The Development of a Synthetic Method for Planetary Object Recognition Based on Neural Networks

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The development of a synthetic method for planetary object recognition based on the integration of two architectures, Mask R-CNN and the convolutional neural network (CNN) U-Net, is presented. The proposed method was verified on lunar craters of various categories selected from images obtained by modern satellite missions. Object recognition is performed using criteria such as the ratio of stratigraphic characteristics, morphological features, and optical structure.

Keywords: neural networks, planetophysical parameters, synthetic method.

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Introduction

Machine learning methods and neural networks (NN) are actively used in modern scientific studies of complex systems, which include the surfaces of celestial bodies [1]. In this paper, we have developed a synthetic method for detecting and studying objects on the surface of planets and their moons. The essence of the synthetic method is to combine two Mask R architectures-CNN and (CNN) UNET. The synthetic method allows both to expand the existing list of studied objects and to categorize them according to the specified morphological and planetary parameters.

1. Research methods

Machine learning is built in Ref. [2,3] using the convolutional neural network (CNN) UNET. This approach has demonstrated high efficiency in identifying a large number of craters. At the same time, the architecture (Mask R-CNN) allows for intelligent indication of objects with a selection of morphological features. There are some differences between the methods described above:

1) UNET is based on training a system on large amounts of data, where features are determined and optimized independently. Morphological parameters are entered by experts in Mask R-CNN, but the amount of training material can be optimized for a specific task.

2) UNET automatically adapts to diverse categories of data. For example, UNET can be applied to other planets. It allows detecting craters of different scales, including objects with complex shapes that do not meet classical morphological criteria (for example, craters degraded due to erosion or craters with a broken structure). Mask R-CNN operates on pre-defined criteria and does not go beyond them.

3) The UNET architecture is able to scale to analyze large amounts of data, process large images, and find new objects in a single iteration. The Mask R-CNN architecture processes each object individually, so it fetches more slowly.

4) The UNET system automatically determines the morphology of the crater, taking into account the small details. Mask R-CNN is more focused on matching predefined morphological features.

Considering all of the above, it can be concluded that the UNET architecture allows you to increase the analyzed system by including new objects, while Mask R-CNN can select those objects from the entire set that meet certain characteristics. At the same time, the UNET system generates identification features independently without proper monitoring, since it is focused specifically on searching for new craters, rather than on selecting certain parameters from an existing set of objects. Thus, the synthetic method allows you to identify the desired objects in two stages. In the first case, the UNET architecture is used, on the basis of which new objects are identified and located, for example, craters [4]. During the second stage, a selection is made from the obtained set of those objects that specifically satisfy the characteristics entered in advance by the expert.

2. Results

This method was verified on optical images of the lunar surface obtained during the „LRO“ and „Kaguya“ missions. Data obtained by the „Kaguya“ and „LRO“ missions are used in this paper for verification [5–7]. It should be noted that the accuracy of obtaining spatial coordinates from space topographic survey data depends on the scale

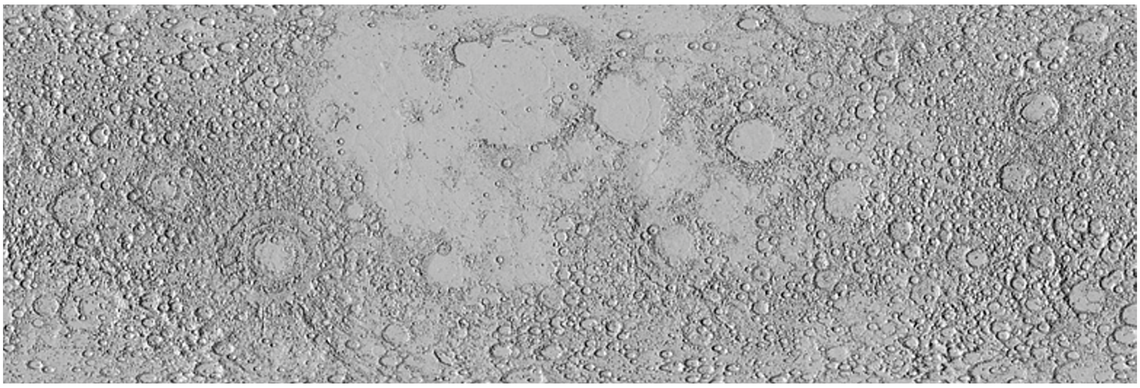

Figure 1. LDTM in the range of $\pm 60^\circ$ in latitude with a resolution ~ 59 m per pixel and height accuracy of $\sim 3-4$ m, based on data from LRO (LOLA) and SELENE Kaguya [7].

