# LUNAR CRATER IDENTIFICATION AND COUNTING BY DEEP LEARING

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**ABSTRACT:** It is a powerful tool to count lunar craters for estimating lunar age. It has been up to human eyes to identify and/or count lunar craters with lunar images. However, there are many difficulties in this way due to have potential errors by human eyes. Recently, Christopher(2019) and Silburt et al.(2016) carried to identify the craters at Mars and Moon. Although the results have about 10% error, the cause of error can be clearly defined as using machine. We will try to identify and/or count lunar crates using previous or modified deep-learning model. The data required for learning and testing is WAC/NAC in LROC. We consider to apply to the data of ShadowCam, based on the experience gained through this study, although there are some problems to be solved. The problems; 1) whether or not the model, which is learned with WAC/NAC in LROC, can be applied to the data of ShadowCam, after studying the optical properties of PSR, 2) the distortion of topography on polar region. We expect that there are technological advances for calculating the age of solar system bodies by crater counting using deep-learning.
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## 1. INTRODUCTION

Research methods for estimating the age of surface creation using surface craters in objects such as Moon, Mars, where the atmosphere is sparse, and airless bodies are very common. The moon is estimated to be about 4.5 billion years old, but it's not clear when the moon is. So many people are still doing research on the age of the moon, and the methods of study are also diverse.

### 1.1 Sheets for Papers and Typing Lunar Age by Crater Counting

The method of estimating the age of a solarsystem body using crater counting is applied to airless body or the crater have many craters due to the lack. The age of the moon estimated using crater counting can be calculated from the radiometric age and the relative age.
Radiometric age calculation is estimated by deriving a parameterized function of crater diameter and number, Neukum et al. (2001) (Eq. 1) and Neukum et al. (2001) applies a number of functions from Hartmann et al.(2007) (Eq.2). There is listed in table 1.

$$\mathrm{N}(1) = \alpha(\exp(\beta T) - 1) + \gamma T \quad (1)$$

$$\mathrm{N}(1) = \alpha(\exp(\beta T) - 1) + \gamma T + \delta T^2 \quad (2)$$

Table 1. Parameters for function (Robbins, 2014)

| | α | β | γ | δ |
|---|---|---|---|---|
| Original data* | $9.83\cdot10^{-31}$ | 16.7 | $1.19\cdot10^{-3}$ | |
| Original data* | $9.83\cdot10^{-41}$ | 22.6 | $9.49\cdot10^{-4}$ | $1.88\cdot10^{-4}$ |
| HPF | Fit did not converge | | | |
| HPF | $9.07\cdot10^{-53}$ | 29.6 | $1.38\cdot10^{-4}$ | $4.43\cdot10^{-4}$ |
| NPF | $8.56\cdot10^{-32}$ | 17.3 | $1.29\cdot10^{-3}$ | |
| NPF | $6.61\cdot10^{-44}$ | 24.4 | $9.45\cdot10^{-4}$ | $2.00\cdot10^{-3}$ |

| | | | | |
|---|---|---|---|---|
| NPF | $9.36 \cdot 10^{-54}$ | 30.3 | $1.93 \cdot 10^{-3}$ | |
| NPF | $2.55 \cdot 10^{-38}$ | 21.1 | $3.18 \cdot 10^{-3}$ | $-4.20 \cdot 10^{-4}$ |

* ”Original data” refers to the raw counts discussed throughout Robbins (2014) work except for the Apollo 14, Cone, North Ray, and South Ray craters.
HPF: Hartmann et al.(2007)
NPF: Neukum et al.(2001)

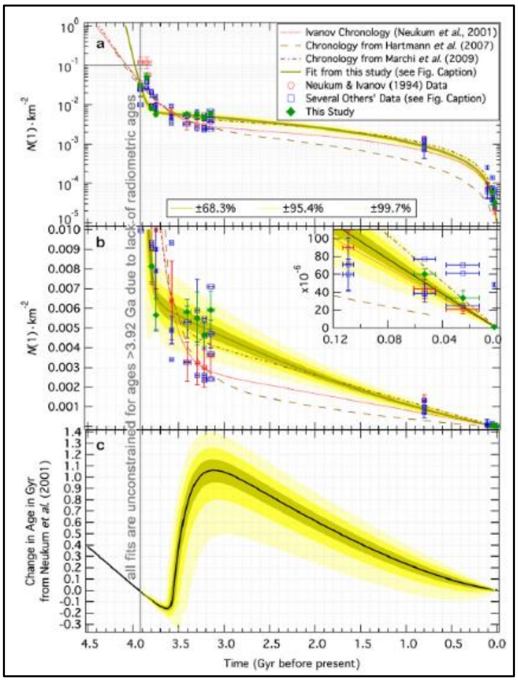



Figure 1. Radiometric age calculated by HPF and NPF. Panel a is log scale, panel b is focused to near 120Myr, and panel c is different with new chronology and class chronology

