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Quantitatively characterizing sandy soil structure altered by microbial-induced carbonate precipitation (MICP) using multi-level thresholding segmentation on synchrotron radiation imaging

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Abstract: The influences of biological, chemical, and flow processes on soil structure through microbial-induced carbonate precipitation (MICP) are not yet fully understood. In this study, we use the Kapur entropy (KE) multi-level thresholding segmentation algorithm to quantitatively characterize sandy soil structure altered by MICP treatment. A sandy soil specimen was treated by MICP and scanned by the synchrotron radiation micro-CT with a resolution of 6.5 μm . After validation, tri-level thresholding segmentation using KE successfully separated the precipitated calcium carbonate crystals from sand particles and pores. Spatial distribution of porosity, pore structure parameters, and flow characteristics were calculated for quantitative characterization. The size effect of the specimen was discovered to be a key factor affecting the performance of MICP treated soil. The results offer pore-scale insights of MICP treatment effect, and the quantitative understanding confirms the importance of the KE multi-level thresholding segmentation algorithm.

Keywords: Soil structure; Micro-CT; Multi-level thresholding; Genetic algorithm; Microbially induced carbonate precipitation

1. Introduction

Microbial-induced carbonate precipitation (MICP) is a novel environment-friendly and sustainable soil stabilization technique (Dejong et al., 2013; Shashank et al., 2016). It utilizes the natural bio-geochemical reactions to result in inorganic cementation between soil grains, which improves the engineering properties of soils, e.g., permeability, bearing capacity, liquefaction resistance and erosion resistance (Frankel & Bazylinski, 2003; Whiffin et al., 2007; Dejong et al., 2010; Liu et al., 2020).

The joint effect of the size, shape, and arrangement of soil particles and the interaction between them is collectively referred to as soil structure, and the engineering properties of soils depend on

the soil structure (Mitchell and Soga, 2005). During the process of MICP, the carbonate precipitation within the pore space volume altered the former soil structure. But how the biological, chemical, and flow process of MICP influence soil structure is still not fully understood (Jiang et al., 2020).

Micro-computed tomography (micro-CT), with a cross section pixel size in the micrometer range, is an efficient tool to reveal the minute details of soil structure owing to its non-invasive fluoroscopy and high spatial resolution (Oda et al., 2004; Sleutel et al., 2008; Hasan & Alshibli, 2010). Advanced micro-CT imaging techniques based on synchrotron radiation further enhance the spatial resolution and avoid common artifacts (Schropp et al., 2012) to reveal more minute details of soil structures (Voltolini et al., 2017). In addition, the spatial structures of soils can be characterized by three-dimensional reconstruction (Li et al., 2017). However, the quantitative characterization results largely rely on subjective operator judgements for factors such as sample differences, equipment parameter adjustments, and noise. This is especially true when performing image segmentation to separate different substances. For the grayscale images of the soil obtained by micro-CT scanning, the watershed algorithm (Taylor et al., 2015; Zheng & Hryciw., 2016) and the single thresholding (Sezgin et al., 2004) methods can be used for binary segmentation to separate the particles from the pores. However, as for the soil treated by MICP, binary segmentation is incapable of differentiating the precipitated calcium carbonate crystals from the soil particles and pores in that three greyscales exist (Wang et al., 2011; Houston et al., 2013; Wei et al., 2019). Therefore, previous characterization methods can only provide the general morphological description of the soil structure of MICP treated soils; but the extent to which the soil structure and flow characteristics are altered by MICP remains unclear (Dejong et al., 2013). Obviously, developing more reliable indicators is needed (Iaasonov et al., 2009; Baveye et al., 2010; Cnudde & Boone, 2013).

Multi-level thresholding subdivides different objects in the image by setting multiple thresholds (Para et al., 2016). It holds much potential in segmenting the soils treated by MICP, as multiple thresholds distinguishing different types of particles can be identified. The selection criteria of multi-level thresholding based on the division of histogram regions, such as the Otsu (Otsu, 1979) and Kapur entropy algorithms (Kapur et al., 1985), can be used to determine multiple thresholds (Bhandari et al., 2016). Previous studies indicated that, when applied to soil images of micro-CT, Otsu thresholding might lead to unreliable results (Houston et al., 2013). Moreover, studies have

confirmed the advantages of Kapur entropy in multi-level thresholding segmentation; this is because no prior knowledge is required, and small objects in the image can be retained (Wu et al., 2015; Pare et al., 2016). However, few works on segmenting the MICP treated soil using multi-level thresholding has been implemented.

