Automatic Detection of Sub-Kilometer Craters in High Resolution Planetary Images

PI: Tomasz F. Stepinski, *Lunar and Planetary Institute*
Co –PI: Wei Ding, *University of Massachusetts Boston*

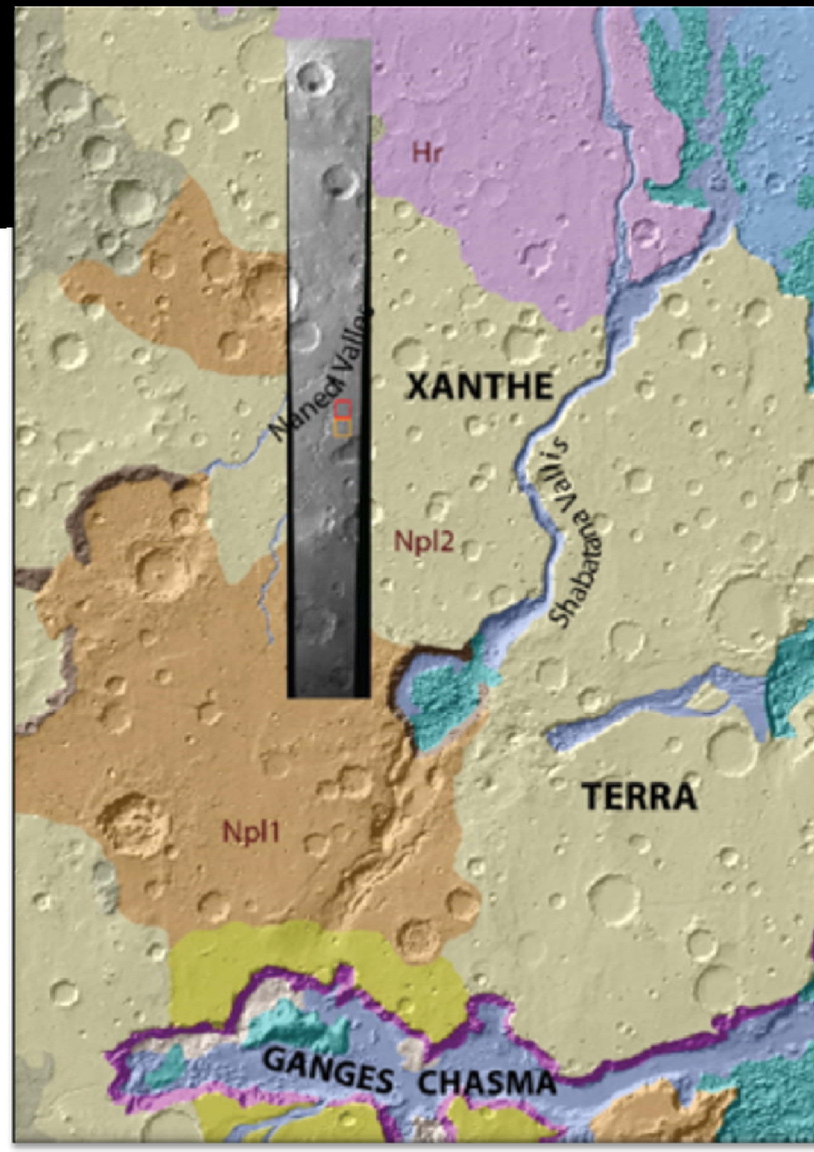
NASA Ames Research Center Conference CIDU/AISRP, October 14th-16th, 2009

Motivation

- Impact craters are among the most studied features on surfaces of planets
  - Measuring remotely the relative ages of geologic formations on planets
  - The nature of degradational processes
  - Regional variations in geologic material
  - Distribution of subsurface volatile
  - Etc.
- No comprehensive catalogs of smaller, sub-kilometer craters exist for any planetary body

Project objective

- To study and deliver a research-grade solution for automated detection of sub-kilometer size craters in high resolution planetary images.



