18th Annual Conference IAMG 2017

Semi-Automated Texture Classification for Geometallurgical Applications

Julián M. Ortiz, Ph. D.
Associate Professor
The Robert M. Buchan Department of Mining
(Cross-appointed Department of Geological Sciences and Geological Engineering)
Queen's University

Yesenia Marulanda, M. Sc.
M.Sc. Student
Departamento de Ingenieria de Minas
Universidad de Chile

Queen's University

Overview

- Applied research on texture analysis in collaboration with BHP-Billiton
- Three stages:
  1. Proof of concept of texture classification
  2. Further development of algorithms and applications
  3. Pilot testing with real images
- Many research ideas came out of this work – potential application to different settings

- Three graduate students:
  - Rodrigo Lobos (B.Sc. and M.Sc. Electrical Eng.)
  - Gonzalo Diaz (B.Sc. and M.Sc. Electrical Eng., Ph.D. Mining Eng.)
  - Yesenia Marulanda (B.Sc. Surveying Eng., M.Sc. Mining Eng.)

- Photographs from a porphyry copper deposit
- Two experienced geologists contributed to logging, for validation purposes

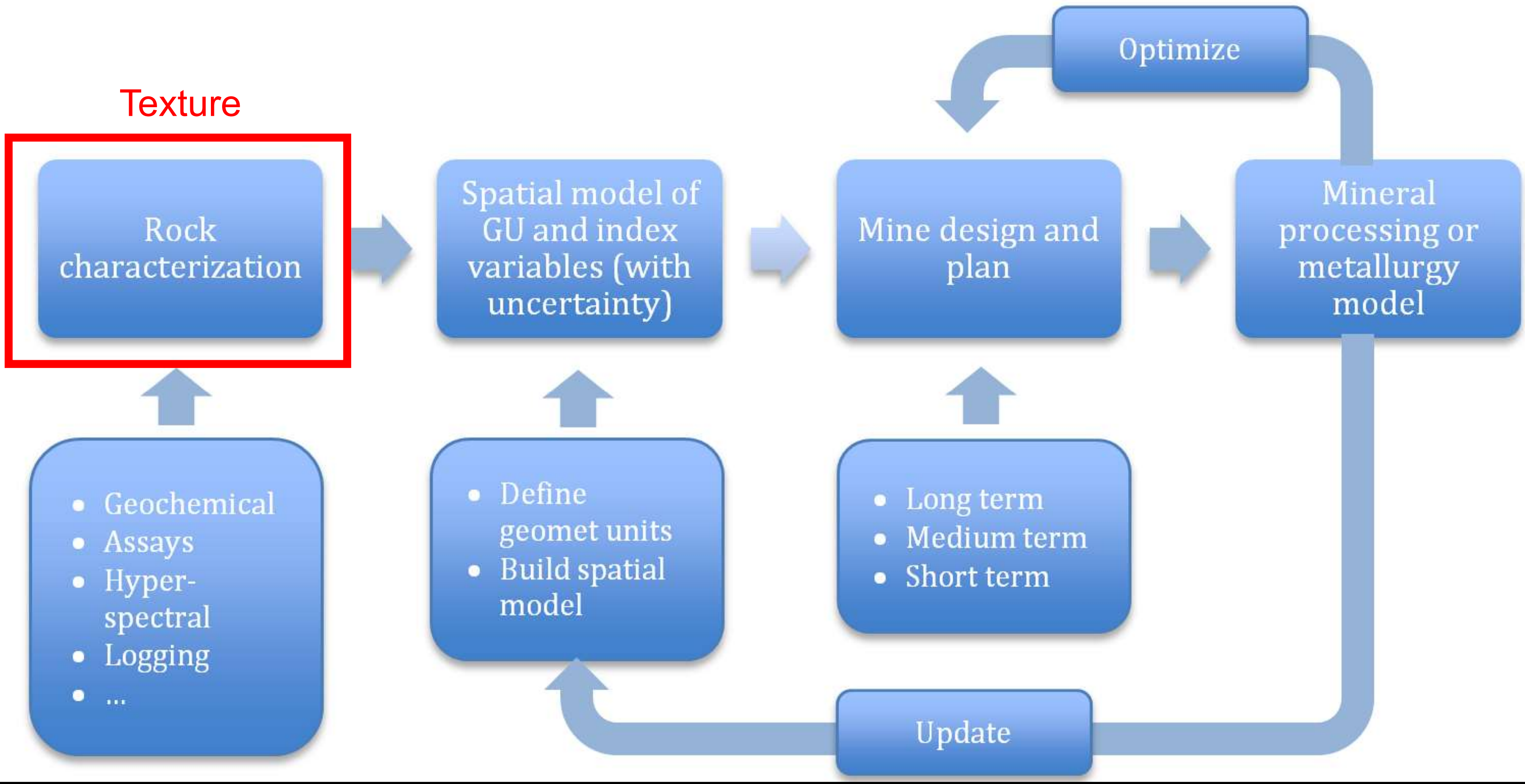
Geometallurgy

- A definition:

  Geometallurgy combines geological, mining and metallurgical information to create **spatially-based predictive models for mining, mineral processing an metallurgy** that can be used **to optimize the decisions**, given all other key project constraints such as environmental restrictions, water availability and energy efficiency.

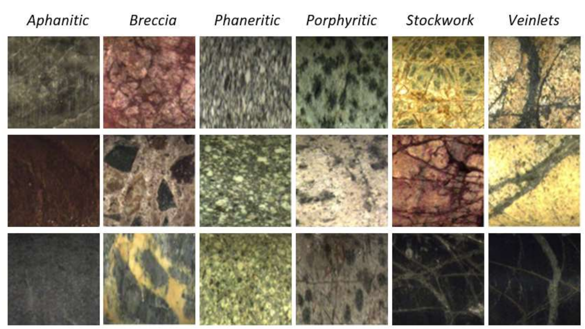
Texture characterization → Spatial model of texture classes → Geometallurgical units

