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Machine Learning for Atmospheric Drag Prediction of LEO satellites

Hiroshi Kato[1], Kyohei Akiyama[1], Yuki Akiyama[1], Takushi Sakamoto[1], Takehiro Matsumoto[1], Saori Ikeda[1], Hideaki Hinagawa[1], and Shinichi Nakamura[1]
[1] *Japan Aerospace Exploration Agency, 305-8505, Sengen 2-1-1, Tsukuba, Japan*

Abstract

In this study, a new atmospheric drag prediction method for spacecraft using machine learning is proposed. In the proposed method, a machine learning model is constructed with the orbital decay rate of each spacecraft and the space environment factors having a strong influence on the upper atmosphere. To demonstrate the effectiveness of the proposed method, the analysis of two satellites, ALOS-2 and GCOM-W1, is conducted. The results show that the proposed method based on machine learning can predict the atmospheric drag with a relatively good accuracy.

Keywords: Spacecraft orbit, Atmospheric drag, Machine learning, Space environment

Introduction

Spacecraft orbit prediction with high accuracy can make satellite operation service more efficient and reduce the security risk posed by the re-entry of massive space debris objects. Spacecraft at low Earth orbit (LEO) less than an altitude of 1000 km encounter an effect of acceleration due to atmospheric drag. Realizing spacecraft orbit prediction with high accuracy requires knowledge about the atmospheric drag of each spacecraft, which is calculated based on the atmospheric density around the spacecraft and the ballistic coefficient (Cd*A/M). However, there is little observation information about the atmosphere at an altitude 100 km or higher where most spacecraft exist, and the ballistic coefficient of most spacecraft in orbit is not well-known. Therefore, it is usually difficult to predict atmospheric drag [1], although many kinds of research such as in [2, 3] have made progress to improve prediction accuracy.

In this study, a new atmospheric drag prediction method for spacecraft using machine learning is proposed. The proposed method aims to predict the atmospheric drag on spacecraft only by using information about the space environment, which strongly affects the upper atmospheric density. The proposed method generates satellite-specific models by machine learning. Creating the model for each satellite make us not to handle the uncertainty information, such as Cd or A/M, for each satellite.

Method

In this study, a new atmospheric drag prediction method for spacecraft using machine learning is proposed. In this study, a model is used to predict the orbital decay rate (Adot), which denotes the semi-major axis change rate per day due to the atmospheric drag. The model is expressed in Eqn 1.

$$Adot_{t+N} = f(X_{t-T|t}), \tag{1}$$

Here, X is the space environment information, subscript t is the current date and time, t-T on the right side of Eqn 1 is the date before T day (for example, T = 1 means one day ago), $t + N$ on the left side of Eqn 1 is the estimated future date (for example, N = 1 is one day after). In other words, Eqn 1 expresses the prediction of Adot after N days using space environment information up to T days before.

The creation of model f in Eqn 1 is the same as solving the multivariate regression problem. Various methods are available as solutions, although identifying the best method prior to its application to the data is difficult. Therefore, the four methods, elastic net, random forest, Gaussian process regression, and neural network, are applied, and the method with the highest prediction accuracy is selected.

The proposed approach is mainly constructed with the following three elements:

1. Spacecraft orbit information database
2. Space environment information database
3. Atmospheric drag modeling technique

Spacecraft orbit information database

At present, the time-series Adot data of 21 JAXA's satellites has been organized as the spacecraft orbit information database. The Adot data of each satellite was derived from definitive orbit, which was estimated by the JAXA Space Tracking and Communications Center (STCC). As another source of the spacecraft orbit information database, two-line element (TLE) is made available for easy access by the scientific community. However, the accuracy of such information is low compared with that of definitive orbit provided by JAXA. As the first step to demonstrate the effectiveness of the proposed method, time-series Adot data from JAXA is employed as the source of the database.

In this study, the two satellites listed in Table 1 were selected to demonstrate the effectiveness of the proposed method. Table 1 lists the three satellites to be analyzed, the controlled mean altitude of each satellite, the data period of each satellite.

