Ensemble Deep Learning Approach for Identifying Directional Fractures in Rock CT Scan Images

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앙상블 딥러닝 기반 암석 코어 CT 영상 내 균열의 식별

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Abstract

Characterization of fracture in rock mass is critical to understand its impact on mechanical and hydraulic rock properties. The recent introduction of computed tomography (CT) scan into geological sample characterization has provided geoscientists with an effective tool for analyzing fracture network in rock mass. However, owing to the intricacy of the uninterest background and the blurry appearance of fracture, the accurate and quantitative extraction of fracture from rock CT image remains a challenging task. In this study, we present an ensemble deep learning approach for automatically detecting and segmenting fractures in rock CT images with high accuracy. This approach composes 2 stages: (1) fracture detection in terms of rotated bounding boxes; (2) fracture segmentation in detected bounding box. The applicability of this approach has been demonstrated on CT scan images of fractured rock. The results demonstrates that our approach can achieve a high dice score of up to 0.932 and outperform other deep learning approaches including Mask R-CNN and U-Net alone.

1. Introduction

Fractures are typical structural features found in rocks that govern rock mass mechanical stability and also serve as important channels for subsurface fluid movement. The characterization of fracture properties including fracture orientation and length, fracture aperture and fracture wall roughness therefore plays important role in many rock engineering applications. As a non-destructive testing method, CT scan is commonly used for analyzing the internal structure of rock samples including fracture (Andrä et al., 2013). For quantitative analysis of fractures, the segmentation procedure is required to separate the fracture voxels from the rest (i.e., minerals, pores) in a CT scan image. There is currently no standard method for fracture segmentation in CT scan images that provides satisfactory results. To segment fractures, manual or automatic thresholding in combination with ridge filters such as Hessian or Frangi filter is typically used. These techniques, on the other hand, are not only time-consuming and user-biased, but also suffer from the complexity of an uninterested background as well as low resolution of CT image.

In this paper, we propose a novel method for extracting fracture geometry information from CT scan images automatically and reliably. The suggested method consists of two parts: (1) detecting the fracture in terms of a rotated bounding box (rBbox) using Faster R-CNN (Ren et al., 2016) and (2) segmenting the fracture inside the detected bounding boxes using U-Net (Ronneberger et al., 2015). The main idea is to use the bounding box to offer prior spatial information to aid the segmentation process while also eliminating as much background as possible from segmentation consideration. Accordingly, such integration is able to address the challenges of segmenting very fine fracture as well as the complexity in background.

2. Data preparation and method

2.1 Data preparation

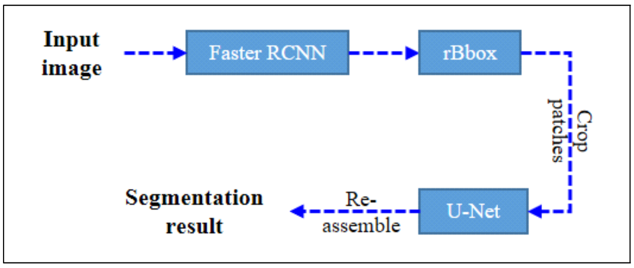
The CT scan images utilized in this study were obtained by scanning hollow cylinders of artificially fractured granite, sandstone and shale rocks. The CT scan images are displayed in grayscale, with values ranging from 0 (black, low density material) to 255 (white, high density material). The fractures appear as dark and arbitrary-oriented curved line with varying thickness along their length in the images. Totally, fracture detection dataset composes of 800 CT scan images, which were carefully labeled for fractures with rotated bounding boxes. We split the dataset into 3 portions of 600:100:100 images for training, validation and testing purpose. The entire dataset was preprocessed with a non-local means filter and the CLAHE (Contrast Limited Adaptive Histogram Equalization) before being fed into the network to eliminate noise and also enhance phase contrast.

To construct a segmentation dataset, we must label each pixel in the CT image with two categories (i.e., fracture and background). Since this task is difficult and time-consuming, only a subset of the above-mentioned 800 CT images were chosen for fracture segmentation annotation. Afterward, these CT images will be cropped into patches based on the ground truth bounding boxes. Each patch is then padded with zero padding to a fixed size of 256x256 as requirement of same size input image of U-Net. In all, 450 CT images were labeled, in which 280 images (1965 patches), 70 images (466 patches) and 100 (753 patches) were used for training, validation and testing, respectively.