The meaning of N (1) in the above function means the number of craters 1 km or more in diameter, that is, the crater density within 1 million $km^2$(Figure 1). Robbins (2014) used the above functions to calculate the radiometric age of the lunar surface using the crater counting.

Relative age is to calculate crater density against crater diameter for a specific area where age is known and to estimate relative age as reference on this density. The crater collision frequency of the lunar surface began to decrease after Late Heavy Bombardment of the Solar System, and the collision frequency of the smaller craters was relatively higher than that of the larger craters. The result, which varies from region to region, allows us to estimate moon surface age relatively (Figure 2).

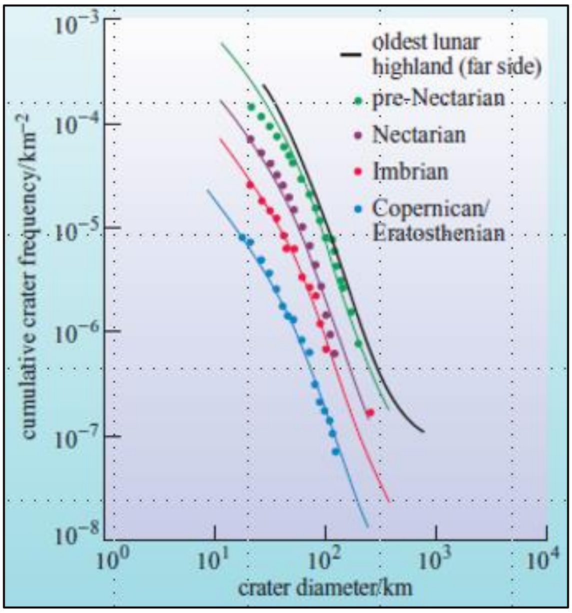



Figure 2. Cumulative crater with crater diameter. Pre-Nectarian: ~3.92-4.2 Gyr, Nectarian: 3.85-3.92 Gyr, Imbrian: 3-3.85Gyr, Copernican-Eratosthenian: after 3Gyr.(″*An Introduction to Solar System*″ ©The Open University)

### 1.2 Considering to Count Craters

The lunar surface has not been fixed since its formation, but has been changed in various forms by various situation. When colliding, the impactor and surface are melted by pressure and temperature (melting), and the surface melted floats (flooding) and blankets the existing craters as it flows (blanketing). And, the moment the impactor hits the surface, the material on the collision surface will spring up and fall around, forming a secondary crater. It has a different shape depending on the collision angle of the impactor, the surface properties, the nature and size of the impactor, and the topography of the surface. We, however, do not include the secondary crater on crater counting for age estimating, and we have to need identify the craters. In addition, to calculate exactly the age, we consider all of them such as, the superposition, mass wasting, and volcanic crater, and among them have to count the crater by collision. Therefore, the most important factor in calculating age by using crater counting is crater identification problem considering all the above items in lunar images. The human eye is still the most accurate, but unstable human error is a problem, and counting and counting numerous craters by eye is also a matter of time and labor. Crater counting with deep learning was attempted, and the next chapter introduces crater counting with deep learning on the moon and Mars.

## 2. PAST AND CURRENT RESEARCHES

Crater counting of solar system objects is the most important issue in identifying craters in images, and Crater Detection Algorithms (hereafter CDAs) have been most applied. Crater identification in images began in 1962 by Hough discussing the problem of identifying crater rims. In this chapter, we introduce an example of deep-learning using the images of Moon and Mars. Initially, craters were identified by enhancing the edges of the rims as identifying the crater rims in the panchromatic image. In addition, this method has been developed into genetic algorithms by Honda, Lijima, & Konishi, 2002, and radial consistency algorithms by Earl, Chicarro, Koeberl, Marchetti, & Milnes, 2005 and others(Stepinski, Ding and Vilalta). It is concluded that this is not very different from the result of the stereo images (Figure 3).

