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Recognition of micro-cracks in coal based on super-resolution and Hessian filtering techniques

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ABSTRACT

Micro-cracks in coal play an important role in the safe mining and coalbed methane extraction processes. The propagation and nucleation of micro-cracks during coal mining are key factors that cause the damage of the coal formation and the overlaying rocks. They are also the main transport ways for the coalbed methane. Therefore, accurate characterization of the micro-cracks in coal is crucial in uncovering the coal failure and the gas transports mechanisms. Imaging methods, such as X-ray CT scan provides an effective way in obtaining the 3D fracture distribution in a coal rock. However, accurate extraction of the fractures in the greyscale CT images remains to be improved, especially for those faint micro-cracks. The difficulties are mainly caused by the limited CT image resolution and the precise segmentation of the micro-cracks influenced by surrounding noises. In this paper, we first used super-resolution and greyscale enhancement techniques to improve the 3D image resolution and quality obtained through the industrial CT scanning. With these applied preprocessing steps, more details of the CT image could be identified. Then multi-scale Hessian filtering techniques was employed to enhance the identification and segmentation of the fractures. Through Hessian filtering, the faint micro-cracks were accurately recognized. Moreover, a connectivity check postprocessing eliminated the noises in the segmented image. The successful recognition of micro-cracks enabled the further studies on the mechanical and transport properties of coal through image-based calculation methods.

Keywords: coal resource, Hessian matrix, super-resolution, micro-crack segmentation

1. INTRODUCTION

Coal is the largest production and consumption energy resource of China. According to the China Statistical Yearbook 2020, the total primary energy production and consumption were 3.97 billion and 4.87 billion tons of standard coal in 2019, respectively. Among them, the raw coal accounted for 68.6% and 57.7% of the total primary energy production and consumption of China[1]. Most of the coal production in China is by underground mining. Meanwhile, due to the depletion of coal resources near the surface, the coal mining goes deeper. The high in-situ stresses in deep underground leading to a high risk of rock burst, water inrush and gas outburst. In addition, China is rich in coalbed methane recourses, the green mining of the coalbed methane can provide relative clean energy, and have very important economic and social significance[2]. In order to accomplish a safe and green mining of the coal resources, it is imperative to have a deeper understanding the coal failure mechanism and gas transport mechanisms.

The study of coal failure and fluid transport mechanisms have always been an important topic for researchers. Traditional investigations are conducted mainly through mechanical and flooding tests based on core samples. However, the influence of cracks or fractures inside the sample which determines the coal apparent mechanical and transport properties[3] can be hardly revealed. From mesoscopic point of view, the stress redistribution induced by coal mining leads to the generation, nucleation, expansion and connection of the interior micro-cracks[4-6]. The evolution of fractures and its influence on the coal damage and transport mechanisms are thus the key to uncover the variation of macroscopic properties of coal during the mining.

In recent years, imaging methods, such as X-ray computed tomography (CT), magnetic resonance imaging (MRI), focused ion beam-scanning electron microscopy (FIB-SEM), provide mineral composition, irregular pore and fracture morphology information at different scale inside a coal sample. Such critical information opens new ways in investigating the mechanical and transport properties of coal. Among these imaging methods, the X-ray CT as a nondestructive 3D observation tool has been widely used in underground mining related studies.

The extraction of concerned information from the greyscale CT images or segmentation of the image into void and mineral spaces is a non-trivial work. Even the binary classification of the CT images into void and matrix phase is usually complicate, especially for those with micro-cracks. The segmentation process is complicated by the presence of sub-voxel features and CT image noises. Although a lot of researches have been performed on the segmentation of CT image, there is still not a standard procedure for the processing. Several morphological methods, such as edge detection and wavelet transform were used for fracture recognition. However, these methods cannot accurately take into account both small and large cracks at the same time[8]. When large cracks are clearly identified, the micro-cracks can hardly be extracted. When micro-cracks are identified, lots of matrix phase voxels are falsely identified as crack phase[7].

In summary, the fracture extraction in coal CT image generally encounters the following problems:

(1) Morphology of the fracture is complex. Fractures with irregular geometry are randomly distributed in the CT image. It is difficult to accurately identify fractures by feature classification. As a result, those methods cannot take into account all kinds of fractures in the coal, which limits its application.

