Fracture Characterization of McMurdo Dry Valley Sandstones with Ilastik Machine Learning Image Segmentation Software

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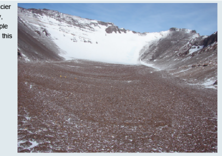
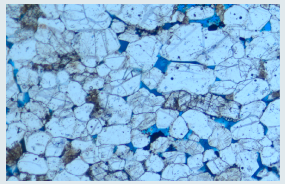
Right: Rock glacier in Mullins Valley, Antarctica, sample collection site in this study.



1. Introduction



Left: thin section of Beacon sandstone cobble from Mullins Valley, Antarctica. Density of fractures and other voids makes data collection and interpretation challenging.

Environmental stress-driven subcritical cracking:

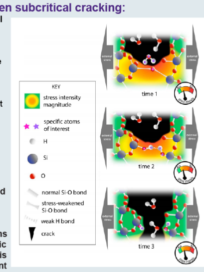
Increasingly recognized as critical to weathering, soil production, facilitating erosion, etc.

Most studies in natural settings have focused on development of macroscopic fractures, but microfractures have major influence on rock mechanics and development of larger fractures.

Problems to overcome for practical micro-scale fracture analysis:

Data volume – single thin section may have thousands of cracks and crack segments

Interpretation – not all linear or curvilinear features in thin sections represent void space. A systematic means of interpreting void space is needed. We present a time-efficient method for collection and processing of microscopic crack data



Above: Chemophysical process involved in environmental stress-driven subcritical fracturing [Eppes and Keanini, 2017]

Objectives: Efficiency, Automation, Consistency

Efficiency – Hand analysis of thin section microfractures can take upwards of 20 hours. In order to acquire the large data sets necessary for microfracture analysis across the McMurdo Valleys, we needed to develop a process to be as efficienct as possible to get these data.

Automation – The key to efficiency would turn out to be automation with machine learning software. Instead of spending 20+ hours on one thin section, time would be dedicated to developing a model to analyze future samples rapidly.

Consistency – This automated process would need to be comparable to human analyzed thin sections. Any misidentified object will lead to errors in the results, as the program will continue to misidentify similar objects through all the samples processed.

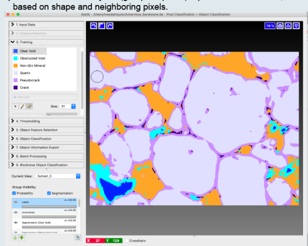
2. Ilastik

Ilastik is a user-friendly image segmentation tool that uses a machine learning algorithm. It was developed primarily for biologists, but is flexible for other applications.

We have trained a predictive model to:

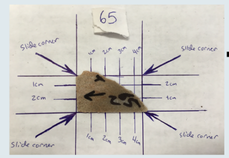
1) Classify pixels in rock thin sections into several different categories based on color, brightness, contrast, texture, etc. (see section 3) and

2) Determine whether objects (groups of pixels) represent real fractures, based on shape and neighboring pixels.



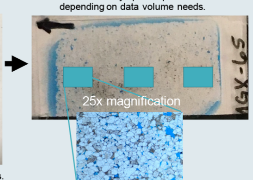
Above: Screenshot showing classified sandstone sample in Ilastik

3. Workflow



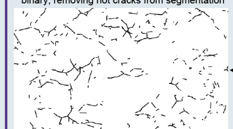
1. Collect oriented sample, produce thin sections.

2. Take evenly spaced photos depending on data volume needs.



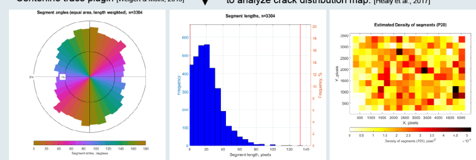
3. Export crack and void segmentation from Ilastik prediction model

4. Use Imagej and Photoshop to convert to binary, removing not cracks from segmentation



5. Convert to vector (.svg) using Inkscape - Centerline trace plugin [Weigert & Moini, 2018]

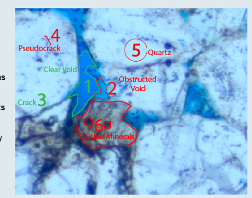
6. Using .svg as input, use FracPaQ to analyze crack distribution map. [Healy et al., 2017]