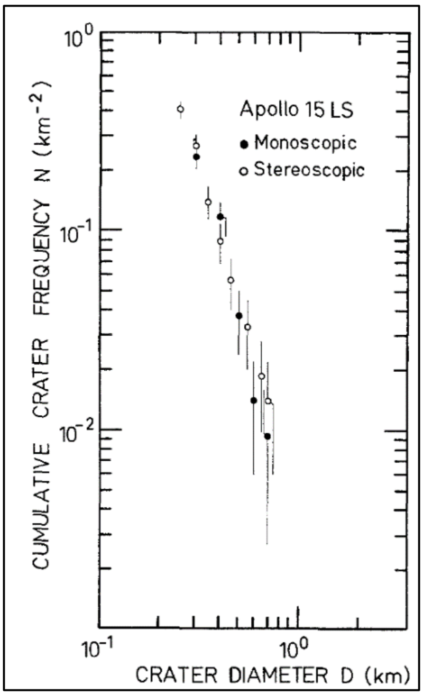



Figure 3. The result of monoscopic image and stereoscopic image at Apollo 15 landing site. (Neukum, KöNIG, and Arkani-Hamed, 1975)

Stepinski, Ding and Vilalta mentions, that there are two issues for toward robust detection of craters; 1) identification of craters from topography, 2) identification of craters from images. The case 1) is applied on flooding algorithm by O'Callagnan & Mark (1984), and the same method is applied with different data set in the case of Mars and Moon (Figure 4). In this case, the core module is to detect craters that have crescent-like shadows by shadows (Figure 5).

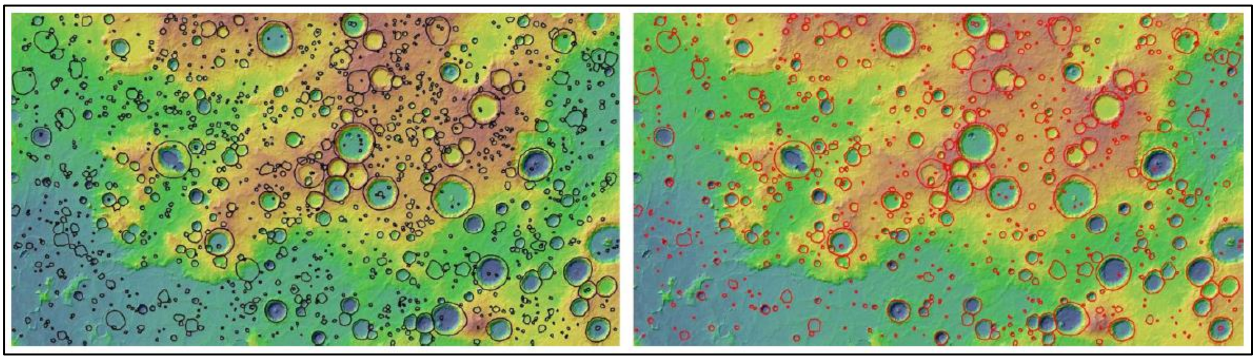


Figure 4. Crater detection from topographic data. left) craters and candidated crater, right) craters. (Stepinski, Ding and Vilalta)

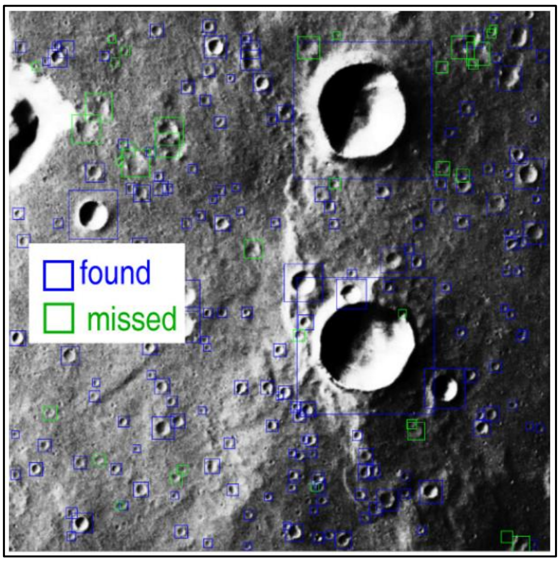



Figure 5. The result by “candidates” module (Stepinski, Ding and Vilalta)

There are many problems in CDAs such as, complex nature of craters, large variation in shape by illumination, orders of magnitude size differences, and overlap and degradation, and human error during labeling.