(2) Noises are widely distributed in the CT image. These noises due to the X-ray source, the detector, and beam harden are inherent to the CT image, which cannot be eliminated in the scanning process. High level of noise will degrade the segmentation of fractures. There is a need to use appropriate noise reduction filters to optimize the CT image.

(3) A large number of micro-cracks. These micro-cracks are usually very thin in the limited resolution CT images. Some parts show sub-voxels features. As a results, these micro-cracks are hard to be accurately identified.

In order to overcome the difficulties in the identification process of coal fractures, it is desirable to increase the image resolution before segmentation and adopt an improved method to better identify the micro-cracks in the segmentation process. In this paper, we propose the follow workflow to gain a better segmentation of the CT images, especially the identification of micro-cracks.

(1) The waifu2x (https://github.com/nagadomi/waifu2x) super-resolution convolutional neural network is used to obtain a higher resolution CT scanning images.

(2) The greyscale CT image is enhanced by the sharpen operation in the ImageJ (https://imagej.net/) to obtain a larger gray gradient.

(3) The gray gradient is identified by Hessian matrix, which calculates the gray gradient, to better identify the obvious fractures as well as the faint micro-cracks.

(4) A connectivity check post-process was performed to eliminate the noises in the segmented image.

2. METHODS

2.1 Coal sample

The coal sample was collected in deep underground mining site in China at depth of 1100m. The average thickness of the coal seam is 3.3m which characterized as a medium thick coal layer. Cracks in the coal seam is relatively developed. A standard cylinder sample with a diameter of 25 mm and height of 50 mm was drilled. The measured gas permeability of the intact sample is 0.19×10^{-15} m². The sample was then put into the uniaxial compression machine. With a slow loading rate and servo control, the sample was carefully loaded just before its peak strength. As a result, multi-scale fractures were formed in the sample. Then, it was used for the CT scan.

2.2 CT scan

The industrial CT scanning equipment (ACTIS300-320/225) in the state key laboratory of coal resources and safety mining of China university of mining and technology (Beijing) is used to observe the interior structures of the coal sample. The CT scan equipment is shown in Fig. 1. After scanning data reconstruction, 1500 slices of 32-bit grayscale images with size of 934 × 934 pixels were obtained. The image resolution is 28.57 μm and the interval distance between slices is also 28.57 μm. Fig. 2 shows one slice of the data sets. The region with the darkest color is void space which includes pores and fractures. Coal matrix with larger density shows brighter color.

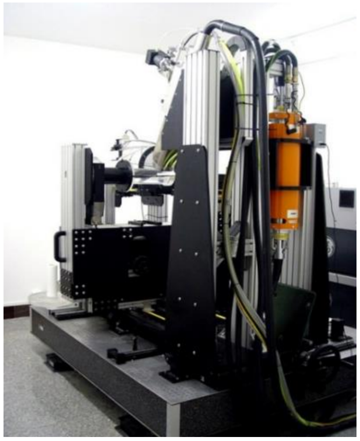


Fig. 1. CT scanning equipment

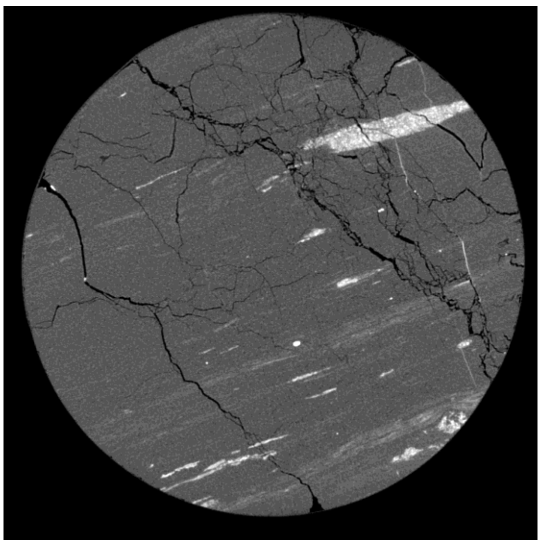
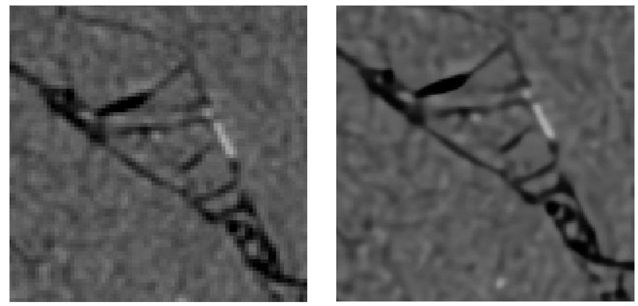


