Internal structure recognition of EPS composite soil using fully convolutional network

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ABSTRACT

As a geotechnical backfill material, expanded polystyrene (EPS) composite soil has the advantages of low weight, high strength and easy in-site handling. This study applies the fully convolutional network (FCN) to identify each individual EPS bead on the cross-section planes of EPS composite soil samples. FCN is a powerful deep learning architecture that can make pixel-level classification of images. This paper introduces the structure of the FCN model, the data preparation and model training for the EPS bead identification task. The trained FCN model is capable of recognizing and assisting quantitative assessment of the internal structure of EPS composite soil.

Keywords: EPS composite soil, fully convolutional network, image processing, deep learning

1 INTRODUCTION

Expanded polystyrene (EPS) composite soil is a new kind of lightweight geomaterial first introduced in Japan in the 1980s. EPS composite soil has an improved strength over the raw soil due to the presence of cement and has a low unit weight due to the addition of superlight EPS (Gao et al., 2012; Miao et al., 2012). The non-uniform distribution of EPS beads can lead to heterogeneous behavior of EPS composite soil and the heterogeneity is significant when the EPS content is relatively low, say below 50% by volume. However, this issue has not been emphasized in previous studies.

With the rapid development of deep neural network, various algorithms of deep learning have been developed and widely used in image processing, data representation, signal processing, game, and so on (Bengio, 2009; Long et al., 2015). Some preliminary applications of deep learning algorithms in civil engineering have been reported as well, for example in concrete crack detection (Deng, 2019).

This paper aims at applying a deep learning model to identify individual EPS bead over a cross-section area of an EPS composite soil sample. The achievement in this study will facilitate quantitative study of the non-uniform distribution of EPS beads and its association with EPS composite soil behavior.

2 FULLY CONVOLUTIONAL NETWORKS

Fully convolutional network (FCN) is a convolutional network that can make classification at pixel level, which means that FCN can classify each pixel into predefined categories and thus allowing pixelwise detection of objects in an image.

The FCN structure is recalled briefly here as shown in Fig. 1. The FCN we used is modified from a VGG-19 convolutional network. Basically, there are four types of operation in the FCN: convolution and activation (denoted by ‘conv’ in Fig. 1), pooling (denoted by ‘pool’ in Fig. 1) and upsampling by deconvolution (corresponding to layers marked with an ‘x’ above it in Fig. 1), skip connection (denoted by the curved arrows in Fig. 1). Pooling and prediction layers are shown as rectangles while other layers shown as vertical lines. The fineness of the grids in the rectangles represents the density of pixels in the images in the corresponding layers. See details of the architecture and its advantages in reference (Long et al., 2015).
Fig. 1. Architecture of FCN

3 DATASET AND MODEL TRAINING

3.1 Dataset preparation

Cylindrical samples with a diameter of 39 mm and a height of 80 mm were first loaded in triaxial compression tests. Then, the samples were taken out from the triaxial compression apparatus and carefully sliced to expose cross-sections, as shown in Fig. 2. The interval between two successive cross-sections is 2.5 mm. The average EPS bead diameter is 2.5 mm, too. As a result, 30 cross-sections can be obtained so as to fully expose the internal structure of an EPS composite soil sample. In Fig. 2, the white particles are EPS beads embedded in the lower bulk. Some craters are left at locations where EPS beads are removed from the bulk. Both the embedded EPS beads and the craters should be recognized as EPS beads in the FCN model. Since the image processing results will be used to evaluate the heterogeneity of the spatial distributions of EPS bead, it is desired that full circle areas will be recognized through FCN.

A total of 16 EPS composite soil samples were sliced and each sample yields 120 photos. These samples have an EPS content by volume ranging from 25% to 100%. A total of 1920 photos were obtained. These photos were then cropped so that the photo edges just touch the sample’s cross-section boundary in the photo. Finally, the pixel dimensions of each photo were adjusted to be 250×250.

