SPARK+AI SUMMIT 2018

The Hunt For Lunar Ice

Nagib Hakim, Intel Corporation

#AISAIS18

Acknowledgements

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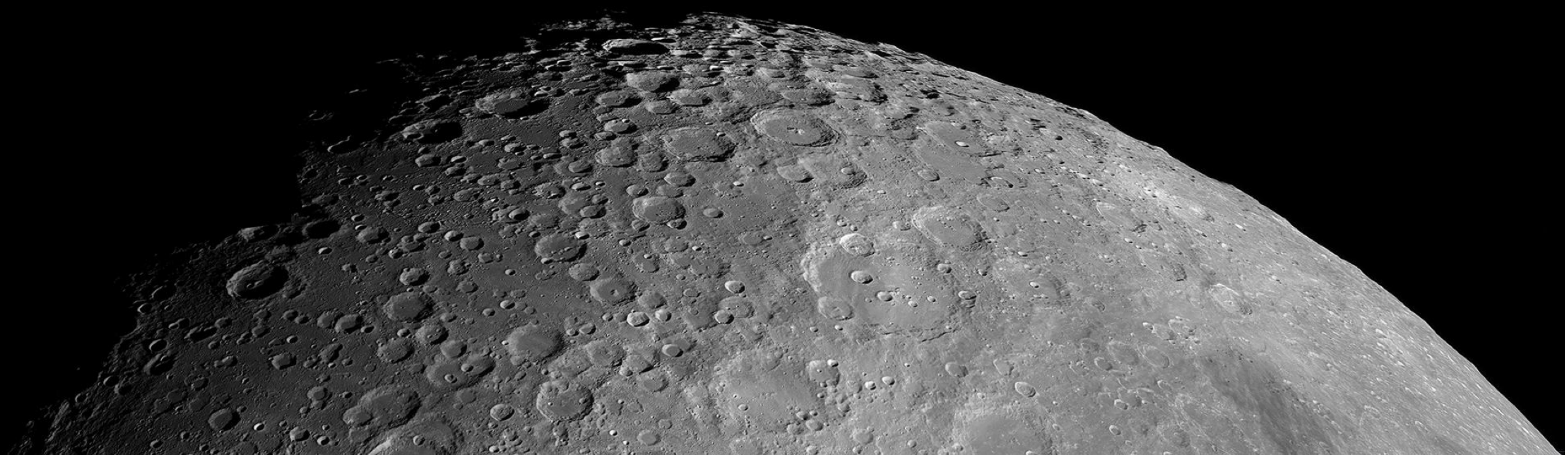
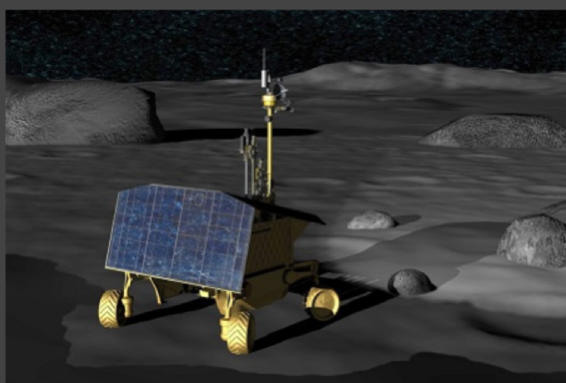
Intel's partnership with the NASA Frontier Development Lab (FDL)

- FDL: AI Research accelerator for space data science
  - Joint Space Science + AI
- Intel Provides Sponsorship, Mentoring, and Resources

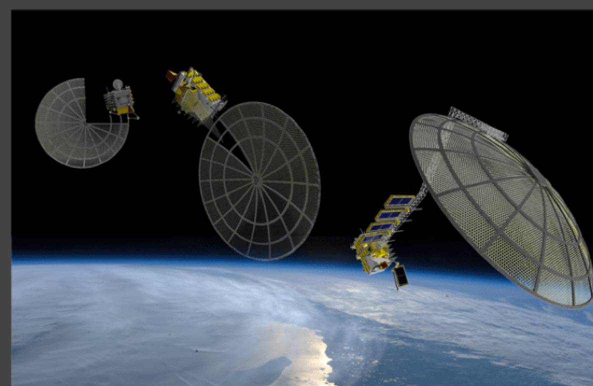
The Opportunity



Why are Lunar Resources Important?



