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Potential applications of deep learning in automatic rock joint trace mapping in a rock mass

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Abstract. In blasted rock slopes and underground openings, rock joints are visible in different forms. Rock joints are often exposed as planes confining rock blocks and visible as traces on a well-blasted, smooth rock mass surface. A realistic rock joint model should include both visual forms of joints in a rock mass: i.e., both joint traces and joint planes. Imaged-based 2D semantic segmentation using deep learning via the Convolutional Neural Network (CNN) has shown promising results in extracting joint traces in a rock mass. In 3D analysis, research studies using deep learning have demonstrated outperforming results in automatically extracting joint planes from an unstructured 3D point cloud compared to state-of-the-art methods. We discuss a pilot study using 3D true colour point cloud and their source and derived 2D images in this paper. In the study, we aim to implement and compare various CNN-based networks found in the literature for automatic extraction of joint traces from laser scanning and photogrammetry data. Extracted joint traces can then be clustered and connected to potential joint planes as joint objects in a discrete joint model. This can contribute to a more accurate estimation of rock joint persistence. The goal of the study is to compare the efficiency and accuracy between using 2D images and 3D point cloud as input data. Data are collected from two infrastructure projects with blasted rock slopes and tunnels in Norway.

1. Introduction

Digital mapping of rock discontinuities in a rock mass, using data via laser scanning, photogrammetry, or a combination of both, has been used frequently by designers and researcher in engineering geology. Automatic extraction of the geometry of rock discontinuities likely provides less biased and much more accurate data than manual mapping. The data are useful for supporting engineering geologists in carrying out calculations with less uncertainty and in making decisions.

The ultimate goals of rock joint mapping are to obtain a realistic rock mass characterisation and localise the form and volume of rock blocks that can be subject to failure and require rock support. Rock discontinuities can be observed, traced, and measured on a rock mass surface based on two forms — planes and traces (Figure 1). Joint edges (see also Figure 1) are regarded here as the convex or concave intersection between joint planes and are not to be mixed with traces. Automatic or semi-automatic methods for extraction of exposed planes using 3D point clouds of rock masses have been studied for many years [1–6]. Identification of only exposed rock joint planes in a rock mass does not provide a full and realistic rock joint model. Joint traces, which are continuations of joint planes within the rock mass, contribute to the understanding of the persistence of a joint. Therefore, the extraction of joint traces is essential and is the focus of this study.

For linear structures like rock joint traces, studies have been done using rule-based image processing techniques, such as canny edge detection [7,8]. The major limitation of this approach is the difficulty in finding the right parameters or threshold values to extract the relevant information. Different computer vision methods have been used for feature segmentation and pattern recognition for image data [9]. Recently, deep learning methods are being applied for localisation of features. Compared to conventional machine learning methods, which often depend on hand-crafted features, deep learning adopts a more automated approach via learning and has achieved strong performance in feature extraction [10].

Among supervised deep learning methods for semantic segmentation, the Convolutional Neural Network (CNN) has been a common approach. In a CNN, a weight filter (kernel) computes a feature map via convoluting the input object [10]. A deep CNN-based network typically consists of connected convolutional layers in which the input first goes through a repeated pooling processes (down-sampling) for extraction of a feature map in each layer, the feature maps among middle layers are integrated, and finally a probability map of each class (e.g. 'joint' and 'not joint') of the same size as the input is generated as output via deconvolution (up-sampling). Many CNN-based networks trained on benchmarked (image, video, point cloud) datasets are available from open-source platforms.

The key challenges of applying deep CNN-based networks for extraction of rock joint traces in civil engineering projects are typically two-fold: (1) large-scale datasets and relatively small-scale features to be extracted — leading to high computation cost to process many images or points acquired from a rock mass typically of tens to hundreds of meters in dimension, and extract features at millimetres to centimetres in scale; (2) lack of large labelled data from diverse rock types and environments — annotating joint traces for supervised learning tasks is time-consuming and can sometimes be subjective. The lack of datasets from diverse site settings brings up a question of how well the trained deep learning models can be applied to unseen data or a new environment.

Addressing the abovementioned challenges, we propose a series of experiments to test the robustness of using CNN-based networks for rock joint trace extraction, aiming at answering the following questions:

- Q1: What is the optimal pixel size and extent of the input images or point sets?
- Q2: How well can a trained model be transferred to a new environment?
- Q3: How much do other data attributes, such as grey-scale, depth, and normal contribute to the performance?
- Q4: Does point-based convolution provide better performance for creating rock joint trace maps than image-based convolution despite more demanding computational resources?

