Anomaly detection of propulsion system of spacecrafts with Light GBM

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ABSTRACT

Future spacecrafts require robust operations for long-term missions to the Moon or Mars. Automatic anomaly detection with machine learning, in this context, plays a significant role because it enables early symptom detection and proactive redundant switching which preserves components in the long mission. In this research, we adopted Light GBM, one of the machine learning models, to investigate such anomaly. We especially focused on the telemetry data of propulsion system of H-II Transfer Vehicle (HTV) to resolve typical problems of deep-space mission spacecrafts, a thruster failure. The data was collected from multiple types of thruster maneuvers performed at simulator training. The results showed the effectiveness of the proposed method.

1. INTRODUCTION

Deep space mission spacecrafts require robust architecture of systems to support long-term operations. One of key devices for long-term mission is a thruster. Modern spacecrafts' thrusters are mounted in canted angles to allow multiple thrusters to control a single axis while a single thruster can also control multiple axis. With this design, total numbers of thrusters can be significantly reduced because loss of a single thruster can be compensated by other thrusters. However, due to its complex interdependency, it is difficult to identify which thruster has failed. To support deep space exploration missions, we propose a method of anomaly detections to identify failed thrusters and reconfiguration of thruster arrangements for continuous operations.

2. ANOMALY DETECTION OF PROPULSION SYSTEMS

Several data-driven monitoring techniques for propulsion systems have been developed in aerospace (Hayton et al., 2007, Schwabacher et al., 2009, Iverson et al., 2012). Hayton (2007) proposed static and dynamic novelty detection methods to detect anomalous behavior in a jet engine. However, those research focus on anomaly detections in subsystem level rather than in component level. So, with these methodologies, it is hard to identify a single failed thruster. In this research, we developed a method to detect anomalies for individual thrusters using specific telemetries of propulsion system.

3. METHODOLOGY

We propose a methodology to detect faults for individual thruster utilizing the data of thruster duty with a machine learning-based method. We visualized the analysis results with heatmap as an effective Human-Machine Interface (HMI).

3.1. Data

HTV has fourteen Reaction Control System (RCS) thrusters and two Main Engines (ME) per two strings. One of possible anomalies is a failure of RCS thruster. Data of thruster duty of RCS #1-24 for some maneuvers were selected based on the interviews with specialists.

3.2. Algorithm of anomaly detection

Learning-based model for anomaly detection was utilized. We selected a classification method as there are sufficient data for both normal and abnormal states. We applied Light GBM, which was proposed by Ke et al. (2017) and one of novel Gradient Boosting Decision Tree (GBDT) algorithms to deal with large number of data and features. We used the library of lgb in python. Accuracy was calculated from classification results of test data to verify the effectiveness of the proposed method.

3.3. Visualizing results for Human-Machine Interface (HMI)

Lastly, we visualized the degree of incidences of each RCS by heatmaps. Rasmussen (1983) pointed out that human operators generally obtain qualitative models of their operating systems, ongoing tasks, or situations and utilize them for effective operations. Moreover, the qualitative models are constructed based on a variety of information quantitative data. There is therefore a conversion process of the quantitative data into qualitative models, and one of the major challenges of the Human Machine Interface (HMI) design is said to be how to reduce work/cognitive load of the conversion process of human operators. In this respect, the qualitative models or representations should be regarded as important as quantitative representations, and that is why the heatmap representation of the degree of incidences for each RCS was adopted in this analysis.

The heatmap represents how each RCS contributed to the anomaly events. The degree of incidences as quantitative data is converted into heatmaps as qualitative representations, which could reduce the work/cognitive load of the co1nversion process by the human operators. The heatmap representations are consequently expected to provide multiple telemetries from systemic view and support intuitive situational awareness of the human operators.

