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Submicron structure random field on granular soil material with retinex algorithm optimization

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Abstract. In this paper, a Retinex scale optimized image enhancement algorithm is proposed, which can enhance the micro vision image and eliminate the influence of the uneven illumination. Based on that, a random geometric model of the microstructure of granular materials is established with Monte-Carlo method, the numerical simulation including consolidation process of granular materials is compared with the experimental data. The results have proved that the random field method with Retinex image enhancement algorithm is effective, the image of microstructure of granular materials becomes clear and the contrast ratio is improved, after using Retinex image enhancement algorithm to enhance the CT image. The fidelity of enhanced image is higher than that dealing with other method, which have explained that the algorithm can preserve the microstructure information of the image well. The result of numerical simulation is similar with the one obtained from conventional three axis consolidation test, which proves that the simulation result is reliable.

1 Introduction

How to establish the relationship between macro and micro is the key problem to be solved in the study of non-homogeneity of rock and soil materials across scales. In the research of multi-scale model, different macro and micro relationship rules are established based on different assumptions generally, to solve the problem of weak coupling or strong coupling scale (Landis E N. et al. 2003; Andrade J E. et al. 2006).

In this paper, the Monte Carlo method is adopted to randomly generate a polygonal element with a given size and surface features, to describe the various structural elements in the granular materials. According to the characteristics of the microstructure, the generated polygonal cells are composed of classic particle cell, confabulation unit and pore cell.

Based on the Retinex theory, this paper has defined the optimization criterion according to contrast statistics and proposed scale optimized Retinex algorithm. The image filtering technique and image enhancement method are used, to analyse the root cause of hindering micro visual images enhancement, aim at the problem of uneven illumination of the micro vision image, and enhance the micro vision image, improving the contrast and simultaneously eliminating the influence of the uneven illumination.

2 Retinex algorithm of Scale optimization

Land et al (1971,1977,1983) had proposed Retinex theory in the literature. Retinex is the compound word of retina and cortex, which represents a model of human vision perception of color and brightness. The model considers that the human eyes can stably perceive the object's colors and details when the same object is under different illuminations or in the shadow, without being effected by illumination change. According to the theory, the feeling caused by feature point in the human eye is determined by the reflection function of the object, this function is only related to the properties and the composition of the material, and it is not related to the distribution and transformation of the light intensity. So, in the computer vision image with uneven illumination, one or more paths can be taken around a pixel point to calculate the average value of the pixel path as the light component. The gray value of the pixel is divided by the light component to get the reflection component, that is for eliminating the effect of the light. The center / surround Retinex using Gauss form function can estimate the light component very well. The scale parameter of Gauss's function has the function of balancing and compressing the dynamic range and retaining the original image information. The larger the parameter, the more the gray dynamic range is compressed, and details will be affected accordingly; the smaller the parameter, the more the image is sharpening.

2.1 Retinex algorithm of Scale optimization design

Micro visual images which adopt coaxial illumination is enlarged by microscope magnification, making 68 μ m high, 85 μm width field to obtain the light illumination energy disperse to 1200 x 1500 pixels of image, and the

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image intensity density becomes extremely weak. Due to the uneven distribution of light intensity of the light source coaxial, the gray value of pixels in the central region is different from the surrounding area. If the illumination is too large, the light intensity in the center region of the image will be saturated. So, a moderate intensity of light is needed. But this will lead to low overall image pixel gray value, and low contrast between metal lines corresponding to the pixel gray value and the substrate pixel gray value. In order to eliminate the influence of uneven illumination, the center / surround Retinex model is the best choice, the reflection component is obtained by estimating the light component to observe the morphology of the line.

According to this feature, a selection criterion of image enhancement scale optimization is proposed in this paper, the parameters of the selected Gauss scale parameters can be optimized and the estimated light component is the best based on this criterion. In the ideal reflection component image, the gray level's contrast of metal line and the pixel contrast of substrate is large and the difference between them is small, it actually calls for the mean value of the local contrast is large enough while the variance of contrast in different regions is as small as possible. Conversely, if the smooth transition would lead to the overlarge of the compressed dynamic range , It will lead to the combination of the pixels of different materials so that the details of microstructure will be damaged, the corresponding results include the contrast of the local area is not uniform and the variance of contrast becomes larger; If the smoothing is not enough, there is a bias in the estimation of the illumination component, the effect of uneven illumination is insufficient, still hinder the improvement of contrast, thus the average contrast is small (Elad 2005).