Silburt et al. (2018) attempted to deep-learn the moon craters with supplemented these problems. Convolutional Neural Network (hereafter CNN) used digital elevation model (hereafter DEM) data implemented by Lunar Orbiter Laser Altimeter (hereafter LOLA) on Lunar Reconnaissance Orbiter (hereafter LRO) and Laser Altimeter (hereafter LALT) on Selene. The results are as follows (Figure 6, Figure 7, table 2), and the error of about ~ 11% appears.

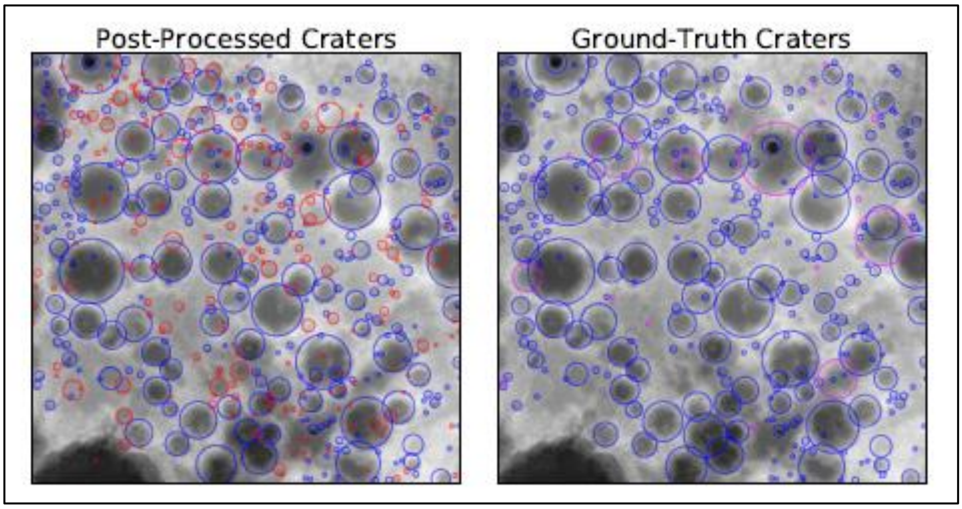



Figure 6. Post-processed craters and ground-truth crater (Silburt et al. 2018)

