Experimental Study to Determine the Best Compression Ratio of High-Resolution Images of Small Bodies for the Martian Moons eXploration Mission*

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Data transmission rate is one of the biggest limiting factors in space exploration because transmitting images is largely restricted by the bitrate. This issue can be crucial for JAXA’s future sample-return mission, such as the Martian Moons eXploration (MMX) mission. High-resolution images are important in selecting the most scientifically interesting and safest landing/sampling sites, although the strategy of rapidly sending each image (> 114 MB) with a limited bitrate (< 32 Kbps) has to be considered. Lossy compression can significantly reduce the file size; however, the highly compressed images can be scientifically worthless. Therefore, determining the best compression ratio is necessary. Here, we develop a method to analyze the influence of image compression using image quality indices, Structural SIMilarity (SSIM) and image entropy. Moreover, by measuring the Cumulative Size Frequency Distribution (CSFD) of regolith grains in images with different amounts of compression, the loss of scientific value of images can be measured. We then carefully confirm that image quality indices can truly determine the best compression ratio. Using this method, the spacecraft can autonomously find the best compression ratio, compress an image and send it to the ground in a few minutes using a limited transmission rate.

Key Words: Data Transmission Rate, Best Compression Ratio, Martian Moons eXploration (MMX), Space Exploration

Nomenclature

B: constant used in the definition of CSFD
C: constant used in the definition of SSIM
D: diameter of a grain particle
H: entropy of an image
K: constant used in the definition of SSIM
μ: mean intensity (value)
L: bit depth
N: number of image pixels
p: compression ratio
σ: standard deviation (error)
x: image vector of a raw image
y: image vector of a compressed image

Subscripts

min: indicator for the minimum
i: indicator for the ith value
j: indicator for the jth value
x: member of x
y: member of y

1. Introduction

More than 20 spacecraft are currently exploring extraterrestrial bodies in the solar system. Among the most common onboard instruments is a visible imaging camera, which usually requires the largest amount of data to be transmitted. Camera specifications, such as the focal length, total pixels, angle of view, image size, shutter speed, and required resources (i.e., size, weight, and power) are determined by various factors including scientific/engineering needs, available resources of spacecraft, and the cost. However, due to the recent technological advances in camera performance, data transmission rate has become one of the biggest issues. Obtaining high-resolution images is now an easier task than transmitting them.

Such a situation will have significant impacts on the design of the future spacecraft missions. This is, in fact, an imminent issue for the Martian Moons eXploration (MMX) mission, which is scheduled for launch in 2024.1) The mission is a sample-return mission, and the major objective is to obtain the most scientifically interesting samples safely from Phobos, one of the satellites of Mars. Phobos has two hypotheses for its origin: the capture of a primitive asteroid2) and the giant impact,3) which come from analyzing the data of previous missions. The MMX mission is expected to collect samples that will clarify which formation theory is correct. Importantly, the selection of the safest, most scientifically interesting landing/sampling sites depends largely on detailed analyses of the remote-sensing data4) consisting mostly of visible and infrared images. Thus, much higher-resolution images than those collected on previous missions will be required to determine the critical areas for landing and sampling.
For this reason, the onboard cameras of the MMX spacecraft, TElescopic Nadir imager for GeOmOrphology (TENGOO) and Optical RadiOmeter composed of CHromatic Imagers (OROCHI), will have higher resolutions than the camera of previous JAXA’s missions such as Hayabusa2,\textsuperscript{5,6} the size and the bit depth of TENGOO/OROCHI are planned to be 3296 $\times$ 2472 pixels and 16 bits, respectively. The file size of a raw image can be up to 114 MB with 7 colors, which can take approximately 8 hours for transmission to Earth even with 32 Kbps bitrate, which is not practical for the limited observational period (i.e., in total, approximately 2 yr in the Phobos proximity orbit). Furthermore, during the landing phase, the spacecraft can stay on the surface of Phobos for only approximately 3 hr. During this short time, scientists/spacecraft should somehow determine the exact locations for collecting samples, which does not allow us to spend more than 1 hr for data transmission. Therefore, it is necessary to develop an adequate strategy for transmitting high-resolution images with important information using a limited transmission rate.