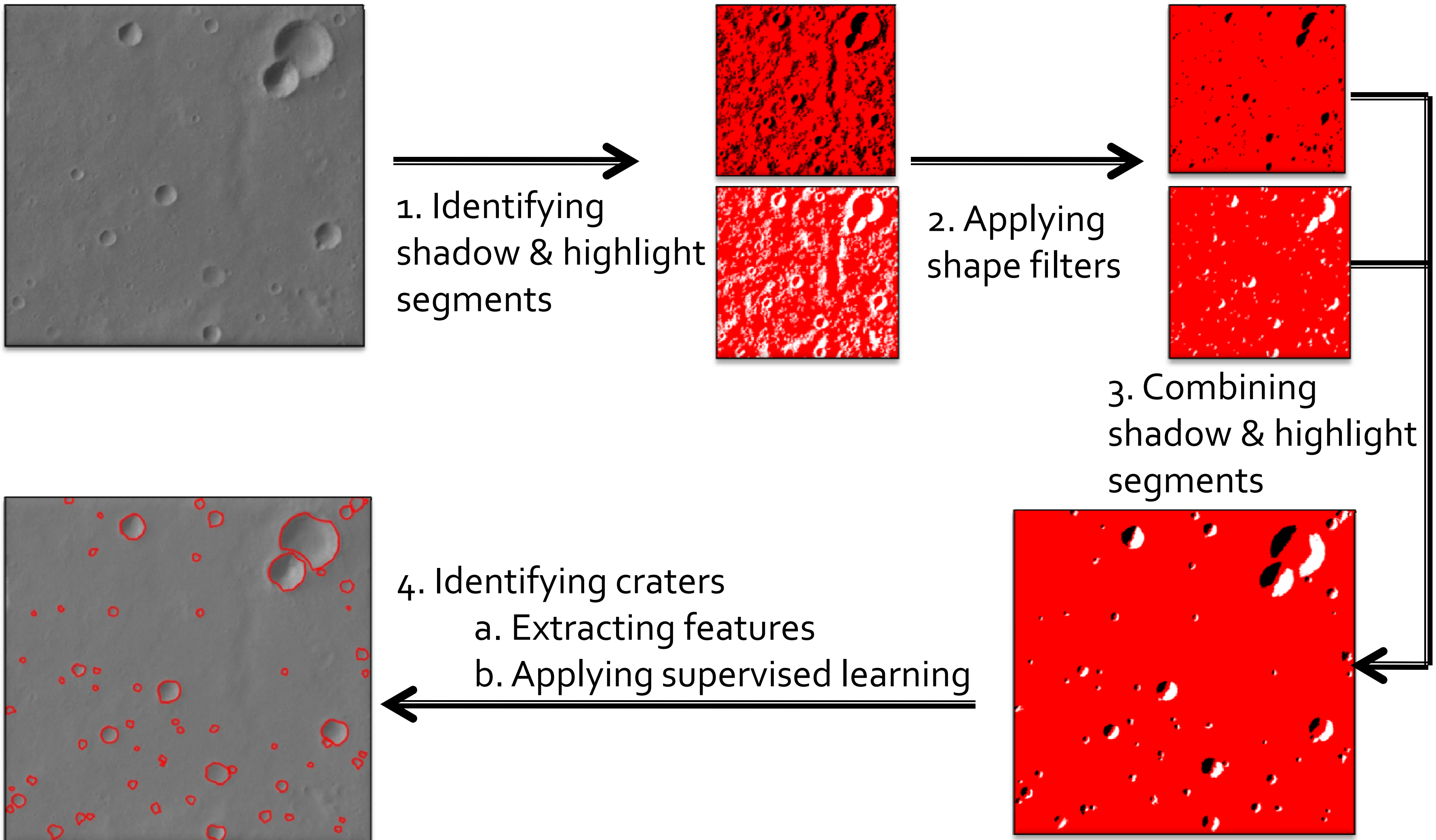
Key milestones

- **2009:** Development of core crater detection algorithm and its variants
- **2009-2010:** Testing on images for different regions on Mars
- **2009-2011:** Development of a processing pipeline for large scale surveys of craters
- **2011-2012:** Testing on high resolution images of the Moon, Mercury, and other planetary bodies.

Expected impact

- Making possible assembling global, “million crater” catalogs of sub-kilometer craters on Mars, Mercury, and the Moon to help understand past and present geological processes.

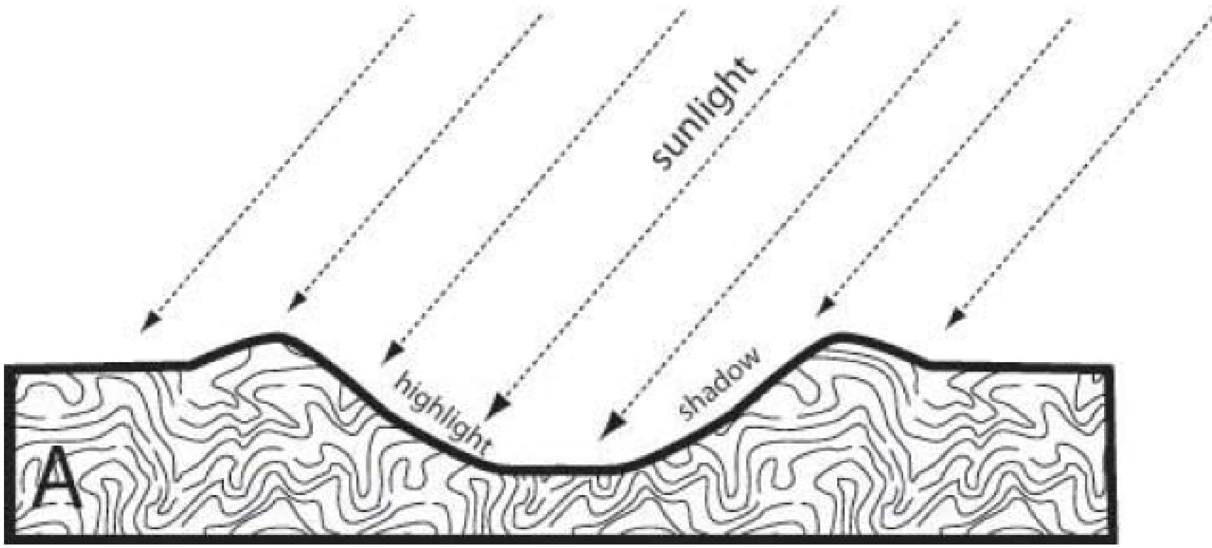
Our method

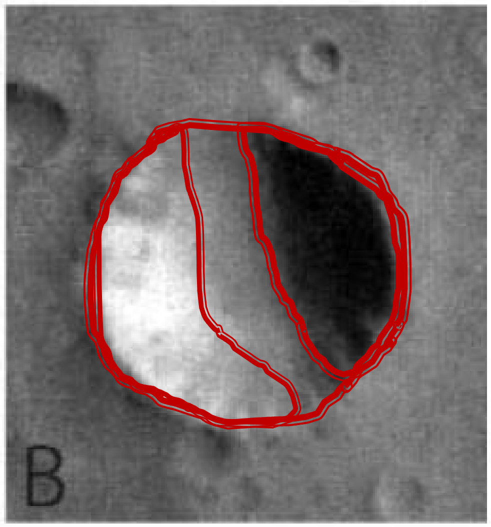

1. Identifying shadow & highlight segments
2. Applying shape filters
3. Combining shadow & highlight segments
4. Identifying craters
a. Extracting features
b. Applying supervised learning

Enabling technical innovations

- Shape Filters
  - Template matching
  - KNN querying
- Feature Extraction
  - Mathematical morphology-based features
  - Haar-like texture-based features
- Supervised Learning
  - Ensemble method
  - Transfer learning

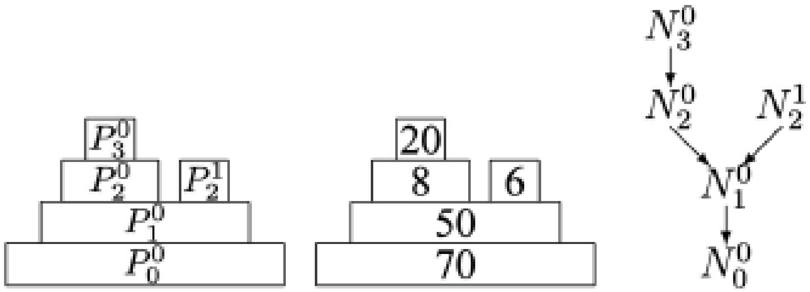
Key insight





Highlight & shadow segments

- Joint shape-size pattern spectra together with the Max-trees
  - Connected filtering, a mathematical morphology technique
  - Connected operators are used to compute pattern spectra using a Max-tree



