LROC-PANGU-GAN

Closing the Simulation Gap in Learning Crater Segmentation with Planetary Simulators

Jaewon La[1], Jaime Phadke[1], Matt Hutton[4], Marius Schwinning[4], Gabriele De Canio[4], Florian Renk[4], Lars Kunze[2], and **Matthew Gadd**[3]

[1]Balliol College, [2]Cognitive Robotics Group (CRG), [3]Mobile Robotics Group (MRG), University of Oxford
[4]European Space Operations Centre, European Space Agency (ESA)

University of Oxford

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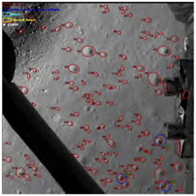
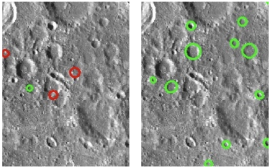
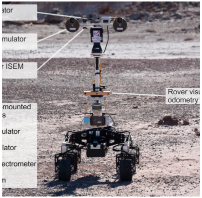
Motivation



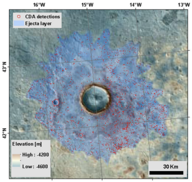
B. Maass et al. “Crater navigation system for autonomous precision landing on the moon”. In: *Guidance, Control, and Dynamics* (2020)



L. M. Downes et al. “Lunar terrain relative navigation using a convolutional neural network for visual crater detection”. In: *ACC*. 2020

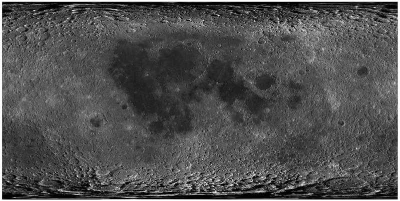


M. R. Balme et al. “The 2016 UK Space Agency Mars Utah Rover Field Investigation”. In: *Planetary and Space Science* (2019)

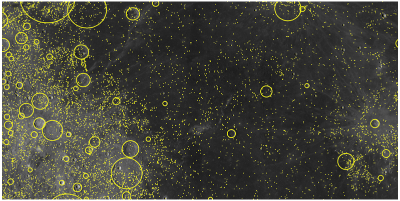


A. Lagain et al. “Model age derivation of large martian impact craters, using automatic crater counting methods”. In: *Earth and Space Science* (2021)

LRO, LROC, Crater Database

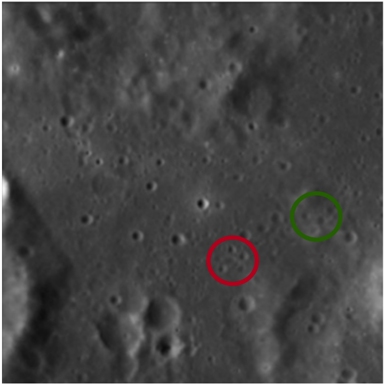


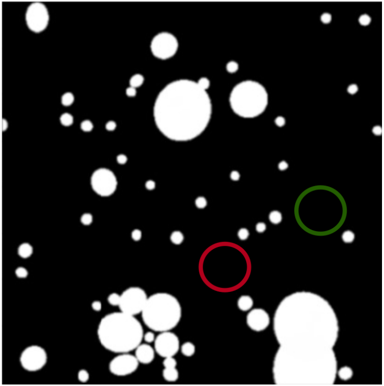
M. S. Robinson et al. "Lunar reconnaissance orbiter camera (LROC) instrument overview". In: *Space Science Reviews* (2010)



S. Robbins. "Developing a global lunar crater database, complete for craters≥1 km". In: *LPSC*. 2016

LROC labels



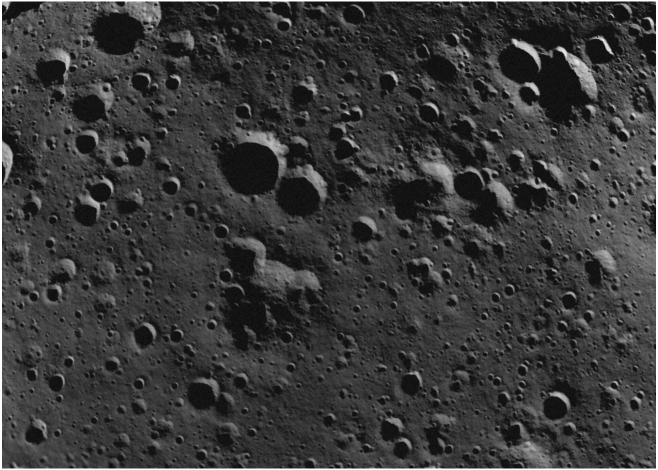


Many small craters are missing but –

"the maximum scores are reached when 100% of the annotations are kept"

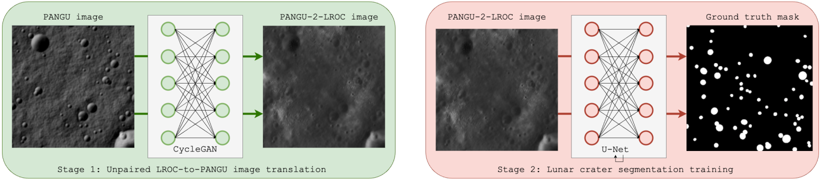
O. Petit et al. "Handling missing annotations for semantic segmentation with deep convnets". In: *DLMIA/ML-CDS*. 2018