The efficient transmission of image data can be achieved using the data compression. Many lossy compression schemes have been proposed to significantly reduce the size of an image; however, highly compressed images can be distorted and become scientifically useless. Theoretical studies based on compression sensing theory may be required to figure out the best compression scheme for a given image, though this approach can take a large amount of time to be developed. Our approach is to determine the best compression ratio by using the compression scheme for a general purpose, which is already available for space missions. The best compression ratio should make the sizes of images as small as possible without losing scientific importance. We explore a strategy to figure out the best compression ratio for high-resolution images expected to be obtained during the Phobos proximity phase of the MMX mission.

2. Image of the Surface of Phobos

2.1. Simulated image of Phobos

If we had high-resolution images of Phobos similar to those expected to be obtained during the MMX mission, we could simply use them to study the best image compression ratio. However, no such images are available from previous missions, which poses the challenge of determining a compression ratio for images which have not yet been obtained. Simulating realistic surface images by computer graphics may be possible, but is not that easy because of many unknown variables, such as the shape of surface rocks, their textures, and their responses to different illumination conditions which can significantly impact scientific analyses. We thus take an experimental approach, where we develop a simulated Phobos surface and take high-resolution images using similar illumination conditions to those which will be experienced during the MMX mission.

As a simulated material of Phobos regolith (often simply called “simulant”), the Univ. Tokyo Phobos Simulant, Tagish lake-Based (UTPS-TB)\textsuperscript{61} was used, in which many kinds of rocks on the Earth were crushed and blended with each other in order to make their reflectance and mechanical properties match with the Phobos regolith, which were constrained by observations from both prior spacecraft missions and ground-based telescopes. The surface of Phobos can be simulated by processing that simulant and preparing appropriate illumination conditions. By taking digital photographs, high-resolution images similar to those expected from MMX cameras can be obtained.

The simulated Phobos surface image was obtained using the following processes. UTPS-TB was spread on a foundation having a size of approximately 30 $\times$ 30 cm. A camera having the focal length of 100 mm was fixed so that the image obtained was not blurred due to camera shake. The camera took shots from 30 cm directly above the simulant. The exposure time was 0.6 s and the f-number was 32, which were determined to make the image bright enough, and at the same time avoid any objects in the image from getting blurred due to depth of field. The size of the image was set to be 3296 $\times$ 2472 pixels, which is the same size as that of the MMX cameras. A floodlight was used as the sunlight and the incidence angle (phase angle) was set to 30°, which is a favorable angle to detect each object on the surface. The color is grayscale and the resolution of the image is 10 $\mu$m/pixel. Note that this resolution is sufficient for identifying several tens of centimeters of surface rocks, which is required for the landing safety of the MMX lander. The simulated image is shown in Fig. 1.

2.2. Compression of the image by JPEG2000

The image was then compressed using JPEG2000. JPEG2000 is one of the famous and widely used image compression techniques developed by the Joint Photographic Experts Group (JPEG) and standardized by ISO/IEC 15444.\textsuperscript{7,8} It is generally used for medical images,\textsuperscript{9} astronomical images,\textsuperscript{10,11} and the High-Resolution Imaging Science Experiment (HiRISE), which is a camera instrument on NASA’s Mars Reconnaissance Orbiter (MRO).\textsuperscript{12} Moreover, our use of JPEG2000 is motivated by its planned use as a lossy com-
pression technique for the MMX mission. Although there are an enormous number of image compression techniques such as JPEG, PNG, and TIFF, our study is catered to the MMX mission, and therefore focuses on JPEG2000 compression. Future studies may address the influence of other compression techniques that apply to other camera instruments for future space probes. The image was compressed in different compression ratios, \( p \), which is defined as

\[
p = \left(1 - \frac{\text{size}_{\text{compressed}}}{\text{size}_{\text{original}}} \right) \times 100 \% ,
\]

where, \( \text{size}_{\text{compressed}} \) and \( \text{size}_{\text{original}} \) are file sizes of compressed, original images, respectively. Examples of compressed images are shown in Fig. 2. Note that the original file size is 8.1 MB, and the minimum compression ratio image for JPEG2000 is a lossless compression image where pixel values are exactly the same as those in the raw image. For the image used in this study, this lossless compression has a value of \( p = 70\% \).