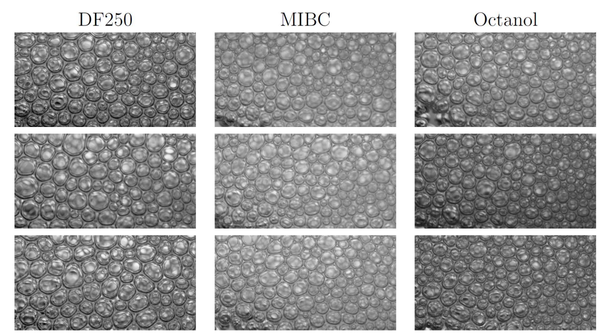
Motivation

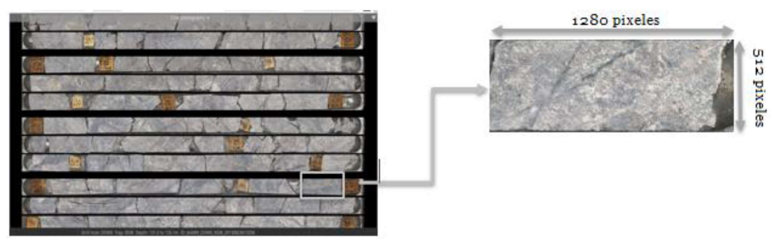

Texture
Rock characterization
Spatial model of GU and index variables (with uncertainty)
Mine design and plan
Mineral processing or metallurgy model
Optimize
Update
• Geochemical
• Assays
• Hyper-spectral
• Logging
• ...
• Define geomet units
• Build spatial model
• Long term
• Medium term
• Short term

Summary: textures characterization and classification

- Assumption: Link between textures and mineral processing performance
- Method: Make use of drillhole photographic records to automate the texture logging
- Goals:
  - Create a methodology for texture classification with a small database of textures labelled in 6 categories and apply to real data
  - Apply to other texture settings



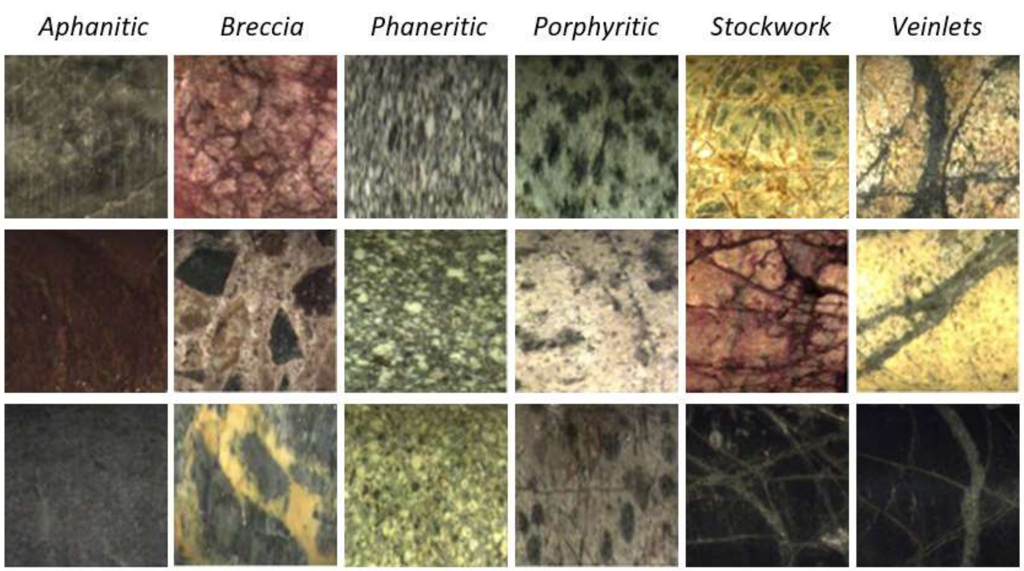


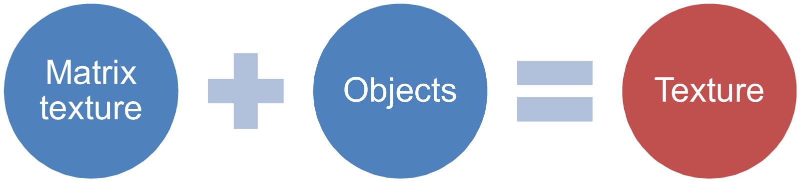


Databases
- 16 x 6 photos of clean textures for proof of concept (all labelled)
- Scanned high resolution drillcore images of 1200m at a porphyry copper deposit (150m used)

1. Proof of concept stage

- Proof of concept of texture classification
  - Small database of 96 images of “clean textures”
    - 16 images per class
    - 6 classes
    - All images labelled





Lobos et al. (2016) Analysis and classification of natural rock textures based on new transform-based features, Math Geosci 48(7):835-870

1. Proof of concept stage

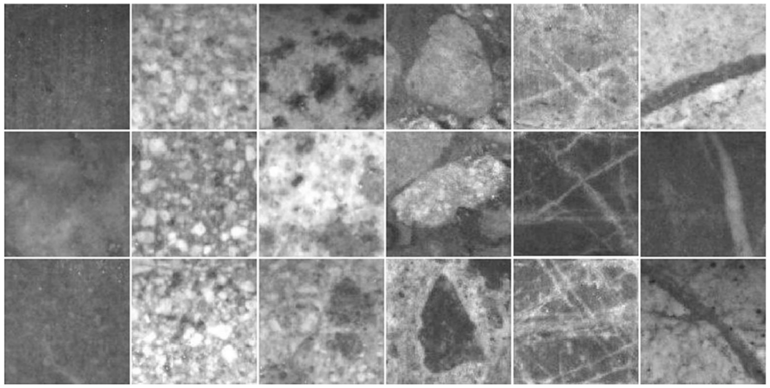
- All images converted to gray-scale
- Formally, we seek to find a rule that maximizes the conditional probability of class *Y* being *i*, given the image *z*

$$g^*(z) = \underset{i \in \mathscr{Y}}{\operatorname{argmax}} P(Y = i | Z = z), \quad \forall z \in \mathscr{Z}$$

