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Introduction to Data Mining

RPIF-3D workshop supported by Europlanets & FP7 i-Mars project

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Mars Orbiters with high-resolution visible cameras

Spacecraft	Launch date	Start operations	Finish	Camera instruments
Viking Orbiter (NASA)	20-Aug-75	22-Jun-76	17-Aug-80	VIS (8m-1km)
Mars Global Surveyor (NASA)	7-Nov-96	11-Sep-97	5-Nov-06	MOC-NA (1.5m-12m)
2001 Mars Odyssey (NASA)	7-Apr-01	24-Oct-01	N/A	THEMIS-VIS (17m-75m)
Mars Express (ESA)	2-Jun-03	25-Dec-03	N/A	HRSC (11m-100m)
Mars Reconnaissance Orbiter (NASA)	12-Aug-05	10-Mar-06	N/A	CTX (5-6m),HIRISE (0.25m-0.5m)
Mars Orbiter Mission (ISRO)	5-Nov-13	24-Sep-14	N/A	MCC (19.5m -4km)
Trace Gas Orbiter (ESA)	14-Mar-16	N/A	N/A	CASSIS (4.5m)

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Mars orbiters: high resolution imaging data

Cameras	Years	Resolution (m)	No. Images
~~Mariner 9~~	~~1971-1972~~	~~100-3000~~	~~7329~~
Viking Orbiter 1	1976-1980	8-1800	~32000
Viking Orbiter 2	1976-1978	8-1800	~15000
MOC-NA	1997-2006	1.5-12	97097
~~MOC-WA~~	~~1997-2006~~	~~240-7500~~	~~146571~~
THEMIS	2002-	18-36	~200000
HRSC	2004-	12.5-25	~5000 (nadir)
CTX	2006-	5-6	~75000
HiRISE	2006-	0.25-0.5	~75000

Processes that can be automated

1. ~~Automated Co-Registration & Orthorectification (ACRO) software~~
   – ~~8 June 2016 11:30-12:30~~
2. Automated change detection from high-resolution co-registered imagery
   – 9 June 2016 10:00-11:00
3. Automatic planetary image quality assessment
   – 9 June 2016 10:00-11:00

<u>Fundamental design principle: The developed software should require the minimum user involvement</u>

– Automatic means that you don't need to spend hours tweaking the parameters each and every time

Preliminary Analysis – Repeat Coverage

Objectives

1. How many high-resolution images are there in total?
   – Two different high-resolution thresholds (20m/pixel, 100m/pixel)
2. How many overlap with each other?
3. Where are the regions where multi-temporal analysis is feasible?
4. Is global-scale change detection within reach?
5. If time/illumination constraints are imposed, is it still possible to look for dynamic features at a global scale
   – Season-Epoch that images were acquired
   – Mean incidence angle constraints

Repeat coverage analysis method

- Download image footprints from ODE:
  – http://ode.rsl.wustl.edu/mars/indextools.aspx?displaypage=footprint
- For each footprint
  – Fill the footprint interior
    - Several "shape-filling" algorithms available on the web
  – Rasterise the footprint: Using a sampling step S, check if (i*S, j*S) belong to the footprint interior
  – S = 0.01°, i.e. ~600m in the equator
    - Footprints are from the images before the co-registration, so finer rasterisation would ignore the initial mis-registration errors of the footprint
- Collect all footprints of images that satisfy specific metadata requirements
  – E.g. epoch, season, incidence angle
- Make a repeat coverage map
  – Colour scale shows how many times a region has been mapped

Metadata Specifications

1. Two resolution ranges: (1) Res<20m, (2) 100<Res<20m
2. Four "Epochs": (1) Martian Year 10-12, (2) Martian Year 23-25, (3) Martian Year 26-28, (4) Martian Year 29-31
    1. Analysis conducted two years ago, using data up to July 2013
3. Four (Northern hemisphere) seasons
4. Six Incidence Angle ranges: Step of 15°

- Combining these requirements, tens of maps were published (and eventually will be released through the webGIS)
    - Global maps: Mollweide projection; Polar maps: Polar stereographic
    - In http://www.i-mars.eu/web-gis the "High-Res Repeat Coverage" layer is the one with all images with Resolution<100m