Max-Tree

Feature extraction I

- Mathematical morphology-based features
  - Seven Hu Moments
  - Circularity and Elongation
  - Distance, similarity, and area ratio between shadow and highlight segments

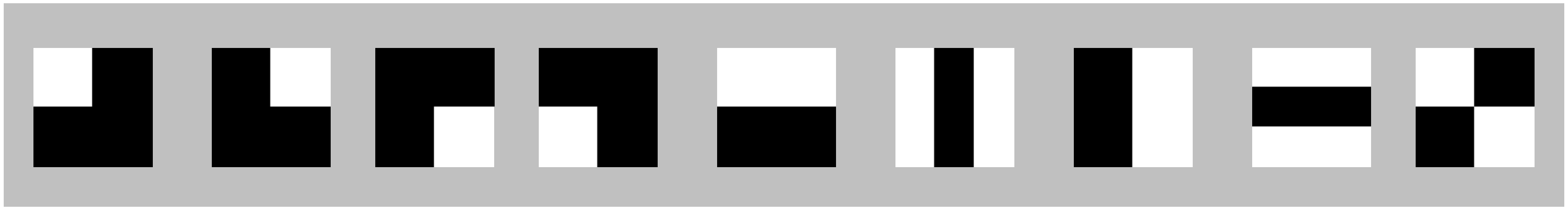
Invariant to translation, scale, and rotation

Feature extraction II

- Haar-like features

(inspired by the face-detection method introduced in [Viola & Jones 2004])

  - Based on simple texture-based features
  - Reminiscent of Haar basis functions



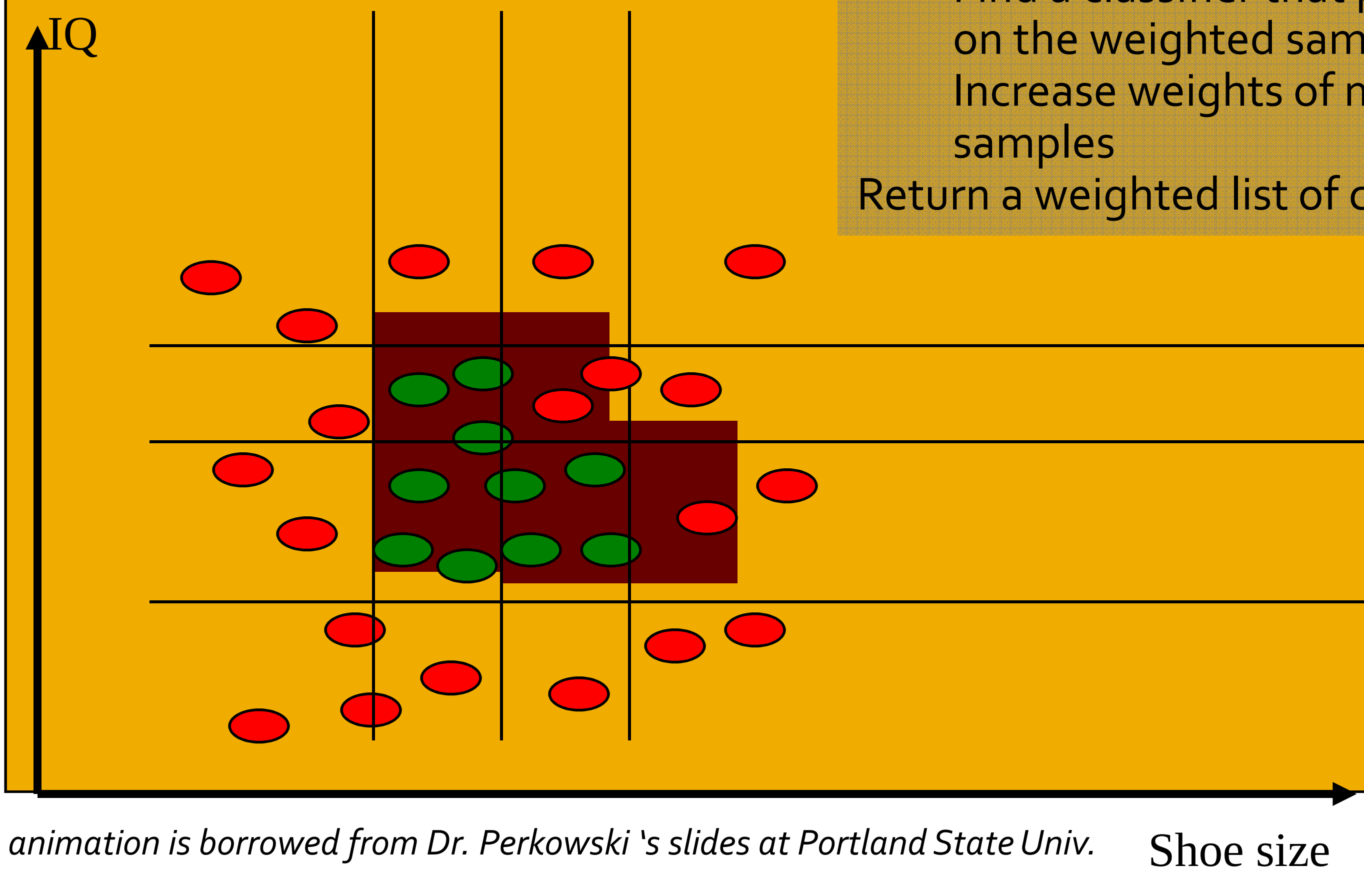
Supervised learning: ensemble methods

- AdaBoost agglomerates many weak classifiers into one strong classifier.

- The training error of the strong classifier approaches zero exponentially in the number of rounds [Schapire 1997].

