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Research on the Trend of Rock Fissures based on Grey Prediction Method

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Abstract

The internal microstructure of rock determines its stress-strain state under the action of external force, and then controls its macro-mechanical response and failure mechanism. The study of rock fissures has important practical significance for finding minerals, hydrogeology, and engineering geology. In this paper, for prediction based on two-dimensional X-ray computed tomography (CT) images, a rock fracture prediction method based on gray prediction method is proposed. Each pixel in the image at the same position in each stage of the lower rock is arranged in sequence, and the RGB value of the corresponding pixel in the next stage is predicted by the gray prediction method. Calculate its residuals and test its prediction effect.

Keywords

Rock Fracture; Grey Prediction Method; Information Extraction; RGB Channel.

1. Introduction

Rock fissures are one of the most important factors in understanding the failure mechanism of geotechnical materials. The initiation, trend and merging of fissures play an important role in the structural stability of dams, bridges and tunnels[1]. Therefore, it is necessary to understand the prediction of rock fissures. Essential in engineering practice.

Relevant scholars have used various means to monitor the whole process of rock fracture evolution in real time. Qin Changan et al.[2] used a high-speed camera to observe the crack propagation law in real time during the whole process of specimen rupture. Su Fangsheng et al.[3] combined the digital image correlation method to capture the evolution law of the surface deformation field in the whole process of crack initiation, expansion and penetration in real time.[4] quantified the crack propagation mode by DIC technique. ZHANG[5], SONG[6], etc. have related research. LU et al.[7] used high-speed microscopic observation combined with DIC technology to further study the crack propagation law from a mesoscopic perspective. However, such methods cannot monitor the evolution of rock fissures in real time, nor can they predict the direction of rock fissures.

In order to realize the real-time monitoring of the internal fracture process of the rock, related scholars have used indirect methods such as acoustic emission (AE) positioning to study the evolution law of internal fractures in the sample. The basic principle is to capture the strain energy (ie AE signal) released during rock fracture, and indirectly infer the spatial distribution of rock fractures through the

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inversion of parameters such as acoustic emission counts and amplitudes[8]. QIN[9], YAO[10], etc. analyzed the propagation law of fractures in the rock based on the acoustic emission positioning technology. Liu Feiyue et al.[11] inverted the dynamic stress field change of rock fracture by using the acoustic emission spatial three-dimensional positioning information. However, in the process of research, the emission of sound waves is easily affected by changes in the surrounding environment, which will cause errors.

Combined with the above content, this study is devoted to predicting the fracture trend of the next stage by using the CT images of the four stages under the continuous action of the rock, and extracting the original data by pixelating the CT images of the initial four stages to establish a gray prediction model. Carry out prediction, visualize the prediction data to obtain the image of the fifth stage, and compare it with the original image to obtain the prediction effect, which provides a new idea and method for collecting and predicting rock fractures.

2. Basic Model

2.1 Model System Principles

In this paper, the method of image digitization is used to predict the trend of cracks. First, the CT image is obtained to obtain the RGB image, and then the image is digitized to obtain the value of the RGB channel of each pixel in the image as the original data for prediction. analyze.

The evolution process of rock fissures changes within a certain time and space range. With the increase of pressure, its shape always changes with time. This change is not easy to be expressed by a clear mathematical model, which is consistent with the The requirements of gray prediction[12], in addition, there are only five stages in the CT image of the rock interior read through the test, and there are only five groups of RGB values for each pixel at the same position, so the number of samples is insufficient, so this paper chooses the gray prediction method to analyze the rocks. The trend of internal fractures is predicted.

2.2 Image Digitization

The digitization of an image is to divide an image into small units (called pixels or pixels). These individual pixels can be represented by a single quantized area. In a computer, each color can be represented by RGB. The three color components are combined, so for the computer, each pixel computer stores the values of the three colors of RGB, and the range of the three color components is 0-255. The width and height of the image correspond to the picture pixels. The number of points, the more the number of pixels per unit area, the higher the resolution of the picture, the corresponding space occupied will be larger.

The GetPixel function in python can return the RGB value of each point function and save the result in a txt file to realize the conversion of images to numbers, so that the data can be calculated. After the operation is completed, the Putpixel function can be used to convert the txt file. RGB values are converted into images, realizing the conversion from numbers to images.

2.3 Grey Forecasting Model

The gray prediction model is an algorithm for predicting the gray system. It is established by using less or inaccurate original sequences that represent the behavior characteristics of the gray system to generate and transform, and reveal the process of continuous change and development of things within the system[13]. In other words, the ecosystem is a gray system[14]. Grey prediction has the advantages of small computational workload; samples do not need to be distributed regularly; quantitative analysis and qualitative analysis results will not be inconsistent; high prediction accuracy. The modeling mechanism of grey prediction is:

(1) Processing raw data to generate data.

