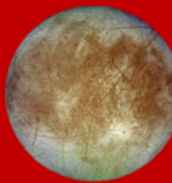
Machine learning detection of Chaos Terrain on Europa as a proof-of-concept for use with future data



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Abstract

Jupiter's moon, Europa, is partially covered in Chaos Terrain, marked by irregular ice floes that are indicative of massive disruption, reorientation, and refreezing experienced on Europa's surface due to Jupiter's gravity. Creating software to automatically detect Europa's jigsaw-like ice floes will accelerate scientific analysis of such terrains once higher resolution images of the moon arrive in the fall of 2022 from the Juno spacecraft and later from the forthcoming Europa Clipper mission. In this project, a U-net, a deep learning semantic segmentation model, was applied to images of the surface of Europa taken by the Galileo spacecraft to automatically detect ice floes in the moon's Chaos Terrains. To measure the quality of the program developed, the Intersection over Union (IoU), a metric that measures the goodness of fit for semantic segmentation, was calculated. Throughout the course of the project, the IoU increased from a value of 0.0012 to 0.286 by adjusting hyperparameters including learning rate and epochs. In the coming months, we intend to further improve the performance of the U-net. Once the algorithm is sufficiently capable of identifying floes in the Chaos Terrains, it may later assist in selection of regions of interest for further study on Europa or even landing sites for a future proposed lander.

Introduction

- Irregular ice floes on Europa illustrate disruption, reorientation, and refreezing on Europa's surface due to tidal heating imparted by gravity from Jupiter (Schmidt et al., 2011).
- Machine learning algorithms are often used to detect surface features on planetary bodies.
  - Counting craters to estimate planetary surface age (Kneissl et al., 2011)
  - Mapping volcanic features or sand dunes (Palafox et al., 2017)
- Machine learning should be able to identify refrozen ice floes on Europa

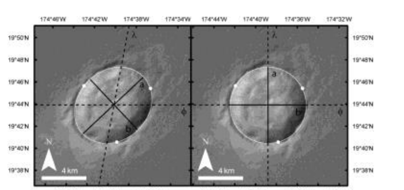

Figure 1: Example of what a crater-counting software might look like. This example is from CraterTools, developed by Kneissl et al. (2011)

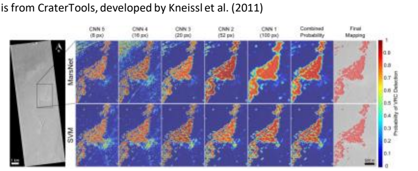

Figure 2: Example of a convolutional neural network architecture for detecting irregularly-shaped surface features on Mars developed by Palafox et al. (2017) In this instance, the algorithm highlighted Volcanic Rootless Cones.

Methodology

- Convolutional neural networks are common in image analysis
  - Approximates the functionality of a human visual cortex (Goodfellow et al., 2013)
  - Requires extensive data to train and test the program.
  - Communications problems with the Galileo spacecraft limited dataset to 23 total images (19 training, 4 testing)
- U-nets are deep convolutional neural networks that are designed for image segmentation with fewer testing images
  - Algorithm developed to detect the outer membranes of cells in biomedical images (Hao, 2019).
  - Also used to detect Above-Anvil Cirrus Plumes (Liles et. al., 2020).
  - Like ice floes on Europa, detected features from images in both studies cannot be isolated using basic edge detection, denoising, or arithmetic

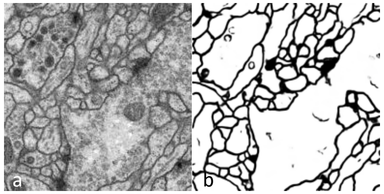

Figure 3: a. Original image to be segmented; b. U-net performance (Hao, 2019)

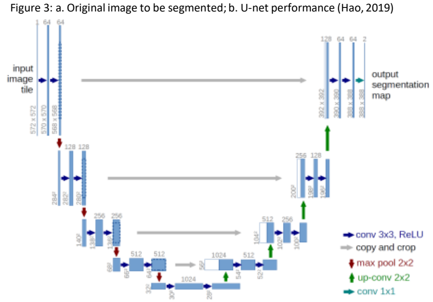

Figure 4: U-net architecture (Hao, 2019)

Acknowledgements

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Results

- U-net programmed using Keras and Tensorflow in Python
- Learning rate reduced from 1×10^{-4} to 1×10^{-5}
- Original U-net was set to run for 5 epochs and 2000 steps per epoch, best performance on the Chaos Terrains with 40 epochs and 32 steps per epoch.
- Functioned best when ice floes were hand-labeled using loose-fitting polygons rather than exact edge-mapping.
- U-net output for a given pixel had to exceed a value of 0.3 for visualization to show positive detection (Figure 5)

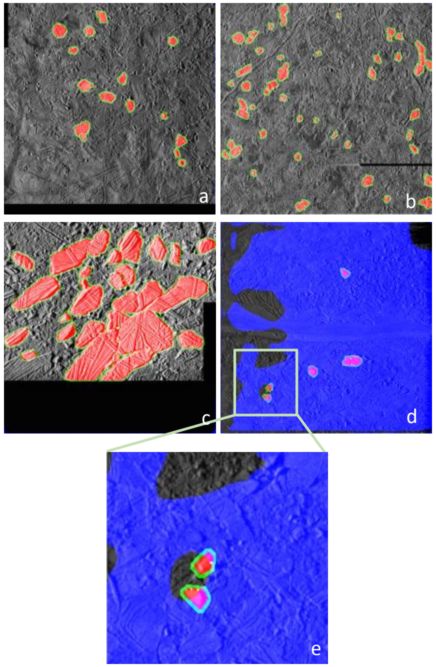

Figure 5: Results of U-net performed on four test images of Chaos Terrain on Europa's surface. False positives (no floe present) are shown in blue, false negatives (floe present) are shown in red, true negatives (no floe present) are grey, and true positives (correctly detected floes) are magenta. Image (e) is zoomed in from image (d), where all four colors are visible.

Conclusion: While there is significant room for improvement, an end-to-end pipeline that inputs images directly from Galileo through the U-net is complete and runs without error.

Conclusion

Intersection over Union (IoU), a metric that measures the goodness of fit for semantic segmentation, was calculated to measure the quality of the U-net:

$$\mathrm{IoU} = \frac{\text{area of intersection}}{\text{area of union}}$$

- Area of Intersection (red, Figure 5) = total area of true positives, where training polygons outlining ice floes match algorithm's detection of floes
- Area of Union = areas where the algorithm or human labeled a pixel as a floe (sum of true positive, false positive, false negative) (Liles et. al., 2020)
- Over study, IoU increased from 0 to 0.286

Future Work

- Further fine-tuning of hyperparameters
- Augmentation of data to combat small sample size
- Continued refinement of human-drawn labels
- Apply k-fold cross-validation (Figure 6) to dataset to quantitatively evaluate effects of hyperparameter settings during model training

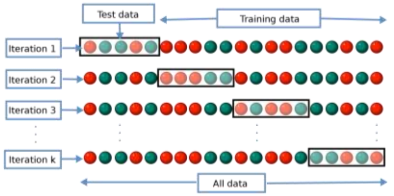

Figure 6: Rotating testing and training data in this depiction of k-fold cross-validation (Gufosowa - Own work, CC BY-SA 4.0).

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