ANN-based bubble tracking algorithm for clay slurries containing large gas bubbles using X-ray CT

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ABSTRACT: Gassy clay is a widely-distributed natural composite material consisting of a saturated clay matrix incorporating large gas bubbles. This study aims to develop a novel method to non-destructively monitor the strain field evolution of drying kaolinite slurry samples, with entrained gas bubbles, using X-ray computed tomography (CT). During the drying process, the kaolinite sample is scanned several times at decreasing water content (reducing soil volume). Individual bubbles are identified within the kaolinite sample and their morphology and location are measured via image processing. A bubble-tracking algorithm links associated bubbles between different scans using bubble location and morphology information. The morphology of individual bubbles changes as the soil volume reduces under increased suction during the drying process. Therefore, an artificial neural network (ANN) is adopted to enhance the bubble-tracking algorithm. This method shows great accuracy based on verification with manually linked bubbles. Hence, the three-dimensional (3D) displacement field of bubbles was determined within the soil sample. Finally, the evolution of the 3D displacement field is discussed, both before and after desiccation crack formation.

KEY WORDS: Desiccation crack; Fine-grained soil; Strain field; X-ray computed tomography.

1 INTRODUCTION

The formation of desiccation cracks in drying clay slurries dramatically alters their mechanical and hydraulic properties and leads to engineering problems for geotechnical and agricultural structures, such as dams, roads, landfills, agricultural irrigation, etc. [1-3]. Desiccation cracks with polygonal network are also observed in various geological features [4]. Laboratory experiments and numerical simulations have also been employed to characterise the mechanism of desiccation cracks [5-7]. Desiccation cracks tend to nucleate at large surface pores, where capillary pressure generates stress concentration, and the cracks propagate with the further invasion of air into the locally enlarged pores [5]. Previous experimental studies mainly adopted digital cameras to monitor the deformation and crack formation, based on the 2D characterisation of the drying soil surface. However, limited information exists about the 3D deformation within drying soils.

X-ray computed tomography (CT) has been widely applied to coarse-grained materials, e.g., to non-destructively monitor the internal fabric evolution in sand samples [8-9]. Various particle-tracking techniques were developed to monitor the kinematic information with time-lapse scanning [10]. The quantification of particle movement provides new insights on shear band formation [11-12], particle breakage, etc. [13]. Recently, X-ray CT has been applied to monitor the 3D deformation of fine-grained soils under 1D compression [14] and triaxial shearing [15] conditions. The 3D measurements reveal non-uniform and localised deformation.

The tracking techniques can be primarily classified into two groups: (i) digital image correlation (DIC) calculates the cross-correlation between neighbouring monitor windows [16]; (ii) marker-based tracking (MBT) methods link individual markers based on their morphology and location information [11-12]. Both approaches have been widely used to calculate the deformation in geomaterials. The DIC method, relying on the texture of grey-scale images, does not work if textures are too small to identify, whereas the produced strain fields have a low resolution if the texture is too large. For sand samples, MBT provides valuable kinematic information of individual particles [17]. Different MBT methods have been proposed based on particle shape parameters and positions [11-12, 18]. Recently, a similar method was introduced to track the mica particles within a kaolinite matrix [14]. However, the markers tracked in MBT methods are typically the solid particles, such that their morphology remains constant throughout the testing.

In this paper, a novel MBT approach is developed for the internal bubbles entrained in a kaolinite matrix during the drying process. The morphology and location of individual bubbles within a kaolinite sample are extracted from a series of X-ray CT images obtained at different (progressively reducing) water content. An artificial neural network (ANN) algorithm was trained to determine the correlation factors between bubbles within different scans. The suitability of various bubble parameter groupings is examined for the bubble tracking algorithm. Then, 3D displacement fields are obtained from tracked bubbles to characterise the deformation and desiccation-crack formation process for the drying kaolinite sample. The novel technique can help better understand the sample's internal evolution that occurs during desiccation cracking.
2 METHODS

2.1 Soil tested and scanning procedure

Kaolinite slurry was prepared at a water content of 151% (about 3 times greater than its liquid limit). The slurry material was poured into a plastic container, with 32.7-mm inner diameter, for performing a drying test at ambient laboratory temperature.

During the drying process, a series of five X-ray CT scans was collected using the TESCAN CoreTOM apparatus (voltage at 160 keV). In other words, the X-ray scanning of the drying kaolinite sample was performed for progressively reducing water contents of S1 = 48.4%, S2 = 35.3%, S3 = 26.5%, S4 = 23.2%, and S5 = 13.9%. The sample’s wet mass (and hence its water content) at each scan was determined by a precision scale. The reconstructed X-ray images have a resolution of 20 μm along three orthogonal directions.

2.2 Image processing and bubbles tracking

The grey values in the reconstructed X-ray images reflect the X-ray attenuation of different materials present. As shown in Figure 1(a), a high contrast exists between air, plastic (of the container side-wall), and kaolinite. A series of image processing steps were conducted to extract individual air bubbles (entrained in the kaolinite matrix) from the grey-scale images, as follows. First, a median filter was used to reduce image noise. Next, the threshold values between air, plastic and kaolinite were determined from grey-value histogram. Then individual air bubbles were identified, each labelled with different IDs. In Figure 1(b), individual gas bubbles with varying size (volume and surface area) and shape are represented with different colours, and the bubbles seem to be evenly distributed in the kaolinite sample.

The extracted 3D bubble surfaces were analysed to obtain their location and morphology information. The locations (x, y, and z coordinates) of the bubble centroids were determined. Bubble morphology was quantified in terms of volume, surface area, sphericity (SP), aspect ratio (AR), and convexity (CON). SP compares the surface area of a bubble and its volume-equivalent sphere. AR compares three principal dimensions, i.e., maximum, intermedia and minimum. CON compares the bubble volume and the volume of its convex hull. Detailed descriptions of the image processing and shape analysing can be obtained in [19].