Table 1: Satellites to be analyzed

Satellite name	Mean altitude	Data period
ALOS-2	630 km	2014/5/24 – 2017/12/31
GCOM-W1	700 km	2012/5/17 – 2017/12/31

Space environment information database

Table 2 lists the 11 space environment factors in the database. The solar activity index (F10.7, etc.) and the geomagnetic activity index (Ap, etc.) are widely known factors that have a strong influence on upper atmospheric density. In addition, there are various other factors as space environment information that may possibly influence the atmospheric drag on spacecraft. Therefore, space environmental factors that may affect upper atmospheric density even slightly are included in the database. Moreover, some of the space environmental factors listed in Table 2 are transformed or split by ground trajectory of satellites or latitude when creating a machine learning model.

Table 2: Factors in the space environment information database

Name	Source
Solar activity index	NOAA
Geomagnetic activity index	NOAA
Total electron content	International GNSS Service
Moon age	N/A
Sun distance	N/A
Proton flux	JAXA
Reflectance	MODIS
Brightness temperature	MODIS
Temperature at 10 mbar	JRA
Relative humidity at 300 mbar	JRA
Cloud amount	JRA

Atmospheric drag modeling technique

First, the model structure should be determined. We use the space environment information up to 83 days ago as the explanatory variables of model *f* in Eqn 1. In this study, the models of two cases are created—the nowcast model and the forecast model. The nowcast model employs *Adot* at present as the object variable, and the forecast model employs *Adot* at one day after. The models of both cases are shown in Eqns 2 and 3, respectively.

$$Adot_t = f(X_{t-83|t}), \tag{2}$$

$$Adot_{t+1} = f(X_{t-83|t}), \tag{3}$$

In machine learning, it is necessary to pay attention to the overfitting problem. This problem results in poor performance of the machine learning model. An overfitted model cannot accurately estimate unknown data other than the learned data. There are several approaches to avoiding the overfitting problem. The typical approach is to reduce explanatory variables from the machine learning model. As more than 1000 explanatory variables are used in this study, there may be an overfitting problem.

In this study, the elastic net and the random forest were employed to reduce the explanatory variables from the machine learning model. The elastic net can drive many coefficients of explanatory variables to zero by solving the linear regression model with the L1 and L2 norm penalties. In addition, the random forest can estimate the index of importance for each explanatory variable by ensemble learning.

The modeling process is described as follows: The first step is to determine the model structure as shown in Eqns 2 and 3. Then the data is divided into two parts: data for learning and data for testing (prediction). Next, four machine learning methods are sequentially applied to the learning data. The first machine learning method is the elastic net. The elastic net can create the model and identify the effective explanatory variables for model prediction by driving the coefficients of noneffective explanatory variables to zero. The second machine learning method is the random forest. The random forest is applied to the data for learning, and the explanatory variables whose coefficients are not zero-driven by the elastic net are used for creating the model. The random forest can create the model and also extract the importance of the explanatory variables. In this study, explanatory variables whose importance exceeds 1% of the top importance are extracted as the effective explanatory variables for prediction. The third and fourth machine learning methods are Gaussian process regression and the neural network, respectively. Two machine learning models are created with only the extracted important explanatory variables. Finally, the random forest is applied to the data again, and this step is called the re-random forest. At this step, only the extracted important explanatory variables are employed to create the model, unlike the random forest of the second step. Here, the hyperparameters of each method are optimized using the cross-validation method or other optimization methods, such as the quasi-Newton method. After the creation of models for each method, each model is applied to the data for prediction, and the sum of absolute error between each model's prediction result and the data for prediction is calculated. Finally, the model with the smallest error is selected as the best model.

The modeling process can be summarized as follows:

