Automatic Fracture Extraction in Laboratory Rock Sample using Deep Learning method

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ABSTRACT: Fractures play a crucial role in the hydromechanical behavior of rocks. To investigate the fundamental fracturing mechanism, the imagery of hydraulic fracture evolution is captured in laboratory testing of rock specimens. Conventionally, temporal-spatial characteristics of rock fractures must be identified and extracted manually or by image processing techniques (IPTs) for interpretation, requiring enormous time and labor with low accuracy. This paper develops a deep learning-based method that quickly and automatically identifies and extracts hydraulically induced fractures in rock specimens at the pixel level.
The applicability of this method is validated through image datasets from hydraulic fracturing tests. This method shows better effectiveness and efficiency than previous IPTs. The accuracy of the deep learning method reaches 99 percent and the average processing speed is only 389 ms per image when adopting an NVIDIA Tesla T4 GPU, saving a large amount of time compared to human work.

Keywords: deep learning, hydraulic fracture, fracture extraction, image processing.

Table 1. Terminology in machine learning.

Terminology	Definition
Convolutional Neural Network (CNN)	A kind of neural network specifically used for image recognition and tasks that involve the processing of pixel data
Architecture	The structure of a neural network building up by layers of neurons
Loss function	A function that compares the target and predicted output values
Learning rate	A parameter determining the decrease of the loss value
Epoch	The training process with all the training data for one cycle
Optimizer	A function that modifies the attributes of the neural network
Inference speed	The time that trained neural networks make predictions (or inferences) on each input data
Precision, recall and F1 score	The metrics measuring the accuracy of predictions of a neural network (a value ranging from 0 to 1, ‘0’ meaning a low accuracy while ‘1’ meaning perfect accuracy)

1 INTRODUCTION

Hydraulic fracturing has been widely used in geo-engineering areas including hydrocarbon extraction, the disposal of waste drill cuttings underground, heat production from geothermal reservoirs and fault reactivation in mining (Adachi et al., 2007). To study the mechanism of the fracturing process, lots of physical experiments were performed to capture the temporal evolution of fractures (AlDajani, 2017; AlDajani, 2022; Li, 2019; Roshankhas et al., 2018). The temporal evolution of the fracturing is done by taking high-resolution and high-speed images and analyze them. Up to now this analysis has usually been done "manually" (AlDajani, 2022; Wang et al., 2021). Such manual analysis is a very time-consuming process, even though benefitting from the expertise of the researchers. Considering these challenges, this paper aims to test the capability of machine learning in the fracture extraction from the images of rock specimens in a hydraulic fracturing test. As a first step, we will consider a single fracture image taken toward the end of the fracturing process.

With the rapid developments in image processing techniques, advanced image process techniques (IPTs) have been utilized for fracture detection in the field of structure defect inspection, such as inspection of steel structures, tunnels, and asphalt surfaces (Spencer et al. 2019; Xu et al. 2021). The IPTs are usually based on different types of thresholding techniques. One representative of these thresholding techniques is called binarization: the original three-channel RGB images containing fractures go through grayscale, threshold manipulation, and binarization to obtain the fracture sketch. Other approaches apply a combination of thresholding techniques, such as edge detection and morphological operations (German et al. 2012; Xu et al. 2021). However, the generalization capability and adaptability of these IPTs are poor, and all of them lack intelligence and automation. With the development of deep learning (DL) techniques, convolutional neural networks (CNNs) have been widely applied for image segmentation, instance segmentation, object detection, etc. In the field of civil engineering, deep CNNs have shown satisfactory performance in recognizing defects and extracting fractures (Dang et al. 2022; Guo et al. 2021). Though semantic segmentation can extract fractures from an image at pixel-level, the performance of a segmentation model is subject to a given training dataset. To the knowledge of the authors, there have not yet been any reported studies that use CNNs for the fracture segmentation of laboratory-scale hydraulically fractured rock specimens, mainly due to the lack of high-quality fracture images from advanced laboratory testing.

In this study, a deep learning approach based on the state-of-the-art segmentation model 'Linknet' was adopted for the processing and analysis of fracture images from laboratory rock specimens. Image data from a set of hydraulic fracture tests conducted at MIT (AlDajani, 2022) are pre-processed and labeled as training data. The performances between this deep learning-based model and traditional processing approaches are compared on the inference speed and a series of metrics including IOU, precision, recall, F1 score. Additionally, a stitching algorithm was compiled for identifying hydraulically induced fractures from raw specimen images at any size.

