Automatic Rock Detection and Classification in Natural Scenes

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Master's Presentation

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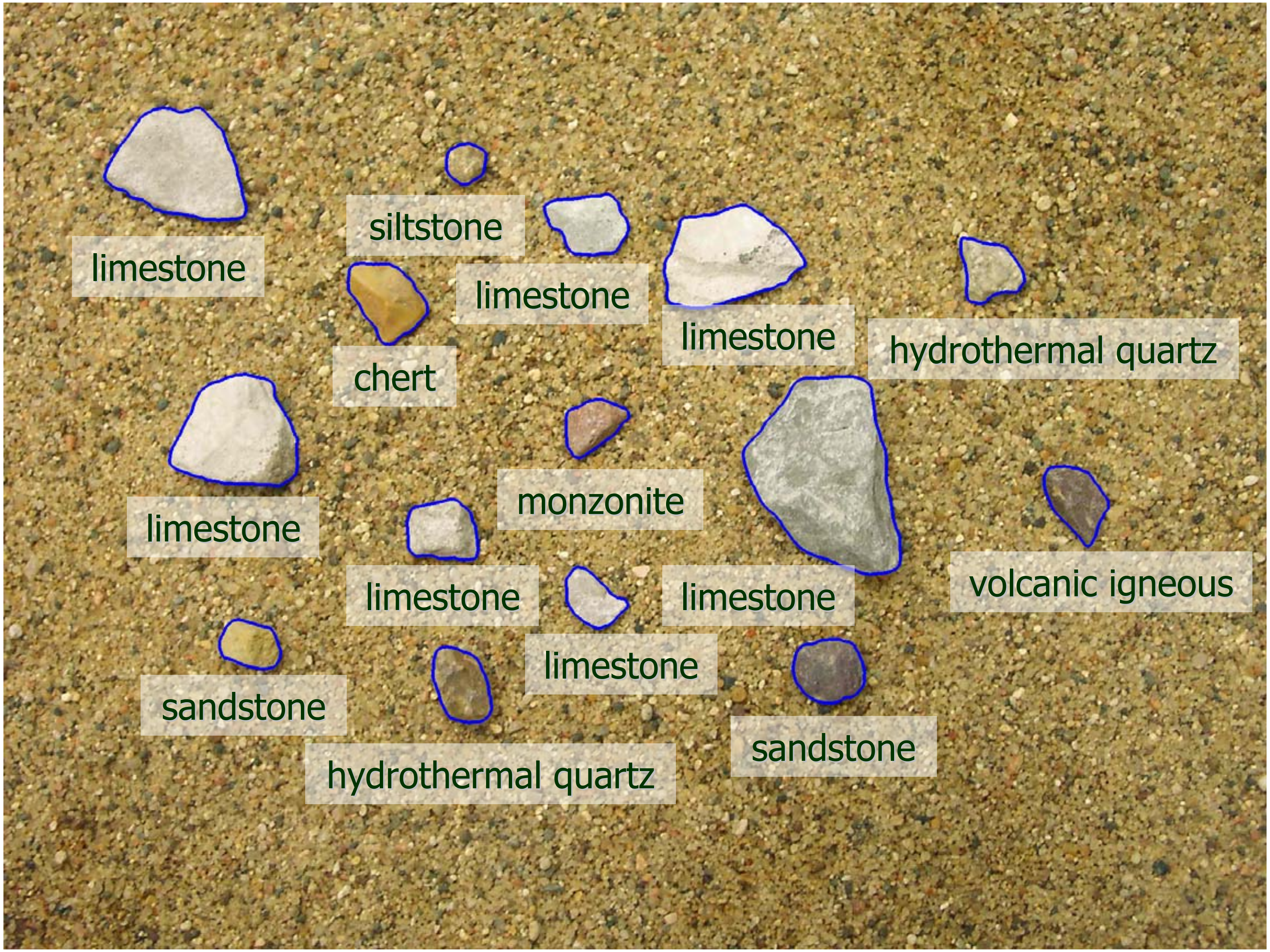
Introduction



Motivations

- Intelligent selection and compression of data
- Exploration efficiency
- Repeatable and robust operations
- Assistance in robot path planning

Problem Definition

- Detection
  - Locate as many rocks as possible while minimizing false detections
- Segmentation
  - Accurately localize boundaries
- Classification
  - Geologic classes
  - Features: albedo, color, texture, shape

Approach

Rock Detection/Segmentation

↓

Feature Extraction

↓

Geologic Classification

Outline

- Introduction
- Feature Extraction
- Rock Detection and Segmentation
- Geologic Classification
- Conclusions

Outline

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Feature Extraction

- Features for detecting or geologically classifying rocks:
  - Albedo and Color
  - Texture
  - Shape
- Assume that we have an accurate boundary for each rock
- In later sections, use these features for:
  - Rock detection
  - Geologic classification

Albedo and Color

- Rock composition
  - Red: oxidized iron
  - Black: carbonaceous (organic) material

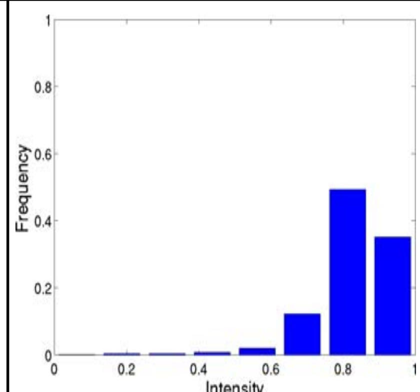
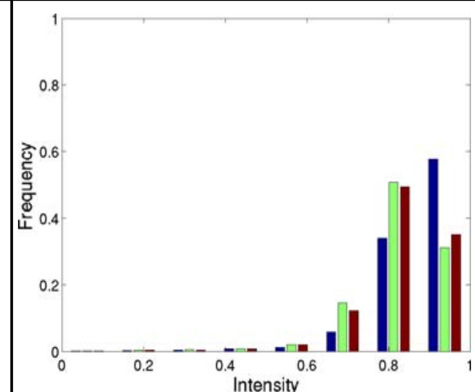
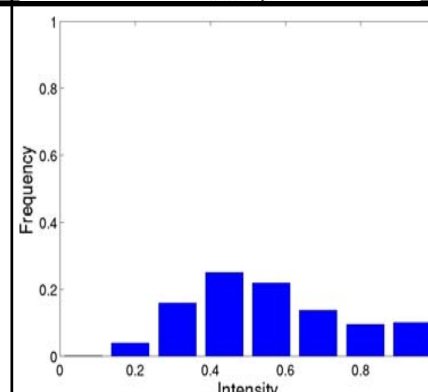
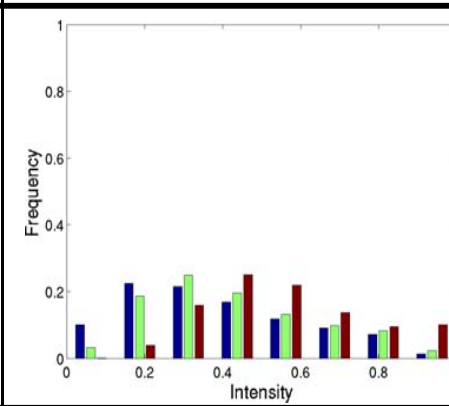
limestone

limestone with calcite crystals

limestone

volcanic igneous

Albedo and Color

Rock	Intensity Mean	Intensity Variance	Intensity Histogram	Color Histogram (RGB, HSV or CIELAB)
	0.83	0.011		
	0.56	0.042		

Texture

- Size, shape, arrangement of component elements
- Grains: size, distribution, sorting, permeability, shape, orientation
- Surface markings: polish, striations, pits

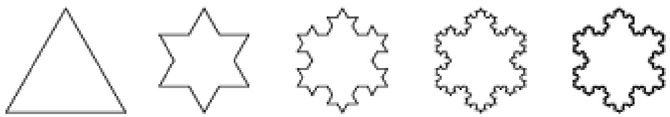
two amphibolite pebbles cemented together

sandstone with fine-grained quartz

limestone with abrasion marks

Fractal Dimension

- Measures self-similarity



- Defined according to:

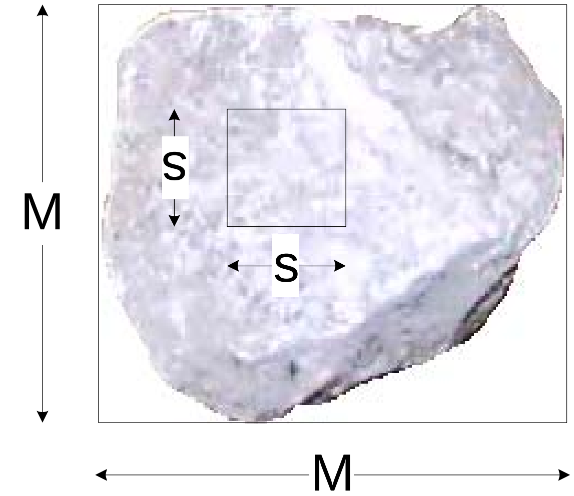
$$1 = Nr^{FractalDimension}$$

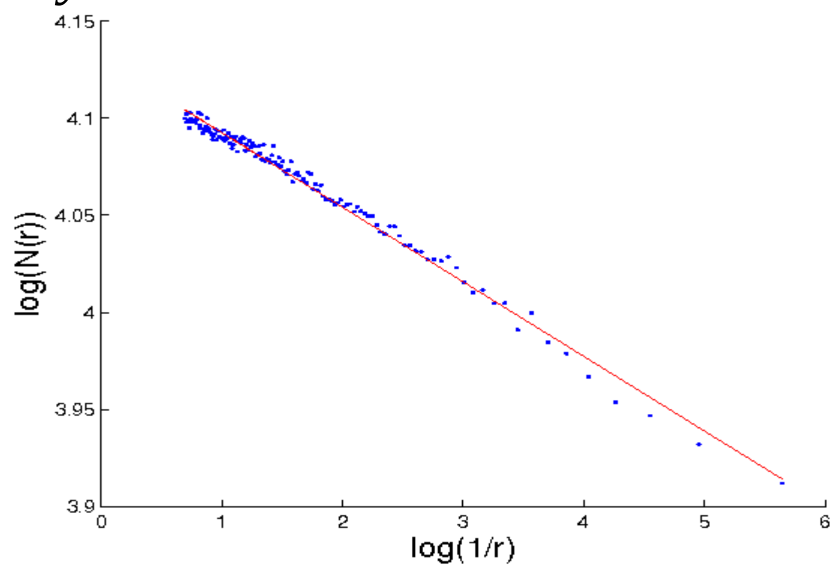
- For many boxes of size s x s:

$$N_r = \sum_i \max graylevel - \min graylevel + 1$$

where r = s / M

- Fractal dimension is the slope in a log(N_r) by log(1/r) plot





Co-occurrence Statistics

- Grey level co-occurrence matrix:

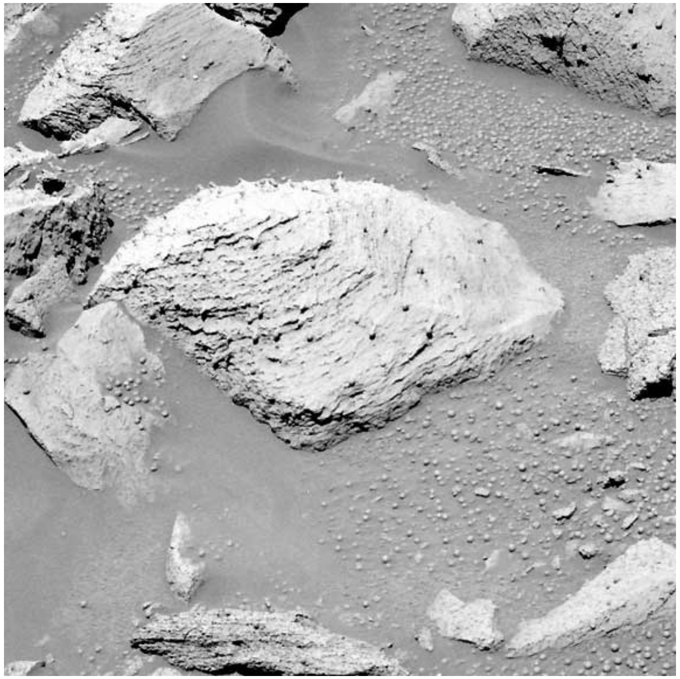
  $$P_{d,\alpha}(i,j) = \left|\left\{\left((r,s),(t,v)\right) : I(r,s) = i, I(t,v) = j\right\}\right|$$

  where d is the distance at an angle α between pixels of intensities i and j and |.| is the cardinality of a set
- Contrast $$\sum_i \sum_j (i-j)^2 P_d(i,j)$$
- Correlation $$\sum_i \sum_j \frac{(i-\mu_x)(j-\mu_y)P_d(i,j)}{\sigma_x \sigma_y}$$
- Energy $$\sum_i \sum_j P_d^2(i,j)$$
- Homogeneity $$\sum_i \sum_j \frac{P_d(i,j)}{1+|i-j|}$$

Directional Histogram

- Convolve with directional masks

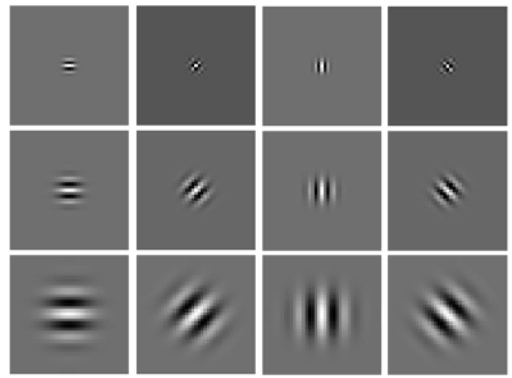
- For each mask, sum responses over image
- Form normalized histogram



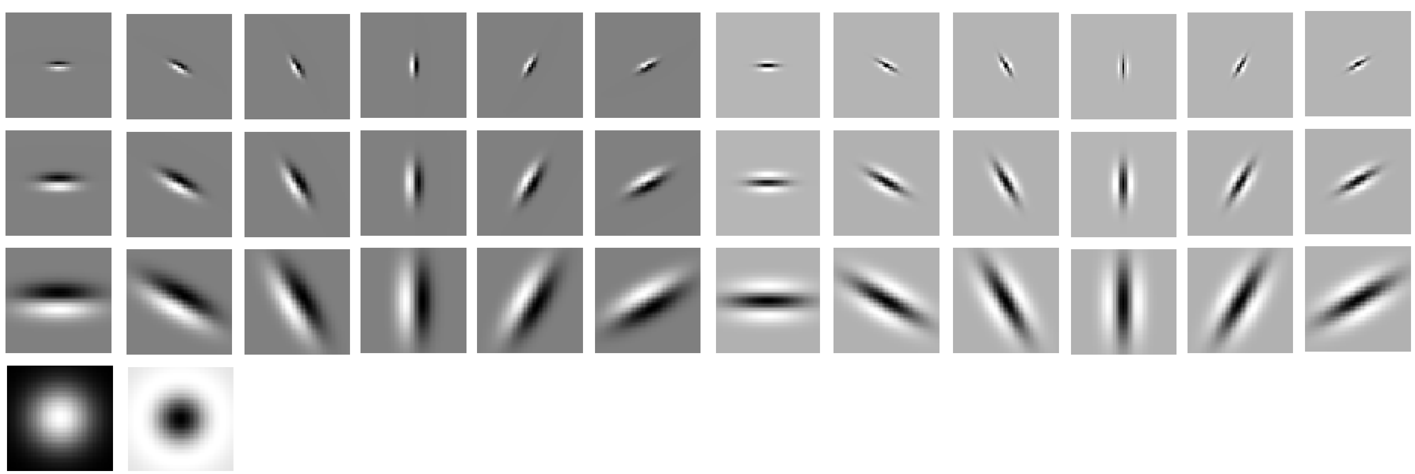
Courtesy of NASA/JPL-Caltech

Textons: Filter Banks

- Filter banks:
  - Gabor

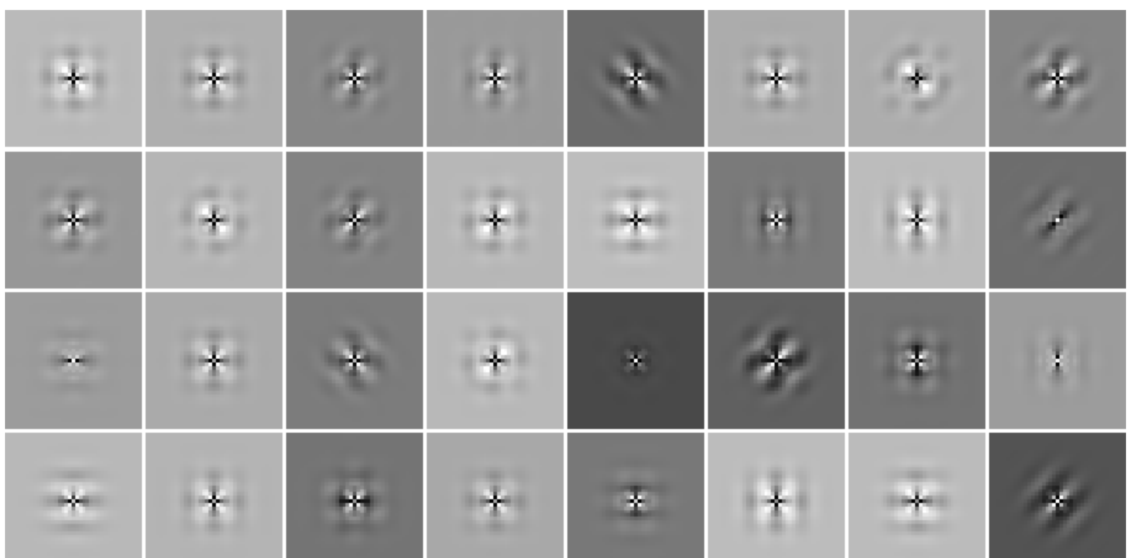


  - MR8



Textons: Forming Textons

- Convolve filters with all images
- Aggregate responses
- Cluster responses to form textons
- Example textons:

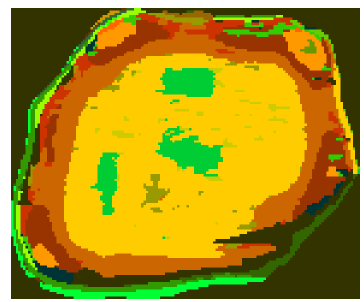


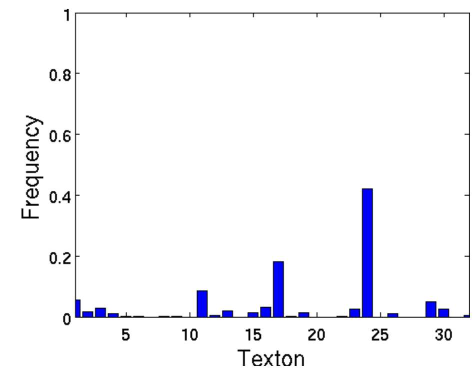
Textons: Computing Histograms

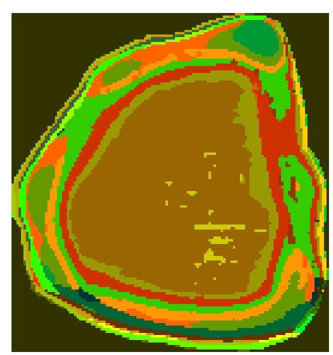
- Compute nearest texton for each pixel
- Form texton histogram

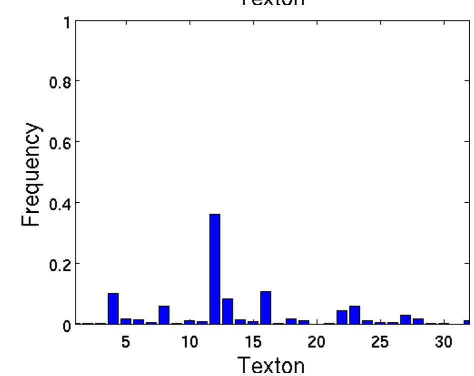
Texton Map

Texton Histogram









Shape

- Form: overall shape
  - Reflects conditions of deposition
  - Affects settling velocity and mode of transport
- Roundness: sharpness of corners
  - Caused by impacts during transport
  - Increases with distance of travel

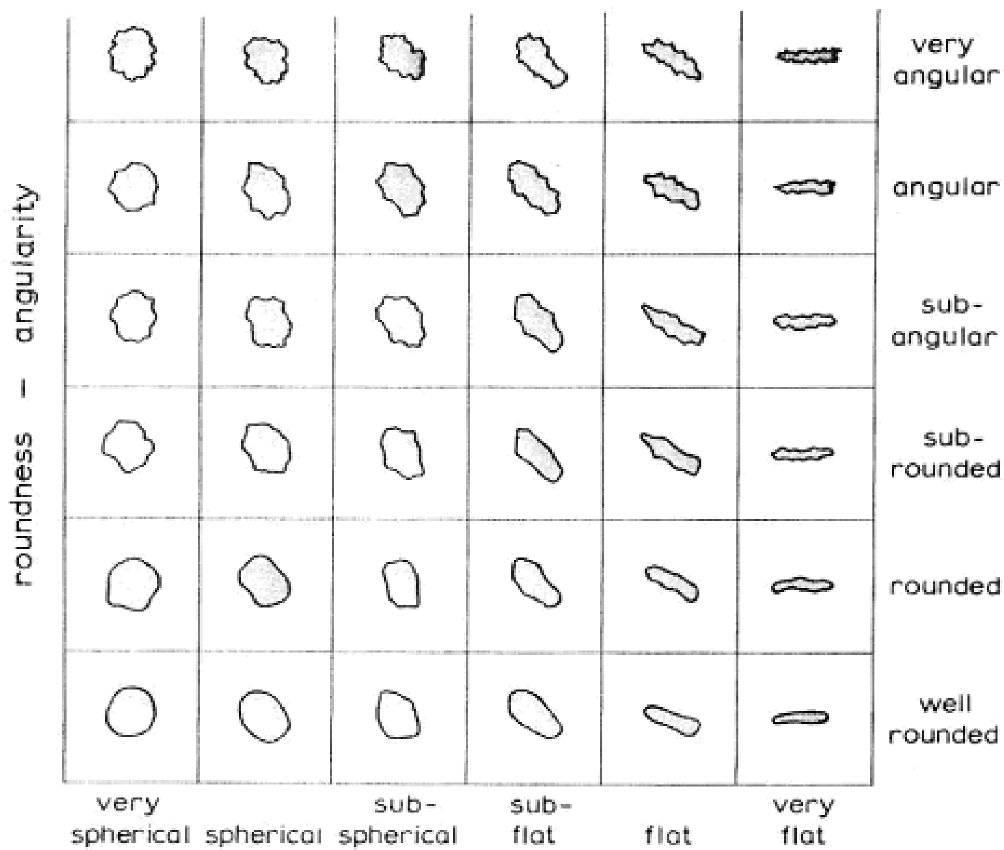
circular

elliptical
round

angular

Shape

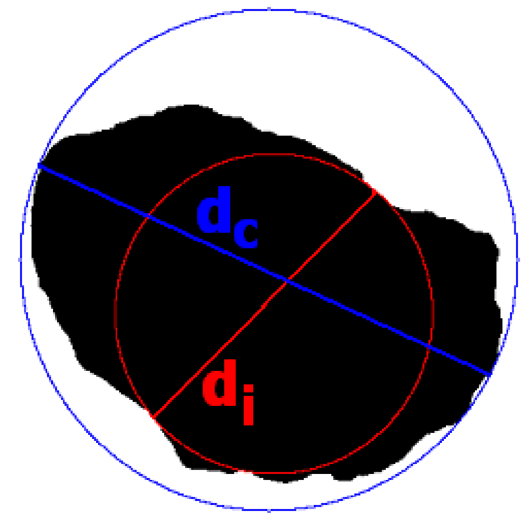
- Geologists use sphericity and roundness
- Often measured with a visual chart



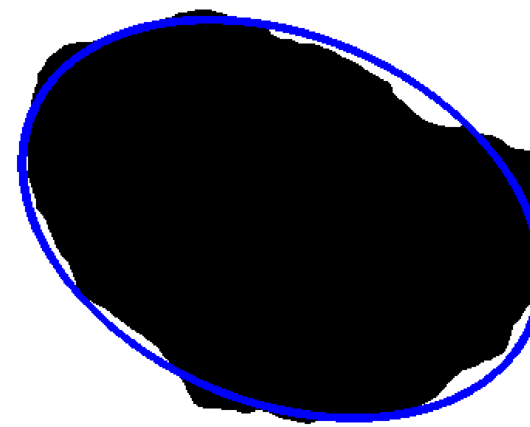
R.S. Crofts. A visual measure of shingle particle form for use in the field. *Journal of Sedimentary Petrology*, 44:931–934, 1974.

Form Metrics

- Riley Sphericity: $$\sqrt{\frac{d_i}{d_c}}$$



- Elongation:
  - Ratio of minor and major axes of best-fitting ellipse
- Ellipse Error:
  - Average distance from each boundary point to the closest point on the best-fit ellipse



Form Metrics

- Circular Variance:

$$\frac{1}{N}\sum_{i=1}^{N}\left(\left\|p_i-\mu\right\|-\mu_r\right)^2$$

- Elliptic Variance:

$$\frac{1}{N\mu_{rc}}\sum_{i=1}^{N}\left(\sqrt{(p_i-\mu)^T C^{-1}(p_i-\mu)}-\mu_{rc}\right)^2$$

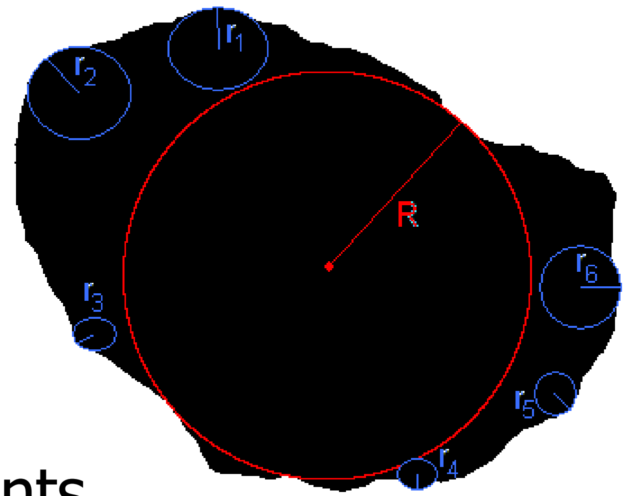
where $\mu=\sum_{i=1}^{N}p_i$ $\quad \mu_r=\sum_{i=1}^{N}\left\|p_i-\mu\right\|$ $\quad \mu_{rc}=\sum_{i=1}^{N}\sqrt{(p_i-\mu)^T C^{-1}(p_i-\mu)}$

$$C=\frac{1}{N}\sum_{1}^{N}(p_i-\mu)(p_i-\mu)^T$$

$p_i = (x_i,y_i)$ is the i^{th} contour point and N is the number of contour points

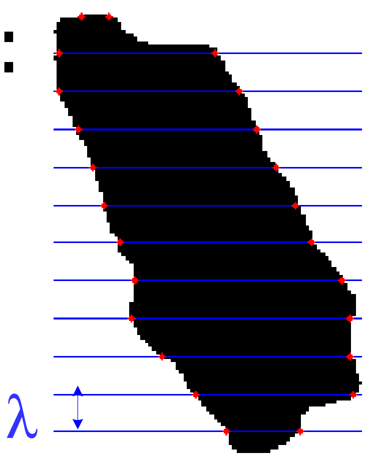
Roundness Metrics

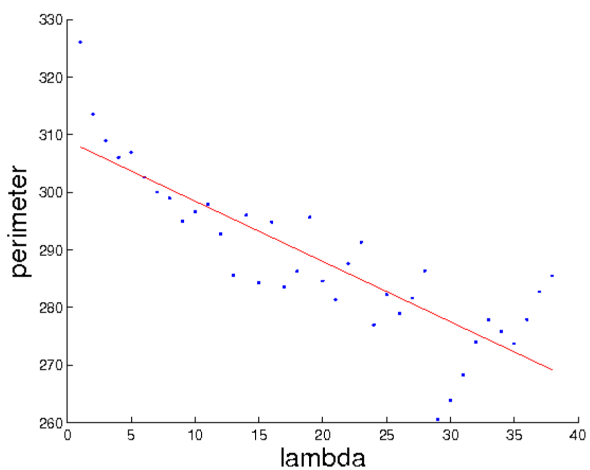
- Wadell Roundness: $\dfrac{\sum_{i=1}^{N} r_i}{NR}$



- Angularity:
  - Standard deviation of the curvature at all boundary points

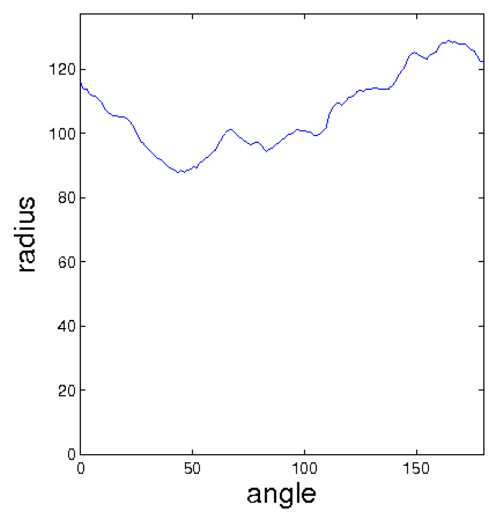
- Fractal Dimension:
  - Box dimension
  - Divider dimension

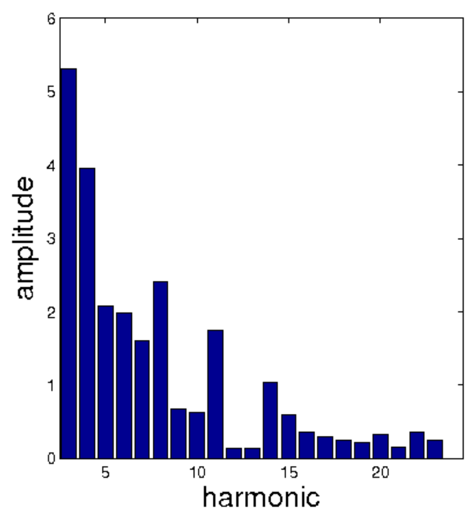


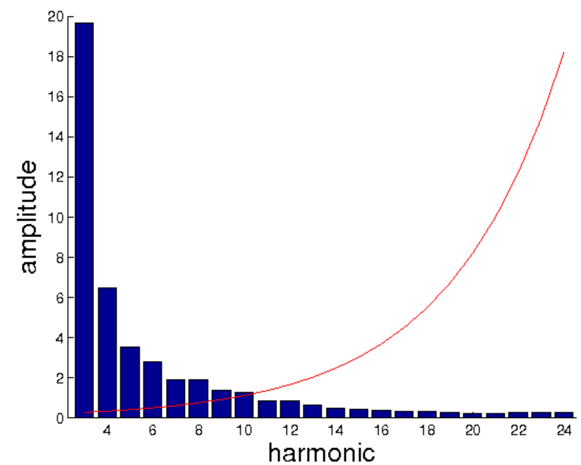


Roundness Metrics

- Diepenbroek Roundness:
  - Distance from each boundary point from the centroid forms a 1-D signal
  - Take a weighted sum of the Fourier transform of the signal







blue: average Fourier transform
red: normalization function

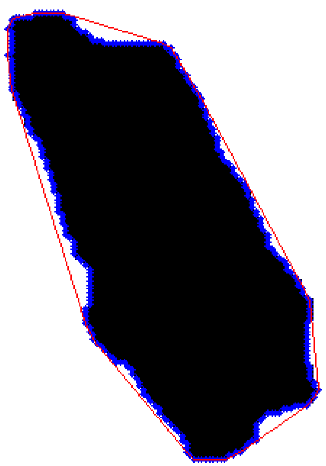
Other Metrics

- Compactness/Circularity

$$\frac{\sqrt{Area}}{Perimeter} \qquad \frac{Perimeter^2}{Area}$$

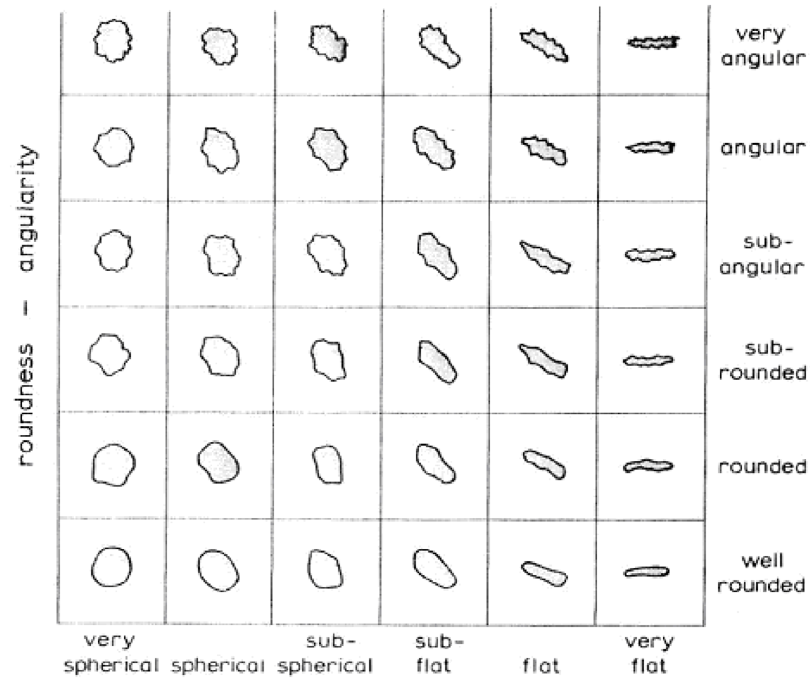
- Convexity

$$\frac{Perimeter_{convexhull}}{Perimeter_{rock}} \text{ or } \frac{Area_{convexhull}}{Area_{rock}}$$