Global Mars Surface Coverage Statistics

Camera	Coverage (Res<20m)
VO 1 & 2	0.56%
MOC-NA	5.27%
THEMIS-VIS	61.08%
HRSC	64.39%
CTX	82.71%
HiRiSE	1.39%

Season (NH)	Coverage (Res<20m)
Spring	66.41%
Summer	47.79%
Autumn	38.16%
Winter	49.02%

Period	Coverage (Res<20m)
MY 12-14	0.56%
MY 23-25	3.16%
MY 26-28	59.93%
MY 29-31	88.53%

Global Mars Repeat Coverage Statistics

- Resolution <100m: 99.3% of Mars has been mapped more than once
- Resolution <20m: 96.2% of Mars has been mapped more than once
- For ~45% of Mars there is an HRSC ORI and DTM available

Season	Mapped twice or more (10^6 km^2)	Mapped thrice or more (10^6 km^2)
NH Spring	48.3	20.1
NH Summer	25.3	8.8
NH Autumn	18.8	6.2
NH Winter	26.7	9.9
All Seasons	121.3	89.0
Asia: 44.5 M km2, Africa: 30.2 M km^2, N. America: 24.7 M km^2, S. America: 17.8 M km^2, Antarctica: 14M km^2, Europe: 10.2 M km^2, Oceania: 8.5 M km^2		

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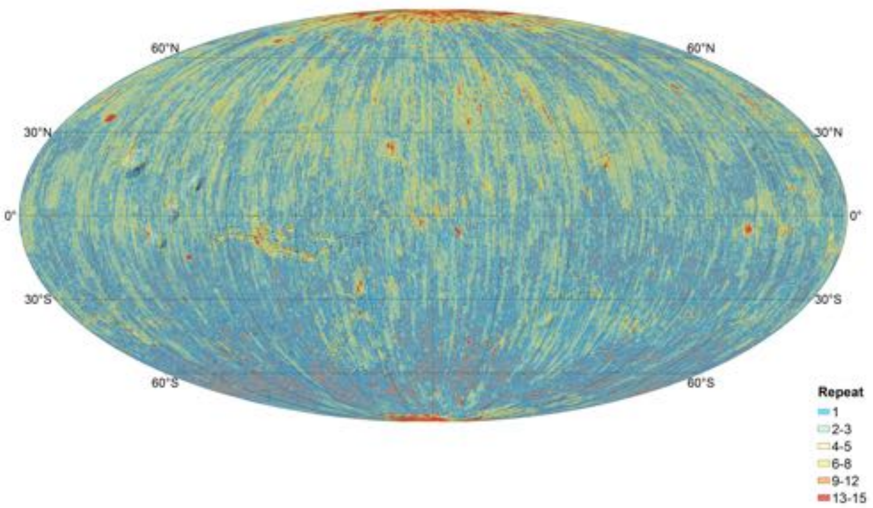
Repeat Coverage with Res<20m, 29<MY<31



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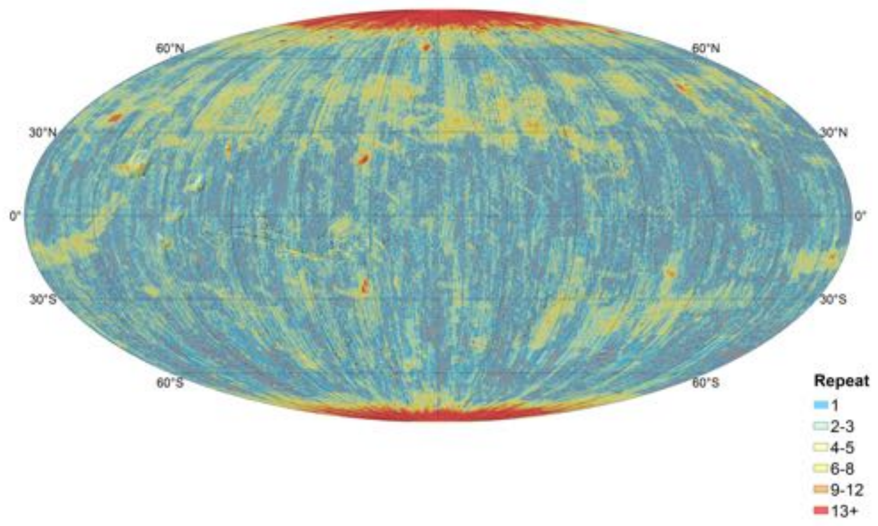
Repeat Coverage with 60<Inc_Ang<75, Res<100m