(2) After revising the residuals, establish the differential differential equation.

(3) Analysis Based on Convergence of Correlation Degree.

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(4) The data obtained by the GM model can only be used after inverse generation and reduction.

(5) Using the "five-step modeling (system qualitative analysis, factor analysis, preliminary quantification, dynamic quantification, optimization)" method to establish a differential differential equation model GM (1, 1) prediction model.

The specific principles of the GM(1,1) model are as follows:

1) Inspection and Processing of Data

In order to ensure the feasibility of the GM(1,1) modeling method, it is necessary to perform necessary inspection processing on the known data. Let the original data column be , calculate the level ratio of the sequence:

$$\lambda(k)=\frac{x^{(0)}(k-1)}{x^{(0)}(k)},k=2,3,...,n \tag{1}$$

If all grade ratios fall within the tolerance coverage interval $X=(e^{\frac{-2}{n+1}},e^{\frac{2}{n+1}})$, Then the sequence $x^{(0)}$ can establish a GM (1, 1) model and can make gray predictions. Otherwise, do appropriate transformation processing on the data, such as translation transformation, otherwise, you need to do appropriate transformation on the data, such as translation transformation:

$$y^{(0)}=x^{(0)}(k)+c,k=1,2,...,n \tag{2}$$

Take c so that the level ratio of the data column falls within the acceptable coverage.

2) Build a GM(1,1) Model

Let $x^{(0)}=(x^{(0)}(1),x^{(0)}(2),...,x^{(0)}(n))$ meet the above requirements, and use it as the data column to establish a GM (1, 1) model:

$$x^{(0)}(k)+az^{(1)}(k)=b \tag{3}$$

The estimated values of a and b are obtained by regression analysis, so the corresponding whitening model is:

$$\frac{dx^{(1)}(t)}{dt}+ax^{(1)}(t)=b \tag{4}$$

The solution is:

$$x^{(1)}(t)=(x^{(0)}(t)-\frac{b}{a})e^{-a(t-1)}+\frac{b}{a} \tag{5}$$

So get the predicted value:

$$\hat{x}^{(1)}(k+1)=(\hat{x}^{(0)}(1)-\frac{b}{a})e^{-ak}+\frac{b}{a},k=1,2,...,n-1 \tag{6}$$

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So that the corresponding predicted value is:

$$\hat{x}^{(0)}(k+1)=\hat{x}^{(1)}(k+1)-\hat{x}^{(1)}(k), k=1,2,\ldots,n-1 \tag{7}$$

3) Test Predicted Value

Residual Test:

$$\varepsilon(k)=\frac{x^{(0)}(k)-\hat{x}^{(0)}(k)}{x^{(0)}(k)}, k=1,2,\ldots,n \tag{8}$$

If there is $|\varepsilon(k)|<0.1$ for all the data, it is considered to meet the higher requirements, and $|\varepsilon(k)|<0.2$ is considered to meet the general requirements.

3. Test example

3.1 Original Image Production

The rock selected in this test is coarse-grained red sandstone, and the specimen has a granular clastic structure, which is composed of clastic particles and interstitials, among which the clastic particles are mainly quartz, feldspar and debris. The particle size varies from 0.5-30mm. The rock is processed into a 100mm×100mm×100mm cube specimen (as shown in Figure 1), and then the rock specimen is labeled (CGRS-CT, coarse grain red sandstone-CT). The test equipment for this test includes uniaxial compression loading System and industrial CT scanning imaging system, the uniaxial compression loading system adopts TAW-3000 electro-hydraulic servo rock loading press, adopts uniaxial cyclic loading and unloading loading method, and combines industrial CT scanning for testing. Four rock samples of the same batch and the same specification were selected for uniaxial compressive strength test, and the peak strength of each rock sample was calculated, which were 36.32, 41.96, 49.53, and 39.92 MPa, respectively. The peak strength of the sample is about 41.93 MPa. The stage scanning points of the CT scanning test are set to 0%, 30%, 70%, 90% of the peak strength and the corresponding axial stresses are 0, 12.58, 29.35, and 37.74 MPa after the specimen is ruptured. The original CT image is cropped into an image of 500×500 pixels. The abscissa of the selected position is (400, 900) and the ordinate is (800, 1300). The result is shown in Figure 2.

