Research Article

Reconstruction and Analysis of Tight Sandstone Digital Rock Combined with X-Ray CT Scanning and Multiple-Point Geostatistics Algorithm

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Unconventional rocks such as tight sandstone and shale usually develop multiscale complex pore structures, with dimensions ranging from nanometers to millimeters, and the full range can be difficult to characterize for natural samples. In this paper, we developed a new hybrid digital rock construction approach to mimic the pore space of tight sandstone by combining X-ray CT scanning and multiple-point geostatistics algorithm (MPGA). First, a three-dimensional macropore digital rock describing the macroscopic pore structure of tight sandstone was constructed by micro-CT scanning. Then, high-resolution scanning electron microscopy (SEM) was performed on the tight sandstone sample, and the three-dimensional micropore digital rock was reconstructed by MPGA. Finally, the macropore digital rock and the micropore digital rock were superimposed into the full-pore digital rock. In addition, the nuclear magnetic resonance (NMR) response of digital rocks is simulated using a random walk method, and seepage simulation was performed by the lattice Boltzmann method (LBM). The results show that the full-pore digital rock has the same anisotropy and good connectivity as the actual rock. The porosity, NMR response, and permeability are in good agreement with the experimental values.

1. Introduction

Looking around the world, with the depletion of conventional fossil energy, unconventional hydrocarbon resources will be the most realistic resource type in this change [1]. However, the production and development of unconventional hydrocarbon resources are still facing many difficulties. From the point of view of production practice, the unconventional reservoir usually has no commercial production and its development often relies on large-scale hydraulic fracturing, which has the characteristics of high initial production, rapid decline, low recovery, and so on [2–4]. Since the macroscopic phenomena are often the result of microfactors, the rock structure and percolation mechanism of unconventional reservoirs studied at microscale are key means to the aforementioned macroproblems and improve the production capacity

eventually. Nevertheless, unconventional reservoir rock is usually characterized by low porosity and permeability, fine pore throat, complex pore structure, and developed fracture network [5–7], the laboratory experiment is difficult to carry out, and the routine rock modeling methods such as capillary model are hard to describe the true and microscopic structure of unconventional rocks.

In face of these challenges, digital rock technology is currently expected to be the key to solve the above puzzles in unconventional reservoirs. Digital rock technology originated in the 1970s and was proposed for comprehensively mimicking the real rock by imaging and mathematical algorithm, which has gradually developed into a promising tool in the study of porous media [8–13]. Based on the digital rock models, the microstructure of the rock can be quantitatively characterized and microseepage simulation can be carried out as well. Digital rocks have enabled important

breakthroughs in understanding how fluid enters pore spaces and the mechanisms of water/oil and gas seepage [14–16].

At present, the methods of digital rock reconstruction mainly include physical experiments, numerical reconstructions, and hybrid modeling. There is an extensive literature on these various approaches, and we summarize here their general philosophy and some of their limitations. Physical experiment methods have high accuracy and are widely used but are vulnerable to the tradeoff between resolution and dimension [17, 18]. Compared with the physical experiment method, the numerical reconstruction method has the advantages of low cost and high efficiency and can reconstruct different types of digital rocks. However, the drawback of the numerical reconstruction is that there are some differences between the model and the real rock [19–23]. To address the shortcomings of the single modeling method, some scholars have proposed the idea of mixing different modeling methods with each other, i.e., hybrid modeling methods [24–28]. For example, Talukdar et al. combined the truncated Gaussian random field method (TGRFM) with the characteristic of fast modeling speed and the simulated annealing method (SAM) with the characteristic of more accurate modeling and used the images generated by TGRFM as input to SAM to establish a digital rock with higher model quality. Politis et al. and Liu et al. reconstructed 3D digital rocks by combining the process-based method (PBM) and SAM. The basic process of their modeling is similar. First, use the PBM to construct the initial 3D digital rock and then use the initial model as the input of SAM. When the conditions of SAM are reached, a hybrid digital rock is generated. Compared with the traditional SAM, their method is more efficient in modeling and the model is more accurate. More recently, Lin et al. introduced a hybrid modeling method that combines physical experiments and numerical reconstruction. First, a 3D macropore digital rock was constructed by micro-CT; second, using high-resolution 2D SEM images, a micropore digital rock was constructed by SAM; last, a superposition method was used to construct the digital rock including the full range of pore structures. This method not only keeps the accuracy of the macropore image but also contains microstructure information. Hybrid modeling methods have improved modeling accuracy and efficiency and overcome some limitations of single modeling methods.