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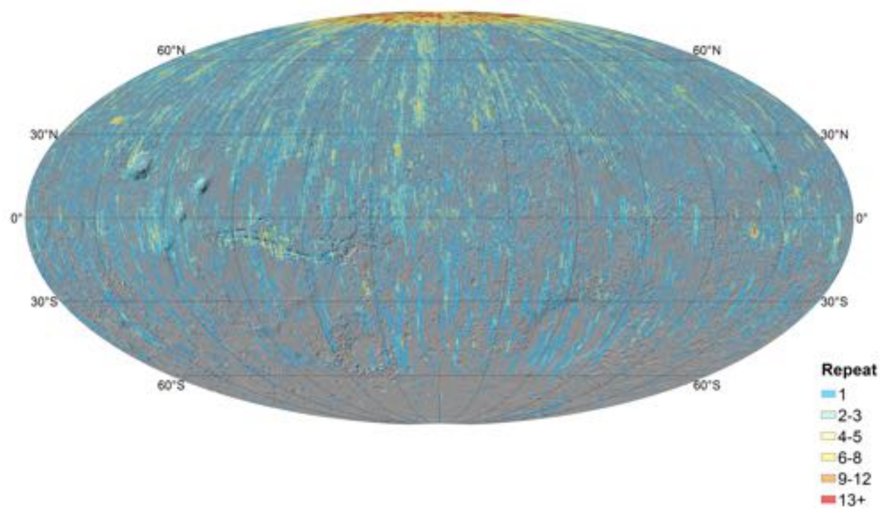
Repeat Coverage with Res<20m, North Hemisphere Summer



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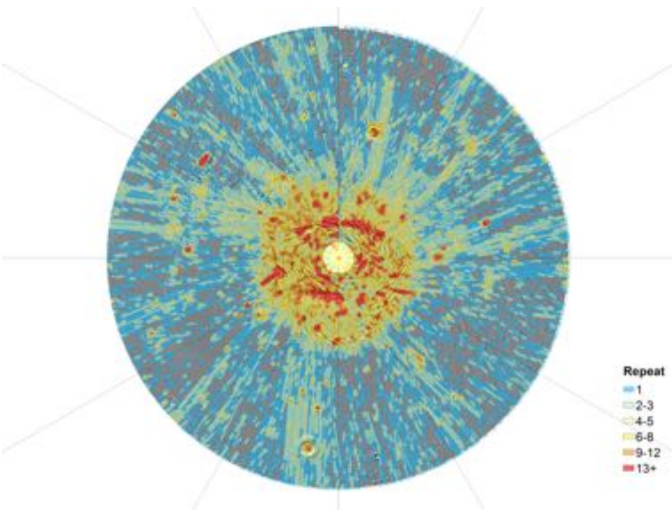
North-Pole Coverage with Res<20m, North Hemisphere Summer



You can download 30 maps from the following link:

https://www.dropbox.com/sh/imn5cg126r0x4vb/AADZ0dRGWYwUUcQHZ20KYZI1a?dl=0

<u>If you use them, please cite:</u>

P. Sidiropoulos and J.-P. Muller, "On the status of orbital high-resolution repeat imaging of Mars for the observation of dynamic surface processes", Planetary and Space Science, Vol. 117, pp. 207-222, 2015.

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Conclusions from the initial data analysis

1. There are enough high-resolution image data to perform batch-mode change detection
2. There are large regions of Mars where change detection can take into account additional constraints, such as the season when the image was acquired or the incidence angle
   – E.g. 3 images of resolution finer than 100m/pixel for (North-Hemisphere) Spring exists for an area that is double the area of Europe
3. There are large gaps, mostly in polar regions during night-time
   – THEMIS night map has only 100m/pixel resolution
4. Imaging is not homogenous but there are ROIs (Regions of Interest) for which much more data exist
   – Each point of Gale crater has been mapped on average 93.5 times (Res.<20m), there is still 3.8% of Mars that has been mapped less than twice with Res.<20m

