Lunar Crater Detection via Region-based Convolutional Neural Networks

Lunar Crater Detection via Region-based Convolutional Neural Networks

Ebrahim Emami[1], Touqeer Ahmad[1], George Bebis[1], Ara Nefian[2], and Terry Fong[2] at [1]University of Nevada, Reno, USA (ebrahim@nevada.unr.edu) and [2]NASA Ames Research Center, USA

Introduction: Craters are the most dominant landmarks on many celestial bodies and the detection of craters has various applications in planetary science. Due to the enormous and growing amount of planetary data, large scale manual crater detection is laborious and impractical and autonomous crater detection approaches are desired [1][2]. In this paper we propose an advanced crater detection algorithm (CDA) based on the state-of-the-art object detection techniques. Using our customized Region-based Convolutional Neural Network (Faster R-CNN) [3], we achieve to detect 92% of craters on our test site images captured by Lunar Reconnaissance Orbiter (LRO).

There have been various CDAs proposed in the literature, including supervised and unsupervised approaches. Unsupervised CDAs employ fast image processing techniques to detect craters based on visual characteristics such as the circular rims. Supervised approaches however, utilize classification techniques to detect craters using more robust but slower to compute features. A major group of CDAs employ a combination of both techniques to obtain both efficiency and accuracy. In particular, these algorithms first detect a set of hypothesis using faster to compute image processing techniques (hypothesis generation) and then classify the hypotheses as crater or non-crater using more sophisticated machine learning algorithms (hypothesis verification). The two phase approach has been the most practical and acceptable crater detection approach in the literature. Despite the large amount of work proposed in the literature, due to the challenging nature of automatic crater detection, most of these works are only applicable to limited test sites, and are not accepted as a general purpose crater detection approaches [2][4].

Deep learning techniques have recently become popular in the field of computer vision. In contrast to the conventional machine learning algorithms for classification, based on the describing images with a set of representative features followed by classification, deep neural networks learn suitable features and the classification model both during training. To a limited extent, these advanced techniques have been employed in crater detection applications in a few studies such as [1][2][5]. In this work, we put one step forward, by proposing a fast and accurate crater detection approach based on Faster R-CNN in which the two conventional phases of crater detection, namely hypothesis generation and verification, are implicitly integrated into a single network, trainable end-to-end.

R-CNNs have recently gained success in the field of object detection. These networks classify various regions of an image using Convolutional Neural Networks (CNN). To reduce the computational costs of detection, Faster R-CNN shares convolutional computations between various regions of interest which are fed to the detection network, achieving real-time and accurate performance [3].

Crater Detection via Faster R-CNN: CDAs classify and localize craters of various sizes and appearances in all image regions. This is inherently a well suited application for an R-CNN architecture. Li et al. have previously evaluated the performance of a Faster-RCNN with the original architecture to detect craters as a case study [5]. In the current work however, we customize and propose a Faster-RCNN architecture for crater detection based on our crater detection CNN employed in [2].

Faster R-CNN typically works by first passing the input image through several convolutional layers. Region Proposal Network(RPN) then takes the last convolutional layer`s feature maps as input and outputs a set of regions of likely positions of the objects. In particular, RPN generates region proposals by overlaying a small window on various locations of the input and feeding these regions into a box-regression layer and a box-classification layer to obtain objectness scores and refined object locations. ROI pooling layer then takes the region proposals which have high objectness scores and scales them to fixed size feature maps which can be classified by the object detection network. This network outputs the final classification label and a further refinement of the object`s bounding box position. The objective function used for minimization during Faster R-CNN training sums the total losses of the RPN and object detection networks. These networks each have two loss terms for both classification and bounding box regression where the classification loss is typically log loss, and regression loss is smooth L1 [3].

Inspired from the original Faster-RCNN, we employ a crater detection network with the following architecture. Our network is particularly a smaller R-CNN based on the crater detection CNN employed in [2] with three convolutional layers. The number of convolutional filters in these layers are 32, 64, and 128 (with the filter sizes of 5×5, 3×3, and 3×3) respectively. The RPN uses windows of size 3×3 in three scales to detect various size regions. Unlike the original Faster-RCNN, due to the square shape of craters, a single square aspect ratio is used by our RPN, resulting in only three anchors in each position. This modification results in simpler network architecture, faster training and test performance, and higher accuracy in crater detection based on our preliminary experiments. The final object detection network contains two fully connected layers with 1024 and 512 hidden units respectively.

