Attitude Estimation of Space Objects Using Imaging Observations and Deep Learning

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ABSTRACT

Optical measurements such as photometric observations and imaging observations have been widely applied for the estimation of the shape, surface properties, and attitude motion of space objects. Those informations enable us to improve the efficiency of active debris removal (ADR) and to investigate the health of the satellites. Although photometric observation is low-cost, previous study pointed out that initial values of attitude are necessary for high-precision estimation. Imaging observation by image matching method was examined to estimate those initial values in the previous study, considering that imaging observation is effective, especially for GEO objects. The purpose of this paper is to improve accuracy, robustness, and calculation cost of imaging observation applying machine learning, and to reveal the system requirement of imaging observation of GEO objects. The feasibility of imaging observation with existing optical system was verified, and by imaging simulation with different resolutions. Also comparing Convlutional Neural Network (CNNs) with estimation based on conventional image matching, it was clarified that the problems in the previous research were overcome.

1. INTRODUCTION

In recent years, as the number of space debris on orbit increases, the risk of collision of satellites with space debris increases. It is believed that Active Debris Removal (ADR) is necessary to guarantee the continuous space development in the future in that ADR is the most effective way to reduce the number of space debris. Estimation of the shape, surface properties, and attitude motion of space objects is needed to prepare for ADR and/or to monitor the health of satellites. Optical measurements such as photometric observations and imaging observations have been researched as techniques for those estimations. Photometric observation-based methods use light curves, the time history of the brightness of a space object, and was originally used to estimate the attitude motion of asteroids. For rocket bodies, assuming the simplified shape, estimation of shape and attitude motion from light curves has been demonstrated in [1]. Imaging observation-based methods use images captured by optical telescope. Adaptive optics removes the effect of atmospheric fluctuations and enables us to get clearer images of space objects [2]. Kyushu University has conducted studies on the state estimation of space object on GEO orbit with photometric observations using Unscented Kalman Filter (UKF) and Multiple-model Adaptive Estimation (MMAE) [3]. However, estimation by this method requires the initial attitude and the initial angular velocity of a space object, and how to decide these is a problem. Therefore, a method of determining these using imaging observation was proposed, and its feasibility was examined by simulation [4].

The previous study assumed that the shape and surface properties of a space object were known. A set of captured images corresponding to various attitude angles was generated from the three-dimensional model created in 3DCG software. It was supposed that the attitude of a space object can be estimated by finding the image that has the highest similarity to the target image. However, the technique based on the similarity comparison of images do not work if the target object is not perfectly centered in the image. It is necessary to increase the number of images in the set to improve the accuracy, so that there is also a problem that the calculation cost for one estimation increases. The purpose of this paper is to improve these problems by applying convolutional neural networks (CNN), and to reveal the system requirement of the imaging observation of GEO space objects. CNN is a kind of machine learning and has been widely used for image recognition. Also, in the field of SSA, the application of CNNs are studied for the classification of space objects by photometric observation [5] and satellite anomaly detection [6].

2. METHOD

2.1 Quaternion based attitude comparison

Instead of the Euler angle used in previous study, the attitude of the space object is represented by quaternion in the following equation,

$$\tilde{q} = \begin{bmatrix} v_x \sin\frac{\theta}{2} \\ v_y \sin\frac{\theta}{2} \\ v_z \sin\frac{\theta}{2} \\ \cos\frac{\theta}{2} \end{bmatrix} \tag{1}$$

where $[v_x \quad v_y \quad v_z]^{\mathrm{T}}$ is a unit vector of rotation axis, and θ is a rotation angle. When an object is rotated with two different quaternions in sequence, the total rotation can be represented by using quaternion product as follows:

$$\tilde{q} \otimes \tilde{p} = \begin{bmatrix} q_w & q_z & -q_y & q_x \\ -q_z & q_w & q_x & q_y \\ q_y & -q_x & q_w & q_z \\ -q_x & -q_y & -q_z & q_w \end{bmatrix} \begin{bmatrix} p_x \\ p_y \\ p_z \\ p_w \end{bmatrix} \tag{2}$$

where $\tilde{p}$ and $\tilde{q}$ represent the primary and secondary rotation, and $\otimes$ means quaternion product. Error quaternion between true attitude and estimated attitude is calculated as following equation,

$$\tilde{e} = \tilde{q} \otimes \tilde{p}^{-1} = \begin{bmatrix} q_w & q_z & -q_y & q_x \\ -q_z & q_w & q_x & q_y \\ q_y & -q_x & q_w & q_z \\ -q_x & -q_y & -q_z & q_w \end{bmatrix} \begin{bmatrix} -p_x \\ -p_y \\ -p_z \\ p_w \end{bmatrix} \tag{3}$$

where $\tilde{q}$ is the true quaternion, $\tilde{p}$ is the estimated quaternion, and $\tilde{e}$ is the error quaternion.