- But we only have access to a set of samples

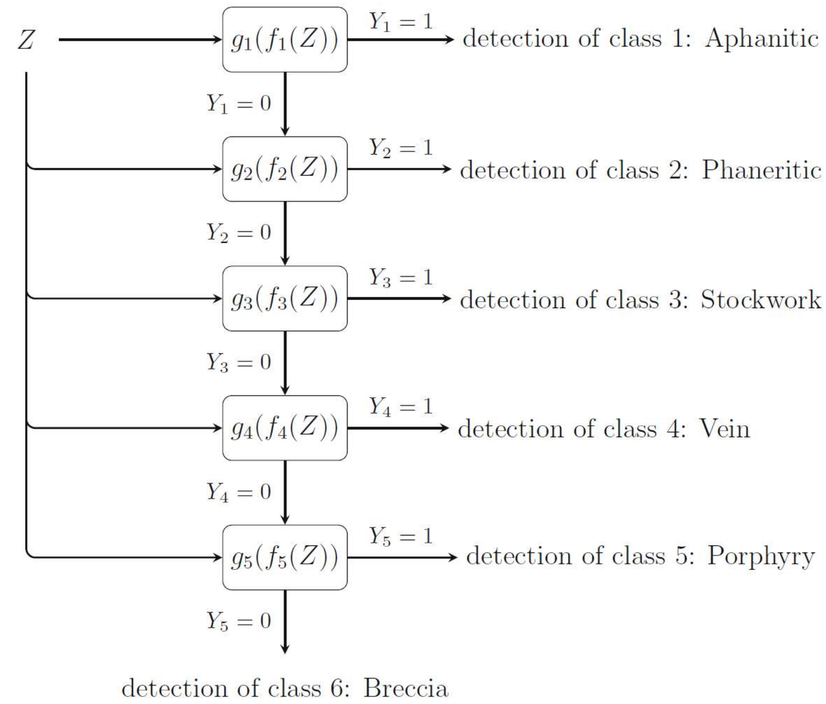
$$\mathscr{D} = \{(z_1, y_1), (z_2, y_2), \dots, (z_N, y_N)\}$$

- To reduce the dimensionality of the problem, we apply Feature Extraction, hoping to keep almost all the information of *Z* to discriminate the hidden variable *Y*



1. Proof of concept stage

- After exploring, we proposed a **sequential approach using binary classifiers**
- Each simple binary classifier was designed to capture what makes the image class distinctive from the rest
- This allows to keep a low complexity in the classifier and make it flexible (for example to add new classes)
- SVM was used to classify based on these extracted features designed for every class

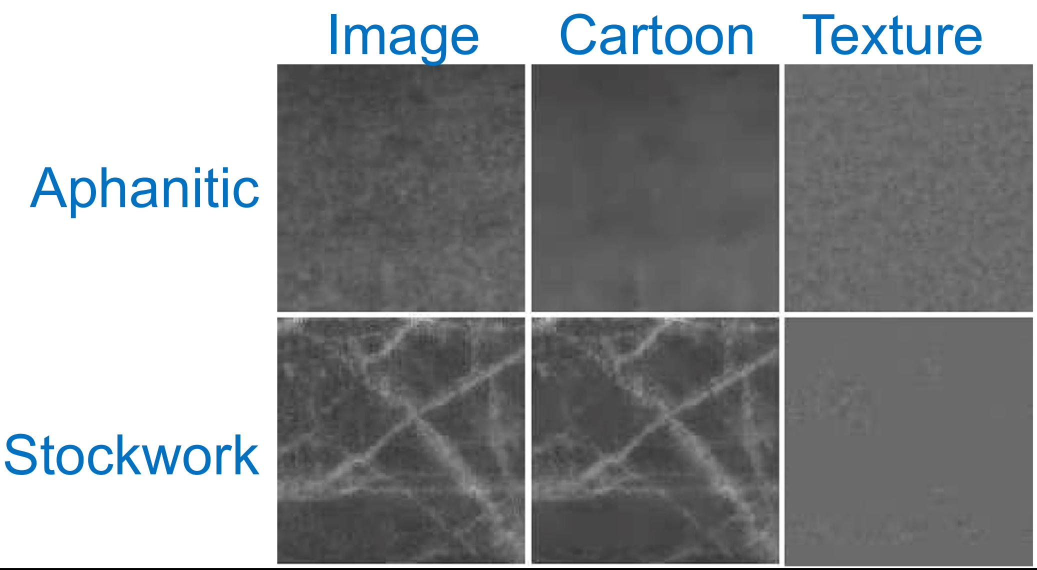


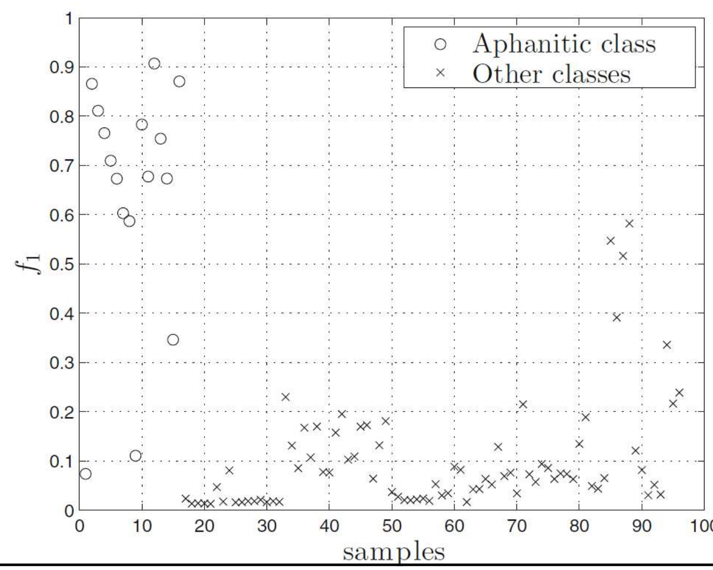
Therefore, the key is: What are the features?