### 2.3. The influence of the compression

Because of the unique compression technique of JPEG2000, which involves Discrete Wavelet Transform (DWT) and Embedded Block Coding with Optimal Truncation (EBCOT), high-frequency components in images are more likely to be lost rather than low-frequency components, which means that the smaller the size of the structure, the earlier it is blurred and becomes difficult to be distinguished. The lowest compression ratio image, 70.00% (Fig. 1), has all of the same pixel values as the raw image, and thus, they cannot be distinguished from one another. Finding differences between the raw image and each compressed image in the range from 80.00% to 98.00% is difficult without zooming in, although each file size is shrunk at the expense of some information. However, after the compression ratio reaches 99.00% (Fig. 2-top), fine surface roughness starts to change slightly, and at higher compression ratios, this difference in roughness becomes more noticeable. At \( p > 99.90\% \), the image is completely altered and becomes blurred (Fig. 2-middle).

In addition to this change, the outline of each particle in the image starts to get blurred as the compression ratio rises. This difference becomes prominent and many small particles are not able to be detected at a ratio higher than 99.90%. At the ratio of 99.99%, the image is totally distorted, and nothing can be reliably identified (Fig. 2-bottom). In short, as the compression ratio increases, initially the surface roughness changes, then the profile of particles gets blurred and small particles become difficult to be identified. Finally, the image is completely distorted and nothing can be seen.

### 3. Analysis of the Image Quality

To determine the best compression ratio, we explore objective methods involving the calculation of image quality indices to analyze the change in image quality caused by image compression. Because such methods can be completed without the aid of manual analysis, they provide a fast means for identifying the best compression ratio using a computer algorithm.

#### 3.1. Structural SIMilarity (SSIM)

There are many objective methods to analyze the quality of images, and Structural SIMilarity (SSIM) is one of the most widely used quality indices.\(^{13}\) The basic concept of SSIM to evaluate the quality of images consists of three comparisons: luminance, contrast, and structure comparisons. These comparisons are conducted, mainly focusing on the mean intensity and standard deviation of images. Suppose
\( \mathbf{x} \) is a raw image containing all of the pixel values, while \( \mathbf{y} \) represents a compressed image. \( x_i \) and \( y_i \) are the pixel values of \( \mathbf{x} \) and \( \mathbf{y} \). The mean intensity of \( \mathbf{x} \) and \( \mathbf{y} \) are defined as
\[
\mu_x = \frac{1}{N} \sum_{i=1}^{N} x_i,
\]
and
\[
\mu_y = \frac{1}{N} \sum_{i=1}^{N} y_i.
\]
In SSIM, the luminance comparison function \( l(x, y) \) is written as
\[
l(x, y) = \frac{2\mu_x\mu_y + C_1}{\mu_x^2 + \mu_y^2 + C_1}
\]
where, \( C_1 \) is a constant. Then, we can conduct a contrast comparison. The standard deviation of \( \mathbf{x} \) and \( \mathbf{y} \) are defined as
\[
\sigma_x = \left[ \frac{1}{N-1} \sum_{i=1}^{N} (x_i - \mu_x)^2 \right]^{1/2},
\]
and
\[
\sigma_y = \left[ \frac{1}{N-1} \sum_{i=1}^{N} (y_i - \mu_y)^2 \right]^{1/2}.
\]
The contrast comparison function \( c(x, y) \) is written as
\[
c(x, y) = \frac{2\sigma_x\sigma_y + C_2}{\sigma_x^2 + \sigma_y^2 + C_2},
\]
where, \( C_2 \) is a constant. Structure comparison is not affected by luminance and contrast, and thus the structures of the two images are expressed as \( \frac{\mathbf{x} - \mu_x}{\sigma_x} \) and \( \frac{\mathbf{y} - \mu_y}{\sigma_y} \). The structural similarity can be measured by correlating the two vectors, and that correlation is equivalent to the correlation coefficient between \( \mathbf{x} \) and \( \mathbf{y} \). In this case, the structure comparison function \( s(x, y) \) can be written as
\[
s(x, y) = \frac{\sigma_{x,y} + C_3}{\sigma_x\sigma_y + C_3},
\]
where, \( C_3 \) is a constant. Finally, \( SSIM(x, y) \) is defined (using Eqs. (4), (7), (8)) as
\[
SSIM(x, y) = [l(x, y)]^\alpha \cdot [c(x, y)]^\beta \cdot [s(x, y)]^\gamma.
\]
Here, the three parameters of \( \alpha > 0, \beta > 0, \gamma > 0 \) are introduced to adjust the relative importance of each component. For simplicity, in this study \( \alpha = \beta = \gamma = 1 \) and \( C_1 = C_2 = 2 \) stand as in Wang et al.\(^{13}\) Using these values, the SSIM can be rewritten as
\[
SSIM(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{x,y} + C_2)}{\mu_x^2 + \mu_y^2 + C_1(\sigma_x^2 + \sigma_y^2 + C_2)}.
\]
Moreover, we define \( C_1 \) and \( C_2 \) in reference to Wang et al.\(^{13}\) such that
\[
C_1 = (K_1L)^2, \quad C_2 = (K_2L)^2,
\]
where, \( L \) is the bit depth of the image (i.e., 255 for this study). \( K_1 \) and \( K_2 \) are small constants that have conditions of \( K_1 \ll 1 \) and \( K_2 \ll 1 \). In this work, \( K_1 = 0.01 \) and \( K_2 = 0.03 \) as in Wang et al.\(^{13}\)