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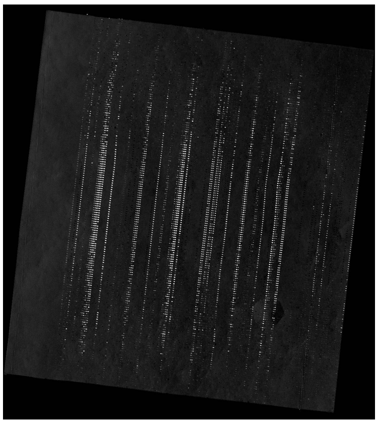
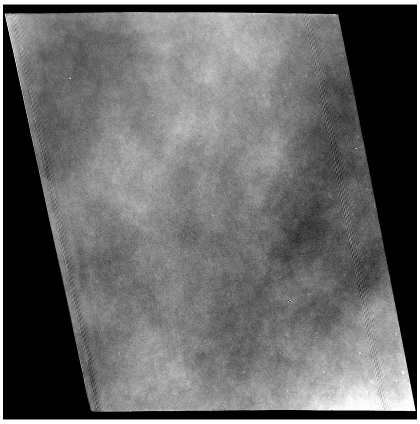
Automatic Planetary Image Quality Assessment (1)

- After exploring the dataset capabilities, the fun part can start
  - …but not yet!
- What about the images of low visual quality?
  - They often represent a waste of time (left panel)
  - But they may be correlated with natural processes (right panel)





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Automatic Planetary Image Quality Assessment (2)

- Overall, the number of high-resolution images of low visual quality is unknown
  - <u>We would like to estimate these and screen these images</u>

<u>Objectives</u>

1. To build software that automatically assesses the (visual) image quality of (Mars) orbiter images
   - Demonstrate that planetary (visual) image quality is possible to be gauged with current image processing and pattern recognition technology
2. To make this software robust, compact and efficient, so as to be able to "clean up" all current Mars orbital datasets within a realistic time-frame
3. To build software which determines the cause of the visual quality degradation
   - Demonstrate that the class of low-quality images is separable into sub-classes, each expressing a distinct image degradation cause
4. To explore possible future uses of this technology

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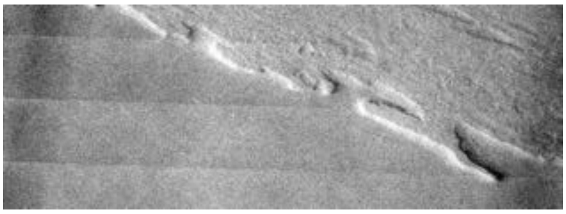
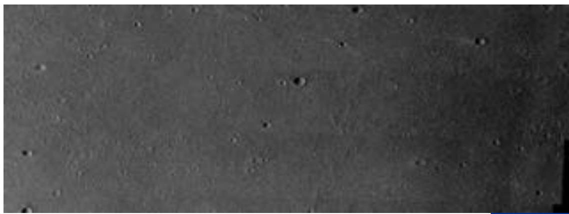
THEMIS: (Manual) Quality Rating

THEMIS-VIS Image Rating 1:

THEMIS-VIS Image Rating 2:



THEMIS-VIS Image Rating 3:



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Viking Orbiter Missions

- Viking Orbiter 1 & 2: Twin missions
  - Viking 1
    - Launched: 20 August 1975, Mars orbit insertion: 19 June 1976, Worked until 17 August 1980
    - Acquired: ~32,000 images
  - Viking 2
    - Launched: 9 September 1975, Mars orbit insertion: 7 August 1976,Worked until 25 July 1978
    - Acquired: ~15,000 images
- Viking 1 & 2 have acquired images covering the entire Mars surface with resolution finer than 1km/pixel
  - ~27% of Mars surface with resolution finer than 100m/pixel
  - ~0.6% of Mars surface with resolution 8-20m/pixel
- VIS imaging system (both in Viking 1 and 2): Vidicon frame cameras
  - no CCD, no pushbroom

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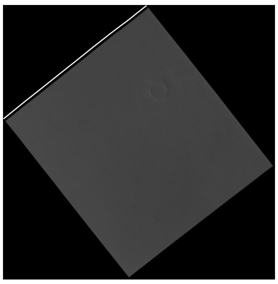
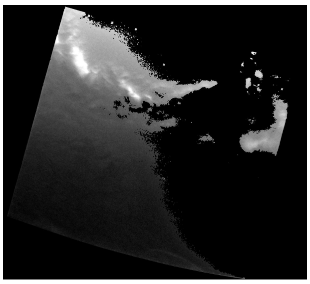
Viking Orbiter image problems