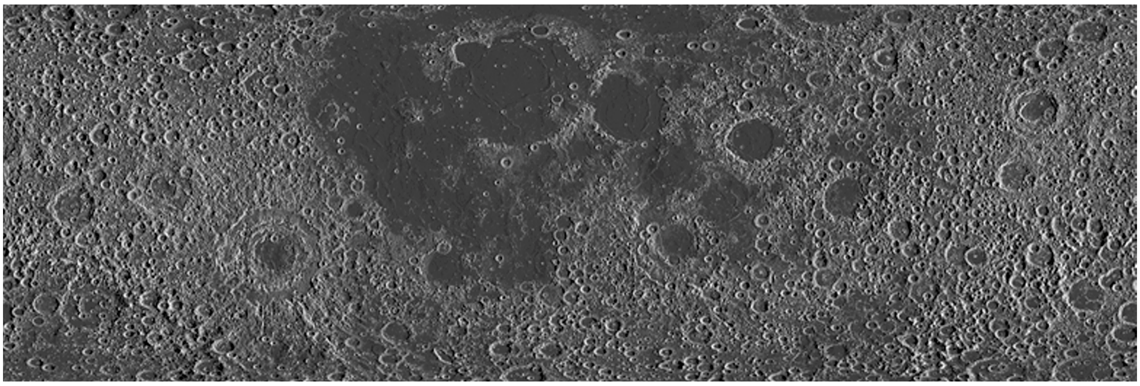

Figure 2. LDTM image after inversion.

and parameters of the images being processed, as well as the methods of their photogrammetric processing. It is possible to say that the accuracy of topographic surveys directly depends on the resolution of the images, which is expressed in metric unit per pixel. The method developed in this paper solves the problem of image classification. The training of the analytical system of the method was performed on a training sample from images obtained by satellite missions. The method was tested on a lunar digital terrain model (LDTM) in the range of $\pm 60^\circ$ in latitude with a resolution of ~ 59 m per pixel and heigh accuracy of $\sim 3-4$ m, based on data from LRO (LOLA) and SELENE Kaguya [7] (fig. 1). Fig. 2 shows an inversion of the original digital relief of the Moon model for the selected area of the digital model.

The accuracy provided by this approach was assessed visually. When training the NN model, a fragment of the digital map was manually selected, and the most characteristic crater boundary was highlighted in the selected area (Fig. 3, *a*). Based on such a training model, the software system learned how to search for identical objects in satellite images. The training set included images obtained by LRO (NASA), divided into fragments of a relatively small size (125×125 px) in the amount of about nine hundred pieces. Using the original LRO image size 1800×950 px, the NN is able to recognize up to 200 craters in less than 3 min. On average, model training lasts 40 epochs (iterations), the duration of each is 1 h. During one epoch, the image is divided into separate tiles (batches), which are analyzed using NN. Next, the value of the NN activation function (AF) (based on gradient descent) is determined. When passing through one epoch, the weights of the observations are approximated. If there are few epochs, then the NN becomes undertrained, and if there are many epochs, it becomes overtrained. In the latter case, the NN begins to identify patterns during training that are actually absent. The optimal epoch value includes the „cut-off function" (COF). In this case, a diagram of AF values is constructed, and if the values do not match the last one, the training procedure is terminated. In practice, a pre-formed AF is initially taken and a random number of epochs is taken, and after the COF, the formed AF value corresponding to a smaller number of epochs is already taken. Fig. 3, *b* shows a machine sample of craters on a digital model fragment accepted for processing. The discrepancy between the manual classification option and the machine classification turned out to be around 4 px. The scale and coordinates of the objects were not

