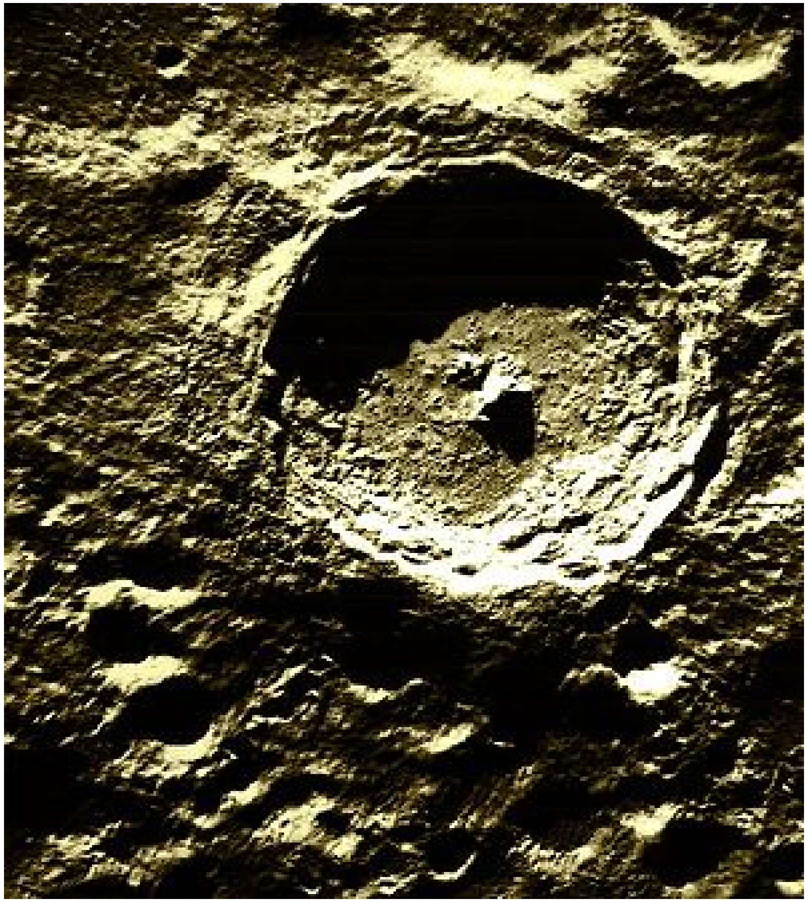
AUTOMATIC DETECTION OF SUB KILOMETER CRATERS IN HIGH RESOLUTION PLANETARY IMAGES.



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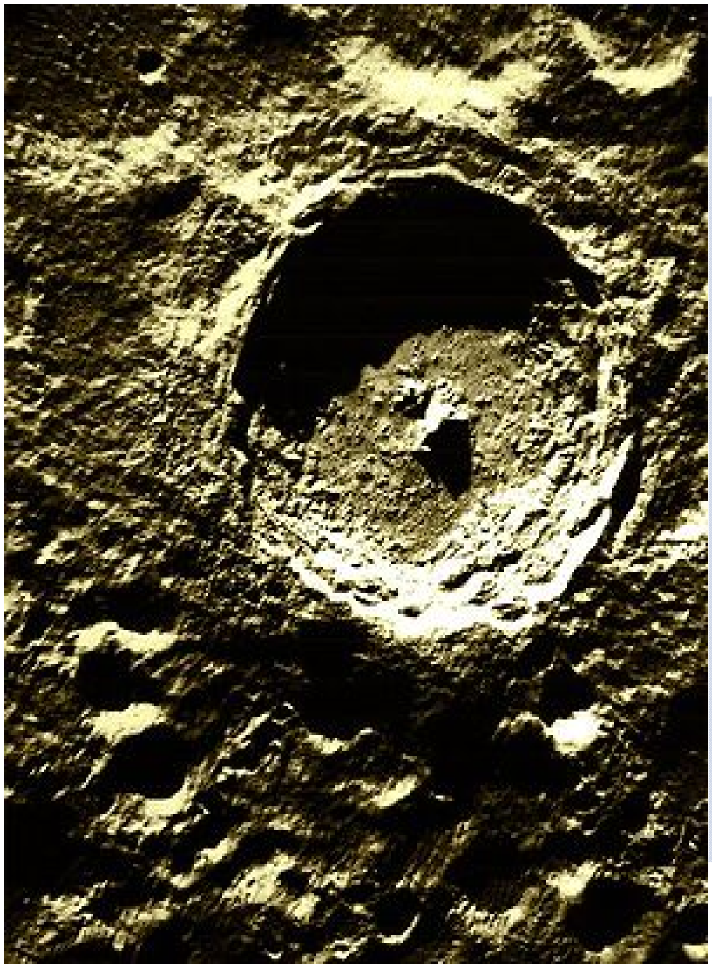
CHRIS STILLMAN
KARTIK PANJABI

INTRODUCTION



- Formed by collision of meteoroids with planetary surfaces.
- Most studied geomorphic planetary features.
- Initially this was studied visual inspection of images.
- All surveys are done manually at present.

INTRODUCTION

- Importance of Carter Study
  - *Determine, if life ever arose on Mars*
  - *Determine the evolution of the surface and interior of Mars*
  - *Prepare for human exploration*

FACTS

- Technical details of method can be evaluated with 12.5 m/pixel.
- Detection percentage of method is ~70%.
- System detects over 35K craters in this image.
- Average crater density is 0.5 craters/sq. km
- Daniel Barringer was first guy to identify the Crater.

AUTOMATING THE PROCESS

- Most comprehensive surveys catalogs of craters in MARS contain information 42,283 and 57,633.
- This craters are larger than 5km in diameter.
- There exists craters sub-km craters.
- So compiling this larger data manually is laborious and impractical.

AUTOMATING THE PROCESS

- Automating surveys can deliver the regional or global coverage.
- Earlier method were not developed beyond the demonstration stage.
- This method did not demonstrated to be robust to changes, hence limiting in actual applications.

AIM OF PAPER

- Present different approach to auto-detection of craters in panchromatic planetary images.
- CDA-Crater Detection Algorithm with mathematical morphology.
- Observation that a crater can be recognized in an image as pair of crescent-like highlight and shadow regions.
- Focus is on surveys of sub-km craters.