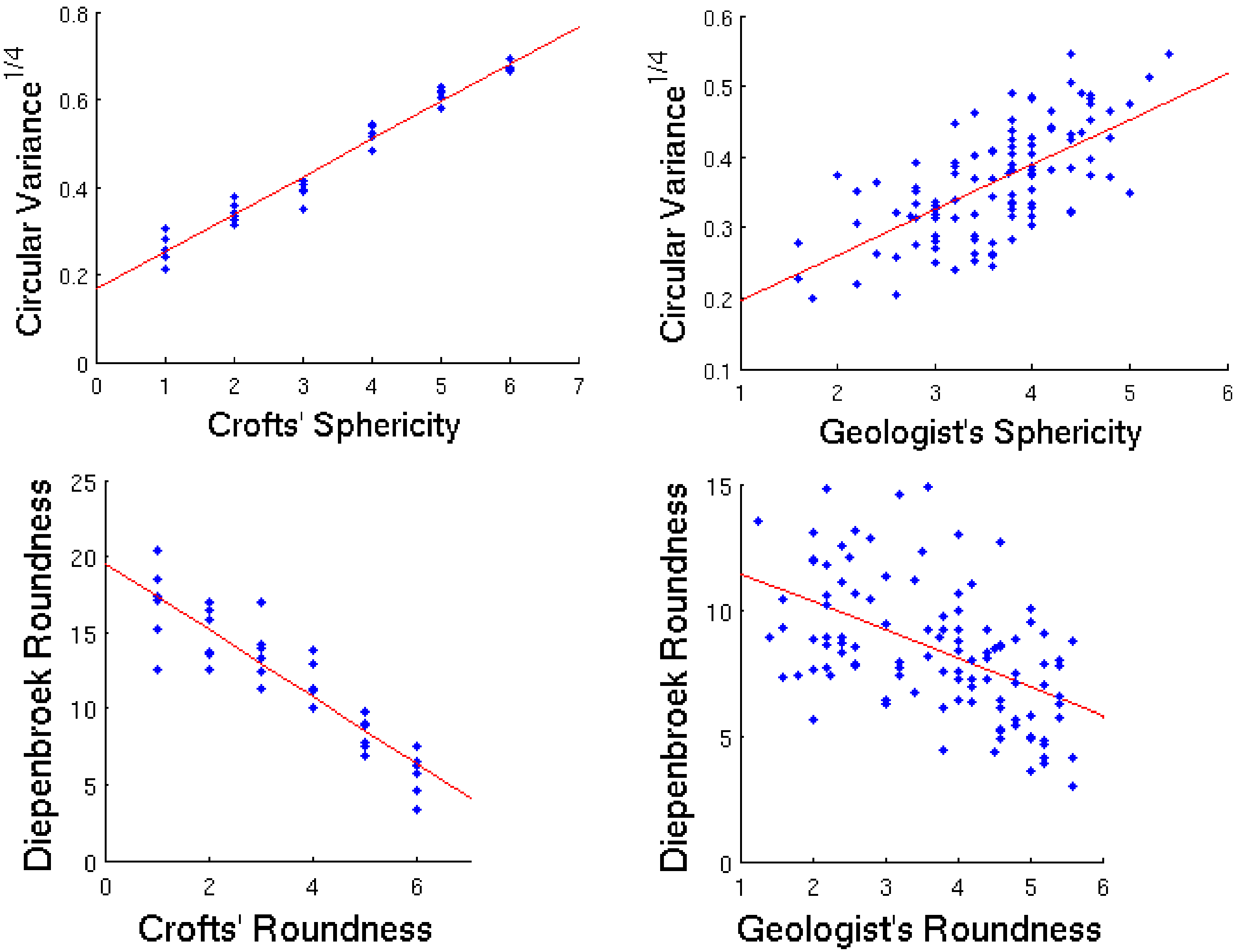
Experiments

- Purpose: determine accuracy of sphericity and roundness metrics
  - Correlation coefficient between computed metric and ground truth measures quality of linear fit
- Data sets:
  - Crofts' chart
  - Measurement by geologists from image
  - Measurement by geologists from physical rock



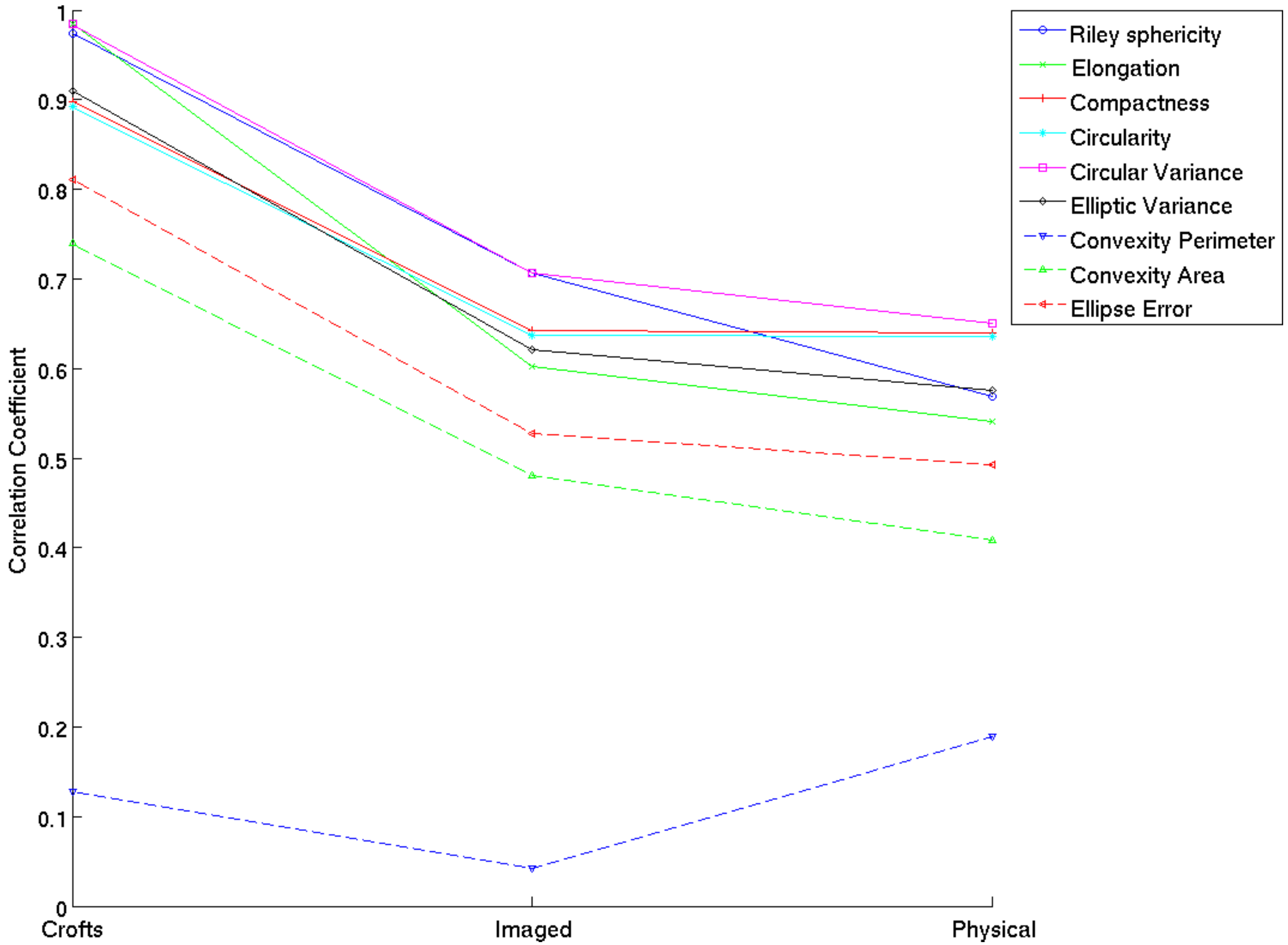
Results

- Plot computed measure vs. geologist's measure



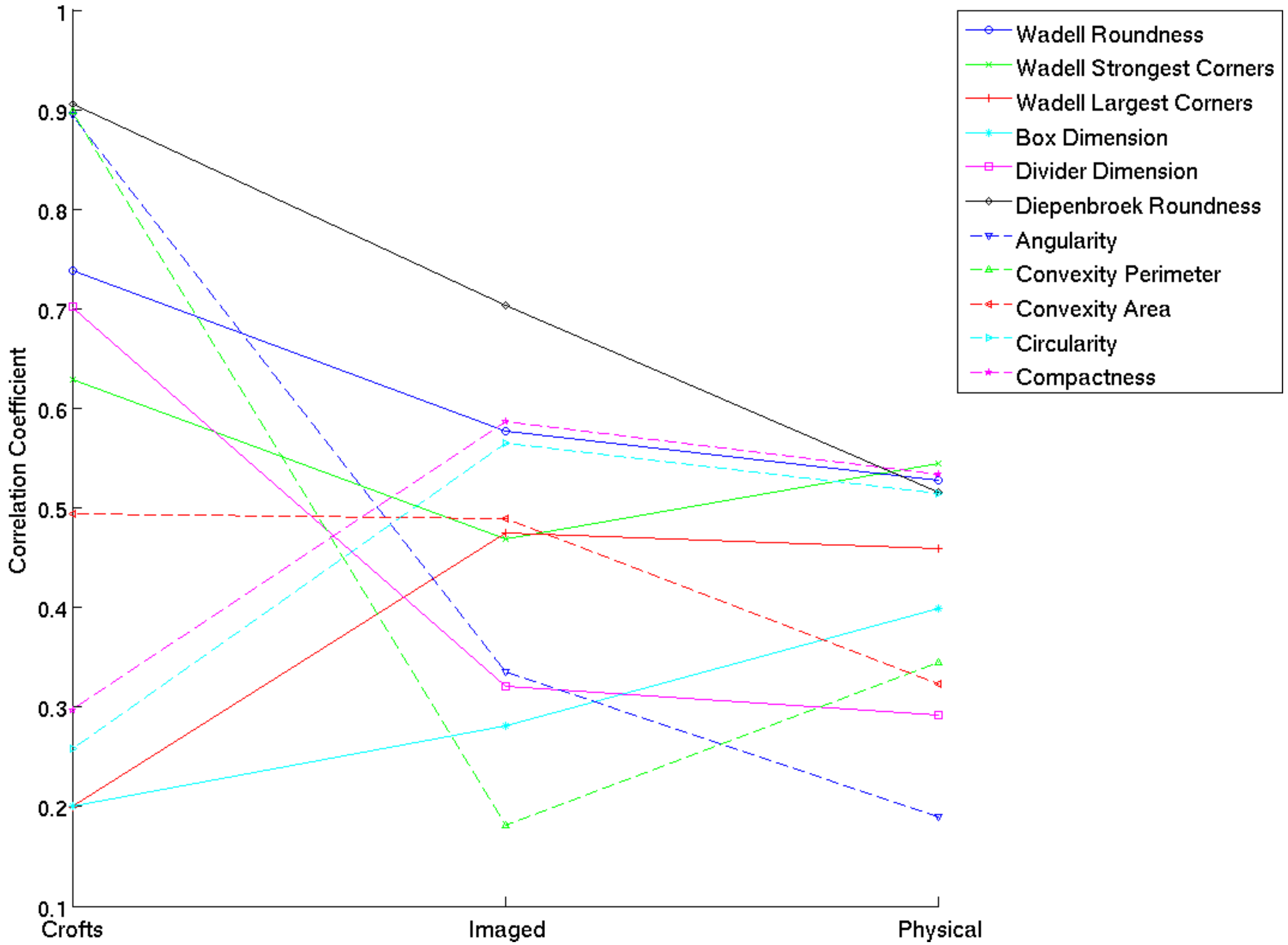
Sphericity Accuracy

- Compute correlation coefficients:



Roundness Accuracy

- Compute correlation coefficients:



Outline

- Introduction
- Feature Extraction
- Rock Detection and Segmentation
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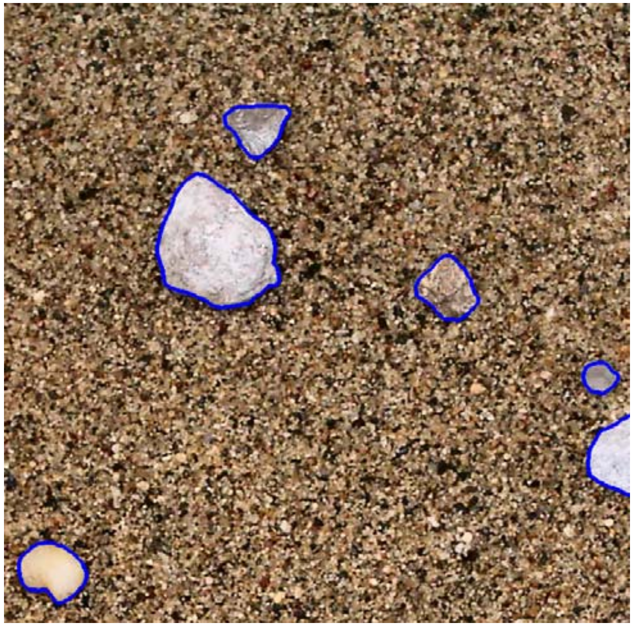
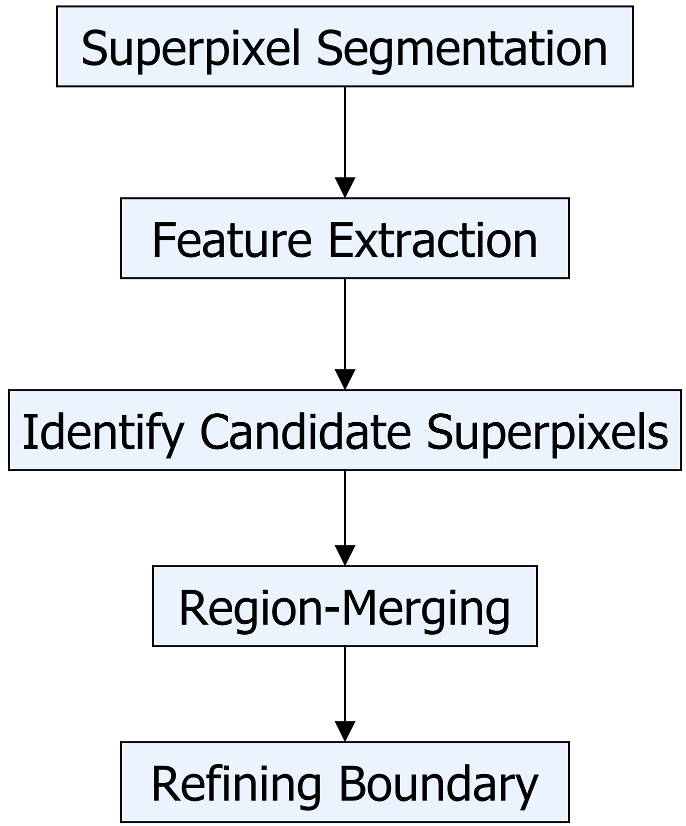
Rock Detection & Segmentation

