Fast Rock Segmentation

Using Artificial Intelligence to Approach Human-Level Accuracy

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Abstract

Image-based rock fragmentation sensing in mining and quarry applications includes an important rock boundary delineation step, which is commonly referred to as rock segmentation. This article presents a novel approach to solve this problem, using artificial intelligence. In the proposed technique, prior knowledge of previously analyzed images is encoded into mathematical/statistical models. A set of human labeled images are used as training inputs. These images are used to train neural networks through an optimization process. The networks can then be used in real time for rock delineation.

To build the models, a special type of deep artificial neural network is used as a pixel classifier. The proposed classifier provides a label for each pixel, (edge, rock, or fine) by analyzing a plurality of pixels within the image. Advances in the field of machine learning allow the developed network to contain a large number of parameters. The increased number of parameters is a strong factor in the classifier's ability to better predict the correct class for each pixel.

The proposed deep learning based segmentation approach is combined with 3D imaging followed by post processing to provide a unified fragmentation sensing solution. Results of the automatic segmentation are compared with human labeled segmentations using the percentage passing curves for 64 rock images of size 1,280 x 960 pixels.

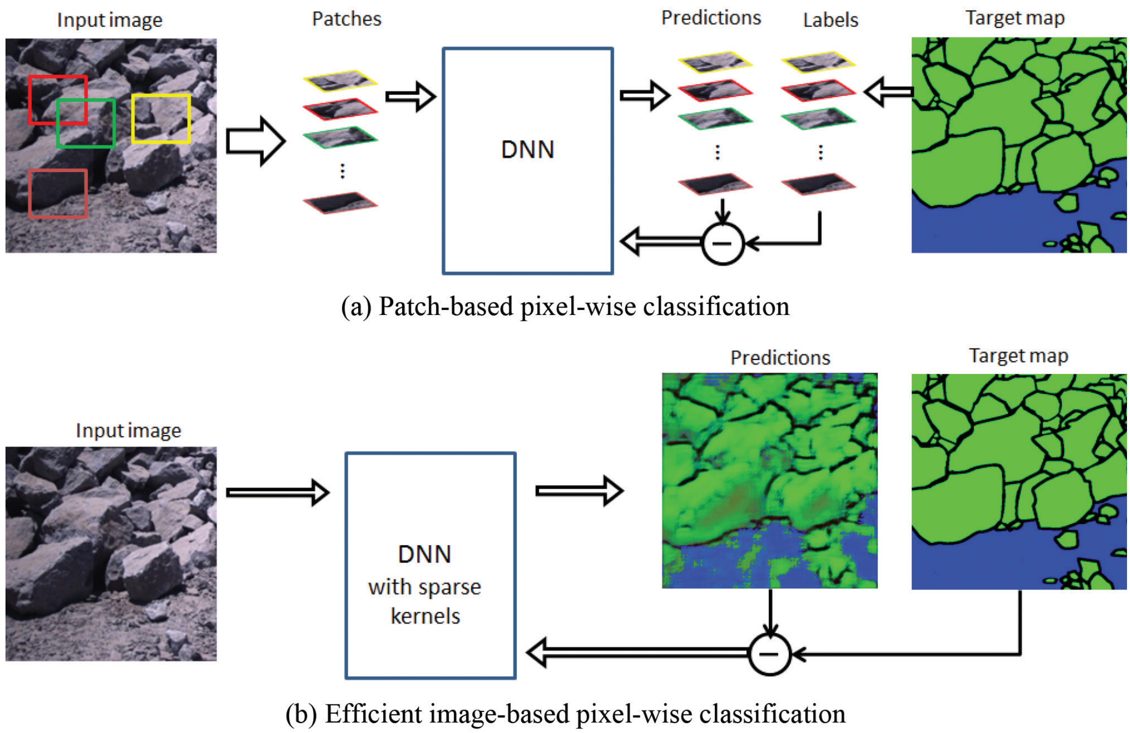


Figure 1. Comparison of patch-based scanning and the efficient image-based pixel-wise classification.