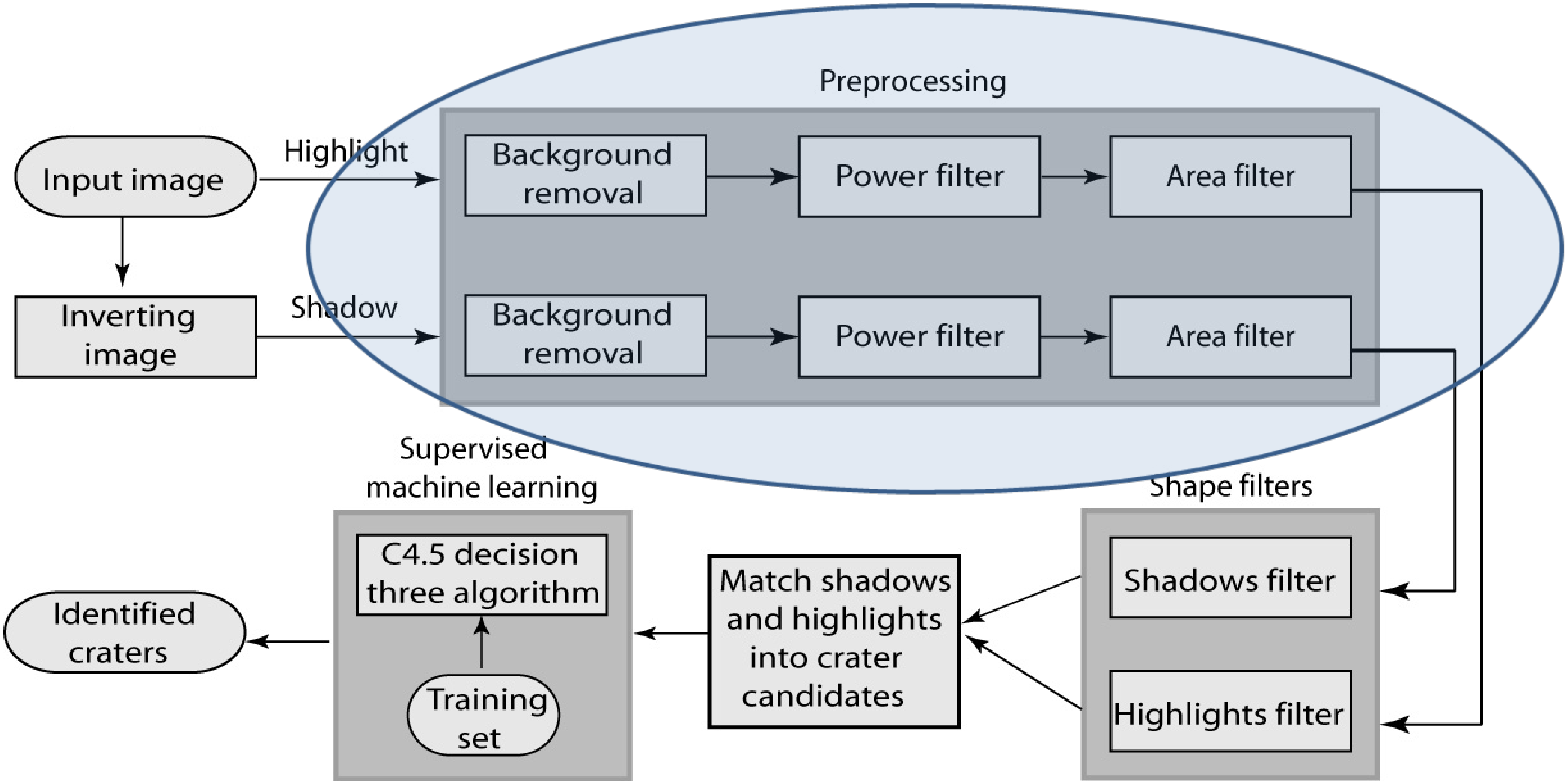
CONTENTS OF PAPER

- Methods
  - Describes the core crater identification
- Results
  - Results of applying methods to very large images or MARS
- Conclusion
  - Conclusion and Future directions of Research.

METHODS

- Preprocessing
- Shape Filters
- Matching Highlight and Shadow Regions
- Supervised classification.

METHODS


Preprocessing
Input image
Highlight
Shadow
Inverting image
Background removal
Power filter
Area filter
Background removal
Power filter
Area filter
Supervised machine learning
Shape filters
C4.5 decision three algorithm
Training set
Match shadows and highlights into crater candidates
Shadows filter
Highlights filter
Identified craters

PREPROCESSING

- Image of planetary surface contains many highlights and shadows that’s not required. Methods employed for it are as follows
  - Background Removal
  - Power Filter
  - Area Filter