Continued Lunar Exploration
In Situ Resource Utilisation
(ISRU)

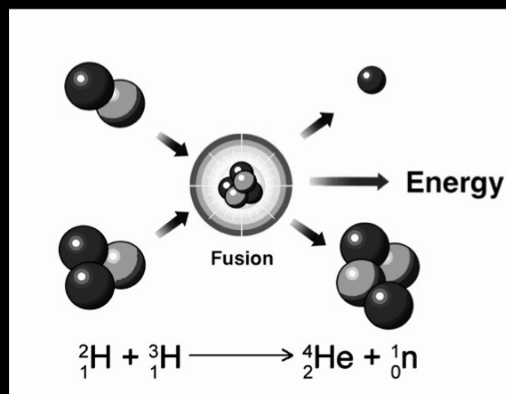


Launchpad for Scientific /
Economic Activity in CisLunar
Space

Import Resources to Earth to
contribute to the global
economy

Critical Lunar Resources

Rare Earths



Helium-3 Isotope

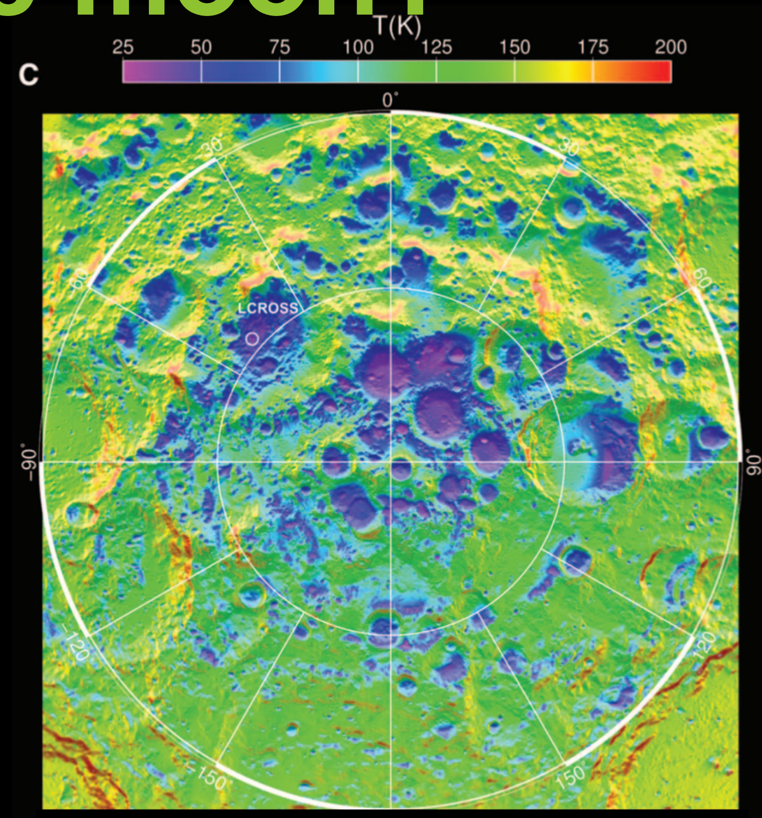
Silicates

Water

Where is water on the moon?

- Surface is anhydrous but there may be reservoirs.
- Craters near the poles
  - Low obliquity means the floors are in permanent shadow.
  - Surface temperatures measured below 40K
  - Water ice may be thermally stable
- Indirect evidence
  - Neutron Spectrometer on Lunar Prospector
  - 5.6 ± 2.9 wt% in regolith by LCROSS