1. Proof of concept stage

- **Aphanitic**:
  - Texture-cartoon separation
  - Difference between total variation (TV) of image and cartoon

$$f_1(z) \equiv \frac{|\parallel \nabla z \parallel_{\ell_1} - \parallel \nabla z_\sigma^u \parallel_{\ell_1}|}{\parallel \nabla z \parallel_{\ell_1}} \in [0, 1]$$

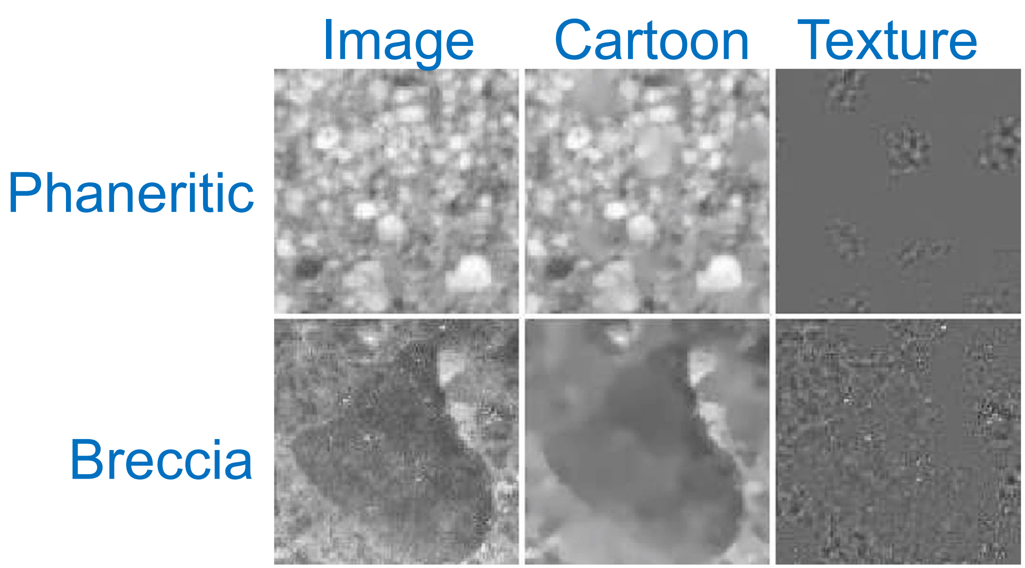


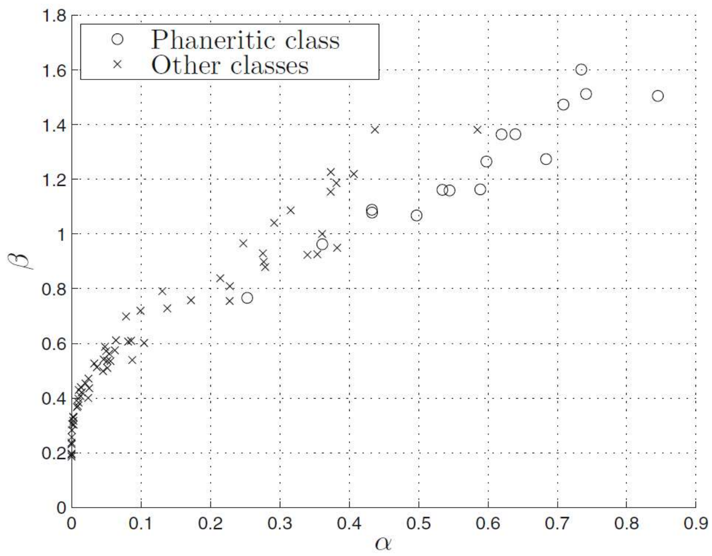


1. Proof of concept stage

- **Phaneritic**:
  - Texture-cartoon separation
  - Wavelet transform of the cartoon + fitting of a Generalized Gaussian Density
  - α spread and β shape parameters

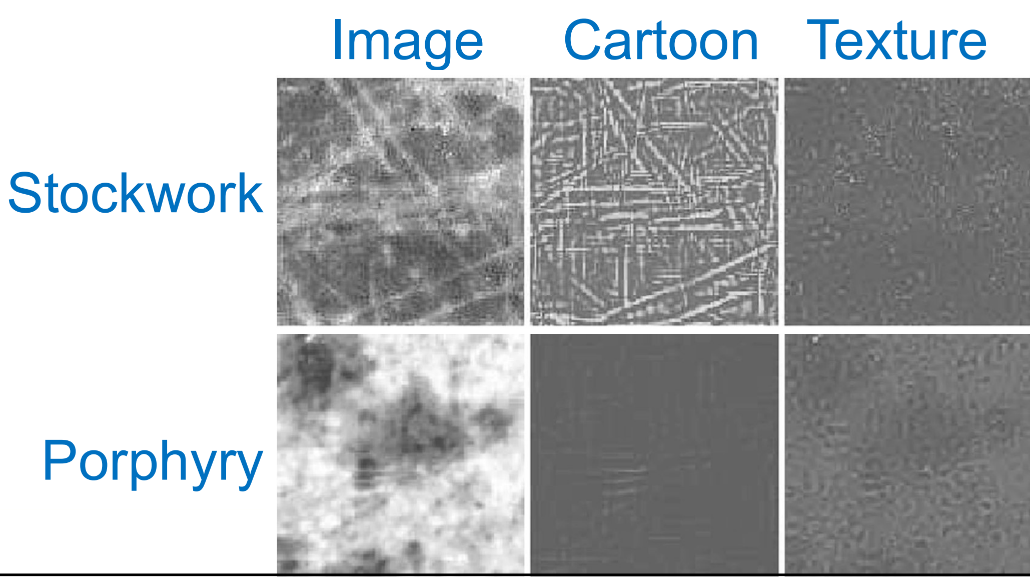
$$f_2 \equiv \begin{pmatrix} \alpha_1 & \beta_1 \\ \alpha_2 & \beta_2 \\ \vdots & \vdots \\ \alpha_9 & \beta_9 \end{pmatrix}$$