- Detect rocks with an accurately localized boundary
- Use hand-segmentation for training
- Two-step, multi-scale approach:
  - Superpixel segmentation
  - Region-merging

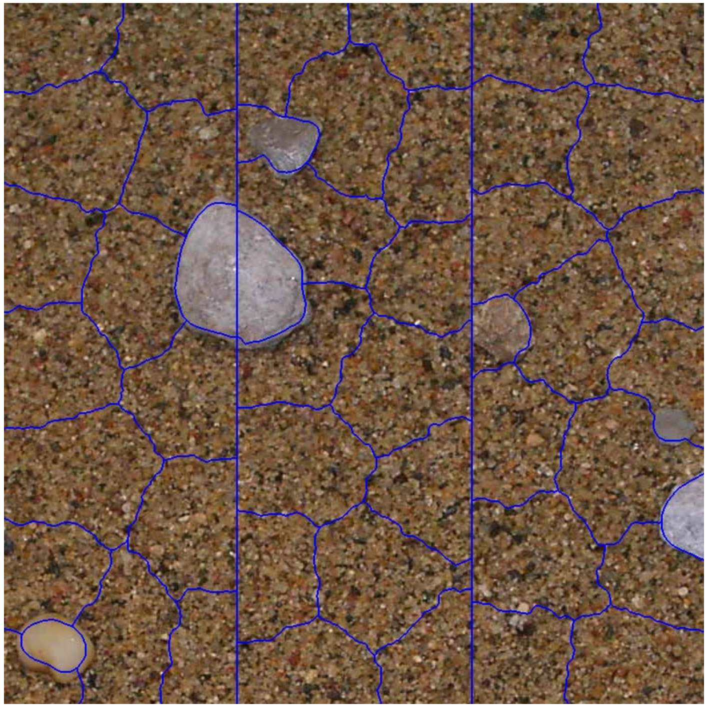


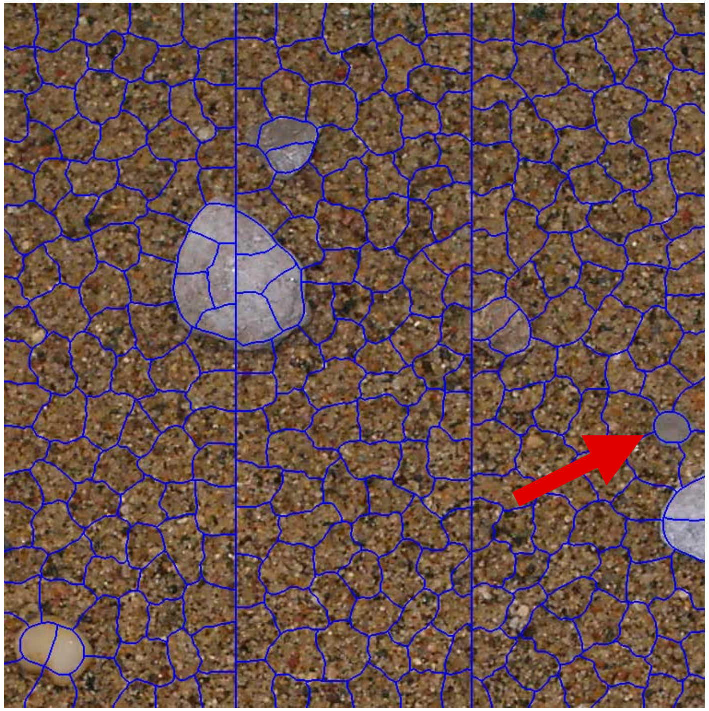
Rock Detection & Segmentation



Superpixel Segmentation

- Normalized-cuts + boundary detector
  (Greg Mori, Simon Fraser University)
- Perform at 4 scales





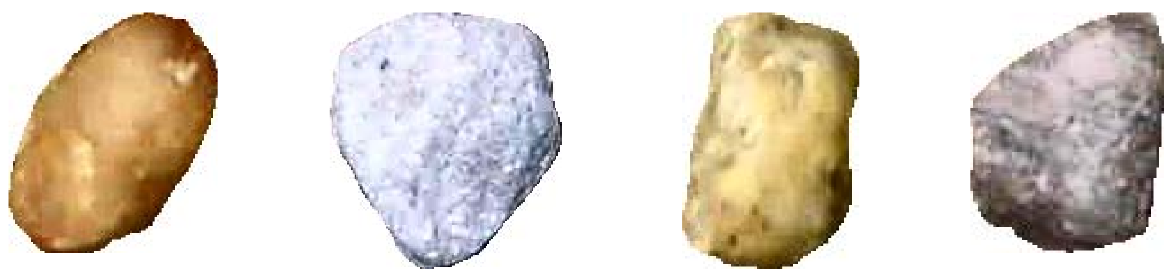
Region Features

- Features that can distinguish rock regions from non-rock regions
- As previously described:
  - Intensity, Color
  - Texture
  - Shape
- Also compute difference between superpixel and context region

Region Features

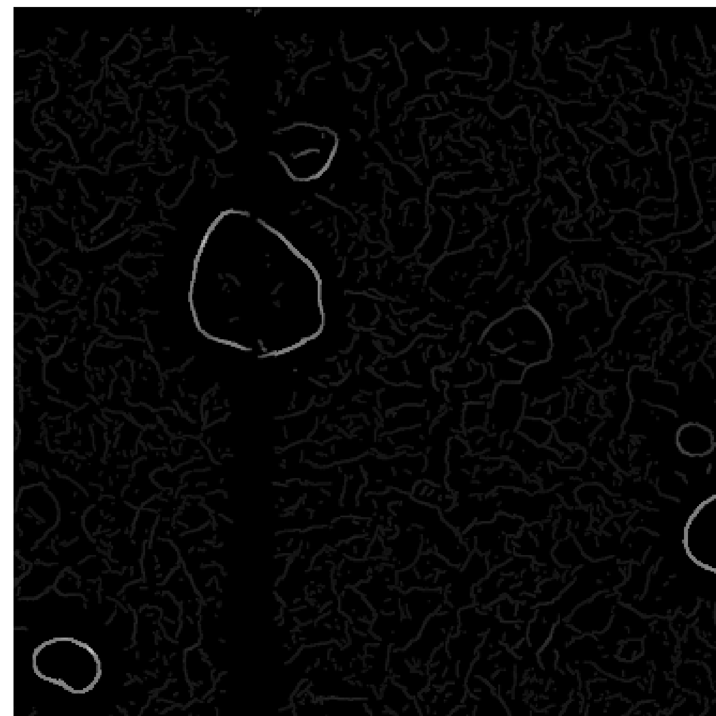
- Shading
  - – Linear gradient due to directional lighting

  - – Darker near boundary/highlight in center
    - Quadratic gradient
    - Mean intensity near center – mean intensity near boundary



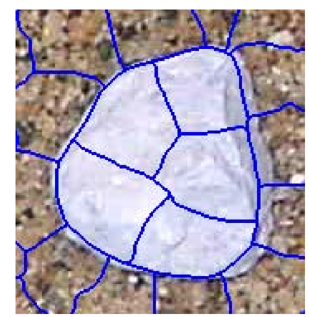
Region Features

- Boundary contours
  - Natural image boundary detection
    (Martin, Fowlkes, Malik, UC Berkeley)



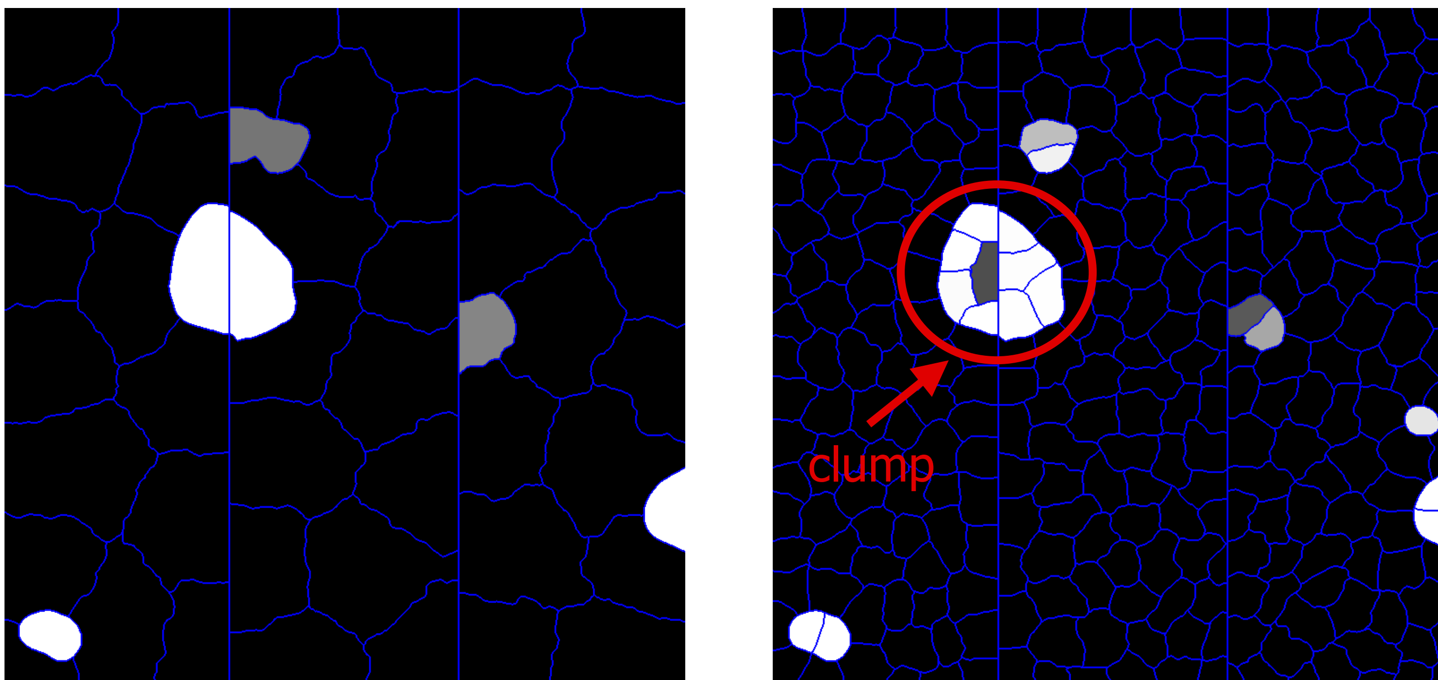
Detection: Train Classifiers

- On all known rocks and superpixels in training images:
  - – Compute intensity, color, texture, shape, shading, boundary contour features
- Train two SVM classifiers:
  - – Simple (intensity, color, texture features)
    - Applicable to parts of rocks
  - – Powerful (all features)
    - Only applicable to full rocks



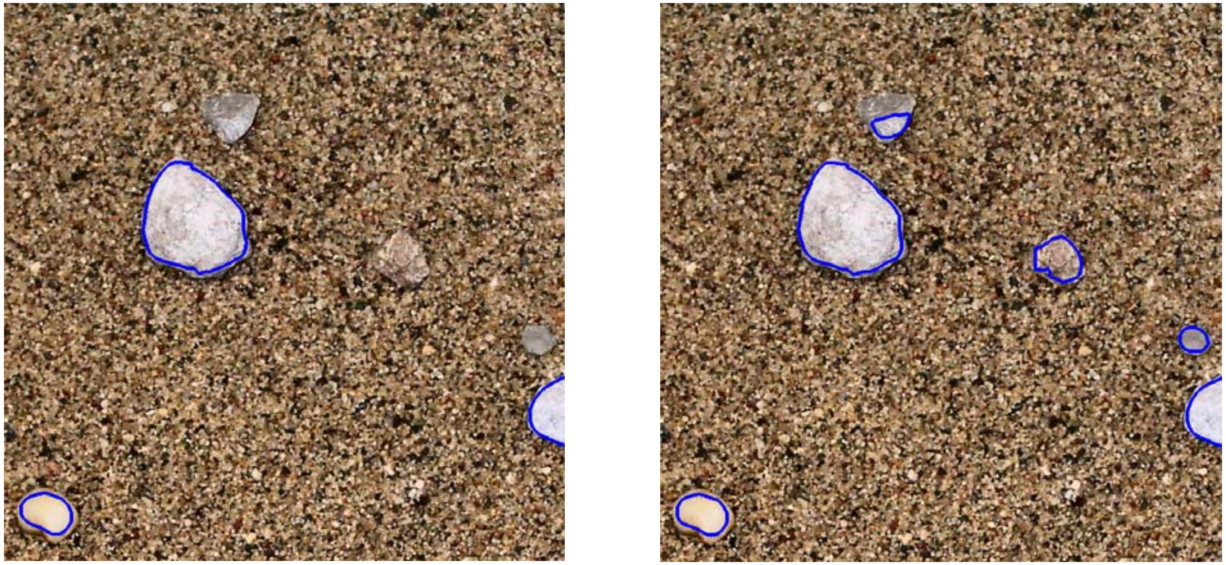
Detection: Candidate Regions

- On test image, apply *simple classifier* to all superpixels at all scales
- Identify most likely rock regions



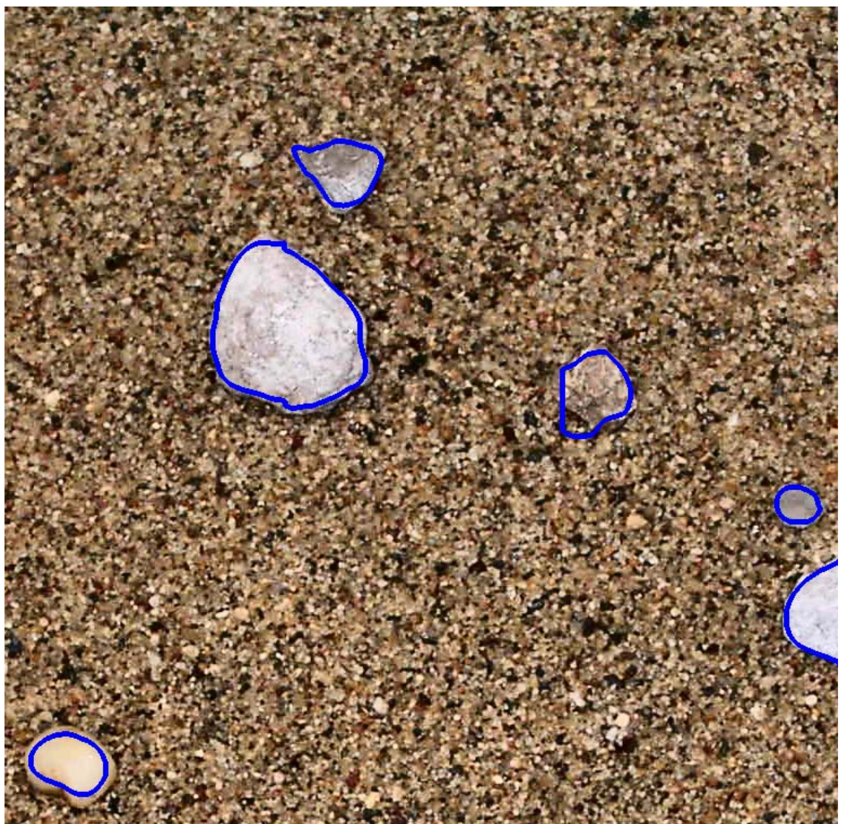
Detection: Region-Merging

- For each clump (up to 10 superpixels):
  - Evaluate all features on all combinations of superpixels
  - Apply *powerful classifier* to each combination to identify most likely rocks