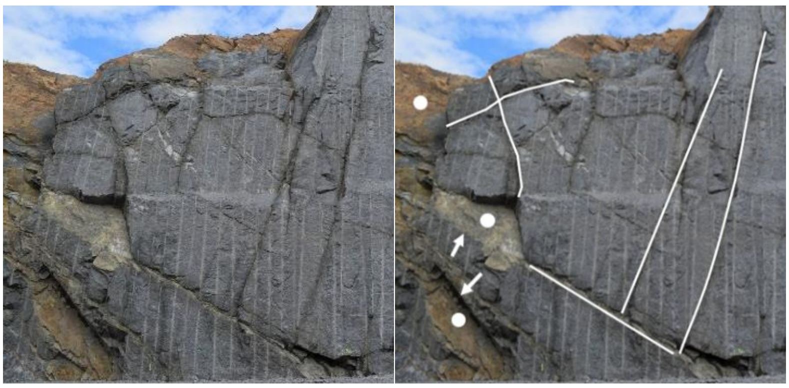

Figure 1. Different forms of rock joints and their examples in a rock cut illustrated in the image to the right: joint planes (dots), joint traces (lines), and joint edges (arrows). Modified from [11]. Credit: Norwegian Public Roads Administration.

2. Related work

2.1. Image-based convolution
Image-based semantic segmentation on joint traces is typically pixel-wise. Imaged-based crack segmentation using deep learning has been widely applied for defect detection in man-made materials, such as asphalt and concrete [12], masonry wall [13], and steel [14]. Rock cores [15] and rock mass [16,17] have also been studied. These studies generally develop and compare the performance of models built using state-of-the-art CNN models such as DeepLabv3+ [18]. DeepLabv3+ is a deep neural network that consists of an encoder with dilated convolution that encodes contextual information at multi-scale levels, and a decoder that recovers object boundaries [18]. The current study will take advantage of using transfer learning to implement an open-source pretrained DeepLabv3+ model for semantic segmentation of images of rocks.

Unlike man-made materials and small-scale rock samples, whose surfaces are often homogeneous and regular, rock mass surfaces are usually irregular due to natural variations and large-scale. In addition, the noisy background rock mass can hinder the extraction of the less populated joint traces leading to noise or inaccuracy in the crack segmentation results.

2.2. Point-based convolution
Point-based semantic segmentation on joint traces is typically a fine-grained point-wise 3D segmentation task. Unlike images that contain pixels with constant resolution, a point cloud of naturally-occurring materials is typically unstructured. Early research on part segmentation for point sets tended to handcraft or convert points to regular voxel grids or images. This approach may result in unnecessarily voluminous data [19] and may fail to preserve the geometry of the extracted features. PointCONV [20] is state-of-the-art point-based CNN method for semantic segmentation. It adopts Monte Carlo discretization to approximate the 3D convolution operator on 3D point sets [20]. Azhari *et al*. [21] apply PointCONV for extraction of rock joints in an unstructured point cloud. Instead of using volumetric-style point convolution. Lin *et al*. [22] argue that interior points are seldom acquired by 3D sensors and LiDAR, and propose FPConv for local flattening of a 3D point cloud to perform regular 2D convolution.

2.3. Labelling strategy
Unlike the usual pixel-wise annotation practice, a simplified rock joint trace annotation strategy by using thin straight lines to reduce labelling time and computation cost is proposed [17]. Further, a weighted loss function that alleviates labelling uncertainty and class imbalance is proposed [23]. The uncertainty in labelling [23] is a function of the distance from the edge pixel, assuming that the closer a pixel is to the object's edge, the more uncertain its label is.

2.4. Data imbalance
A representative image of nature would contain much fewer pixels of 'joint trace' than 'not joint trace.' To overcome such data imbalance, several strategies have been proposed. For example, to avoid false negatives, weighted cross entropy as loss function in training gives a greater penalty to misclassification of the minority classes [13][24]. Azhari *et al.* [21] and Dong *et al.* [25] use the focal loss suggested by Lin *et al.* [26] in training by giving more weights to hard positive examples in a class imbalance scenario. Bressan *et al.* [23] increase the weight of a class to reflect the pixel ratio between the class and the entire image.

Similar to image pixels, the points that are sampled along joint or crack openings are typically sparser than their background materials. Chen *et al.* [27] use the synthetic minority over-sampling technique (SMOTE) to generate more sampling points along joint traces in a point cloud of a tunnel face. Azhari *et al.* implement voxelisation followed by down-sampling to reduce the total number of points in the point cloud for deep learning input, but maintains the sparse nature of the points along rock discontinuities [21].

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3. Methodology and discussions

3.1. Data pre-processing

Datasets from two civil engineering projects in Norway are used in this study.