Introduction

Mines and quarries can see significant productivity and performance benefits by controlling material sizes (McKee, Chitmobo, & Morrell, 1995; Sellers & Gumede, 2012). During the past decade, image-based fragmentation analysis has been applied to estimate rock size distributions in order to optimize procedures in mines and quarries. Using a roving camera and operator assisted analysis Maerz, Franklin, and Coursen (1987) measured the size distribution of the blasted rock and eliminated the need for manual sieve analysis. Since then, many others have introduced automated and manual methods for fragmentation analysis and improved upon existing approaches (Girdner, Kemeny, Srikant, & McGill, 1996; Smith & Kemeny, 1993; Palangio, Palangio, & Maerz, 2005; Tafazoli & Ziraknejad, 2009; Raina, 2013).

In image-based fragmentation, rock boundaries are identified in the image, and an image scaling is applied to transform rock pixel sizes into real world dimensions. Usually geometric references, such as regularly shaped objects (discs and basketballs) (Siddigui, Ali Shah, & Behan, 2009), or the known size of an excavator bucket (Zeng, Chow, Baumann, & Tafazoli, 2012), are used to determine the proper scaling factor. In recent years, 3D imaging and sensing have also been incorporated to improve rock delineation. Specific methods include using camera-laser combinations and stereo imaging to measure rock fragmentation on conveyor belts (Noy, 2013; Thurley, 2013; Dislaire, Illing, Laurent, & Pirard, 2013) as well as portable fragmentation analysis devices with 3D imaging sensors (Sameti, et al., 2014).

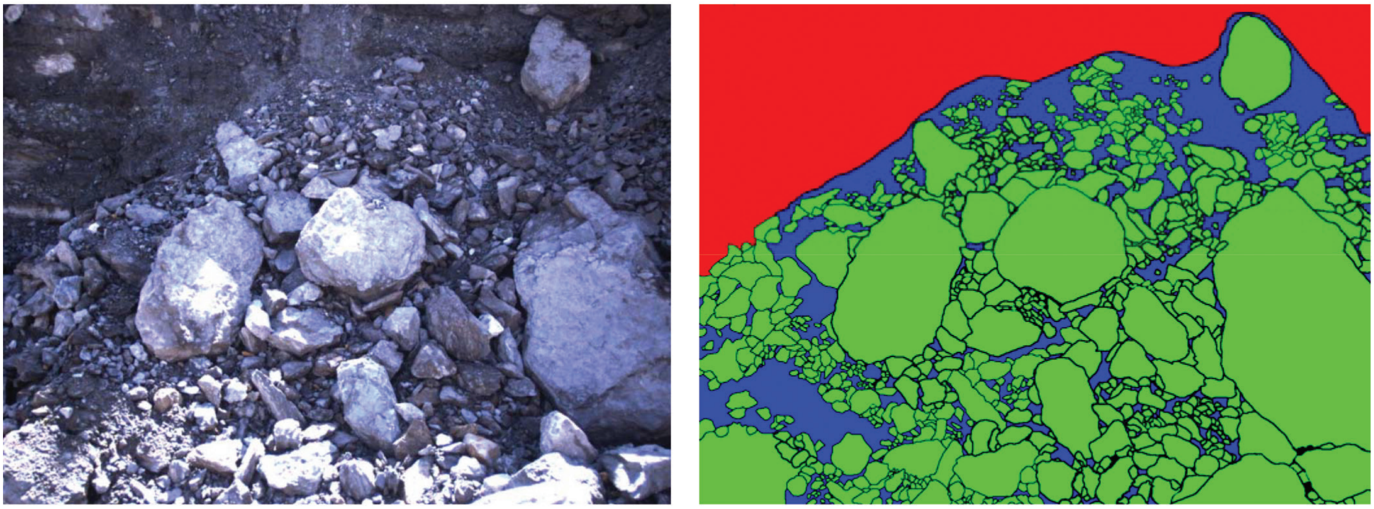
As mentioned above, a necessary step for image-based fragmentation analysis is accurate rock segmentation. This step can be automated, manual or a combination of both. The main challenge in rock segmentation is having reliable segmentation unaffected by variations in lighting, poor image contrast, and complex rock texture and presentation. In this article, we address this central problem of rock fragmentation, namely, the automatic segmentation of rock images. Reliable automated segmentation continues to be a challenge despite over 25 years of research. One reason may be the irregular nature of fragmented material, which makes it more difficult to segment compared to other image segmentation processes, such as facial recognition, where there are common features present in all the objects being segmented. A solution to this problem, however, is essential for any automated pipeline rock fragmentation analysis.