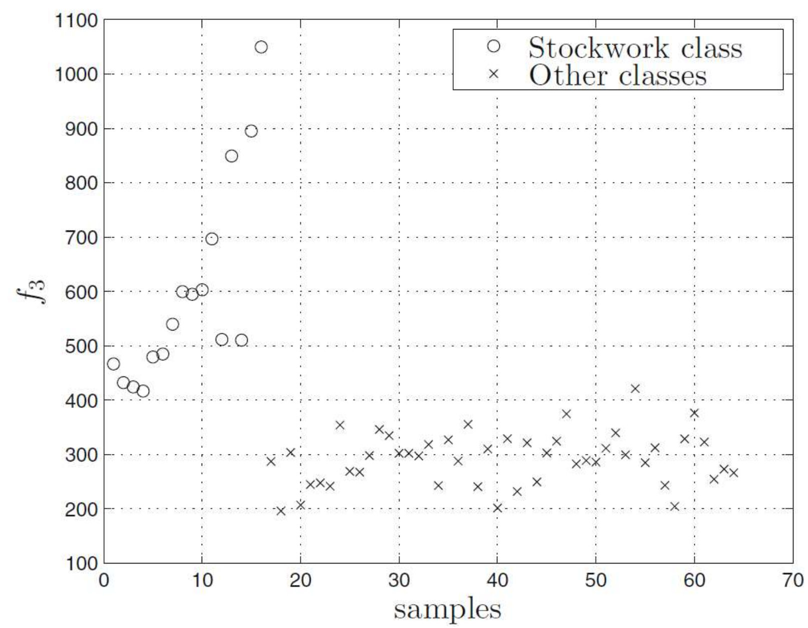




1. Proof of concept stage

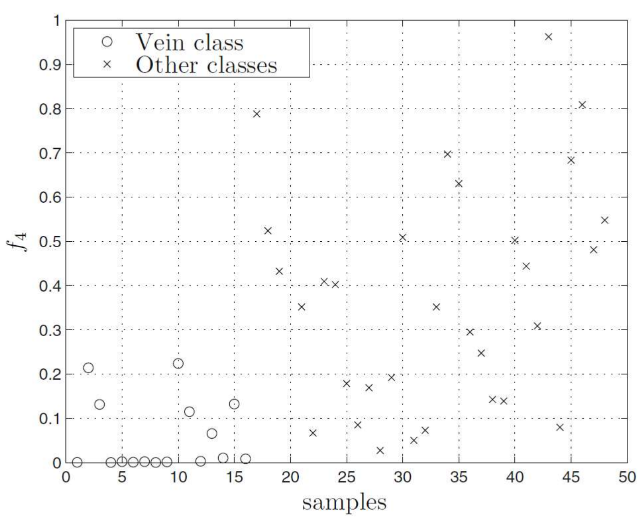
- **Stockwork**:
  - Texture-cartoon separation
  - Shearlet transform applied to geometric forms
  - “Orientation energy” is high in Stockwork

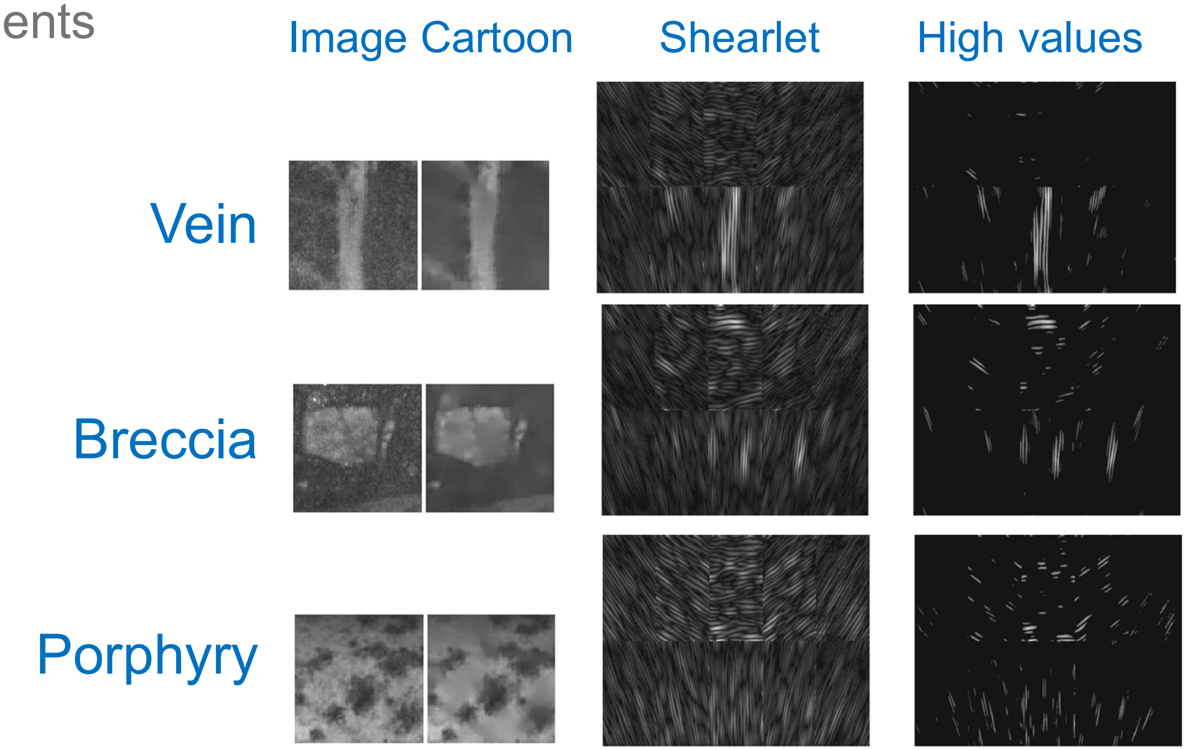




1. Proof of concept stage

- **Vein**:
  - Isotropy in Shearlet Transform
  - Ratio in most significant coefficients in two orthogonal directions

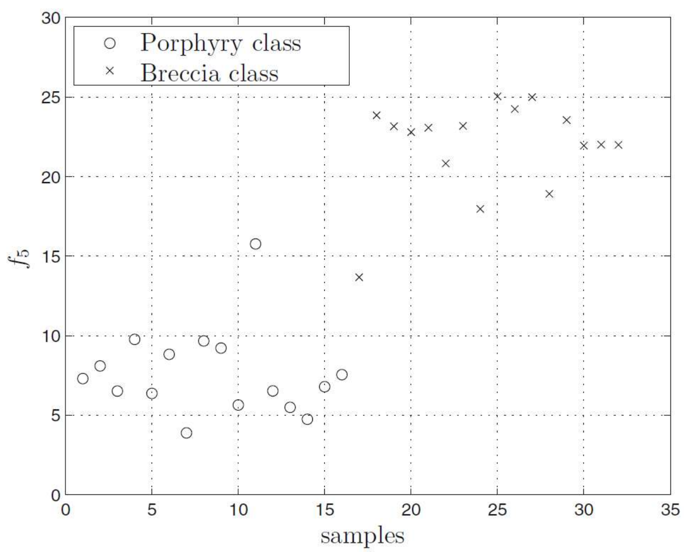




1. Proof of concept stage

- **Porphyry vs Breccia**:
  - Local Binary Pattern (LBP)