Fig. 2. CT image of the coal sample

2.3 Super-resolution based on convolutional neural network

The convolutional neural network (CNN) is a feedforward neural network. In recent years, due to its excellent performance in the field of image processing, it has become one of the most popular tools[9]. The CNN is a multi-layer artificial neural network specially designed to process 2-D input data. Compared with the fully connected network, CNN has less network connection number and weight parameters. The training and learning process of CNN is realized by averaging and weighting the convolution kernel and convolution layer. A small network connection number and weight parameters mean that the training process is relatively quick and easy to be applied in image processing[10][11].

The super resolution image reconstruction (SRIR) is a technology uses CNN which can convert low-resolution images into high-resolution images . The SRIR can enhance the CT image resolution and overcome the limited resolution of a CT scan equipment. It is proved to be useful in many practical cases, which can not only improve the image clarity, but also enhance the image details. The SRIR of our CT images plays an important role in the subsequent micro-crack recognition. We use the SRIR software, i.e., waifu2x, to improve the CT image quality. As shown in Fig. 3, the clarity is greatly improved, and the fracture edge is smoother compared with the original image.



(a) (b)

Fig. 3. Comparison of CT images before and after super-resolution processing, (a) a small region of the CT image, (b) the same region after super-resolution processing

2.4 Grayscale enhancement

Image grayscale enhancement, also known as contrast enhancement or contrast stretching, aims to improve the visual effect of the image and get more direct, clear and easy to extract image information.

The sub-region grayscale enhancement is used, which divides the gray range of the original image into two or more regions. The enhancement on target region and inhibition other regions are performed at the same time. The principle of the sub-region linear transformation is similar to the linear grayscale transformation, as shown in Eq.1. The basic principle can also be visualized as shown in Fig. 4.

$$\mathrm{g}(x,y)=\begin{cases}\frac{c}{a}\times f(x,y) & [0,a)\\ \frac{d-c}{b-a}\times(f(x,y)-a)+c, & [a,b]\\ \frac{255-d}{255-b}\times(f(x,y)-b)+d, & (b,255]\end{cases} \quad (1)$$

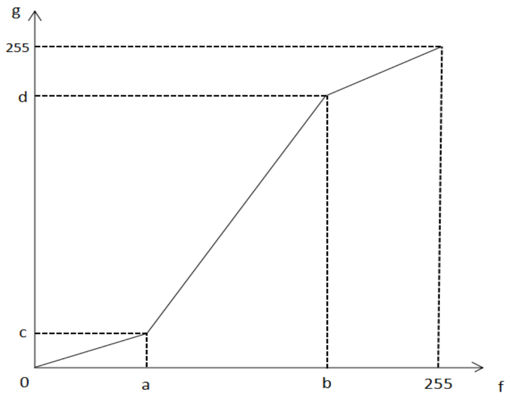
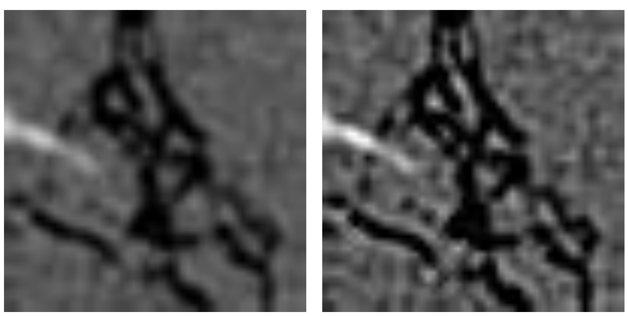


Fig. 4. Piecewise linear enhancement

The effect of grayscale enhancement depends on the partition points a and b and the enhancement parameters for each region. This paper uses ImageJ software for grayscale enhancement. As shown in Fig. 5, compared with the original image, the enhanced image has clearer cracks, which plays a nonnegligible role in the fracture extraction.



