Supervised or Unsupervised Learning? A Different Perspective on Data-driven Health Monitoring System for Satellite Operators

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Abstract

Unsupervised anomaly detection is common in the research of satellite health monitoring (SHM) but its unsupervised nature makes it hard to demonstrate precision and reliability in real practice. With the aim to make satellite operators more confident in using data-driven SHM in real scenarios, this paper explores the possibilities to transform a common unsupervised nature of SHM (due to the lack of anomaly labels) into a supervised problem. Specifically, we find two potential ways to achieve this goal and discuss their usefulness in automating several important SHM processes.

1 Introduction

Due to the lack of labelled data, most satellite health monitoring (SHM) systems focus on unsupervised anomaly detection (to name a few [Pilastre *et al.*, 2020; Ahn *et al.*, 2020; Abdelghafar *et al.*, 2019; Hundman *et al.*, 2018; Yairi *et al.*, 2017; Yairi *et al.*, 2012; Takeishi and Yairi, 2014]), where housekeeping (HK) data are used to train a model of normal patterns and then anomaly score of a given data point/segment is computed based on its deviation from the trained model.

However, in contrast to supervised learning methods, these unsupervised SHM systems are not attractive enough to satellite operators in real-world applications because the unsupervised results either need costly manual checks from satellite experts or fail to demonstrate precision and reliability. Moreover, counter-intuitively, satellite operators want to automate the manual monitoring process or to ensure the normally-outsourced monitoring operations rather than discovering new patterns of anomalies in the HK data.[1] Overall, satellite operators are more interested in using machine learning technologies to reduce their operating loads, in which the operation processes are usually complex, repetitive, error-prone, and hard to be automated.

Having this in mind, we explore a few possibilities and found two ways to perform supervised learning despite the lack of labelled data (i.e., normal vs. anomalies). In the first method, we utilize the heterogeneity of satellite HK data and learn signal thresholds with a regression tree in a supervised manner. Our key insight does not only make the thresholds adaptive according to the multi-modal characteristic of satellite HK data efficiently, but also save long hours of satellite operators because before our method they need to set the constant thresholds for each signal.

In the second method, we utilize the fact that satellite operators record important events of a satellite in a logbook and we use a random forest-based algorithm to learn the logbook events directly from HK data. This method provides qualitative results and is useful for satellite operators to verify the logbook recorded by human operators. Note that this method could also be extended to verify status signals embedded inside the HK data or commands recorded by human operators.

Merits of our system are twofold. First, our system is based on a supervised learning approach and is able to verify complex satellite operations in a more effective and efficient way. This is especially true nowadays, where satellite operators start to delegate the mundane monitoring tasks to outsiders (i.e., non-experts). Second, our system reduces workloads of satellite operators significantly and makes multiple satellites monitoring possible, in contrast to conventional systems where at least one human operator is required to monitor the HK data non-stop during the lifespan of a satellite.

2 Satellite Housekeeping Data

The satellite HK data we are using in this study share the common characteristics of a typical modern satellite system, where the data has high dimensionality (many signal measurements), heterogeneity (signals consist of continuous variable signals and discrete status signals), temporal dependence (time-series data), multi-modality (different operations resulting in different data patterns), missing data (due to different data sampling rate or transmission errors), and trivial outliers (due to measurement of transmission errors).

Due to these complexities, we pre-process the data in order to have more machine learning-friendly data. We first use a percentile filter to remove trivial outliers caused by errors in data measurement or transmission to avoid interference. Both removed and missing data are then filled with the immediately preceding value. The continuous variables in the

[1] Satellites designers might find the past anomalies important when designing a new satellite but in general satellite operators focus on ensuring that satellites function as designed.