In order to achieve the goal of eliminating the effect of illumination uniformity and image fidelity, a selection of a reasonable scale parameter c is needed. The optimization of the standard is to make the reflection image component of the local area contrast biggest, and make the variance of contrast in different regions least at the same time. So:

$$r(x,y,c)=\exp\{\ln i(x,y)-\ln[i(x,y)*G(x,y,c)\} \quad (1)$$

Here, $r(x,y,c)$ represents the reflection component of the pixel (x,y) controlled by c . The enhanced reflection component image is denoted as $\mathrm{R}(c)$, in this component image, five windows are taken to calculate the local contrast. The windows' center pixels are distributed in the whole image evenly. This measurement is to avoid the point by point calculation of the neighborhood contrast of pixels in the whole image, so as to reducing the calculation amount. The selected window size is better as large as the size that can include the linear part and substrate part, according to the imaging system parameters disposed in this project, the window size is 120×120 pixels, and the five windows are distributed on the upper left, upper right, center, left and right of the image. The contrast m_k of the k - window can be calculated according to formula（2)：

$$m_k=\frac{I_{k,\mathrm{Max}}-I_{k,\mathrm{Min}}}{I_{k,\mathrm{Max}}+I_{k,\mathrm{Min}}} \quad (2)$$

The calculating formula of the average window contrast $\overline{\mathrm{M}}[\bullet]$ and the variance $\sigma[\bullet]$ can be defined as follows:

$$\overline{M}[\bullet]=\frac{1}{5}\sum_{k=1}^{5}m_k \quad (3)$$

$$\sigma[\bullet]=\frac{1}{5}\sum_{k=1}^{5}(m_k-\overline{M})^2 \quad (4)$$

According to the analysis above, based on the optimal criterion of the average value of the window contrast and variance structure scale, the calculating formula can be defined as follows:

$$J(c)=\arg\min_{c}\{\frac{A_1}{1+\overline{M}[\boldsymbol{W}(\boldsymbol{R}(c))]}+A_2\times\sigma[\boldsymbol{W}(\boldsymbol{R}(c))]\} \quad (5)$$

The W[•] represents choosing uniformly distributed windows in the reflection component image $\mathrm{R}(c)$. The optimization criterion defined by the formula (5) is composed of two parts, its function are as follows: The first part is to maximize the overall contrast, plus 1 in the denominator, in order to avoid the window contrast of the blank image area becomes zero; The second part minimizes the variance of the contrast of all windows to preserve detail information. Positive constants are used to make the two parts A_1 and A_2 numerical equilibrium, its ratio is as same as the ratio of the mean of the contrast and the magnitude of the variance of enhanced image, in the practical application, the ratios mentioned above can be chosen according to experience. Finally, the optimal scale parameter c is substituted in formula (1) to calculate the reflection component image, the scale optimization of Retinex image enhancement can be obtained.

2.2 Algorithm simulation

In order to test the adaptability of the algorithm to the illumination change, the simulation experiment was carried out with the manual simulated image. The simulated image is composed of black and white stripes with a width of 15 pixels， its structure is similar to that of the photoresist mask, simulating the intensity distribution of coaxial light source in the form of Gauss's function, The light component model is shown in the formula (6):

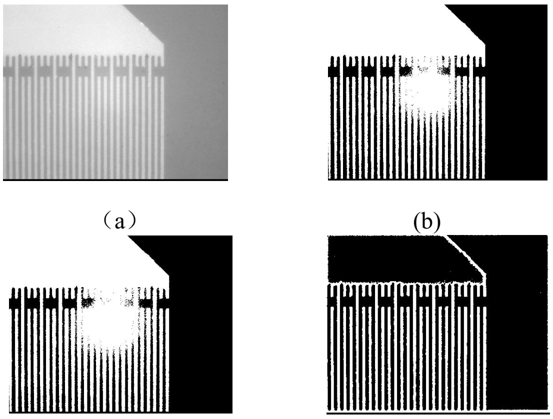
$$l(x,y)=1+\frac{l}{2\pi\gamma}\exp(-\frac{x^2+y^2}{\gamma^2}) \quad (6)$$

The γ is the coaxial halo size, l is the modulation ratio of coaxial light and ambient light. The halo scale parameters take 265, 270, 275,... 310, generating 10 images in the simulation. In this paper, the scale optimized Retinex algorithm is proposed to deal with the simulated image, the results obtained are in the normalized mean square error (NMSE) operation with the original simulated image, to measure the fidelity of the image before and after the enhancement. Treatment results are shown in Table 1, although the image light component changes, the reflection component of the smoothing function is unchanged, so Gauss scale estimation values are almost the same, and the estimated value of the scale is related to the number of fringe pixels. The simulation results show that the Retinex enhancement algorithm based on scale optimization can adapt to the changes of light intensity and scale.