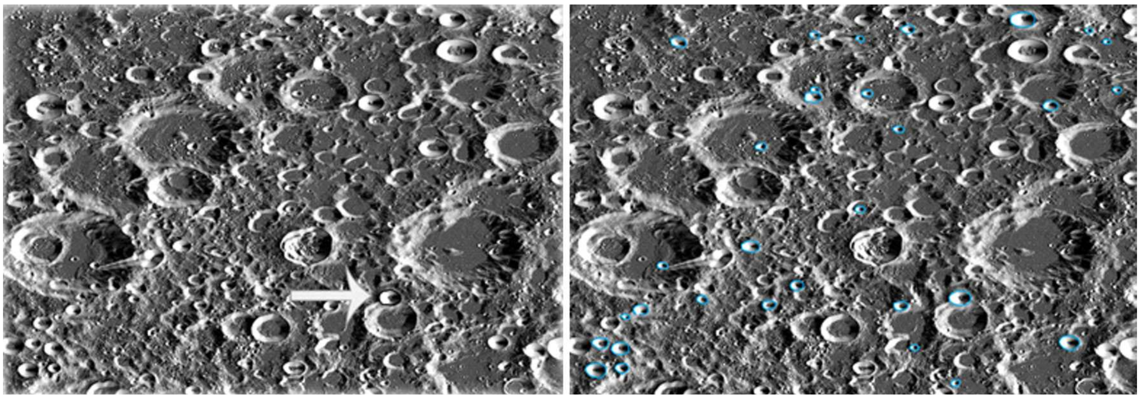

Figure 3. Images with manual selection of craters (*a*), *b* — with machine.

Quantitative results of NN data processing

Criterion	Value (range of values) of criterion
pCNNR	53 % < pCNNR < 99 %
P	62 % < P < 98 %
F1s	77 %

determined precisely at this stage, the key aspects here were the image itself and how the NN would capture this image.

The main criteria for the operation of NN — Post-CNN Recall (pCNNR), Precision (P), F1-score (F1s) — for the data set used are presented in the table.

In the future, it is planned to explore the objects included in our catalog of lunar craters with accurate selenocentric dynamic coordinates, registered with Rospatent RU 2019620426 dated 18.03.2019.

Conclusion

Currently, we used optical images for the following reasons:

1) Many more maps, crater catalogs, and training samples have been created for optical images;

2) there is no coherent „grainy" noise characteristic of radar data in optical images;

3) For many missions, optical cameras have better spatial resolution compared to radars;

4) Computer vision methods (CNN, segmentation, classification) are traditionally better developed for RGB images. But in further research, there are plans to further train the model on other types of data (for example, radar images).

It should be noted that sampling using NN is not always ideal, as there is a problem of under-training of the model. At the same time, there are structures that are missing from the sample, which indicates that the NN understands what they are trying to teach it. The discrepancy between manual and machine classification can be visually determined by 2 px on average. At the same time, there is a problem of detecting small craters that are difficult to identify due to pixelation. If the crater is less than 3m in radius, it will be difficult to distinguish it. In order to obtain universal NN, a number of conditions must be met: images with optimal resolution should be used; the maximum number of objects should be analyzed in the images, and the images involved in the training should differ in contrast, the angles at which the lunar surface is photographed, and the number of objects in the image. In future work, it is planned to use the Digital Selenocentric Dynamic Catalog (DSDC) of optical observations of the „Clementine", „Kaguya", „LRO" and „Apollo" missions of the visible and reverse sides of the Moon, both freely available and obtained during joint research.

It should also be noted that the surface of the Moon was studied as part of the work, but the developed method is planned to be used on such celestial bodies as Mars, Cerrera and Titan in the future, the relevant work has already begun, the authors have topographic data from the missions „Mars Global Surveyor", „Dawn" and „Cassini", as well as sets of images of the surface of the listed celestial bodies.

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Conflict of interest

The authors declare that they have no conflict of interest.

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