To perform segmentation, we use a special type of deep artificial neural network as a pixel classifier. The label of each pixel (edge, rock, or fine) is predicted from raw pixel values within a square window centered on each pixel. The input layer maps each window pixel to a neuron. It is followed by a succession of convolutional and max-pooling layers which preserve 2D information and extract features with increasing levels of abstraction. The output layer produces a calibrated probability for each class.

Method

Our solution to automatic rock segmentation is based on a Deep Neural Network (DNN) used as a pixel classifier (Krizhevsky, Sutskever, & Hinton, 2012). The network computes the probability of a pixel being a fragmented portion (pr), an edge of a fragmented portion (pe), or a region of fines (pf), using as input the optical image intensity in a square window centered on the pixel itself. An image is then segmented by classifying all of its pixels. The DNN is trained on a different stack with similar characteristics, in which rock segmentations were manually annotated.

In general, the DNN is initially configured and trained using training images that have been examined and labeled. For ex-



(a) Captured Image (b) Manual segmentation

Figure 2. Sample image along with manual segmentation. In manual segmentation, green region shows fragmented material portion, black region shows edge of a fragmented portion, blue region shows fine regions, and areas outside region of interest are marked with red color.

ample, regions of images of fragmented materials may be labeled to indicate whether the region is a fragmented portion, an edge of a fragmented portion, a void, or a region of fines. The images are then saved along with labeling information as labeled training images. It is desirable to have a sufficient number of labeled training images under differing lighting and environmental conditions, differing scale, and differing types of fragmented material. A portion of the labeled training images may be used to train the network and a further portion may be set aside for validation of the neural network to evaluate training effectiveness.

During training, the weights for the neural network are initialized to a certain value and the training images are used to provide the input pixel data sets. The pixel classification output at the output layer is then compared to the labeled training images and a cost function is evaluated expressing the difference between the output layer classification and the labeled classification for a plurality of inputs to the neural network. A minimization algorithm, such as a batch gradient descent minimization, is then applied to determine new values for the weights. This step generally involves determining the gradient of the cost function using a backpropagation algorithm.

Obviously, using a sliding window setup to predict the class label of each pixel by providing a local region (patch) around that pixel as input, is extremely inefficient. Surrounding patches of pixels have large overlaps, which leads to a lot of redundant computation. Another drawback is that thousands of training image patches can be extracted from a single image, but due to the efficiency problems, it is impossible to use all available training samples. Usually only a small subset is randomly sampled for training (Li, Zhao, & Wang, 2014).

In this article, we use the convolution and pooling layers with d-regularly sparse kernels to eliminate all redundant computations. Using these layers, we have achieved 1,500 times speedup in forward and backward propagation. **Figure 1** compares the patch-based scanning and the efficient image-based pixel-wise classification. During training the input images and the target map will be used to train the DNN weights. The obtained weights will be used to predict the labels for arbitrary input.

We have used a watershed algorithm (Vincent & Soille, 1991) to close edges around fragmented portions in the composite pixel classification output, where gradients in the image are examined on the basis of the pixel classification output. Pixels having a higher pe should correspond to ridges in the watershed while pixels having a low pe and high pf should correspond to catchment basin regions.

Experiment

In order to evaluate the proposed method, we used 64 manually segmented images of 1,280 x 960 pixels. **Figure 2** shows a sample captured image along with its manual segmentation. Green represents the fragmented material, black represents the edge of a fragmented portion, blue represents fines, and red represents areas outside the region of interest.

An automatic segmentation method was applied. First, the pixel classification using DNN was applied to these images. Then, watershed segmentation was applied on the probability maps which resulted from the pixel classification step, and closed boundaries were obtained. Then, automatic segmentation was compared to manual segmentation using two error metrics:

- Warping error: a segmentation metric that shows topological disagreements between automatic labeling and ground truth; it accounts for the number of splits and mergers required to obtain the candidate segmentation from ground truth.
- Pixel error: a segmentation metric that shows the number of pixel locations at which the automatic labeling disagrees with ground truth.