In this study, grayscale image sequences of an MICP-treated quartz silty sand column were obtained using synchrotron radiation micro-CT. A novel multi-level thresholding algorithm was proposed to identify the thresholds for directly separating calcium carbonate crystals from sand particles and pores. The applicability and accuracy of the algorithm were validated by four indices. Quantitative comparisons of soil structures and flow characteristics between representative element volumes with and without calcium carbonate crystals were performed using the maximal ball algorithm (Dong & Blunt, 2009; Arand & Hesser, 2017) and the lattice Boltzmann method (Chen & Doolen, 1998; Guo et al., 2020). Micro-scale insights of MICP treatment effect were gained from the study; reversely, the quantitative understanding confirms the importance of the KE multi-level thresholding segmentation algorithm.

2. Algorithm principle

Kapur entropy (Kapur et al., 1985) (KE) considers the gray-scale probability of the pixels in a digital image and maximizes the amount of information in the image after segmentation. The entropy value is calculated in accordance with the probability in the gray level class (i.e., the proportion of the pixel amount at a certain gray level to the total pixel amount in the class); therefore, the size of the target and its background are not sensitive enough to retain the small target in the image (Wu et al., 2015). In terms of Shannon entropy, the histogram entropy H of a grayscale image is defined as:

$$H = -\sum_{i=0}^{l-1} p_i \ln p_i \quad (1)$$

where l is the gray level of a digital image, and p_i is the probability of the i th gray level. For a digital image with an 8-bit depth, the value of l is 256 (2^8).

Assume a binary threshold t segments the digital image as group object (O) and group background (B), the discrete probability distributions of O and B yield:

$$\left\{ \frac{p_0}{\sum_{i=0}^t p_i}, \frac{p_1}{\sum_{i=0}^t p_i}, \dots, \frac{p_t}{\sum_{i=0}^t p_i} \right\} \quad (2)$$

$$\left\{ \frac{p_{t+1}}{1 - \sum_{i=0}^t p_i}, \frac{p_{t+2}}{1 - \sum_{i=0}^t p_i}, \dots, \frac{p_{l-1}}{1 - \sum_{i=0}^t p_i} \right\} \quad (3)$$

Based on the definition in Eq. (1), the entropies of the object and background are $H_O(t)$ and $H_B(t)$, respectively, which yields:

$$H_O(t) = - \sum_{i=0}^t \frac{p_i}{\sum_{i=0}^t p_i} \ln \frac{p_i}{\sum_{i=0}^t p_i} = \ln \sum_{i=0}^t p_i - \frac{\sum_{i=0}^t p_i \ln p_i}{\sum_{i=0}^t p_i} \quad (4)$$

$$H_B(t) = - \sum_{i=t+1}^{l-1} \frac{p_i}{1 - \sum_{i=0}^t p_i} \ln \frac{p_i}{1 - \sum_{i=0}^t p_i} = \ln(1 - \sum_{i=0}^t p_i) + \frac{H + \sum_{i=0}^t p_i \ln p_i}{1 - \sum_{i=0}^t p_i} \quad (5)$$

Thus, the total entropy of the image, $H(t)$, yields:

$$H(t) = H_O(t) + H_B(t) = \frac{H + \sum_{i=0}^t p_i \ln p_i}{1 - \sum_{i=0}^t p_i} - \frac{\sum_{i=0}^t p_i \ln p_i}{\sum_{i=0}^t p_i} + \ln \sum_{i=0}^t p_i (1 - \sum_{i=0}^t p_i) \quad (6)$$

An optimal threshold value t^* exists that maximizes $H(t)$, which yields:

$$t^* = \arg \max_{0 \leq t \leq l-1} H(t) \quad (7)$$

When extended to multi-level thresholding, assume that n thresholds $t_1, t_2, \dots, t_n$ exist,

which satisfies $t_1 < t_2 < \dots < t_n$. The total entropy yields:

$$H(t_1, t_2, \dots, t_n) = \ln \left(\sum_{i=0}^{t_1} p_i \right) + \ln \left(\sum_{i=t_1+1}^{t_2} p_i \right) + \ln \left(\sum_{i=t_n+1}^{l-1} p_i \right) + \ln \left(\sum_{i=t_n}^{l-1} p_i \right) - \frac{\sum_{i=0}^{t_1} p_i \ln p_i}{\sum_{i=0}^t p_i} - \frac{\sum_{i=t_1+1}^{t_2} p_i \ln p_i}{\sum_{i=t_1+1}^{t_2} p_i} - L - \frac{\sum_{i=t_n+1}^{l-1} p_i \ln p_i}{\sum_{i=t_n+1}^{l-1} p_i} \quad (8)$$