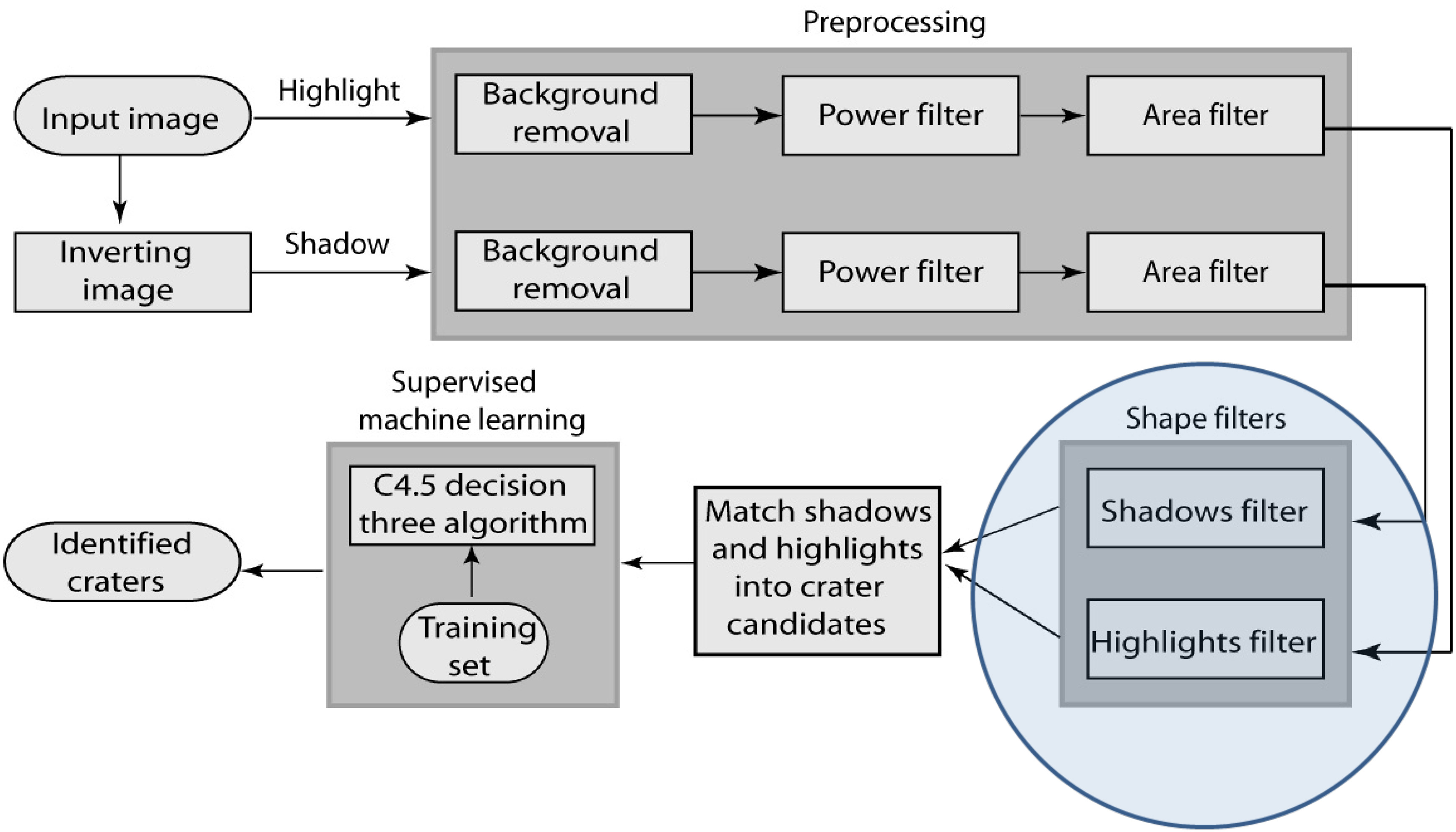
PREPROCESSING

- Background Removal
  - Removes background features such as mountains.
  - Median filter applied to images, this gives us the global features of background.
  - Subtracting this gives us image that has no large background features.
  - Test sites uses 201 pixels wide circular window.

PREPROCESSING

- Power Filters
  - Removes the feature that are invisible.
  - Implement as attribute filter with power attribute $P=A(h_a-h_b)^2$
  - h_a is gray level.
  - h_b is gray level of darkest neighboring feature.
- Area Filters
  - Removes all the features that are too small for crater detection.

METHODS



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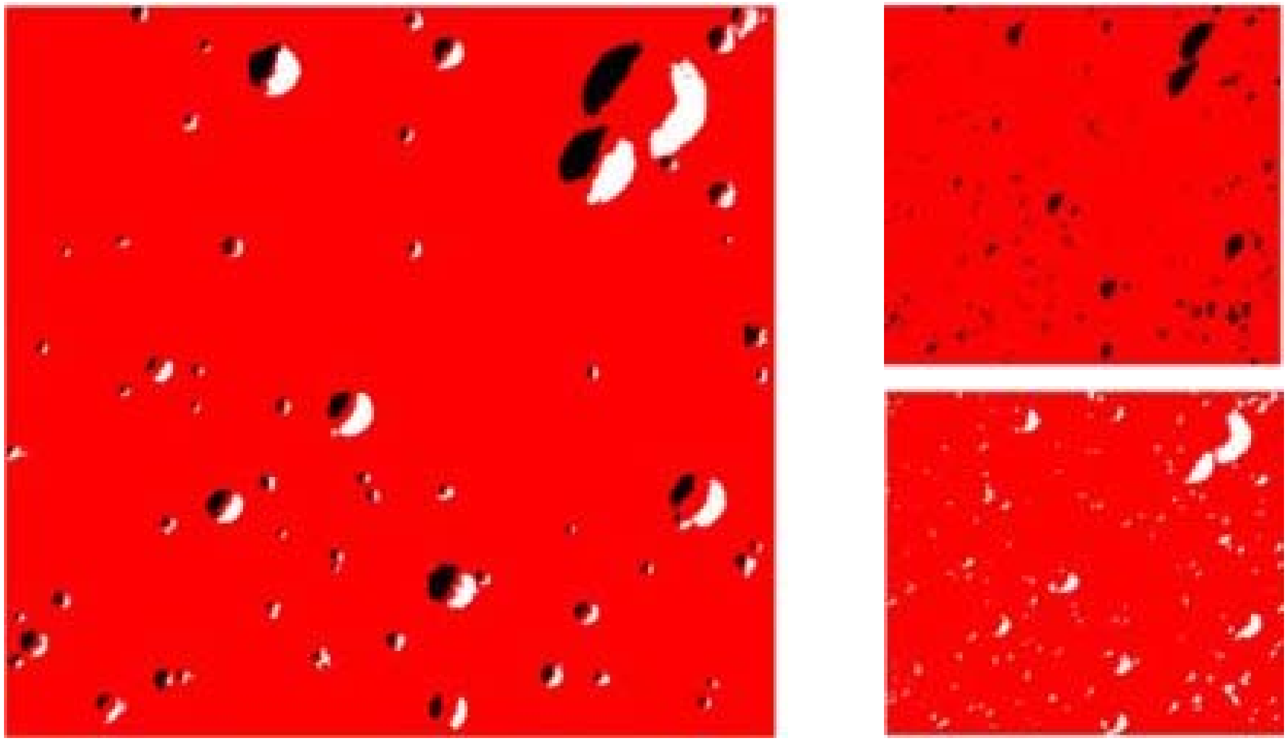
SHAPE FILTERS



Discriminate the crater-regions from non-crater regions.

