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On-Orbit Mass Property Estimation for Spacecraft Cargo using Operation Data by Machine Learning

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Abstract

The purpose of this study is to establish the methodology to estimate the mass property accurately enough from cargo spacecraft dynamics data and improve the control performance. For the estimation, the most plausible mass property to explain the response relationship between the control and feedback of spacecraft dynamics is calculated by applying the regression method as one of the machine learning algorithms and collecting training data from the existing HTV operation and simulation. To utilize this method in the actual HTV-X operation, the following two results derived from machine learning must be acceptable for the operators: 1) the variation and amount of operation data for sufficiently accurate estimation, and 2) the integrity of regression coefficients against the actual spacecraft characteristics. By considering these two points, the feasibility of this mass property estimation method is discussed.

Keywords: Mass Property Estimation, HTV, Machine Learning, Regression Analysis

Introduction

JAXA has successfully launched and operated HTV (H-II Transfer Vehicle) which is rendezvous mission to the ISS six times by 2017. The mass property of the visiting vehicle such as the HTV is more easily changed than that of general spacecraft from the influence of propellant consumption, the cargo, and the refuse. Therefore, there is a demand to carefully place the cargo. A new-generation cargo vehicle called the HTV-X is now being developed [1]. The HTV-X has some noticeable characteristics compared with the current HTV. One of the major characteristics is the module composition concept. As shown in Fig. 1, the HTV-X consists of two modules—the Service Module and the Pressurized Module. Due to the reduced number of modules, the mass property of the HTV-X is influenced by external and internal changes more than the HTV. The mass property of the HTV is estimated prior to launch of the spacecraft. The mass property is updated during the operation using only the data estimated prior to launch. The mass property is not updated using data that can be obtained during the operation, such as telemetry data. However, the mass property calculated prior to launch is unreliable, particularly during the return operation due to the uncertainty regarding the placement of refuse. The calculated error results in wasted propellant consumption because of the control disturbance caused by the error. The National Aeronautics and Space Administration (NASA) has recently planned to hand over the ISS to a commercial organization in the mid-2020's. Should various commercial demands emerge for the transport of supplies to the ISS in the future, flexibility will become a vital factor in meeting such demands. And in a future lunar transfer vehicle extended from the HTV-X, a lunar probe could also be loaded as cargo. Therefore, in order to flexibly and efficiently operate the current ISS resupply mission by the

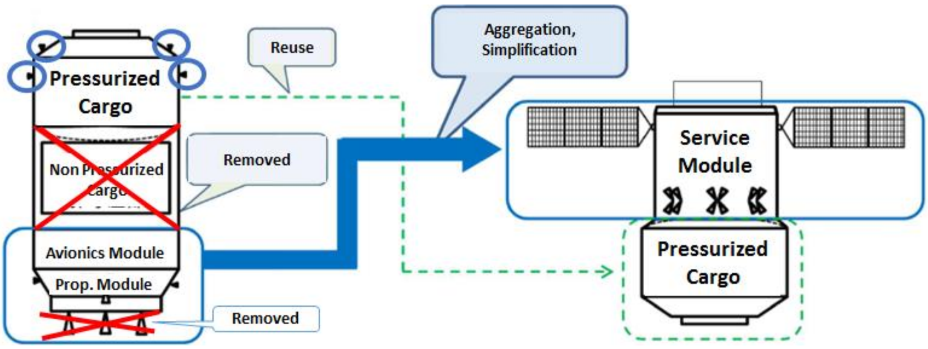

Fig. 1: Comparison between HTV and HTV-X

HTV-X, as well as prepare for future diverse cargo demands, it is an essential functionality to adaptively estimate the mass property [2,3] and update the vehicle control algorithm based on the estimation.