4. EXPERIMENTAL RESULTS

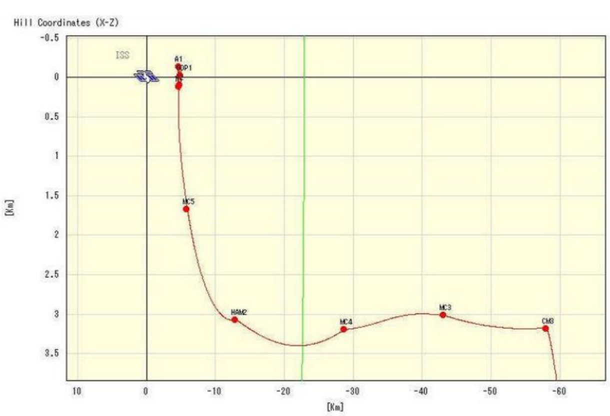
To verify the proposed method, telemetry data during simulations for H-II Transfer Vehicle (HTV) was utilized. There are several maneuvers to approach the International Space Station (ISS). We collected the data of RCS including anomaly data for some maneuvers during HTV simulations. There are two types of maneuvers: x and z translation. Then the data was split into training and test data. Figure **1**shows HTV flight profile. Table 1 shows the numbers of data for an experiment. The numbers of data in normal and abnormal during each maneuver were set to same for training data. We used model of HAM0 for testing the data of HAM2 as they have similar characteristics for maneuvers.

Table 1. Number of data for training and test.

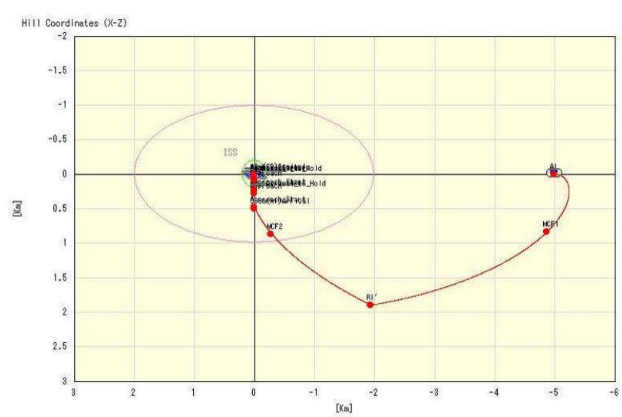
Training		
Maneuver type	normal	abnormal
HAM0	98	98
HAM2	-	-
T1	53	53
RI’	123	123
Test		
Maneuver type	normal	abnormal
HAM0	10	105
HAM2	202	-
T1	10	15
RI’	20	238

4.1. Results of classification

Firstly, we trained classification models of Light GBM for each maneuver type with training data. We set a hyper-parameter of the number of trees in Light GBM to 100. Then we performed classification for test data. Accuracy was calculated with the numbers of data, classified correctly, divided by total numbers of data. The numbers of data and accuracy for each maneuver are shown in Table 2. Accuracy of maneuvers in x translation were more than 77 % while one of RI’ maneuver was 69%.



(a) Flight profile until Approach Initiation (AI) point.



(b) Flight profile after Approach Initiation (AI) point.

Figure 1. Flight profiles of HTV (Hotta et al., 2012)

Table 2. Classification results for test data.

Maneuver type	Correct	All	Accuracy
HAM0	89	115	77%
T1	20	25	80%
HAM2 (4/19)	66	66	100%
HAM2 (8/2)	68	68	100%
HAM2 (8/23)	67	68	99%
RI’	178	258	69%

4.2. Improving accuracy with tuning number of trees

The number of trees in Light GBM affects accuracy of classification results. To improve the accuracy of classification models, hyper-parameter of the number of trees was adjusted based on a learning curve. The number of trees were optimized for each type of maneuvers. Table 3 shows the improved results with number of trees.

Table 3. Analysis results after tunings hyper-parameter.

Maneuver type	Correct	All	Accuracy (N=number of trees)
HAM0	90	115	77% (N=50)
T1	20	25	80% (N=30)
HAM2 (4/19)	66	66	100% (N=70)
HAM2 (8/2)	68	68	100% (N=70)
HAM2 (8/23)	68	68	100% (N=70)
RI’	178	258	69% (N=100)

HAM2 maneuvers had 100% accuracy while results of HAM0 and T1 are around 80%. Result of RI’ was little bit lower with 69%.