SHAPE FILTERS

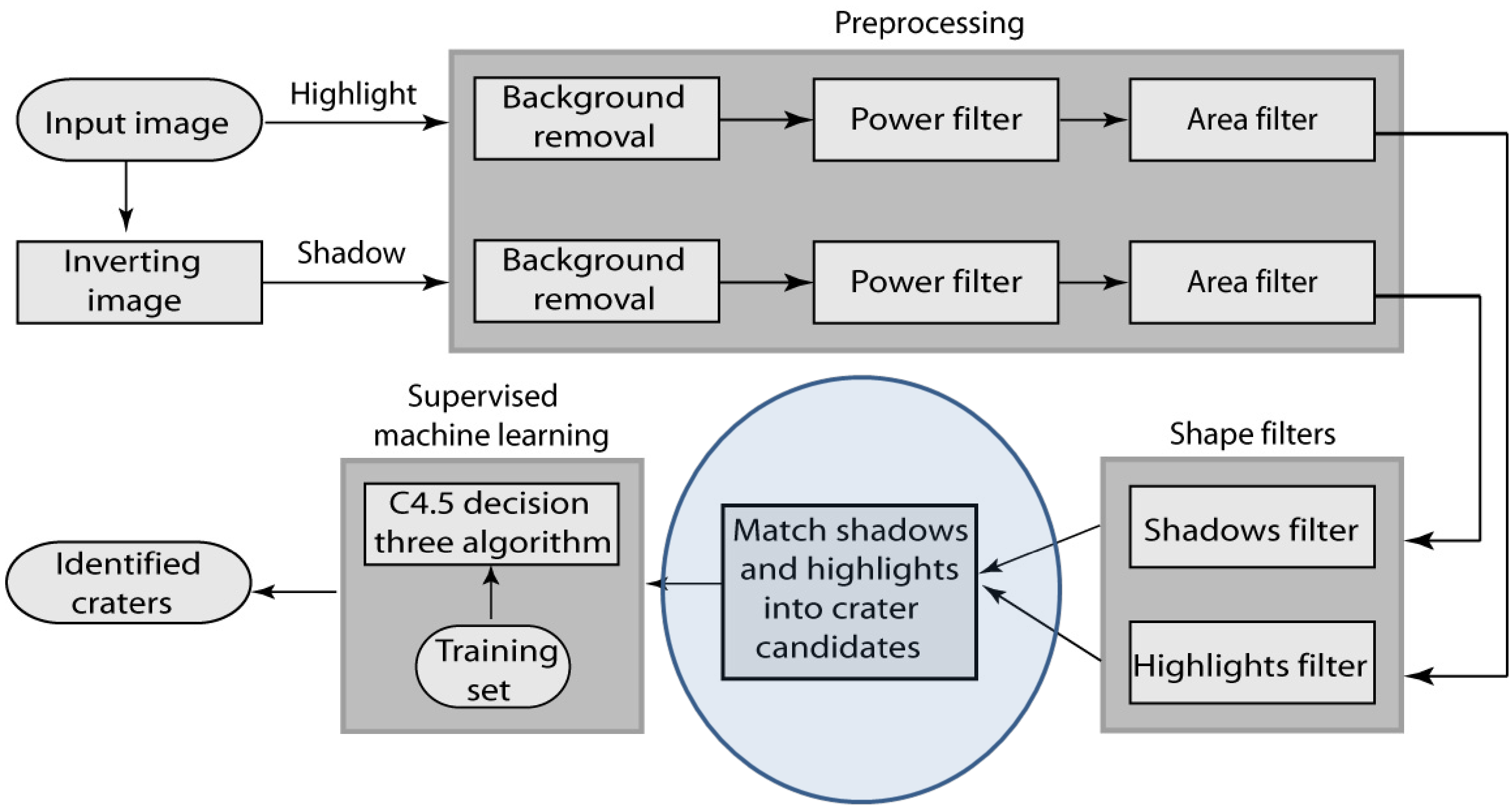
- shape filter uses pre-collected reference shapes to identify matching shapes.
- 17 reference shapes for highlight regions

- 12 reference shapes for dark regions

SHAPE FILTER

- The attributes of highlight and shadow regions: Hu’s seven moment invariants.
- Euclidean Distance: <=0.05
- Highlight regions and highlight references ;
- Shadow regions and shadow references.

METHODS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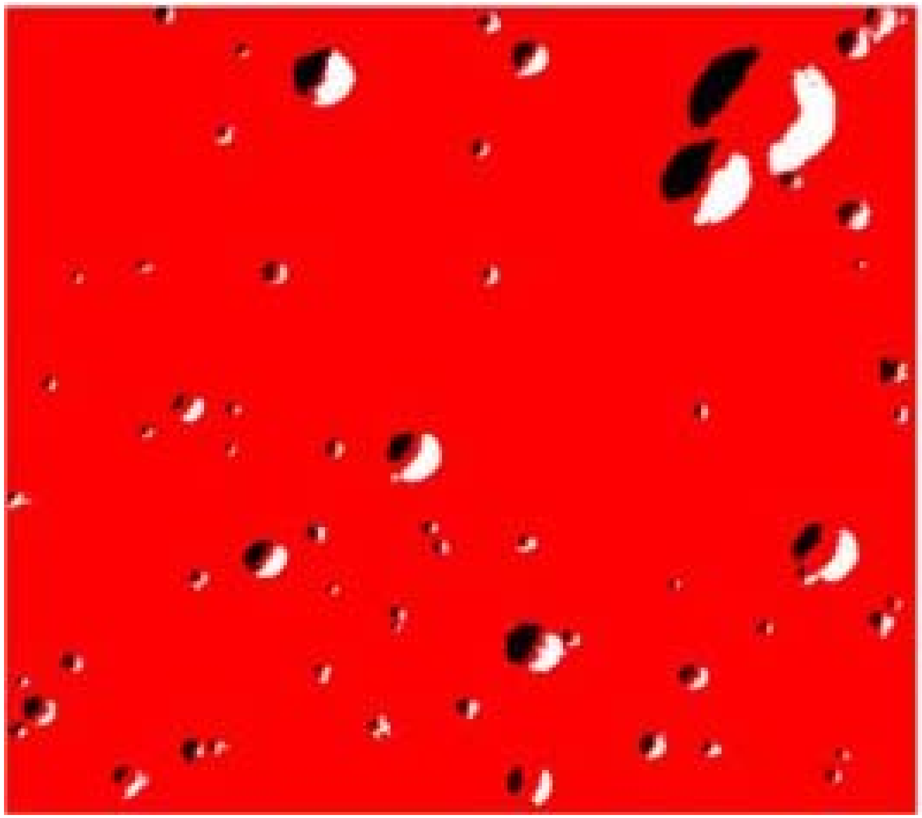
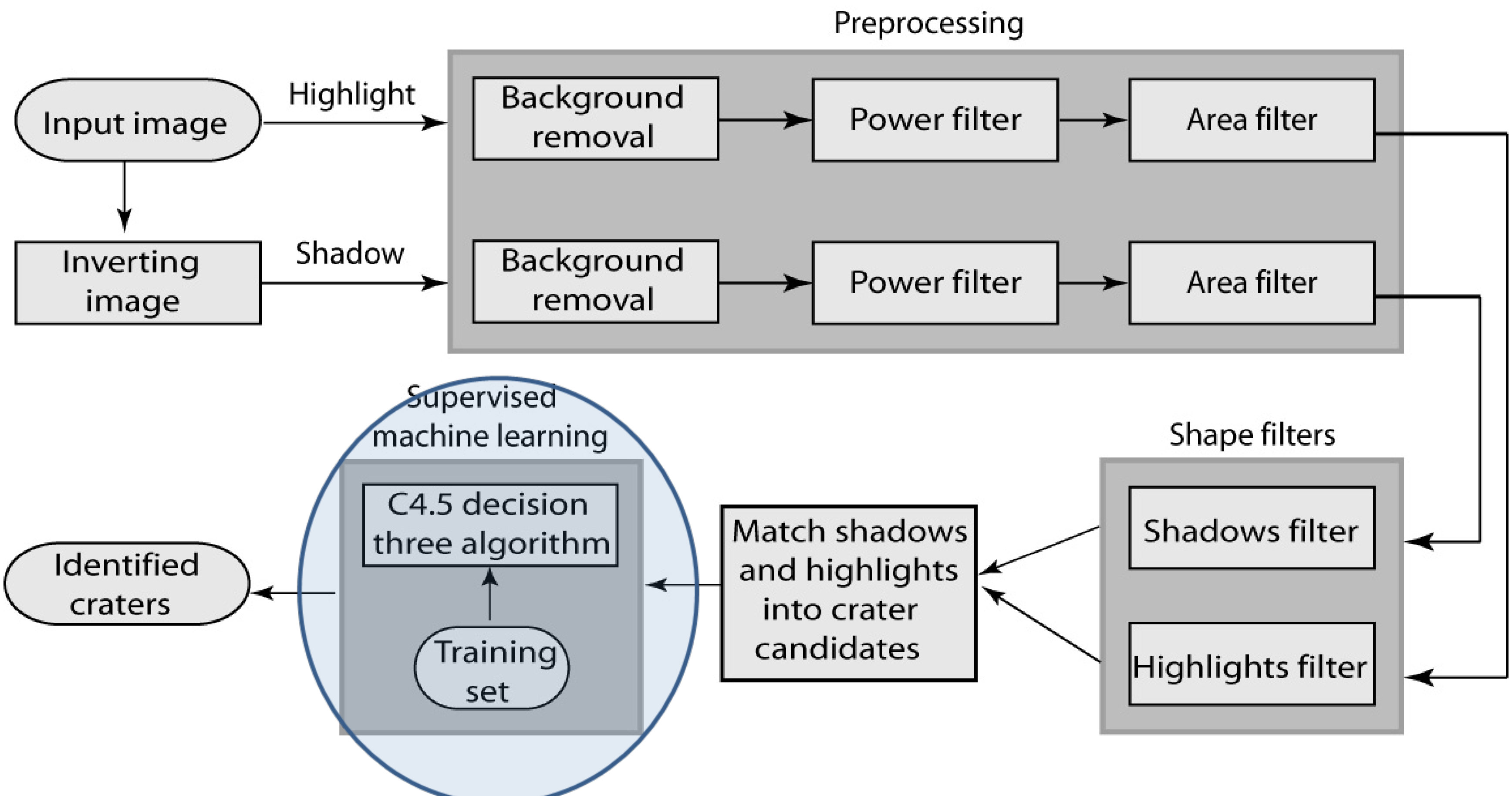
MATCHING HIGHLIGHT AND SHADOW REGIONS