In Situ measurements are needed

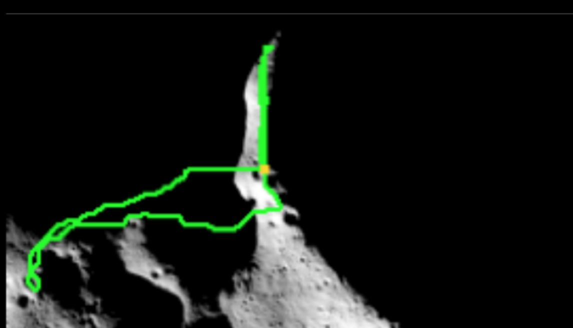


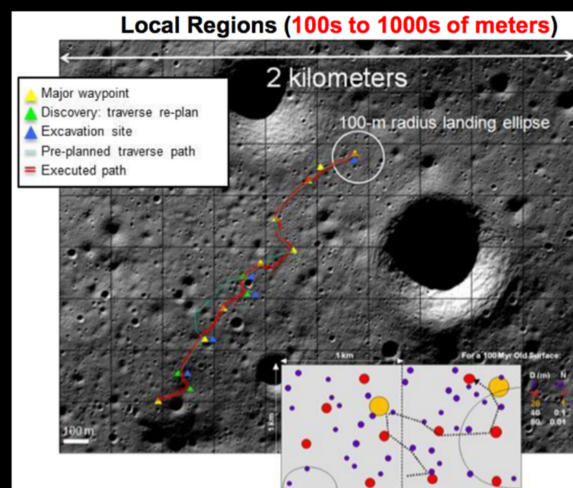
Simulated annual average near-surface temperatures
Paige et al., Science 330 (2010); www.sciencemag.org

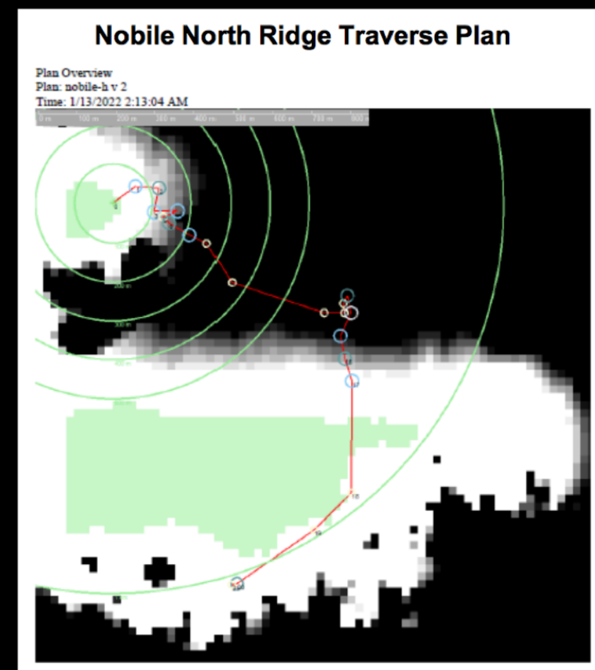
Landers and Rovers

Difficulties of traverse planning

- Direct line of sight to Earth for communications
- Direct line of sight to the Sun for solar cells
- Maximum Slope







Shackleton (left), Malapert Peak (right)
Otten et al., 3D representation of the largest pruned component from the Malapert Peak example and resulting shortest route. IEEE 2015

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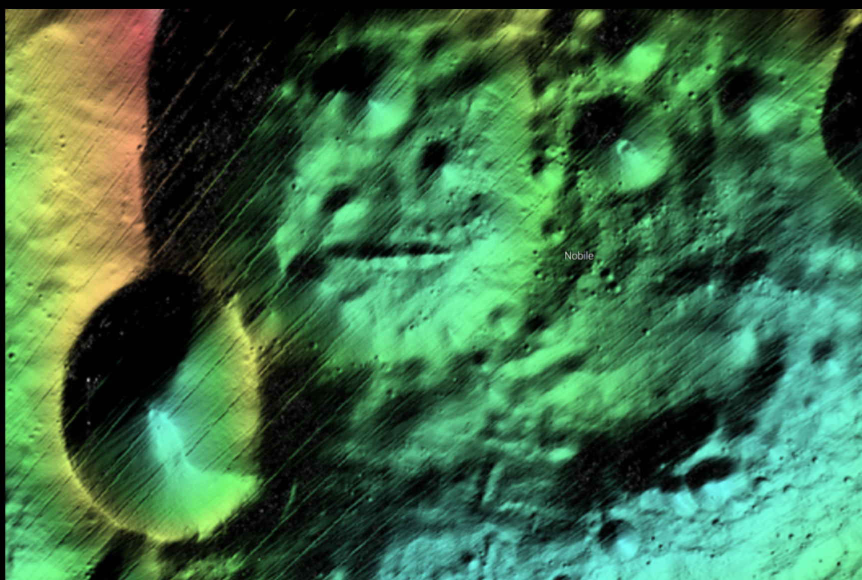
LRO Mapping Issues