The procedure of the bubble tracking algorithm starts with the morphology and location information of individual bubbles and involves the following steps. Firstly, a small portion of the bubbles have unusual shape parameters (e.g., SP>1, which is mainly caused by low bubble-to-pixel size ratio), such that they were excluded from further analysis. Next, the coordinate system was unified between different scans, and then 145 bubbles were manually linked between scans for ANN model training and validation. Finally, the trained ANN model was used to compare all possible links between bubbles in sequential scans.

The coordination system was not consistent between scans due to the movement of the drying kaolinite sample. Thus, a unique coordination system was defined for all scans, using the sample container base (contact surface), and considering a unique bubble, as follows. First, the centre and perpendicular vector of the container base were determined; these being chosen as the origin and the z-axis of the unified coordination system. Then, a unique bubble was selected across scans to define the y-axis. All bubbles aligned well between different scans after the coordination system update.

Figure 1 shows the architecture of the ANN model with a three-layer structure. The location and morphology parameters of two bubbles in sequential scans were compared to identify if they were correlated. The difference of parameters (ΔXi) were imported into the ANN model to estimate a correlation factor (Y ∈ [0,1]) between two bubbles in sequential scans. A ranking system was developed to uniquely link bubbles, such that bubbles with the highest correlation factor Y were linked first. For this purpose, 145 bubbles were manually linked between scans S1 and S2 for the training and verification of the ANN tracking algorithm. In other words, the weight of the neural unit (wim) was obtained using 100 manually linked bubbles between S1 and S2, with the other 45 manually linked bubbles used for verification purposes.

3 RESULTS AND DISCUSSION

3.1 Bubble morphology analysis

The sizes and shapes of individual bubbles change during the drying process, such that bubble tracking based on morphology information could be problematic. As shown in Figure 3, a bubble in different scans was extracted, its size...
(volume and surface area) decreasing almost proportionally during the sample drying/shrinkage process. However, changes in the shape (i.e., SP, AR, and CON) of the bubble were unpredictable. This could pose a threat to the efficacy of the presented bubble-tracking algorithm.

Figure 3. Changing morphology of specific bubble in five scans (for reducing water content of kaolinite sample).

3.2 ANN tracking model optimisation

Eight parameters (i.e., x, y, z coordinates and the volume, surface area, SP, AR, and CON) were extracted from each bubble. The feasibility of applying different parameter combinations for bubble tracking should be examined. For this purpose, various groupings of parameters were adopted in the ANN model. Figure 4 shows the cumulative probability of correlation factors for 2830 bubbles between scans S1 and S2 for nine different parameter combinations investigated.

![Graph showing the cumulative probability of correlation factors](image)

Figure 4. Relevance of all linked bubbles for various bubble parameter groupings investigated. Note: SP, sphericity; AR, aspect ratio; CON convexity.

As evident from Figure 4, parameter groups including location (x, y, z) and volume show the best performance. Whereas the parameter group with SP, AR, and CON shows the worst performance, since these parameters change randomly during the shrinkage process. In other words, these shape parameters will reduce the tracking accuracy if combined with bubble location and size parameters. Further calculations show that the bubble parameter group selected (i.e., x, y, z coordinates and volume) has 100% accuracy for the 45 sets of manually selected bubble validations, and the highest relevance mean, and small standard deviation.

3.3 Displacement field

3D displacement fields were calculated based on the linked bubbles between scans. Figure 5 shows the displacement field obtained between scans S1 and S2 (for reducing water content from 48.4% to 35.3%). The three colours (green, blue, and red) represent the displacement of the upper, middle, and lower sample depth/zones. The bubbles mainly move downwards, with little horizontal displacement occurring at these relatively high water contents, as compared to the air-entry value. As expected, bubbles nearer the top surface of the sample undergo more significant downward vertical movement, with a maximum displacement of 0.82 mm, whereas the minimum displacement of 0.004 mm occurred for bubbles located close to the container base.

![Displacement field of S1-S2 (water content reducing from 48.4% to 35.3%)](image)

Figure 5. Displacement field of S1-S2 (water content reducing from 48.4% to 35.3%).

The kaolinite sample, of thickness 5.02 mm for S1, was separated into 261 layers. Bubbles were associated with individual layers based on their centroid locations. The averaged vertical displacements of all bubbles in each layer, occurring between scans S1 and S2, are shown in Figure 6. The linear relationship between mean vertical displacement and layer depth indicates a uniform vertical strain occurred over the sample thickness between S1 and S2.
deformation response of the drying sample with entrained gas bubbles.

A series of image processing techniques was adopted to extract individual bubbles, and their location and morphology information. The bubble size (volume and surface area) was found to reduce almost proportionally during the drying process, whereas bubble shape parameters (e.g., AR, SP, and CON) changed randomly.

The ANN model was trained and validated with manually linked bubbles between successive scans of the drying kaolinite sample. Among different bubble parameter groupings investigated, the combination of bubble location and volume shows the best tracking performance. However, shape parameters (AR, SP, and CON) are not suitable for bubble tracking, since they change randomly during drying.

For drying at higher water content, the entrained bubbles experience primarily vertical displacement, bubbles located near the top surface of the sample undergoing a higher downward vertical displacement. Furthermore, the linear relationship between vertical displacement and depth in the sample indicates a uniform vertical strain distribution occurred over the sample thickness. Horizontal displacement became more prominent at lower water content, caused by crack formation close to the container side-wall.

REFERENCES


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