Detection: Refine Boundary

- Resolve overlapping rocks across scales by taking the most probable one

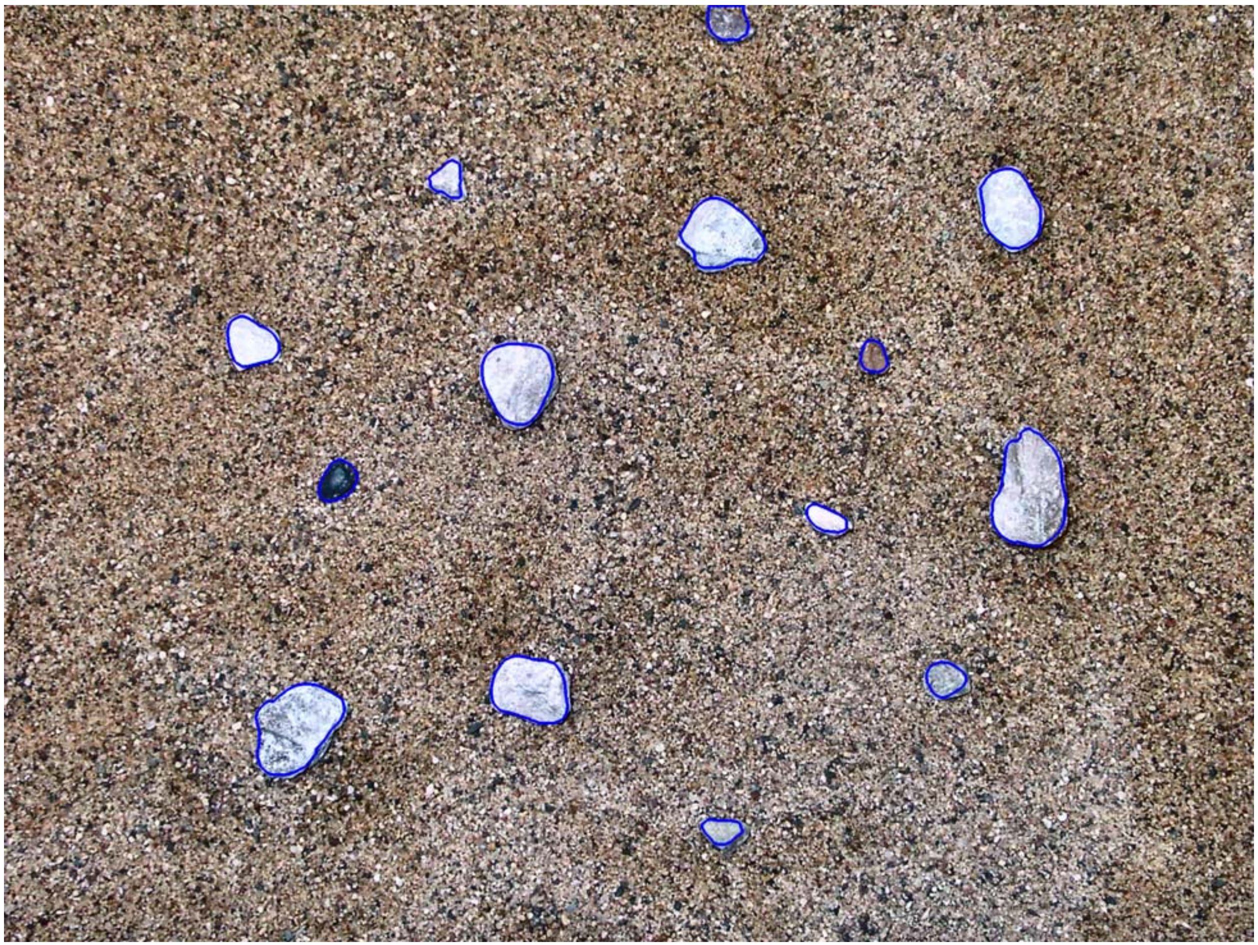


Experiments

- Purpose: determine performance of rock detection and segmentation
  - – Region labeling accuracy
  - – Rock detection accuracy
  - – Boundary localization accuracy
- Data set:
  - – 8 images
  - – Approximately 15 rocks in each
  - – Hand labeled for ground truth

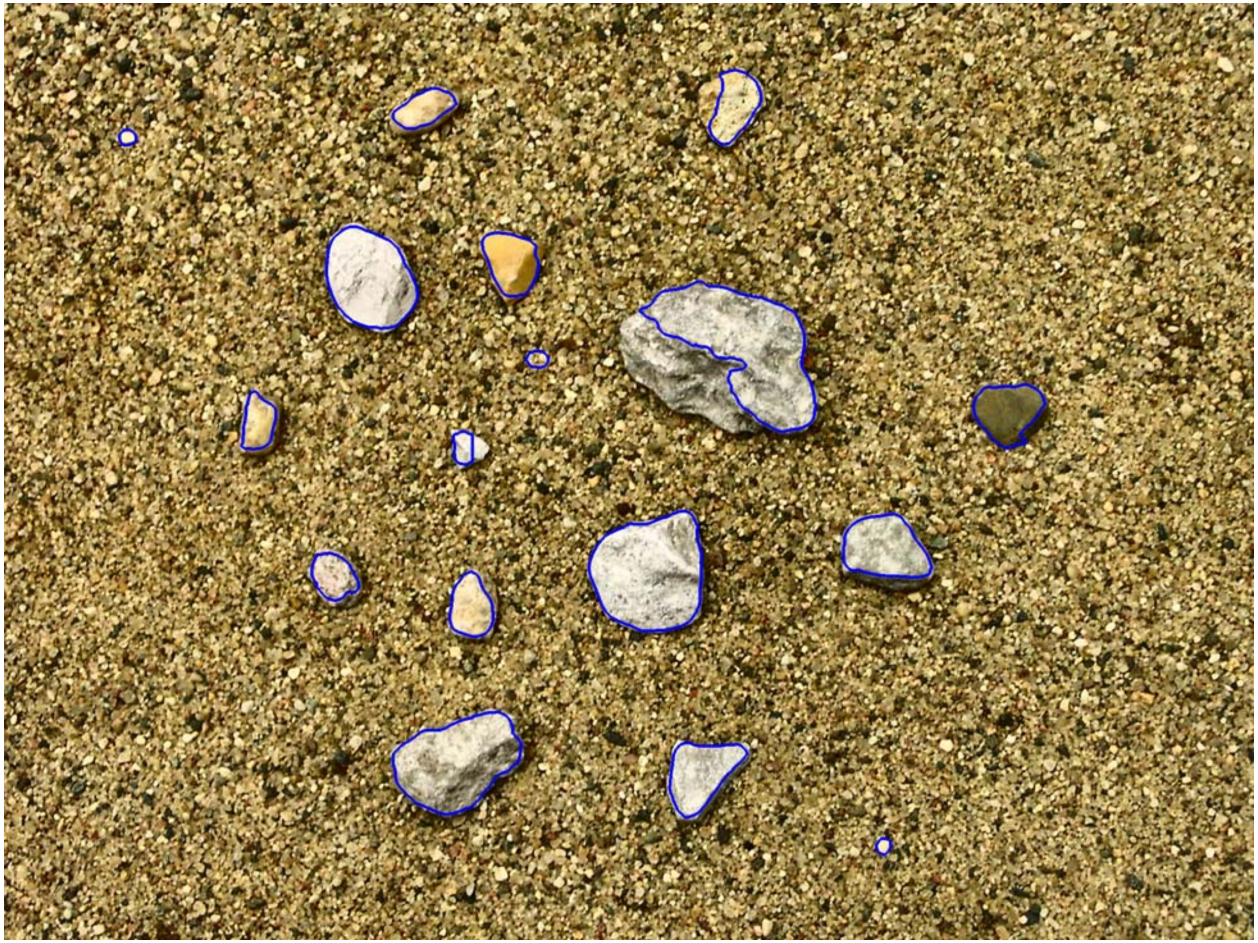
Results

- Example results:



Results

- Example results:



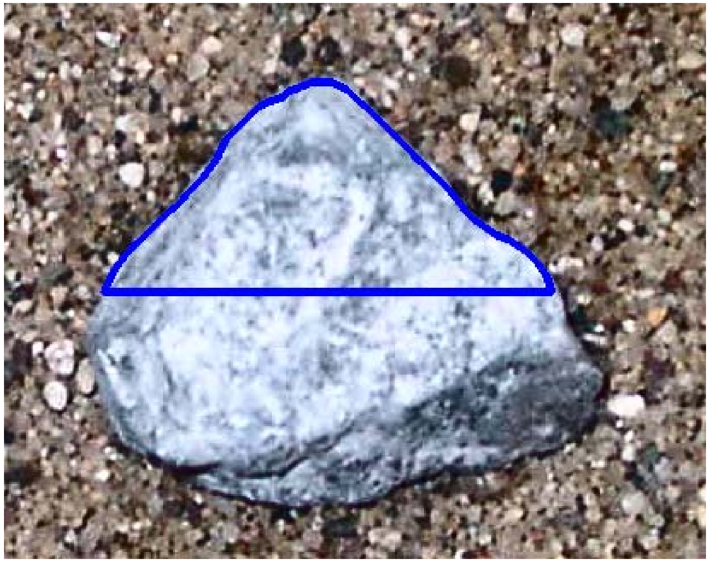
Region Labeling Accuracy

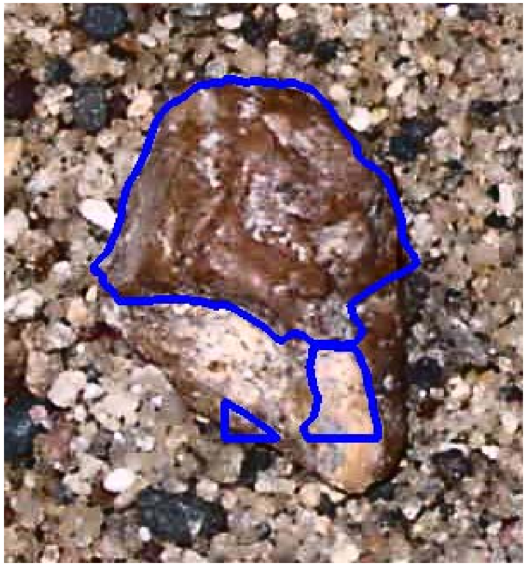
- Cross-validation accuracy of rock vs. non-rock classifier

Feature Set	Accuracy (%)
All	**99.6**
Intensity/Color	**98.9**
Texture	**99.1**
Shape	98.4
Shading	97.9
Boundary Contours	98.0

Rock Detection Accuracy

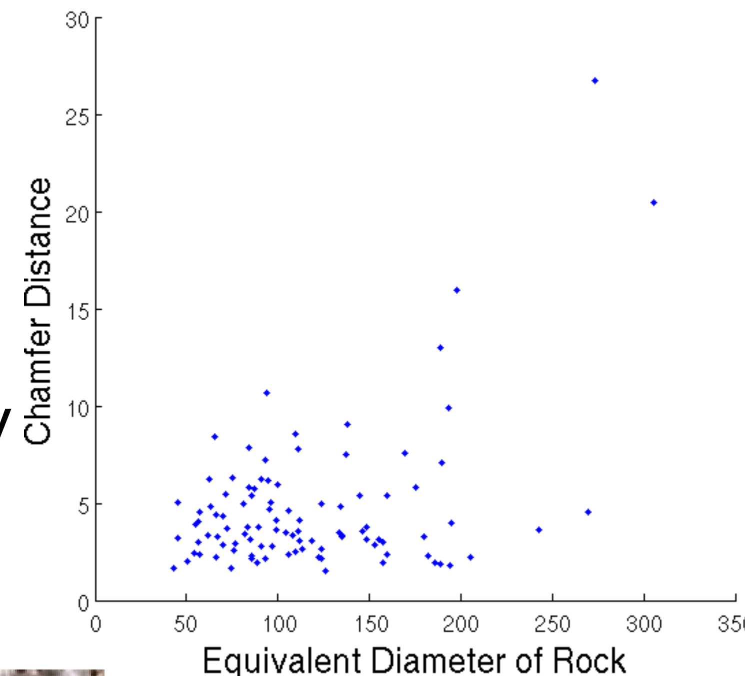
- Only 1 rock missed completely
- Average precision: 85.9%
- Average recall: 87.7%
- Errors:





Boundary Localization Accuracy

- Measured with Chamfer distance:
  - Average distance from detected boundary point to ground truth boundary point
- Errors:



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Geologic Classification

- Igneous
- Metamorphic
- Sedimentary: chemical, clastic

chemical

clastic

Geologic Classification

- Compute feature vector on all rocks:
  - Albedo, color, texture, shape
- Train k-NN or SVM classifier on subset of rocks
- Apply classifier to remaining rocks

Experiments

- Purpose: determine classification accuracy
  - Compare classifiers and feature sets
- Data set:
  - Geologist's classification of 100 rocks
  - Select a subset of these with 19 rocks per class: chemical, clastic
- Leave-out-one-rock cross-validation
- Average results over multiple trials

Results

- Compare classifiers:

Classifier	Classification Accuracy (%)
1-NN	82.4
2-NN	**83.4**
3-NN	82.9
4-NN	82.1
5-NN	78.9
6-NN	77.6
SVM	**86.3**

Results

- Compare features:

Feature Set	Classification Accuracy (%)
All	86.3
Intensity/Color	86.1
Texture	76.3
Shape	70.0

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Summary

- Features:
  - CIELAB histograms most successful color measure
  - Texton approach with MR8 filter bank most useful for texture
  - Accurate automated measures found for sphericity and roundness (circular variance and Diepenbroek roundness)
- Rock detection and segmentation:
  - Accurately detected and localized most rocks
- Geologic classification:
  - Current features shown successful
  - Feature CIELAB histograms most useful

Contributions

- Automated sphericity and roundness measures for geologists
- Multi-scale rock detection with accurate boundary localization
- First attempt at geologic classification using more than just texture

Future Work

- Features:
  - Better color balancing or calibration needed
  - Other possible filter banks to try in texton approach
  - More possibilities for Fourier analysis of shape
  - Effect of viewpoint on shape
- Rock detection and segmentation:
  - Other possible superpixel segmentation algorithms
  - More difficult data set desirable (overlapping rocks, directional lighting)
- Geologic classification:
  - Effect of boundary localization errors on classification
  - Larger and more diverse data set required

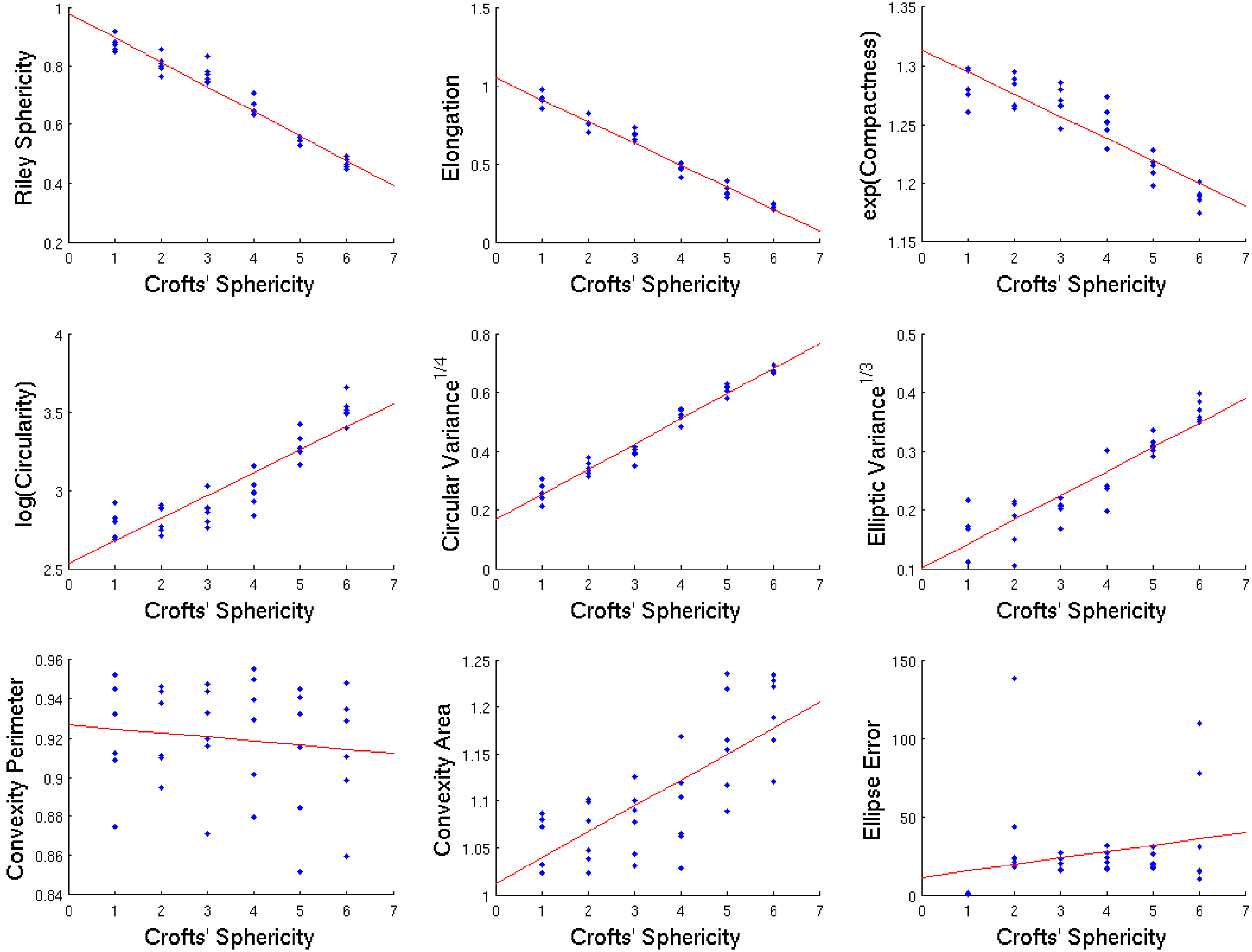
Acknowledgments

- Master's committee: David Wettergreen, Alyosha Efros, David Thompson
- Geb Thomas and Ingrid Ukstins Peate at the University of Iowa for providing the data set

