Crater Detection using Hypothesis Generation and Convolutional Neural Network (CNN)

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Abstract

Craters are found on the surface of the Moon, Mars and other celestial bodies. Digital elevation model (DEM) based and image based are the two approaches for crater detection. Image based technique is more popular.

The main challenges, this area has faced are:-
(i) Generating a large number of training samples is essential for greater accuracy in the crater detection.
(ii) Detecting a large number of craters in different sizes from large sized high quality surface imagery is highly complexity in nature.

Here, unsupervised techniques are used to generate all possible subsamples from the high quality imagery, which are to be verified using supervised algorithm such as CNN.

Method

The method consists of two phases:
(i) Image Sample Creation or Hypothesis Generation
(ii) Hypothesis Verification

(i) Hypothesis Generation (HG):

Hypothesis Generation (HG) algorithm takes imagery of resolution 1m/pixel and generates the hypothetical image subsamples, which are probable craters.

One of these two algorithms will be used for sample creation.

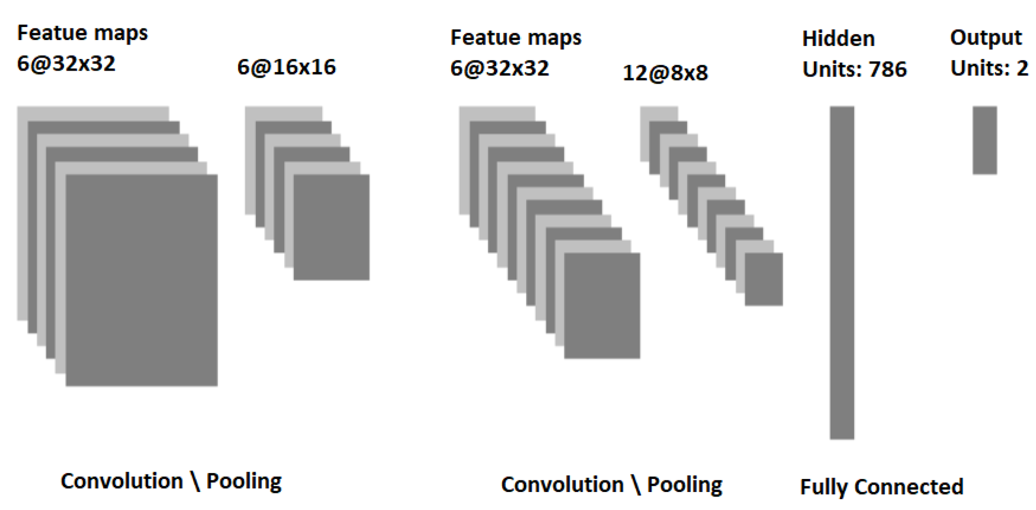
Hough Transform

1. Median filter is applied to smooth the imagery, I.
2. Gaussian filter is applied on I at multiple scales to obtain smoothed images I_1, I_2, and I_3.
-Steps 3-5 are performed on images I_1, I_2, and I_3 :
3. Canny edge detector is applied to detect the edges.
4. Hough circle transform is applied and the enclosing bounding box B_c encloses each detected circle.
5. Overlapping detections (B_s) are combined.

Highlight Shadow

1. The negative image (N) is obtained by negating the input image (I).
2. Large features are removed using:
I = I – MI
N = N – MN
where MI and MN are smoothed images obtained by median filtering of I and N respectively.
3. I and N are changed to binary using a threshold.
4. Connected components C_I and C_N are extracted from binarized I and N respectively.
5. The enclosing bounding box b_i for each $c_i \in C_I$ and b_j for each $c_j \in C_N$ are found, *calling them B_I and B_N respectively.*
6. The pairs of highlight ($b_i \in B_I$) and shadow ($b_j \in B_N$) regions are matched when:
distance (b_i, b_j) $< 2\times($***max***$($***area***(b_i), ***area***$(b_j)))^{0.5}$
7. The enclosing bounding box B_C are found to enclose each paired region and the remaining unpaired regions.
8. Overlapping detections (B_S) are combined.

(ii) Hypothesis Verification



$\mathbf{CNN_{32}C_2F_1}$ Network

Hypothesis verification have supervised model, to categorize the samples into craters and non-craters. We are using Convolutional Neural Network $\mathbf{CNN_{32}\ C_2F_1}$ here.