Approach

Machine learning methods such as Deep Learning have achieved great results. However, in this research, we adopt a method of fitting the operational data of spacecraft to the equation of motion. More specifically, training data consisting of thruster ejection data and observation data of motion state change is fitted to the equation of motion, and the mass property and other aspects of the spacecraft are estimated as parameters. The reasons for using such a method are as follows: First, the spacecraft's behavior as the subject of this research can be described by classical equations of motion except for the influence of disturbances; therefore, parameters can be estimated with high accuracy by fitting to that equation. When fitting to a complicated model such as Deep Learning, etc., over-learning occurs and there is a high possibility that the spacecraft's actual behavior cannot be modeled appropriately, thereby affecting the reliability of the estimation result. Such methods as Deep Learning often use a model as a black box. However, as reliability is regarded as being important in the operation of spacecraft, it is currently difficult to use the value estimated from the black box. Conversely, in the case of recursive estimation based on the equation of motion, the model is a white box and can be easily verified by using the existing simulator. Therefore, we have an advantage in terms of reliability when using the estimation results of actual spacecraft operations. Finally, such application to various types of future spacecraft may be possible. The estimation of mass property is needed not only for the transfer vehicle for the ISS such as the HTV but also for the planetary probe to return large mass samples and for future transport vehicles that reciprocate between space stations and the ground while exchanging packages. While the system architecture of such spacecraft varies, this model is mainly occupied by general dynamics information, thus making it difficult to be affected by the architecture. Hence, it is a simple and versatile estimation model, and the expansion of future application is also expected.

Modelling Problem as Regression Analysis

In this study, the feasibility of mass property estimation based on regression analysis is demonstrated by using the actual HTV design and operation data. Because its regression equations are obvious and undoubtedly reliable, the analysis looks relatively simple. While this analysis is a case of classic simple machine learning, there are specific difficulties due to the spacecraft characteristics. Therefore, the challenge of this study is to apply the classic regression analysis approach for a specific spacecraft while maintaining the simplicity. The following subsections describe the analysis in detail.

HTV model

Although the HTV has been already operated six times, the vehicle design largely remains unchanged. In particular, the thruster design is common to all six vehicles. The thruster subsystem is composed of two strings, with each string having 14 thrusters. Except for large burn maneuvers, all small and medium burn maneuvers and attitude controls are executed by this 14-thruster set. Each thruster has a different position and orientation at the body fixed coordination (BFC) to realize 6 DoF control. The following equations represent the position and orientation of the 14 thrusters.

$$\overrightarrow{\mathrm{pos}}_n^{BFC} = \begin{bmatrix} pos\_x_n^{BFC} \\ pos\_y_n^{BFC} \\ pos\_z_n^{BFC} \end{bmatrix} \tag{1}$$

$$\overrightarrow{\mathrm{ori}}_n^{BFC} = \begin{bmatrix} ori\_x_n^{BFC} \\ ori\_y_n^{BFC} \\ ori\_z_n^{BFC} \end{bmatrix} \tag{2}$$

where $\overrightarrow{\mathrm{pos}}_n^{BFC}$ and $\overrightarrow{\mathrm{ori}}_n^{BFC}$ are the 3-dimensional vectors of n^{th} thruster position and orientation at the BFC, respectively, and n is an integer to show the index of 14 thrusters ($1 \leq n \leq 14$).

In each control, the flight software automatically assigns a specific firing time duration called on-time to a specific thruster. Although the thrusting impulse is expected to be proportional to the on-time, the actual force deviates slightly from the expected force due to the condition of each thruster. The deviation is mainly governed by the interval time that indicates the elapsed time after the last firing. Therefore, the model used to estimate the firing force of a thruster with a given on-time and interval time can be defined. The model is generally called an impulse bit model. Once a constant thrusting force such as thrst = 120 [N] is given, the thrusting force of the n^{th} thruster is estimated by the following equation:

$$\mathrm{frc} = \mathrm{thrst} \times IB(onT_n, intrvlT_n) \tag{3}$$

where frc is the force result by thruster firing, IB is the impulse bit model and onT_n and $intrvlT_n$ are the on-time and interval time of the n^{th} thruster, respectively. In this study, the impulse bit model was created based on the curve fitting of ground experiments. Therefore, it entails a substantial amount of uncertainty.

