Automatic Lunar Crater Detection from Optical Images and Elevation Maps

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Data

We used a variety of data to both train our models and obtain predictions from them:
- **Optical images** of the moon’s surface from Lunar Reconnaissance Orbiter Narrow Angle Cameras of size 600x400 pixels with a resolution of 1 meter per pixel, along with an accompanying crater catalog from the Emami lab at the University of Nevada-Reno. Optical images have high resolution, but also have shadows that can interfere with detection.
- **Digital Elevation Models** (DEM’s) from the LRO-Kaguya merged DEM, downsampled to 118 meters per pixel. These were accompanied by two crater catalogs, the LROC crater dataset for craters < 20 km in diameter, and the Head et al catalogue for craters > 20 km in diameter. DEM’s are not affected by lighting changes, but are expensive to compute at high resolution, and are thus often downsampled.
- To analyze how our models transfer to other planetary bodies, we used DEM’s of **Mars** (from the Mars MGS MOLA DEM) to obtain crater predictions from models trained on lunar craters. For prediction of craters on Mars, we also used the Salamunicar MA132843GT crater catalogue as a ground-truth to evaluate our accuracy.
- The most critical issue with this project is that the ground-truth catalogs are **incomplete**. They are all manually recorded by experts, but they do miss craters, and there are sometimes disagreements between them.

Models

We built a variety of tools to analyze our lunar data:
- A **template-matching pipeline**, built from scratch using OpenCV, that adds missing labels to our images before training our models.
- **Faster R-CNN**, a common object-detection model that inputs an image into a convolutional neural network, uses a region proposal network (RPN) that scans the resulting feature map for regions that may have objects in them, then outputs bounding boxes around its predictions. We adapted Faster R-CNN for our project so it detects craters from optical images.
- **DeepMoon** is a lunar crater detection model consisting of a convolutional neural network adapted from the UNET architecture. For the first half of its layers, it downsamples, and then upsamples for the second half, all while maintaining short-cut connections between the layers. Finally, it uses template matching to extract the craters from the target masks.

Project Summary

Our final project approaches the problem of automatic crater detection using a variety of models and data sources. We trained two types of models, an extension of Faster R-CNN, a common object detection method, and DeepMoon, a state-of-the-art lunar crater detection model, to identify craters and compare them to ground-truth crater catalogs. We trained our models on both optical images and digital elevation models (DEM’s) of the Moon’s surface. Lastly, we saw that these models were able to detect craters on other planetary bodies (Mercury and Mars) as well.

Experiments and Results

**Faster-RCNN: Crater discovery using convolutional neural network for object detection**

- **Test set results**
  - Faster-RCNN test set predictions on model trained without template-generated labels. Both “false positive” predictions (circled in black) are actually true craters.
  - Both of the original false positives are labeled during template matching, and are successfully predicted by the model, but this time as true positives. Note that this model also discovers several new “false positives” now, which are all true craters as well.

**DeepMoon: UNet architecture with crater-specific post-processing**

- batch loss on validation data for training with and without dilated convolutions
- The model with dilated convolution layers produces a smoother curve with lower loss in the initial training phase.

**Transfer learning to other astronomical bodies: Mercury and Mars**

- **Failure**
  - Mercury DEM Image
  - DeepMoon with dilated conv on optical images
  - DeepMoon baseline on Mars DEMs
- **Excellent performance**
  - Precision Recall

Evaluation

<table>
<thead>
<tr>
<th>Filter Type</th>
<th>Precision</th>
<th>Recall</th>
</tr>
</thead>
<tbody>
<tr>
<td>No filtering</td>
<td>0.36</td>
<td>0.19</td>
</tr>
<tr>
<td>Filtering for craters with diam. &gt; 20 pixels</td>
<td>0.58</td>
<td>0.22</td>
</tr>
<tr>
<td>Faster R-CNN baseline</td>
<td>0.84</td>
<td>0.51</td>
</tr>
<tr>
<td>Faster R-CNN with template-generated labels</td>
<td>0.85</td>
<td>0.50</td>
</tr>
<tr>
<td>DeepMoon with dilated conv</td>
<td>0.64</td>
<td>0.36</td>
</tr>
<tr>
<td>DeepMoon with dilated conv on optical images</td>
<td>0.67</td>
<td>0.32</td>
</tr>
<tr>
<td>DeepMoon baseline on Mars DEMs</td>
<td>0.93</td>
<td>0.36</td>
</tr>
</tbody>
</table>

References


Conclusion and Next Steps

- **Faster-RCNN and DeepMoon perform well on mid-sized craters. Both need higher-resolution DEM’s or better techniques for detecting craters in optical images, as well as more complete labels, to detect craters across different size scales.**
- DeepMoon is somewhat sensitive to domain shift, with decreased performance when evaluated on Mars DEM’s. Despite the different properties of Mercury and Mars, however, DeepMoon can detect many craters.