(a) (b)

Fig. 5. Comparison of CT images before and after grayscale enhancement, (a) a small region of the CT image, (b) the same region with grayscale enhancement processing

2.5 Fracture extraction by the Hessian filter

Hessian matrix is a square matrix composed of the second-order partial derivatives which is powerful in distinguishing the planar features from a 3D dataset[12]. For the 3-D image data, the Hessian matrix is a 3×3 symmetry matrix of the second-order partial derivatives of the input image $I(x,y,z)$:

$$H=\begin{bmatrix} I_{xx} & I_{xy} & I_{xz} \\ I_{yx} & I_{yy} & I_{yz} \\ I_{zx} & I_{zy} & I_{zz} \end{bmatrix} \quad (2)$$

The Hessian matrix comprises the second derivative of the intensity change around each point in the 3-D data set. It describes the local curvature of the data in a small region around each point. According to the linear space scale theory, the second order derivative of the original image can be calculated by convolving the derivatives of Gaussians. The element in the Hessian matrix, I_{xx} for example, can be expressed as:

$$I_{xx}=\left(B\cdot\frac{\partial^2}{\partial x^2}G(x,y,z,s)\right)*I(x,y,z) \quad (3)$$

where B is a factor that can be used for normalization, s is a factor of scale, and G represents a Gaussian function. In one dimension, the Gaussian function is defined as:

$$G(x,s)=C\cdot e^{-\frac{x^2}{2s^2}} \quad (4)$$

where C is also a factor used for normalization. The convolution in Eq. (3) can be considered as that the image data $I(x,y,z)$ is compared to the probe kernel (the second derivative of G). According to the matching degree of them, the bright and dark features and the broader and narrow features in the image can be identified.

Extending this concept to a 3D image, the convolution is carried out in multiple directions to determine the elements in the Hessian matrix. Since the elements in the Hessian matrix is second-order derivatives, they are invariant to grey value offsets, scaling and linear greyscale variations throughout a dataset. In contrast, they depend on the grayscale contrast in the local area[12]. With the Hessian matrix known for each voxel, the eigenvectors and eigenvalues of the matrix can be calculated, which describe the local principal direction and magnitude respectively. These eigenvalues can be used to determine the morphological features in the images. The method is suitable for extracting micro-cracks in CT scanning images, because the micro-crack voxels have very similar greyscale value with its surrounding voxels, but the grayscale contrasts with the nearby area showed detectable difference.

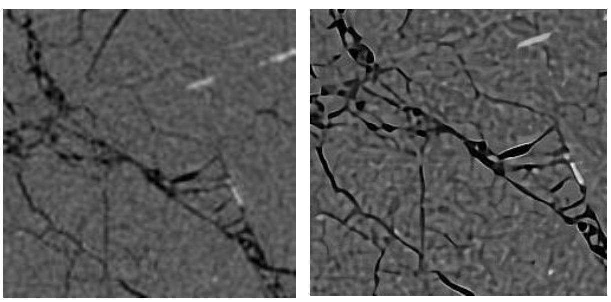
It should be noted, there are multiple size fractures distributed in the sample, as shown in Fig. 2. The method should be applied to account for these multi-scale fractures, especially for those micro-cracks. This can be accomplished by using different scale factor s in Eqs (3) and (4). A good identification of the multi-scale fractures can be achieved by combining the Hessian analysis on several scale.

3. RESULTS

3.1 CT image preprocessing

In this paper, we used waifu2x to magnify each CT image slice twice of its original size. Each magnified image has a size of 1868 × 1868 pixels and showed more detailed information, such as the micro-cracks are more obvious, the magnified fracture boundaries are clearer. At the same time, it can also reduce noise. It should be noted that some micro-cracks are still difficult to identify due to the inherent characteristics of the super-resolution technique.

Next, we employed the image grayscale enhancement to further improve the image quality. The sharpening operation in ImageJ was used to enhance the grayscale of the fractures. Several unidentified micro-cracks after the super-resolution operation were recognized with the image grayscale enhancement processing. The comparison of the image pairs before and after the processing are shown in Fig.6.



(a) (b)

Fig. 6. Comparison of CT images before and after precrocessing , (a) a small region of the CT image, (b) the same region after the precrocessing

3.2 Fracture extraction

The CT images after the preprocessing were loaded in ImageJ and changed to 8 bit grayscale image. A region of interest (ROI) is defined, which is a cylinder region of the coal sample.