As the translational force and rotational torque imposed by the sum of 14 thruster firings ultimately control the dynamics of the vehicle, the force $(\overrightarrow{F}^{BFC})$ and torque around the center of gravity $(\overrightarrow{T}^{CG})$ are defined by Eqs. 4, 5, 6 and 7 as follows:

$$\vec{F}^{BFC} = \sum_{n=1}^{14} -\mathrm{frc}(onT_n, intrvlT_n) \cdot \overrightarrow{\mathrm{ori}}_n^{BFC} \tag{4}$$

$$\vec{T}^{CG} = \sum_{n=1}^{14} -\mathrm{frc}(onT_n, intrvlT_n)\, \overrightarrow{\mathrm{pos}}_n^{CG} \times \overrightarrow{ori}_n^{CG} \tag{5}$$

$$\overrightarrow{\mathrm{pos}}_n^{CG} = \overrightarrow{\mathrm{pos}}_n^{BFC} - \overrightarrow{cg}^{BFC} \tag{6}$$

$$\overrightarrow{\mathrm{ori}}_n^{CG} = \overrightarrow{\mathrm{ori}}_n^{BFC} \tag{7}$$

where Eqs. 4 and 5 are derived from the Newton's equation and Euler's equation, and $\overrightarrow{\mathrm{pos}}_n^{CG}$ indicates the thruster position at the Center of Gravity coordination (CG) that moves along $\overrightarrow{cg}^{BFC} = \left[cg_x^{BFC}, cg_y^{BFC}, cg_z^{BFC}\right]$, the center of gravity position vector at the BFC, while keeping parallel to the BFC. Because the CG is parallel to the BFC, as shown in Eq. 7, the thruster orientation vector is exactly the same at both CG and BFC.

Learning Data

The actual HTV is equipped with several dynamics sensors: the gyro sensor, Earth Sensor Assembly (ESA), GPS, and an accelerometer. Obviously, the accelerometer data can be directly compared with the calculation result of Newton's equation. To use Euler's equation as a regression equation, angular acceleration data is essential. However, the HTV does not directly measure the angular acceleration, which in this study is calculated from the time variation of the angular velocity measured by the gyro sensor.

Unfortunately, there is currently no sensor to count the actual on-time and interval time, but the on-time and interval time set by the software are downloaded to the ground from the vehicle as telemetry data. Then this data is applied to estimate the translational force and torque based on Eqs. 4 and 5.

One of the difficulties in this parameter estimation is that the mass property chronologically changes due to propellant consumption. Although this chronological property change also might be modelled, it will surely increase the uncertainty about the estimation and adversely affect accuracy. In case the time span is sufficiently short without any large burn thrusting during the span, the mass property could be assumed using constant parameters. Therefore, this study basically utilized a relatively small amount of data acquired from attitude control without any large burn maneuver.

Regression Analysis

In this regression analysis, the objective variables (y) are the acceleration vector ($\mathrm{d}\vec{v}$) and angular acceleration vector ($\mathrm{d}\vec{\omega}$). The learning data gives the two measured objective vectors: $\mathrm{d}\vec{v}^{measured}$ and $\mathrm{d}\vec{\omega}^{measured}$. Both vectors are also estimated based on the Newton's equation and Euler's equation with the measured on-time and interval time. Therefore, the following equations can be defined as the problem formulation of this regression analysis.