Experiments and Results: We have employed our network to detect craters on LRO images. Around 200 image tiles of size 600×400 pixels which each contain several labeled craters are used for training. We have also randomly picked 20 similar images for testing and validation. These images are fully labeled manually, and contain around 270 labeled craters in total. While the labeled craters have the size of at least 20×20 pixels, the smaller craters are not considered in our evaluations.

All modules of the Faster R-CNN are trained jointly end-to-end. Adam optimization [6] with back-propagation are used for training with the batch size of a single image and learning rate of 0.0001. The trained network is then applied for crater detection on 10 test images. The common recall and precision rates calculated as follows are used to evaluate the carter detection performance.

$$Recall = \frac{TP}{TP + FN}\ ,\ \ Precision = \frac{TP}{TP + FP}$$

where TP, FP, and FN represent the number of true positive, false positive, and false negatives respectively. A true positive is defined as a detection with $IoU > 30\%$ with a ground truth crater, where IoU is calculated as the intersection over the union of the corresponding bounding boxes.

Figure 1. illustrates the performance of our network on two sample test images, where the true detections are represented with green boxes and the undetected craters are shown in blue. In summary, we were able to obtain the recall rate of 92% and the precision rate of 96.5% on the test images using our crater detection network. As it can be inferred from Figure 1, the false negatives are mainly the severely eroded craters. Such craters share visual characteristics with many uncratered regions of our training images which are used as non-crater samples for training. The lack of a larger number of such eroded craters in our training set causes this lower detection rate.

Conclusions: Our promising crater detection results show the great potential in the application of Faster R-based CNNs for crater detection. Further research in this area can show R-CNNs` outperformance compared to the conventional CDAs. This is especially of importance, considering the fact that a major part of the CDAs proposed in the literature, have not been accepted by the planetary science community as general purpose automatic crater detection tools.

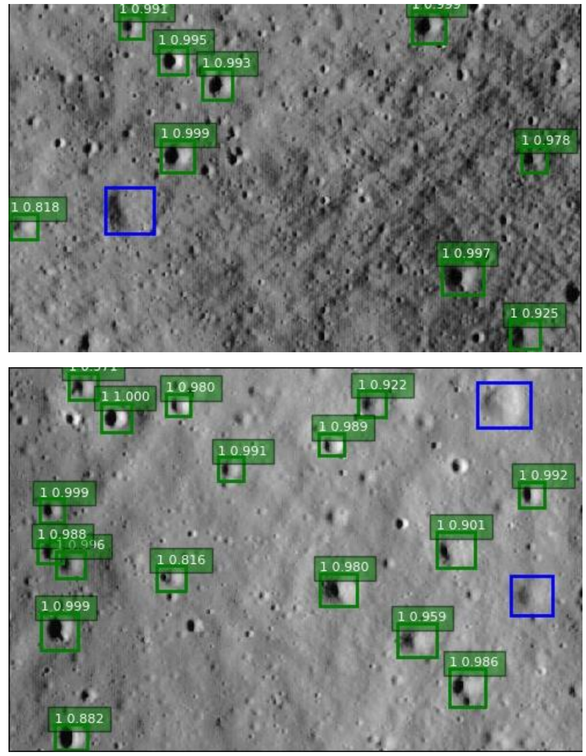

Figure 1. Crater detection results of our Faster R-CNN on sample test images. True positives and false negatives are represented with green and blue boxes respectively.

Acknowledgements: This material is based upon work supported by NASA EPSCoR under cooperative agreement No. NNX11AM09A.

References:

[1] Cohen, J. P., Lo, H. Z., Lu, T., & Ding, W. (2016). Crater detection via convolutional neural networks. arXiv preprint arXiv:1601.00978.

[2] Emami, E., Bebis, G., Nefian, A., & Fong, T. (2015). Automatic Crater Detection Using Convex Grouping and Convolutional Neural Networks. International Symposium on Visual Computing (pp. 213-224).

[3] Ren, S., et al. (2015). Faster R-CNN: Towards real-time object detection with region proposal networks. Advances in neural information processing systems (pp. 91-99).

[4] Emami, E., Bebis, G., Nefian, A., & Fong, T. (2017). On Crater Verification Using Mislocalized Crater Regions. IEEE Winter Conference on Applications of Computer Vision, (pp. 1098-1104).

[5] Li, W. et al., (2017). Recognizing terrain features on terrestrial surface using a deep learning model--An example with crater detection. ACM SIGSPATIAL Workshop on Artificial Intelligence and Deep Learning for Geographic Knowledge Discovery.

[6] Kingma, D., & Ba, J. (2014). Adam: A method for stochastic optimization. arXiv preprint arXiv:1412. 6980.