Dataset 1 belongs to the rock cut domain. This dataset is collected during construction of new rock cuts and consists of drone photos and dense point clouds derived via structure-from-motion (SFM). Orthomosaic images with a customised viewing angle onto rock cut faces are generated.

Dataset 2 belongs to the rock tunnel domain. This dataset is collected during construction of new rock tunnels and consists of handheld camera photos and high-resolution LiDAR point clouds of the blasted tunnel face. The blasted tunnel surface of the LiDAR point cloud is cleaned. 2D images of the LiDAR point cloud are generated via planar projection of the spherical projection of the 3D point cloud (Figure 2).

The input data types to deep learning are divided into two groups: 2D images and 3D point clouds. Their specifications are listed in Table 1. The 2D images and 3D point clouds are cropped/segmented to the desired shape for deep learning. The grey channel for each pixel is computed by taking the average value of the RGB values.

Figure 2. 2D image projected from spherical projection of point cloud. An example from a blasted rock tunnel face from Dataset 2 (looking downwards).

Table 1. Overview of input data to deep learning

Input data type	Data source	Average pixel size/ point distance	Channels			
			RGB	*Grey*	*Depth*	*Normals*
	Dataset 1 - rock cuts					
2D images	Orthomosaic	< 1 cm	✓	✓	✓	
3D point clouds	SFM	Few mm	✓	✓	✓	✓
	Dataset 2 – rock tunnels					
2D images	Handheld Camera	Varied	✓	✓		
	2D spherical projection	Few mm	✓	✓	✓	✓
3D point clouds	LiDAR	Few mm	✓	✓	✓	✓

3.2. Data annotation

Following the coarse labelling strategy proposed by Asadi *et al.* [17], joint traces are labelled on 2D images as polylines along the centre of the joint traces. All the pixels intersecting the polylines are labelled as 'joint trace.'

For point clouds, the points along the joint traces are picked up first by drawing a polyline along the joint trace on the point cloud (Figure 3), then by sampling the points within a specific distance, or buffer, along the polylines. During the study, different buffer radii will be tested.

Figure 3. Annotation of rock joint traces using polylines in a dense point cloud. An example from a rock cut from Dataset 1.

3.3. Deep learning experiments
Four sets of experiments – I, II, III and IV are performed corresponding to the research questions raised in Section 1.

Experiment sets I, II, and III are performed on 2D images with various channel depths using DeepLabv3+ [18] pretrained on concrete cracks. Transfer learning using pretrained models with additional channels (i.e., grey, depth, and normal channels in addition to RGB) are performed with a channel-wise dropout suggested by de La Comble and Prepin [28] to avoid underfitting of the added channels during training. The overview of experiment sets I, II, and III are presented in Table 2.

Experiment set IV involves using 3D convolution-based methods including PointCONV [20] and FPConv [22] on 3D point clouds. In order to make comparison with semantic segmentation using 2D images, the configuration of the kernel sizes and input point cloud resolution is based on the best case from experiment set I (Table 2).

To overcome labelling uncertainty and class imbalance, the weighted loss function proposed by Bressan *et al.* [23] is adapted inversely, assuming that the closer the pixel is to the polyline labels, the lower the uncertainty its labelling is.

3.4. Evaluation metrics and interpretation
Common evaluation metrics for pixel-wise semantic segmentation, including precision, recall, and F1-score are used. Accuracy (i.e., number of correct predicted pixels over total number of pixels) is considered irrelevant due to class imbalance [13].

The SEG-GRAD-CAM method proposed by Vinogradova *et al.* [29], a gradient-based method for interpreting semantic segmentation that generate heatmap of pixel relevance for the segmentation task, is used to assist with understanding the training results.

3.5. Potential limitations for the pilot study
For each domain, only one rock type is used. The diversity of the data can be limited. Data augmentation in the form of stretching, random cropping, blurring, noise, rotation, etc. is used to alleviate this potential problem. There are uncertainty and subjectivity in labelling the rock joint traces. A quality assurance work flow should be applied to enhance the data quality.

3.6. Result implications for rock mass characterisation
Rock joint persistence and orientation (i.e. strike/dip) are updated via extending mapped rock joint planes with their associated rock joint traces that are extracted using deep learning. As illustrated in

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Figure 4, rock joint persistence is expected to increase by including rock joint traces, whereas the overall orientation to be more representative. These two rock joint parameters are used to compare the results of rock joint trace mapping for each case (I-a to I-d, II-a to II-d, and III-a to III-e) in the proposed experiments.