$$\min \mathrm{L}(\mathrm{y}^{msrd}, \mathrm{y}^{estmtd}) = |\mathrm{d}\vec{v}^{msrd} - \mathrm{d}\vec{v}^{estmtd}| + |\mathrm{d}\vec{\omega}^{msrd} - \mathrm{d}\vec{\omega}^{estmtd}| \tag{8}$$

$$\mathrm{d}\vec{v}^{estmtd} = \mathrm{dt} \cdot \vec{F}^{BFC}(onT_n^{msrd}, intrvlT_n^{msrd})/M \tag{9}$$

$$\mathrm{d}\vec{\omega}^{estmtd} = \mathrm{dt} \cdot \vec{T}^{CG}(onT_n^{msrd}, intrvlT_n^{msrd})/I^{CG} \tag{10}$$

where dt is the sampling time of the data, M is the vehicle mass, and I^{CG} is the moment of inertia around the center of gravity. Obviously, the explanatory variables are the measured on-time (onT_n^{msrd}) and measured interval time ($intrvlT_n^{msrd}$) in this regression analysis. Several regression parameters are generally optimized to minimize a loss function as in Eq. 8.

Optimization Algorithm

As defined in Eq. 8, a mathematical minimization process is essential to solve this problem. Although there are various optimization approaches, a simple global optimization method is applied here. To eliminate the initial value dependency and avoid a local minimum, the minimization process starts from optimization based on a heuristic algorithm—the Genetic Algorithm (GA). After the GA finds an optimum parameter set as the result of a random and wide search, the parameters are used as initial values for a gradient-based algorithm optimization known as Sequential Quadratic Programming (SQP). While the SQP result depends on the initial values, it can also return a well minimized result by using the derivatives. This combination is expected to lead a global optimum parameter set.

Result

In order to use this parameter estimation in actual HTV or HTV-X operations, its reliability must be verified in advance. Thus, first of all, the performance of the estimation method is checked against the simulation data. The advantage of using simulation data is cheating the right parameters, which means that reliability can be discussed by directly comparing the estimated parameters and the right parameters. On the other hand, the obvious disadvantage is

not using the actual data. In the actual operation data, various and unexpected noises are imposed because of internal and external uncertainty; moreover, the data rate is also not constant due to the limitations of space communication. Of course, the noises can be simulated even in the simulation data. However, the simulated noises are generated by some models, which are different from reality to some extent. Therefore, it is also essential to check whether the method works properly with the actual data.
In this study, feasibility is discussed by combining the estimation based on simulation data and that based on HTV-6 operation data. In the estimation, the range of each parameter is normalized. The range is set to the true value of each parameter $\pm 5\ cm$, which is normalized ± 0.9 when the true value of each parameter is set to 0, therefore the estimation result is non-dimensional.

Estimation Based on Simulation Data

As the estimation only uses dynamics data, a simple 6 DoF simulator was created by MATLAB/Simulink. Although the actual flight software is not applied, the control algorithm of the simulator is almost equivalent. To effectively utilize the simulator, the following three features should be implemented: 1) mass property parameter setting variation, 2) random noise generation, and 3) maneuver setting variation. To show the robustness of the estimation algorithm, the algorithm should be capable of estimating various mass property parameters; therefore, the mass property parameters should be flexibly changed on the simulator. While various noises are imposed on the dynamics as discussed above, some noises can be estimated. For example, the position and orientation of a thruster may slightly deviate from the design. This deviation range is determined by the HTV contractor's manufacturing capability, and the distribution is expected to be the standard deviation distribution. Likewise, each sensor and the thruster also have a constant bias and random noise that can be calculated based on engineering data. These noises are also implemented in the simulator and randomly changed at each run. Figs. 2 and 3 show the GNC simulation model and an example of sensor data from simulation, respectively. Table 1 shows the estimation results using the simulation data.