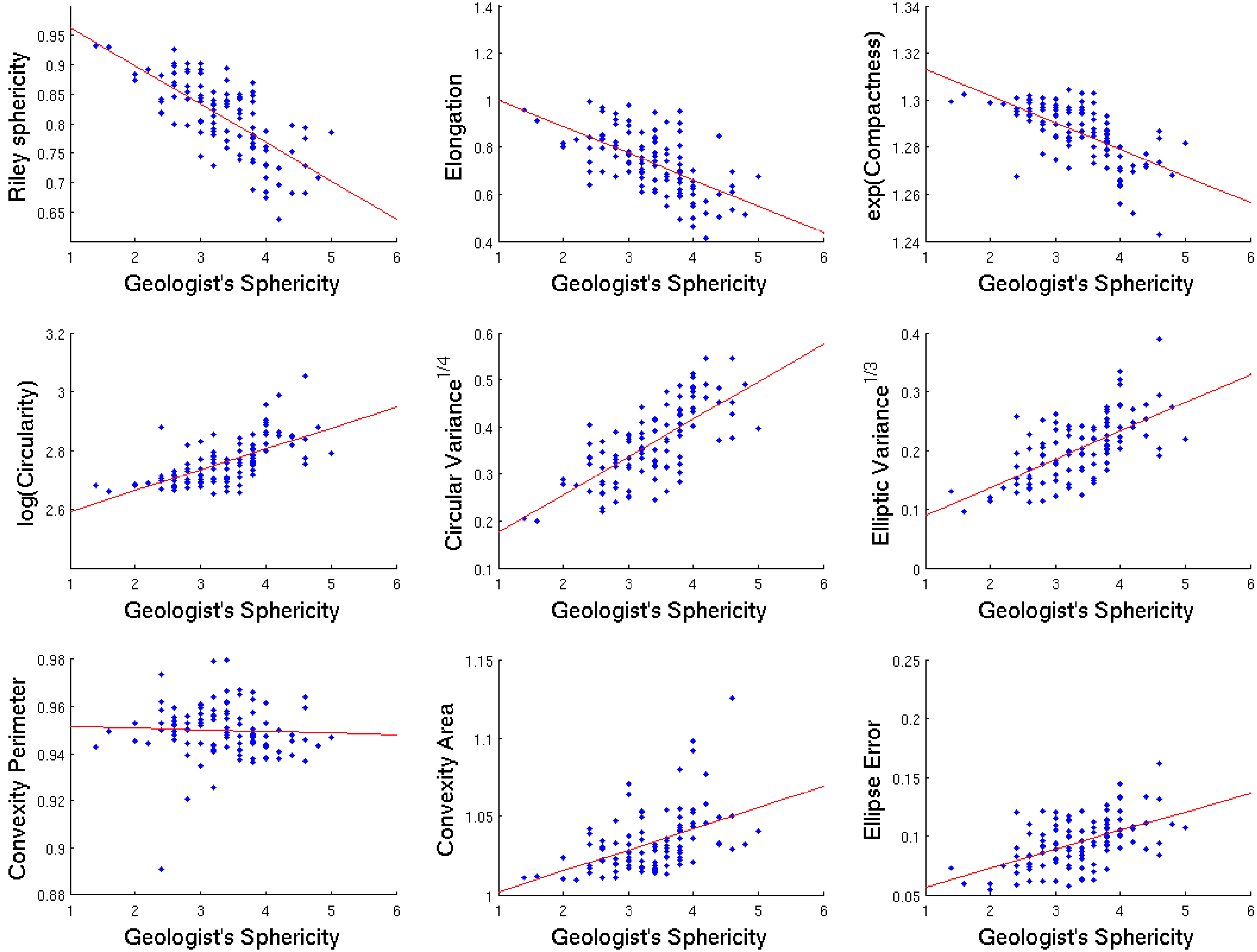
Questions?

Extra Slides

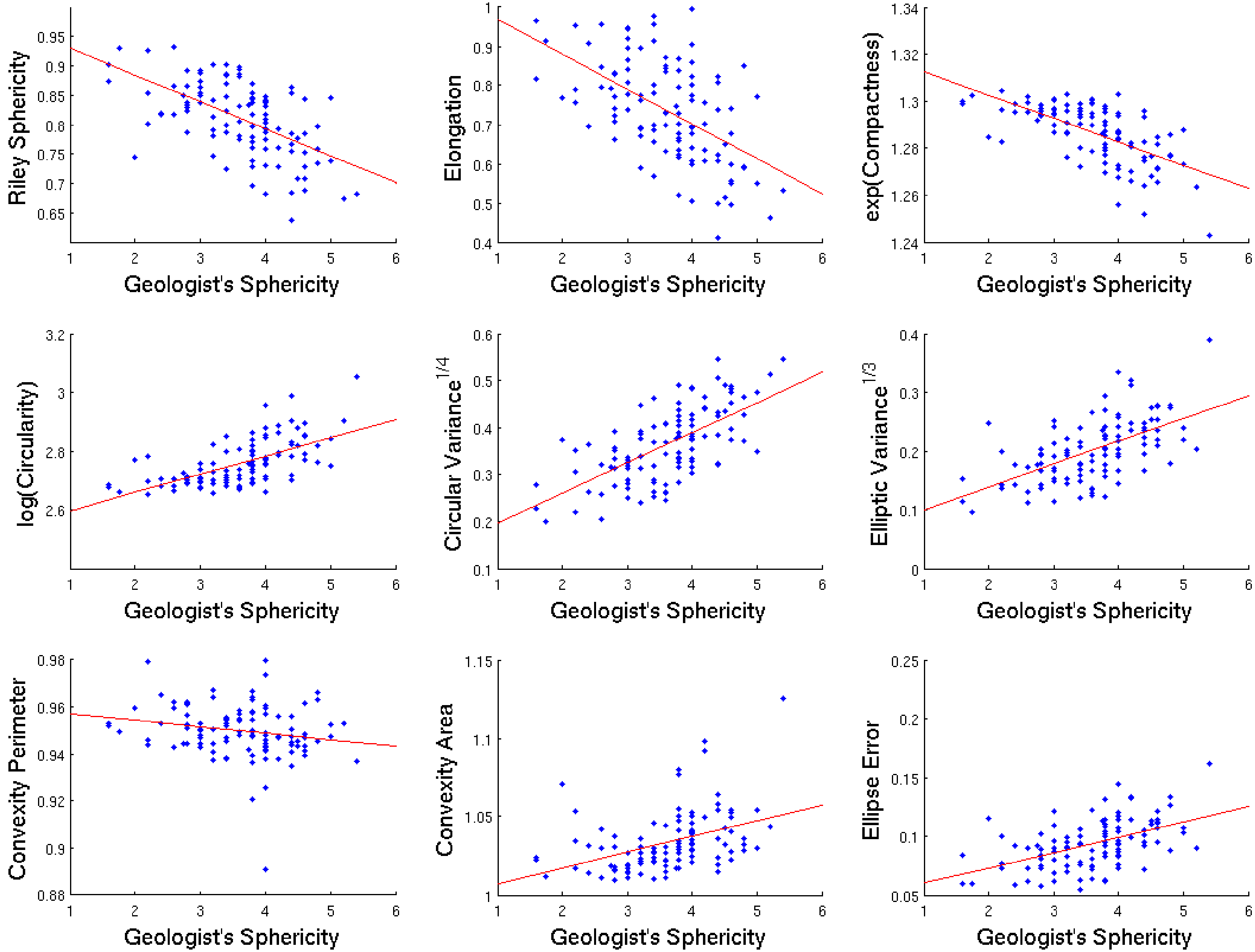
Crofts' Sphericity



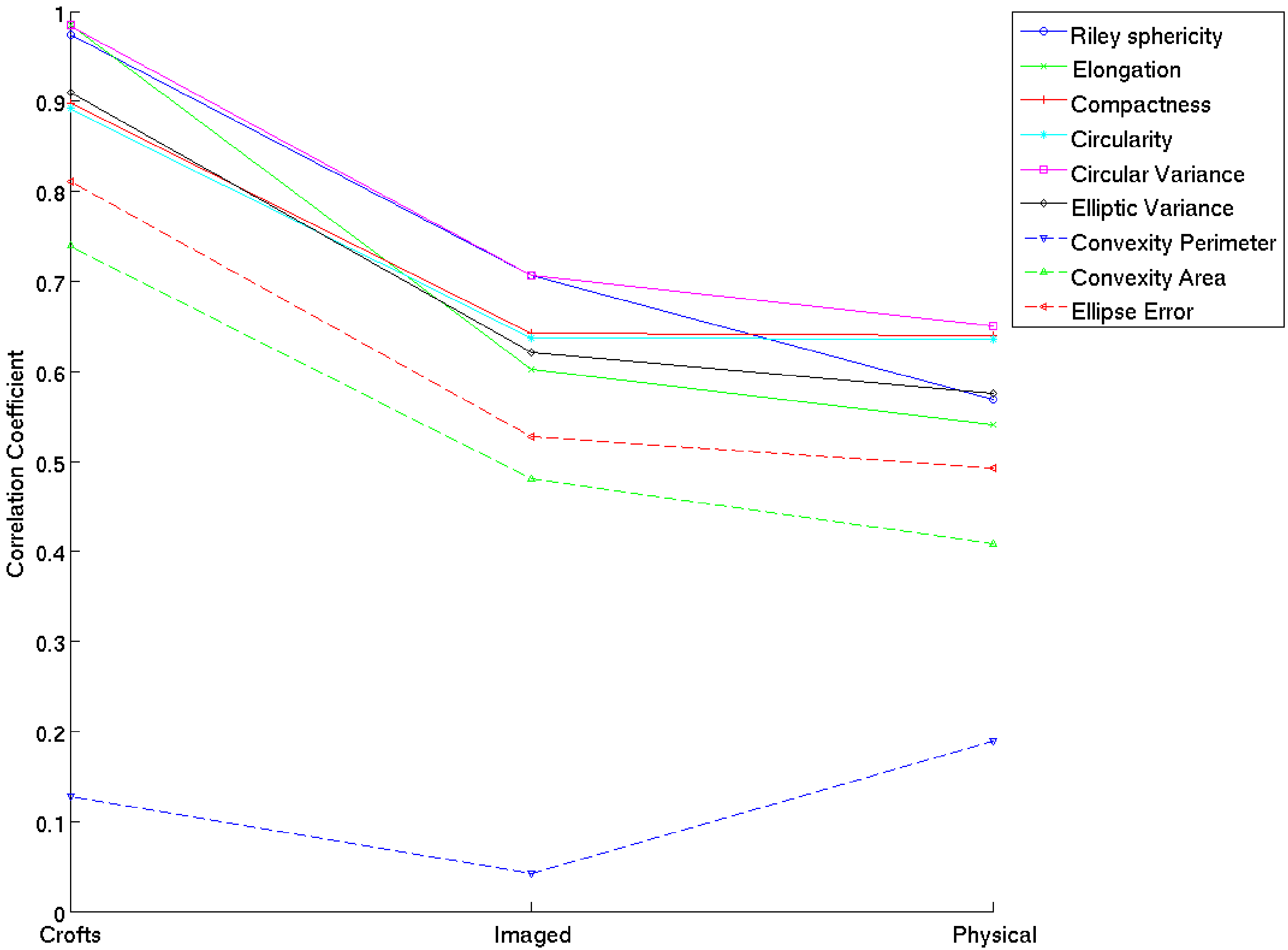
Geologists' Sphericity (Imaged)



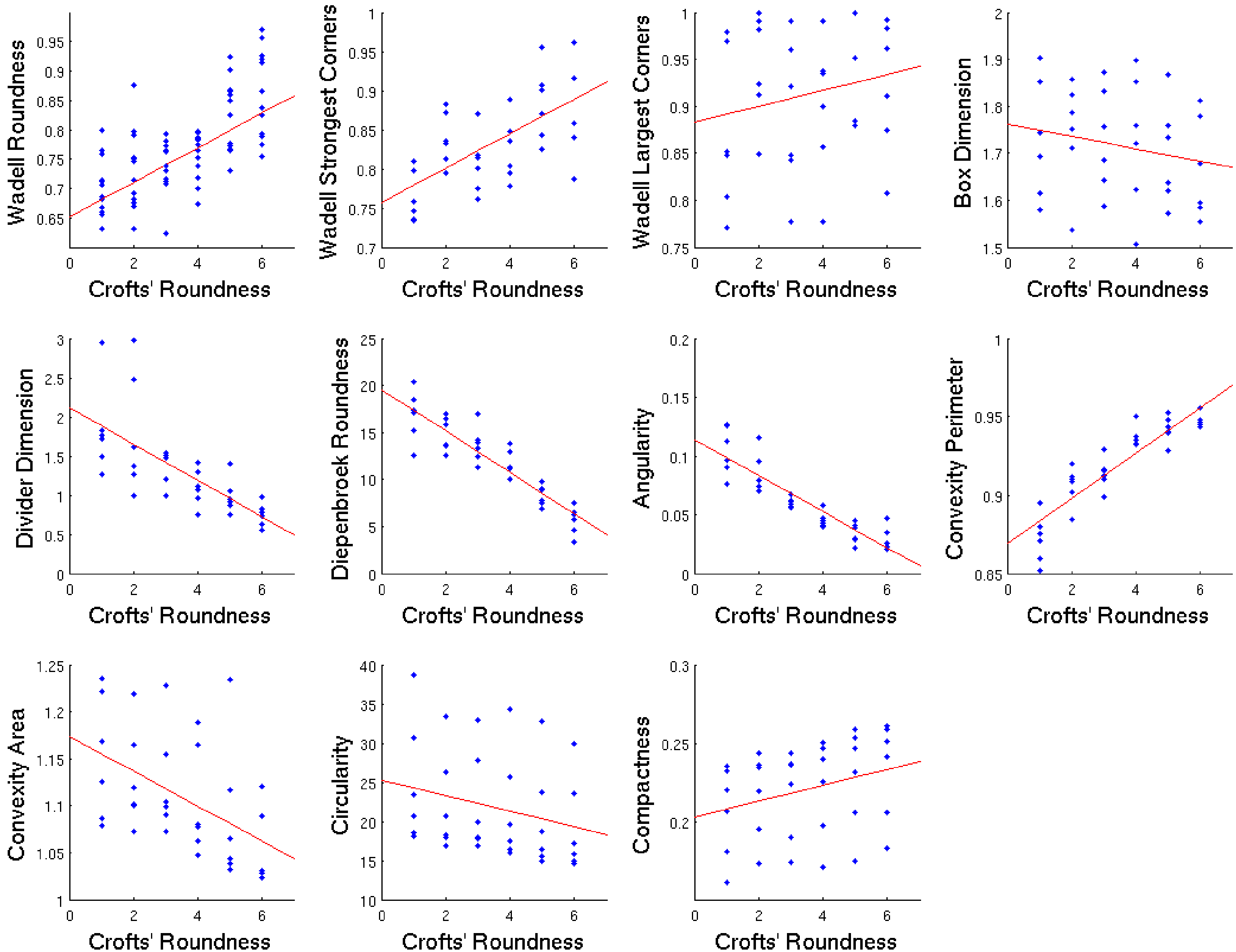
Geologists' Sphericity (Physical)



