**VERIFICATION OF SUPER-RESOLUTION METHOD FOR LUNAR POLAR DEM BY GENERATIVE ADVERSARIAL NETWORKS.** K. Ogino<sup>1</sup>, K. Ibuka<sup>2</sup>, M. Goto<sup>1</sup>, M. Ohtake<sup>3</sup> and H. Demura<sup>3</sup> <sup>1</sup>GS of Computer Sci. and Eng., Univ. of Aizu, (<u>m5261147@u-aizu.ac.jp</u>), <sup>2</sup>School of Computer Sci. and Eng., Univ. of Aizu, <sup>3</sup>Aizu Research Center for Space Informatics, Univ. of Aizu (Aizu-Wakamatsu City, Fukushima 965-8580, JAPAN, <u>demura@u-aizu.ac.jp</u>).

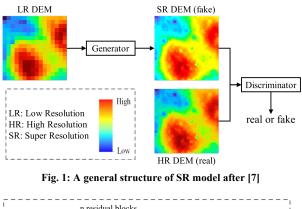
**Introduction:** DEM (Digital Elevation Model) is one of the most popular representations for topographies. The DEM has been used in lunar research field due to its usability for both science and exploration. Recently, lunar polar regions have great interest because the area is expected to provide volatiles such as water [1]. The polar region has been selected a target to send astronauts and rovers by various organizations such as space agencies, private companies, and universities [2, 3, 4].

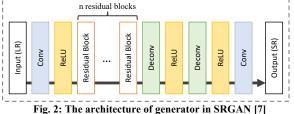
The region is covered with DEM in 5 m resolution and without higher one based on LRO NAC, although we need high resolution DEM by the scale of human for astronauts and rovers to move and operate equipment. This research focuses on how to make high resolution DEM from only pre-existing one, because we hard to arrange high resolution images for stereogrammetry due to poor illuminations and polar shadows.

This research aims to verify usefulness of the superresolution method based on GAN (Generative Adversarial Networks), as applied to the lunar DEM. This research selects SRGAN (Super-Resolution GAN) [5], which is evaluated as the best method in Zhang and Yu (2022) [6] with DEM on the Earth. We'd like to verify availability of SRGAN to the Moon, because exogenic processes are different in the Earth and the Moon.

**Data:** This research uses LOLA GDR in polar stereographic projection for the South Pole (- $87.5^{\circ}$  to the south pole) [8] as dataset. The resolution of the DEM is 20 m/pixel for the high-resolution DEM and 80 m/pixel for the low-resolution DEM, because SRGAN has been applied to the Earth DEM with promising results in upscaling factor 4x [7].

Experiments: This research compares SRGAN with a bicubic interpolation as typical super-resolution methods. This Bicubic is one of the pixel interpolation algorithms that is often compared in papers of superresolution to the proposed method [5, 6, 7]. SRGAN is developed as a photo super-resolution method based on generative adversarial networks in 2017 [5]. Structure of SRGAN model is shown in Fig. 1. It consists of DEM generator G and DEM discriminator D. G generates fake DEM, and D determines whether the generated DEM is real or fake. Fig. 2 shows the architecture of the G. It takes a low-resolution DEM as input and generates super-resolution DEM as output. The low-resolution DEM is trained through some convolutional layers, residual blocks, Rectified Linear Units (ReLUs), deconvolutional layers.





Learning rate of our model in generator and discriminator is set as 0.0000001, which follows Zhang and Yu (2022) [6]. We change only number of epochs from 100 to 2000, because it is not enough to train the model.

South polar DEM in high-resolution is divided into three groups:  $64 \times 64$ ,  $128 \times 128$ , and  $256 \times 256$  pixels. That in low-resolution is divided into the same three groups:  $16 \times 16$ ,  $32 \times 32$ , and  $64 \times 64$  pixels as preprocessing. The number of images shows 13398, 3480, 840, respectively. The dataset is also divided into training data and test one, whose ratio shows 8: 2.

The generated DEM ( $64 \times 64$ ,  $128 \times 128$ ,  $256 \times 256$  pixels) is evaluated by PSNR, SSIM, RMSE-Elevation, and Reconstructed error. This reconstruction error is defined as areal percentage with elevation error less than 10 meters.