- Cameras were of previous (Cathode Ray Tube) technology
  - Lotsof problems in correctly storing the representation of the images
    - Burst Noise
    - DN Quantisation problems
    - Horizontal Stripes
    - Vertical Stripes
    - Salt & Pepper Noise
    - Low contrast
- Viking Orbiter arrived in a turbulent Mars era
  - Violent dust storms
  - Clouds causing gravity waves

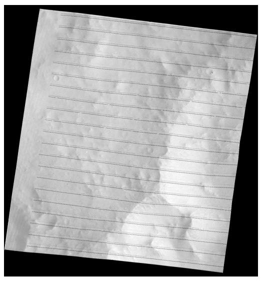
"Internal" Viking Orbiter low-quality images



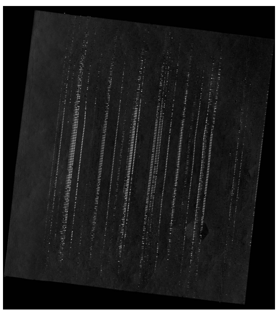
Low Contrast



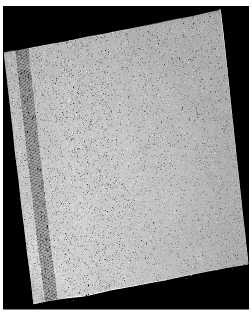
DN Quantisation



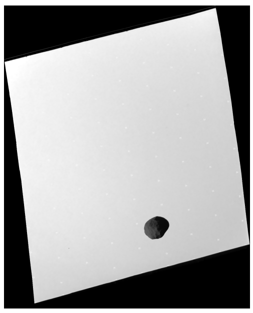
Horizontal Stripes



Vertical Stripes

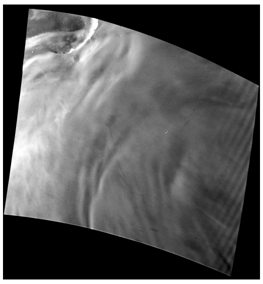


Salt & Pepper Noise

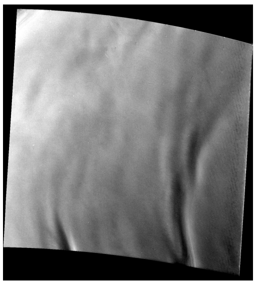


Burst Noise

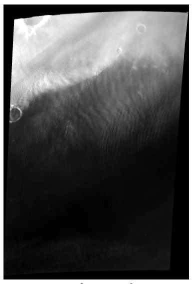
“External” Viking Orbiter low-quality images



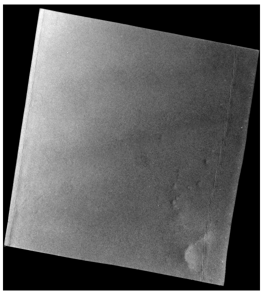
Clouds



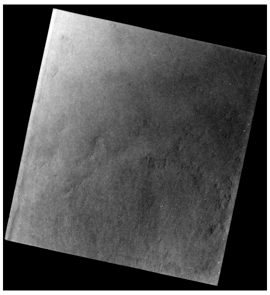
Clouds



Clouds



Dust



Dust

Dust

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Viking Orbiter (Manual) Image Quality Annotation

- 8,594 Viking Orbiter Images
- 5 star rating system
  - 1-star: Image with no scientific meaning
  - 2-star: Image for which the general idea of what is depicted can be assumed, but significant details are missed due to quality degradation
  - 3-star: Image with obvious flaws, which however don’t degrade/modify/eliminate the largest image parts
  - 4-star: Good quality image with a small number of artefacts, or medium contract or low level of noise
  - 5-star: Good quality image with high contrast and no artefacts
- Statistics
  - 1-star: 780 (9.1%)
  - 2-star: 1055 (12.3%)
  - 3-star: 1615 (18.8%)
  - 4-star: 2939 (34.2%)
  - 5-star: 2205 (25.7%)

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Viking Orbiter (Manual) Image Quality Annotation