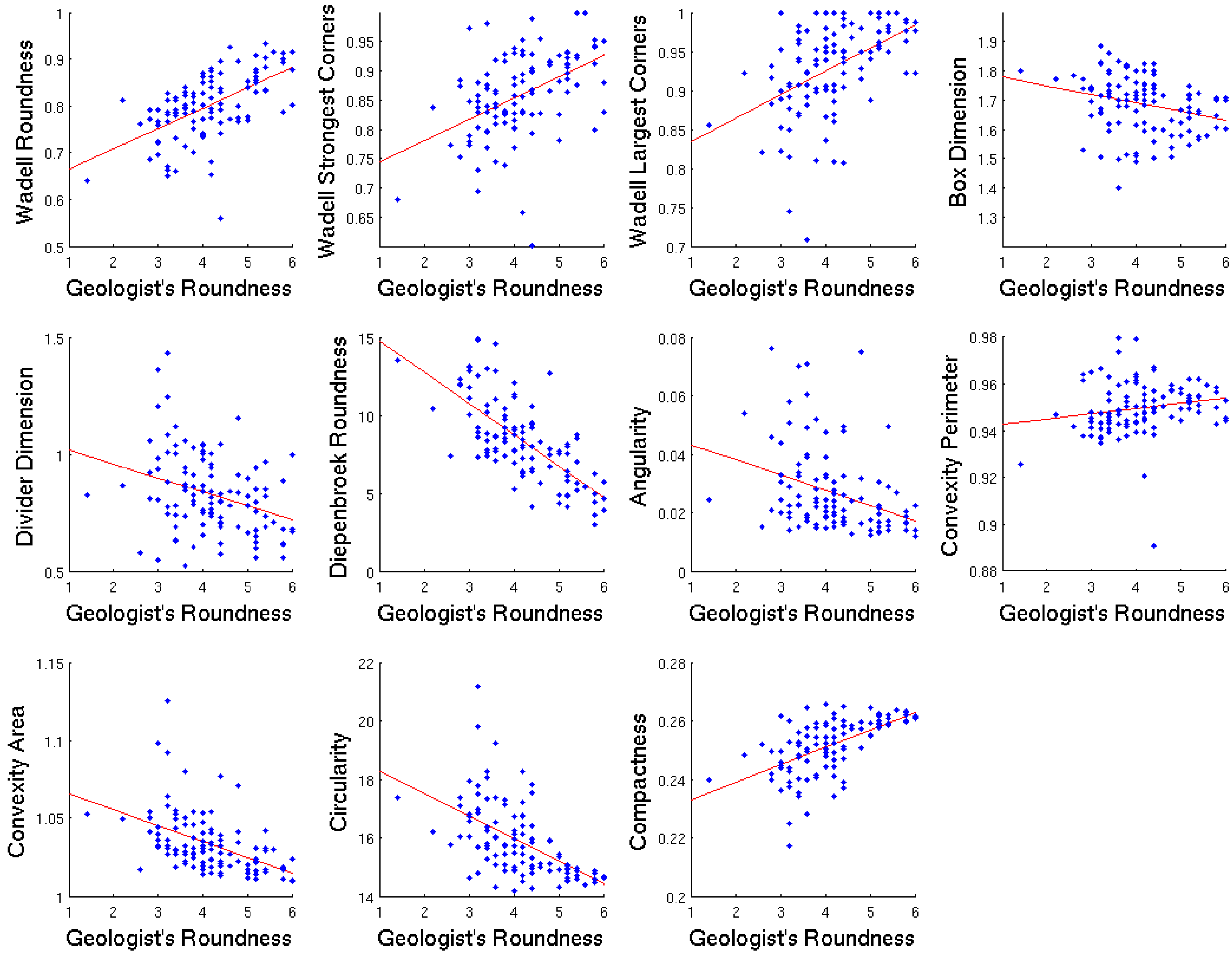
Sphericity Correlation Coefficient



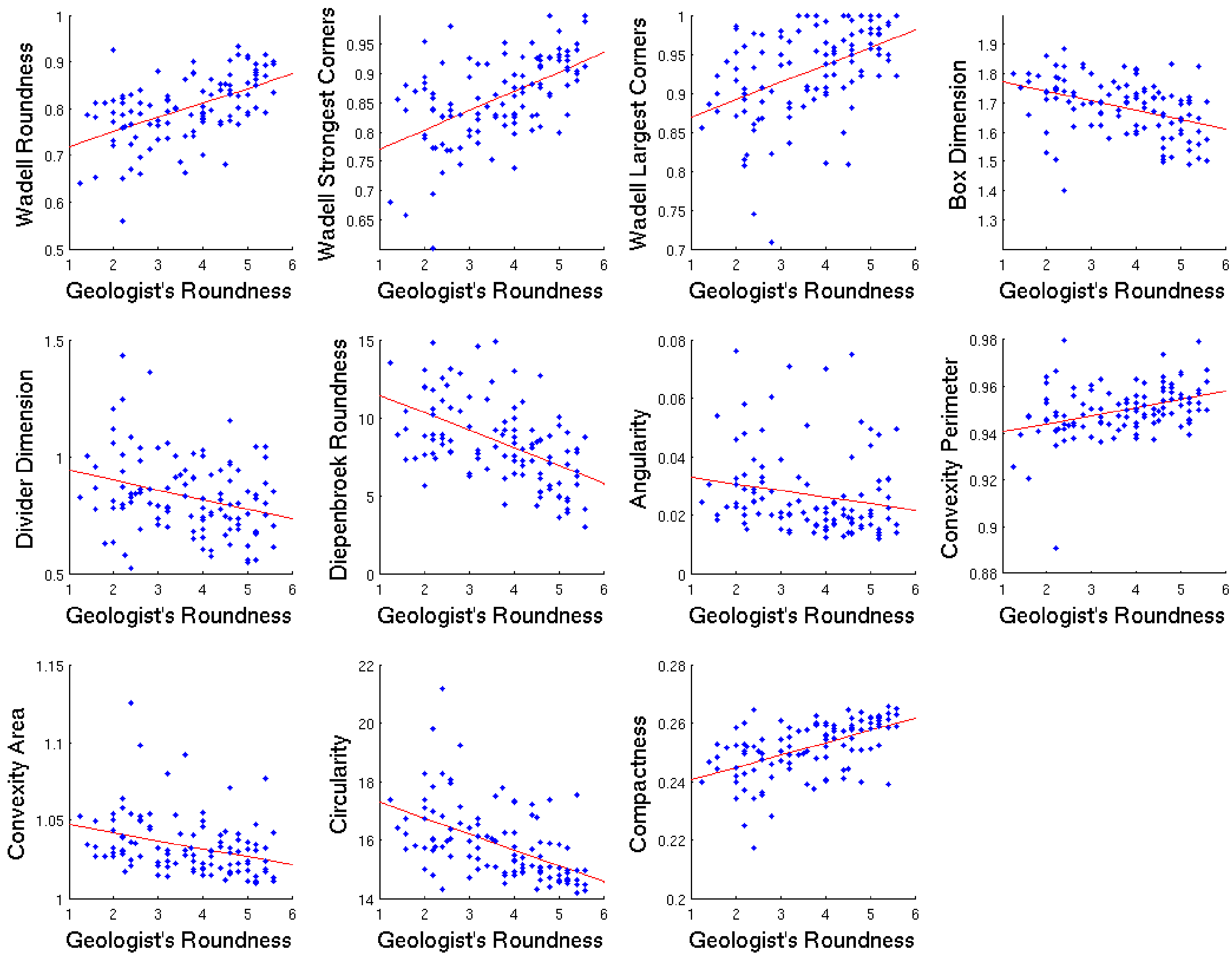
Crofts’ Roundness



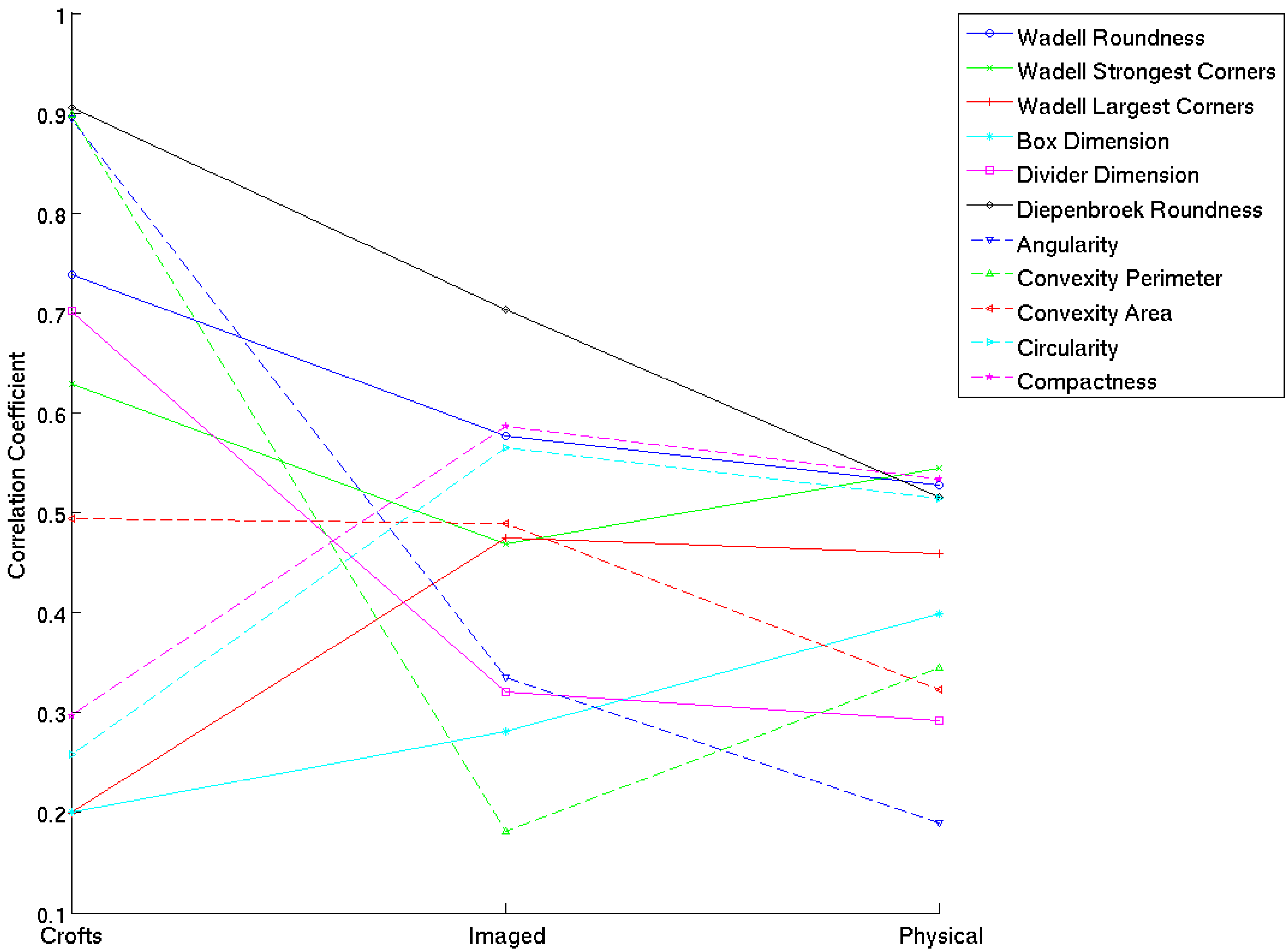
Geologists’ Roundness (Imaged)



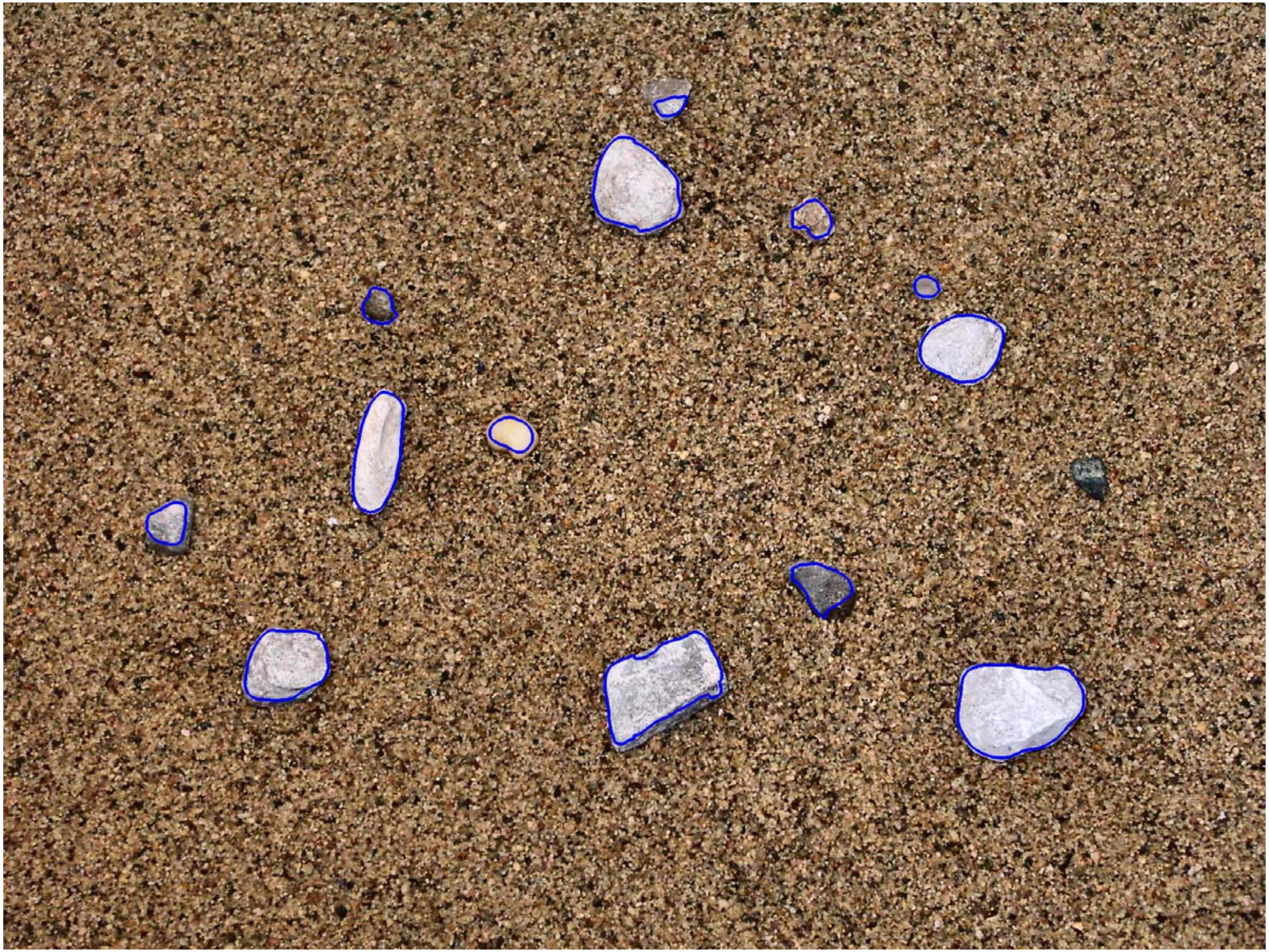
Geologists' Roundness (Physical)