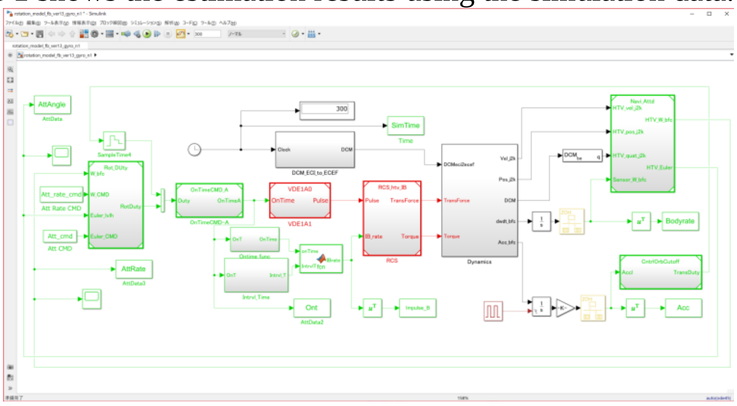

Fig. 2. HTV GNC Simulink model

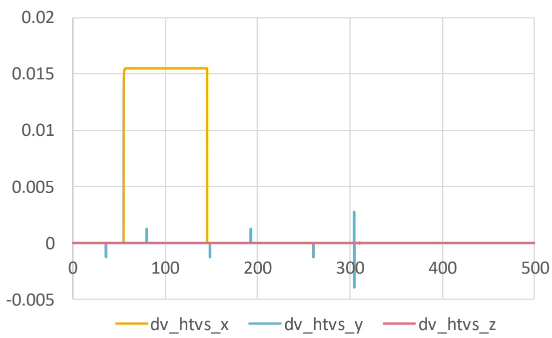

Fig. 3: acceleration data by simulation

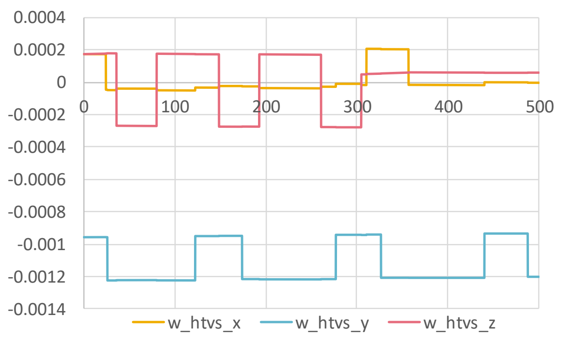

Fig. 4: angular velocity data by simulation

Table. 1. Estimation results using simulation data

	x	y	z
true value	0	0	0
estimated value	0.000494	-0.00019	-0.01267

Estimation Based on HTV-6 Operation Data

Estimation is conducted using HTV-6 operation data as well as simulation data. The data for estimation is selected from the perspective of conducting translation maneuver using the selected data on which the maneuver is fired by RCS and not the main engine. Table 2 shows the estimation results using operation data. The center of gravity value analysed prior to launch is set to the true value. Compared to using simulation data, there are two issues to discuss. One is the estimation result in the x direction. The second is the accuracy of estimation. The x direction cannot be estimated using operation data, as the operation data is not considered suitable for estimation of the x direction since this data is for the x direction maneuver. The estimation accuracy is thus reduced compared to using simulation data. This is because the simulation data is very ideal and the operation data has noise that is not considered during the simulation. Therefore, the accuracy is reduced.

Table. 2. Estimation results using operation data

	x	y	z
true value	0	0	0
estimated value	-0.9	-0.1014	0.118162

Conclusion

In this study, the methodology to estimate the mass property with sufficient accuracy from cargo spacecraft dynamics data and improve the control performance was established.

For the estimation, the most plausible mass property to explain the response relationship between the control and feedback of spacecraft dynamics is calculated by applying the regression method as one of the machine learning algorithms and collecting training data from the existing HTV operation and simulation. To utilize this method in the actual HTV-X operation, the following two results derived from machine learning must be acceptable for the operators: 1) the variation and amount of operation data for sufficiently accurate estimation, and 2) the integrity of regression coefficients against the actual spacecraft characteristics. By considering these two points, the feasibility of this mass property estimation method is discussed. The issues are also discussed using operation data. For future work, the types of operation data needed to estimate all directions must be discussed. Moreover, the algorithm must be improved to increase the accuracy of estimation.

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