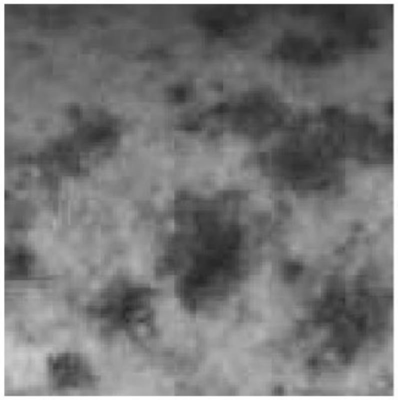
$$f_5 = \frac{\frac{1}{n}\sum_{i=1}^{n}(h_i - \overline{h})^4}{\left(\frac{1}{n}\sum_{i=1}^{n}(h_i - \overline{h})^2\right)^2}$$

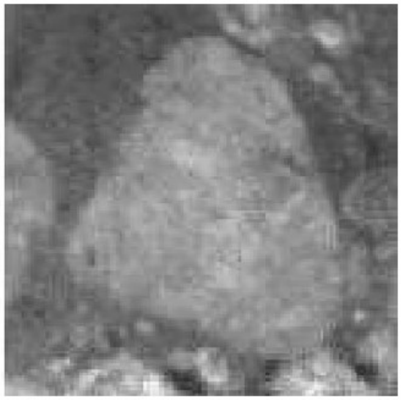


Porphyry

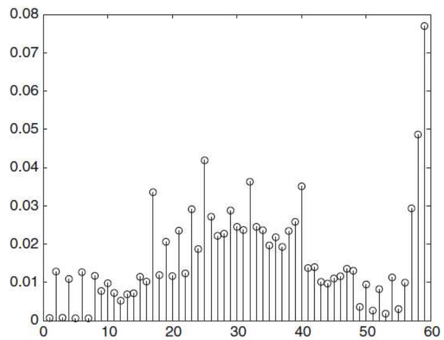
Breccia

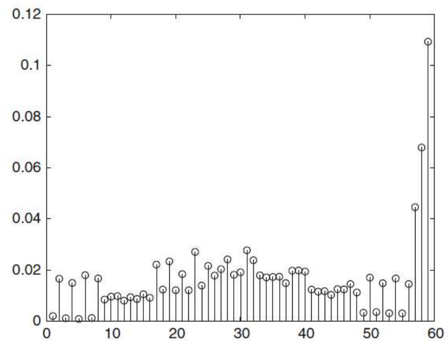
Image





LBP histogram

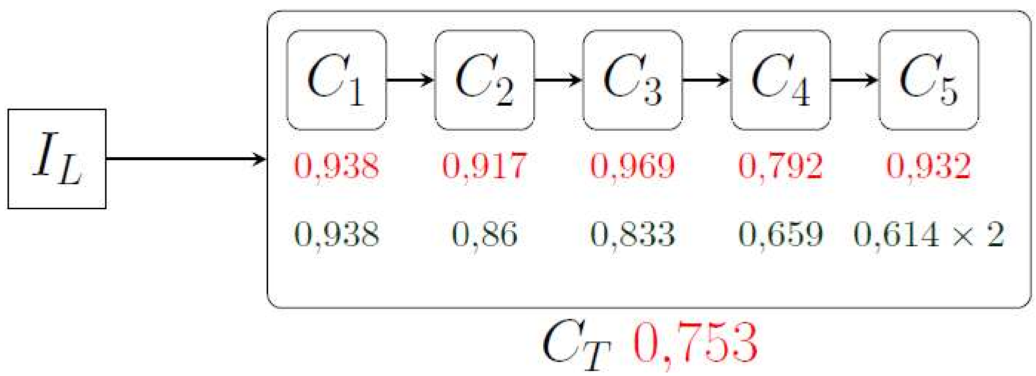




1. Proof of concept stage

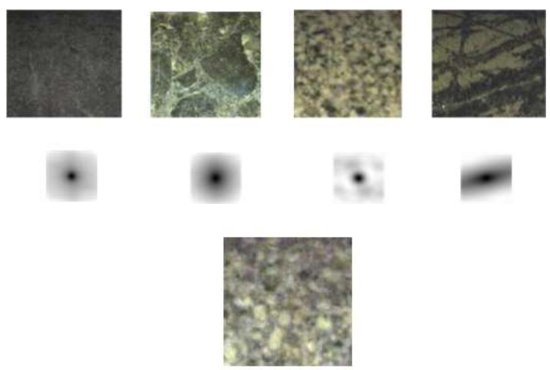
- Performance is the product of individual success rates

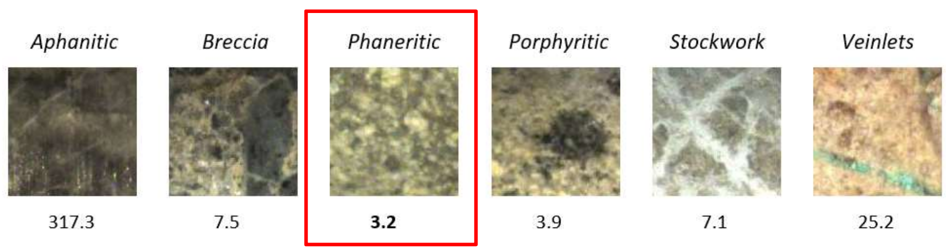
$$P(g_{\text{chain}}(X) = Y | Y = l) = \prod_{i=1}^{l} P(g_i(X_i) = Y_i)$$



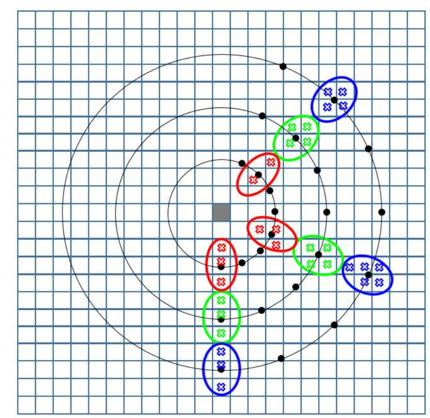
2. Further developments

- Further development of algorithms and applications
  - Use of variogram map
  - Use of compact variogram





$$\gamma(h) = \frac{1}{2N(h)} \sum_{k=1}^{N(h)} \left(Z(x_k) - Z(x_k + h)\right)^2$$