- From 1,835 low-quality images (1-star and 2-star images) we found how many have the predetermined low-quality patterns
  - Dust: 822
  - Low Contrast: 301
  - Salt and Pepper: 92
  - Clouds: 81
  - DN Quantisation: 40
  - Horizontal Stripes: 29
  - Vertical Stripes: 16
  - Burst Noise: 6
  - Other (not defined low-quality pattern): 20
- Dust the most common visual obscuration
- The used set of low-quality patterns express the Viking Orbiter degradations
  - Only 20 (i.e. 1%) of the low-quality images have some low-quality pattern not defined in the list

Automatic Image Quality Assessment

- Build an automatic pipeline that will provide results as close as possible to manual annotations
  - Ill-defined problem, since manual annotations always have a degree of uncertainty
    - With the 5-star rating we model the uncertainty by defining that “correct automatic annotation is when the quality automatically assessed is within 1-star distance from the manual one”.
- Two-stage problem:
  1. Assess the overall image quality
  2. If the image is found of low-quality (1-star or 2-star), estimate the low-quality patterns found in the image

Automatic IQA Pipeline – Technical Specifications (1)

- Image quality assessment: Image processing sub-domain that focus on the assessment of the visual quality of an image
  - Full-reference image quality assessment: The original image is known and an image copy (e.g. a compressed image) is compared to it
  - Reduced-reference image quality assessment: Some information about how the image content should look like is known, but the original image (or the "correct" image) is not available
  - **No-reference (or blind) image quality assessment: No information about how the image content should look like is known**

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Automatic IQA Pipeline – Technical Specifications (2)

- No-reference image quality assessment:
  - Based on the assumption that low-quality images are not random pixel matrices, but they present some low-quality patterns that can be modelled
  - Typically SoA methods try to detect "blurring" and "noise"
    - In planetary images, blur is apparent in "dust", "low contrast", "clouds", "noise" in "salt and pepper noise", "burst noise"
- Our approach:
  - Deep learning approach
  - Extract 6 image quality descriptors, each expressing a different low-quality sub-class
    - 3 from the literature
    - 3 newly developed
  - Combine their classification scores into an SVM meta-classifier

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Quantitative separability of high and low quality images

- Preliminary results
  - High-quality images
    - 91% correct classification
  - Low-quality images
    - 93% correct classification

- Conclusion: High and low visual quality planetary images can be automatically discriminated using automatic techniques

Sub-class separability of low-quality images

- Input set: the correctly automatically assessed 1-star and 2-star images
- Preliminary results
  - Only for dust
    - 13% false acceptance
    - 16% false rejection

- It appears that low-quality patterns can be also detected using automatic techniques

How to use automatically identified low-quality patterns

1. Clean existing planetary image databases
2. Place on-board a spacecraft to discard on-the-fly low-quality images, when the imaging purpose demands good visual quality
   – E.g. when attempting stereo coverage
3. Extract spatio-temporal information of low-quality patterns
   – E.g. detect areas and times that atmospheric dust was intense
4. Compare with the measurements of other instruments
   – E.g. compare atmospheric dust measurements with the visual quality degradation that they cause

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Automated Change Detection

- After defining the dataset, cleaning it and co-registering the data, automatic change detection is performed.
- Change detection is performed in a pairwise manner
  – "Before" and "After" image
- Since input images are firstly co-registered to HRSC, a DTM is available
  – The resolution difference may be too large, so the DTM has limited significance, but is better than nothing
- The basic idea is to develop modules, each of which focus on specific visual class of changes, and combine the modules output in a (meta-) classifier