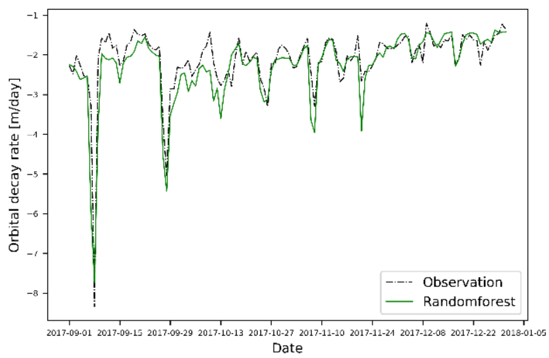
1. Determine the model structure.
2. Divide the data for learning and prediction.
3. Start to learn the model by each method for learning data.
   A) Elastic net
      ① Create model f_1 by using X.
      ② Reduce the number of explanatory variables of model $X \to X_1$.
   B) Random forest
      ① Create model f_2 by using X_1.
      ② Reduce the number of explanatory variables of model $X_1 \to X_2$.
   C) Gaussian process regression
      ① Create model f_3 by using X_2.
   D) Neural network
      ① Create model f_4 by using X_2.
   E) Re-random forest
      ① Create model f_5 by using X_2.
4. Calculate the sum of absolute error between the data for prediction and each model's prediction result.
5. Determine the model with the smallest error as the best model f_{best}.

Results and Discussion

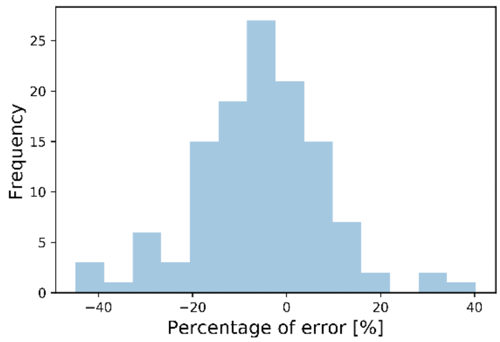
This section presents the model prediction results and discussion for each satellite. The machine learning models of all the satellites are created from start date of each satellite data to August 31, 2017. Then the machine learning models are applied to test data from September 1, 2017 to show the effectiveness of the machine learning models.

First, a comparison of the orbital decay rates of the ALOS-2 satellite between the model predictions and the observations is shown in Figs. 1 and 2. In both figures, (a) shows the time-series data, and (b) shows the histogram of relative error between the prediction and observation of each day. In (a), the dotted-dashed line shows the observation, and the colored line shows the prediction by the machine learning model. The best machine learning models in the two cases were the random forest.

The comparison between Fig. 1 and Fig. 2 shows that the nowcast model has a relatively good agreement with the observation compared to the forecast model. In addition, it is confirmed that the relative error of the nowcast model (-45% − +40%) is smaller than that of the forecast model (-72% − +57%). Moreover, the results show that the maximum relative error was recorded in early September 2017 when a solar flare occurred.

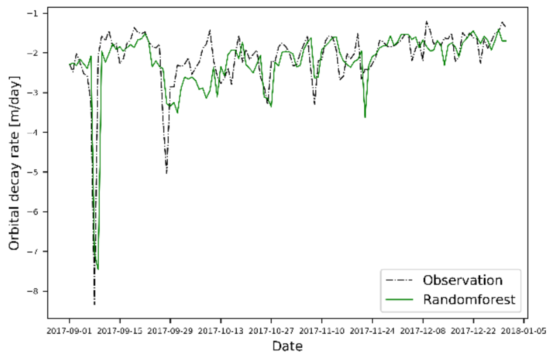


(a) Time-series

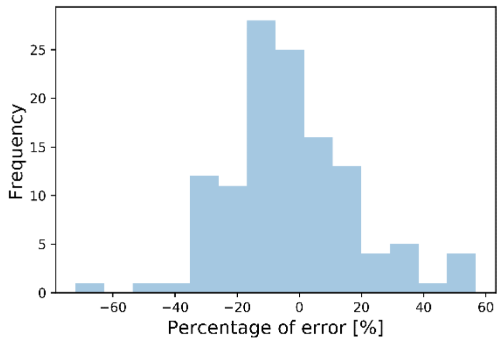


(b) Histogram

Fig 1: Comparison of orbital decay rates between nowcast model predictions and observations of the ALOS-2 satellite



