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Quantitative Characterization of Pore–Fracture Structures in Deep Coal Reservoirs Based on the QSGS Method

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Abstract

This study aims to improve the characterization of multiscale pore structures in coal by constructing a more representative digital core model. Mercury intrusion porosimetry, micro-CT scanning, Avizo-based image processing, and the quartet structure generation set (QSGS) method were integrated to reconstruct the pore–fracture networks of four coal samples. Mercury intrusion data were used to determine porosity and pore-size distribution, while micro-CT images were applied to establish three-dimensional pore network models. To overcome the resolution limitation of CT imaging, the QSGS method was further used to supplement unresolved micropores. The results indicate that the proposed multiscale digital core can more accurately represent the pore structure of coal samples. Connectivity analysis based on Euler number, tortuosity, and coordination number shows clear differences in pore connectivity among the samples. This approach provides an effective method for pore structure characterization and offers a basis for permeability prediction and coalbed methane development.

Keywords

Multiscale digital core; Coal pore structure; Micro-CT; QSGS method

1. Introduction

In recent years, multiscale digital cores have attracted increasing attention in the study of coal pore structures, as they enable the effective integration of microscopic and macroscopic structural information. The construction of multiscale digital cores can more accurately reconstruct the internal structure of coal samples, thereby improving the accuracy of permeability prediction and gas disaster prevention.

Traditional methods for characterizing pore structures, such as mercury intrusion porosimetry and scanning electron microscopy, can provide partial pore information. However, these methods have certain limitations, including sample destructiveness and difficulty in obtaining complete three-dimensional structural information. Computed tomography (CT) technology, with its advantages of non-destructive testing, high resolution, and three-dimensional imaging, can be combined with Avizo software to establish three-dimensional models of coal samples and visually characterize the spatial distribution of pores. Nevertheless, due to the limited resolution of CT scanning, some micropores cannot be effectively identified.

To address this limitation, this study employs a four-parameter stochastic generation method to supplement the micropores that cannot be recognized by CT images. The pores are further classified into micropores, small pores, mesopores, and macropores, and their structural characteristics are analyzed. On this basis, a multiscale digital core that more accurately represents the real pore structure of coal samples is constructed, providing theoretical support and data references for coal resource exploration, mining, and gas control.

2. Construction of a Multiscale Digital Core

2.1. Mercury Intrusion Porosimetry

Mercury intrusion porosimetry was conducted in the laboratory to determine the porosity of crushed coal samples with particle sizes smaller than 1 cm. To ensure experimental accuracy, ten small crushed particles were selected from each coal sample. The coal samples were numbered 10, 39, 40, and 45. The measured porosities were 3.0937%, 3.0948%, 7.4406%, and 6.2361%, respectively.

At different scales, the identification of pore structures in coal samples varies due to differences in imaging resolution. According to the pore size classification, micropores are defined as pores with diameters smaller than 10 nm; small pores have diameters ranging from 10 to 100 nm; mesopores range from 100 to 1000 nm; and macropores are larger than 1000 nm in diameter. the four coal samples exhibit well-developed pore structures in the micropore, small-pore, and macropore ranges.

Owing to the resolution limitation of CT imaging, isolated pores cannot be identified solely through CT images. Therefore, the pore sizes discussed here represent the actual pore sizes calculated from mercury intrusion experimental data.

2.2. CT Scanning

Micron-scale CT scanning was performed on four cylindrical coal–rock samples from the HL block, each with a diameter of approximately 1 cm, using a phoenix v|tome|x s CT scanner. The purpose was to identify and analyze micron-scale pores within the coal–rock samples.

The voxel size of the core scanning data was 7.7 μm. During scanning, the coal–rock sample was first fixed in place, after which X-rays emitted from the radiation source passed through the sample. In this process, the intensity of the X-rays was attenuated. The attenuated X-rays were then received by the detector, and the corresponding signals were automatically captured and stored by the image acquisition software integrated into the scanning system. Subsequently, the coal–rock sample was rotated by a certain angle for repeated scanning and recording [1].

After CT scanning, approximately 1,000 two-dimensional CT grayscale images were obtained for each sample. By stacking these two-dimensional grayscale images, a three-dimensional volumetric dataset of the coal–rock sample could be reconstructed [2].