AdaBoost - the idea

Initialize sample weights
For each cycle:
    Find a classifier that performs well on the weighted sample
    Increase weights of misclassified samples
Return a weighted list of classifiers

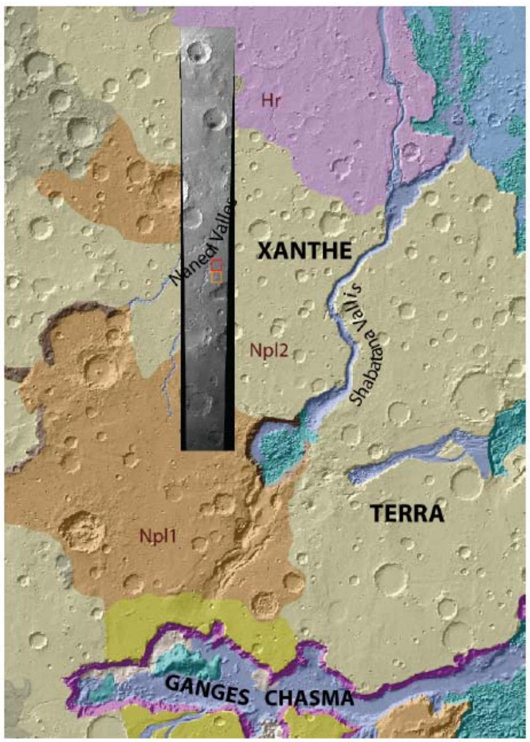


The animation is borrowed from Dr. Perkowski 's slides at Portland State Univ.

Learning classification functions

- Mathematical morphology-based features
  - AdaBoost + C4.5
- Haar-like features
  - AdaBoost + Decision Stumps
    - Feature selection (out of thousands of features)
    - Building a strong classifier using many weak classifiers and simple features

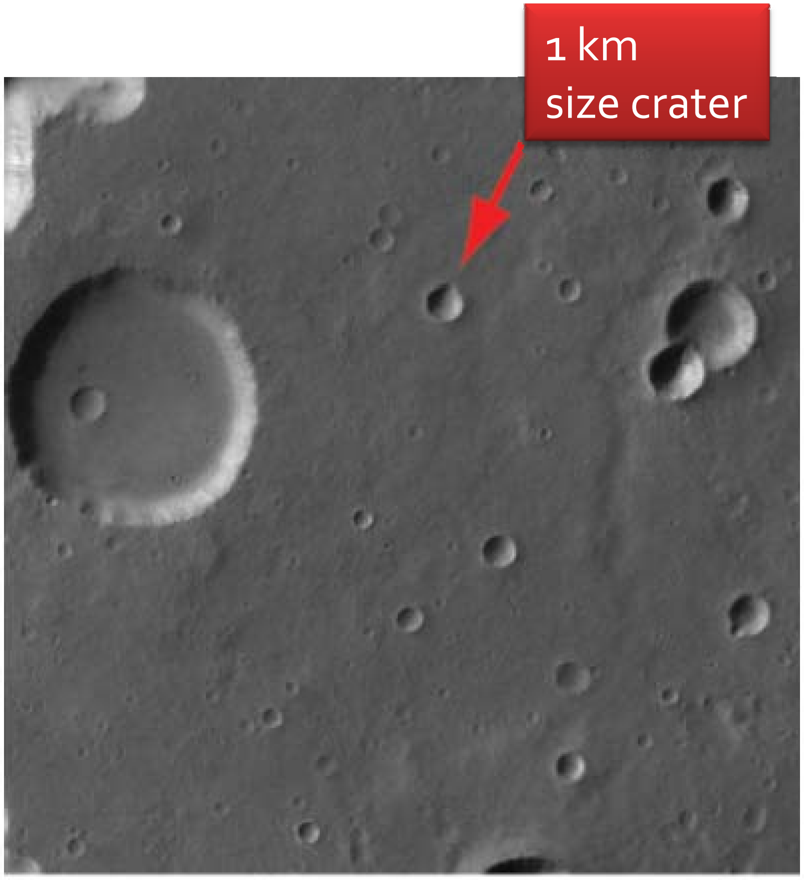
Geographical and geologic context of the data site