The pixels in each photo were labeled by drawing fully filled circles at the corresponding white EPS bead areas and the crater areas. The soil, white EPS area, crater area and photo background were respectively labeled into four categories. The pixel labels are visualized by rendering the label image with colors, as presented in Fig. 3.

3.2 Model training

Training the whole FCN from scratch is highly time-consuming but it has been proved not necessary (Long et al., 2015). As was done in the original FCN model proposed by Long et al. (2015), the parameters obtained in a VGG-19 network were used as initialization. The training process is actually a fine-tuning of the trainable parameters of the FCN. The FCN was implemented in Tensorflow 1.8.0 using python 3.6 in Anaconda 3 environment. The fine-tuning training use Adaptive Moment Estimation optimizer and per-pixel cross-entropy loss. The learning rate follows an exponential decay with an initial learning rate of 1e-4, a decay rate of 0.1 and a decay step of 5e4. It takes about 2.5 h to train the model. 70% photos are used for training and 30% used for validation.

Fig. 2. Sample slicing and cross-section photos.

(a) EPS content = 25%

(b) EPS content = 50%

(c) EPS content = 75%

(d) EPS content = 100%

Fig. 3. Original photos and visualized image labels.
4 MODEL PERFORMANCE AND IMPROVEMENT

4.1 Model performance

Fig. 4 shows that the loss drops sharply in the first 200 epochs and then decays slowly until the training was terminated after 2500 epochs. The loss was finally stabilized around 0.5. Fig. 5 shows that the trained FCN can overall satisfactorily detect the locations of white EPS beads and craters. Let us check the local performance of the trained model in four circles marked from 1 to 4 in Fig. 5 (a). In circle 1, the photo presents an EPS bead with a sharp end and some straight edges and the model successfully predicts an area close to a circle as wished. In circle 2, the photo presents a crater with an incomplete curved boundary and the model successfully captures a full circle area as hoped. In circle 3, the crater boundary is clearer than that in circle 2 but the model prediction in circle 3 is less precise than that in circle 2. In circle 4, the current trained model can capture the locations of EPS beads but the prediction of inter-bead boundaries and some crater areas are not accurate enough. The model performs better for low EPS content case than for high EPS content case.

4.2 Model improvement

To further improve the model performance, two refinements are made to the dataset.

(1) Each photo in the original dataset (referred as full-color dataset hereafter) was equally divided into 9 smaller photos without overlap.

(2) The photos in the cropped-color dataset are transferred into gray-scale photos, referred as cropped-gray dataset.

Fig. 6 and Table 1 present comparisons of model performance on the three datasets mentioned above. Both the cropped-color and cropped-gray datasets improve the performance of the trained FCN model. Removing color information in the cropped-gray dataset further enhances the prediction accuracy by reducing overlap between recognized EPS beads and by lowering mistakes as shown in Fig. 6.
It is noted that our labels are highly unbalanced, that is, the soil and background label pixels largely outnumber the EPS bead and crater pixels. However, it has been shown that this unbalance does not significantly influence the model performance. The dataset can be extended by randomly mirroring, rotating and/or patching. But this does not produce noticeable improvement in model performance. Unfortunately, our model still cannot completely eliminate the EPS bead overlap in the predicted images. The authors think that this drawback will not adversely influence the study of the spatial distribution of EPS beads.

Table 1. Comparisons of model performance on different datasets.

| Dataset       | Dataset size | Training epochs | Validation loss |
|---------------|--------------|-----------------|-----------------|
| full-color    | 1920         | 2500            | 0.610           |
| cropped-color | 17280        | 2500            | 0.540           |
| cropped-gray  | 17280        | 3000            | 0.510           |

5 CONCLUSIONS

A FCN model was trained using cross-section photos of EPS composite soils to identify individual EPS beads. The trained FCN model can satisfactorily identify EPS bead locations and in most cases give precise boundaries of EPS beads. The shortcomings of the trained model are discussed as well. Next step work would be to develop some indices to assess the spatial distribution of EPS beads in a soil sample and associate them with mechanical parameters.

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