2.3. Establishment of the Multiscale Pore–Fracture Model

Similar to other imaging techniques, CT imaging is inevitably affected by noise and artifacts. Therefore, image processing is required after scanning, mainly including cropping, denoising, and threshold segmentation. In this study, the CT images of the four coal samples were imported into Avizo software. After image loading, preprocessing, cropping, and three-dimensional reconstruction, the 3D structures of the coal samples were obtained [3].

Based on the measured porosity, interactive threshold selection was performed using high-resolution CT grayscale images and Avizo software. To ensure consistency between the measured coal samples and the reconstructed 3D models, the original uncropped CT images were used for image processing and porosity calculation. During threshold adjustment, the segmentation results of pores and fractures could be observed in real time, and the threshold closest to the measured porosity was selected[4]. Common threshold segmentation methods include automatic thresholding, adaptive thresholding, brightness-difference thresholding, interactive thresholding, and watershed thresholding. In this study, the interactive thresholding method was adopted.

Theoretically, a larger coal sample volume can more accurately represent the pore structure and macroscopic properties of coal. However, increasing the sample size also imposes higher requirements on computational and storage capacity. To balance computational efficiency and experimental accuracy, the representative elementary volume (REV) method was employed[5]. The REV can reduce data volume and improve computational efficiency while maintaining structural representativeness.

By analyzing the variation in porosity with the size of the binarized image, a size range was selected in which the porosity remained relatively stable and close to that of the original sample. Considering computational and storage limitations, the REV size of the four coal–rock samples was uniformly set as $100 \times 100 \times 100\ \mu m^3$. Based on this REV, three-dimensional pore network models were constructed.

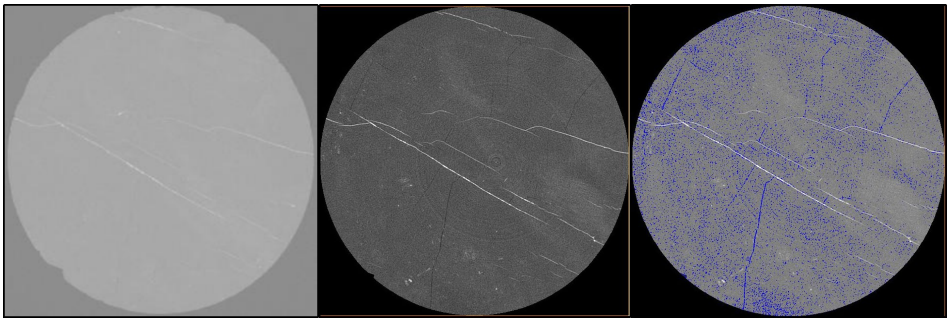


Figure 1. Image Processing Procedure

2.4. Principle of the QSGS Method

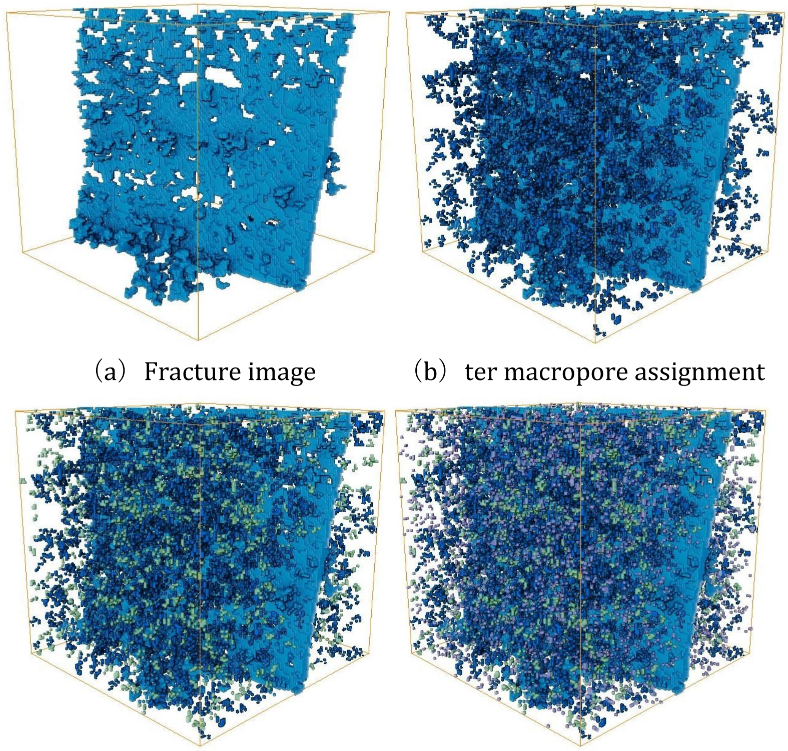
Due to the limited resolution of CT imaging, small-scale pores cannot be effectively identified. Therefore, the quartet structure generation set (QSGS) method was adopted in this study to supplement the missing micropores in the digital core reconstructed from X-ray CT images.