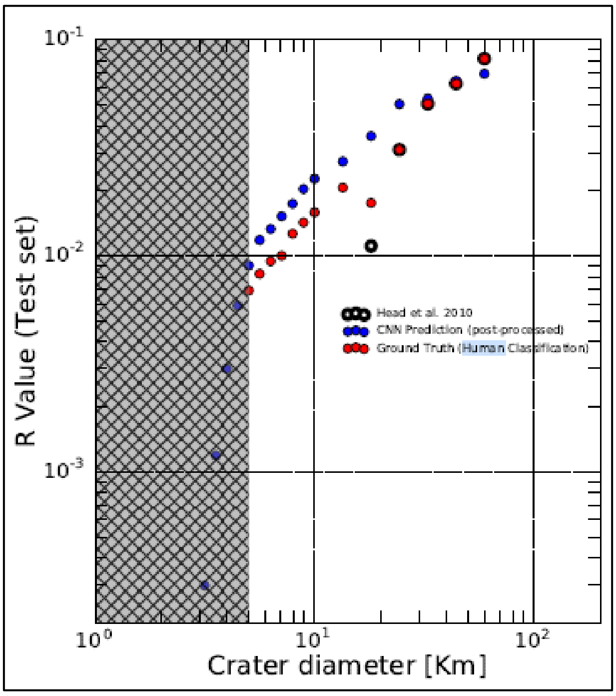


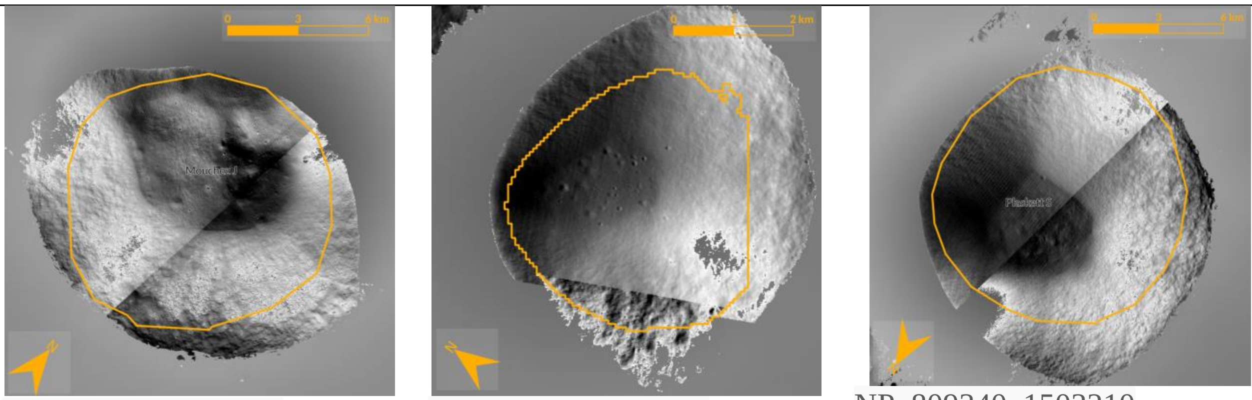

Figure 7. Lunar crater size-frequency distribution by deep-learning model (Silburt et al. 2018)

Table 2. Accuracy metrics by post-CNN (Silburt et al. 2018)

| **Accuracy Metric** | Post-CNN (validation) | Post-processed (validation) | Post-CNN (test) | Post-processed (test) |
|---|---|---|---|---|
| Recall | 56%±20% | 92% | 57% ± 20% | 92% |
| Recall (r<15 pixels) | 83% ± 16% | - | 83% ± 13% | - |
| Precision | 81% ± 16% | 53% | 80% ± 15% | 56% |
| New crater % | 12% ± 11% | 45% | 14% ± 13% | 42% |
| False positive rate | - | - | - | 11% ± 7% |
| Frac..lon. error | $10\%^{+2\%}_{-2\%}$ | $13\%^{+10\%}_{-7\%}$ | $10\%^{+2\%}_{-2\%}$ | $11\%^{+9\%}_{-6\%}$ |
| Frac. Lat. error | $10\%^{+2\%}_{-2\%}$ | $10\%^{+8\%}_{-5\%}$ | $10\%^{+2\%}_{-2\%}$ | $9\%^{+7\%}_{-5\%}$ |
| Frac. Radius error | $8\%^{+2\%}_{-2\%}$ | $6\%^{+5\%}_{-3\%}$ | $8\%^{+1\%}_{-1\%}$ | $7\%^{+5\%}_{-4\%}$ |

## 3. APPLYING IMAGES OF SHADOW REGION

The goal of this study is to identify the craters from the permanent shadow area image of the Moon obtained by ShadowCam. Therefore, based on the model constructed using the Moon crater, we want to learn the craters that exist in the shadow region. Recently, the LROC team provided images of the permanent shadow region by increasing the SNR using multiple polar images (Figure 8). Some craters were taken 100%, but some parts were taken, so we plan to use only 100% footage for training and testing (Figure 8).



NP_794550_3214780
Lat. 79.455
Lon. 321.478
Coverage: 100%

NP_807700_0537590
Lat. 80.77
Lon. 53.759
Coverage: 100%

NP_809340_1503210
Lat.
Lon.
Coverage:

Figure 8. Permanent Shadow Region by NAC/LROC (https://www.lroc.asu.edu/psr/)

We plan to conduct research in two ways (Figure 9). In case 2), we plan to use the map data by WAC/LRO. The map data by WAC/LRO are corrected in geometry and photometry correction. We are going to crop the map for the reasonable size. The data is published on Planetary Data System (PDS), anyone can download them.