2 HYDRAULIC FRACTURE TESTING AND DATA PREPROCESSING

Figure 1 shows the hydraulic fracture testing apparatus at the MIT rock mechanics laboratory (AlDajani, 2022). This testing apparatus applied quasi-true triaxial loads onto a specimen and pressurizes an artificial crack (flaw) in the rock to produce hydraulic fractures. Connected to the data acquisition system were high-speed and high-resolution cameras that record the fracturing process during the test. Prismatic Opalinus Shale specimens with a single vertical and central flaw were clamped by the pressurization device, which applied out-of-plane stress onto the specimen and injects liquid into its central flaw while measuring the internal flaw pressure. The main testing steps included loading, saturation, then pressurization. First, biaxial loads were applied onto the specimen and then the pressurization device put the specimen in a quasi-true triaxial stress state. Second, liquid was injected into the flaw until it is saturated. Finally, the hydraulic system was closed, and liquid was injected into the flaw to build up pressure and produce hydraulic fractures.

During the hydraulic fracture tests, images of the fractured rock specimens were captured by the high-resolution camera. After the image data collection process, 155 high-resolution original fracture images were collected, with a 350-dpi spatial resolution. The original image sizes vary from

1800×3504 to 2200×4224, and were labeled manually. However, for deep learning model training, the input size is generally limited to 512×512 in a segmentation model. Therefore, the original images had to be cropped into small batches with a uniform resolution of 512×512 pixels through a Python program for standardized inputting. Since a sufficiently large dataset is essential for deep learning algorithms, data augmentation is commonly adopted to enlarge the dataset size and avoid overfitting during the training process (Hou et al., 2020). During the cropping process, data augmentation was also utilized including rotating, vertical flip, and horizontal flip to produce 3684 (512x512) images. In order to enhance the purity of the dataset and lower the computational demand, some small batches without fractures were discarded. The hydraulic fracture pattern extracted by deep learning model will be further studied manually to explore the fundamental fracturing mechanism.