Image samples of size 32x32 generated using HG algorithms or sliding window approach are input to a CNN having two convolutional layers and one fully connected layer.

Datasets

Our crater detection data consists of 578 images of size 500x500, collected from the Lunar Reconnaissance Orbiter Camera (LROC) Calibrated Data Record Narrow Angle Camera (CDRNAC).

Training set 1: The training set 1 is generated by sliding window approach (Brute Force approach) on the imagery. The number of samples is very high.

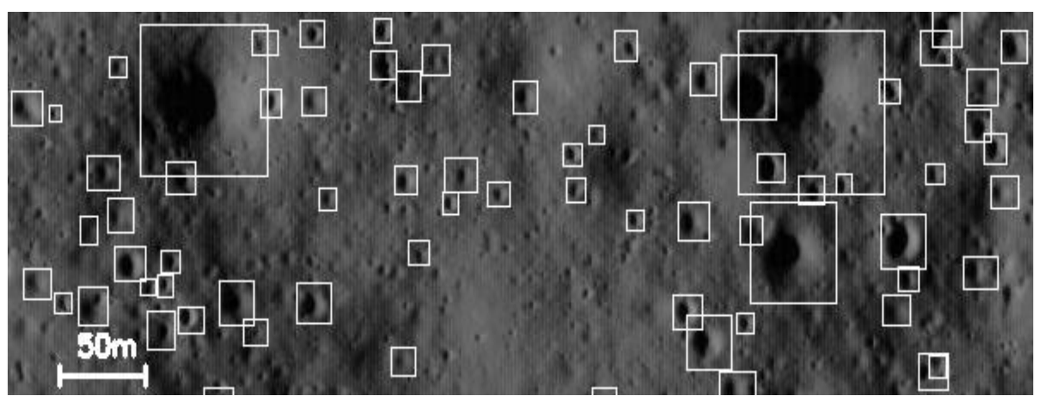
Training set 2: The training set 2 is generated by HG algorithm on the imagery. Once the set is generated, if a crater sample is not hypothesized, then this crater will remain unidentified. So, the recall rate of the HG algorithm must be very high.

Test set 1: This set of image samples are generated in similar fashion to Training set 1.

Test set 2: The hypothesis generated by HG algorithm are used as Test set 2.

Results

The results are the labelled imagery to identify the craters in it. The crater detection technique is evaluated in the testing phase.



Sample test site with all labeled craters shown in white.

Evaluation

The result is evaluated by the following metrics.

<u>Recall and Precision</u>:

$$\text{Precision} = \frac{TP}{GP} \times 100$$

$$\text{Recall} = \frac{TP}{TP+FP} \times 100$$

where TP, FP, and GP are the number of true positives, false positives, and ground truth craters, respectively.

<u>Intersection over union (IOU)</u> :

$$\text{IOU}(B_i, B_J) = \frac{\text{Area}(B_i \cap B_J)}{\text{Area}(B_i \cup B_J)}$$

where B_i, B_J are two sample rectangular regions. B_i and B_J are clustered together if IOU(B_i , B_J) is greater than a predefined threshold.

	Sliding Window	Hough Transform	Highlight Shadow
Recall	99.61	99.61	98.49
Avg. IOU between GT and hypothesis	40.20 σ=11.13	47.96 σ=15.96	45.08 σ=13.34
Avg. IOU between GT and the highest overlapping hypothesis	56.64 σ=10.07	59.38 σ=12.92	61.85 σ=13.52
Avg. number of hypotheses	2813	773	436

The Highlight shadow algorithm minimizes the number of hypothesis, having decent Recall. Hough Transform gives better recall, while the number of created hypothesis is relatively higher than highlight shadow resulting in low performance.

Conclusions

Craters are important characteristics of the surface of Moon, Mars and other celestial bodies.

- HG algorithm is improving the performance with respect to sliding window approach.
- This approach has been implemented for the size of craters in range 10-100m diameter. The reason behind this limit is the lack of ground truth availability. It can be improved for the other size of craters.

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Reference

1. J. Cohen et al., “Crater Detection via Convolutional Neural Networks,” 47th Lunar Planetary Science Conference, USA, 2016.
2. E. Ebrahim et al. "Crater Detection Using Unsupervised Algorithms and Convolutional Neural Networks." *IEEE Transactions on Geoscience and Remote Sensing* (2019).