In this work, based on the hybrid method combining physical experiments and numerical reconstructions, we further develop a new combination method that integrated macropores constructed by X-ray CT and micropores reconstructed by MPGA. We utilized micro-CT to image the macropore structure of tight sandstone and constructed the macropore digital rock and used the SEM to image the micropores of tight sandstone and reconstructed the micropore digital rock using MPGA. Through the superposition of micropore and macropore digital rocks, the full-pore digital rock of tight sandstone was obtained, and the physical properties and seepage characteristics of the digital rocks were compared and analyzed.

2. Sandstone Modeling

2.1. 3D Macropore Reconstruction by X-Ray CT. Computerized tomography (CT) imaging has the advantages of high accuracy and being nondestructive and is widely used in the field of rock physics [29, 30]. As illustrated in Figure 1, the working principle of CT is that when X-rays are irradiated and penetrated through the sample, the energy will be attenuated differently and the attenuation process accords with the attenuation formula as follows:

$$I = I_0 e^{-\sum \mu_i x_i}. \quad (1)$$

In formula (1), I is the intensity after attenuation, I_0 is the original intensity, μ_i is the attenuation coefficient of component i to ray, and x_i is the length of ray passing through component i . When X-rays penetrate the sample, the detector detects the attenuated ray intensity and imitates it on the detector.

The core of CT imaging is to reconstruct the gray image of the sample. There are two basic reconstruction algorithms: analytical method and iterative method. At present, FDK reconstruction algorithm is more commonly used, and the formula of the FDK algorithm is as follows [29, 31–33]:

$$\begin{aligned} p'(\beta, a, b) &= \left(\frac{R}{\sqrt{RR + aa + bb}} p(\beta, a, b) g^n(a) \right), \\ F_{FDK}(x, y, z) &= \int_0^{2\pi} \frac{R^2}{U(x, y, \beta)^2} p'(\beta, a, b) d\beta, \\ a &= R \tan \gamma, \\ b &= \frac{q}{\cos \gamma}, \\ k &= \arctan \frac{q}{R} = \arctan \frac{b}{\sqrt{RR + aa}}, \\ U(x, y, \beta) &= R + x \cos \beta + y \sin \beta. \end{aligned} \quad (2)$$

In formula (2), $U(x, y, \beta)$ is the total attenuation coefficient, q is the length of the projection data in a certain direction, $p(\beta, a, b)$ is the collected projection data, $p'(\beta, a, b)$ is the weighted filtering of the projection data, $F_{FDK}(x, y, z)$ is the back projection reconstruction of the weighted filter projection data, $g^n(a)$ is a one-dimensional filter, R is the orbital radius, γ is the fan angle of the cone beam, β is the cone angle of the cone beam, and a and b are the positions on the detector.

We used an UltraXRM-L200 CT scanner to image the macropores ($>1.2 \mu\text{m}$) of the tight sandstone. The sandstone sample was selected and made into a cylinder with approximately 1.2 mm diameter and 1.4 mm length, and its porosity was 12.16% and gas permeability was $0.413 \times 10^{-3} \mu\text{m}^2$. The resolution of CT imaging was 1.2 micron/pixel, and 996 CT grayscale images were obtained. The original grayscale images (Figure 2) were preprocessed through contrast enhancement and a median filter. We used an improved threshold segmentation method considering

FIGURE 1: Schematic diagram of X-ray CT imaging [28].

FIGURE 2: 3D grayscale image of the tight sandstone (a) and 2D grayscale image cross section (b).

pore fractal characteristics to make the optimal segmentation [34]. Figure 3 shows a binary image of tight sandstone by micro-CT (white is pore; black is solid). Figure 4 presents a 3D macropore digital rock obtained by processing CT images, whose physical size is $0.12 \text{ mm} \times 0.12 \text{ mm} \times 0.12 \text{ mm}$ and voxel size is $100 \times 100 \times 100$. From CT scanning, we can see that the sample contains primary pores and secondary pores. The primary pores have straight edges, clean pore interiors, and large pore radii. The secondary pores mainly include intragranular pores and marginal pores of feldspar and detritus, a small amount of dissolved pores in carbonate cements, and the intercrystalline pores in clay minerals.

2.2. 3D Micropore Reconstruction by MPGA. To characterize smaller pores, we imaged the same sample scanned by CT using scanning electron microscopy (SEM); the imaging resolution of SEM images is 0.3 micron/pixel (Figure 5(a)); the same image processing used for the CT images was used to generate the binary SEM images, as shown in Figure 5(b).