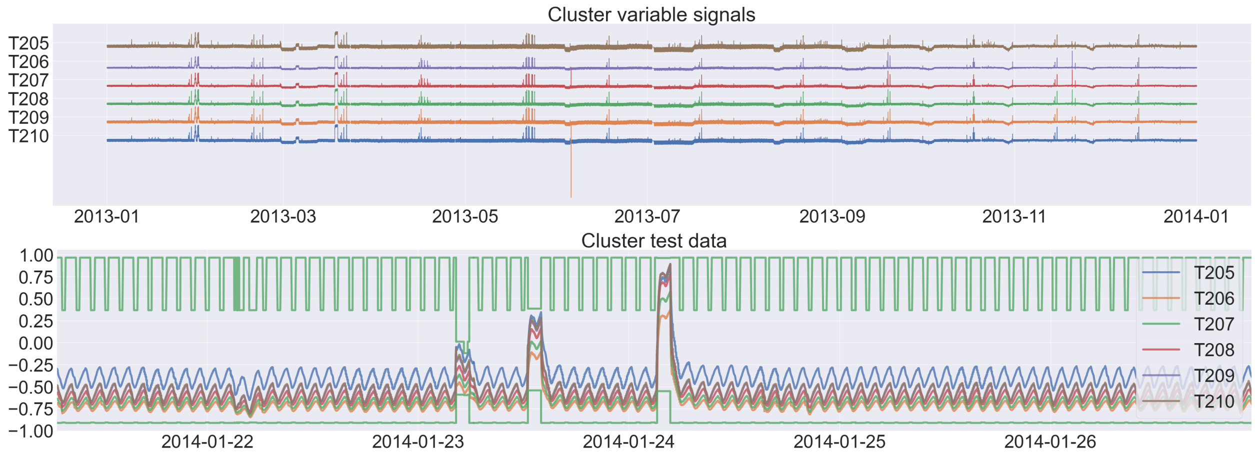

Figure 1: **Top**: 6 continuous HK data of one hierarchical cluster. **Bottom**: The learnt adaptive thresholds (upper and lower green lines).

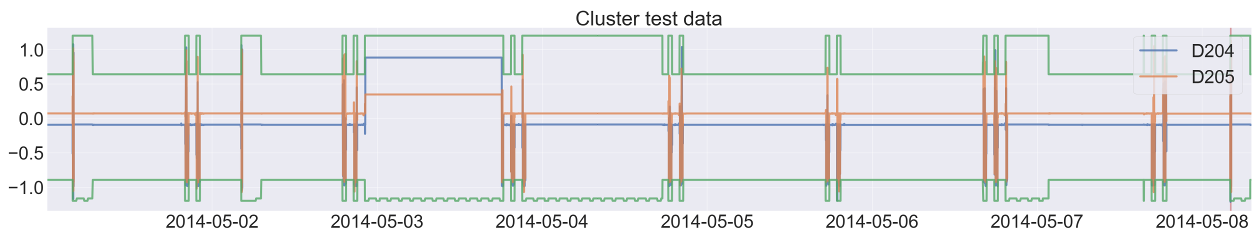

Figure 2: The learnt adaptive thresholds (upper and lower green lines) of another hierarchical cluster consists of 2 continuous HK data.

HK data are normalized into range of ± 1 and the categorical variables are converted to an integer number starting from 1 in descending order of frequency for each variable (refer to [Yairi *et al.*, 2017] for more details).

Moreover, we use a simple algorithm to select informative signals for machine learning in order to speed up the training and test processes. Specifically, signals irrelevant for health monitoring, such as signals related to timer and signals with low variation (almost constant over time) are excluded. Then, we use one year of satellite HK data for training and use the subsequent data for tests in the following experiments.

3 Satellite Health Monitoring

3.1 Adaptive Limits Learning

Most satellite operators manually preset constant thresholds for satellite HK data as a primitive way to verify operations. This approach is known to cause many false alarms during operations, as the constant thresholds cannot accommodate the multi-modality and increasing dynamics in HK data. Moreover, satellite operators usually set the constant thresholds based on experience and a more effective approach is crucial to support the coming satellite constellation era.

A clever regression tree-based algorithm was proposed to learn the limit values of continuous signals using the status signals as conditions [Yairi *et al.*, 2004]. Learning the limit values from the past telemetry data in this way is more effective and is expected to reduce the difficulty of setting them beforehand. Nevertheless, this method has a few limitations, where one regression tree is required for each continuous signal (i.e., the models are learnt separately) and the correlation among the continuous signals is not taken into consideration.

To improve this limitation, we propose to use a multivariate regression tree (MRT) [De'ath, 2002] to learn the empirical model by using multiple related continuous signals as our target variables, resulting in a multi-input multi-output model. MRT inherits the merits of a common regression tree, where it is easy to train, strong against overfitting, and the learnt model is explainable. Additional merits of MRT include: (i) able to consider relationships between the target variables and optimizes all the targets together; (ii) is simpler than a stack of univariate regression tree (URT) model; and (iii) is faster to train and is computationally less expensive.

In practice, target continuous variables can be selected manually by human operators or by an algorithm. Here, we apply hierarchical clustering onto the HK data to group continuous signals with similar structures. Figure 1 (top) shows 6 signals with similar structures in one of the hierarchical clusters. Using these 6 signals as our multi-targets, we apply a MRT to learn the adaptive limits collectively. Figure 1 (bottom) shows the learnt adaptive thresholds (the upper and lower green lines) produced by MRT for test data. We can see that the target variables stay inside the learnt thresholds and do not cause unintentional false alarm.