Percentage passing curves for size distribution of rocks in pixel space were also obtained for the 64 test images.

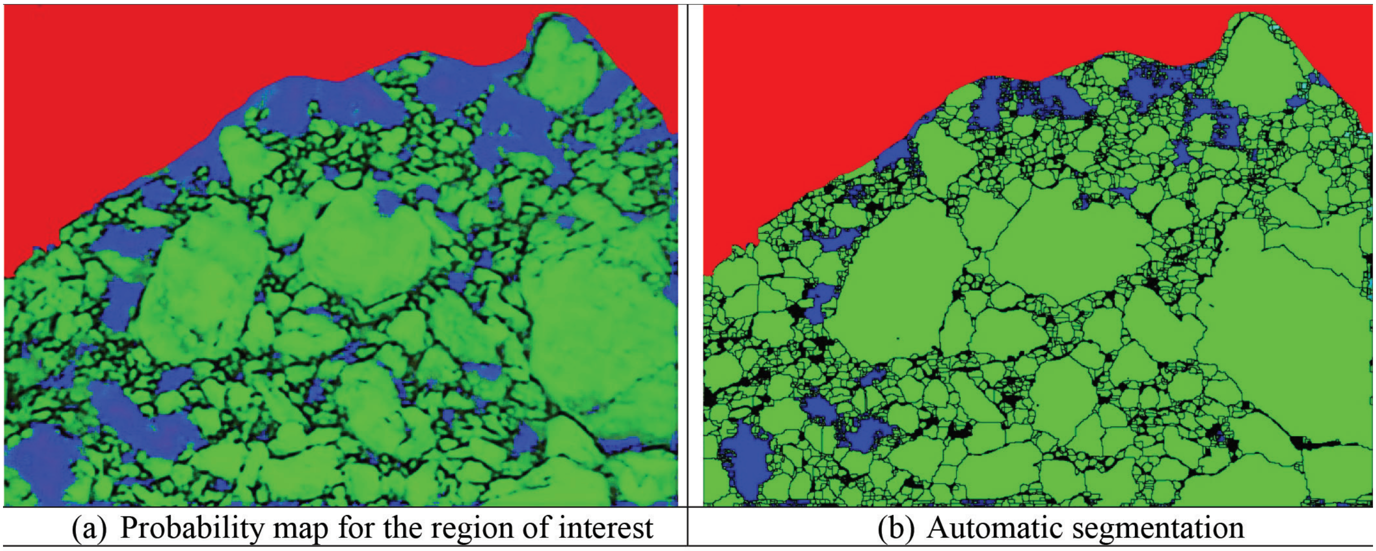


Figure 3. Probability map for the sample image, along with the segmentation obtained after using watershed on the probability map.

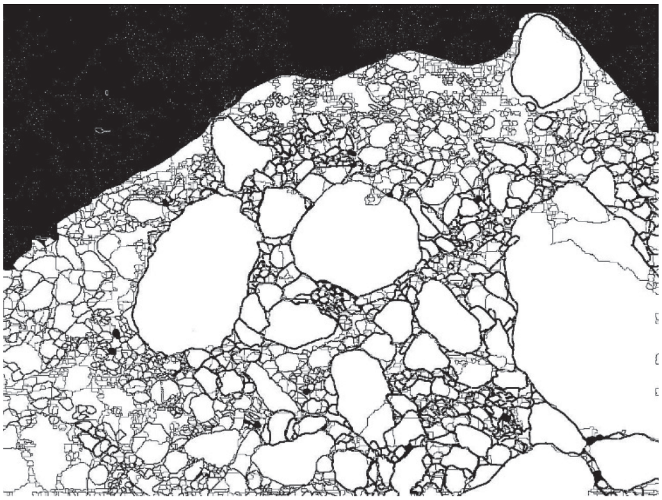


Figure 4. Warped automatic segmentation of the sample image to its ground truth.

Warping error [$.10^{-6}$]	Pixel error
44.3 ± 15	(4.09 ± 1.4) %

Table 1. Average warping and pixel errors for the 64 test images

Results

In the following section we outline the results of the automatic segmentation algorithm compared to the labelled test data. We then demonstrate the performance of the automatic segmentation on images captured from a sieving test.