(a) Time-series

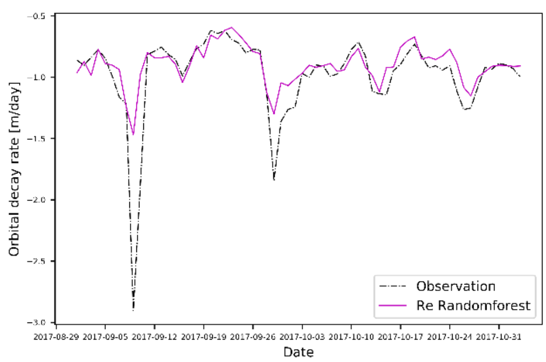


(b) Histogram

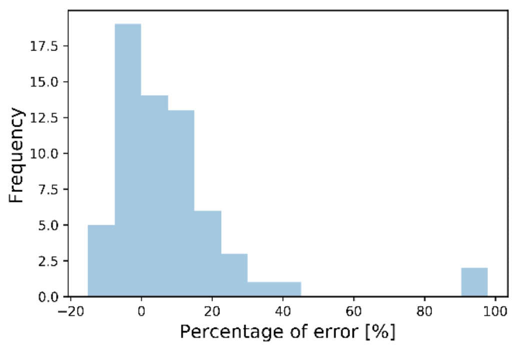
Fig 2: Comparison of orbital decay rates between forecast model predictions and observations of the ALOS-2 satellite

Next, the results of the GCOM-W1 satellite are shown in Figs. 3 and 4. The best machine learning models in the two cases were the re-random forest and the random forest, respectively.

As in the results of the ALOS-2 satellite, the nowcast model has a relatively good agreement with the observation compared to the forecast model. In addition, it is confirmed that the relative error of the nowcast model (-15% – +98%) is smaller than that of the forecast model (-20% – +159%). Moreover, the results show that the maximum relative error was recorded in early September 2017 when a solar flare occurred, as in the results of the ALOS-2 satellite.

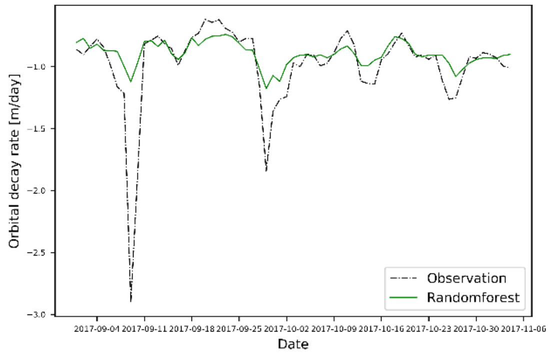


(a) Nowcast

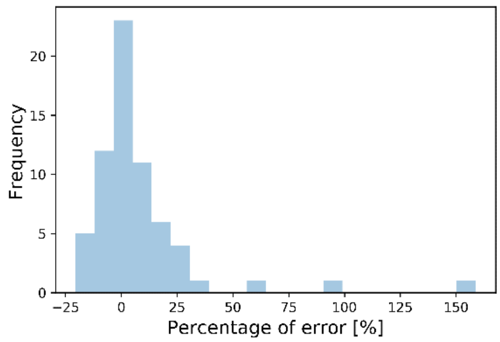


(b) Histogram

Fig 3: Comparison of orbital decay rates between nowcast model predictions and observations of the GCOM-W1 satellite



(a) Nowcast



(b) Histogram

Fig 4: Comparison of orbital decay rates between forecast model predictions and observations of the GCOM-W1 satellite

Conclusion

In this study, a new atmospheric drag prediction method for spacecraft using machine learning was proposed. In the proposed method, a machine learning model was constructed with the space environment factors having a strong influence on the upper atmospheric density as explanatory variables and the orbital decay rate of each spacecraft as the objective variable. To demonstrate the effectiveness of the proposed method, a space environment information database was constructed, and the analysis of two satellites was conducted.

The results showed that the proposed method could predict the orbital decay rates of the satellite with relatively good accuracy. However, the prediction accuracy of the proposed method was still not enough for real applications. In addition, the results showed that the proposed method failed to predict the orbital decay rate of the satellite when the solar flare occurred.

These observations suggest that the proposed method should be improved. Therefore, we have two plans. The first plan is to store new space environmental factors, which may have sensitive to the orbital decay rate of the satellite more, to the space environment information database, because there is a possibility that the space environmental factors stored in the current space information database are enough. The second plan is to utilize prediction values of space environmental factors in the proposed method, because the proposed method with only space environment information to date fails to predict the orbital decay rate of the satellite on the day occuring intense atmospheric fluctuations like solar flare.

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