IMAGE COMPLETION FOR SHADED AREA AROUND LUNAR POLES. Y. Matsuo[1], H. Demura[1], M. Ohtake[1], Y. Daket[1], H. Sato[2], [1]The University of Aizu, Aizu-Wakamatsu, Fukushima 965-8580, Japan, [2]Japan Aerospace Exploration Agency, 3-1-1 Yoshinodai, Chuo-ku, Sagamihara, Kanagawa 252-5210, Japan (s1250029@u-aizu.ac.jp, demura@u-aizu.ac.jp)

Introduction: Polar explorations of the Moon have been planned because the existence of water ice in the lunar polar region has been suggested based on the information from several types of onboard imaging cameras such as visible to infrared spectrometers [1]. The advancement in imaging technology brings further clues for water ice. However, images obtained from the lunar polar region often include shaded areas due to insufficient light intensity and have invalid pixels in Figure 1. The effect of shading can not be excluded in the case of calculating physical properties, such as reflectance. Invalid pixels do not show effective values. They are derived from saturated or no signal. These problems make it difficult to integrate images into a map.

This research aims to complete images around the lunar poles by two tasks; One is estimating correct pixel values in shaded areas. The other is plausibly filling the invalid pixels. Deep neural networks and generative adversarial networks (GANs) have been successful in estimating pixel values in shaded regions and filling invalid pixels [2, 3] in recent years. We propose a new method using GANs framework to tackle these two tasks at the same time. Experiments are conducted to validate the proposed method by comparing original images and generated images on several evaluation metrics.

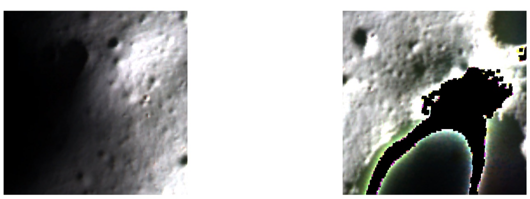

Figure 1: Incomplete images
left: shaded area, right: invalid pixels

Dataset: We used images of the lunar surface in five visible bands, which is 20 m/pixel in spatial resolution captured by Multiband Imager (MI) onboard the SELenological and ENgineering Explorer (SELENE) [4]. The MI data products bring mineralogical, geological, and topographic understandings. We used MI Level 3 dataset, which contains reflectance data after the map-projection. MI Level 3 dataset has the advantage in processing and analysis without any considerations for solar altitude because they contain reflectance values normalized to the standard geometry.

We have manually selected 55 pairs of the MI images, which ranged from 80S to 85S in degree, which captured at different times. One is the data including shaded areas or invalid pixels termed as 'incomplete image' in Figure 1. The other is the image including relatively a few shaded areas and no invalid pixels termed as 'complete image'. These pairs have been cropped on the same coordinates. The total number of pixels is 24866365. In addition, we have made masks termed as 'shadow mask' by applying Otsu's method to subtraction of pairs. The mask provides the location of the shaded areas with the networks in order to estimate correct values. We have divided the dataset into 44 pairs for the training set and 11 pairs for the test set.

Methods: In this research, we propose a method to estimate correct pixel values in shaded areas and to fill invalid pixels on incomplete images simultaneously by using Conditional GANs. CGANs consists of two players: a generator "G" and a discriminator "D". These two players are competing in zero-sum game, in which the generator G aims to produce an objective image from an input image. The discriminator D is forced to classify if it is a generated image by G or a real one from the dataset. Thus, adversarial competition progressively facilitates each other. We propose Shaded Area Detection and Translation & Completion Layer (SAD and TC Layer) based on U-Net [5] as generators and uses two discriminators D1, D2 in Figure 2. U-Net has the capability of learning the mapping between the input image and the output image, and U-Net based network is usually used as a generator of CGANs.

The first SAD Layer detects shaded areas to be estimated termed as 'detected shadow mask' in the top left of Figure 2. The second TC Layer estimates correct values in the areas and fills invalid pixels at the same time as shown in the bottom left of Figure 2. The detailed structure of the generator, SAD Layer, and the discriminator, D1, are similar to G1 and D1 of ST-CGAN [3]. As the TC Layer, we incorporate the mechanism of Partial Convolutions [2] to G2 of [3]. We also replace the discriminator, D2, with U-Net based one [6], which classifies whether a generated image or a real one pixel-wise. While a simple discriminator is difficult to obtain global information, a U-Net-based discriminator is able to learn features both locally and globally.

We use loss functions that are nearly the same as proposed in [2, 3]. They mainly consist of adversarial loss and L1 loss, but we further propose adversarial loss with the estimated areas as fake or the other as true, respectively using the U-Net based discriminator, D2.