The value of SSIM is in the range from 0.0 to 1.0, which shows a higher quality when the value is higher. It takes 1.0 if an image is totally the same with the original image.

### 3.2 Image entropy

In a basic sense, compression of images changes each pixel value from the original image, which leads to the loss of important information and scientific value. How much each value of a pixel changes from the original can be measured by subtracting the values of a compressed image from the values in the raw image. We thus obtain difference images for every compression ratio by calculating the pixel differences between Raw and compressed images.

Figure 3 shows difference images for three different compression ratios: 70.00%, 99.90% and 99.99%. The 70.00% compressed image show any differences compared to the raw image, so its difference image has no features and has a value of zero for all pixels (Fig. 3-top). At first, when the compression ratio rises, the difference images remain featureless. However, when \( p \) reaches 99.60% some patterns appear and become prominent at higher ratios such as 99.90% (Fig. 3-middle). The patterns then start to exhibit recognizable structures as the ratio approaches 99.99% (Fig. 3-bottom). This trend can also be explained using a histogram of differences in the pixels, which is shown in Fig. 4. In the difference image of 70.00%, all pixels have the value of zero. When the compression ratio increases, each pixel starts to have some differences larger/smaller than zero and the variety of differences becomes larger at higher ratios, drawing some patterns and structures in the difference images.

When we can see some patterns or structures in the difference images, this means that the compressed images have lost some pattern or structure information. Stated differently, we can measure how much information has been lost in the compression images by analyzing the difference images. We therefore make use of the image entropy, in addition to SSIM, to analyze the trend in the difference images, where differences of the pixels start to have a wider variety of values as the compression ratio becomes higher.

Suppose \( n[k, l] \) is the value of the \( k \)th column and the \( l \)th row in a difference image. The probability of having the value of \( n[k, l] \) for each pixel, \( p[k, l] \) can be calculated as
\[
p[k, l] = \frac{N_{n[k,l]}}{N_{total}},
\]
where, \( N_{n[k,l]} \) is the number of pixels having the value of \( n[k, l] \) and \( N_{total} \) is the total number of pixels in the image, which is \( 3296 \times 2472 \) pixels in this study. With reference to Shannon and Weaver,\(^{14}\) the image entropy \( H \) is defined as
\[
H = -\sum_{k} \sum_{l} p[k, l] \log_2(p[k, l]).
\]
This entropy becomes higher if the degree of randomness in an image is higher, which means that having a larger variety of differences and showing patterns/structures in a difference image increases the entropy value. In other words, an increase in entropy shows the loss of information and a change in the image quality.
3.3. Image quality analysis by SSIM and image entropy

Figure 5 shows the result of the analysis of the image quality using SSIM and image entropy. Overall, SSIM decreases as the compression ratio increases. Particularly, the value suddenly starts to decrease when the compression ratio reaches 99.00%. It took 1.25 min (75 s) to calculate the SSIM for all images. On the other hand, the image entropy continuously increases as the ratio rises. Similarly, the entropy gets dramatically higher after the ratio of 99.00%. The calculation time for image entropy was 1.20 min (72 s), which was slightly faster than calculating SSIM. All of the computations were conducted on a laptop computer equipped with an Intel Core i7 3.5 GHz processor and RAM of 16 GB and using Python scripts.

