Lunar Crater Detection Walkthrough – A Review

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Abstract - *The study shows various attempts made on detection of craters and its segmentation based on sizes and several features. We have studied some of the previous work done in the field of crater detection using deep learning approaches and presented a literature survey considering some of the most recognized work over the globe. This study is presented in order to get a quick glimpse of existing work in the field for a researcher to validate and try different approaches.*

Key Words: Crater Detection Algorithms (CDA), digital terrain models(DTMs), ERU-Net, R-CNN

INTRODUCTION

Craters are features commonly used as research landmarks compared with the other landforms such as rocks, mountains, cliffs and many others. Because of their simple and unique geometry and relatively established appearance under different conditions, the authors decided to select craters as ideal landmarks for detection and spacecraft localization. Currently, there are a lot of on-going studies mainly on craters detection and optical navigation systems for the moon and these studies still adopt a complex and similar approach such as detection using the Hough transform method.

BACKGROUND

The first lunar exploration spacecraft named Luna 1 was flown to the moon in January 1959. Nonetheless, this mission did not give too much impact as it did not land on the moon itself. Due to the enthusiasm to continue the journey of previous research pioneers, Luna 2 became the first spacecraft to land on the moon's surface in late 1959. These histories of moon explorations became a motivation for a new researcher and moon explorer to find out more about Lunar and its unique features. A crater plays a vital feature to estimate the age of the moon's surface when any sample specimen is not available. An autonomous crater detection algorithm will help space research scientists to reduce their laboratory works of manually identifying those craters. Previously, several automatic and semi-automatic crater detection algorithms were proposed, but their accuracy was not enough for craters chronology and they have yet to be fully tested for practical uses (example: spacecraft navigation).

LITERATURE REVIEW

1. Arpita Baronia, Jyoti Sarup : This paper proposed K- Nearest Neighbour(KNN), Singular Value Decomposition(SVD) for detection of crater based on shape and size and also Hybrid method takes the advantages of both SVD and KNN. Hybrid method gives better results in case of Mean Square Error(MSE) and Peak Signal to Noise Ratio(PSNR). KNN performs better than SVD. Crater attributes (shape, size) have been computed by using segmentation and distance approximation methods. In the process, Chandrayaan 1 data is used for estimation and detection of craters.

2. Ebrahim Emami, Touqeer Ahmad, George Bebis, Ara Nefian, Terry Fong : In this work, by proposing a fast and accurate crater detection approach based on Faster R-CNN is presented in which the two conventional phases of crater detection (hypothesis generation and verification), are implicitly integrated into a single network. 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. The network is employed 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. Randomly picked 20 similar images for testing and validation. These images are fully labeled manually, and contain around 270 labeled craters in total. The study shows Faster R-CNN outperformed 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.

3. Wang, S.; Fan, Z.; Li, Z.; Zhang, H.; Wei C. : have proposed a new convolutional neural network termed ERU-Net (effective residual U-Net) to recognize craters from lunar digital elevation model (DEM) images. ERU-Net first detects crater edges in lunar DEM data. Then, it uses template matching to compute the position and size of craters. ERU-Net is based on U-Net and uses the residual convolution block instead of the traditional convolution, which combines the advantages of U-Net and residual network. In ERU-Net, the size of the input image is the same as that of the output image.

ERU-Net gets better recognition results when its network structure is deepened. The evaluation method used in the general semantic segmentation task is IOU (intersection over union) of the network. The IOU score is the standard performance measure for the semantic segmentation. The method targets at the rim of the crater, and it can recognize overlap craters. In theory, they have proposed a network can recognize all kinds of impact craters. In the lunar crater recognition, the model achieves high recall (83.59%) and precision (84.80%) on DEM. The recall of their method is higher than those of other deep learning methods. The experiment results show that it is feasible to exploit networks to recognize craters from the lunar DEM.