PANGU simulator



S. Parkes et al. "Planet surface simulation with pangu". In: *Space Ops*. 2004

Two-stage system overview

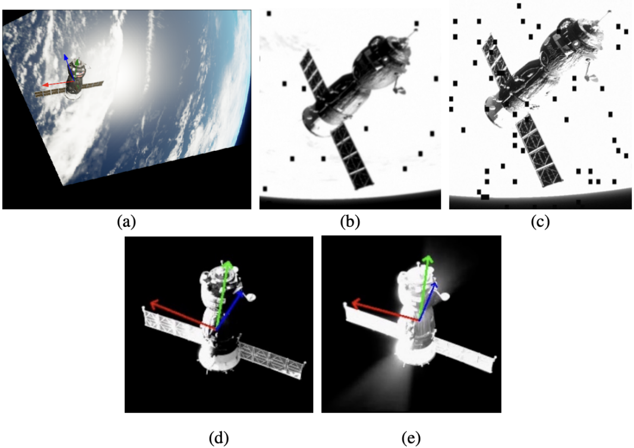


1. `Stage 1:` Transforming simulated images of the lunar landscape from PANGU into "LROC-esque" images
2. `Stage 2:` These outputs used to train downstream models e.g. for segmenting and detecting lunar craters

T. Bruls et al. "Generating all the roads to rome: Road layout randomization for improved road marking segmentation". In: *ITSC*. 2019

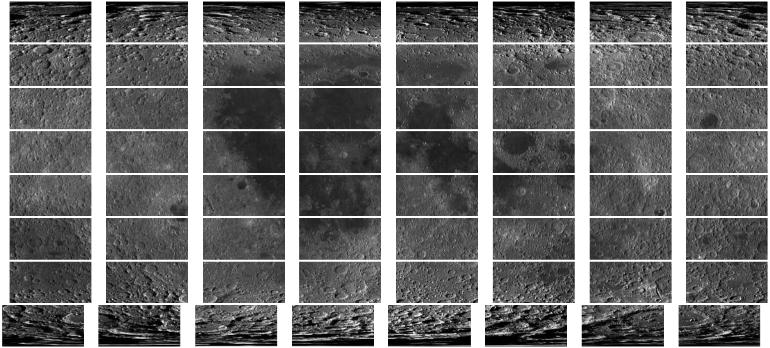
R. Barth et al. "Optimising realism of synthetic images using cycle generative adversarial networks for improved part segmentation". In: *Computers and Electronics in Agriculture* (2020)

Related work



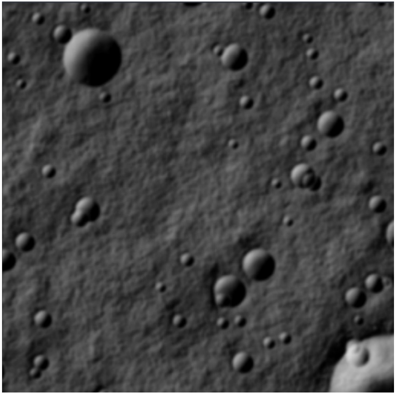
P. F. Proença et al. "Deep learning for spacecraft pose estimation from photorealistic rendering". In: *ICRA*. 2020

Dataset generation



1. LROC image tiled, to capture fine-features
2. PANGU images with similar surface area
3. *Unpaired* for CycleGAN training
4. *Crater labels* (PANGU) also tiled (U-Net training)

Synthesis example



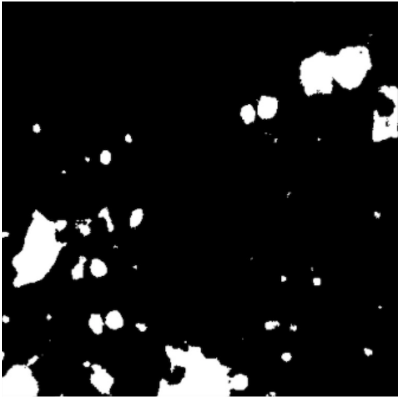
PANGU

1. Computer-generated
2. Lacks realism and detail

PANGU2LROC

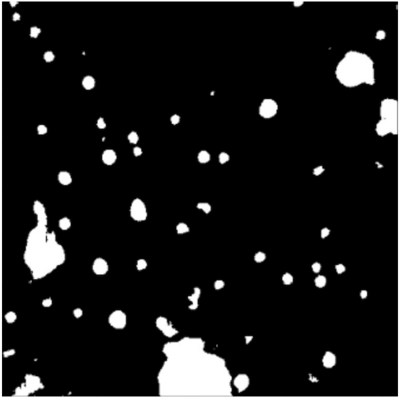
1. Realistic and visually striking
2. Textures, shadows, etc

Segmentation example



Trained on PANGU

1. Large craters have broken borders – e.g. bottom middle
2. Many small craters missing



Trained on PANGU2LROC

1. Large craters more closely following the true outline
2. More comprehensive capture of the small craters

Conclusion

Summary

1. Closing the realism gap for rendered images from planetary simulators
2. Improving the training of a downstream lunar crater segmentation model

Future work

1. Robust in-simulator testing of lunar operations
2. More modern synthesis methods (e.g. latent diffusion models)