Five rules to be considered as a crater candidate:

1. **Distance <=1.65sqr(AH)**
2. **Size<=4**
3. **Elongation <=3**
4. **Elongation<individual**
5. **Angle**

METHODS



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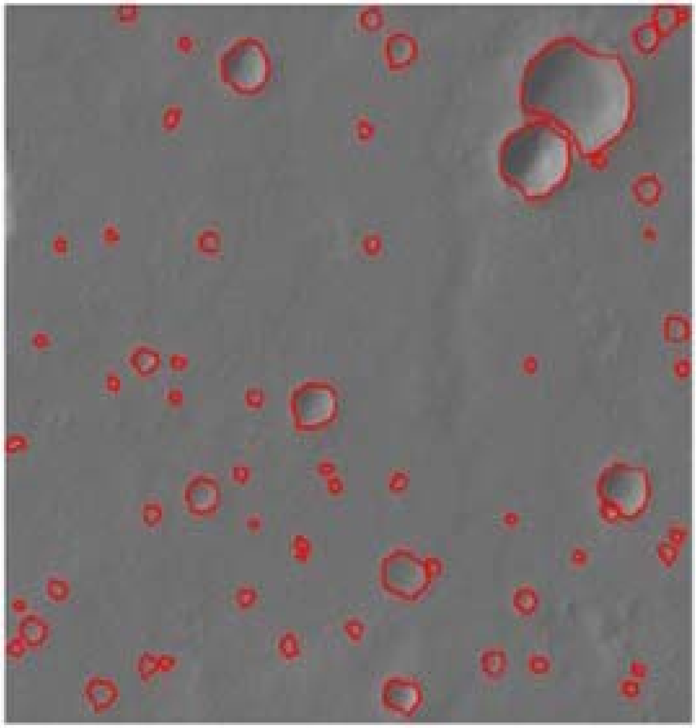
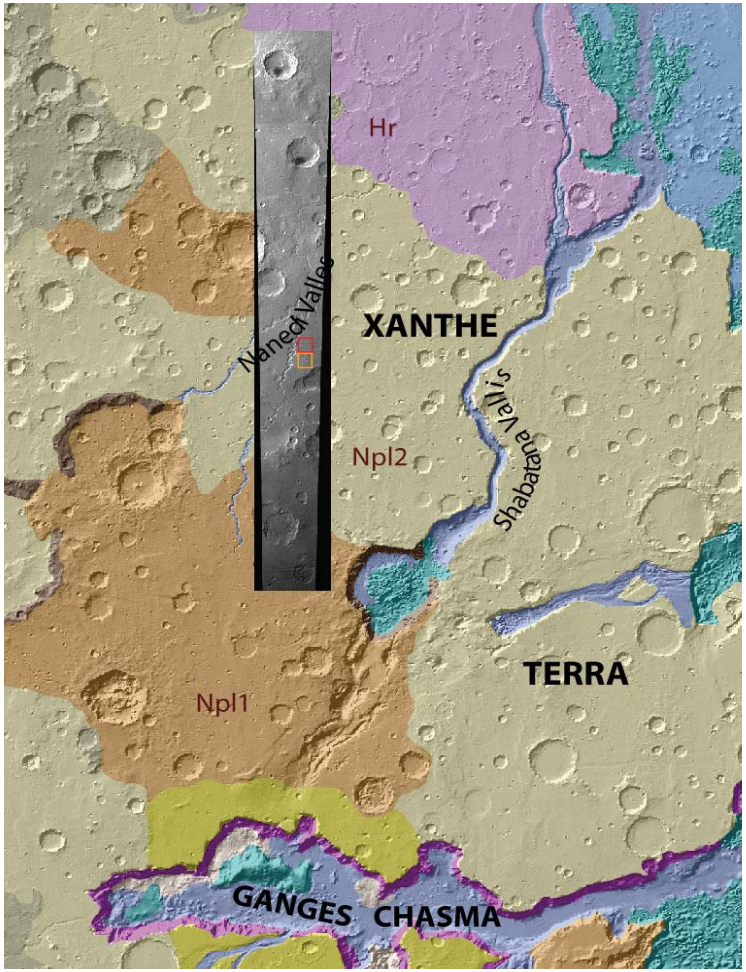
SUPERVISED CLASSIFICATION