The two analyses show that, as the compression ratio rises, the image quality is steadily diminished, and then it dramatically decreases for \( p > 99.00\% \). Therefore, the value of the compression ratio just before the sudden decrease in image quality (i.e., 98.00%) can reasonably be determined to be the best compression ratio.

4. Confirmation Using Manual Analysis

SSIM and image entropy can be useful methods to determine the best compression ratio; however, for space exploration missions that usually require massive funding and have little chance to be conducted again, the reliability of those methods must be confirmed. We have to evaluate whether or not the compressed images obtained using those methods are truly suitable for space exploration missions. By defining the scientific value of high-resolution images for missions, the amount of the scientific value loss caused by image compression can be measured, which enables us to evaluate compressed images. Thus, we define the scientific value using the concept of Cumulative Size Frequency Distribution (CSFD) of rock gravel and measure the amount of loss.

4.1. Cumulative Size Frequency Distribution (CSFD)

One of the most attractive objects in images of the surface of celestial bodies is rock gravel. In geology, particles in rock
The difference between \( \alpha \) from different celestial bodies and areas has enormously contributed to the understanding of the characteristics and geological processes of celestial bodies. Moreover, one of the most important elements for the safety of landing a spacecraft is the particle (boulder) distribution.\(^{35}\) Only a difference of 0.5 in the value of \( \alpha \) leads to very different conclusions; for example, about the surface of properties of celestial bodies and the geological processes shaping them. Thus, calculating \( \alpha \) precisely is extremely important, and miscalculation of the value of \( \alpha \) in an image would contribute to the loss of its scientific value.

Therefore, this study defined the scientific value of images as the detectability of rock gravel in the image. The slope of CSFD therefore provides an index by which to measure the loss of scientific value. A change in the value of the slope of CSFD in compressed images can be used to quantify the loss of the image’s scientific value.

### 4.3. Manual measurements of the size of particles

Using Fiji,\(^{36}\) which is an open image-processing software, the size of each particle was measured manually. The outlines of all particles in the images were overlapped with ellipses (Fig. 7). This process exactly determines the size of particles, and therefore overlapping was carefully conducted. If the ellipses did not properly fit the profile of particles, we moved the ellipses or changed the size of the ellipses until they best-fitted the outline of particles. Then, the length of the semi-major axis of each ellipse was measured as the size of each particle. This method of size measurement by fitting ellipses was used in previous studies, such as Tancredi et al.\(^{37}\)

In this manner, the size of particles was measured in seven different compression ratio images, which were raw (70.00%), 90.00%, 95.00%, 98.00%, 99.00%, 99.90% and 99.95% compressed images. Those were selected based on the observation of the Section 2.3, which shows that in the range of 70.00% to 98.00% there are no huge differences between the raw image and compressed images, while higher ratio compressed images revealed dramatic changes as compared to the raw image.

### 4.4. Method of fitting power-law distribution

Using the data of the size of each particle, the slope values of CSFD were calculated by plotting the cumulative number of particles per area and fitting power-law distribution to it. As the fitting method, Clauset et al.\(^{38}\) showed that a method consisting maximum-likelihood fitting method and goodness-of-fit tests based on Kolmogorov-Smirnov static and likeli
C has the condition of
\[
\int_{x_{\text{min}}}^{\infty} p(x)dx = \int_{x_{\text{min}}}^{\infty} Cx^{-(\alpha+1)}dx = \frac{n}{\text{area}},
\]
where \( n \) is the total number of particles in the image and \( \text{area} \) is the unit of the surface area in the image. Therefore, \( C \) can be defined as
\[
C = \frac{n}{\text{area}} \cdot \alpha x_{\text{min}}^{\alpha}.
\]
In that case, Eqs. (15) and (16) are written as
\[
p(x)dx = \frac{n}{\text{area}} \cdot \frac{\alpha}{x_{\text{min}}} \left( \frac{x}{x_{\text{min}}} \right)^{-(\alpha+1)}dx,
\]
\[
CCDF(x) = \frac{n}{\text{area}} \left( \frac{x}{x_{\text{min}}} \right)^{-\alpha}.
\]