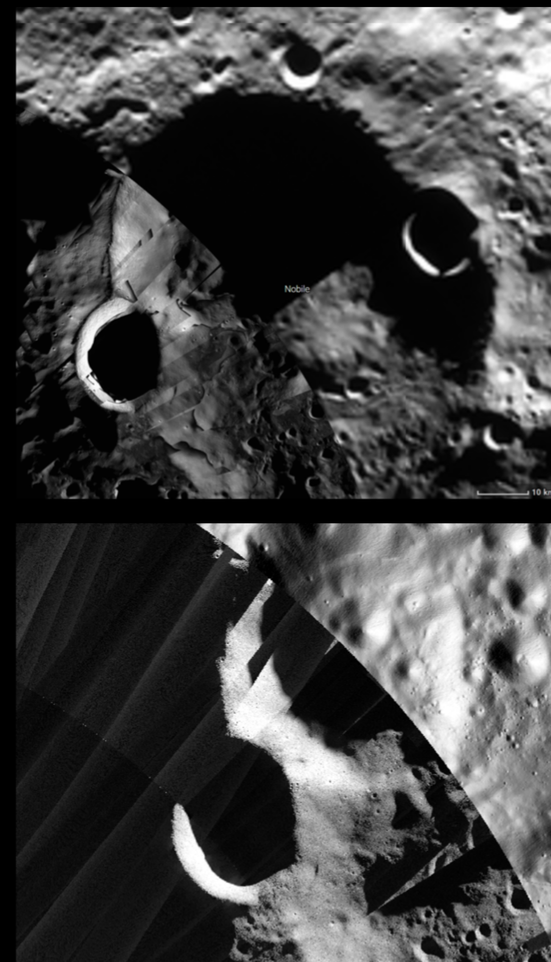


Lunar Orbiter Laser Altimeter
Digital Elevation Model (LOLA DEM)
20m resolution

Narrow Angle Camera (NAC) optical images
0.5m resolution

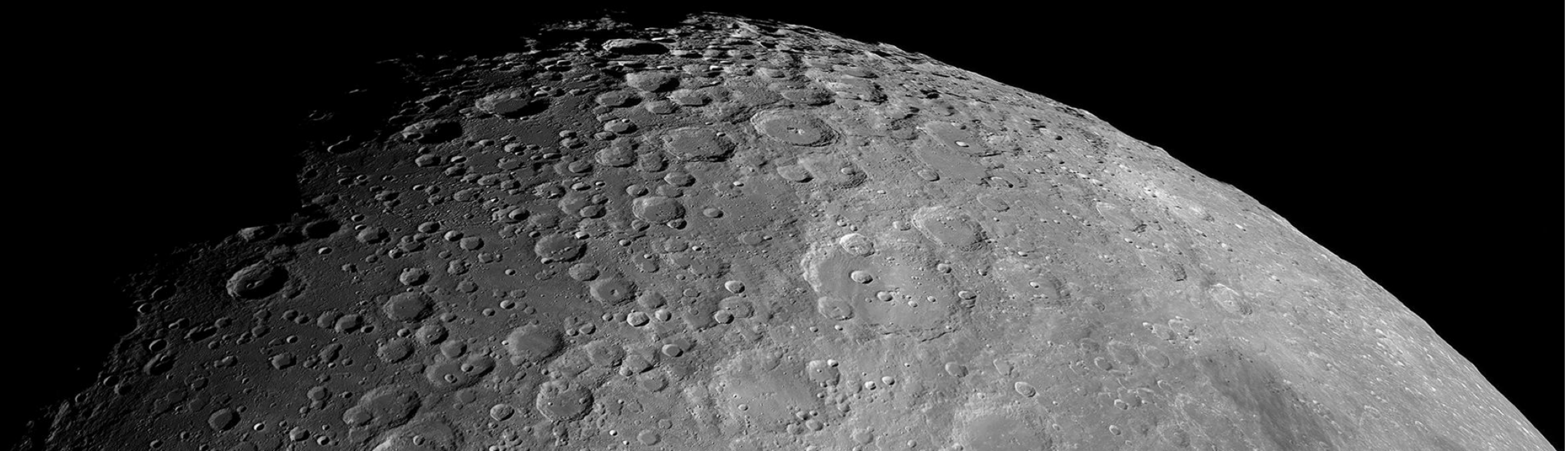
Summary

- Most of Lunar water is in PSRs at the poles
- Mapping at the poles is problematic
  - Co-registrations issues
  - Artefacts
  - Image illumination
- Labour intensive data preparation is required before meaningful mission planning can be conducted

