Rock surface porosity measurement and pore distribution analysis based on hole wall images

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Abstract. This study proposes a method that uses image processing technology to identify, calculate, and analyze the pore structure in hole wall images. First, the R, B, and G components of a hole wall image are adjusted on the basis of an appropriate threshold to eliminate the effects of drilling fluid attached to the hole wall. Second, the hole wall image is converted into an S component image in the HSV color space to distinguish the pores and dark gray texture of the rock. Third, the best segmentation threshold of the S component image is obtained by the maximum interclass variance method, and the threshold is used to binarize the S component image. Finally, mathematical morphological operations are performed on the binary image to eliminate defects. On the basis of the identified pore structure in the hole wall image, the surface porosity of the rock can be calculated, and the pore distribution characteristics can be further analyzed. The results of this work provide ideas for measuring the porosity of deep rocks and analyzing their pore distribution.

1. Introduction

Porosity is the ratio of the sum of all pore space volumes in a rock to the total volume of the rock. It is one of the most important physical parameters for rock mass quality evaluation, reservoir classification, and seepage characteristic research [1-3]. Therefore, accurately measuring rock porosity is important. Conventional methods for measuring rock porosity mainly include laboratory test methods and field data evaluation methods [4]. Laboratory test methods include the capillary pressure curve method, casting slice method, scanning electron microscope method, CT scanning method, etc. [5-8]. Field data evaluation methods include resistivity logging, nuclear magnetic resonance logging, seismic inversion, etc. [9-12]. Conventional laboratory methods can obtain a large number of parameters, but the test process is cumbersome, and they are difficult to use in measuring the porosity of deep rock core samples. Field data evaluation methods are large in scale and suffer from low accuracy; hence, they cannot easily meet the requirements of fine structure descriptions for rock mass. These drawbacks highlight the need to develop a method for simply, quickly, and accurately measuring rock porosity.

When a research target is larger than a given characteristic unit, the surface porosity is equal to the porosity [13]. Many scholars have carried out extensive studies on methods for calculating porosity using rock images [14-15]. Most existing research is based on rock images obtained by slicing or scanning rock core images. The process is complex, and the cost is high. Hence, this approach is...
difficult to implement when a core is missing or broken. These drawbacks restrict the research scale to laboratory samples and hinder the measurement and analysis of the porosity distribution in a wide range of rocks. With the rapid development of borehole camera technology, obtaining images of the internal structure of rock masses, especially high-resolution optical images of the entire borehole wall, is no longer difficult. A hole wall image obtained by borehole camera technology contains actual pore structure information, including its size, azimuth, depth, etc. However, it also contains information that may affect pore identification, such as drilling fluid, rock texture, and shadows caused by uneven illumination [16]. Therefore, a processing method for hole wall images is needed to identify pore structures and then calculate and analyze porosity. This work mainly explores the identification and calculation of the pore structures in hole wall images on the basis of image preprocessing, conversion of the color space, optimal threshold binarization, mathematical morphology operation, etc. The goal is to eliminate redundant structural information, accurately identify pore structures in hole wall images, and thereby calculate rock surface porosity and analyze pore distribution.

2. Borehole camera technology

Borehole camera technology uses optical principles to enable the direct observation of internal boreholes. The technology first appeared in the mid-1950s and later experienced three development stages, namely, borehole photography, borehole camera, and digital optical imaging [17]. At present, the digital panoramic borehole camera system developed by the Institute of Rock and Soil Mechanics of the Chinese Academy of Sciences is one of the most representative borehole optical imaging systems in the world. The maximum resolution of this system is 0.1 mm; hence, the system can only identify pores with diameters greater than 0.1 mm. However, with the continuous improvement of the resolution of optical imaging equipment, the system is expected to be suitable for identifying small diameter pores in the future.

![Figure 1. Structural diagram of digital panoramic drilling camera system](image)

The main innovation of digital optical imaging technology lies in the realization of panoramic images and the breakthrough of digital technology. The digital panoramic borehole camera system uses a special truncated cone mirror to reflect the 360° borehole wall into a flat panoramic image. The depth encoder and magnetic compass superimpose the depth and azimuth information. The CCD camera located in the probe captures and records the panoramic image. The panoramic image captured by the camera presents a distorted circular ring, which hinders the direct observation of the hole wall’s structural information from the figure. Therefore, the panoramic image should be restored as an unfolded plane image and 3D core virtual image by using an inverse algorithm, as shown in Figure 2.
Related image processing approaches can be applied to the unfolded plane image to further obtain the structural information of the hole wall.