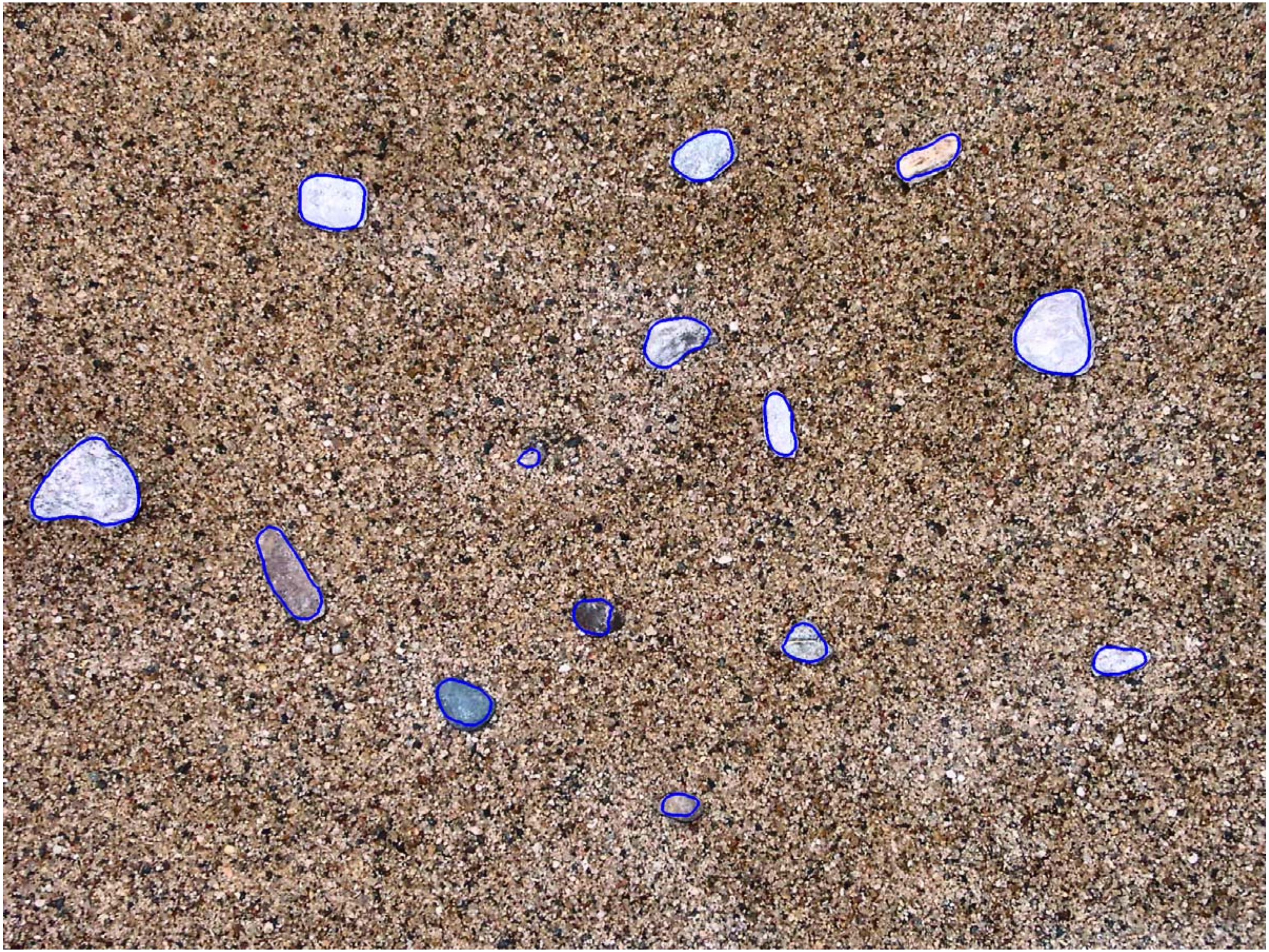
Roundness Correlation Coefficient



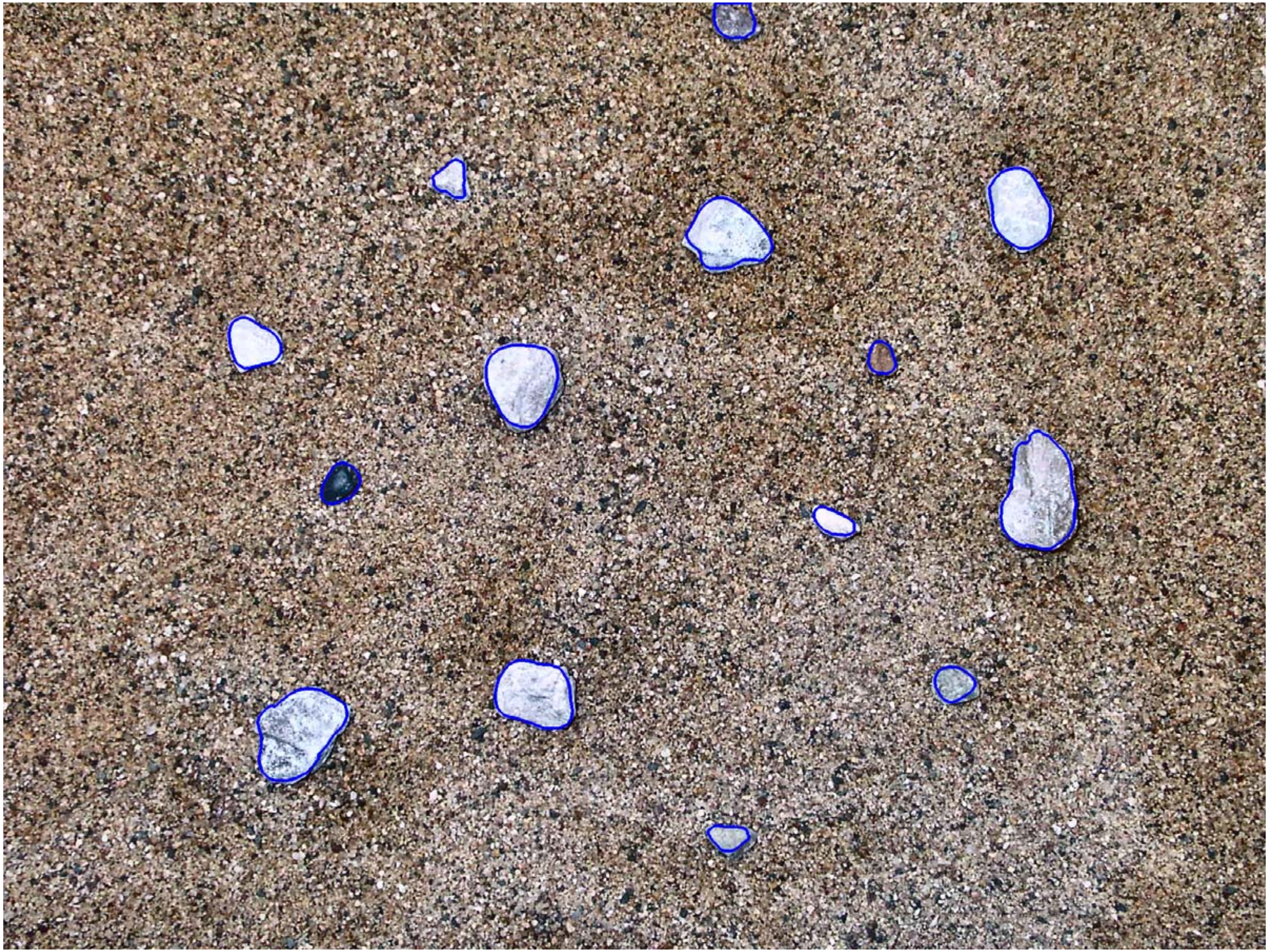
Detection: Image 1



Detection: Image 2



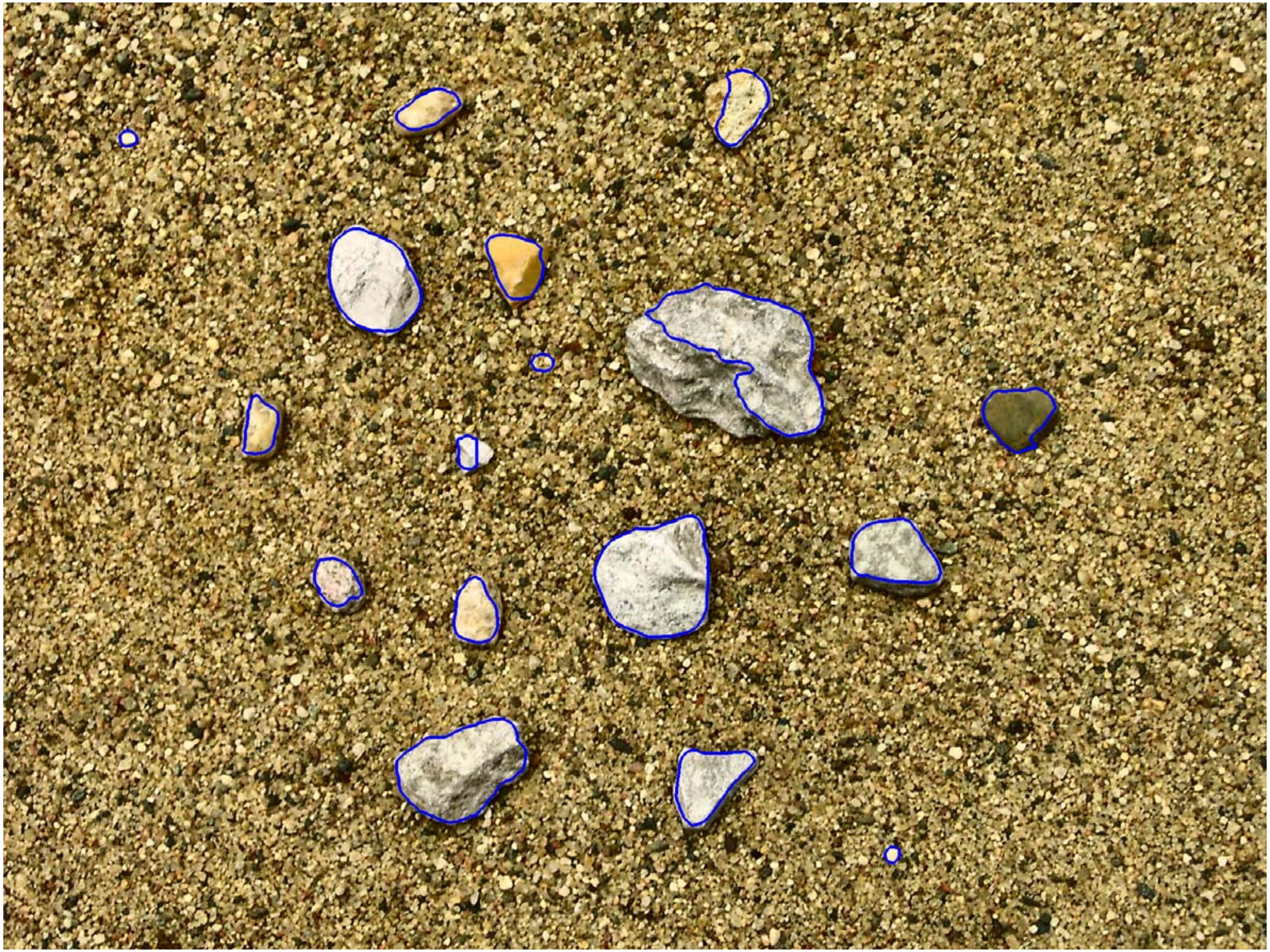
Detection: Image 3



Detection: Image 4

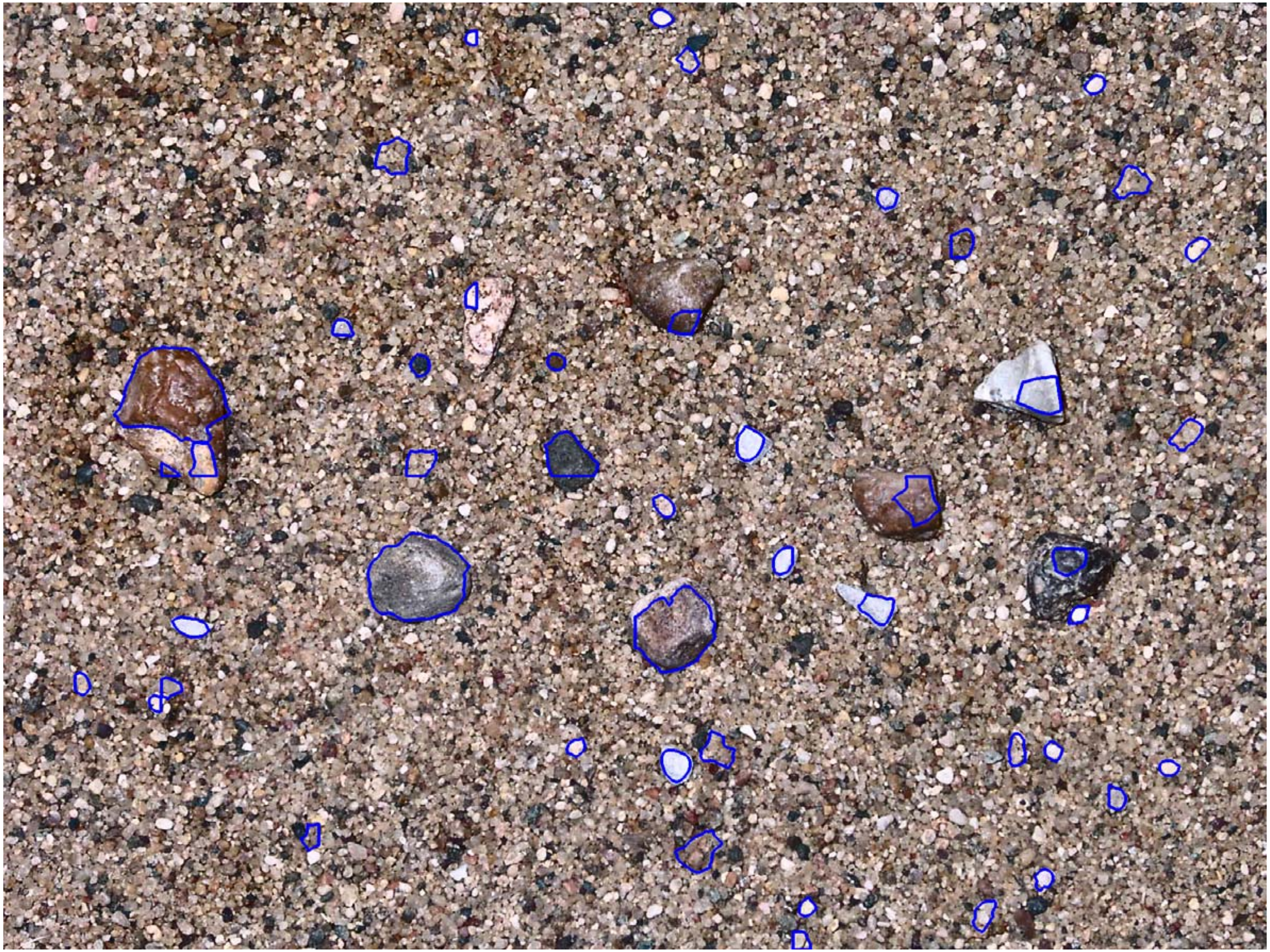
Detection: Image 5

Detection: Image 6



Detection: Image 7

Detection: Image 8



Region Labeling Accuracy

Feature Set	Region Labeling Accuracy (%)
All	99.6
Intensity/Color	98.9
Intensity	97.4
Mean	96.7
Variance	94.9
Mean Difference	96.6
Variance Difference	94.3
Histogram	97.4
Histogram Difference χ^2	96.3
Histogram Difference Euclidean	95.3
RGB Color	97.5
HSV Color	98.5
CIELab Color	98.9
Texture	99.1
Co-occurrence Statistics	98.3
Contrast	98.8
Correlation	95.7
Energy	94.8
Homogeneity	97.3
Textons	99.0
Texton Histogram	99.0
Texton Histogram Difference χ^2	92.7
Texton Histogram Difference Euclidean	94.3

Region Labeling Accuracy

Shading	97.9
Gradient x-y	94.9
Gradient Error	92.8
Quadratic Error	93.8
Inner/Outer Mean Difference	96.2
Boundary Contours	98.0
Shape	98.4
Angularity	98.9
Convex Perimeter	92.8
Convex Area	92.7
Circularity	92.7
Compactness	93.7
Elongation	92.8
Circular Variance	92.7
Elliptic Variance	92.7
Diepenbroek Roundness	96.5

Geologic Classification Accuracy

Feature	Classification Accuracy (%)
All	86.3
Intensity/Color	86.1
Intensity Mean and Variance	60.3
Intensity Histogram	56.1
RGB Mean and Variance	73.9
RGB Histogram	74.2
HSV Mean and Variance	67.9
HSV Histogram	73.4
CIELAB Mean and Variance	84.2
CIELAB Histogram	85.3
Texture	76.3
Fractal Dimension	58.9
Co-occurrence Statistics	58.4
Directionality Histogram	61.8
Textons Histogram (Gabor)	67.4
Texton Histogram (MR8)	79.5

Geologic Classification Accuracy

Shape	70.0
Riley Sphericity	41.8
Elongation	41.6
Ellipse Error	62.1
Circular Variance	36.3
Elliptic Variance	54.2
Wadell Roundness	75.5
Wadell Roundness (Strongest Corners)	78.2
Wadell Roundness (Largest Corners)	72.6
Angularity	48.7
Fractal Dimension (Box)	56.1
Fractal Dimension (Divider)	38.2
Diepenbroek Roundness	67.6
Compactness	50.8
Circularity	41.6
Convex Perimeter	35.2
Convex Area	44.7