Considering the sub-voxel features of the micro-cracks and the multi-scale feature of the fractures, the minimum Gaussian smoothing scale s_{min} is set as 0.5 and the maximum aperture s_{max} is set as 3.0. The step between Gaussian smoothing scales s_{step} is set as 0.5 and resulting a 6 step calculations. These values will influence the accuracy of multi-scale fractures extraction results[13].

The elements in Hessian matrix is calculated and based on which the eigenvalues are calculated and sorted for each voxel. After the 6 scale calculations, a normalization step is performed.

With the help of MSHFF.ijm plugin in ImageJ[11], the calculations for fracture recognition were automatically performed based on the selected s_{step} , s_{min} and s_{max}. Before the calculation, a threshold value of 100 is manually selected to set the bright mineral voxels (gray values larger than 100) to Not a Number (NaN). As a result, these mineral voxels will not influence the following Hessian matrix filtering. Combining the super-resolution and the grayscale enhancement preprocessing steps and the subsequent Hessian filtering approach, multi-scale fractures, including the faint micro-cracks can be clearly identified, as shown in Fig. 7.

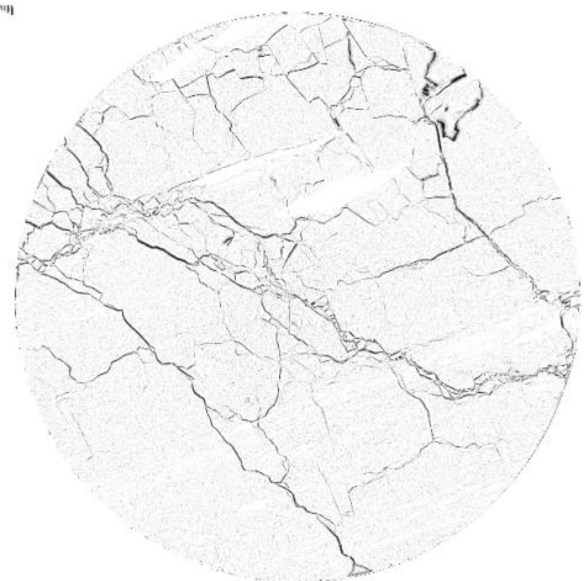


Fig. 7. CT image filtered by Hessian matrix

3.3 Postprocessing of the image

Due to the fact that some parts of the micro-cracks are in sub-voxels range, we chose s_{min} as 0.5 in the calculation to better recognize these micro-cracks. However, this is achieved at the expense of lots of isolated noises in the Hessian matrix filtered images.

In order to eliminate these noises, we developed a Matlab script which uses the bwconncomp function in the Image Processing Toolbox. The general idea is that the multi-scale fractures are connected with each other and distributed along the longitude of the sample but the noises are isolated. By only extracting these connected fracture voxels throughout the sample, the noises are naturally eliminated. All the black voxels in the Hessian filtered image were first labeled and clustered into different groups. By comparing the labels of the clusters present in the top and bottom image slices, the labeled clusters connected between the two slices were selected. These clusters were the multi-scale fractures in the sample. By retaining these clusters and eliminating the non-connected noises, the fractures were successfully extracted. One image slice of the final segmentation in shown in Fig.8.

Fig. 8. Binary graph judged by connectivity

The reconstructed 3D model of the segmentation result is shown in Fig.9.

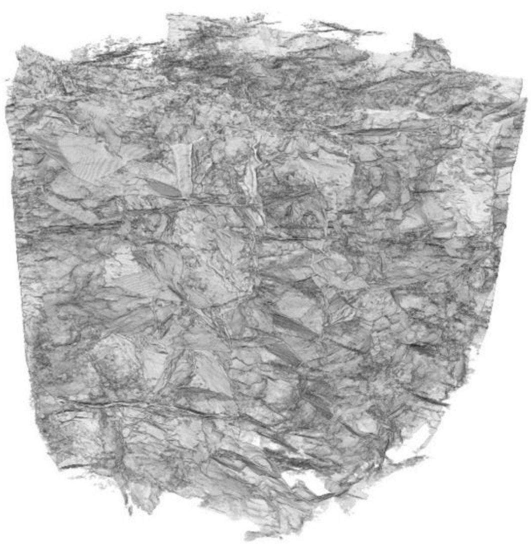
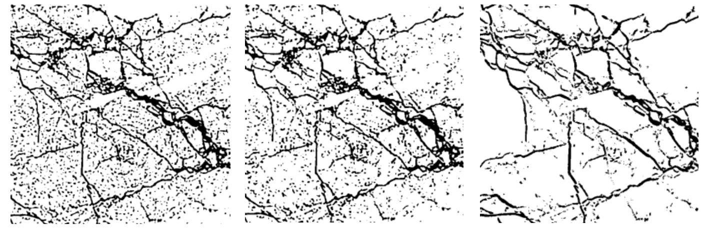