Multiple-point geostatistics algorithm (MPGA) was originally used in geostatistics to deal with continuous geological entities at reservoir scale. The basis of MPGA is to replace the variation function of two-point geological statistics algorithm with a training image. The basic idea of this algorithm is to extract the image patterns of features from the training images and then restore these patterns to the final model [20, 21, 35]. In this work, we used MPGA to produce micropores in sandstone, and the basic steps are as follows:

- (1) Using the two-dimensional SEM binary image as the initial training image, the training image is scanned by the determined two-dimensional data template to construct a search tree.
- (2) Extract 0.5% of the pixel points from the two-dimensional training image used for each simulation as the horizontal direction (such as the x - y direction) condition data and assign it to the nearest network node. A two-dimensional slice such as the y - z

FIGURE 3: Binary image of tight sandstone by micro-CT (white is pore; black is solid).

FIGURE 4: 3D macropore digital rock using X-ray CT scanning method (blue is solid; green is pore; black is background).

(a)

(b)

FIGURE 5: Grayscale image (a) and binary image (b) of tight sandstone by SEM (white is pore; black is solid).

direction or the x - z direction is selected as a vertical direction condition for simulation.

- (3) Sequentially access all the nodes to be simulated with the determined random path, and for each node on the path, the condition data event is extracted together with the data template of the same size in step (1) and the condition data obtained in step (2). The conditional probability distribution function is obtained from the search tree, and the Monte Carlo method is used to extract the simulated value of the point; the simulation is continued as a new condition of the subsequent simulation until the two-dimensional image is generated.
- (4) The two-dimensional image simulated in step (3) is used as the training image to continue the simulation in the next step, and the first three steps are repeated until the next layer of the image is generated.
- (5) Repeat the first 4 steps until the simulation yields N new two-dimensional images.

In the process of simulation, the edge processing of the reconstructed image uses the target edge probability function. Since the simulated digital rock has only two parts of the pore and the skeleton, the porosity of the two-dimensional SEM binary is used as its target edge value and the servosystem is used to ensure the accuracy of the simulation results. The simulated N images are sequentially superimposed to obtain a three-dimensional digital rock of $N \times N \times N$. For the processing of excessive condition data, the method of setting the lower limit value is adopted. If the number of repetitions obtained by scanning the training image using the template is lower than the lower limit value, the condition data farthest from the center point is removed, the data are rescanned until the set lower limit value is reached, and then the conditional probability value of the point is obtained at this time. For the processing of only one conditional data, the edge probability at this time can be used as the conditional probability.

Figure 6 shows the micropore digital rock constructed by the MPGA, whose physical size is $0.12 \text{ mm} \times 0.12 \text{ mm} \times 0.12 \text{ mm}$ and the voxel size is $400 \times 400 \times 400$.

2.3. Full-Pore Model. We used the superposition method [27] to integrate two digital rocks. According to the resolution ratio of the macropore digital rock to micropore digital rock i ($i=4$), the voxels of macropore digital rock were divided into $i \times i \times i$ voxels. The voxel refinement diagram is shown in Figure 7.

The pores of both digital rocks are superimposed, and the superimposed pores I_S is

$$I_S = I_A \cup I_B, \quad (3)$$

where I_A and I_B represent the pore space of macropore digital rock and micropore digital rock, respectively. Because the pore pixels and solid pixels of the binary image are characterized by 0 and 1, respectively, the superposition operation is

FIGURE 6: 3D micropore digital rock by MPGA (blue is pore; red is solid).

$$\begin{aligned} 0 + 0 &= 0, \\ 0 + 1 &= 0, \\ 1 + 0 &= 0, \\ 1 + 1 &= 1. \end{aligned} \quad (4)$$

Figure 8 presents the full-pore digital rock of tight sandstone constructed by the superposition method, whose voxel size is $400 \times 400 \times 400$ and resolution is 0.3 micron/pixel.

3. Structural Characteristics of the Sandstone Model

3.1. Connectivity Analysis. We calculate the porosity of the digital rocks by using the following equation:

$$\phi = \frac{V_p}{V_p + V_s}, \quad (5)$$

where V_p is the volume of all pores, which contains the connected pores and the dead pores in the digital rock, m^3 . V_s is the volume solid matrix, m^3 . Here, the pore volume and solid matrix volume of digital rocks are calculated by counting the number of voxels labeled as 0 and the number of voxels labeled as 1, respectively.

We evaluated the connectivity of digital rocks using the connected porosity. Connected porosity ϕ_c is defined by the following formula:

$$\phi_c = \frac{V'}{V_p + V_s}, \quad (6)$$

where V' is the volume of connected pores, m^3 .

