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New pore space characterization method of shale matrix formation by considering organic and inorganic pores

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ABSTRACT

A shale matrix is too tight to be described using conventional methods, and digital core technology is becoming an alternative method. Because both organic and inorganic pores exist in the shale matrix, a digital core and a pore network model that could describe these two types of pores at the same time are constructed in this paper. Firstly, the inorganic pore digital core is constructed based on the multiple-point statistics method, and the organic pore digital core is constructed based on the Markov chain Monte Carlo method. The two types of digital cores are superposed together according to a superposition algorithm, which includes information about the shale organic and inorganic pores. The pore network models of different constructed digital cores are extracted using the pore space medial axis method. Finally, based on these platforms, the geometry and topology structure properties, the pore size distribution and the coordination number of a shale sample are analyzed. The results show that the pore size distribution of the shale sample generally ranges from 2 nm to 100 nm, mainly distributing from 5 nm to 20 nm. The coordination number is almost always in the range of 2–3. The digital core results match well with the experimental results to some extent for our study case.

1. Introduction

A complex shale pore structure includes nano organic pores in organic matter, micron–nano inorganic pores in inorganic mineral and micron-millimeter natural fractures (Wang and Reed, 2009). The shale pore is too small to be studied using conventional methods. At present, the methods commonly used to study the shale pore structure include a scanning electron microscope (SEM) (Clarkson et al., 2013), a focused ion beam scanning electron microscope (FIB-SEM) (Bai et al., 2013), atomic force microscopy (AFM) (Javadpour, 2009), nano CT, and transmission electron microscope scanning methods. Combined with an energy dispersive spectrometer (EDS) or a backscattered electron image (BEI), the three-dimensional distribution image of different mineral compositions can also be obtained.

Based on the above equipment, the digital core images of shale can be captured. Digital core construction methods are divided into the following two classes: (1) the physical construction method in which focused ion beam scanning electron microscopy or nano CT can directly construct real 3D digital cores; and (2) the random reconstruct algorithm in which 2D scanning electron microscopy, atomic force microscopy, and a transmission electron microscope can only obtain two-dimensional image data, and digital cores are reconstructed using random reconstruction algorithms. The reconstruction methods commonly used include a Gauss simulation (Joshi, 1974), simulated annealing (Hazlett, 1997), the process-based simulation method (Bryant and Blunt, 1992), multiple point statistics (Okabe and Blunt, 2004), the sequential indicator simulation (Keehm, 2003), the Markov stochastic reconstruction method (Wu et al., 2006) and various hybrid methods (Hidajat et al., 2002; Liu et al., 2009; Okabe and Blunt, 2007; Yao et al., 2013).

However, for either the physical construction method or the random reconstruction algorithm using 2D image data, only single-scale or single-component digital cores can be constructed, which are not accurate enough for the strong heterogeneity of shale (Yang et al., 2015). It is also very difficult to consider organic and inorganic pores simultaneously. Therefore, constructing

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digital cores containing both an organic pore and an inorganic pore is the focus of this paper.

First, the inorganic pore digital core was constructed based on the multiple-point statistics method, and the organic pore digital core was constructed based on the Markov chain Monte Carlo method. The two digital cores were combined together according to a superposition method. This superimposed digital core contains both inorganic pore information and organic pore information. Second, the pore network models were extracted from the superimposed digital core according to the medial axis thinning algorithm. Finally, based on the pore network models, the geometry and topology properties of the shale samples were analyzed and compared with the experimental results.

2. Superposition method to construct the digital core of shale

A high resolution 2D image is often available using optical or electronic equipment. The 3D pore space can be reconstructed from 2D images using statistical methods by considering the porosity information, lineal path function, two-point autocorrelation function, etc. Traditional porosity and two-point statistical techniques usually cannot reproduce the long-range connectivity of the pore space for using low-order information, especially for tight porous media (Adler et al., 1992; Biswal et al., 1999; Hazlett, 1997; Levitz, 1998; Quiblier, 1984). To establish a complicated pore space with submicron structures, the multiple-point statistics method is used to capture the large-scale inorganic pore space, and the Markov chain Monte Carlo (MCMC) method is used to capture the small-scale organic pore space.

2.1. Multiple-point statistics (MPS) method for the inorganic pore space

Multiple-point statistics comes from a geostatistical method to reconstruct large-scale patterns using pixel-based representations (Caers, 2001; Mariethoz and Caers, 2014). This method is a good way to reconstruct higher resolution 3D images from readily available 2D microscopic images. MPS can characterize the correlation between many points compared with traditional two-point geostatistics. The main difference between MPS and two-point geostatistics is that they determine the conditional probability differently. MPS uses training images instead of a variogram function to reproduce the geological spatial structure.

We use the following steps to construct the pore space:

(1) Use a template scanning two-dimensional training images and build a search tree.

Suppose the data template is τ and the template center is $\mathbf{u}$, and the other positions on this template are $\mathbf{u}_\alpha = \mathbf{u} + \mathbf{h}_\alpha; \alpha = 1, \ldots, n$, where h_α is the vector from the center position pointing to the other positions. Therefore, the data template τ is composed of n locations $\mathbf{u}_\alpha$ and a central location $\mathbf{u}$. Take Fig. 1 as an example. The 2D template size is $\mathbf{9} \times \mathbf{9}$, and $\mathbf{u}_\alpha$ is determined by the center element $\mathbf{u}$ and the 80 other elements.