2.2 Convolutional Neural Networks

Neural Network is a method of machine learning and its application to various problem has expanded in recent years. Especially, Convolutional Neural Network (CNN) is commonly used for image recognition. Unlike ordinary neural networks, CNNs contain two types of layers which called “convolutional layers” and “pooling layers”. These layers enable CNN to reduce dimensions without losing important features contained in each part of images. In this paper, a CNN model that estimates quaternion of the attitude of the space object from its image was constructed. Fig. 1 shows an example of a model of the CNN in this paper. Its outputs are four independent real numbers from -1 to 1, so it must be normalized to satisfy the defining equation (1).

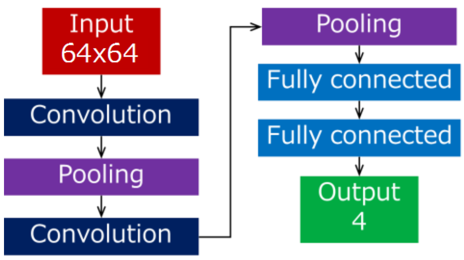


Fig. 1 model of the CNN in this paper

2.3 Generating images of space object

Attitudes in the training dataset should be generated from quaternions distributed as evenly as possible, so each vertex of a geodesic dome centered on the origin was defined as rotation axis of quaternion. Geodesic dome is a polyhedron obtained by dividing an icosahedron by triangle faces close to an equilateral triangle. Quaternion of attitudes in the testing dataset should be distributed randomly. A face in the geodesic dome was randomly selected, and the vector of the point randomly plotted in the face were used as their rotation axis. Then, their rotation angles were decided randomly from 0 to π.

The target space object model is JCSAT-3, a GEO satellite which has been ended its operation. Fig. 2 shows its 3D model made with Blender, a 3DCG software. Its specifications are shown in Table 1 and its surface properties are shown in Table 2. Rendering of the clear image which was the source of the captured image was also done in the blender.

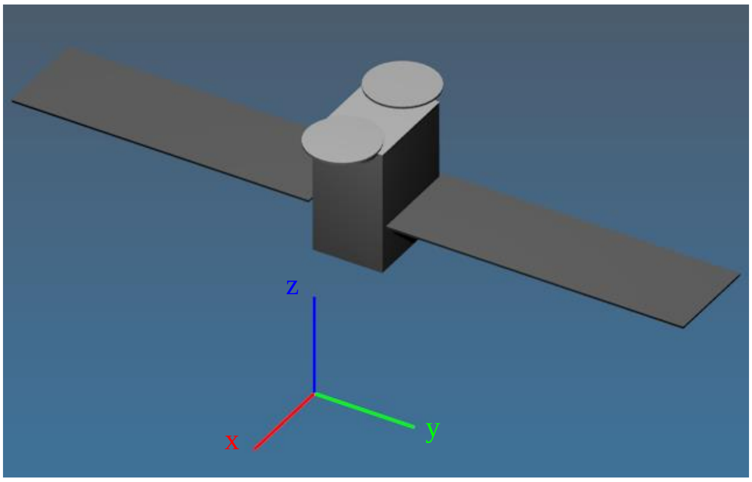


Fig. 2. 3D model of the target space object

Table 1 Size of the target space object

Height stowed	4.9m
Width stowed	2.8 × 3.8m
Solar arrays deployed	26.9m

Table 2 Surface properties of the target space object

	Specular	Diffusion	Absorption
Bus	0.1	0.6	0.3
Paddles	0.76	0.16	0.3
Antenna	0.16	0.56	0.28

Rendering in blender requires the angle between the observer, the satellite and the sun. Considering the requirements for observation, the positional relation between the observer, space object, and sun is limited. For example, to make observations, the sun must be below the horizon for the observer, that is, the elevation angle of the sun must be negative. Assuming that the observer, satellite, and sun are all on the equatorial plane, simulation conditions were determined as shown in Table 3 to satisfy these requirements.