An assembly of optimal thresholds $\{t_1^*, t_2^*, \dots, t_n^*\}$ exists that maximizes the total entropy, that is

$$\{t_1^*, t_2^*, \dots, t_n^*\} = \arg \max_{0 \leq t_1 < t_2 < \dots < t_n \leq l-1} H(t_1, t_2, \dots, t_n) \quad (9)$$

3. Material and methods

3.1 MICP treatment

A soil sample treated by MICP was prepared in the laboratory. Quartz sand C190 Accusand (70–120 mesh, Unimin Corporation, Le-Sueur, USA) with a specific gravity of 2.65 and porosity of 0.699 was used. Considering the high-precision imaging and subsequent test results for processing, the particle size distribution primarily ranges from 0.15 to 0.21 mm. The bacterial species (*Sporosarcina pasteurii*, ATCC 11859) was offered by the China General Microbiological Culture Collection Center. The turbidimetric method was used to detect biomass in the configured bacterial solution (Sutton, 2011). At a wavelength of 600 nm, the characterization of turbidity (OD600) was 0.63. A cementation solution consisting of 1 mol/L urea and 1 mol/L CaCl_2 was used to provide chemicals that induce calcite precipitation during treatment.

Figure 1 sketches the configuration of the MICP cementation test. A grouting liquid container, a peristaltic pump, a sand column sample, and a waste liquid container were used for MICP cementation. Specifically, the peristaltic pump injects the grouting liquid, controlling the grouting speed and volume. A sand column mold, made of round transparent plexiglass pipe with an inner diameter of 10 mm and height of 100 mm, contains the sand column. The preparation of such a small specimen is for the accuracy of the micro-CT scanning. The sample preparation process was executed as follows. First, the bottom of the column mold was covered with a layer of rapid qualitative filter paper; the side hose was filled with a piece of gauze to avoid leakage of sand particles. During the sample preparation, water was added, and sand was gradually added to the mold by occasionally tapping the side wall to allow the sand particles to sink freely, avoiding stratification during sedimentation. As the height of the sand column reached about 50 mm, the addition of sand was halted, and the remaining space of the mold was filled with pieces of gauze to prevent the emergence of sand during grouting. Finally, the bottom and top threads of the mold were tightened with raw tape to avoid water leakage.

Fig. 1 Sketched configuration of MICP cementation

Grouting was performed at a constant temperature of 30 °C. The bacterial liquid was first injected from the grouting port at a rate of 0.2 ml/min and a pressure of 0.2 bar, until the turbid and yellow bacterial liquid flowed out of the stock outlet. After standing for 2 h, the cementation solution was injected at a rate of 0.02 ml/min for 40 h; then, a round of grouting batch was completed. Only two grouting batches were conducted, because the amount of carbonate precipitation is deliberately controlled for the accuracy validation of the KE multi-level algorithm. The permeability coefficient was measured before and after each grouting batch. To ensure the specimen was not disturbed, sample preparation and MICP treatment were continuously performed in situ before micro-CT scanning. For convenience, the sample was defined as an “initial sample” and a “cemented sample” before and after MICP cementation, respectively.

The sand column is a one-dimensional seepage system that follows Darcy’s law. The permeability coefficient was measured by a constant head permeability test. Table 1 lists the measured flow rates and permeability coefficients. After two rounds of grouting, the flow rate across the sample decreased from 3.7 to 1.05 mL/min (71.62%), while the permeability coefficient decreased from 0.0379 to 0.0138 cm/s (63.59%). Obviously, carbonate precipitation induced clogging within the pores of the sand column (Chu & Ivanov, 2012).

145

Table 1 Permeability measuring results

Grouting round	Parameters	
	Flow rate (mL·min ⁻¹)	Permeability coefficient (cm·s ⁻¹)
	3.70	0.0379
1	2.48	0.0294
2	1.05	0.0138

146 3.2 Synchrotron radiation micro-CT imaging

147 Industrial CT has been widely used to study the microstructure of geomaterials (Ketcham &
148 Carlson, 2011; Wildenschild & Sheppard, 2013). However, for substances with small density
149 differences, the imaging effect of industrial CT based on absorption contrast imaging tends to be
150 dim, which is not conducive for discovering minute details. Synchrotron radiation (SR) is a type of
151 electromagnetic radiation emitted by charged particles when accelerated in a curved orbit and
152 features high brilliance, flux, and collimation, owing to its extremely intense and high energy
153 (Zanette et al., 2011). Using an SR light source, micro-CT yields higher imaging resolution than
154 ordinary X-ray sources. Moreover, a phase contrast is supplemented with traditional absorption
155 contrast imaging, which effectively eliminates artifacts (Xiao et al., 2014). In this context, micro-
156 CT imaging was conducted with a resolution of 6.5 μm in the BL13W1 beamline of the Shanghai
157 Synchrotron Radiation Facility (SSRF), an advanced third-generation light source in China. The
158 sample was gently and carefully transferred into the working chamber of BL13W1 and fixed onto a
159 turntable. No disturbance occurred during the transfer and fixation processes. As the microfocus X-
160 ray source was fixed, the sample was rotated 360° along the horizontal direction at a constant speed
161 to obtain perspective images of the entire sample.