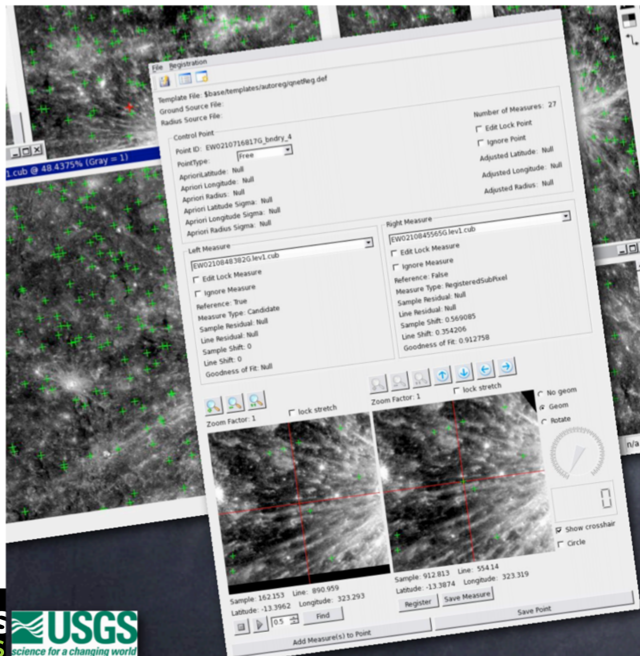


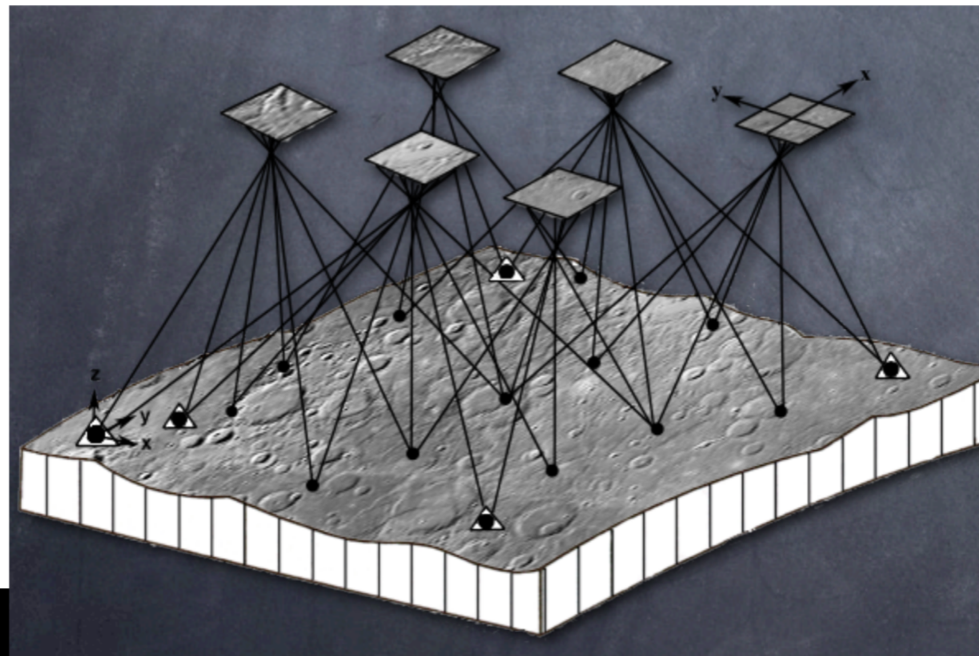
Nobile Crater: optical image mosaic overlaid over DEM

The Approach



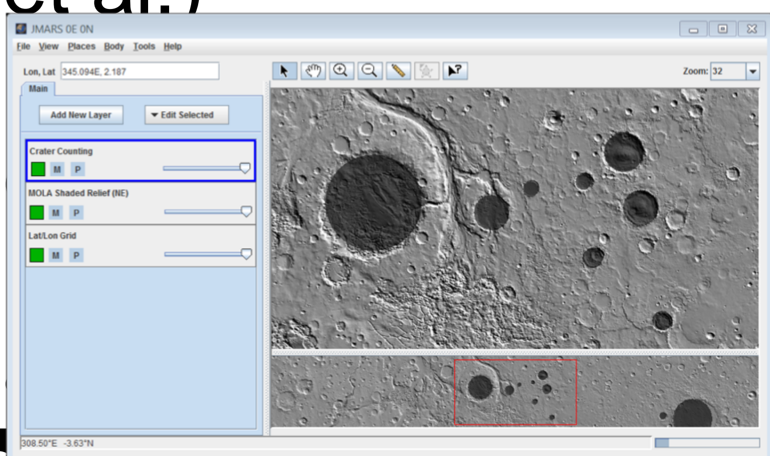
Improving Maps Conventionally,
how do we solve co-registration and artefacts?