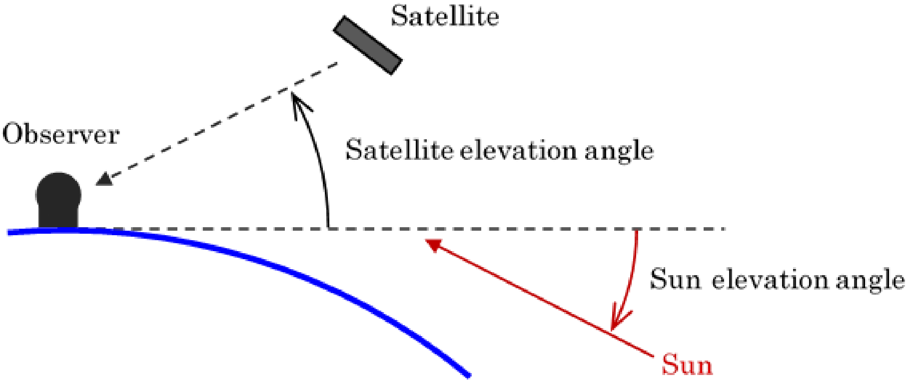
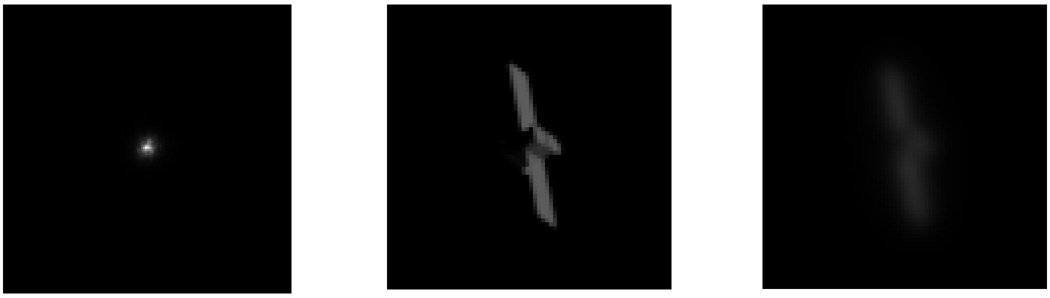


Fig. 3. Requirements for observation

Table 3 Simulation conditions about satellite and the sun

Satellite elevation angle	35°
Sun elevation angle	-20°
Distance from observer to satellite	38180km

In order to take account of atmospheric fluctuations and the effects of the optical system, point spread function (PSF) was simulated using SOAPY(a library for adaptive optics simulation). As an actual observing system, the case of using William Herschel telescope (WHT) was assumed. In other cases, simulations were performed assuming resolution 5 times that of WHT. Fig. 4 shows examples of PSF, clear image, and PSF applied image in those cases.



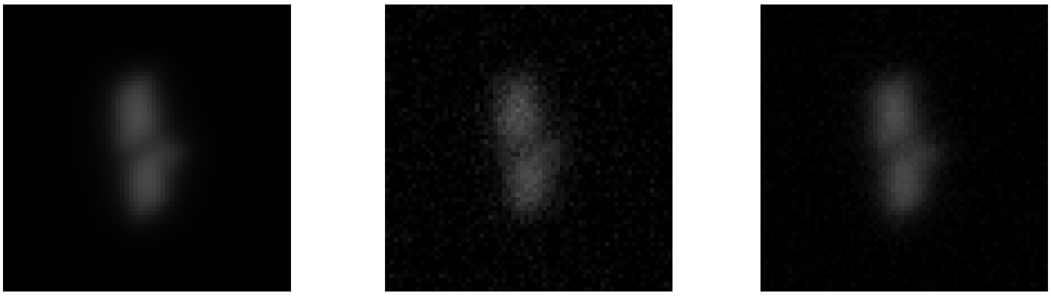
(a) PSF (b) Clear image (c) PSF applied

Fig. 4

Sensor noise was reproduced by adding Gaussian noise to the image. The standard deviation of the noise $\boldsymbol{\sigma_{noise}}$ is represented by signal-to-noise ratio (SNR) as follows,

$$\boldsymbol{\sigma_{noise}} = \frac{\boldsymbol{\sigma_{signal}}}{\boldsymbol{SNR}} = \frac{\sqrt{\sum(\boldsymbol{I}(\boldsymbol{i},\boldsymbol{j}) - \bar{\boldsymbol{I}})^2}}{\boldsymbol{SNR}} \qquad (\mathbf{4})$$

where $I(i,j)$ means pixel brightness at position (i,j) on the image and $\bar{I}$ means average brightness of the image. Adding Gaussian noise generated with σ_{noise} as the standard deviation, images as shown in Fig. 5 are obtained.