162 Figure 2 illustrates the operating principles of the imaging device. The vertical tomographic
163 interval of the scanning was set to 20 μm . The sand column was scanned for 120 min to obtain
164 11226 tomography scanning images, with 32-bit grayscale in TIFF format. The initial sample was
165 first scanned by SR micro-CT and moved down gently to perform the MICP cementation test to
166 obtain the cemented sample.

Fig. 2 Operating principle of SR micro-CT imaging

3.3 Image preprocessing

The original tomographic sequence images obtained by SR micro-CT need to be preprocessed to improve image clarity, to suppress irrelevant information, and to properly digitalized the image for later quantitative characterization (Xiong et al., 2020). An open-source software, ImageJ, was used to transform the original 32-bit grayscale image into an 8-bit image to efficiently downscale the data space. Subsequently, histogram equalization and smooth filtering were implemented. Figures 3 (a), (b), and (c) show a cross-sectional scanning image of the cemented sample and the subsequent histogram of the equalized and smooth filtered samples, respectively.

(a) Original image

(b) Histogram equalized image

(c) Smooth-filtered image

Fig. 3 Image preprocessing

3.4 Identifying multi-level thresholds

Figures 4 (a) and (b) compare the preprocessed images of the initial and cemented samples and their magnification boxes at the same height. The cemented sample seems more compact than the

initial sample, apart from the occurrence of voids. Specifically, a class of new substances with higher grayscale occurs between the sand particles and pores of the cemented sample. Previous studies confirm that the carbonate precipitation produced by micro-organisms is fixed around sand particles (Muynck et al., 2010; Dejone et al., 2013).

Therefore, two thresholds, t_1^* and t_2^* , are used for the tri-level segmentation, which satisfies:

$$(t_1^*, t_2^*) = \arg \max_{0 \leq s_1 < s_2 \leq l-1} H(t_1, t_2) \quad (10)$$

Fig. 4 Sectional variation after MICP-cementation (a) initial sample; (b) cemented sample.

During scanning, influencing factors (e.g., the instability of light intensity and inhomogeneous spatial distribution of substances) may cause the imaging effect of the transverse section to vary significantly along the axial direction, resulting in threshold variation when performing multi-level segmentation (Cnudde & Boone, 2013). Therefore, varying thresholding arrays was introduced into the scanning image sequence for more precise segmentation. Specifically, given the circular cross sections of the cylinder sample under scanning, a square image is inscribed for thresholding sampling, which can be easily transformed into a digital matrix; thus, maximal information can be obtained from the ascribed square. Then, KE multi-level algorithm was applied to the square image sequence to identify a thresholding matrix with m rows and 2 columns. The thresholding matrix was applied for the tri-level thresholding of the entire image sequences of both samples. Figure 5 shows the entire process, and Fig. 5 (b) uses part of the image sequence for the demonstration. Such a batch processing strategy is nested into the presented the KE multi-level algorithm algorithm for processing numerous micro-CT scan sequence images.

Fig. 5 Identifying tri-level threshold matrix (a) inscribed square sampling; (b) part of sampled image sequence

4. Results

4.1 Thresholding segmentation

Watershed and OTSU algorithms were introduced to compare the performance of the KE multi-level algorithm. The watershed algorithm is designed based on the principle of identifying individual geographic catchment area by the downhill flow flowing to the local low point. Previous studies show that the watershed algorithm separates regularly shaped particles in a typical soil specimen. However, a single sand particle may be divided into two or more parts because of the limitation of its algorithm principle (Zheng & Hryciw, 2016; Sun et al., 2019). The OTSU algorithm (also known as the maximum inter-class variance method) determines the segmentation threshold based on the criterion of maximizing the variance between the target and the background classes. The OTSU algorithm is a robust method owing to its simple principle and convenient implementation, which is suitable for images with low complexity, but it performs poorly for segmenting soil CT images (Otsu, 1979; Houston et al., 2013).