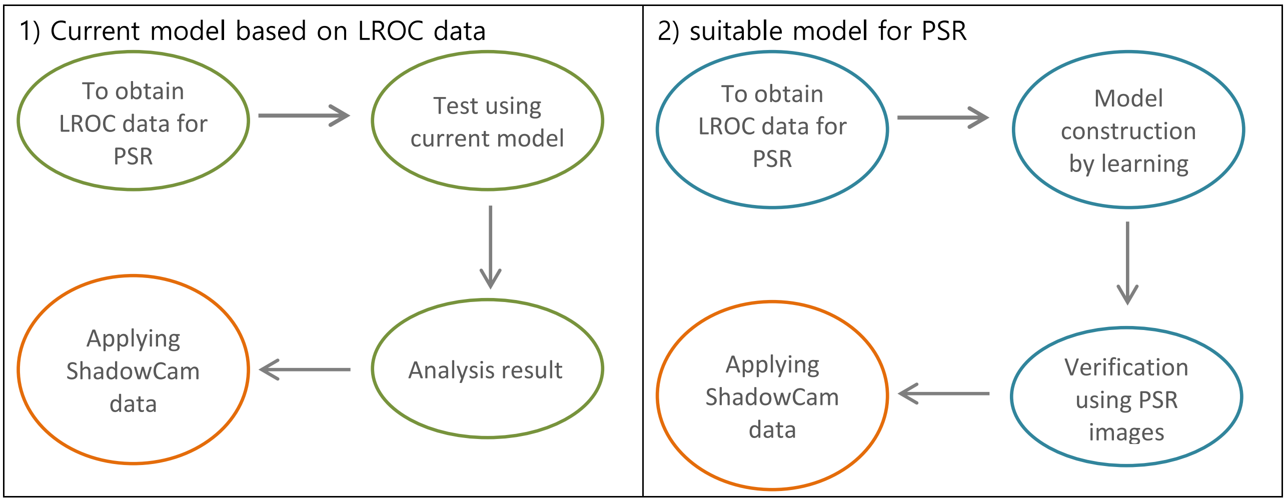
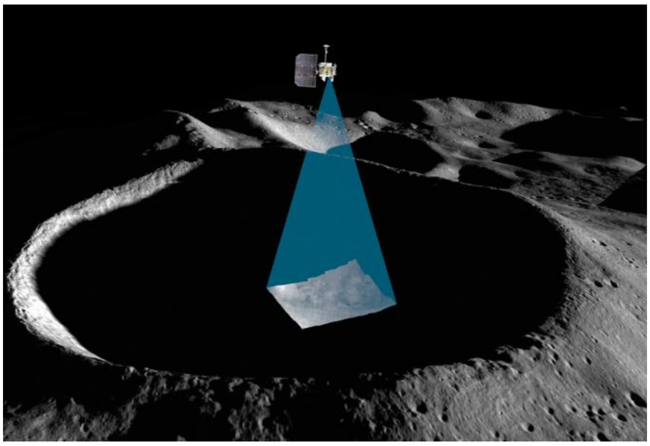



Figure 9. research processing

## 4. DISCUSS

ShadowCam will be mounted on the Korea Pathfinder Lunar Orbiter (hereafter KPLO), scheduled for launch in December 2020, to photograph permanent shades. Permanent shadow region is the area where the sun's light does not come in at all due to the shadow of the terrain due to the small tilt of the celestial axis. The water on the Moon may be to exist in permanent shadow region where the temperature is very low because it does not contain sunlight in the form of ice, and ShadowCam aims to explore the water here (Figure 10).



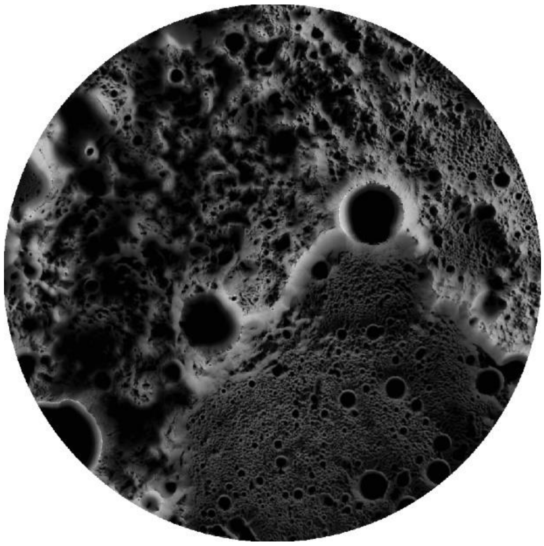


Figure 10. left) imaginary picture of ShadowCam (https://www.nasa.gov/feature/nasa-selects-shadowcam-to-fly-on-korea-pathfinder-lunar-orbiter)
right) Map of PSR at high latitude (https://www.lroc.asu.edu/psr/)

We are not able to do observation at PSR be directly observed. The images of PSR are made using secondary scattering by the walls of the craters or terrain around the PSR. It is, therefore, expected that it is different from the existing image because it is the image observed by the changed light, such as wavelength and intensity etc. We try to analyze the image characteristics of secondary scattering using crater images of Mercury and Ceres' PSR, and then apply them to the model. We expect that the results are very useful for crater identification along with image acquisition of PSR of the Moon that has never been revealed previously.

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