Suppose an attribute S has m possible states $\{s_k; k = 1,\ldots,m\}$. A data event $d(\mathbf{u})$ composed of states at different locations, shown in Fig. 2(c), is defined by

$$d(\mathbf{u}) = \{i(\mathbf{u});\ \ i(\mathbf{u}_\alpha) = i(\mathbf{u} + \mathbf{h}_\alpha) = s_{k_\alpha}; \alpha = 1, \ldots, n\} \tag{1}$$

where $i(\mathbf{u} + \mathbf{h}_\alpha)$ indicates the state value at position $\mathbf{u}_\alpha$; $d(\mathbf{u})$ indicates the state value of $i(\mathbf{u}_1), \ldots, i(\mathbf{u}_n)$ at n positions, which are $s_{k1},\ldots,s_{kn}$. Fig. 2 shows the process of obtaining a data event using the template to scan the training image. The purpose of scanning the training image using the data template is to get statistical probability of a data event $d(\mathbf{u})$.

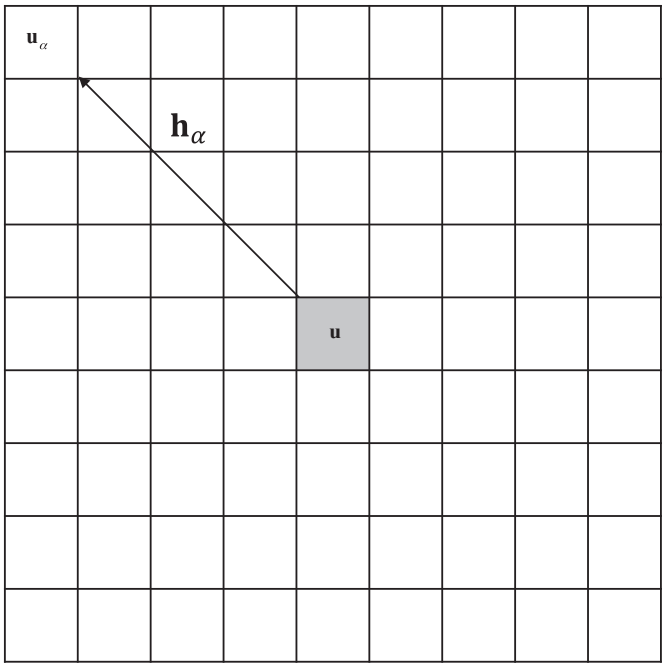

Fig. 1. A 9 × 9 template to capture multiple-point statistics. The template is used to scan the training image, and each data event of any possible pattern of the pore space and skeleton is recorded.

$$\text{Prob}\{d(\mathbf{u})\} = \text{Prob}\{i(\mathbf{u});\ \ i(\mathbf{u}_\alpha) = s_{k_\alpha}; \alpha = 1, \ldots, n\} \tag{2}$$

When a data event in the training image is the same as a data event $d(\mathbf{u})$, we call it a replicate. The ratio between the replicate number of data events $n(d(\mathbf{u}))$ and the size of the effective training image (or eroded image) N_n is the occurrence probability of this data event. N_n is also the number of different center locations of the template over the training image.

$$\text{Prob}\{i(\mathbf{u});\ \ i(\mathbf{u}_\alpha) = s_{k_\alpha}; \alpha = 1, \ldots, n\} = \frac{n(d(\mathbf{u}))}{N_n} \tag{3}$$

For any simulation point $\mathbf{u}$, the conditional probability distribution function (CPDF) of attribute $i(\mathbf{u})$ takes one value of m possible states and should be determined at the conditions that give n condition data values $i(\mathbf{u}_\alpha)$. According to the Bayesian conditional probability formula, the CPDF can be expressed as (Zhang et al., 2010)

$$\text{Prob}\{i(\mathbf{u}) = s_k | d(\mathbf{u})\} = \frac{\text{Prob}\{i(\mathbf{u}) = s_k \text{ and } i(\mathbf{u}_\alpha) = s_{k_\alpha}; \alpha = 1, \ldots, n\}}{\text{Prob}\{i(\mathbf{u}_\alpha) = s_{k_\alpha}; \alpha = 1, \ldots, n\}} \tag{4}$$

where the denominator $\text{Prob}\{i(\mathbf{u}_\alpha) = s_{k_\alpha}; \alpha = 1,\ldots,n\}$ is the occurrence probability of the data event, and it can be inferred by counting the number $n(d(\mathbf{u}))$ of replicates of the conditioning data event $d(\mathbf{u}) = \{i(\mathbf{u});\ i(\mathbf{u}_\alpha) = i(\mathbf{u} + \mathbf{h}_\alpha) = s_{k_\alpha}; \alpha = 1,\ldots,n\}$ in the associated effective training image (or eroded training image); the numerator $\text{Prob}\{i(\mathbf{u}) = s_k \text{ and } i(\mathbf{u}_\alpha) = s_{k_\alpha}; \alpha = 1,\ldots,n\}$ is the probability of both the data event and the simulation point $\mathbf{u}$ taking some state value existing together, and it can be obtained by counting the number $n_k(d(\mathbf{u}))$ of replicates, among the $n(d(\mathbf{u}))$ previous ones, associated with a central value $d(\mathbf{u})$ equal to s_k. The CPDF can also be expressed as