Figure 6 (a) shows the segmentation results of a typical sectional slide image after preprocessing. Segmentation algorithms, including watershed, OTSU, and KE multi-level algorithm algorithms, were used to obtain the segmented image, as shown in Figs. 6 (b–d). The watershed method can only dimly acquires boundaries between particles and pores, let alone effectively distinguish the calcium carbonate crystals. Although the OTSU algorithm can implement tri-level segmentation on the processed image when comparing Figs. 6 (c) and (a), the pixels that should be the original sand particles were inaccurately segmented as carbonate granules. Figure 6 (d) shows that the KE multi-level algorithm algorithm distinctly segments the calcium carbonate crystals from

the original sand particles and pores and complies well with the three-phase distribution pattern observed in Fig. 6 (a). In addition to the implementation of only two rounds of grouting batches, the volume proportion of calcium carbonate crystals is smaller than that of either sand particles or pores. The watershed algorithm is based on image morphology and prefers to determine object boundaries without classifying the objects. OTSU prefers the uniformity of the gray level of pixels within the class, making the areas occupied by the object and the background equal. KE identifies the thresholds in accordance with the grayscale in-class probability, which retains tiny objects from the background well.

Fig. 6 Comparison of image segmentation results

(a) Preprocessed image; (b) Watershed; (c) OTSU; (d) KE

Table 2 compares the detailed parameters of the three segmentation algorithms. The watershed does not have a defined threshold value, while OTSU and KE have dual thresholds of 113 and 168,

and 124 and 202. The running time of KE costs more than that of OTSU but less than that of Watershed. The PSNR and RMSE indices (Bhandari et al., 2016) were used to characterize the intensity and correctness of the segmented images compared with the preprocessed images. KE had maximum PSNR and minimum RMSE; thus, images segmented by KE had the best quality among the three algorithms. In addition, SSIM and FSIM (Wang et al., 2004) were used to represent the similarity of the segmented and preprocessed images. KE had the maximums of SSIM and FSIM and retained the most phase details among the three algorithms.

Table 2 Comparison of quality results of different image segmentation algorithms

Items	KE	Watershed	OTSU
Threshold	(124,202)	-	(113,168)
PSNR	38.3634	17.5455	34.2196
RMSE	37.4533	106.0584	46.0757
SSIM	0.7532	0.1780	0.7450
FSIM	0.8312	0.7189	0.8131

* PSNR: peak signal noise ratio; RMSE: Root Mean Square Error; SSIM: Structural Similarity Index Measure; FSIM: Feature Similarity Index Measure.

Based on the tri-level segmentation results in Fig. 6 (d), the extraction of a single class of substance can be realized when merging the pixels of the other two classes by assigning them the same grayscale values of 0 or 255. Figure 7 (a) shows the extraction results of soil pores and the voids in solid particles. The existence of voids should correspond to the space for tiny sand particles introduced by grouting. Figure 7 (b) shows the distribution of the calcium carbonate crystals within the section. The calcium carbonate crystals are not uniformly distributed but locally gather within a band. Figure 7 (c) shows the merged result of Figs. 7 (a) and (b) by image morphology operation, and the MICP-cementation effect can be noted. Comparing Figs. 7 (a) and (c) reveals that the soil pores tend to be slimmer after carbonate precipitation.

(a) (b) (c).

Fig. 7 MICP-cementation effect (a) soil pores and voids (in black); (b) carbonate precipitation granules (in black);
(c) soil pores and voids with carbonate granules space (in black)

3D reconstruction was performed for visualization using the total images segmented by the KE algorithms. Figures 8 (a) and (b) show the reconstructed model of the initial and cemented samples, respectively. Multiple voids were distinctly observed at the surface of the cemented model. In addition, the appearance comparison of both models confirms the deductions of the cemented sample in Fig. 4. Considering the numerous sand particles contained in the micro-CT scanning sample, completely characterizing the particles or pores in the sample is difficult owing to the limitations of current computer storage and computing capacity. To simplify the quantitative analysis process and to ensure sufficient representativeness, the detailed 3D profile of both particles and pores and the coordinates of their contact points, can be captured and visualized by a representative elementary volume (REV). A REV is a small volume containing multiple inclusions, over which a measurement can be made to yield values of apparent properties representative of the whole (Bear, 1972). The method is common and well-studied, and determining the unified REV is crucial for studying the microscale structure of sands. We introduced hypothesis testing in a previous study by comparing the convergence of internal structural parameters of REV when different REV sizes were selected. This study uses the inherited method and does not elaborate in detail (Esmaili et al., 2010; Liu et al., 2019). Figure 8 shows that a group of three cubic REV s at the top, middle, and bottom of the longitudinal axis were extracted from the cemented model. For all the REV cubes, the dimensions were all $300 \times 300 \times 300$ pixels ($1.95 \times 1.95 \times 1.95$ mm); the size was determined by statistical analysis. Subsequently, the carbonate precipitation in the three REV s was removed using the above-mentioned method; and the corresponding groups of three new REV s belonging to the comparison model, were obtained. The difference between the two groups of REV s is only the existence of carbonate precipitation. The REV s of the cemented model were consecutively labeled as REV1-1, REV2-1, REV3-1, from the bottom to the top; those of the comparison model were REV1-2, REV2-2, and REV3-2.