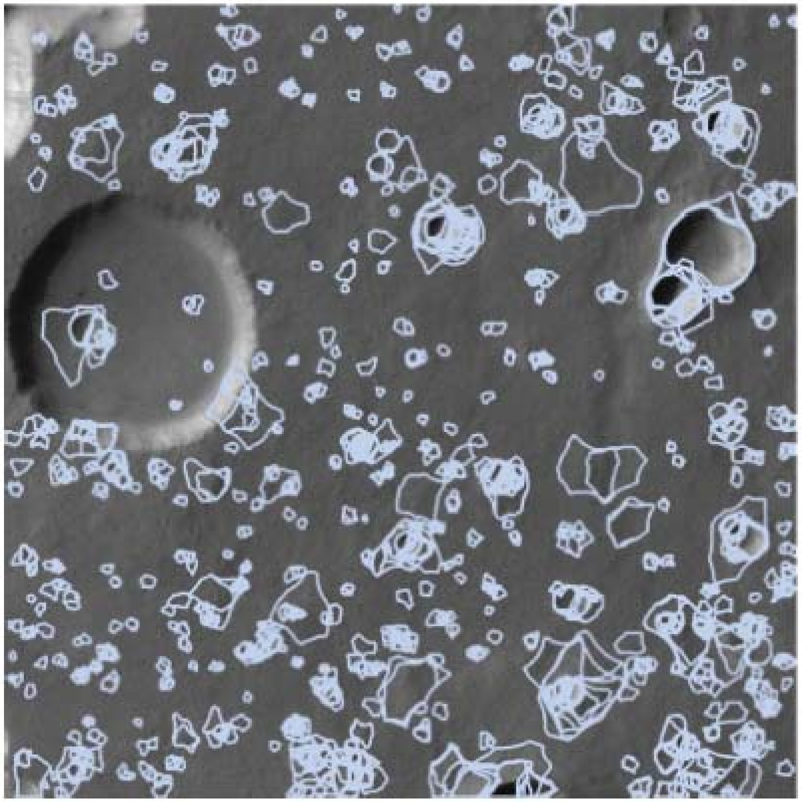


Training Site

Test Site

Training site

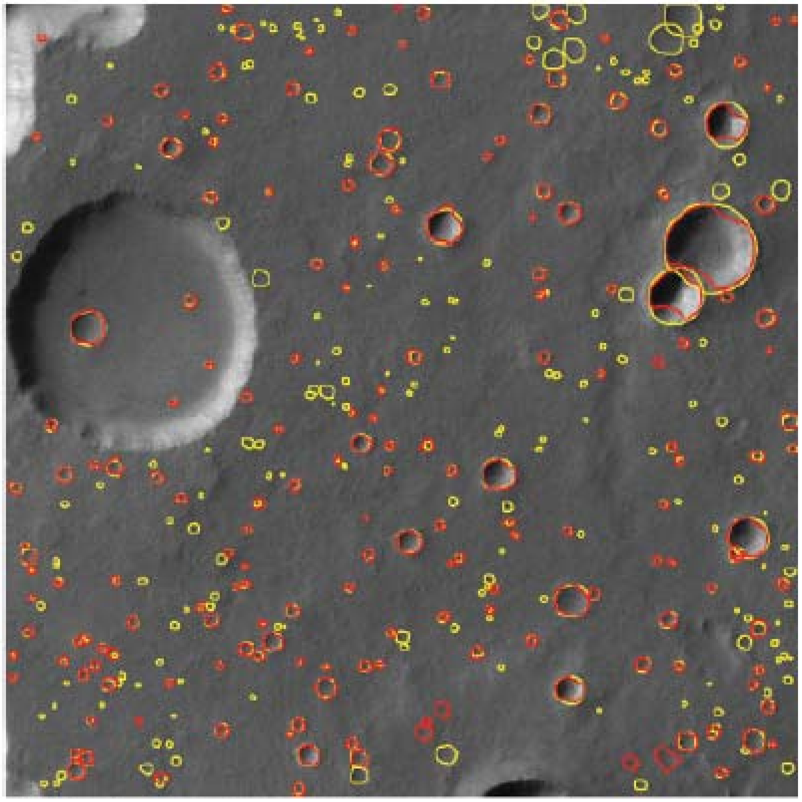




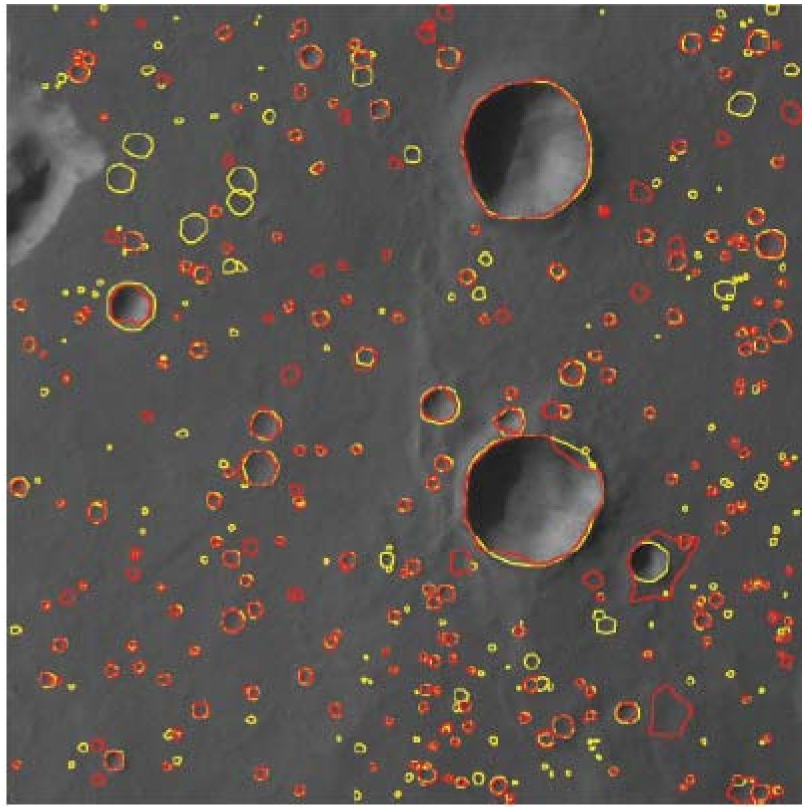
Crater Candidates

Experimental results using morphology-based features

Training site



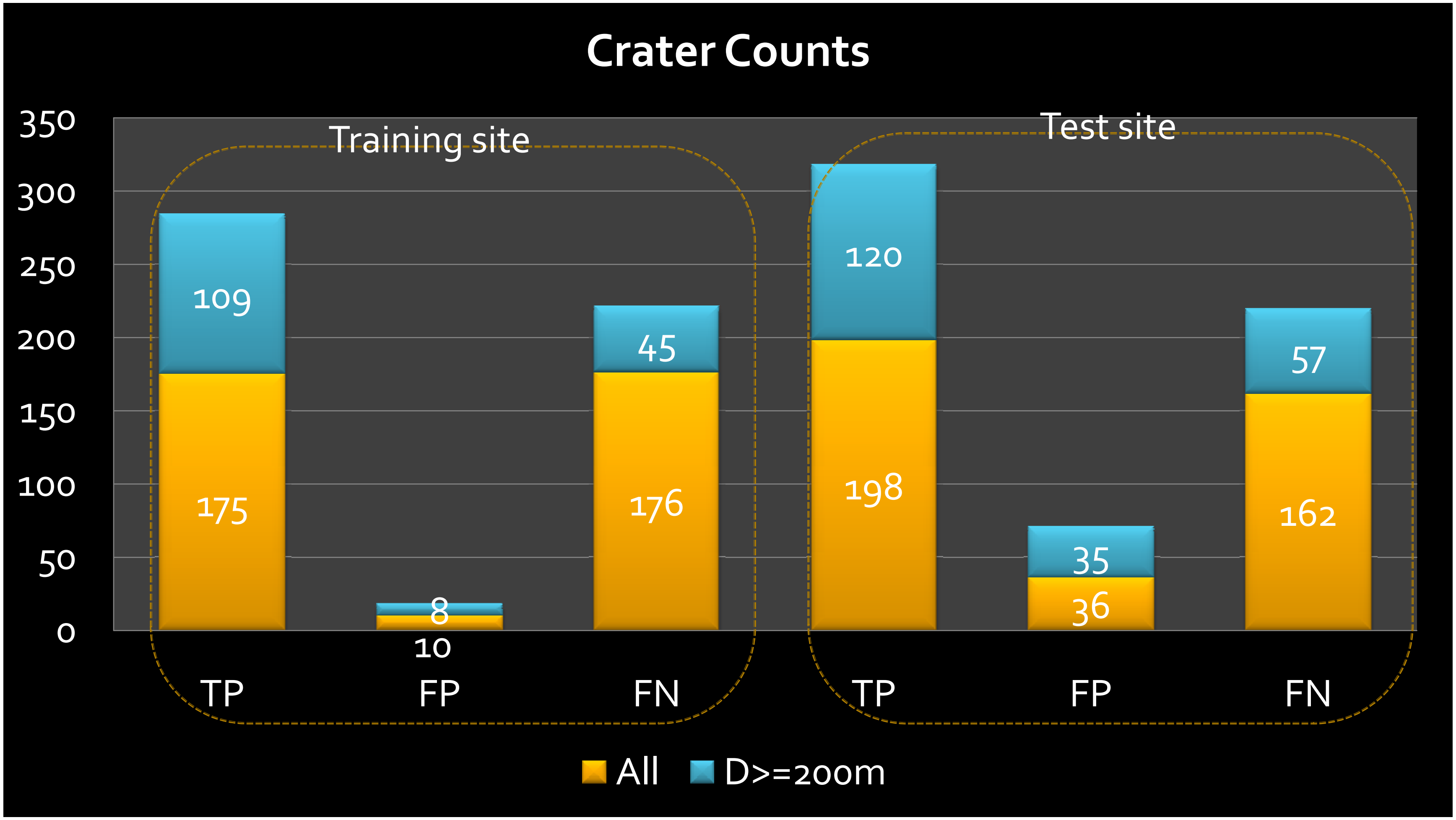