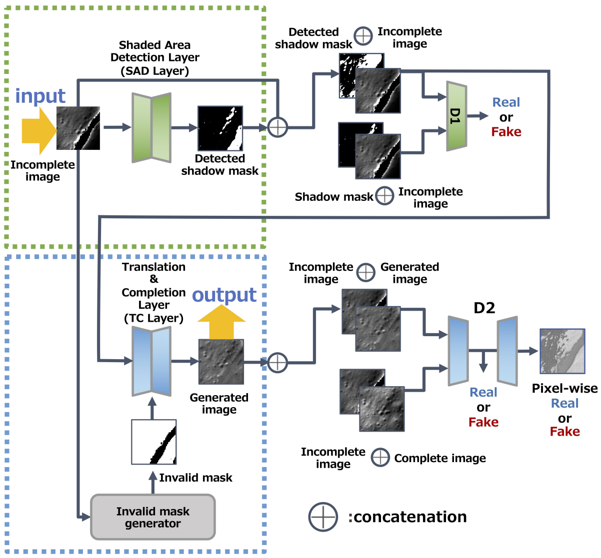

Figure 2: Network Architecture

Training settings: We used Adam optimizer with $lr = 0.0002$, $\beta_1 = 0.5$, $\beta_2 = 0.999$. Augmentations were adopted by cropping MI images randomly (256×256) and flipping them (horizontally and vertically) during a training session. We trained the networks on two NVIDIA RTX2070 SUPER GPUs (8 GB) with a batch size of 8.

Experimental Results: We conducted an experiment to verify the effectiveness of our trained model and evaluated the model from two perspectives: visual quality, and completion performance. We used the Peak Signal-to-Noise Ratio (PSNR), Structural Similarity (SSIM), and Multi-Scale Structural Similarity (MS-SSIM) as the metrics between the complete image and the generated complete image.

Figure 3 shows examples of the incomplete images (input) and the generated images (output) along with their PSNR and SSIM. For simplicity, it is displayed in gray-scale with 1 band which is 415 nm. Our method obtained good performance qualitatively on some of the datasets and showed improvements on PSNR and SSIM. The values seemed to be estimated correctly especially for (c), which the images having no invalid pixels. It can be very useful for image matching. Table 1 shows the comparison between the incomplete images (input) and generated complete images (output) in evaluation metrics for the test set on average. It demonstrates the improvement in all evaluation metrics.

Discussion: This research produced complete images while improving the perceptual quality. Good results were obtained although the dataset was extremely small.

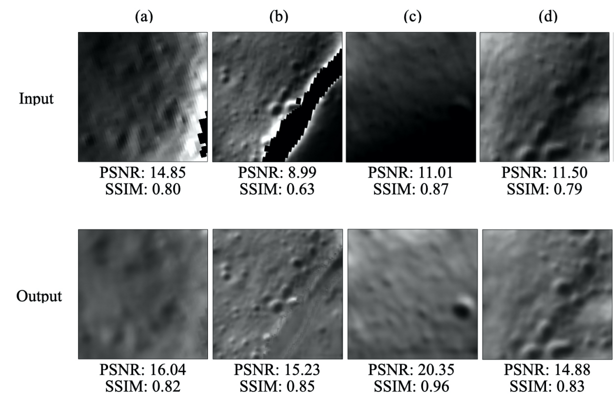

Figure 3: Qualitative and Quantitative results
Images having invalid pixels (a), (b). Images having no invalid pixels (c), (d).

Table 1: Average quantitative results

	PSNR	SSIM	MS-SSIM
input	11.96	0.84	0.67
output	17.66	0.87	0.72

We expect more robust and accurate results by improving the quantity and quality of the dataset.

Conclusion: This research accomplished completing MI images by estimating correct values in shaded areas and by plausibly filling the invalid pixels. We also demonstrated their effectiveness by experiments. Our experimental results showed good performance and indicate that this method has the possibility to assist in mosaicking images of the polar region. To the best of our knowledge, the method achieving the two tasks simultaneously is a new approach applied to lunar surface images. We plan to extend this work by expanding the datasets and incorporating new training dataset such as synthetic shaded images.

References: **[1]** T. Hoshino et al. In: *Acta Astronautica* (2020). **[2]** G. Liu et al. In: *Proceedings of the European Conference on Computer Vision (ECCV)*. 2018, pp. 85–100. **[3]** J. Wang, X. Li, and J. Yang. In: *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. 2018, pp. 1788–1797. **[4]** M. Ohtake et al. In: *Earth, planets and space* 60.4 (2008), pp. 257–264. **[5]** O. Ronneberger, P. Fischer, and T. Brox. In: *International Conference on Medical image computing and computer-assisted intervention*. Springer. 2015, pp. 234–241. **[6]** E. Schönfeld, B. Schiele, and A. Khoreva. 2020. arXiv: 2002.12655 [cs.CV].