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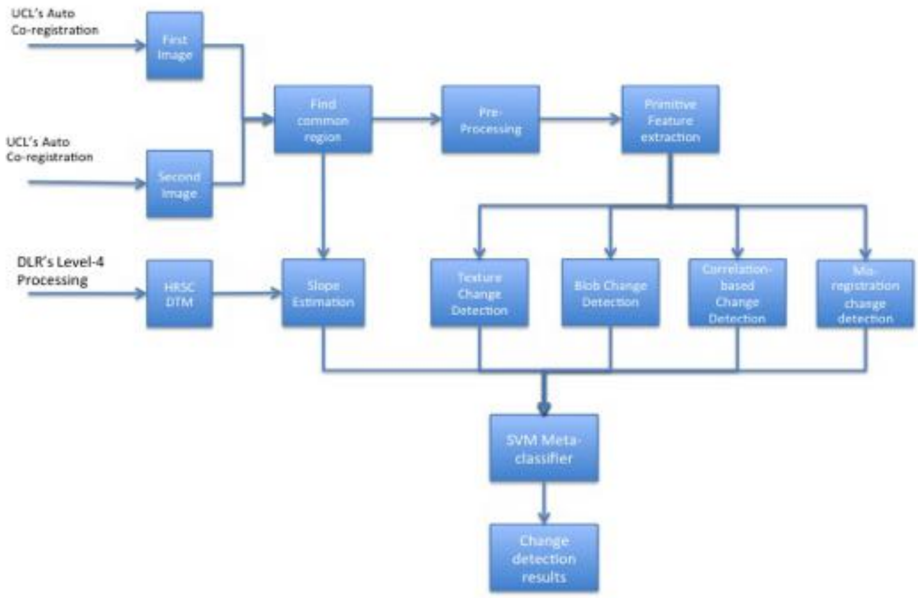
Change Detection Pipeline Flowchart



Change Detection Pipeline – First Module

1. <u>Detection of image texture changes</u>

- Based on SIFT and Bag-of-Words (BoW)
- Image texture changes are correlated to a number of surface changes
  - E.g. gullies, RSLs, etc.
- Bag-of-Words
  - Create a set of "codewords" that express the texture of the image
    - Each codeword is a SIFT vector
  - Project all SIFT points to the "codewords" and estimate the histogram
  - The histogram is the image BoW representation
- Within i-Mars context, we estimate a codeword for each image and a BoW for each ROI and we estimate their correspondence

Change Detection Pipeline – Second Module

2. Blob Detection

- The goal is to detect homogenously coloured irregular shapes (i.e. blobs) that are present on only one of the two images
- This is how a number of surface changes visibly appear
  - E.g. slope streaks, new impact craters
- We have developed a novel, random-walk algorithm that search in pairs of images to detect blobs
- Random-walk algorithm basic principle: Start from an image pixel and create a path based on a stochastic process
  - In each step the next pixel is selected based on the pixel neighbourhood
  - If there is a "blob-based" change then the random walks characteristics differ in the two images

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Change Detection Pipeline – Third Module

3. Shape-based change detection

- A number of surface changes change the shape of the surface (e.g. aeolian processes)
- A simple way to detect shape-based changes is through their mutual registration
- After matching the images we triangulate the matched points
  - Triangles with large areas mean that no points were matched in their interior, therefore the shape is difference
  - Triangles with small areas confirm that the area hasn't changed

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Change Detection Pipeline – Fourth Module

4. <u>Motion-based change detection</u>

- All of the above changes are "semantic shift" changes, i.e. the surface on a specific ROI has changed semantic meaning
  - E.g. a flat area becomes an "impact crater", a slope streak fades, etc.
- There are changes for which the change is not correlated with a "semantic shift" but with "motion"
  - E.g. dune migration
- Theoretically, we can't distinguish "local motion" from unsystematic co-registration residuals
- We assume that there is a local motion when
  - The co-registration residuals of a ROI are systematic
  - Their amplitude is large
  - Their direction is different than the direction of any global systematic residuals

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Meta-classifier

- Each module produce an output for each ROI, which is an estimation whether it is changed or not
- The goal is to build a two-steps classifier, with the second step being a "meta-classifier", i.e. a classifier that takes as an input individual classification results
- The meta-classifier would be a Radial Basis Function Support Vector Machine (RBF SVM)
  - RBF SVMs are optimal in classification cases that the input data are of low dimension
  - The input of this meta-classifier is 5-dimensional
    - 4 dimensions the output of the 4 modules
    - 5^{th} dimension the average slope (based on HRSC DTM)
- <u>But, we don't have any samples to build a classifier</u>
  - We need at least 1,000 samples (500 positive and 500 negative)

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Meta-classifier

Thank you for your help

~~We need at least 1,000 samples (500 positive and 500 negative)~~

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Next steps

- Collect the annotations and build a meta-classifier
- Connect co-registration and change detection pipelines into 1 pipeline that will allow us to do full single-strip processing, i.e.
    1. Select an HRSC single strip
    2. Find all images overlapping with it
    3. Automatically co-register them
    4. Identify the pairs of overlapping images
    5. For each overlapping pair perform change detection
- Full scale processing will start and continue until the end of the project
    - Provide results to Jess for crowdsourcing
    - Release the results