C4.5 decision tree classification algorithm

See side material for definition

EXPERIMENT—TEST SITE

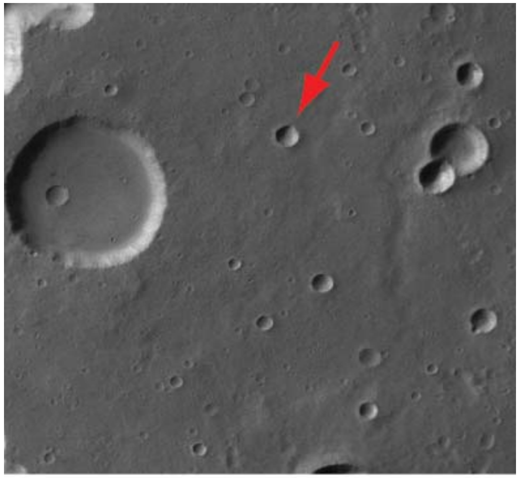


Geographical and geologic map of the test site. The Large rectangle is the test site. (8248*65448 pixels)

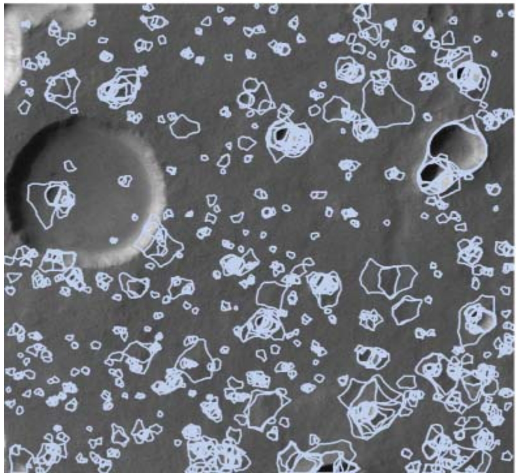
264 tiles

The small red rectangle is the training tile.(1700*1700 pixels)

TRAINING SET



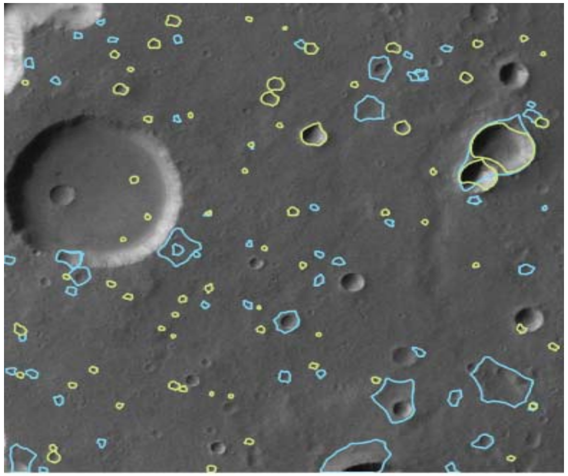
The red arrow indicates a 1 kilometer size crater. A majority of the craters within the tile are sub-km craters.

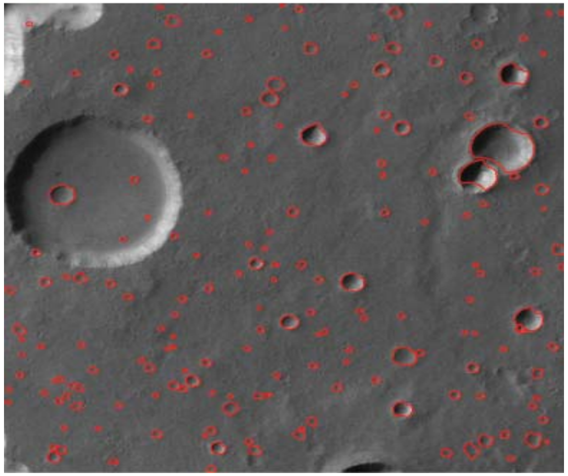


1543 crater candidates were indentified by the algorithm using shape filters, but before applying a supervised classification.

Problem: It also detected many regions that were not craters.

RESULT





Yellow: craters labeled by an expert. (69)
Blue: crater candidates but are not true craters (59)

Training set

1543 candidates.

185 of them as craters. (red ones)

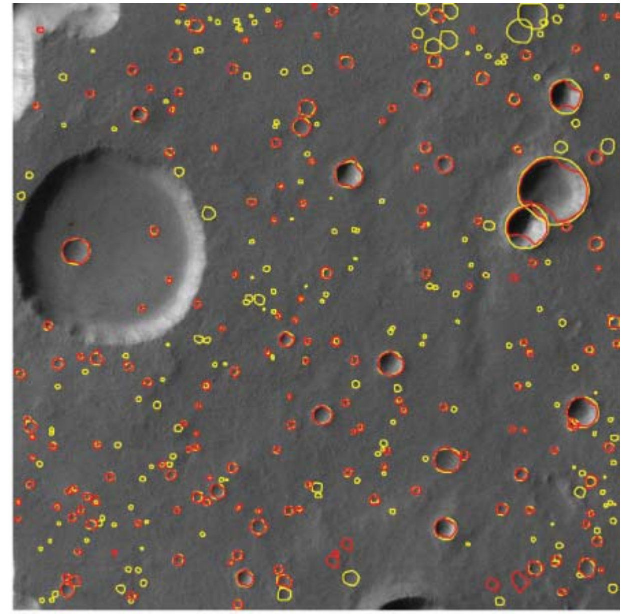
The rest of them are non-craters.

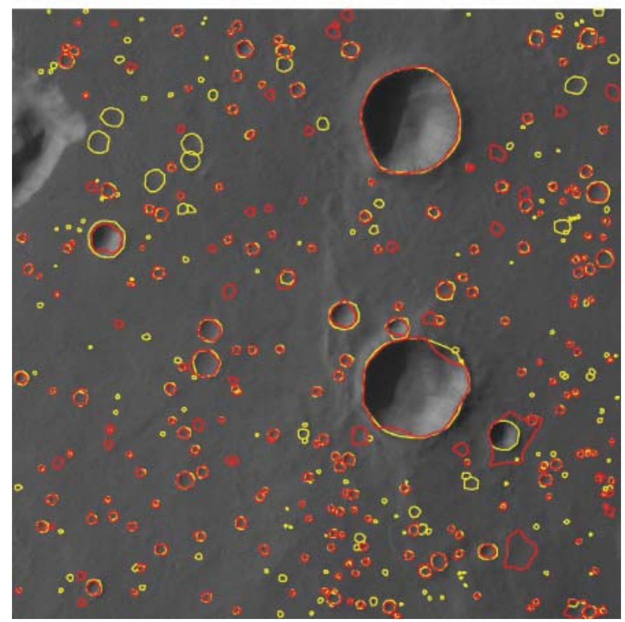
TESTING THE AUTO DETECTION ALGORITHM

- **Performance tested using training and testing tiles.**
  - •On both sites craters were marked for ground truth and quality assessment.
  - •351 craters were use in the Ground Truth data.
  - •360 craters in the test site.