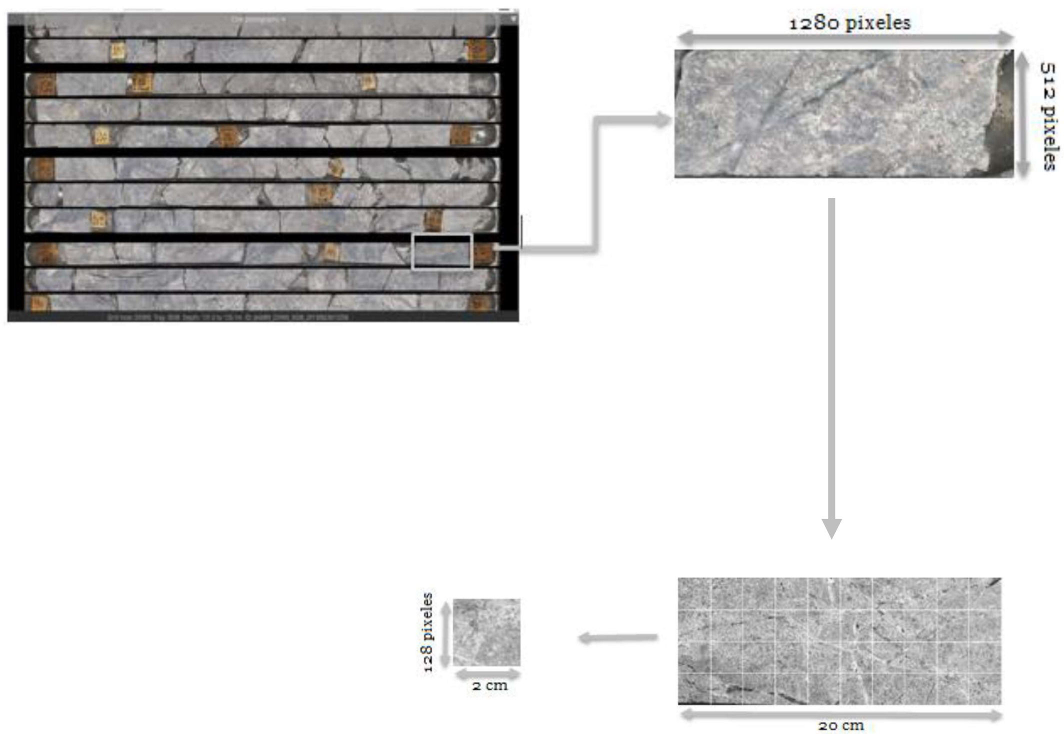


Diaz et al. (2017) Variogram-based description for classification of rock image textures, *to be submitted.*

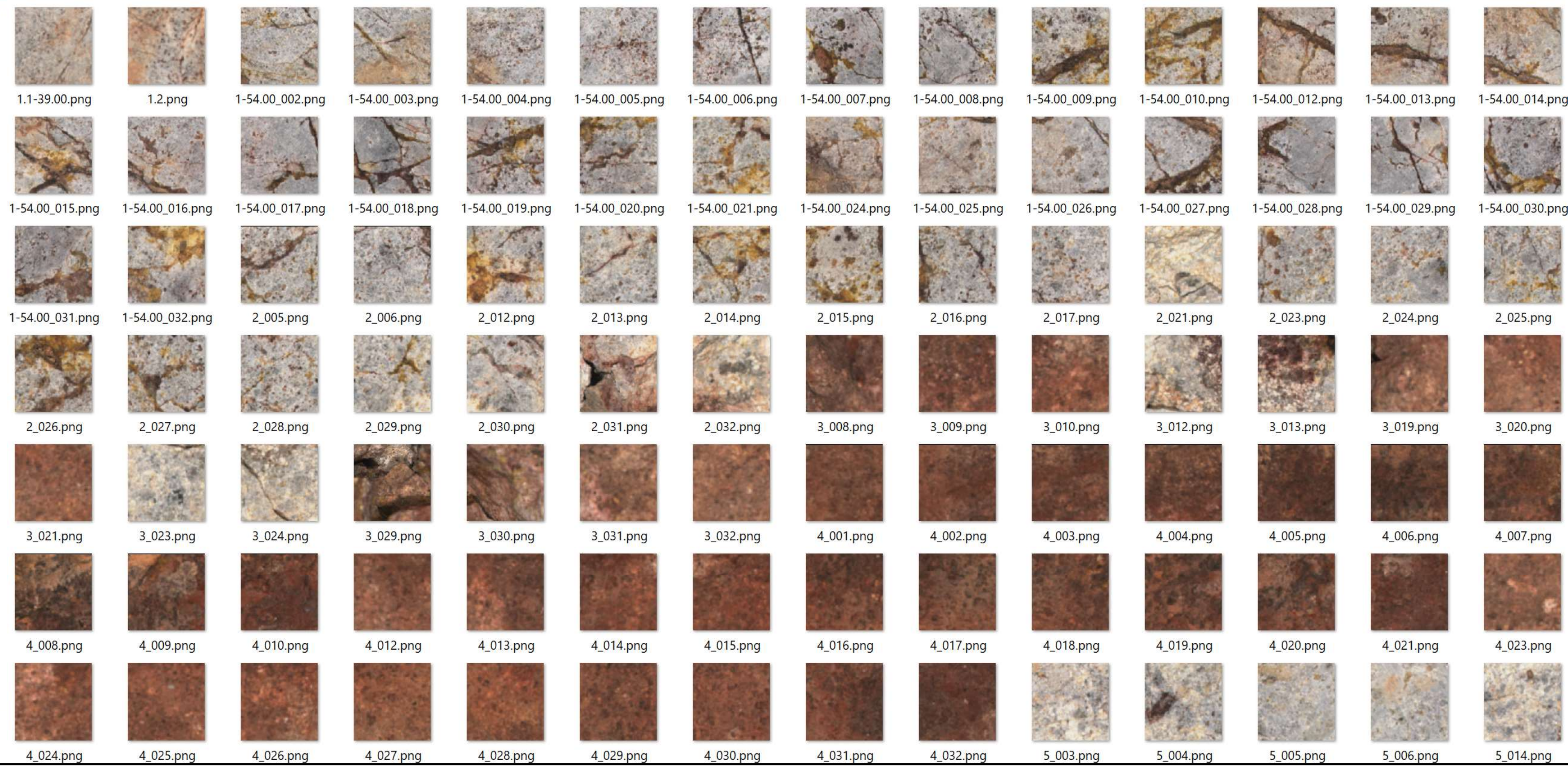
3. Pilot testing with real images

- Pilot testing with real images
- 1200m of high resolution imaging
- Focused on 30 5m composites → 150m
- 14000 images
- 326 samples logged by two geologists (2.34% of total)
- Breccia absent in validation set