Test site



"Craters" identified by our method

True craters identified by an analyst

Evaluation



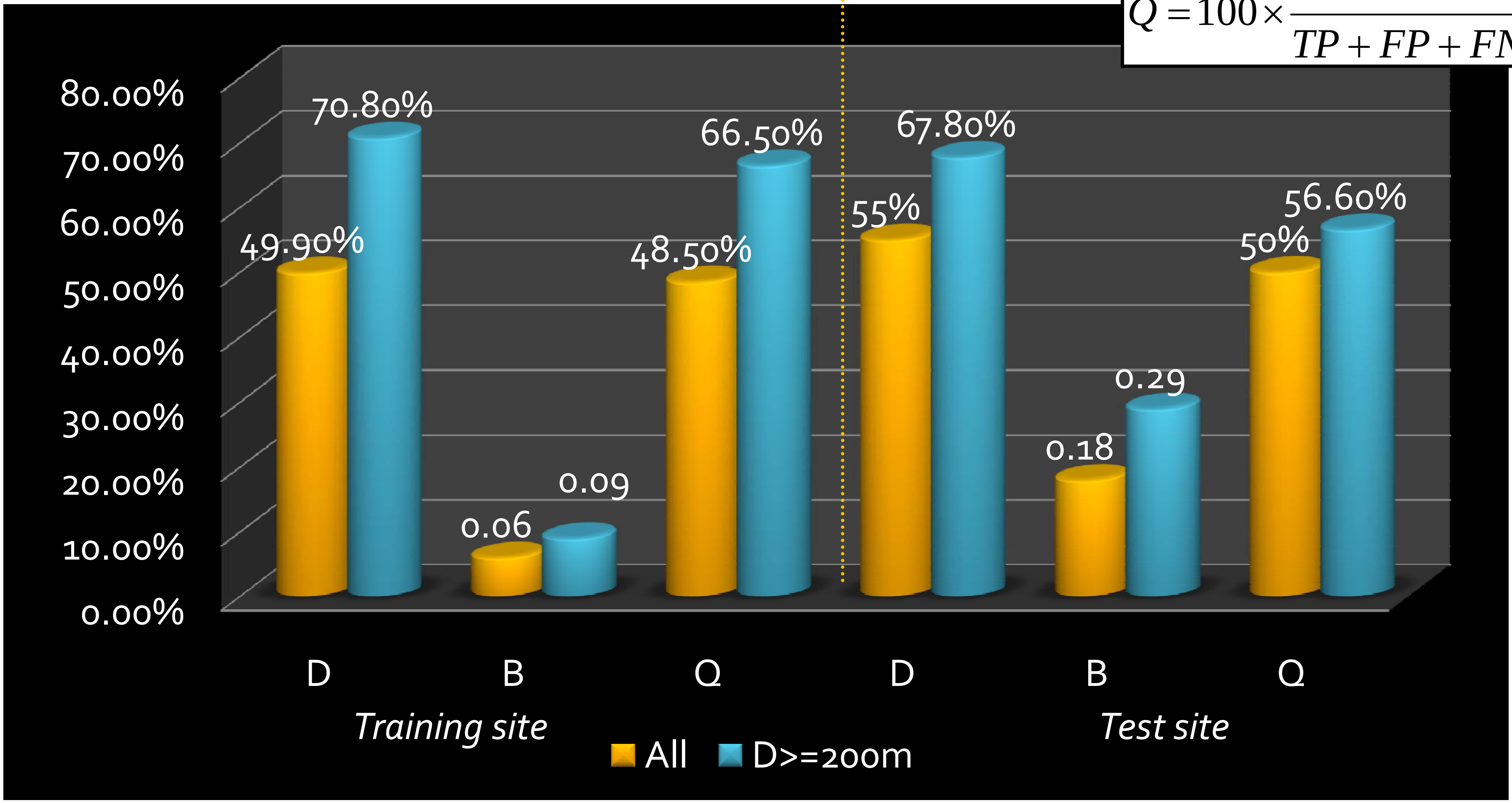
Crater Counts
350
300
250
200
150
100
50
0
Training site
Test site
109
175
8
10
45
176
120
198
35
36
57
162
TP
FP
FN
TP
FP
FN
All
D>=200m