Table 2. Overview of the deep learning experiments using 2D images

Experiment Set	I (half slope and tunnel input)		II		III (half slope and tunnel input)	
	Different pixel/point cloud resolutions		*Transfer learning (TL)[a] across slope and tunnel domains*		*Different channel information*	
Case	I-a	Best (< 1 cm)	II-a	Zero-shot TL, using gray images	III-a	RGB
	I-b	1 cm	II-b	Few-shot TL, using gray images	III-b	Gray
	I-c	3 cm	II-c	Zero-shot TL, using RGB images	III-c	RGB + Gray
	I-d	Stochastic scaling between best resolution and 3 cm	II-d	Few-shot TL, using RGB images	III-d	RGB + Gray + Depth
					III-e	RGB + Gray + Depth + Normals[b]

[a] "Zero-shot" transfer learning from domain A to domain B means that the deep learning model only trains on images from domain A, before it is evaluated in a new domain B. "Few-shot" refers to training using a majority of images from domain A and only a few examples of images from domain B, before evaluating the trained model in domain B.
[b] Only point clouds are used as input to process the normals to the 2D image data channel.

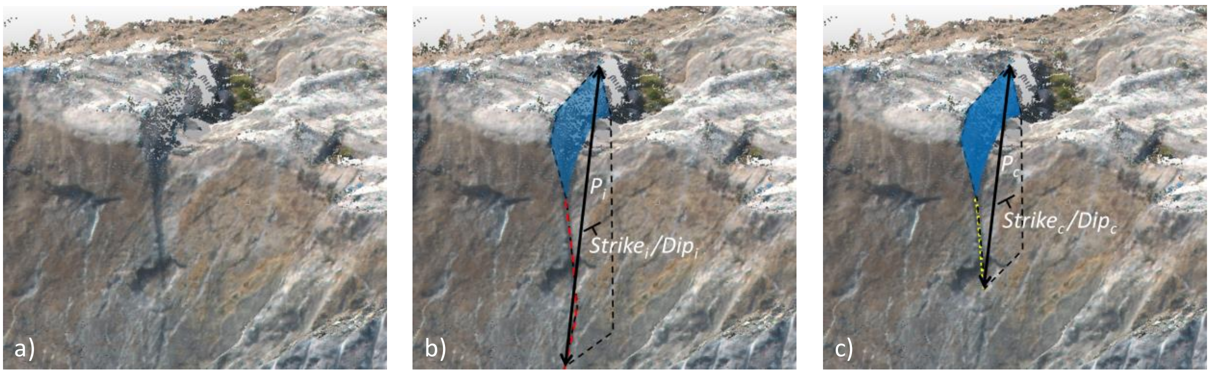

Figure 4. Concept drawing for expected result comparison. a) 3D point cloud of the studied rock cut; b) mapped rock joint plane (blue) extended with a rock joint trace (red dashed) extracted from 2D image and projected onto the 3D point cloud; c) mapped rock joint plane (blue) extended with a rock joint trace (yellow dashed) extracted from the 3D point cloud. $\boldsymbol{P}$ = joint persistence; subscripts $\boldsymbol{i}$ and $\boldsymbol{c}$ denote results using 2D images and 3D point cloud for joint trace extraction respectively.

4. Concluding remarks

This paper presents the methodology of work in progress that applies deep learning for automatic rock joint trace mapping. The work partly uses ground truths from previous work and partly creates new ground truths. The work takes a database of ground truths of rock joint traces as its basis.. Such database contains data of different formats, including images and point clouds, but leads to a single goal towards semantic segmentation of rock joint traces. Expansion for the database can be contributed by digital mapping in the field. Annotation of observed joint traces on images/3D-model in the field provides field-verified ground truths. An open access benchmarked database should be established for future research.

The proposed method is being further developed towards automatic rock joint mapping via connecting the joint traces and connecting the joint traces with joint planes. Implementation to instant prediction in the field is also investigated.

It is expected that further development related to deep learning would lead to instance segmentation such that the output from deep learning will provide individual rock joint trace instances, rather than a bunch of pixels that requires post-processing to extract joint parameters. Other learning techniques can be investigated in the future, such as meta-learning, weakly-supervised (e.g., sparse point labels individual joint trace instances), and self-supervised learning (e.g., contrastive learning). Transfer learning between the image-based and point-based approach should also be explored. For instance, Xu *et al.* [30] propose to copy the filter weights from a 2D convolution network for 2D images to its 3D counterpart for 3D point clouds. The transferability between image-based and point-based representations provides insight about the potential of reducing computation efforts for point-based methods. Other artificial intelligence methods and deep learning architectures for automatic rock joint trace mapping, such as evolutionary algorithm, generative adversarial networks, and graph convolution network should also be explored.

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