Fig. 8 Location of REVs (a) 3D reconstruction model of initial sample; (b) 3D reconstruction model of cemented sample; (c) REVs of cemented model. (d) comparison model

The MICP-cementation effect is more intuitively exhibited in Fig. 9. Figure 9 (a) shows the REV of pores and voids complemented by REV2-1; Fig. 9 (b) shows the REV of all the calcium carbonate crystals in Fig. 9 (a); Fig. 9 (c) shows the REV of the corresponding comparison model in Fig. 9 (a). Comparing Figs. 9 (a) and (c) reveals that the pore connectivity was reduced after the occurrence of carbonate precipitation.

Fig. 9 Demonstration of MICP-cementation effect (a) cemented model; (b) carbonate precipitation granules; (c) comparison model.

4.2 Spatial distribution of porosity

After the thresholding segmentation, the apparent porosity of a single image can be obtained

by calculating the ratio of the pore pixel number to the total pixels. Subsequently, the volume porosity n_v of the sand column can be approximately denoted by the accumulated apparent porosity values of the discrete tomogram sequence, which yields

$$n_v = \sum_l^u n_i(z) dz \quad (11)$$

where l and u represent the lower and upper height limits of the entire sample, respectively; $n_i(z)$ is the apparent porosity of the binary image at height z .

Fig. 10 Spatial distribution of porosities and carbonate content

Figure 10 (a) compares the porosity of the cemented and initial models; their volume porosities are 30.69% and 43.62%, respectively. Comparing both volume porosity values reveals a 29.64% decrease. The apparent porosity of the cemented model increased with fluctuations along the height; the 0–9 mm part is below 30%, and the rest fluctuates at approximately 30%. The low apparent porosity at 0–9 mm may be the consequence of the more adequate MICP reaction; the grouting process redistributed the sand particles. The fluctuation of the apparent porosity from 9–25 mm may

result from the multiple voids of the cemented model, which coincides with the former observation of void existence in Figs. 7 and 8.

Figure 10 (b) shows the apparent porosity of the cemented and comparison models; the content of precipitated carbonate is also indicated. The contents contain distinct variations. At sample heights of 0–2 mm, the apparent porosity of the cemented model varies slightly. However, the porosity of the comparison model varies significantly, primarily because the grouting pressure increases the porosity before precipitation. Furthermore, the content of precipitated carbonate (12%–16%) at 0–2 mm was significantly higher than that in the other parts. Therefore, organic matter in the bacterial liquid tends to clog and accumulate at the bottom inlet; the precipitated carbonate accumulates at the inlet, reducing the porosity after precipitation. Specifically, the minimal apparent porosity of the cemented model (approximately 23%) occurred at 7 mm, whereas the precipitated carbonate content had a relative maximum of approximately 10% at the same height. The maximal precipitated carbonate content occurs at 0.5 mm. Thus, the grouting pressure and the gravity of the upper part of the sample make sand particles gather near the 7-mm height region, lowering the porosity of the comparison model. In addition, the content of precipitated carbonate measured by the weighing method was 7.64%, which is close to the average content (7.58%) in the reconstruction model based on image segmentation; this demonstrates the accuracy of the proposed algorithm.

4.3 Pore structure parameters

As MICP clogs the pores of the soil sample, the parameters of the pore structure characterize the soil structure variation better than the particle group parameters. The maximal ball (MB) algorithm was used to extract the feature parameters of the pore structure from the REV. MB is an algorithm that statistically analyzes the pore network topology structure of porous media. Maximal inscribed spheres are used to characterize the pore space, hollow cylinders are used to characterize the pore throats, and the coordination number is the number of throats connecting pore bodies (Dong & Blunt, 2009; Blunt et al., 2013). Figures 11 (a–f) show the 3D pore networks of the REV of both the cemented and comparison models. They were labeled as PREV1-1, PREV2-1, and PREV3-1 for the cemented model and PREV1-2, PREV2-2, and PREV3-2, for the comparison model.