•The proceeding slide shows both craters marked using the algorithm (red) and those marked by a researcher manually (yellow).

•Top is the training site, Bottom is the test site.





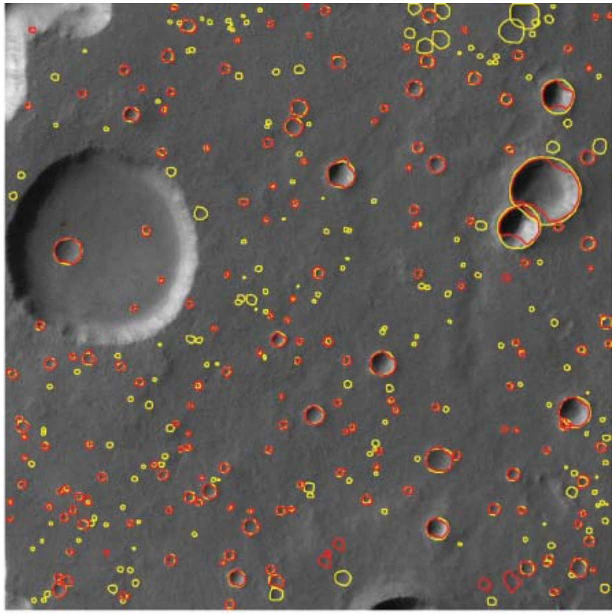
PERFORMANCE TESTED USING TRAINING AND TESTING TILES.

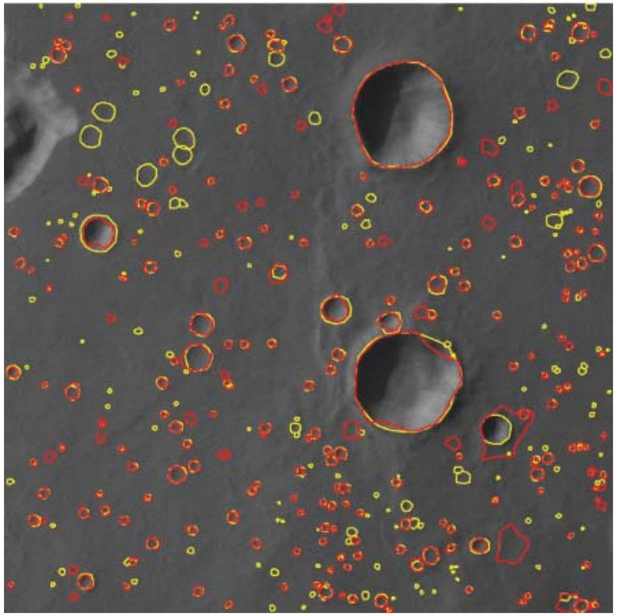
Limitations between the two processes

•The algorithm outlined in this paper was designed for greater than 20 pixels diameters and craters larger than 200 meters.

•The manual method can identify any feature visible to the human eye, therefore much finer in detail than the algorithm.

•Is this a fair comparison?





THE RESULTS

- **Testing the auto detection algorithm**
  - Do to this indiscrepancy only craters greater than 200m in diameter provide the best comparison.
  - The following table list all the data and just the greater than200m data.
- The Indicators

  TP- True Positive

  FP- False Positive

  FN- False Negative

	TP	FP	FN
Training sites (all)	175	10	176
Training Site (D>= 200m)	109	8	45
Test site (all)	198	36	162
Test Site (D>= 200m)	120	35	57

Crater counts

THE RESULTS

- **Testing the auto detection algorithm**
  - True Positives are the # of craters identified as true craters.
  - False Positives are spots identified as a crater but were in fact not.
  - False Negatives are craters that were not detected in the first place.

	TP	FP	FN
Training sites (all)	175	10	176
Training Site (D>= 200m)	109	8	45
Test site (all)	198	36	162
Test Site (D>= 200m)	120	35	57

Crater counts

THE RESULTS

The Grade:

- D is the measure of crater performance
- B is the delineation performance
- Q is the overall measurement of the performance of the algorithm
- from comparing the manual analysis to the algorithm

	D	B	Q
Training sites (all)	49.9%	0.06	48.5%
Training Site (D>= 200m)	70.8%	0.09	66.5%
Test site (all)	55%	0.18	50%
Test Site (D>= 200m)	67.8%	0.29	56.6%

Quality of crater detection

THE RESULTS

- **Testing the auto detection algorithm**

D= 100TP/(TP + FN)

B= FP/TP

Q= 100TP/(TP+FP+FN

	TP	FP	FN
Training sites (all)	175	10	176
Training Site (D>= 200m)	109	8	45
Test site (all)	198	36	162
Test Site (D>= 200m)	120	35	57

Crater counts

THE RESULTS

- Clearly results from the >=200m craters show a higher outcome to those of the complete group.
  - Overall crater detection performance = ~70%
  - Overall algorithm performance= ~55-65%

	D	B	Q
Training sites (all)	49.9%	0.06	48.5%
Training Site (D>= 200m)	70.8%	0.09	66.5%
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Quality of crater detection

PERFORMANCE RESULTS

- The results compare favorably to those in earlier studies of small craters near the Olympus Mons region.
  - eg; D= 70% with a of Q= 62%

SURVEYING SUB-KM CRATERS IN THE HRSC IMAGE

Crater Identification Algorithm

- 2611 tiles were selected for an expanded training set.
  - 1994 examples of characteristic crater shapes
  - 617 examples of characteristic non-crater shapes

- To maximize time and effort this crater identification algorithm is then put into a data processing pipeline.