Table 1 Simulation results of scale optimization retinex algorithm

γ	c	NMSE	γ	c	NMSE
265	16	0.0242	290	17	0.0194
270	14	0.0210	295	17	0.0211
275	14	0.0229	300	17	0.0241
280	14	0.0268	305	15	0.0214
285	14	0.0295	310	17	0.0265

The results are shown in FIG.1. It is obvious that the image which is enhanced in this paper eliminate the impact of uneven illumination, and the result of image segmentation is closer to the micro structure feature of the original image, the enhanced results of the histogram equalization method and the method of filtering can not eliminate the light component successfully.



(a) (b) (c) (d)

Fig. 1 The comparison of enhanced micro-vision images for photomask. (a) Original picture; (b) Image enhanced by histogram equalization method; (c) Image enhanced by the method of the filter; (d) Image enhanced by algorithm proposed in this paper

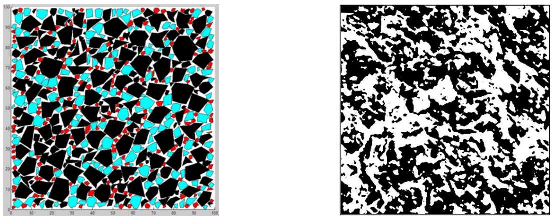
3 Model calculation of geo-materials random field

In this section, we present a random field model of a typical granular materials of consolidation process in the Pearl River delta area of China.

As shown in Table 2, the established model of granular materials microstructure is relatively close to the actual soil sample statistically. FIG.2 is the contrast image of the soil microstructure random field model of soil sample and actual soil sample microstructure, where the black polygon represents the pore unit, polygons in other colors represent different kinds of structural units, and the remaining white space represents structure connection. In soil sample actual microstructure image, the black part represents the pore, and the white part represents the soil skeleton. The soil sample microstructure random field model and the soil sample actual microstructure image are relatively similar, which proves that the proposed modeling method is practical and effective (Fenton. et al. 2007).

Table 2. Microstructure geometric model component statistics of soil sample compared with the test results

Reduced Parameter	Test results	Model results
Void Ratio	1.026	0.998
Silt Content	37.2%	62.8%
Clay Content	37.15%	62.85%



(a) (b)

FIG.2. (a) Soil microstructure random field geometry model & (b) Scanning electron microscopy images of microscopic structure

3.1 Numerical calculation of three axis consolidation of micro random field

The soil samples from an expressway in the Pearl River delta area of China are collected to conduct the indoor triaxial consolidation test. In this test, the curves of pore water pressure versus time of the soil samples are measured. Then the data of the indoor triaxial consolidation test will be used to conduct the finite element numerical simulation with the geometric model above. The parameters of random field geometric model will be given shown as Table 3.

Table 3. Parameters of triaxial consolidation test

Comparison	Width	Height	e	Particle	Clay Particle
Test results	195 μm	400μm	1.026	37.2%	62.8%
Computation results	195 μm	400μm	1.002	35.82%	64.18%

3.2 Calculation results and analysis

Intercept the 10, 50, 100, 200, 300, 500 sub steps of simulation data, count the boundary of each sub step model and the displacement of each node on the right boundary, average them respectively, the curves of average compression of the model's vertical and horizontal directions are therefore obtained. Comparing the body strain with the practical one (such as FIG.3), it is shown that the trend of simulate and practical curves are similar, which proves that the results of simulation are practical and reliable.

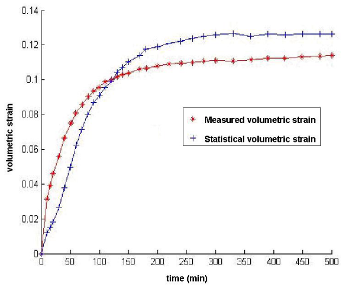


Fig.3 Volumetric strain comparison of model computation results with triaxial test results within each substep

4 Conclusion

(1) The Monte Carlo method is used to generate a certain amount of polygon unit in random shape, size and surface characteristics, which represented all kinds of structural units of granular materials, and these units were randomly distributed to the area of a given size, and the stochastic geometric model for the microstructure of granular materials is established.

(2) The algorithm is suitable for the coaxial light source with different scale and intensity, which can estimate the light component and the reflection component accurately. The effect of the enhanced image are better than that with the method of filtering and histogram equalization. It shows that this algorithm can preserve the microstructure information of the micro image while enhancing the image.

(3) The result of numerical simulation are similar with the one obtained from conventional three axis consolidation test, which proves that the results of simulation are practical and reliable. And the needed modeling parameters are few and easy to obtain from the indoor test.

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