Figure 1. Rock sample

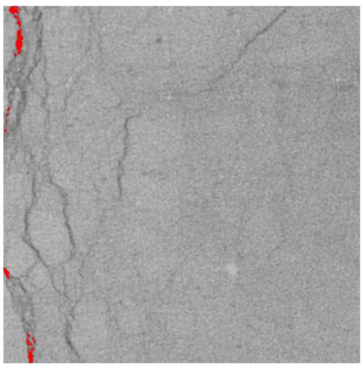

Figure 2. Cropped CT image

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3.2 Predict Crack Orientation

Using the method proposed in 1.2, use python to extract the RGB value of each pixel in the CT image, and extract it in sequence from the first row and the first column. The image of 500 × 500 pixels has a total of 250,000 pixels. The RBG of each pixel is extracted. The values are saved to the txt file, and three columns representing the R, G, and B values are obtained. The three RGB channels of the five-stage CT image are sorted into corresponding three tables, each of which has 250,000 rows, 5 Column data, establish a GM (1, 1) model for the data data in the first four columns of these three tables respectively, and compare the data in the fifth column to obtain the next stage data corresponding to each channel of the three RGB channels , some of the results are shown in Table 1.

Table 1. The first ten pixels are the R channel value and the predicted value

The first stage	The second stage	The third stage	The fourth stage	The fifth stage	Predict the fifth stage
159	195	181	151	160	136
156	195	177	153	161	137
155	194	180	154	164	140
158	192	181	156	163	144
162	192	186	150	162	139
165	193	191	153	165	144
164	193	191	150	170	140
162	191	195	148	181	141
161	192	184	148	175	136
159	195	181	151	160	129

After that, image processing is performed on the RGB value of each pixel in the predicted fifth stage, and the predicted image is obtained as shown in Figure 3.

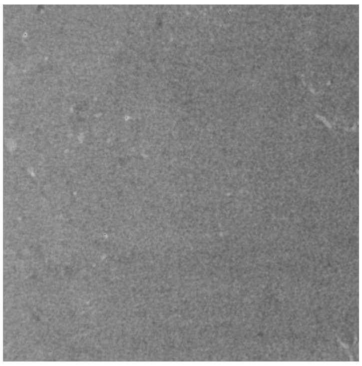

Figure 3. Predicted image

3.3 Test the Predicted Value

Compare the 2,500,000,000 pieces of data predicted in the fifth stage with the actual situation, and use the method proposed in 1.3 to calculate the residual. The calculation results are shown in the following figure.

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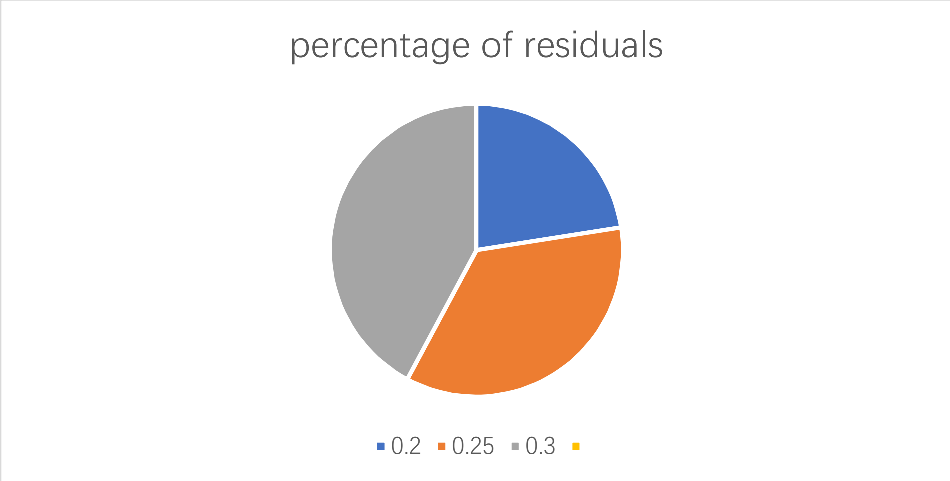

Figure 4. The proportion of residuals

Among them, 46.5% of the data residuals are within 0.2, 73% of the data residuals are within 0.25, and 87.3% of the data residuals are within 0.3, indicating that 46.5% of the data in the model have reached the general standard, and the remaining 40.8 % of the data met the barely acceptable standard.

4. Conclusion

In this paper, CT images are used to collect images and digitize them to obtain the original data, and the gray prediction method is used to predict the data to obtain the change trend of the cracks at the selected position under the condition of continuous application of force, which plays a positive role in revealing the failure mechanism of geotechnical materials. Earth action, fracture paths and the tendency of fracture evolution are closely related to the mechanical properties of rocks, which play a crucial role in engineering practice.

Although the model algorithm in this paper is feasible for the prediction of the fracture trend, there is still room for improvement in the accuracy of the model, such as the improvement of the prediction formula of the grey prediction model, and there are many factors that affect the fracture trend, such as the environment However, this paper only considers the change of fracture direction caused by the change of time pressure, and the data set is small. Re-experiment can obtain more stages of data sets and explore prediction models with higher accuracy. It's all work that can be improved in the future.

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