Quality of crater detection

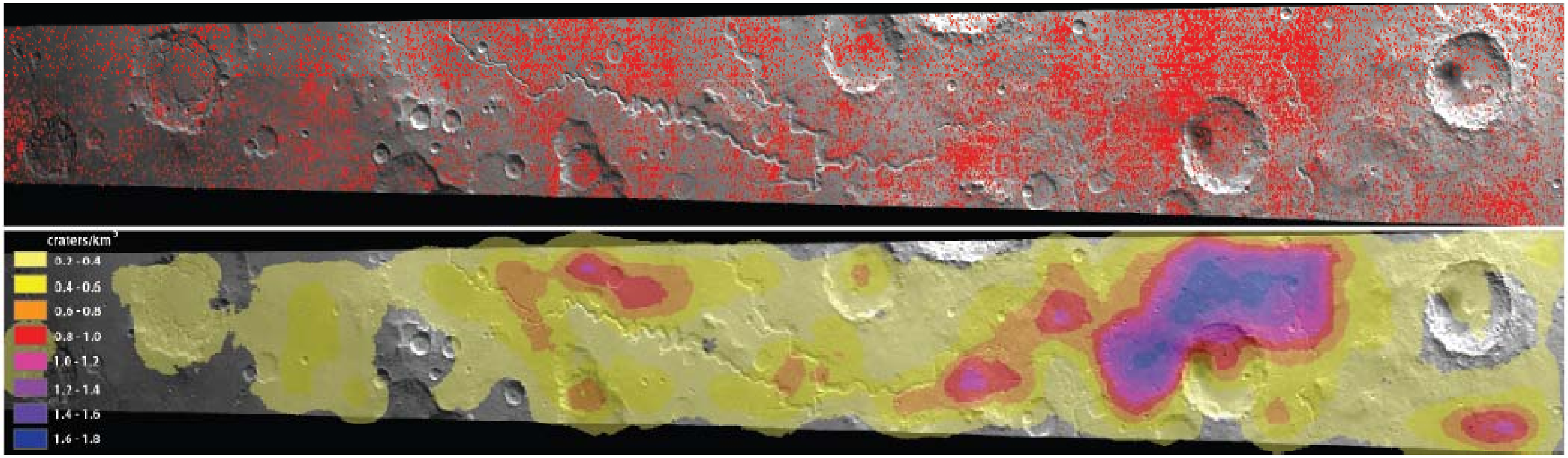
$$D = 100 \times \frac{TP}{TP + FN}$$

$$B = \frac{FP}{TP}$$

$$Q = 100 \times \frac{TP}{TP + FP + FN}$$



Auto-survey of sub-km craters in the HRSC image h0905_0000

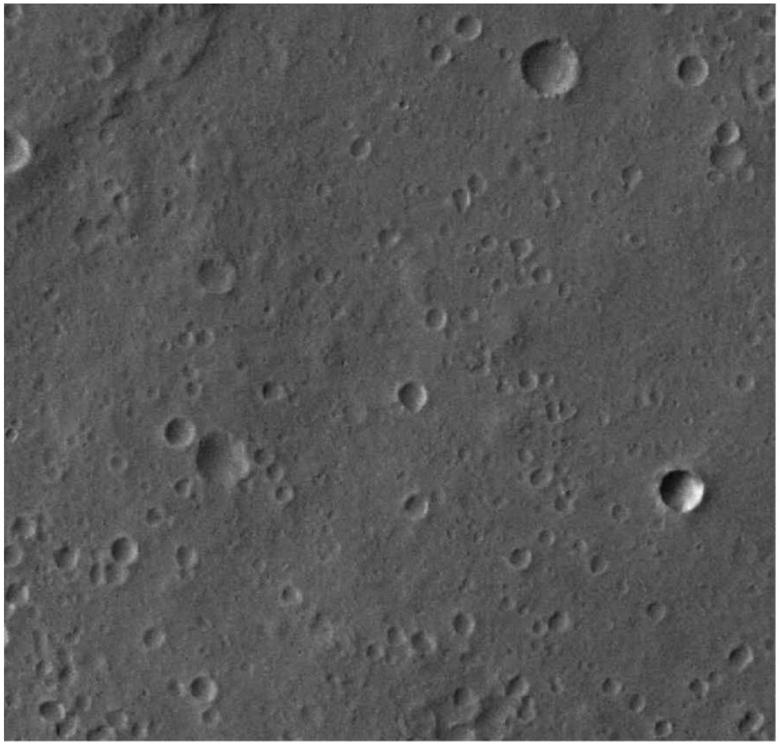
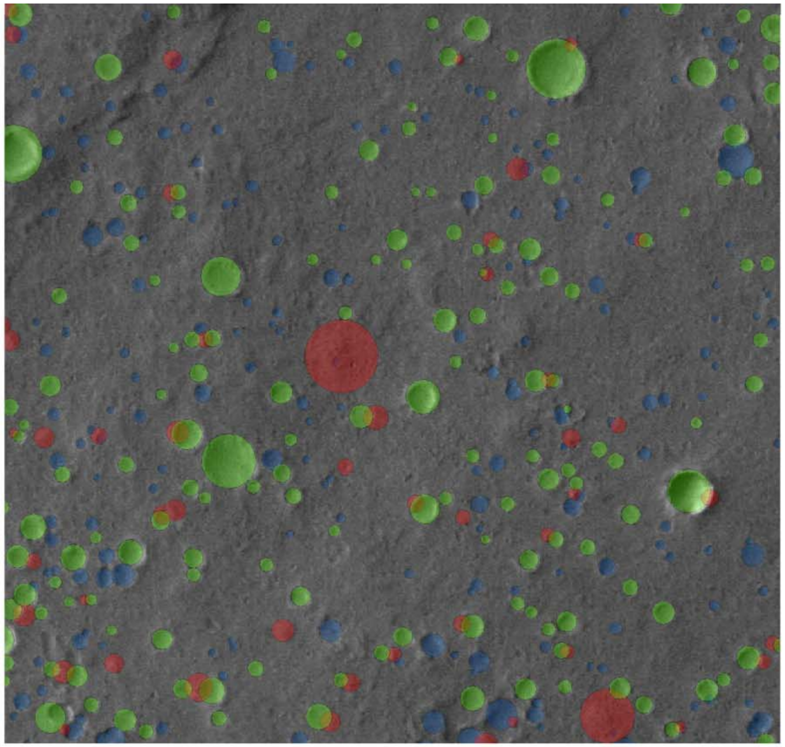