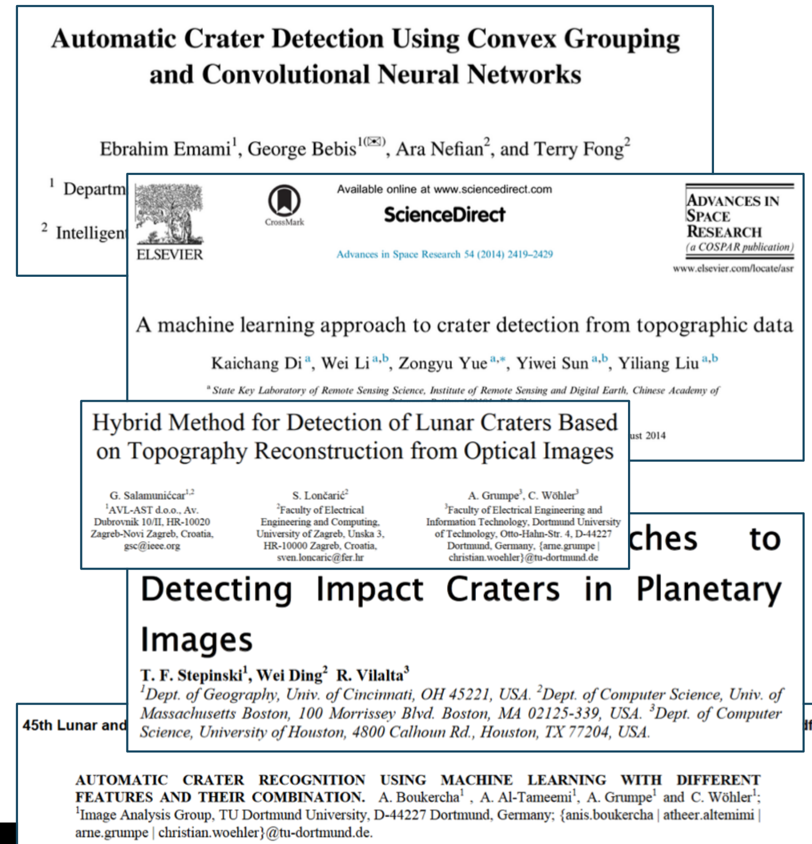




Crater Detection at Present

- ~77 crater detection algorithms published as of 2011 (Salamunićcar et al.)
- …py
-





Automatic Crater Detection Using Convex Grouping and Convolutional Neural Networks

Ebrahim Emami[1], George Bebis[1(✉)], Ara Nefian[2], and Terry Fong[2]

[1] Departm…
[2] Intelligen…

Available online at www.sciencedirect.com
ScienceDirect
Advances in Space Research 54 (2014) 2419–2429
ELSEVIER
ADVANCES IN SPACE RESEARCH (a COSPAR publication)
www.elsevier.com/locate/asr

A machine learning approach to crater detection from topographic data

Kaichang Di[a], Wei Li[a,b], Zongyu Yue[a,*], Yiwei Sun[a,b], Yiliang Liu[a,b]

[a] State Key Laboratory of Remote Sensing Science, Institute of Remote Sensing and Digital Earth, Chinese Academy of …

Hybrid Method for Detection of Lunar Craters Based on Topography Reconstruction from Optical Images

G. Salamunićcar[1,2] — [1]AVL-AST d.o.o., Av. Dubrovnik 10/II, HR-10020 Zagreb-Novi Zagreb, Croatia, gsc@ieee.org
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…ches to Detecting Impact Craters in Planetary Images

T. F. Stepinski[1], Wei Ding[2], R. Vilalta[3]
[1]Dept. of Geography, Univ. of Cincinnati, OH 45221, USA. [2]Dept. of Computer Science, Univ. of Massachusetts Boston, 100 Morrissey Blvd. Boston, MA 02125-339, USA. [3]Dept. of Computer Science, University of Houston, 4800 Calhoun Rd., Houston, TX 77204, USA.