2.2 Method

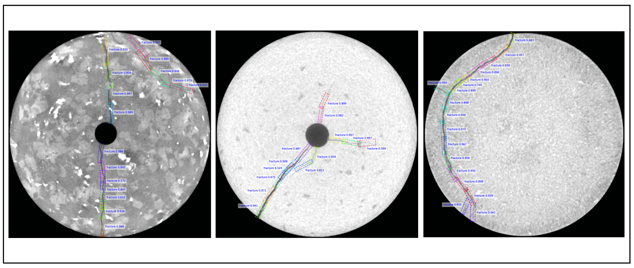
2.2.1 Fracture detection using rotated Faster R-CNN

Faster R-CNN, a regional-based object detection algorithm, was selected to use for fracture detection in CT scan images due to its exceptional performance (Fig. 1). In addition, we modified the Faster R-CNN algorithm to operate with rotated bounding boxes. Comparing to the commonly used bounding box (i.e., axis-align bounding box), rotated bounding box shows a greater adaptability to fit with the elongated shape of fracture, such that minimizing the ratio of background within the bounding box. Commonly, a rotated bounding box has four basic parameters i.e., (xc, yc, w, h) corresponding to center coordinates width and height of the bounding box. Besides, an additional parameter, angle (Θ), is introduced to account for the bounding box orientation.



[Fig. 1] Fracture segmentation pipeline.

Figure 1 depicts the complete pipeline for obtaining fracture segmentation. Regardless of the complexity in operation, Faster R-CNN architecture can be generally divided into 2 major components: region proposal network (RPN) and region based convolutional neural network (R-CNN). Based on feature maps extracted from the backbone network (ResNet-101 combined with Pyramid Feature Network), RPN algorithm will learn to generate a maximum of 512 rotated bounding boxes (so-called proposal bounding box) in which fracture may exist. The ROI-Align layer then uses these proposal bounding boxes to crop feature maps and resizes them to a fixed size of 7x7. These feature maps are consequently passed through R-CNN, which composes of a convolutional layer followed by two sibling branches, for classification and further bounding box coordinate refinement using bounding box regression. Further information on rotated Faster R-CNN's architecture and operations can be found in Pham et al. (2021). Figure 2 shows several examples of fracture detection result using rotated Faster R-CNN.



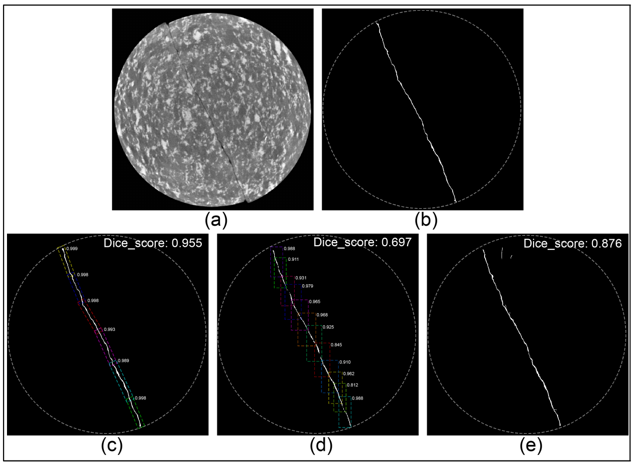
[Fig. 2] Examples of fracture detection using rotated Faster R-CNN.

2.2.2 Fracture segmentation using U-Net

For fracture segmentation in the bounding box, we use a variation of U-Net known as Residual Attention U-Net to segment fracture in detected bounding box. In this variant, the standard contraction block is replaced by a residual block (i.e., a component of ResNet-34) and attention gates are added to each level of skip connection (Oktay et al., 2018). While residual blocks allow the network to learn more sophisticated patterns, attention gates allow the network to focus on specific parts of the image where interested objects exist rather than the entire image. As a result of these two enhancements, the segmentation result's accuracy has substantially increased.

3. Result

Besides the proposed approach, we also implemented Mask R-CNN (He et al., 2017) and U-Net alone using segmentation dataset for comparison purpose. An example of fracture segmentation results obtained from three different approaches is showed in Figure 3.



[Fig. 3] (a) A CT scan image of granite rock, (b) segmentation ground truth, and fracture segmentation results from different methods: (c) rotated Faster R-CNN + U-Net, (d) Mask R-CNN, (e) U-Net.

In summary, the segmentation results on the test set indicate that our method (rotated Faster R-CNN + U-Net) can generate the best average dice score of 0.932, which outperforms U-Net and Mask R-CNN with average improvements of 7.9% and 26.1%, respectively. The following table shows the segmentation performance of each model on the test set.

[Table 1] Fracture segmentation performance using different models.

Model	mAP@0.5	Dice score
Mask R-CNN	0.886	0.739
U-Net	-	0.864
Faster R-CNN + U-Net	**0.897**	**0.932**

4. Conclusion

The segmentation results show that our proposed approach can obtain highly complete fracture segmentations with minimal false positive errors (Fig. 3c). Furthermore, quantitative evaluation using dice score metric indicates that our approach significantly outperforms U-Net and Mask R-CNN at the same cost of annotation.

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