4. Silburt, Ari & Ali-Dib, Mohamad & Zhu, Chenchong & Jackson, Alan & Valencia, Diana & Kissin, Yevgeni & Tamayo, Daniel & Menou, Kristen : Two primary advantages of a deep learning solution over human crater identification are consistency and speed. These needs are primarily satisfied in this paper. In this work they have demonstrated the successful performance of a convolutional neural network (CNN) in recognizing Lunar craters from digital elevation map (DEMs) images. This paper recovered 92% of craters from the human-generated test set and almost double the total number of crater detections. Of these new craters, 15% are smaller in diameter than the minimum crater size in the ground-truth dataset. Their median fractional longitude, latitude and radius errors are 11% or less, representing good agreement with the human-generated datasets. From a manual inspection of 361 new craters we estimate the false positive rate of new craters to be 11%. Moreover, Moon-trained CNN performs well when tested on DEM images of Mercury, detecting a large fraction of craters in each map. These overall results suggest that deep learning will be a useful tool for rapidly and automatically extracting craters on various Solar System bodies.

5. D. Saranyaraj, V. Sivakumar, S. Sivakumar : This paper reviews various algorithms involved for identifying various types of craters, which will highly be influential for any future research work. In addition to this, this paper will also have a brief scenario about high performance computing like parallel computing in pattern recognition which will effectively help in the process of detecting the craters in a much faster and effective way, totally autonomous on the algorithm chosen. They describe briefly the parallelization of object recognition to identify several lunar craters parallel with high synchronization processor speed.

6. T. F. Stepinski, Wei Ding, R. Vilalta : Automating the process of crater detection is key to generate comprehensive surveys of smaller craters. In this paper, they discuss two supervised machine learning techniques for crater detection algorithms (CDA): identification of craters from digital elevation models (also known as range images), and identification of craters from panchromatic images. They present applications of both techniques and demonstrate how such automated analysis has produced new knowledge about planet Mars. The algorithms presented here give reasonably accurate surveys of craters, but can benefit from better training sets. The most important challenge of CDA is to incorporate elements of transfer learning and/or machine learning to allow for efficient addition of training samples as the need arises.

7. Liu, Han: A new algorithm of automatic extraction of multi-size lunar craters has been proposed. The proposed algorithm could detect multi-size craters by using different filters in multi-steps, which is a loop to detect multi-size craters by different size filters. In the first step, the new algorithm will use a larger filter to reduce noise and detect larger craters by using circle fitting at a denoised image. After marked these areas in the original image, it will remove those detected crater areas from the original image and do the noise reduction with a smaller filter again. The new algorithm will repeat the second step several times to finish the detection of whole image. Finally the new algorithm will merge results of these steps and output a final result. The new algorithm has been tested based on the Chang'E Data in the Matlab environment. The result has shown that this new algorithm does have the ability to detect different sized craters on the lunar surface, which has pointed to a way to detect secondary craters automatically.

8. Lei LUO, Lingli MU, Xinyuan WANG, Chao LI, Wei JI, Jinjin ZHAO, Heng CAI : This paper presents a new approach to crater detection that utilizes a digital elevation model instead of images; this enables fully automatic global detection of large craters. Craters were delineated by terrain attributes, and then thresholding maps of terrain attributes were used to transform topographic data into a binary image, finally craters were detected by using the Hough Transform from the binary image. By using the proposed algorithm, they produced a catalog of all craters ≥10 km in diameter on the lunar surface and analyzed their distribution and population characteristics.

9. Vamshi, Gasiganti T.; Martha, Tapas R.; Vinod Kumar K. : Identification of impact craters is a primary requirement to study past geological processes such as impact history. They are also used as proxies for measuring relative ages of various planetary or satellite bodies and help to understand the evolution of planetary surfaces. In this paper, they have presented a new method using object-based image analysis (OBIA) technique to detect impact craters of a wide range of sizes from topographic data. Multiresolution image segmentation of digital terrain models (DTMs) available from NASA's LRO mission was carried out to create objects. Subsequently, objects were classified into impact craters using shape and morphometric criteria resulting in 95% detection accuracy. The methodology developed in a training area in parts of Mare Imbrium in the form of a knowledge-based ruleset when applied in another area, detected impact craters with 90% accuracy. The minimum and maximum sizes (diameters) of impact craters detected in parts of Mare Imbrium by our method are 29 m and 1.5 km, respectively. Diameters of automatically detected impact craters show good correlation ($R2 > 0.85$) with the diameters of manually detected impact craters.