45th Lunar and …

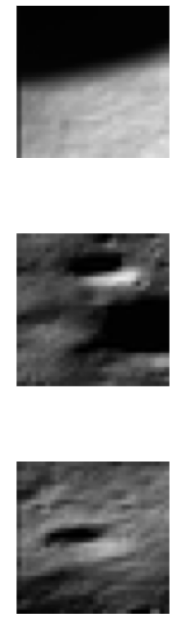
AUTOMATIC CRATER RECOGNITION USING MACHINE LEARNING WITH DIFFERENT FEATURES AND THEIR COMBINATION. A. Boukercha[1], A. Al-Tameemi[1], A. Grumpe[1] and C. Wöhler[1]; [1]Image Analysis Group, TU Dortmund University, D-44227 Dortmund, Germany; {anis.boukercha | atheer.altemimi | arne.grumpe | christian.woehler}@tu-dortmund.de.

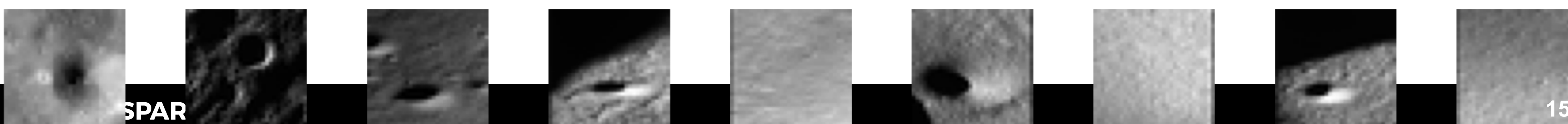
A Deep Learning approach for Crater Detection

- Challenges:
  - Ability to detect small and large craters, as well as overlapping ones.
  - Ability to detect polar as well as equatorial craters

A NEW Features Dataset

18000 Labelled DEM Tiles
16000 Labelled Polar NAC Tiles
6000 Labelled Equatorial NAC Tiles
2800 Annotated DEM craters
450 Annotated NAC craters
And many tens of thousands unlabelled...





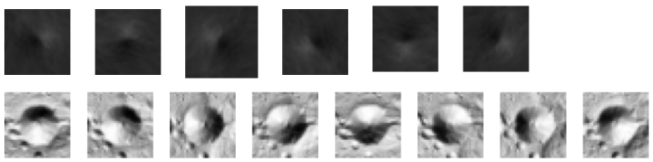
CNN and Single Shot Detection (SSD)

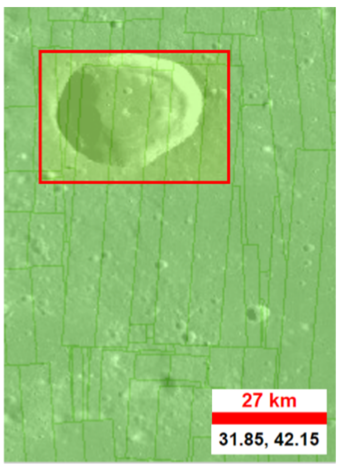
- Phase1: CNN to detect whether a feature is or is not a crater

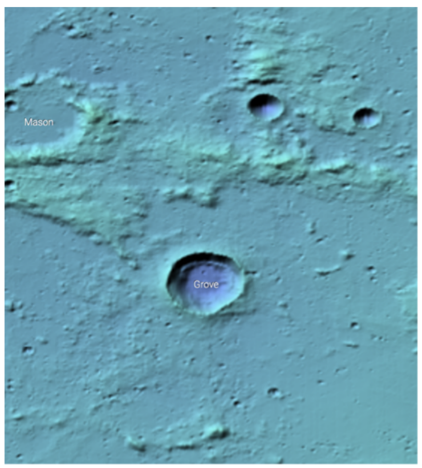
- Phase 2: SSD: Take a tile and detect and classify all craters