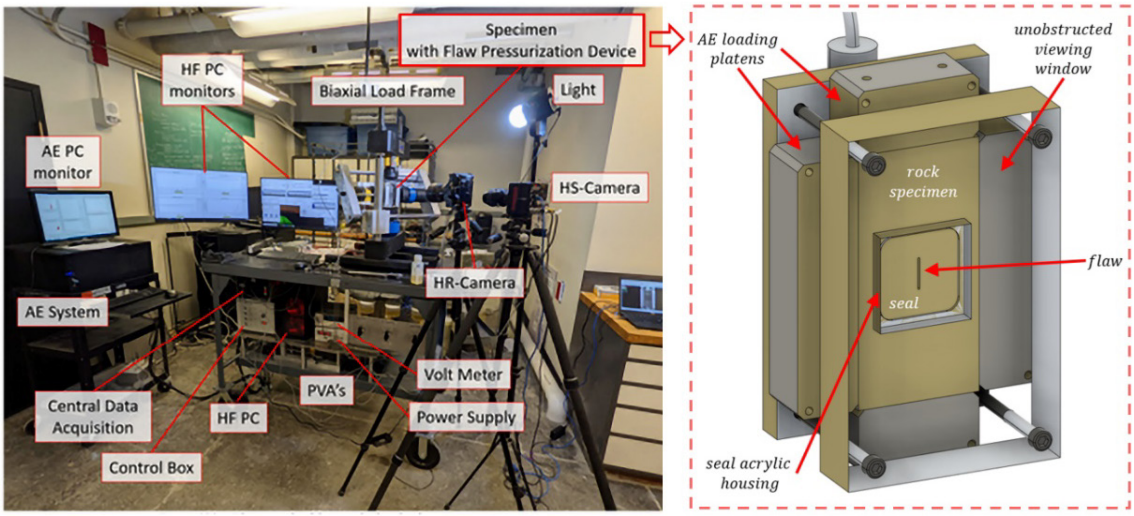


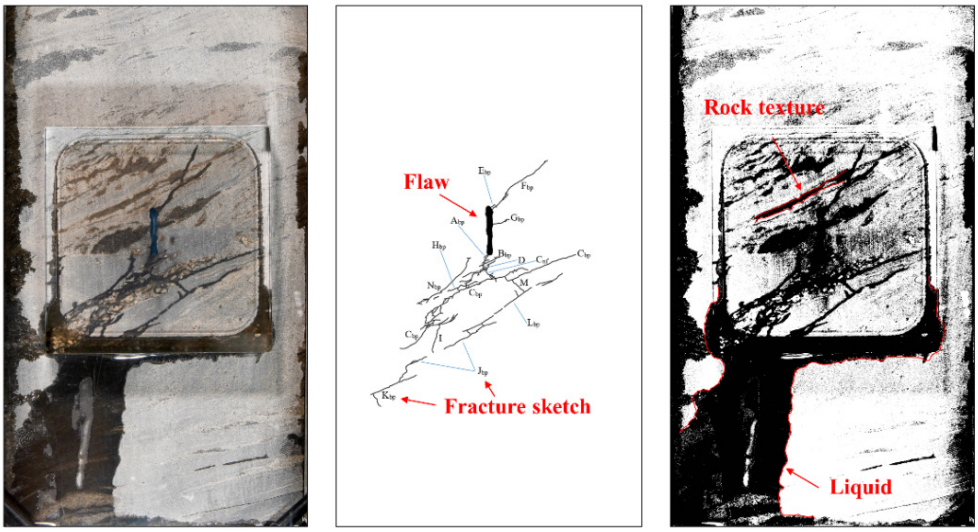
Figure 1. Hydraulic fracture testing apparatus.

3 PROCESSING OF FRACTURE IMAGE

3.1 Challenges of processing fracture images

To facilitate the interpretation of fracture evolution, the fracture sketch has to be picked out from a raw image for further analysis, as shown in Fig.2 (b). However, due to the essential experimental procedure, images collected from the hydraulic fracture testing normally contains interferences, such as liquid and the black elastic bands on the corners of specimens, or shadows between the specimens and the loading platens. These interferences present low contrast to the hydraulic fractures. This poses challenges to construct an efficient and accurate fracture identification and extraction either for manual work or traditional IPTs.

For image processing manually, the researchers will pick out the fractures from raw images, discern experimental accessories and shadows and liquid, as shown in Fig.2 (b). In this sketch, fractures are labelled alphabetically in chronological order, and subscript ‘bp’ refers to bedding plane, and ‘nf’ refers to natural fracture. However, it takes a large amount of time to do this for every image in a single test, let alone for several tests with hundreds of images. When applying traditional IPTs for fracture extraction, it not only captures the fractures, but also captures other things such as shadows and the elastic band and even the rock texture. Take the ‘binarization’ method as an example (Han et al., 2022). The RGB images containing fractures with three channels (Red, Green, and Blue) are transferred into single-channel images, in which the pixel contains a grayscale color range from 0 to 255. By selecting a grayscale value ‘130’ as the threshold, all the pixels with a grayscale value larger than the threshold will be classified as fracture, while the rest pixels with smaller greyscale value than the threshold as background. Due to the lack of intelligence, this method will recognize the noise and interference as fractures, as shown in Fig.2 (c).



(a) Raw fracture image (b) Processed manually (c) Processed by 'binarization'

Figure 2. Processing of raw fracture images.

3.2 *Deep-learning neural network*

A well-known neural network called 'Linknet' is employed for fracture detection tasks due to its outstanding performance on detection tasks. It is one of most efficient and accurate networks of all the existing state-of-the-art semantic pixel-wise segmentation networks (Chaurasia & Culurciello 2017; Wang et al. 2022). For an effective training of DL model, the online platform, Google Colaboratory (Colab), was utilized as it provides high-performance GPUs. An NVIDIA Tesla T4 GPU with 7.5 compute capacity was allocated for training on Colab. During the model training, 90% of the images in the dataset were reserved for training and 10% for testing. The key hyperparameters including the learning rate, epoch, and optimizer were 0.0001, 150, and 'Adam'. Focal loss was applied as a loss function (Lin et al. 2017). In each training epoch, the training loss and validation loss were recorded, as shown in Figure 3.