Labeled Data

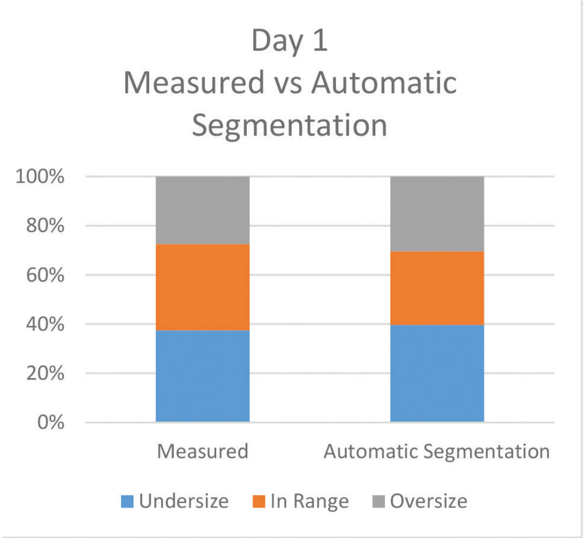
Figure 3 shows the probability map for the sample image, along with the segmentation obtained after using watershed on the probability map. Once again, the green region shows the fragmented material, the black region shows the edge of a fragmented portion, the blue region shows fine regions, and red shows areas outside the region of interest. **Figure 4** shows the warped automatic segmentation of the sample image to the ground truth. **Table 1** shows the average warping and pixel errors for the 64 test images. Both warping and pixel errors are normalized by the total number of pixels within the image. Results show a difference of (8.48 ± 5.26) % between the ground truth and automatic segmentation.

Sieved Rock Test

A test was organized in cooperation with Orica USA at a quarry in Texas. The goal of this test was to evaluate the performance of various automatic segmentation algorithms. This site was chosen as it had a mobile scalping screen, which sorted the material into piles of three sizes. Image data was captured as it was loaded out by an excavator. The piles produced by sorting the material were then measured and used as ground truth data for the test. Measurements were taken over two days and the results were compiled. The charts in **figure 6** show the percentage of undersize (sub 2 inch), in range (2 - 6 inches) and oversize (over 6 inches) particles as measured through automatic segmentation as well as manually surveying the sorted piles.

The automatic segmentation performed quite well, with

Figure 5. Mobile scalping screen used to sort material.



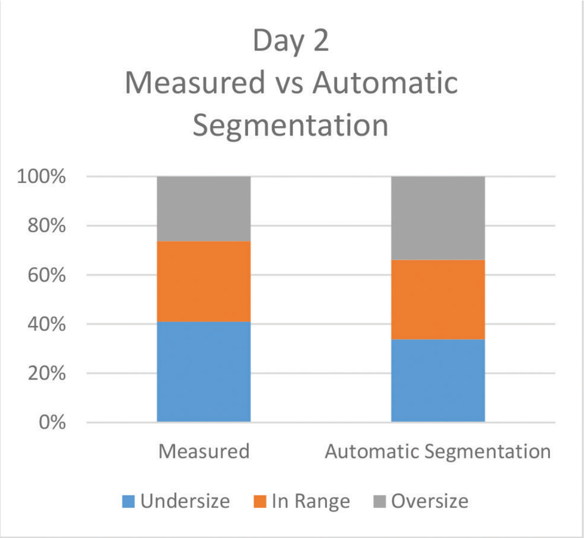


Figure 6. Results comparing automatic segmentation with output of mobile scalping screen over 2 days.

some overestimation of oversize material. One potential reason for this may be that the images were captured prior to excavation. Through the excavation and sorting process rocks that have been damaged due to blasting will break down further, reducing the amount of sorted oversize material.

Conclusion

This article presents a novel approach to rock segmentation, using machine learning techniques. This approach attempts to mitigate the challenges facing rock boundary delineation caused by variations in material texture, suboptimal lighting conditions, and the unknown size and shape of rocks. In the proposed technique, models were built based on training inputs, i.e. pixels within rock images, and used to make decisions for segmentation of test images. Results showed that fast and accurate automatic segmentation can be achieved using this technique.

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