The QSGS method divides the coal sample into solid and non-solid phases, where the coal matrix is regarded as the growing phase and the pores are regarded as the non-growing phase. Initially, the entire model is assumed to consist of pores. Solid-phase growth nuclei are then randomly generated within the reconstruction domain and grow in different directions according to predefined growth probabilities, thereby simulating the gradual cementation process of coal formation .

The generation process mainly includes three steps: seeding, growth, and repetition. First, growth nuclei are randomly distributed in the reconstruction domain according to the distribution probability Pc, which should be lower than the target porosity. Then, each growing grid point expands toward adjacent grid points in different directions according to the directional growth probability Pdi (i = 1, 2, 3, ..., 26). This process is repeated until the model reaches the target porosity. By adjusting the growth probabilities in different directions, the spatial structural characteristics of the porous medium can be controlled [6].

Combined with mercury intrusion porosimetry data, the porosity proportions of micropores, small pores, mesopores, and macropores were calculated. Taking micropores as an example, the micropore volume was obtained by multiplying the pore volume at the micropore stage by the sample mass, and the micropore porosity was calculated as the ratio of micropore volume to the total sample volume. The porosity proportions of the other pore types were calculated in the same manner.

In this study, pores at different scales were generated by controlling porosity, growth nucleus probability, and distribution probability. The growth nucleus probability was set to 0.01 for micropores and small pores, and 0.001 for mesopores and macropores. The model was generated using MATLAB. Taking coal sample No. 10 as an example, the result is shown in Figure 3. The generated model indicates that the QSGS method can effectively restore the micro-scale pores that cannot be identified by CT scanning, thereby improving the completeness of the digital core pore structure.



(a) Fracture image (b) ter macropore assignment

(c) After mesopore assignment (d) After micropore assignment

Figure 2. Pore Reconstruction Process Based on the QSGS Method

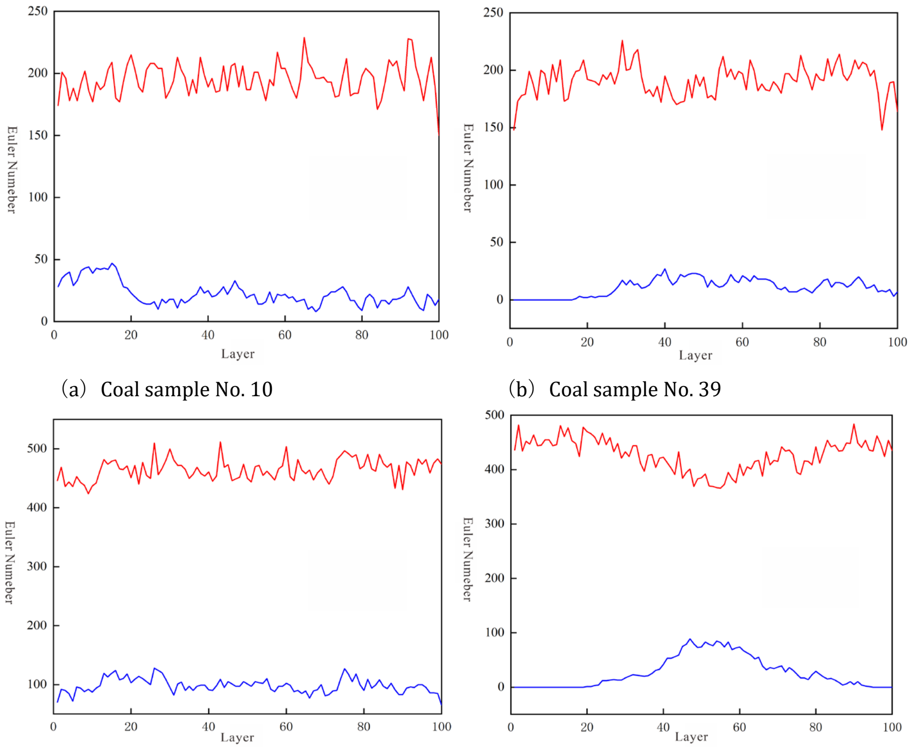
3. Results and Discussion

3.1. Euler Number

The Euler number is an important parameter for characterizing the connectivity of pore networks[7]. In general, a smaller Euler number indicates stronger pore connectivity, whereas a larger Euler number suggests a greater number of isolated pores and poorer connectivity. A negative Euler number usually reflects a highly connected pore network, which is more favorable for fluid flow. In this study, the Euler number of each slice was calculated using the Euler Number module in Avizo. The variation curves before and after pore connection were then plotted to analyze changes in pore connectivity.