![Unfolded plane image and 3D virtual image of core](image)

**Figure 2.** Unfolded plane image and 3D virtual image of core

### 3. Pore structure identification

Pore structure identification involves accurately dividing a hole wall image into the pore target and the rock background. The proposed pore structure identification method based on hole wall images is divided into the following steps: 1) preprocessing of the hole wall image, 2) conversion of the preprocessed hole wall image into a S component image in the HSV color space, 3) binarization of the S component image using the optimal threshold, and 4) implementation of mathematical morphology operations on the binary image. The specific flowchart is shown in Figure 3.

![Flowchart](image)

**Figure 3.** Identification of pore structure in hole wall image

#### 3.1. Hole wall image preprocessing

A hole wall image is obtained by processing the high-definition hole wall video of a rock mass. The cleanliness of the hole wall rock mass affects the quality of the hole wall image and the effect...
structure identification. Therefore, prior to pore structure identification, the image of the hole wall must be preprocessed. Prior to the borehole camera test, the hole wall should be flushed to remove any large stains on the hole wall. However, a small amount of drilling fluid may stick to the hole wall, and the adhered drilling fluid may be misidentified as the pore structure. Therefore, the drilling fluid structure on the hole wall image must be removed prior to the pore identification. The same drilling fluid is usually used in the same borehole. The RGB component values of the drilling fluid structure on the hole wall image are basically the same. Therefore, only one drilling fluid structure needs to be identified on the hole wall image; the RGB value of this structure is then obtained. An appropriate threshold range is set to traverse every pixel in the hole wall image. The R, G, and B values that meet the threshold range are reassigned, and the mud structure is eliminated. The hole wall image used in this work was obtained from a drilling well in Guiyang City, Guizhou Province, China. The well is 55 m deep and has a diameter of 110 mm. The drilling fluid is water-based mud. Figure 4 shows the image of the hole wall at the 12–12.8 m section of the well, which is mudstone formation. The RGB component values of the water-based mud structure on the image are 120, 130, and 150, respectively. The threshold value is set to 20. The pixels with $100 < R < 140$, $110 < G < 150$, and $130 < B < 170$ are screened and reassigned to $R = G = B = 255$. In Figure 4a, a part of the water-based mud structure is marked with a red dashed line. After the adjustment of the R, G, and B component values, the water-based mud structure in Figure 4b becomes a background that does not interfere with pore structure identification.

![Figure 4. Effect diagram of drilling fluid removal](image)

3.2. Conversion of color space
Image binarization is a commonly used method in digital image processing, and it is often adopted as a preprocessing technique for extracting image structure information. It divides the gray value of pixels in a picture into a maximum value and a minimum value through an appropriate threshold so that the image contains only two types of information, namely, the target and background. In this study, the hole wall image needs to be converted into a binary image containing only pores (targets) and nonpores (backgrounds) prior to the pore structure identification. In the RGB color space, the dark gray texture of a rock is close to the color of the pore structure, and the gray values are highly overlapped. Figure 5 shows only one pore at the red line of the original image and gray image. However, it overlaps with the gray value of the dark gray texture of the rock on the right side of the image. Hence, distinguishing the pore from the dark gray texture is difficult. As shown in the binary
map, a large area of the dark gray texture is misidentified as pores. Therefore, before performing binary image segmentation, the pores should be distinguished from the dark gray textures to avoid misidentification.

![Image](image.png)

**Figure 5.** Comparison of gray value of pore and dark gray texture of rock

Although the dark gray texture of the rock and the gray value of the pore structure overlap, the three component values of R, G, and B have large differences. Pores are defects on the hole wall and appear as a dark color on the hole wall image. As the drilling fluid attached to the surface is difficult to completely wash away, the three component values of R, G, and B are not close. By contrast, the R, G, and B components of the dark gray texture of the rock are almost equal. As shown in Figure 6, the difference between the maximum and minimum values of the R, G, and B components of the pore structure at the red line is significantly greater than the difference between the R, G, and B component values of the dark gray texture on the right side of the rock. Therefore, the differences in the R, G, and B component values can be used to distinguish pores from the dark gray texture of rocks.