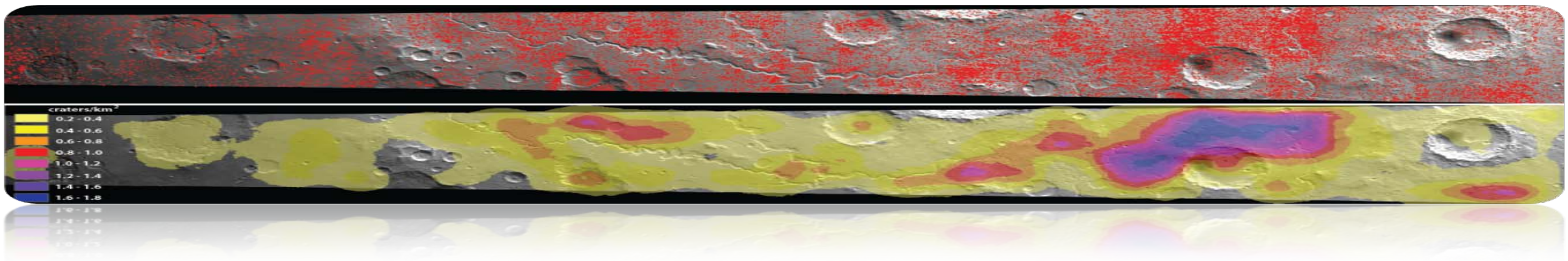
SURVEYING SUB-KM CRATERS IN THE HRSC IMAGE

- The processing pipeline uses scripts to automate the process
  - The supervised classifier uses Java-based routines, found in the WEKA environment
- The pipeline produces:
  - A final catalog of craters
  - A set of ArcGIS project files (each pertains to a single tile)

SURVEYING SUB-KM CRATERS IN THE HRSC IMAGE

- ArcGIS Project
  - Tile info it contains:
    - Tile image
    - Crater candidates
    - Detected craters
  - ArcGIS uses:
    - Produces accurate crater counting in small regions
    - Produces a “carpet coverage” of sub-km craters in a large region.
      - While not as accurate as manual mapping it is much more practical time wise and sufficient for statistical purposes

SURVEYING SUB-KM CRATERS IN THE HRSC IMAGE



35,494 craters identified in the HRSC image

- Areas shown in red or darker colors are areas where crater density exceeds 0.8 craters/km^2 .

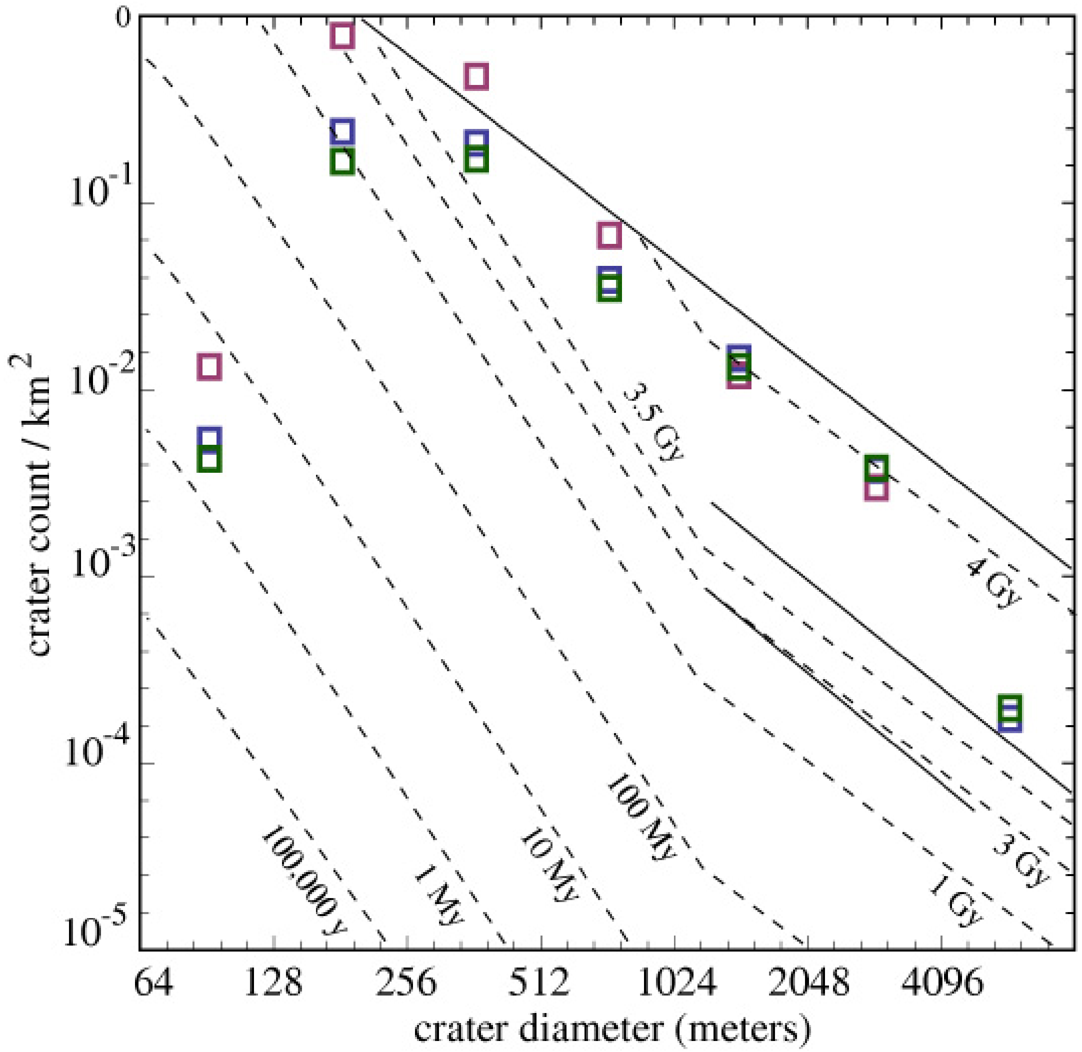
SIZE FREQUENCY DISTRIBUTION OF CRATERS IN THE HRSC IMAGE

- **Craters indentified using the auto-survey span.**

- Observed fall off in the number of craters having diameters smaller than ~200m that the algorithm.

  Green- counts using only craters located outside the crater enhanced area.

  Red- counts using only craters located within the enhanced area



SFD of masked area craters

CONCLUSION

The whole image(h0909_0000, 8248*65448 pixels) took 14 hours to compute;

7 hours for tiling, preprocessing, and shape filters;

6.3 hours for supervised machine learning;

0.6 hours for removing doubles;

10710 pixels/second;

Accuracy about 70%

IMPROVEMENT???

The process of rejecting and/or retaining a shape could be based on machine learning rather than compare and contrast to a limited group of chosen shapes.

IMPROVEMENTS

•Matching criteria could be reviewed and potentially replaced completely by a decision function generated by a supervised classifier that uses a larger training set.

•Other classification methods other than C4.5 method can be tested and may offer improved performance. One such example would be the Support Vector Machine