HAM2 had test data including only normal data. Therefore, the trained model from the data of HAM0 seems to have characteristics of high accurate classification for normal data. As for the result of RI’ maneuver, the accuracy was not high because the numbers of data in z transition maneuver was limited.

4.3. Visualizing degree of incidence with heat map

Incidence for each RCS was calculated with feature importance. We used the library of lgb. Then, we visualized the degree of incidences for each RCS with heatmaps as shown in Figure 2-5. Rotation direction is in vertical axis and RCS number is in horizontal axis. Deeper red highlighted RCS had higher impacts for classifications for each model.

As an instance, heat map of HAM 2 model showed deep red in RCS #1-3 in the roll direction. It implies that the faults of RCS affected the performance of RCS in role direction. The results of HAM0 and T1 showed similar trends while one of RI’ had different effect for RCS in pitch direction. This is because RI’ maneuver is in z translation.

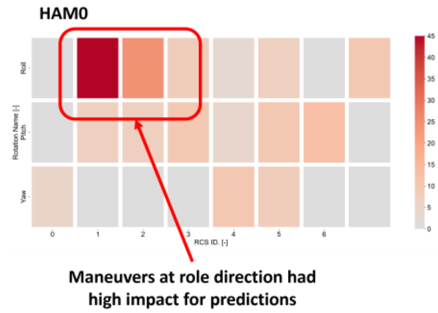


Figure 2. Heat map for HAM0.

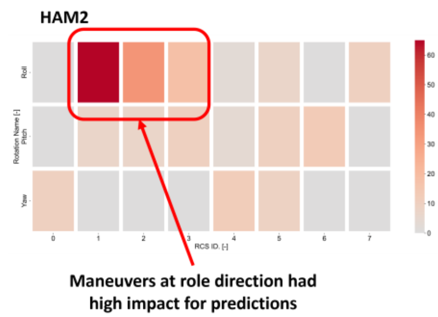


Figure 3. Heat map for HAM2.

Figure 4. Heat map for T1.

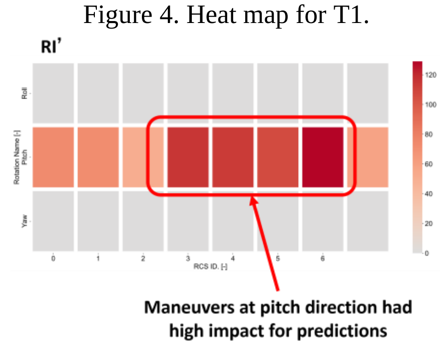


Figure 5. Heat map for RI’.

5. DISCUSSIONS

5.1. Improving models

In this research, we could use only limited data of training and testing. Especially, z translation maneuvers such as RI' maneuvers could not be learned sufficiently due to limited numbers of simulations. To improve the accuracy of classification model, more data are required for both training and testing. For further analysis, we will use simulators for generating more data with more various settings for thruster faults scenarios. Another way to improve accuracy is utilizing other anomaly detection methods such as regression or time-series models. It is necessary to investigate which types of algorithms are effective for the system.

5.2. Operational Support by Effective Human-Machine Interface (HMI)

The dynamics of the future spacecrafts are assumed to be more complex compared to the current ones due to the new configuration of thrusters. While the new configuration of thrusters enables the resilient operations, the complexity could make it difficult for ground controllers to obtain situational awareness and response to anomaly events. One possible way to overcome this problem is to design an effective Human-Machine Interface (HMI) providing information about how to reconfigure the thruster system as a whole, and in this context, the heatmap representations shown in the previous section is one of the effective ways to provide systemic comprehension of the current systems' state.

6. CONCLUSION

Future spacecrafts require robust operations of propulsion systems for longer missions. We proposed the method of machine learning-based anomaly detection of RCS thrusters with telemetries of duty utilizing Light GBM. We verified the method with the data of RCS thrusters during maneuvers in some of HTV8 simulations. More data and failure scenarios are required to improve the accuracy of classification model. Our proposed method provided supportive criteria to identify the failure. Specifically, the heatmap representations enable the human controllers to notice the signs of failure intuitively, which could contribute to the early responses by the operators.

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