Automatic segmentation of rayed craters on the Moon by applying deep learning technique

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Introduction: These days, numerous images of planetary surfaces have been taken. In order to process them efficiently, it is required to reduce human tasks to process those big data. Application of machine learning techniques will be one of the solutions. In this study, we focused on making a thematic map containing rayed craters and their ejecta. Geologic maps are integration of multiple thematic maps and are used to investigate scientific objects and mission planning. In this study, we made the thematic map by applying a machine learning technique, called Efficient Neutral Network (Enet).

Data: Visible and near-infrared images obtained by Terrain Camera (TC) and Multi-band Imagers (MI) were employed. TC and MI were onboard SELENE. Spatial resolution of TC and MI images are ~10 m/pix and ~60 m/pix, respectively. TC observed lunar surface with visible range. MI observed lunar surface in 9 different channels whose wavelength range from 415 to 1055 nm. These images are advantageous to perform global survey in same quality, because they cover the entire lunar surface in same resolution and same illumination condition.

Study area and Method: The region of south Sinus Medii (3x3 degrees in size) was chosen for the training, validating, and the testing fields. The area is located on the nearside mare. Several grabens, sinuous rilles, and remained old crater rims are observed in the region. In order to the automatic segmentation, we employed Enet, a supervised machine learning technique. It is a deep neural network architecture for semantic segmentation. It requires low real-time inference in comparison to other deep neutral networks. To train a model, Enet requires input images with labeled images.

The composite image of TC and MI images were used as the input image. The lunar surface spectral features vary due to the difference in composition and amount of space weathering. Ejecta exposed by rayed craters are not space weathered, therefore they show different spectral features from the surrounding area. Thus, using visible and near-infrared images makes it easier to recognize rayed craters and their ejecta. The composite image is made of TC image as red, MI band ratio image of 749 nm/1001 nm as green, MI band ratio image of 414 nm/749 nm as blue. In order to adjust the gap of spatial resolution between TC and MI images, MI images are artificially interpolated and set to the resolution of 10 m/pix by nearest neighbor.

We also manually prepared the labeled images that have three classes, “rayed craters”, “ejecta”, and “others”. The composite image and the labeled image divided into 576 pieces, 512x512 pixels size each. Among them 504 labeled images were used to train the model. 72 images were used to validate the model.

Results: The small craters (~70 m<D<~1 km) predicted by the trained model met good agreement with the manually extracted craters. Although the predicted ejecta extents were slightly different from expected ones, this difference is negligible. Even manual analyze, it is hard to tell clear end line of ejecta, because they gradually thinner and disappears as they get far from the crater. The predicted large craters (D>~1 km) and their ejecta were not well extracted. The lack of supervised images for the craters can explain the disagreement. There were only ~10 rayed craters larger than 1 km. Referring to ambiguous small craters (D<~70 m), although craters themselves were not well extracted, their ejecta were mapped well. The reason why small craters were not extracted well is explained by the spatial resolution. Their dimeters are close to detection limit, because spatial resolution of MI is ~60 m/pix.

Keywords: Moon, Crater, Machine learning