- Image size is 515 MB
- 8248 * 65448 = 539,815,104 pixels; 14 hours of computing time; 10,710 pixels per second
- Tessellated into 264 tiles; 1700 * 1700 pixels / tile
- 35,495 craters identified automatically

Exploration

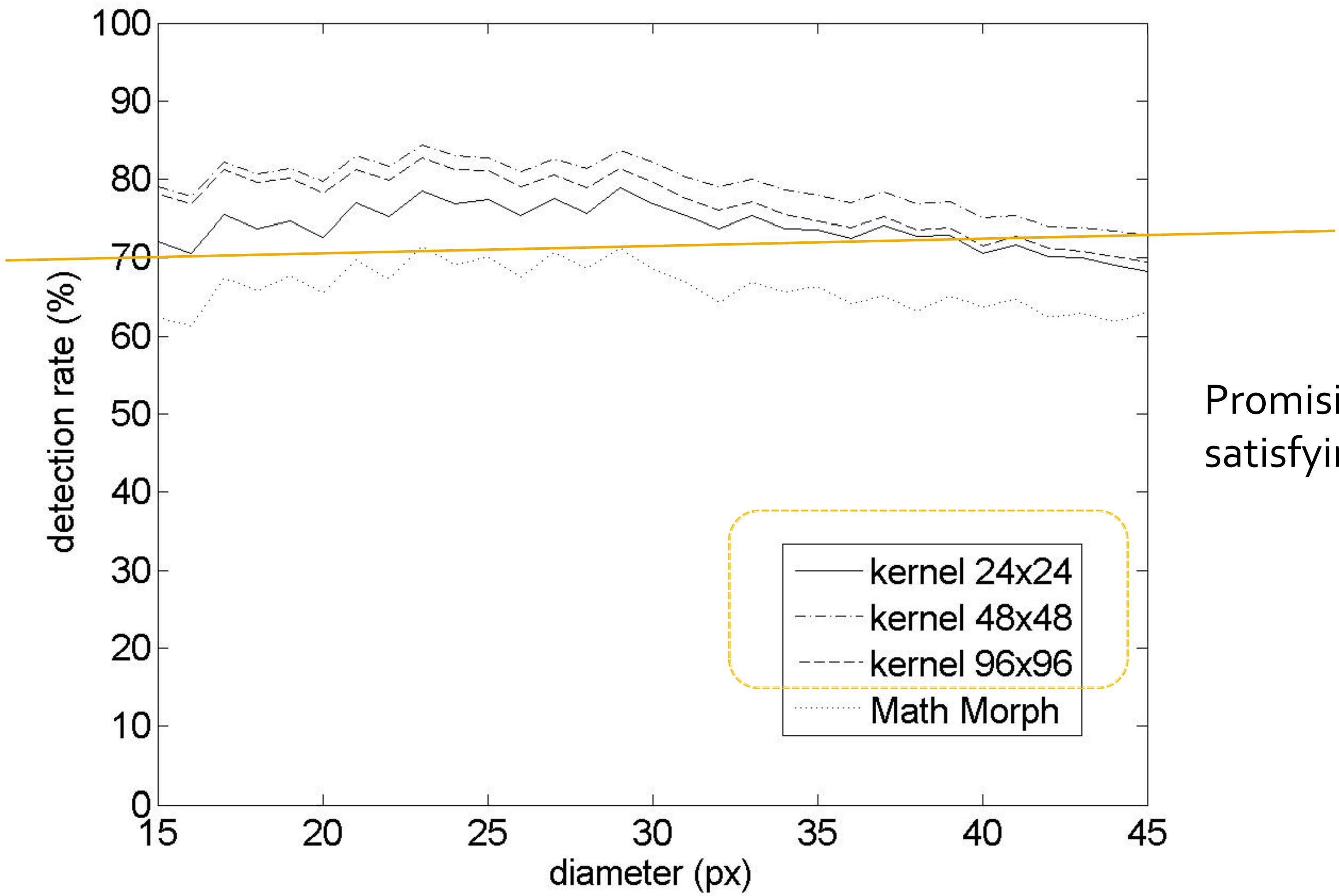
- Shape Filters
  - Current: Template matching
  - Explore: KNN querying
- Feature Extraction
  - Current: Mathematical morphology-based features
  - Explore: Haar-like texture-based features
- Supervised Learning
  - Current: Ensemble method
  - Explore: Transfer learning

Experimental results using Haar-like features

correctly identified craters false detections missed craters

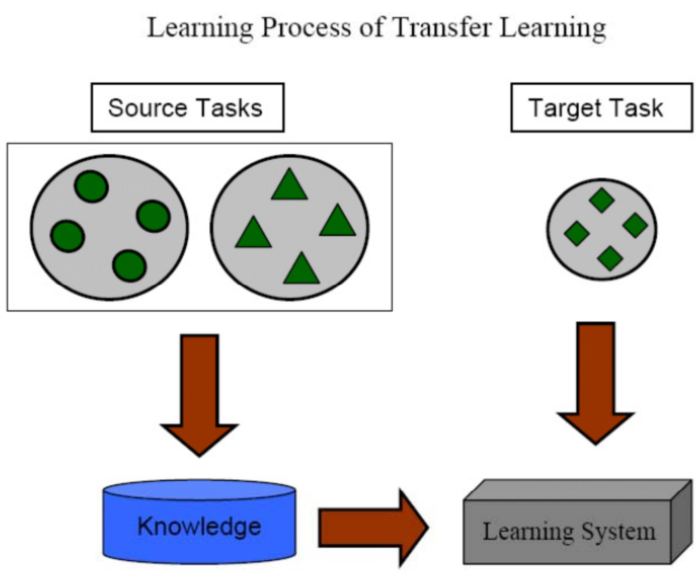
Evaluation



Promising but not satisfying

Transfer learning

- Incorrect Assumption: training and future data are in the same feature space and have the same distribution



This figure is borrowed from [Yang TKDE 2009]

Transfer learning techniques try to transfer the knowledge from previous tasks to a target task when the latter has different data distribution.

Summary

- Using scale and rotation-invariant shape filters to identify crescent-like regions in images
- Developing, evaluating, and assessing new crater detection algorithms
- Automatically surveying craters using the proposed pipeline on regional or global planetary scales

Thanks & Questions