The calculation results are shown in Table 1. The results show that the porosity of the full-pore digital rock is slightly

FIGURE 7: Schematic diagram of voxel refinement.

FIGURE 8: Full-pore digital rock of tight sandstone by the new method (blue is solid; green is void; black is background).

TABLE 1: Porosity comparison between digital rocks and real sandstone.

Parameters	Macropore digital rock	Micropore digital rock	Full-pore digital rock	Real rock
Porosity (%)	11.23	11.76	13.83	—
Connected porosity (%)	9.19	10.47	11.81	12.16

higher than that of the macropore digital rock and the micropore digital rock. The connected porosity of the full-pore digital rock is significantly higher than that of the other two digital rocks, which proves that the addition of micropores improves the pore connectivity of digital rock. In addition, the porosity of the full-pore digital rock is higher than the measured porosity of the actual rock, and the connected porosity is close to the measured porosity, which is consistent with the fact that the laboratory uses nitrogen to measure the rock porosity and the isolated pore cannot be measured. The measured porosity is actually equal to the connected porosity. Due to the strong heterogeneity of the

tight sandstone pore structure, a single simulation method cannot capture the total pore volume, while the full-pore digital rock has better pore connectivity and better consistency with the actual rock in terms of connected porosity.

3.2. NMR Response. In this section, a random walk method is used to simulate the nuclear magnetic resonance (NMR) [36]. This involves simulating the Brownian motion of a diffuse particle called a walker. These walkers diffuse in the pore space, and when they come in contact with a solid surface, their chances of being killed are limited. The

life-time distribution of the walkers is a decay in magnetization, which can be inverted to a T2 distribution by using a curvature-smoothing regularization method [37].

It is acknowledged that the short T2 time in the T2 spectrum represents the small pore space and the long T2 time represents the big pore space [38–40]. We compared the results of the laboratory NMR test on the sandstone sample with the simulation NMR results on digital rocks. The laboratory NMR test was carried out on the tight sandstone core saturated with water using the low-field NMR detection device (MacroMR12-150H-I, Niumag, China), and the NMR test mainly refers to the core analysis method (GBT 29172-2012, China) and the laboratory measurement specification of NMR parameters of rock samples (SY-T6490-2014, China). From Figure 9, we can see that tight sandstone has typical dual pore characteristics, showing the bimodal distribution on the NMR T2 spectrum. Simulation results of the digital rocks show that the T2 distributions of the macropore and micropore digital rocks are narrower and have single modal distributions, the T2 value of micropore digital rock is mainly distributed in the short T2 time range, and the T2 value of macropore digital rock is dominant in the long T2 time, implying that the macropore digital rock mainly mimics the relatively large pores, while the micropore digital rock mainly mimics the relatively small pores. For the full-pore digital rock, the simulated T2 distribution has a bimodal distribution and shows good agreement with the experimental result, although there is a small difference as is attributed to the loss of some fine details of the pore structure (<0.3 microns) in tight sandstone.

By comparative analysis, it can be seen that single resolution imaging and single modeling method cannot reconstruct the pore structure and restore connectivity of tight sandstone digital rock. Combined with X-ray CT and SEM, we can capture micropores and macropores in a complete model using the hybrid modeling method. On the whole, the full-pore digital rock shows good performance in the multiscale pore structure simulation of tight sandstone. At the same time, in the study of tight reservoir, we should also pay special attention to the influence of submicron pores on rock seepage ability.

4. Seepage Properties

We carried out the permeability evaluation on digital rocks by using the lattice Boltzmann method (LBM) [27, 41, 42]. The LBM utilizes the collision, and migration of virtual particle swarms with different velocity directions on discrete spatial grid points to characterize fluid flow, which can effectively simulate complex flows such as porous media flow, convection current, and multiphase flow. LBM is a mesoscopic method, and the basic idea of this method is based on the theory of molecular dynamics. There are three commonly used 3D lattice Boltzmann models, which are divided according to the number of discrete velocity components in 3D space in the direction of fluid continuous motion. Generally, the common dispersion is 15, 19, and 24 components, corresponding to D3Q15, D3Q19, and D3Q24

models, respectively. The more discrete velocity components, the higher the accuracy of the numerical simulation, but at the same time, it brings the calculation problems such as large amount of data and slow simulation speed. Here, we adopt the D3Q19 3D lattice Boltzmann model, and Figure 10 shows the lattice structure, and the velocity discrete Boltzmann-BGK equation is as follows:

$$f_i(r, t) - f_i(r + e_i \delta_t, t + \delta_t) = \frac{1}{\tau} [f_i(r, t) - f_{\text{eqi}}(r, t)], \quad (7)$$

where, $f_i(r, t)$ is the distribution function of the particle in the i direction at t time and position $r(x, y, z)$, e_i is the velocity in the i direction, τ is the relaxation time, and δ_t is the time step, $f_{\text{eqi}}(r, t)$ is the equilibrium distribution function.