The results show that the Euler numbers of the coal samples were generally large before connection, indicating the presence of numerous isolated pores and limited pore connections. After connection, the Euler number of coal sample No. 10 decreased significantly, suggesting a marked reduction in isolated pores and an obvious improvement in connectivity. For coal sample No. 39, the Euler number exhibited considerable fluctuations, and obvious variations remained after connection, indicating a more complex pore structure and weaker connectivity compared with sample No. 10.

Before connection, coal samples No. 40 and No. 45 showed similar Euler number distributions, with relatively large values and strong fluctuations. After connection, the Euler number of sample No. 40 decreased to some extent, but remained relatively high overall. Sample No. 45 also maintained a high Euler number, with a maximum value of approximately 200. Overall, the connectivity improvement of samples No. 40 and No. 45 was limited, and their pore connectivity was relatively moderate.



(a) Coal sample No. 10 (b) Coal sample No. 39

(c) Coal sample No. 40 (d) Coal sample No. 45

Figure 3. Euler Number

3.2. Tortuosity

Tortuosity is a key parameter used to describe the degree of curvature of fluid or molecular transport pathways in porous media. It is defined as the ratio of the actual connected pore-throat path length to the shortest straight-line distance, and it significantly affects the permeability and diffusion properties of coal.

A tortuosity value closer to 1 indicates a smoother and more connected flow path, lower flow resistance, and shorter seepage pathways for gas migration. Among the four coal samples, samples No. 10 and No. 40 exhibit relatively low tortuosity values of 1.332 and 1.379, respectively, indicating better pore connectivity. In contrast, samples No. 39 and No. 45 have higher tortuosity values of 1.906 and 1.739, respectively. Therefore, sample No. 10 shows the best connectivity, whereas sample No. 39 exhibits the poorest connectivity.

3.3. Coordination Number

In a pore network model, the coordination number is an important parameter for characterizing pore connectivity. It refers to the number of throats directly connected to a single pore, reflecting the local connectivity of pore nodes within the network. A higher coordination number indicates stronger connectivity and more favorable fluid flow. When the coordination number is 0, the pore is isolated; when it is 1, the pore is regarded as a dead-end pore. Therefore, the distribution of coordination number can effectively reveal the topological characteristics of coal pore networks [8].

As shown in Figure 12, sample No. 10 mainly has coordination numbers between 3 and 6, with 81.7% of pores having values lower than 6 and 18.3% having values greater than or equal to 6. For sample No. 39, these proportions are 86.3% and 13.7%, respectively, indicating weaker connectivity than sample No. 10. In sample No. 40, coordination numbers between 5 and 9 account for the largest proportion, and pores with coordination numbers greater than or equal to 6 account for 38.1%. For sample No. 45, the proportions of coordination numbers lower than 6 and greater than or equal to 6 are 63% and 37%, respectively[9].

Overall, sample No. 40 shows the highest proportion of large coordination numbers, indicating the best pore network connectivity, followed by sample No. 45. Sample No. 39 exhibits the poorest connectivity among the four samples.

4. Conclusions

- The pores in the coal samples were classified into micropores, small pores, mesopores, and macropores, and their characteristics were analyzed at different scales. The results show that pores of different sizes differ significantly in distribution, morphology, and connectivity. Micropores are widely distributed and have a large specific surface area, playing a key role in coalbed methane adsorption and storage. Small pores and mesopores mainly influence gas diffusion and seepage, while macropores, although fewer in number, are important for forming preferential flow pathways and directly affect gas production.
- The QSGS method can effectively supplement micropores that cannot be identified by CT scanning, thereby improving the completeness of the multiscale digital core. However, its accuracy may fluctuate for certain coal samples, indicating that the algorithm parameters require further optimization. In addition, the current digital core model does not fully consider the effects of mechanical properties, mineral composition, and their interactions with pore structures. Future studies should integrate more experimental data and theoretical models to improve the reliability and applicability of the model.

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