**Results:** The goal of this research is to verify performance of SRGAN for lunar DEM compared with bicubic interpolation. Fig. 3 shows this comparison with 5 columns, whose components are "input DEM in low-resolution", "output DEM by Bicubic (64 x 64, 20 m/pixels)", "output DEM by SRGAN trained at 2000 epochs (64 x 64, 20 m/pixels)", "subtraction from the output by SRGAN to that by Bicubic", and "Truth". All data in grayscale 32 bit shows 1280 m in width. The higher value in grayscale is, the whiter its appearance is. Types of surface feature are selected in three rows for

confirming local area dependence. Top is feature-less region. Middle is heavily crater region. Bottom is a typical crater.

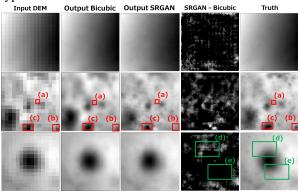


Fig. 3: The super-resolution results

The top row in Fig.3 shows that featureless DEM in low-resolution seems to be similar featureless one in high-resolution. The subtraction from the output by SRGAN to that by Bicubic shows checkered pattern, because Bicubic keeps textures of quantization error in low-resolution.

The middle row in Fig. 3 shows that the outputs by Bicubic appears to be smoothed. The outputs by SRGAN keep more significant features of crater rim than those by Bicubic does. A tiny cater (a) is not generated in both Bicubic and SRGAN, because the diameter of the crater is less than a pixel of lowresolution DEM. A crater (b) similar to the size of pixel is generated by Bicubic, but not done by SRGAN. A crater (c) more than the size of pixel is generated in both Bicubic and SRGAN.

The bottom row shows difference of generated DEMs with change of slopes. This central crater shows that top half is pristine rim (d), bottom half is degraded one (e). SRGAN generates sharper features than Bicubic, because the subtraction from the output by SRGAN to that by Bicubic shows that (d) appears to be more features than (e).

These results show that SRGAN gives a better output than that by Bicubic from viewpoints of visual appearance and of adaptability for change of slopes.

Table 1 shows the evaluation results of superresolution to compare Bicubic with SRGAN. Both show few differences, although visual appearance with rich features of SRGAN is better than that of Bicubic.

Table 1:	Evaluation	result of	generated	DEM

<b>Evaluation Index</b>	Bicubic	SRGAN
PSNR	43.783	34.964
SSIM	0.959	0.948
RMSE-Elevation (m)	1.771	3.451
Reconstruction Error 10m < (%)	99.787	97.427

**Discussion:** SRGAN shows practical accuracy of super-resolution for lunar DEM.

The subtraction result between (d) and (e) shows that SRGAN is more adaptable for high-frequency components such as crater rims and local changes of slopes than Bicubic. Bicubic has difficulty generating sharp features with local changes of slopes, because that interpolates a pixel to smoothly connect the neighboring 16 pixels. SRGAN learns based on the correct pixel values and is able to generate the high-frequency components.

Differences in topographic features between the Earth and the Moon causes a failure to train SRGAN in 100 epochs. Training data in Zhang and Yu (2022) [6] selects DEMs of the mountainous regions on the Earth. DEM on the Earth tend to be generated easily due to sharp relief such as many mountains with valleys, which are not found on the Moon. The number of epochs to train SRGAN is more than Zhang and Yu (2022) [6].

**Conclusion:** This research shows the usefulness of SRGAN for lunar DEM. SRGAN has a performance equivalent to Bicubic as typical super-resolution method. DEM derived from SRGAN exceeds that by Bicubic from a viewpoint of visual appearance with features. SRGAN is one of the reasonable options to improve DEM.

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References: [1] Hoshino et al. (2020) Acta Astronautica. [2] Ivanov et al. (2015) Planet. Space Sci. 117, 45–63. [3] Colaprete et al. (2020) Lunar Planet. Sci. 51. [4] Ohtake et al. (2020) Lunar Planet. Sci. [5] Ledig et al. (2017) IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 681-4690. [6] Zhang and Yu (2022) Sensors, 22, 745. [7] Bekir et al. (2020) doi.org/10.48550/arXiv.2004.04788. [8] LOLA GDR http://imbrium.mit.edu/BROWSE/LOLA GDR/