Then, let us calculate \( \alpha \) of power-law distribution that best fits the observed data having a size is larger than \( x_{\text{min}} \). \( \alpha \) can be calculated using maximum likelihood estimators (MLE). The probability that the data can be fitted by the model is written as
\[
p(x|\alpha) = \prod_{i=1}^{n} \frac{n}{\text{area}} \cdot \frac{\alpha}{x_{\text{min}}} \left( \frac{x_{i}}{x_{\text{min}}} \right)^{-(\alpha+1)},
\]
where, \( x_{i} \) represents the size of particles observed. This probability is called likelihood of the data given by the model and the model (power-law distribution) best fits the data observed when this likelihood is maximized, which leads to the calculation of \( \alpha \). In order to maximize the likelihood, the logarithm \( \mathcal{L} \) of the likelihood is frequently used, and \( \mathcal{L} \) is maximized at the condition of \( \partial \mathcal{L} / \partial \alpha = 0 \). By solving that condition for \( \alpha \), \( \alpha \) can be calculated as
\[
\alpha = n \left[ \sum_{i=1}^{n} \frac{x_{i}}{x_{\text{min}}} \right]^{-1}.
\]
Moreover, the standard error of \( \alpha \) is derived as
\[
\sigma = \frac{\alpha}{\sqrt{n}} + \mathcal{O} \left( \frac{1}{n} \right),
\]
which is explained in Clauset et al.\cite{38}

The next process is to calculate the goodness-of-fit \( D \) of the data observed and the fitted power-law distribution, and find the best \( x_{\text{min}} \), which minimizes \( D \). This operation is conducted using the goodness-of-fit test based on Kolmogorov-Smirnov static (KS static).\cite{40} The maximum distance between \( CCDF \) and cumulative number per area, \( D \) is defined as
\[
D = \max_{x_i > x_{\text{min}}} |y_i - CCDF(x_i)|,
\]
where \( x_{i} \) is the observed size of each particle and \( y_{i} \) is the cumulative number per area of each particle. This \( D \) represents the goodness-of-fit. The best fitting can be achieved when \( D \) is minimized and the best \( x_{\text{min}} \) is obtained under that condition.
Finally, the feasibility of the fitting can be checked using the $p$-value. To calculate the $p$-value, synthetic data is made by applying a semi-parametric bootstrap. In a semi-parametric bootstrap, one data component is obtained randomly from the data observed having a size smaller than the best $x_{\text{min}}$ and the other data is generated using the best-fit power-law distribution under the condition that each value is larger than the best $x_{\text{min}}$. The synthetic data is made combining those two data elements. Note that the total number of the synthetic data is the same as the number of data observed. In this study, synthetic data was made 1000 times. For each synthetic data, the fitting processes are conducted and the minimum of $D$ is calculated. Then, how many times that $D$ is smaller than the $D$ of the first fitting is calculated and the $p$-value is defined as the proportion of this number to the total number of synthetic data, which is 1000 in this study. If the $p$-value is larger than 0.1, the fitting is considered to be feasible.

### 4.5. Result of the manual measurement and fitting

Figure 8 shows the value calculated for alpha and number of particles detected as functions of the compression ratio. The alpha does not change at ratios of 95.00% or less. When the ratio gets higher, a slight change is detected, and particularly for ratios larger than 99.00%, the value changes dramatically. The number of particles detected also decreases slightly for ratios 98.00% or less, and decreases dramatically for ratios larger than 98.00%. Table 2 shows the parameters of each fitting, $x_{\text{min}}$, the number of fitted particles, and $\sigma$ change due to the differences in the particle size data in each compressed image. More importantly, in all images, the $p$-value is larger than 0.1, which shows that all fittings are feasible to some extent. However feasibility starts to be lost, especially when the ratio rises above 99.00%. Given these results, scientific information seems to be lost at ratios larger than 99.00%, which means that the best compression ratio should be 99.00% or less.