(a) No noise (b) $\mathrm{SNR} = 5$ (c) $\mathrm{SNR} = 10$

Fig. 5 Sensor noise simulation

2.4 Simulation cases

The conditions of simulation cases are summarized in Table 4. In case1 and case2, optical system with different performance were assumed in order to clarify the system requirements of the optical system in imaging observation. In order to consider the effect of noise, which was a problem in estimation by image matching method, images without noise were used for estimation in case3. In case 4, the estimation was performed by image matching instead of CNN. It was the same as algorithm used in the previous study except that quaternions were applied. Since the image matching algorithm assumes that the object is always at the center of the image, random clipping was not applied to the images in case 4.

Table 4 Simulation conditions

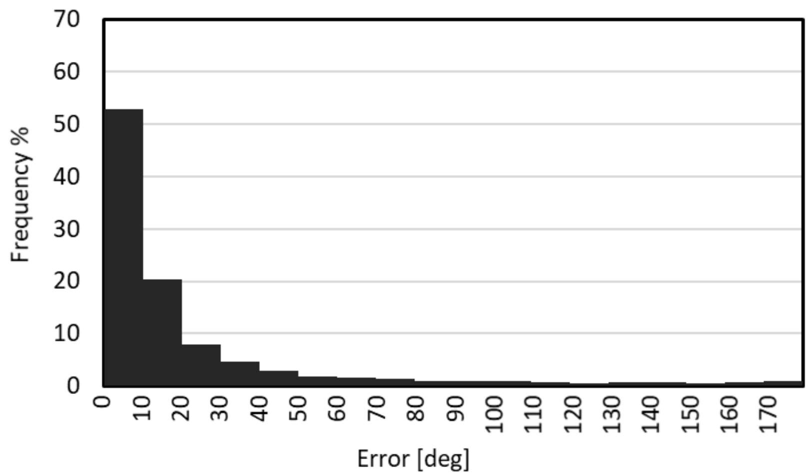
	case1	case2	case3	case4
Resolution ratio with WHT	5	1	5	5
SNR	5	5	No noise	No noise
Estimation method	CNN	CNN	CNN	Image matching
random clipping	w.	w.	w.	w/o

3. RESULTS AND DISCUSSION

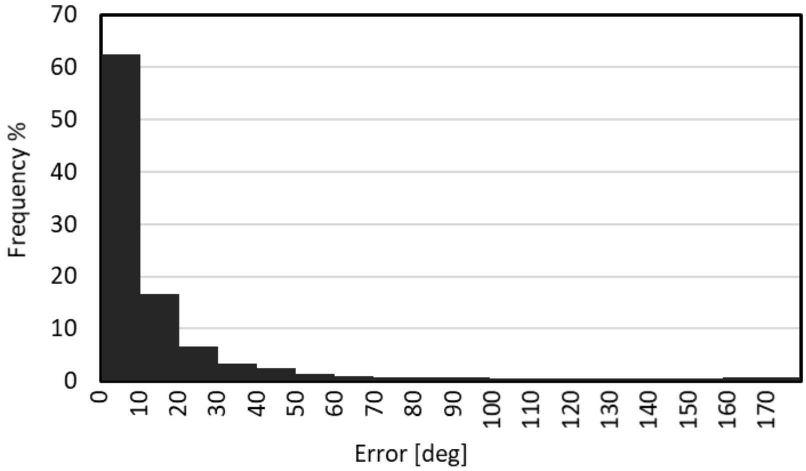
Table 5 shows the results of error angle in each case. Fig. 6 shows the distribution of estimation errors in each case. However, case 2 is omitted because errors in case 2 were almost evenly distributed from 0 to 180 degrees. Although more than 70% fell under 20 degrees in case 1, the average error in case 2 was about 90 degrees, indicating that case2 was not possible to estimate at all. Input images of the other cases were 64x64 pixels, whereas input images of case 2 were 12x12 pixels. Therefore, the reason why the estimated value did not converge is considered to be a lack of resolution. In case 1 and case 3, the error distribution tends to be similar, but in case 3 attitude could be estimated with higher accuracy. It was found that the estimation error increased slightly due to sensor noise. In case 4, about 50% of attitudes could be estimated within errors of 20 degrees or less. However, attitudes could not be estimated correctly as a whole, because there are also many images that produce errors close to 180 degrees. Examples of such images are shown in Fig. 7. In those cases attitude error increased due to the symmetry of the satellite. The similar phenomenon was found even when estimated by CNN, but it did not significantly affect the estimation accuracy.