![Image](image.png)

**Figure 6.** Differences in R, G, and B component values between pores and dark gray texture
The HVS color space is mainly represented by three components, namely, hue (H), saturation (S), and lightness (V) [18]; the S component represents the depth of color, and the value range is [0,1]. It can reflect the size difference between the R, G, and B component values of each pixel in the image. Therefore, converting the hole wall image from the RGB color space into an S component image in the HSV color space can effectively distinguish the dark gray texture of the rock from the pore structure. Equation (1) shows the proposed formula for S component graph conversion. The formula further highlights the difference in the gray values of the pore structure and the dark gray texture of the rock in the S component image. The processing results are shown in Figure 7.

\[
S = \begin{cases} 
\frac{X_{\text{max}} - X_{\text{min}}}{\sqrt{X_{\text{max}}^2 + X_{\text{min}}^2}}, & X_{\text{max}} \neq X_{\text{min}} \\
0, & X_{\text{max}} = X_{\text{min}}
\end{cases}
\]  

(1)

where \(X_{\text{max}} = \max (R,G,B)\); \(X_{\text{min}} = \min (R,G,B)\); and \(\max (R,G,B)\) and \(\min (R,G,B)\) are the maximum and minimum values of the R,G, and B component values of the pixel points in the RGB color space.

![Figure 7. S component image of hole wall image](image)

3.3. Optimal threshold binarization

The maximum between-class variance method [19] is commonly used in image segmentation. It is an algorithm based on global adaptive threshold determination, which was proposed by the Japanese scholar Otsu in 1979. When the target is mistakenly recognized as the background or the background is mistakenly recognized as the target, the difference between the two parts becomes minimal. Therefore, when the optimal threshold is used for segmentation, the variance between classes is the smallest. Hence, the probability of misidentification is also small.

If the total number of pixels in the hole wall image is \(N\), the grayscale range of the image is \([0, L]\), and the number of pixels with grayscale value \(i\) is \(n_i\), then the probability of \(i\) is

\[
P_i = \frac{n_i}{N}
\]

(2)

If the optimal segmentation threshold of the image is \(T\), then the hole wall image can be divided into C1 and C2. C1 is composed of pixels with gray values in \([0, T-1]\). C2 is composed of pixels with gray values in \([T, L]\). The probabilities of C1 and C2 are respectively written as
The gray mean values of C1 and C2 are

\[
\mu_1 = \frac{1}{P_1} \sum_{i=0}^{T-1} i P_i \\
\mu_2 = \frac{1}{P_2} \sum_{i=T}^{L} i P_i
\]

(5)

(6)

The average grayscale of the whole hole wall image is

\[
\mu = \sum_{i=0}^{L} i P_i = P_1 \mu_1 + P_2 \mu_2
\]

(7)

The total variance of the two parts of the image is

\[
\sigma^2 = P_1 (\mu_1 - \mu)^2 + P_2 (\mu_2 - \mu)^2
\]

(8)

Let \( T \) take the values sequentially in the range of \([0, L]\). When \( \sigma^2 \) reaches the maximum value, \( T \) is the optimal segmentation threshold of the hole wall image.

In this work, the total number of pixels of the hole wall image after conversion into the S component image is \(3059 \times 2847\), that is, \(N = 3059 \times 2847\); the gray value range is \([0,1]\), and the optimal segmentation threshold \( T = 0.1647 \). The S component image is binarized according to this threshold, and the result is shown in Figure 8.

![Figure 8. Best threshold binarization of S component image](image)

3.4. Mathematical morphological operations

After the above operation, the hole wall image is completely segmented into a binary image containing only the target and background. The pore target appears to be white with a gray value of 1, and the
background appears to be black with a gray value of 0. However, the image still contains a certain amount of noise that needs to be processed. As shown in Figure 8, the white aperture target has a small amount of black background noise. In the process of binarization, the gray value of the edge pixels of the pore structure is close to the gray value of the background. In this case, information is easily lost in the recognition process, and the recognized pore structure is often slightly smaller than the actual size. The closed operation sets a structural element with an appropriate size and morphological characteristics as a “probe” to collect image information. The structural elements in the image are moved, the relationship between the parts in the image is examined, and calculations are performed. The closed operation fills the small holes in the image, connects adjacent objects, and smoothens the boundaries without significantly changing the area and shape of the object. In this work, a disk-shaped structural element with a pixel size of 30 is selected to perform closed operation on the binarized S component image. It effectively fills the black background noise in the white pore target and smoothly expands the boundary of the white pore target. The identification result is relatively close to the pore structure in the original image (Figure 9).