As noted from Fig. 11, the number of large pores and pore throats decreased significantly after MICP cementation. Specifically, the REV1 pore throats were almost eliminated, and large pores

were mostly transformed to middle and tiny ones without connection. Table 3 contains more details of the comparison between the pore networks of both pore REV. Eleven soil structure parameters (including porosity, pore number, maximum pore radius, average pore radius, average pore volume, minimum pore volume, average coordination number, average shape factor of the pore area (ASFPA), average pore throat length, median pore throat radius, and average pore throat radius) are analyzed and listed in Table 3. The average shape factor of the pore area is a parameter used to characterize the irregular level of the spatial pores; smaller values denote more irregular the pore space. Quantitatively, the porosity of REV1 decreased from 29.09% to 9.28% after cementation; this decreasing trend applies to the porosity of the other two REV. In addition, the four pore parameters decreased significantly, whereas the followers, pore numbers, and ASFPA increased. The decreasing trend applies to the three pore throat parameters and the average coordinate number; however, the decrease degree is not as high as that of the pores. All these trends imply that the calcium carbonate crystals fill the pore throats and divide an originally large pore into multiple smaller ones; thus, the number of irregular and connected pores decreases.

Fig. 11 Pore REV Networks (PREV1-1, PREV2-1, and PREV3-1 are pore REV networks of the cemented model; PREV1-2, PREV2-2, and PREV3-2 are pore REV networks of the comparison model).

Table 3 Values of pore structure parameters of the REV's

Number	PREV1-1	PREV1-2	PREV2-1	PREV2-2	PREV3-1	PREV3-2
Porosity	9.28%	29.09%	23.95%	32.75%	34.44%	41.48%
Maximum pore radius	297.93	410.50	326.08	339.34	347.63	412.174
Average pore radius	13.11	16.09	9.36	23.52	40.91	51.43
Average pore volume	0.12	1.21	0.48	2.60	6.01	8.06
Minimum pore volume	274.63	2471.62	274.63	2471.62	274.63	2471.62
Pore number	5271	1777	3000	998	432	409
Average shape factor of	0.06	0.04	0.09	0.04	0.07	0.04
Average pore throat	361.16	631.78	593.09	608.36	558.53	559.56
Median pore throat	4.37	36.19	39.99	49.75	53.00	53.12
Average pore throat	12.58	46.98	46.76	54.28	55.42	59.66
Average coordination	0.06	0.26	0.16	0.76	1.86	2.20

Furthermore, Fig.12 compares the statistical distributions of the four major pore structure parameters (i.e., coordination number, shape factor of pore area, length, and pore throat radius) and depicts the results as violin plots, which are widely used in data science to illustrate data distribution and probability density. The vertical axis of the violin plot indicates different parameter values, and the width in the horizontal direction represents the occurrence frequency of the parameter at this value. The narrower part of the violin corresponds to a lower frequency of occurrence. The three dotted lines in the violin plot represent the upper quartile, the median, and the lower quartile of the entire data set, respectively, as shown in Fig. 12.

Given the coordinate numbers of the three pairs of PREV's in Fig. 12 (a), the density, maximum, and median values all exhibit decreasing trends after MICP cementation, suggesting a decrease in pore connectivity. As shown in Fig. 12 (b), a significant increase in the PREV's of the cemented models indicates that the pore shapes tend to be more regular after MICP cementation. Figures 12 (c) and (d) show that the length and radius of the pore throat of PREV1, which is located at the bottom of the specimen, decreased significantly after MICP cementation. However, two pairs of upper PREV's do not drop significantly, suggesting that carbonate precipitation growing on the particle surface is not intuitively related to the change effects in the pore roar. In contrast, the shape factor of the pore area does not vary significantly with the specimen height, as shown in Fig. 12 (b).

(a) Distribution of the coordination number

(b) Distribution of pore area shape factors

(c) Distribution of pore throat length

(d) Distribution of pore throat radius

Fig. 12 Comparison of pore structure parameters (in violin plot)

4.4 Flow characteristics

The pores of sandy soil offer an open reservoir in which fluid is transported and porosity is primarily determined by the volume and number of pores. Pore throats are relatively long and narrow passages connecting pores and are like capillaries for fluid migration. Pore throat connectivity helps determine permeability (Vogel & Roth, 2001).