The discrete velocity direction is as follows:

$$e_i = \begin{cases} (0, 0, 0), & i = 0; \\ (\pm 1, 0, 0), (0, \pm 1, 0), (0, 0, \pm 1), & i = 1, \dots, 6; \\ (\pm 1, \pm 1, 0), (\pm 1, 0, \pm 1), (0, \pm 1, \pm 1), & i = 7, \dots, 18. \end{cases} \quad (8)$$

Equilibrium distribution function is as follows:

$$f_{\text{eqi}}(r, t) = \rho \omega_i \left[1 + \frac{e_i u}{c_s^2} + \frac{(e_i u)^2}{2c_s^4} - \frac{u^3}{2c_s^2} \right], \quad (9)$$

where c_s is the lattice sound velocity, dimensionless with $c_s = 1/\sqrt{3}$ and ω_i is the weight factor, $\omega_i = 1/3$, $i = 0$, $\omega_i = 1/18$, $i = 1, \dots, 6$, $\omega_i = 1/36$, $i = 7, \dots, 18$.

Local macrolattice density $\rho(r, t)$, lattice velocity $u(r, t)$, lattice pressure $p(r, t)$, and lattice viscosity $\mu(r, t)$ can be represented by

$$\begin{aligned} \rho(r, t) &= \sum_i f_i(r, t), \\ p(r, t) &= c_s^2 \rho(r, t), \\ u(r, t) &= \frac{\sum_i f_i(r, t) e_i}{\rho(r, t)}, \\ \mu(r, t) &= \frac{2\tau - 1}{6}. \end{aligned} \quad (10)$$

The inlet and outlet boundary is pressure boundary, the initial lattice velocity is 0, and the initial lattice density is 1.

We used the LBM to simulate the seepage process of macropore digital rock (Figure 4), micropore digital rock (Figure 6), and full-pore digital rock (Figure 8) and obtained the inherent permeability of digital rocks. The inherent permeability of full-pore digital rock is $0.377 \times 10^{-3} \mu\text{m}^2$, the inherent permeability of micropore digital rock is $0.093 \times 10^{-3} \mu\text{m}^2$, and the inherent permeability of macropore digital rock is $0.216 \times 10^{-3} \mu\text{m}^2$. The simulation results show that the permeability of full-pore digital rock is larger than that of micropore digital rock and macropore digital rock, suggesting that micropores can greatly improve the conductivity of digital rocks. In addition, the calculated

FIGURE 9: Comparison of NMR response between the simulated results of digital rocks and the experimental result of real sandstone.

FIGURE 10: D3Q19 lattice structure model.

permeability of the full-pore digital rock is consistent with the experimental result ($0.413 \times 10^{-3} \mu\text{m}^2$), which shows that the permeability of the full-pore digital rock is similar to that of the real tight sandstone. The permeability ratio of full-pore digital rock to macropore digital rock is 1.75, which indicates that micropores have great influence on the permeability of digital rock model. Furthermore, we should

fully consider and study the transport characteristics of submicron pores in tight sandstone.

5. Conclusions

In this study, we proposed a new strategy by combining the X-ray CT scanning method and multiple-point geostatistics

algorithm (MPGA) in digital rock. Unlike the existing numerical reconstruction methods, this method is a hybrid of physical experiments and numerical reconstruction, so it not only has the accuracy of the physical experiment method but also has the convenience of the numerical reconstruction method. We compared and analyzed the pore structure and seepage characteristics of the full-pore digital rock constructed by the new hybrid method, the macropore digital rock constructed by the X-ray CT scanning method, and the micropore digital rock constructed by MPGA. The results show that the new hybrid method can better simulate the real rock, and the pore structure and seepage properties of the full-pore digital rock are basically consistent with those of the actual rock. In addition, this study also shows that single-resolution imaging and the single modeling method cannot produce the satisfactory digital rock model, especially for tight sandstone with a multiscale pore system. Furthermore, tight sandstones are generally rich in clay minerals (such as kaolinite, illite, and chlorite), which has great effect on macroelectrical conductivity, elastic modulus, and permeability, and it is thus an interesting direction to construct multiphase multicomponent digital core in the future.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding the publication of this work.

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