Training Regions

Equatorial Region: Grove Crater JPL test site

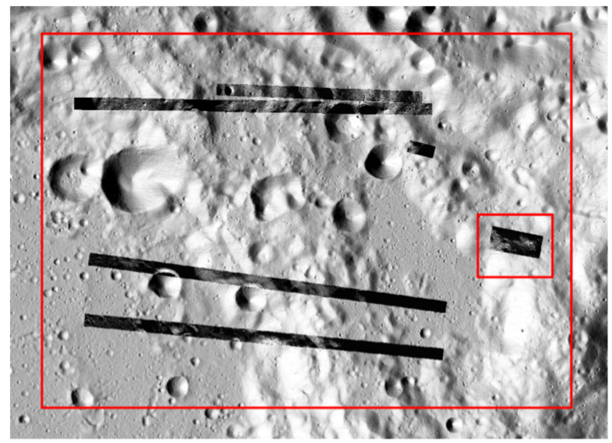




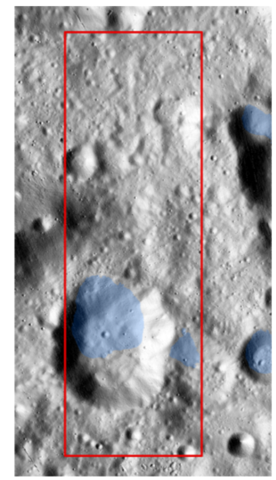


Polar Regions: various locations covering different features

Drygalski



Newton B



Comparison with Previous Work

Group	Vijayan et al.	Di et al.	Emani et al.	**FDL (CNN)**
Year	2013	2014	2015	**2017**
Method	Pattern recognition	Pattern recognition	CNN	**CNN**
Precision (%)	91	87	86	**98**
Error Rate (%)	9	13	14	**2**

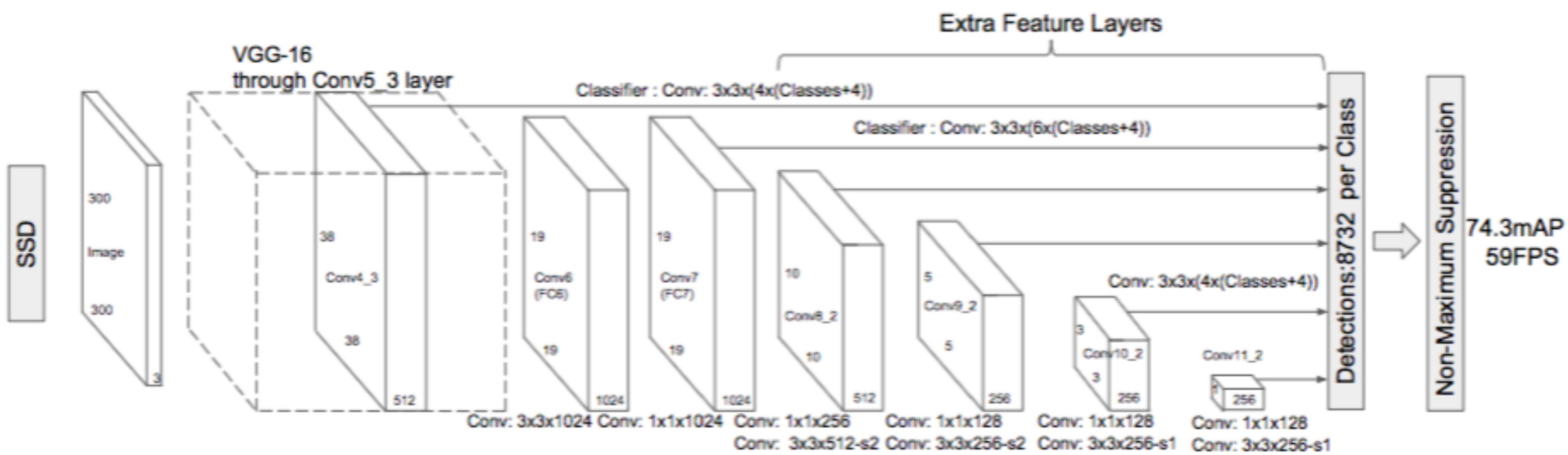
Dataset Influence on Precision

CNN Error Rate (%) vs. Training	
Equatorial on Equatorial	5.05
Equatorial on Polar	9.68
Polar on Polar	2.02
Both on Polar	**1.61**

Speed-up

Group	Human	Single-Layer	**CNN**
Accuracy	Near-Perfect	Poor	**98% Human**
Time (per 1000)	1-2 hours	10 Hours	**1 minute**
Man-Hours	1-2 hours	-	**-**

SSD for Crater detection



Optimizations:

- Prior Box distribution optimization for large and small crater detection
- Image scaling to different sizes

Results: (90% & 78% train / test precision) - Better detection than human labeler.

Future Opportunities / Challenges

- Traverse planning and autonomous roving
- Map + ground truth fusion
- Mining data analytics
- Low-G and loose soil mechanics and control
- Resilient computing
- …

Moonshot: See the model in action

http://www.frontierdevelopmentlab.org/ai-lunar-mapping/moonshot.html#