The meso-scale lattice Boltzmann method (LBM) is used for fluid motion simulation. LBM simulates the interaction between the fluid and complex boundary in porous media to finely characterize the flow behavior and to compute macro physical parameters, including permeability. The basic principle of LBM is that the fluid is discretized into a series of fluid particles. The physical region containing the fluid is divided into a series of lattices, and the time is divided into a series of steps; thus, the fluid particles are constrained to move on a limited grid according to certain collision rules. Furthermore, the density, velocity, and other macro parameters can be obtained by statistical analysis of the relevant fluid particle characteristics (Chen & Doolen, 1998).

The LBM was programmed using MATLAB to simulate the vertical seepage behavior of the six REV in Fig. 8. The LBGK approximate model and D3Q19 grid discrete mode were employed. D3Q19 is a three-dimensional and nineteen velocity components (Guo et al., 2020). Figure 13 shows the spatial flow fields of the six REV obtained by the LBM simulation. The flow paths inside a REV are depicted as blue point clouds, and darker point clouds indicate denser flow. The direction

of seepage flow from the bottom to the top corresponds to the test situation. The point cloud color of the corresponding REV3s of the cemented model appears lighter than that of the flow fields of the REV3s of the comparison model. Thus, the intensity of the flow field, particularly at the bottom of the specimen, is significantly weakened after MICP cementation, which coincides with the pore and pore throat variation trend in Fig. 11 and Table 3.

Fig. 13 Comparison of 3D flow field of REV3s with vertical seepage

Subsequently, the dimensionless seepage coefficients of the two groups of REV3s were

computed by LBM. From the top to the bottom of the specimen, the seepage coefficients of the cemented and comparison groups were 2.354, 0.986, and 0.351, and 3.317, 1.293 and 1.127. Further, the maximal decrease in the seepage coefficient (68.86%) occurred at the bottom of the specimen after MICP cementation; those of the upper and top sections were 29.03% and 23.74%, respectively, suggesting that MICP reduces the permeability of the sand specimen owing to the clogging impact on the pore structure of the sand column. Compared with the results of the constant head test, only the decrease in the permeability coefficient at the bottom through simulation (68.86%) is close to the corresponding result (63.59%), the vertical permeability coefficient of the entire MICP-cemented sample is controlled by the horizontal section with the greatest degree of clogging.

5. Discussion

The inhomogeneity of MICP treated soil is one of the most challenging factors that restricts the up-scale use of MICP in filed application (Tang et al., 2020). Tang et al., (2020) suggest a grouting pressure between 0.1 and 0.3 bar for sand sample, and a grouting speed below 0.042 mol/L/h which can improve the use ratio of cementation solution. Moreover, they point out that excessive grouting pressure would erosion the original soil structure and reduce the solidification effect. In this study, we use a grouting pressure of 0.2 bar, and the grouting speeds of 0.012 mol/L/h and 0.0012 mol/L/h for bacterial liquid and cementation solution, respectively. However, soil erosion still occurred and resulted in voids within the specimen in this study, as noted in Fig. 9. This should attribute to the size effect of the specimen. The synchrotron radiation imaging restricts the specimen size to be 10 mm in diameter and 100 mm in height, significantly smaller than the specimen size used in previous studies. Thus, a grouting pressure of 0.2 bar could be too high for this specimen to result in erosion inside. Therefore, when considering the factors affecting the performance of MICP treated soil, the size effect should not be ignored. Additionally, note the grouting speed of cementation solution is slow; this is because the calcium carbonate crystals are likely to accumulate around the grouting point to hinder the further injection of cementation solution, which eventually result in the uniformity of calcium carbonate inside the specimen (Joer et al., 2002). Our quantitative characterization method using multi-level thresholding segmentation on synchrotron radiation imaging help to better understand the working mechanism of MICP at the pore scale.

6. Conclusion

1) The KE algorithm can efficiently implement multi-level thresholding segmentation on MICP

treated soils to identify triple components, e.g., pores, sand particles, and calcium carbonate crystals.

2) Computing the apparent porosity and calcium carbonate contents along the specimen height suggested that the grouting pressure enlarged the porosity before precipitation, thus increasing the porosity of the comparison model; in addition, the organic matter is preferentially clogged at the grouting inlet, causing accumulation of carbonate precipitation at the inlet, and lowering the porosity after precipitation.

3) The quantitative characterization results of the REV pore structure parameters imply that the occurrence of calcium carbonate crystals fills the pore throats and divides an original large pore into multiple small ones; this process was combined with the pore decrease in irregular and connected degrees.

4) The vertical permeability coefficient of the entire MICP-cemented sample is controlled by the horizontal section with the greatest degree of clogging.

5) The size effect of the specimen is a key factor not to be ignored when considering the factors affecting the performance of MICP treated soil.

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