- **Images preparation needed significant work**



3. Pilot testing with real images



3. Pilot testing with real images

- Procedure
  - **Automated process (64.0% match)**
  - Review of misclassification cases
    - Misclassified samples were analyzed
      - Brightness issues (too dark or too light): 46.3%
      - Contrast issues: 12.96%
      - Crack in core: 11.1%
      - More…
  - Preprocessing (filtering and normalization)
  - Reprocessing (84.8% match)

	Training set	
Class	**%**	**Samples**
Aphanitic	19.0	62
Phaneritic	31.9	104
Stockwork	1.2	4
Vein	25.5	83
Porphyry	22.4	73
Breccia	0.0	0
Total	**100.0**	**326**

		No preprocess						
		Aphanitic	**Phaneritic**	**Stockwork**	**Vein**	**Porphyry**	**Breccia**	**Total**
Training set	**Aphanitic**	14.1	0.0	0.0	2.1	1.8	1.0	**19.0**
	Phaneritic	0.0	14.1	2.5	3.1	0.3	11.9	**31.9**
	Stockwork	0.0	0.0	0.6	0.3	0.0	0.3	**1.2**
	Vein	0.0	0.3	2.5	19.9	0.6	2.2	**25.5**
	Porphyry	0.0	0.0	3.1	2.5	16.0	0.8	**22.4**
	Breccia	0.0	0.0	0.0	0.0	0.0	0.0	**0.0**
	Total	**14.1**	**14.4**	**8.7**	**27.9**	**18.7**	**16.2**	**100.0**

3. Pilot testing with real images

- Procedure
  - Automated process (64.0% match)
  - Review of misclassification cases
    - Misclassified samples were analyzed
      - Brightness issues (too dark or too light): 46.3%
      - Contrast issues: 12.96%
      - Crack in core: 11.1%
      - More…
  - Preprocessing (filtering and normalization)
  - **Reprocessing (84.8% match)**

	Training set	
Class	**%**	**Samples**
Aphanitic	19.0	62
Phaneritic	31.9	104
Stockwork	1.2	4
Vein	25.5	83
Porphyry	22.4	73
Breccia	0.0	0
Total	**100.0**	**326**

		Preprocess						
		Aphanitic	**Phaneritic**	**Stockwork**	**Vein**	**Porphyry**	**Breccia**	**Total**
Training set	**Aphanitic**	17.5	0.0	0.0	1.2	0.0	0.3	**19.0**
	Phaneritic	0.0	24.5	2.1	1.5	0.0	3.8	**31.9**
	Stockwork	0.0	0.0	0.9	0.3	0.0	0.0	**1.2**
	Vein	0.0	0.3	2.5	21.8	0.3	0.6	**25.5**
	Porphyry	0.0	0.0	1.2	0.6	20.2	0.4	**22.4**
	Breccia	0.0	0.0	0.0	0.0	0.0	0.0	**0.0**
	Total	**17.5**	**24.8**	**6.7**	**25.4**	**20.5**	**5.1**	**100.0**

3. Pilot testing with real images

- Procedure
  - **Automated process (64.0% match)**
  - Review of misclassification cases
    - Misclassified samples were analyzed
      - Brightness issues (too dark or too light): 46.3%
      - Contrast issues: 12.96%
      - Crack in core: 11.1%
      - More…
  - Preprocessing (filtering and normalization)
  - **Reprocessing (84.8% match)**

	Training set	
Class	**%**	**Samples**
Aphanitic	19.0	62
Phaneritic	31.9	104
Stockwork	1.2	4
Vein	25.5	83
Porphyry	22.4	73
Breccia	0.0	0
Total	**100.0**	**326**

		Difference (Preprocess - No preprocess)					
		Aphanitic	**Phaneritic**	**Stockwork**	**Vein**	**Porphyry**	**Breccia**
Training set	**Aphanitic**	3.4	0.0	0.0	-0.9	-1.8	-0.7
	Phaneritic	0.0	10.4	-0.4	-1.6	-0.3	-8.1
	Stockwork	0.0	0.0	0.3	0.0	0.0	-0.3
	Vein	0.0	0.0	0.0	1.9	-0.3	-1.6
	Porphyry	0.0	0.0	-1.9	-1.9	4.2	-0.4
	Breccia	0.0	0.0	0.0	0.0	0.0	0.0

3. Pilot testing with real images

- Procedure
  - Automated process (64.0% match)
  - Review of misclassification cases
    - Misclassified samples were analyzed showing
      - Tone issues (too dark or too light): 46.3%
      - Contrast issues: 12.96%
      - Crack in core: 11.1%
      - More…
  - Preprocessing (filtering and normalization)
  - Reprocessing (84.8% match)

	No preprocess		Preprocess	
Class	**%**	**Samples**	**%**	**Samples**
Aphanitic	1.7	236	2.2	304
Phaneritic	3.2	449	4.5	623
Stockwork	14.7	2049	16.0	2228
Vein	24.6	3419	26.4	3668
Porphyry	11.5	1603	15.2	2111
Breccia	44.2	6143	35.7	4965
Total	**100.0**	**13899**	**100.0**	**13899**

In conclusion:
- Using the photographs of drillcores is possible
- We could populate the database with texture classes (up to a % of error), based on a very low number of logged textures done by a geologist, and achieve a good accuracy
- Textures could be used for domaining, and their relationship with mineral processing performance, could be tested

Conclusions

- Texture is often disregarded and not included in numerical models due to the difficulty in its systematic “measurement”
- We showed that with simple features identified, different texture classes can be discriminated
- Systematic application to high resolution photographs is absolutely possible
- There is a need for human supervision of the process, but most of it is automatic and provides accurate results
- Link to metallurgical performance needs to be demonstrated
- Pilot testing could benefit of more logged samples to check accuracy of breccia class
- A systematic QA-QC approach could be used to check a low % of the classified textures

Acknowledgments

Many students, researchers, and developers have contributed to this work. Thanks are due to all of them.