10. Lena M. Downes, Ted J. Steiner, Jonathan P. How : Terrain relative navigation can improve the precision of a spacecraft's navigation estimate by providing measurements to correct for drift in the inertial navigation system. This paper presents a system that uses camera imagery to visually detect craters with a neural network and match these detections with known lunar craters to provide measurements to a navigation filter. By repeatedly performing this process, the navigation system can maintain higher accuracy in its estimate of spacecraft location. Results have demonstrated crater detection and matching that outperforms traditional crater detection in persistence, number of detections, and estimation error achieved with an extended Kalman filter.

CONCLUSION

Crater counting on the Moon and other bodies is crucial to constrain the dynamical history of the Solar System. Many state of the art techniques have been taken into account for such a crucial process. Various algorithms work well enough to get through the detection and identification of craters having different sizes and shapes with better results over the time. Advancement in deep learning has facilitated the whole process of crater detection on various surfaces a lot more feasible than conventional approach. Crater analysis can be used to discover various substances(i.e. water percentage, natural gas, atmospheric elements etc.) present in the subsurface of the planet and autonomous detection of these substances is a question that remains to be answered.

REFERENCES

[1] Arpita Baronia, Jyoti Sarup. Crater Detection on Moon Surface. International Journal of Innovative Technology and Exploring Engineering (IJITEE) ISSN: 2278-3075, Volume-9 Issue-2, December 2019.

[2] Ebrahim Emami, Touqeer Ahmad, George Bebis , Ara Nefian, Terry Fong. Lunar Crater Detection via Region-based Convolutional Neural Networks. 49th Lunar and Planetary Science Conference 2018 (LPI Contrib. No. 2083).

[3] Wang, S.; Fan, Z.; Li, Z.; Zhang, H.; Wei, C. An Effective Lunar Crater Recognition Algorithm Based on Convolutional Neural Network. *Remote Sens.* 2020, *12*, 2694.

[4] Silburt, Ari & Ali-Dib, Mohamad & Zhu, Chenchong & Jackson, Alan & Valencia, Diana & Kissin, Yevgeni & Tamayo, Daniel & Menou, Kristen. (2018). Lunar Crater Identification via Deep Learning. Icarus. 317. 10.1016/j.icarus.2018.06.022.

[5] D. Saranyaraj, V. Sivakumar, S. Sivakumar, 2014, High Performance Computation and Pattern Recognition Techniques for Detecting Lunar Craters Using Satellite Image- A Review, INTERNATIONAL JOURNAL OF ENGINEERING RESEARCH & TECHNOLOGY (IJERT) Volume 03, Issue 02 (February 2014).

[6] T. F. Stepinski, Wei Ding, R. Vilalta, Detecting Impact Craters in Planetary Images Using Machine Learning.

[7] Liu, Han, et al. "A New Auto-Extraction Algorithm of Multi-Size Lunar Craters Based on the Chang'E Data." Applied Mechanics and Materials, vol. 599–601, Trans Tech Publications, Ltd., Aug. 2014, pp. 1340–1345. Crossref, doi:10.4028/www.scientific.net/amm.599-601.1340.

[8] Lei LUO, Lingli MU, Xinyuan WANG, Chao LI, Wei JI, Jinjin ZHAO, Heng CAI, Frontiers of Earth Science, 2013, Vol. 7, Issue (4) : 456-464, DOI: 10.1007/s11707-013-0361-3.

[9] Vamshi, Gasiganti T.; Martha, Tapas R.; Vinod Kumar, K. An object-based classification method for automatic detection of lunar impact craters from topographic data. Advances in Space Research, Volume 57, Issue 9, p. 1978-1988.

[10] Lena M. Downes, Ted J. Steiner, Jonathan P. How. Deep Learning-based crater detection for lunar terrain relative navigation; seal.rpi.edu.