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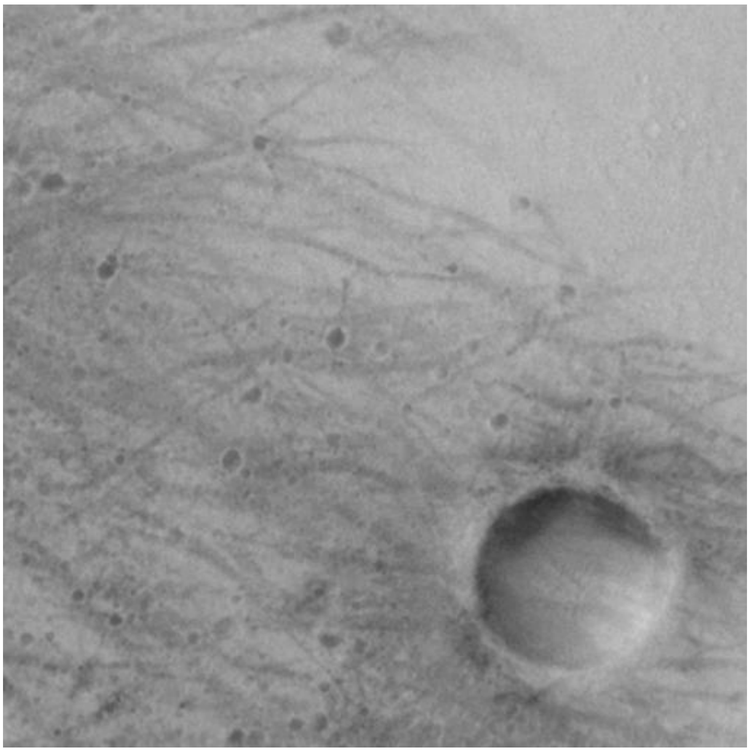
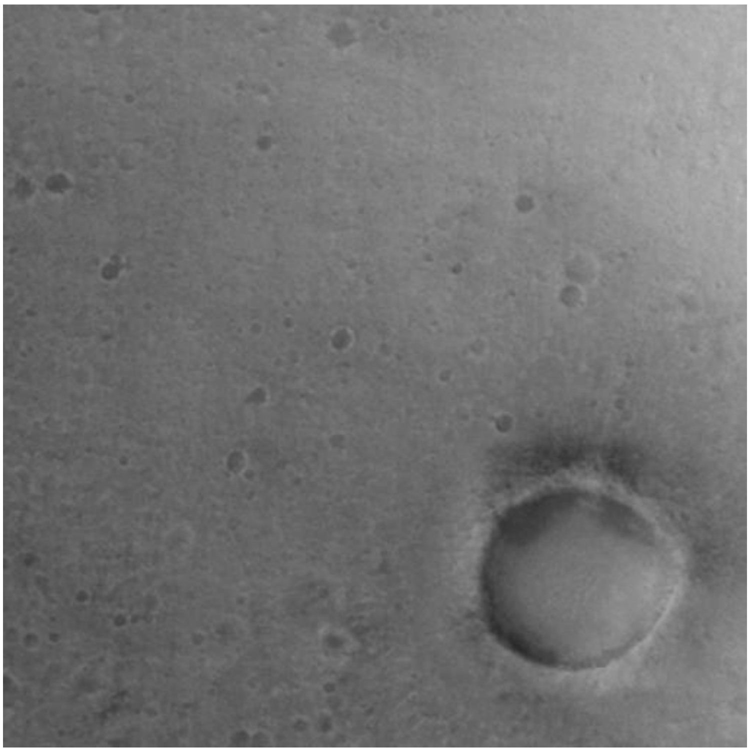
Automated Change Detection - Preliminary Examples (1)



Automated Change Detection - Preliminary Examples (1)



Automated Change Detection - Preliminary Examples (2)

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Automated Change Detection - Preliminary Examples (2)

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Automated Change Detection - Preliminary Examples (3)

Automated Change Detection - Preliminary Examples (3)

Thanks

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