orthogonal slices are set to the conditioning data. That is, the Berea sandstone and S sandstone cores are taken as the test examples. For each porous medium, two representative volume elements (RVE) of 150^3 voxels from different locations are extracted. One is set for the 3D training image so as to provide more real pore space structure patterns, the other for the real model to supply the conditioning data and be compared with the next reconstructed models to validate the proposed method. Two orthogonal 2D slices are chosen from the real model, second RVE, as the conditioning data. The SNESIM algorithm is applied to generate the stochastic porous media through using the 3D training image and multi-grid search template under the constraint of the conditioning data. This paper is organized as follows: Sections mainly gives a brief introduction of SNESIM algorithm including some terminologies while Section 3 describes modeling steps in detail and parameters setting. The evaluation of the accuracy of reconstructed models is going to be demonstrated in Section 4. Section 5 makes a summary of the full text.

2. SNESIM algorithm

SNESIM algorithm is one of the most common methods for discrete variable simulation in MPS, for example pore space (Tahmasebi et al., 2012). To facilitate the understanding of this algorithm, several important terminologies in the algorithm are briefly introduced below.

2.1. Data template and data event

Data template τ_n, as well as search template, consists of central node $\mathbf{u}$ and n vectors $\{\mathbf{u} + \mathbf{h}_\alpha, \alpha = 1,2, \cdots, n\}$ radiating from the center node. A data event d_n is constituted by the data template τ_n and the n data values of the n vectors $\{\mathbf{u} + \mathbf{h}_\alpha, \alpha = 1,2, \cdots, n\}$. A square 7×7 data template and a data event are shown in Fig. 1. In the digitized image, the node is usually substituted for the term “pixel” or “voxel” to represent a minimum unit in the paper. The pixel is used in 2D image and voxel is used in 3D image.

2.2. Training image

A training image is essentially a conceptual model that should try to include all pore structure patterns for porous media. The training image can be derived from the 3D model obtained by micro-CT machine, or from 2D slices such as cast thin sections or scanning electron microscope images. Fig. 2(a) exhibits a training image and Fig. 2(b) shows the training image scanned by a 7×7 search template. One of the key factors that affect the accuracy of reconstructed models is the selection of a training image. The size choice of a training image determines how much pore structure features the training image will contain. In terms of the theory, the simulation result will be better with the training image of larger size. But due to computer properties, such as the CPU, the choice of training images should be comprehensively considered (Liu, 2006). Moreover, the 3D training image should be preferred to 2D training image in that more real pore structures can be included in the