### 4.6. Best compression ratio

Judging from the results of the manual measurement, compressed images obtained using the two objective methods (98.00%) can be regarded as truly suitable for space exploration missions, and the reliability of the two methods is also confirmed. This means that the best compression ratio can be determined in approximately 1 min using SSIM and image entropy.

In order to use the methods, the preparation of several images at different compression ratios is needed beforehand. However, the process of compression can be minimized within a few seconds, and thus it takes only a few minutes for preparing all of the compressed images. In this study, the file size of the image can be shrunk to 2% (162 KB) of the original (8.1 MB), and thus it takes about 40 s to send it to Earth even if the data transmission rate is only 32 Kbps. This means that the process of compressing images, determining the best compression ratio, and transmitting the compressed image to the ground can be completed within a few minutes, while sending a raw image takes as long as 34 min. Therefore, this method can be a powerful tool for future space exploration missions that do not have enough transmission rate to send high-resolution images, such as the MMX mission.

Note that, in critical phases for the future missions, for example, when selecting the landing sites for the MMX mission, this result should be carefully interpreted. As Fig. 9 shows, for $p = 98.00\%$, particles having a size smaller than 1 mm are unable to be identified completely and the total number of particles identified is 148 less than the number in the raw image. Suppose the resolution of the image is 65 mm/pixel, which is the resolution planned for TENGOO during the quasi-satellite orbit of Phobos 11 km from the surface. Scaling our image up, the particles 1 mm in size are equivalent to particles 6.5 m in size, based on our image resolution of 10 μm/pixel for the Phobos simulant. If the resolution is lower than 65 mm/pixel, it is probable that particles smaller than 6.5 m cannot be identified, which may not be appropriate for choosing the landing site. Therefore, when selecting the landing site, images having a compression ratio lower than 98.00% may be needed for safe landing site selection. In order to determine the best compression ratio in every critical phase, different and appropriate methods/criteria are needed, which is a topic for future research.

### 5. Conclusion

We analyzed the change in image quality caused by image compression using the two objective methods, SSIM and image entropy, in order to determine the best compression ratio for high-resolution images of the surface of small bodies and resolve the problem of limited data transmission rate for
gravel started to be dramatically diminish. That compression ratio is
idly detect the exact ratio at which the quality of the images
future space exploration missions such as the MMX mission.

Fig. 9. CSFD of Raw and 98.00% compressed image. The gap between
two data becomes larger when the size is smaller than 1 mm, which means
that particles smaller than 1 mm are more difficult to be identified in
98.00% compared to Raw image.

future space exploration missions such as the MMX mission.
The results show that both objective methods are able to ra-
pidly detect the exact ratio at which the quality of the images
started to be dramatically diminish. That compression ratio is
98.00% for the images in this study.

Moreover, by measuring the change in the slope of the
gavel’s Cumulative Size Frequency Distribution (CSFD), we
carefully confirmed whether or not the best compression
ratio obtained using SSIM and image entropy are truly suit-
able for space exploration missions. Rock gravel in the seven
compressed images was manually analyzed. CSFDs were
plotted, and the index of power-law distribution ($\alpha$) was
determined. The results show that, for compression ratios larger
than 99.00%, scientific information is lost from compressed
images, which means that the best compression ratio should
be 99.00% or less. Therefore, the 98.00% best image com-
pression value determined applying the objective methods
utilized in this study is reliably con-
mirmed. Note that this re-
sult should be interpreted carefully, depending on the phase
of future missions.

The method introduced in this study can determine the
best compression ratio in approximately 1 min, which means
that the process of compressing the image, determining the
best compression ratio and sending the image to Earth can
be completed within a few minutes. More importantly, the
spacecraft can complete the process rapidly and autonom-
ously, which resolves the problem of limited data transmis-
sion rate and will succeed in preserving the scientific value
of high-resolution images collected in future spacecraft mis-
sions, such as the MMX mission.

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