![Figure 9. Result of closed operation of S component image](image)

4. Surface porosity calculation and pore distribution analysis

4.1. Surface porosity calculation

The surface porosity defined in this work is the ratio of the area of the pore structure in the hole wall image to the total area of the image. It is also equivalent to the ratio of the number of pixels of the pore structure in the image to the total number of pixels in the image. The number of pixels of the pore structure is denoted as $M_0$, and the total number of pixels of the image is denoted as $M$. The calculation formula of rock surface porosity $\varphi$ is

$$ \varphi = \frac{M_0}{M} \quad (9) $$

The total pixel number of the hole wall image used in this work is $M = 2847 \times 3059$, and the pixel number of the white pore structure in the hole wall image after pore structure identification is $M_0 = 239761$. Then, the surface porosity is $\varphi = 0.0275$.

4.2. Pore location distribution
The size of surface porosity reflects the overall rock quality, and the distribution of pore structure can further reflect the quality difference at different rock locations. As the hole wall images obtained by borehole cameras contain information on depth and azimuth, the distributions of the depth and azimuth of a pore can be statistically analyzed on the basis of the pore structure identification of the hole wall image.

The ratio of the number of pixels representing the pore structure to the total number of pixels in each row (column) is defined as line porosity and denoted as $\varphi_i$. Line porosity is calculated as follows:

$$\varphi_i = \frac{M_i}{M_a}$$

where $M_i$ is the number of pixels representing the pore structure in the $i$-th row (column) pixel in the hole wall image and $M_a$ is the total number of pixels in the $i$-th row (column) pixel. By calculating the line porosity $\varphi_i$ of each row (column) on the hole wall image and by combining the result with the depth or azimuth data of the line porosity, the distribution of the pore structure on the hole wall image can be analyzed.

For example, the hole wall image herein is taken from the 12.0–12.8 m segment of the borehole with a diameter of 110 mm. The number of pixels is $3059 \times 2847$. Calculation results showed a horizontal line porosity of 3,059 and vertical line porosity of 2,847. By combining these results with the depth and azimuth data provided on the hole wall image, the depth and azimuth distributions of the pores are obtained. As shown in the depth distribution in Figure 10, the pores in the 12.0–12.3 m section are relatively developed, and the line porosity reaches the maximum at 12.27 m. As for the azimuth distribution map in Figure 11, the pores are relatively developed between 30° NNW and 30° NNE, and the line porosity reaches the maximum value at 20° NNW.

![Figure 10. Distribution of surface porosity along borehole depth](image)
4.3. Pore size distribution

The particle size distribution of pores is another parameter that is worthy of attention. On the basis of the identification of the pore structure, the edges of the pores are detected, and the pixel area of each pore in the hole wall image is calculated. Then, the pixel area is converted into the actual area of the pore according to Equation 11. As pores are irregular structures, the diameter of a circle with the same area is used as the equivalent particle size of the pores. Therefore, after calculating the actual area of the pores, the equivalent particle size of the pores can be obtained using the formula for calculating the area of a circle.

$$S_p = \frac{S_{pp}}{S_{ip}} S_i$$

where $S_p$ is the actual pore area, $S_{pp}$ is the pore pixel area, $S_{ip}$ is the image pixel area, and $S_i$ is the actual area of the image.

For the hole wall image used in this work, the mathematical morphology operation yields the edges of the pores. For easy viewing, the image is filled with color, and the pore boundary is displayed in white in Figure 12.

Figure 11. Distribution of surface porosity in azimuth
A total of 245 pore structures are detected in the image. The particle size is calculated equivalently, and the particle size distribution is determined accordingly (Figure 13). The pore particle size mainly ranges from 0 mm to 3 mm, thus accounting for 77.5%. The maximum particle size is 17.63 mm, as denoted by the red pore in Figure 12.

5. Conclusion
To address the difficult measurement of porosity resulting from the challenging process of coring, this study proposes a method for identifying, calculating, and analyzing pore structure on the basis of hole wall images. The method effectively eliminates the influence of complex structure information, accurately identifies the pore structures on hole wall images, and realizes the calculation of rock surface porosity. Pore distribution can be further analyzed using the proposed method and the
measurement data provided by a digital panoramic borehole camera system. The results of this work provide new ideas for the analysis of deep rock pore structures. With breakthroughs in optical measurement technology, the resolution of hole wall images is expected to increase further, and the scope of application of the method proposed in this work will broaden.

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