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Deep Learning-Based Anomaly Detection to Find Changes over the Martian South Pole

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Abstract

We propose a deep learning-based method to detect changes over the Martian surface, with a focus on the South Polar region. The method works by defining most of the images as "normal" and "anomalies" as candidates for changes.

1. Introduction

Although far from the Earth's surface, the Martian surface is not static. Some examples of changes are new impact craters, dust devil tracks, or dark slope streaks. With more than 40 years of orbital observations <100m, the amount of data available on Mars is enormous and too large to find changes manually. Because of this, we believe an automatic method will be useful for scientists to detect changes with a very large number of images.

Automatically detecting changes, especially over the polar region is a difficult problem if not done correct, as transient features and on-off changes are mixed with changes caused by seasons, one of which is the annual cycle of growth and recession of the polar cap, resulting in high number of false positive observations. Previously, Sidiropoulos and Muller [1] have developed a change detection algorithm that has successfully been tested with global Martian data. Their method was successfully trained on non-polar images and obtained reasonable results globally, although the method is far from perfect for the polar regions. Improvements can be made with more observed changes as training data, which we currently lack for Martian images.

2. Methods

To address the absence of reliable training data and to utilise the stack of overlapping data available, especially around the poles, we propose a deep-learning based method to detect anomalies on Martian images. One of the problems in creating a method based on deep learning is the computation and the amount of training samples needed to train the weights of the neurons in the network. Transfer learning is a method in machine learning in which networks which have been successfully trained to solve a specific problem are used to solve other similar problems.

In this research we started with AlexNet [2] Convolutional Neural Network (convnet). AlexNet has been trained to classify 1.2million ImageNet data and has been successfully used in planetary science research to classify features on HiRISE images, also by transfer learning [3]. In transfer learning for AlexNet, we take out the Fully Connected Network (FCN) Layers which works as an image classifier and replace them with a specific goal in mind.

In this research we are working with the assumption that most of the images don't change, and can act as "normal" data, while changes if they exist, are "anomalies". In this way, changes caused by "normal" processes, such as the appearance/ disappearance of ice cap or changes caused by differences in imaging condition are not picked up. To replace the FCN layers we used a OneClassSVM to detect "anomalies" from the other "normal" data.

We have isolated more than 20 regions with more than 30 overlapping ortho-rectified and coregistered (ACRO) [4] images over the south polar region [5], with most of them obtained from the Context Camera (CTX) as regions of interest. As inputs we use images co-registered and orthorectified to Digital Terrain Models from HRSC [6] scaled to neural network inputs. We randomly sampled 2.5km x 2.5km area with 100m overlap between samples, resized to input sizes required by AlexNet (227x227x3) instead of resizing pixel sizes to neural network inputs to ensure that the scales are similar between multi-instrument input images. This decision is made to increase the success rate for anomaly detection for multi-instrument image inputs.

Random image samples from the same region are used to define “normal” data for semi-unsupervised classifier. Distance obtained from OneClassSVM for testing data from the “normal” data are calculated and sorted. Carrying the assumption that most data are “normal” data, anomalies are then separated from normal data by adaptive binary thresholding to divide images into “normal” images and “anomalies”.

3. Results

We tested the method on several areas (areas overlapping B06_012028_0930_XN_87S273W and B02_010344_0985_XN_81S063W) from our regions of interest. Figure (1left) shows an example of an area which have been classified as “normal” by our network, with (1right) showing the same area in different date.

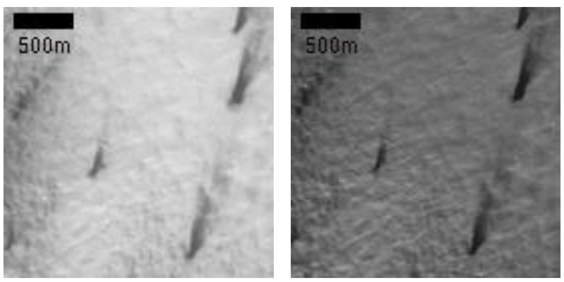

Figure 1(left) An example of detected “normal” data (P06_003206_0946_XI_85S277W, LS 212.06, MY 28) with 1(right) (P06_003562_0946_XI_85S276W, LS 229.25, MY 28) similar area in other image with different imaging condition

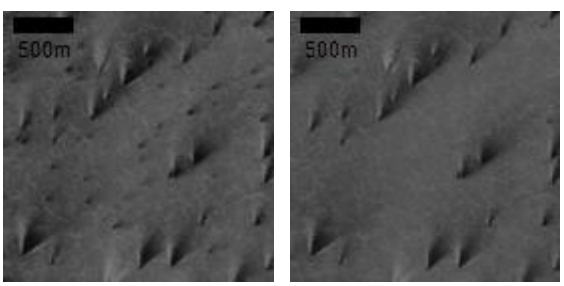

Figure 2(left) An example of detected “anomalies” data (P06_003206_0946_XI_85S277W, LS 212.06, MY 28) with 2(right) (P05_003074_0946_XI_85S277W, LS 205.81, MY 28) a similar area in another image

Figure (2) show an example of an area classified by our network as an “anomaly”, showing new seasonal fans appearing over the area.

4. Conclusions and Future Work

In this paper we have shown the potential of a semi-supervised deep learning method to do change detection research on Martian polar images by detecting anomalies over a region while ignoring expected appearance changes.

Currently we have only tested the method over specific areas out of our region of interest and only used ORIs and DTMs data from CTX. We are planning to test the method over the entire regions of interest for the south polar region. There are other data from different instruments (from MOC-NA until HiRISE) available to widen the dataset. Increase in accuracy and reduction of false positives can be obtained by building a more representative architecture for planetary/ Martian data as well as utilising available but yet unused information particular to Martian or polar data.

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References

[1] Sidiropoulos & Muller: Automatic Detection of Changes on Mars Surface from High-Resolution Orbital Images. EGU Vol. 19. 2017. [2] Krizhevsky, et. al.: Imagenet classification with deep convolutional neural networks. Adv. in Neural Inf. Proc. Sys. 2012. [3] Wagstaff, et al.: Deep Mars: CNN Classification of Mars Imagery for the PDS Imaging Atlas, 2018. [4] Sidiropoulos & Muller: A systematic solution to multi-instrument coregistration of high-resolution planetary images to an orthorectified baseline. IEEE Trans. on Geo and Remote Sens. 2018;56(1):78-92. [5] Putri, et. al.: Coregistration of Mars South Polar CTX Images to HRSC Base Images. EPSC Vol. 11. 2017. [6] Putri, et. al.: A New South Polar Digital Terrain Model of Mars from the High Resolution Stereo Camera (HRSC) onboard of the ESA Mars Express for Tracking Changes over the SPRC. PSS under-review, 2018.