Table 5 Averaged error angle

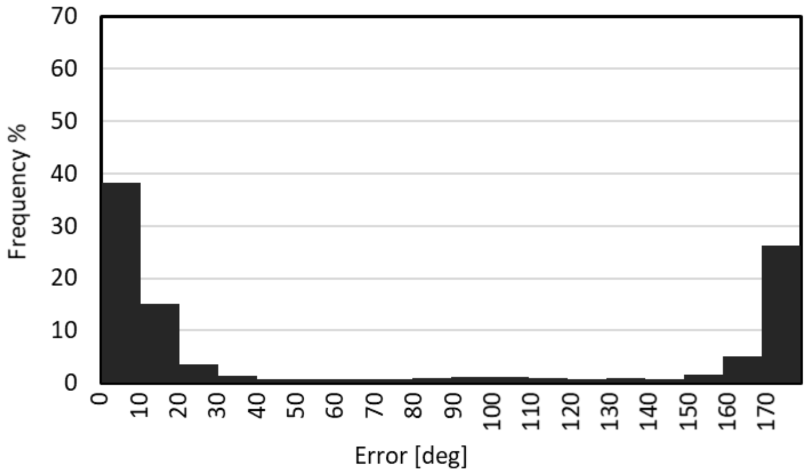
	case1	case2	case3	case4
Averaged error [degrees]	22.4	90.6	18.2	71.1



(a) case 1



(b) case 3



(c) case 4

Fig. 6 Distribution of error angles

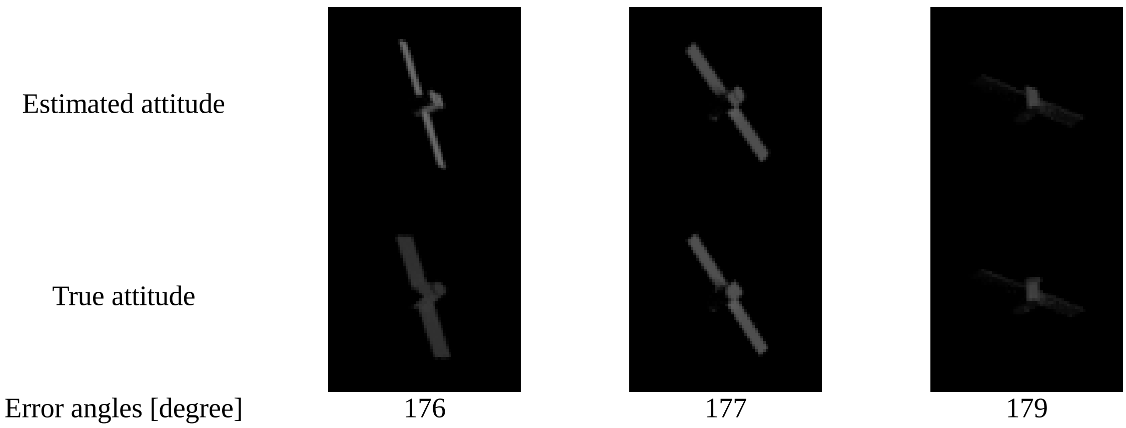


Fig. 7 examples of results in case 4

4. CONCLUSION

In this paper, convolutional neural network (CNN) was applied to imaging observation for attitude estimation of GEO objects. CNNs showed higher performance than more conventional image matching method in previous study. Especially, errors caused by object symmmetry could be significantly reduced. However, it has been clarified that William Harschell telescope (WHT), which is assumed as an existing optical system, has insufficient resolution to perform attitude estimation by imaging observation. Assuming 5 times finer resolution than WHT, more than 70% of attitude error fell under 20 degrees.

5. REFERENCES

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