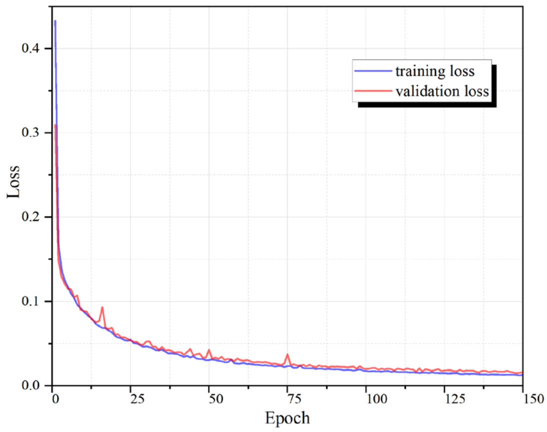
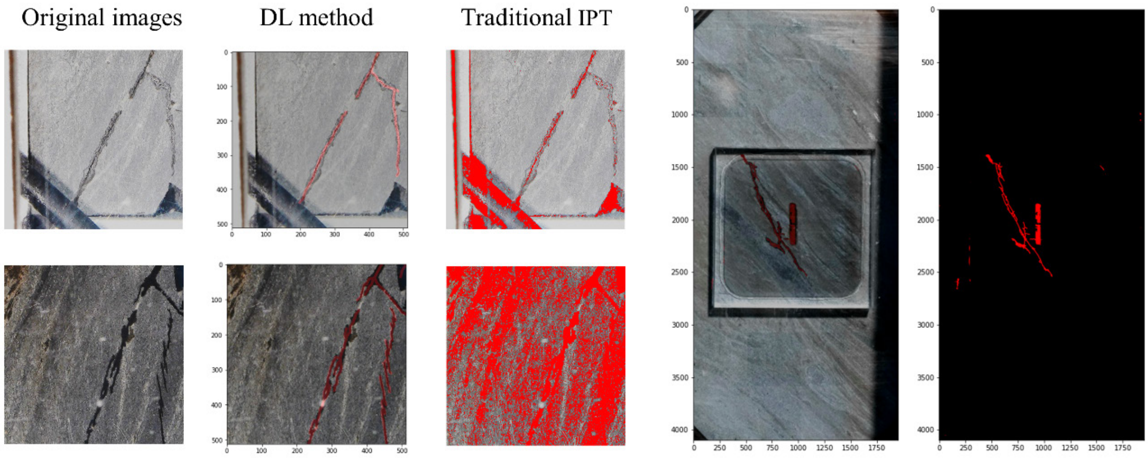


Figure 3. Curves of the loss during model training.

To process raw images with different sizes, stitching was also applied for adaptive input size in this segmentation model. As a measurement of model effectiveness, the average inference speed was also measured from 20 testing images (512×512) to evaluate the model computational efficiency. The inference time was only 389 ms for per fracture image extraction applying the neural network. In engineering practice, the automatic analysis of many images may have to rely on deep learning methods, but may be hindered due to computational demand (e.g., limited GPUs). In this regard, we aimed to strike a balance between model efficiency (e.g., computational time) and effectiveness (e.g., IoU) when selecting a deep learning model.

4 RESULTS

Figure 4 (a) clearly shows that the deep learning method results in better performance than traditional IPTs for fracture detection in standard 512×512 images. With the intelligence, the trained deep learning model was able to recognize the fracture precisely and accurately, while the traditional IPT ‘binarization’ based upon threshold techniques will mistake background noise, dark artifacts, and rock texture as a fracture. For large raw images, the fracture can also be extracted after adopting stitching, as shown in Figure 4 (b) with a size 4097×1593. In addition, the deep learning method can recognize pixels with topological characteristics of the fracture with high accuracy, which is unavailable manually in a short time. For the measurement of the accuracy of a deep learning model, widely utilized performance metrics include intersections over union (IoU), precision, recall, and F1 score (Han et al. 2022), as shown in Table 1. For this dataset, the DNN reached a high accuracy. The IoU, precision, recall, and F1 score reach 0.98, 0.97, 0.98, and 0.98, respectively. The inference time was only 389 ms per fracture image extraction applying the deep learning-based method.



(a) Detection performance of the DL and the IPT (b) Detection from a large-size raw image

Figure 4. Detection performance of deep learning-based method.

5 CONCLUSIONS & DISCUSSIONS

In this study, a deep learning-based method was applied for the image processing of hydraulic fracture in laboratory tests. Applying the deep neural network ‘Linknet’, the fracture in raw images from hydraulic fracturing test are identified and extracted automatically and effectively. In comparison to the previous IPT method, the proposed deep learning-based method demonstrated a high accuracy with an IoU, precision, recall and F1 score of 0.98, 0.97, 0.98 and 0.98, respectively. With intelligence, the deep learning-based method can distinguish fractures from interferences in a raw image like rock texture and shadows. In terms of computation cost and efficiency, the average inference speed of this model is only 389 ms when adopting a NVIDIA Tesla T4 GPU. Hence, it can process hundreds of images in a minute, which is unavailable manually. Implementing this method would reduce the amount of time needed to analyze experiments manually and allocate more time towards conducting experiments and interpreting their results. The deep learning method in laboratory analysis can assist researchers to process their experimental data effectively. The interpretation of the fracture evolution still needs to be conducted by human and further studies will explore the potential of machine learning on this.

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