Classification criteria:

We fed our model training data for the pixel classification as shown at right:

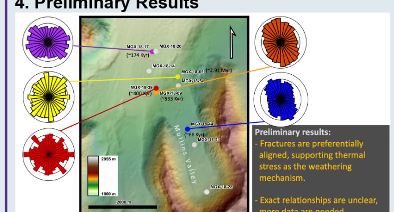
1. **Clear Void** – Blue epoxy with nothing behind
2. **Obstructed Void** – lighter blue epoxy with mineral grains behind it
3. **Crack** – Dark purple/black lineation with high contrast
4. **Pseudocrack** – Lineations with less contrast than cracks
5. **Quartz** – White mineral grains predominant throughout sandstones
6. **Other Minerals** – Other minerals besides quartz, mainly clays, weathered feldspars and micas

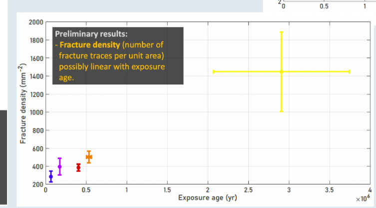


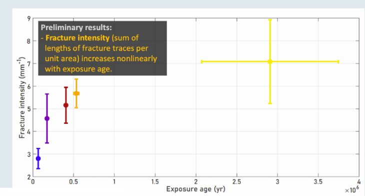
Since dark features shown in grain labeled 6 are similar in color and contrast, we further apply a classifying step based on shape and neighboring pixels to determine whether they are genuine fractures.

All outputs were analyzed in FracPaQ, a Matlab toolbox that quantifies fracture patterns. FracPaQ calculates the fracture trace lengths, density (number of fracture traces per area), intensity (sum of fracture lengths per area), and the connectivity of cracks.

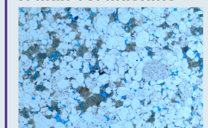
4. Preliminary Results







6. Man vs. Machine

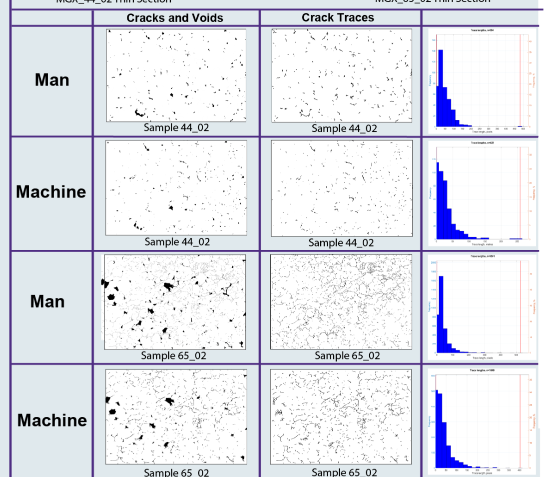


Below is a comparison between manual and automated mapping for two sandstone samples.

Results are broadly similar, although fracture trace length distributions differ significantly. More training of the model will be necessary, though initial results are promising.

MGX_44_02 Thin Section

MGX_65_02 Thin Section



References

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C. Sommer, C. Straehle, U. Köthe and F. A. Hamprecht, "Ilastik: Interactive learning and segmentation toolkit," 2011 IEEE International Symposium on Biomedical Imaging: From Nano to Macro, 2011, pp. 230-233, doi: 10.1109/ISBI.2011.5872394.

D. Healy, R.E. Rizzo, D.G. Cornwell, N.J. Farrell, H. Watkins, N.E. Timms, E. Gomez-Rivas, M. Smith, A Matlab toolbox for the quantification of fracture patterns, J. Struct. Geol., 95 (2017), pp. 1-16.

Schneider, C. A.; Rasband, W. S. & Eliceiri, K. W., NIH Image to ImageJ: 25 years of image analysis, Nature methods (2012) 9(7): 671-675.

Weigert & Moini, Inkscape Centerline Trace (2018)

Inkscape Centerline Trace:
https://github.com/fablabnbg/inkscape-centerline-trace

ImageJ:
https://imagej.nih.gov/ij/download.html

FracPaQ:
http://fracpaq.com/download.html

Ilastik:
https://www.ilastik.org/