Automated Vein Segmentation and Characterization from Core Imagery using Deep Learning

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Summary

Vein detection is a vital process that can reveal valuable information about mineral deposits in drill cores. However, manual analysis of veins in large amounts of core data extracted from geology campsites requires an investment of an enormous amount of time, money, and human effort. Auspiciously, the evolution of Deep Learning (DL) and computer vision in recent decades has facilitated the development of automated image analysis algorithms that can save time and resources when replaced the manual image processing approaches [1]. In this work, we exploit the power of DL models to propose an automated vein segmentation pipeline capable of extracting vein information from 27 kilometers of core in less than 7 hours. Our proposed pipeline generates two reports responsible for describing the structure of the predicted veins and calculating their distribution over the drill holes, respectively.

Theory / Method / Workflow

Our proposed vein characterization model is based on a fully-supervised DL segmentation model, named as Mask-RCNN [2]. The Mask R-CNN model is a semantic segmentation model with over 63 million trainable parameters, that consists of four units as follows:

1. A Feature Pyramid Network (FPN) which generates feature maps in various scales,
2. A convolutional backbone translating each multi-scale feature map into semantic features,
3. A Region Proposal Network (RPN) that outputs candidate regions of interest that are tend to contain vein instances, and
4. A prediction head that outputs the bounding boxes and prediction masks for the predicted veins from the regions of interest.

In this work, after vein segmentation is performed using the Mask-RCNN model, a linear model is used to fit ellipses to the predicted veins. The fitted ellipses are utilized to describe the predicted veins with a limited set of interpretable features. The information regarding predicted veins and including their location and features are collected in a “Vein Features” report. Afterward, the drill cores are divided into intervals with a constant step size, and the vein features report is employed to compute the frequency and area occupancy of veins in each interval. Figure 1 depicts the general overview of the proposed vein characterization framework.

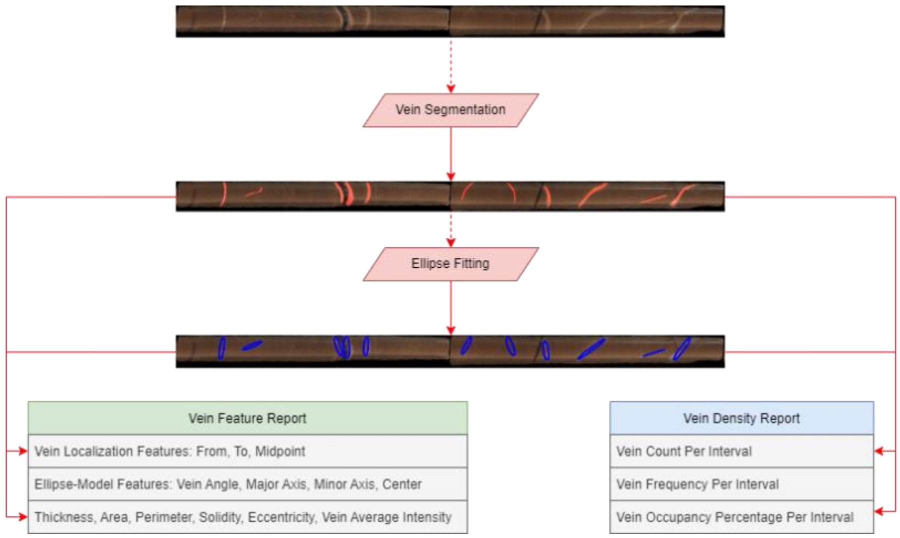

Figure 1. The general overview of the proposed automated vein characterization framework.

Results, Observations, Conclusions

To conduct the empirical results, a Mask-RCNN model is trained with a private dataset containing 8080 training image patches. The Dataset size is increased by 5 times after oversampling. The empirical results imply that the proposed approach successfully logged over 77.32% of vein segments, with a mean intersection-over-union (mIoU) of 36.15%, on a test set containing 966.9 meters of data. The quality of the predicted veins is depicted in the qualitative results in figure 2. The fine-grained prediction and segmentation of which facilitates the geology experts to understand the minerals drill cores better and reduces their workload from going through the entire dataset, to revising two summarized reports.

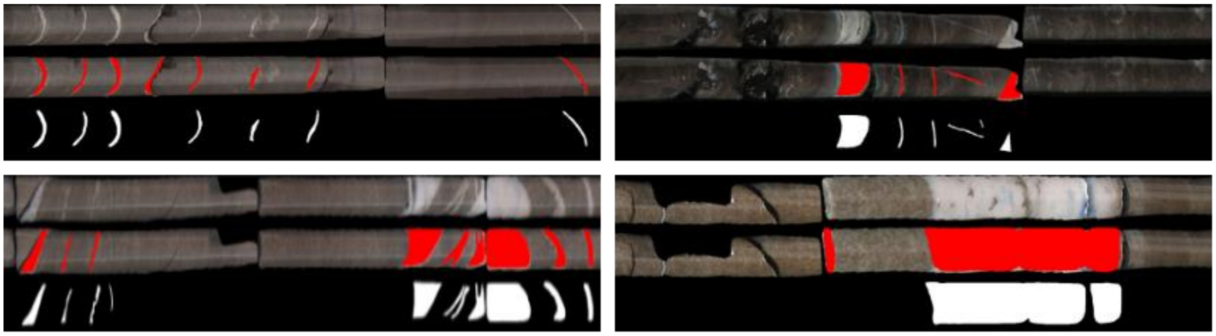

Figure 2. The qualitative vein predictions achieved by the proposed method. In each subfigure, the top, middle, and bottom row show the original image, predicted veins (in red), and the correct labels, respectively.

References

[1] W. Dadong, R. Lagerstrom, C. Sun, C. Laukamp, M. Quigley, L. Whitbourn, P. Mason, P. Connor and L. Fisher, "Automated vein detection for drill core analysis by fusion of hyperspectral and visible image data," in *2016 23rd International Conference on Mechatronics and Machine Vision in Practice (M2VIP)*, 2016.

[2] K. He, G. Gkioxari, P. Dollar and R. Girshick, "Mask r-cnn," in *Proceedings of the IEEE international conference on computer vision*, 2017.