Fig. 9. 3D reconstructed model of the segmentation result

4. COMPARISON WITH OTHER METHODS

In order to verify the result, we compare it with global threshold segmentation and non-local-means filtering. As shown in Fig. 10, the multi-scale fractures are better recognized by the proposed workflow, especially for the micro-cracks which clearly showed better connectivity.



(a) (b) (c)

Fig. 10 Segmentation results by different methods, (a) global threshold segmentation, (b) non-local-means filtering and segmentation, (c) the proposed workflow

In order to quantitatively compare the results of different methods, the following indicators were calculated.

The first one is structural similarity index (SSIM), which characterize the similarity between two images. It is defined as:

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)}$$

where μ_x is the average value of x, μ_y is the average value of y, σ_x^2 is the variance of x, σ_y^2 is the variance of y, and σ_{xy} is the covariance of x and y. $c_1 = (k_1L)^2$, $c_2 = (k_2L)^2$ are constants for maintaining stability. L is the dynamic range of pixel values. $k_1 = 0.01$, and $k_2 = 0.03$. Structural similarity ranges from 0 to 1. SSIM is equal to 1 when images are exactly same.

The second one is peak signal to noise ratio (PSNR) which represent the fidelity of an image after the processing procedure. The processed image will loss information of the original image. In order to measure the quality of the processed image, we usually use the PSNR value to evaluate a certain image processing. It is defined as:

$$PSNR = 10 \times log_{10}(\frac{(2^n - 1)^2}{MSE})$$

where mean square error (MSE) reflects the difference of the estimated quantity. The PSNR value is inversely proportional to image quality.

Image entropy expresses the average information contented in the image source. It is defined as:

$$H = \sum_{i=0}^{255} p_{ij}\log(p_{ij})$$

where p_{ij} is the proportion of pixels with gray value i in the image. Image entropy value is also proportional to image quality.

The measured SSIM, image entropy and PSNR of segmented results by the global threshold segmentation, the non-local-means filtering and the proposed workflow are shown in Table. 1. The image segmentation results processed by the proposed workflow, i.e., by super-resolution and grayscale enhancement preprocessing, the Hessian filtering and connectivity postprocessing have larger values of SSIM and image entropy. The PSNR is lower, which means more image information was saved.

Table. 1. SSIM, Entropy and PSNR of the processed image

Processing method	SSIM	Image entropy	PSNR
Global threshold segmentation	0.959	4.973	28.076
Non-local-means filtering	0.940	4.623	27.619

5. CONCLUSION

Fractures play important role in the coal rock failure and coalbed methane transport processes. The increasing availability of the CT scan enabled the direct observation of interior structures in a coal sample. However, the extraction of the fractures, especially those include micro-cracks, is a nontrivial task.

In this work, industrial CT scan was used to obtain the interior structures of a coal sample collected from deep underground coal mining site in China. A workflow was proposed to better characterize and extract the multi-scale fractures in the CT image. In the process, the super-resolution technique was first used to double the CT image resolution. The greyscale enhancement was employed to increase the contrast between fractures and surrounding rock matrix. With these preprocessing, the CT image quality was greatly improved. Then, the multi-scale Hessian filtering techniques was employed to extract the multi-scale fractures in the image. The faint micro-cracks were successfully recognized through the Hessian filtering. The connectivity check postprocessing was used to decrease the noises in the segmented images.

Compared with other commonly used segmentation method, the proposed workflow showed better accuracy in extracting the multi-scale fractures, especially those micro-fractures. The accurate extraction of multi-scale fractures enabled the further studies on the mechanical and transports properties of coal by image-based calculation methods.

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