On Crater Classification using Deep Convolutional Neural Networks

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Introduction: Crater detection is a common task in the field of planetary science with various important applications. Due the large amount of work and time needed for manual crater detection on large planetary surfaces, the automation of crater detection algorithms (CDA) is desired. With the great advances in the field of computer vision and particularly the success of Deep Neural Networks(DNN) in recent years, it feels natural to employ these advanced techniques to improve the performance of CDAs. In this work, we investigate the performance of the state-of-the-art DNNs on lunar crater classification.

Craters are commonly studied to obtain planetary surface information. Crater counting is used for remote measurement of the relative ages of geologic formations on planets, with the simplified rule that heavily cratered regions are relatively older than the less cratered areas. The study of crater morphologies provides further information such as erosion history of a planet for the scientists. Due to the enormous and increasing amount of planetary images being captured in space exploratory missions, it is desired to detect craters using automatic computer vision based detection algorithms [1][2].

Classification is the key step in automatic crater detection. Numerous approaches of image classification have been proposed in the field of computer vision and a number of those popular techniques have been used in CDAs as well. A conventional supervised CDA runs by the classification of craters which are represented by a set of engineered features [3]. Due to the challenges of automatic crater detection on images, the current CDAs are yet not robust and accurate enough to be employed as general purpose crater detection tools. Significant variations in geological formations of surfaces, imaging and illumination conditions, along with the variations in the size and shape of craters, are among the main challenges of crater detection [1][2].

Deep Convolutional Neural Networks(CNN) have recently achieved the state-the-art performance on challenging computer vision tasks like the ImageNet challenge (ILSVRC) [4]. Unlike the conventional classification techniques based on feature engineering and classification, CNNs learn both features and classification model during training. VGGNet [5], GoogLeNet [6], and ResNet [7] proposed for ILSVRC, have been among the most popular and successful deep CNNs proposed in the past few years. In this work, we extend our study on crater classification [3] to these state-of-the-art image classifiers. To our knowledge, this is the first study on the evaluation of deep CNNs performance in crater detection. In the following we briefly present the distinct features of these networks.

VGGNet: Simplicity and depth are the main features of VGGNets. VGG networks perform convolutional operations using filters of size 3×3 only, resulting in fewer network parameters compared to DNNs with larger filters. VGG16 used in our experiments, is a stack of 13 convolutional layers followed by 3 fully connected layers. A total of 5 max pooling layers are also used through the network [5].

*GoogLeNet***:** In contrast to the idea of simplicity in the architecture, Google introduces the use of *Inception* modules in their DNN. Inception modules apply convolutional filters of sizes 1×1, 3×3, and 5×5 in parallel, and then concatenate the output of these operations. The generous use 1×1 convolutional filters throughout the network acts as a dimensionality reduction technique to decrease the number of parameters and make the training practical [6].

ResNet: Proposed by the Microsoft Research, ResNet is the current best performing CNN architecture which outperforms human on ILSVRC. Besides from the very deep architecture with 152 layers, ResNet uses residual blocks, implemented as shortcut connections which skip one or more layers. The outputs of these connections are added to the outputs of the skipped layers. Residual blocks slightly alter the representation of features throughout the network making the network optimization easier [7]. In our crater detection experiments, a smaller ResNet with 51 layers is used.

Crater detection via transfer learning: Training deep CNNs from scratch is time consuming and requires very large datasets (e. g. ImageNet contains over a million training samples). These networks tend to overfit on small training sets due to their large number of parameters. However, the networks trained on large and general purpose datasets, learn image features which are transferable to other datasets, especially in their earlier layers. Therefore, it is very common to take a base pre-trained network and transfer its learned features to a target application using various strategies which depend on the size and nature of the target dataset [8]. For our crater detection application, we utilize one of these popular transfer learning techniques. In particular, we employ CNNs pre-trained on ImageNet, and then fine-tune these models` parameters for crater detection by further training on our crater datasets.

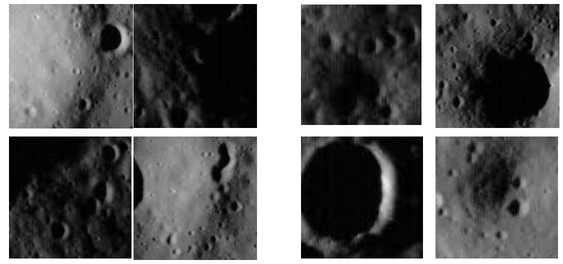
Experiments and Results: For our crater classification experiments, we generated a training, validation and test set with around 14000, 2000, and

7000 image samples respectively. All three datasets have equal portions of positive(i.e., craters) and negative(i.e., non-craters) samples. These samples are extracted from a group of images tiles which are captured by the Lunar Reconnaissance Orbiter (LRO) and partially labeled by the NASA scientists. To generate each dataset, the positive samples were extracted by randomly changing the location and size of the boxes enclosing the ground truth craters. The positive samples keep at least 50% overlap (intersection over union) with the original marked crater boxes. The negative samples were extracted randomly from the uncratered regions of the image tiles. Figure 1. shows several crater and non-crater samples from our test set. For both training and test usage, the samples are resized to 299×299 pixels for GoogLeNet, and 224×224 pixels for VGGNet and ResNet.

In order to employ the base networks which are pre-trained on ImageNet, the output layer of each network is replaced with a fully connected layer of 512 neurons followed by a binary output layer for crater classification. The two added layers` parameters are initialized by a normal distribution and then trained for a few epochs to improve initial values. The whole network is then retrained on the crater detection training set using stochastic gradient decent optimization. The small learning rate of 0.0001 is used in the training process, which is performed on image batches of size 32 until satisfactory accuracy is obtained on the validation set.

To evaluate the classification performance, the well-known recall and precision rates are reported. Figure 2. presents the classification results of the three networks on our test set. As shown on the charts, all three classifiers perform very well on the test set. In particular, while the three networks correctly classify the majority of the positive samples, VGGNet seems to slightly outperform the other two networks with the recall rate of 99.23%. All three networks also correctly classify our randomly extracted non-crater regions with a high rate, resulting in the high precision rates around 99%.

Conclusions: In this work, we investigated the application of the state-of-the-art deep CNNs for crater classification. The high recall and precision rates in our experiments show the great capacity of these networks in discriminating between the craters and other non-crater regions of lunar surface, which encourages the use of these networks in more challenging crater detection tasks. In particular, we plan to utilize deep CNNs for large scale crater detection applications on planetary surfaces. Global crater detection on large sites which exhibit various geological formations overlapping with craters, under various illumination



(a) (b)

Figure 1. Test set samples, (a) non-crater regions and (b) craters.

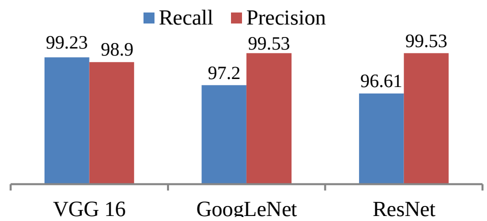


Figure 2. Classification performance of deep CNNs on crater detection test set.

conditions has been a challenging task. Deep CNNs can potentially model these variations and be a step forward toward general purpose crater detection tools.

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