Figure 2 shows another 2 target variables and the learnt adaptive thresholds (the upper and lower green lines) of test data. Similarly, we can see that the learnt thresholds adaptively increase occasionally when the satellite is in different

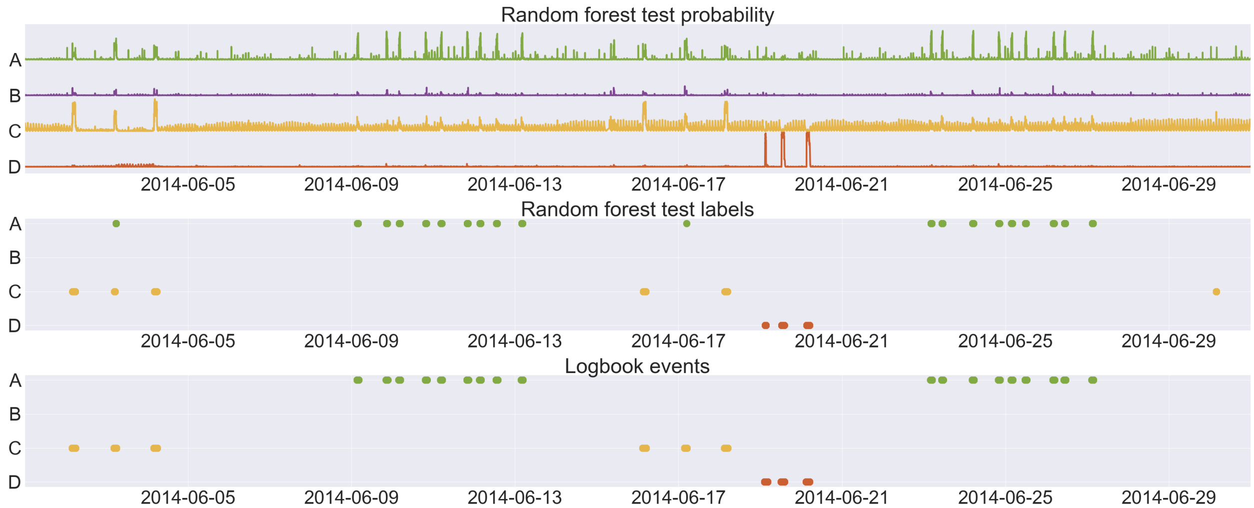

Figure 3: Logbook events (A, B, C, and D) recognition test results in June 2014. **Top**: Test label probabilities of 100 regression trees. **Middle**: Predicted labels of the same regression trees. **Bottom**: Recorded events (ground truth) by satellite operators.

modality (when the target data increases/decreases). With these adaptive changes, MRT successfully reduces the frequency of false alarms. Moreover, a MRT is faster to train and the learnt MRT is applicable to multiple target variables.

3.2 Logbook Events Recognition

Satellite operators record important events during operations for future reference purposes. Using these logbook events as supervised labels, we propose to learn a model to predict the logbook events from continuous HK data. We believe that a successfully learnt model can help verifying the manually recorded logbook events and can potentially generate logbook events in an automatic fashion in the future.

With this motivation, we apply a random forest-based algorithm to learn the logbook events from continuous HK data. We select the random forest algorithm because it is easy to train, strong against overfitting problems, and more importantly, it can perform feature selection along the learning process. As mentioned in Section 2, we use one year of continuous HK data for supervised training and aim to predict the labels of four satellite operating events. Figure 3 (top) summarizes the test label probabilities by using the continuous HK data as inputs while Figure 3 (middle) shows the predicted test labels of the four logbook events. Note that the predicted test labels match with almost all the ground truth logbook events shown in Figure 3 (bottom). For event A, the algorithm predicts two additional events in the beginning and in the middle of June 2014 and this could be an indication that the logbook has some missing records. For event C, there is one missing prediction in the middle of June 2014 and this could be due to the limitation of the random forest algorithm or record errors in the logbook.

In addition, we find that a simpler linear supervised algorithm such as linear discriminant analysis (LDA) and logistic regression also works relatively well when the signals selected by the random forest algorithm above are used. We speculate that this is thanks to the linearity in the satellite system (an artificial engineered system). Overall, this approach of generating logbook events from the continuous HK data helps satellite operators to double confirm the logbook recorded by human operators.

Note that we also generalize this approach by using the status HK data (instead of logbook event) as our supervised labels. Specifically, we find that using the similar approach, the random forest algorithm is able to predict some of the status HK data from the continuous HK data. In this way, applications such as data compression and data verification become possible. For example, only continuous HK data can be transmitted back to the ground station and status HK data can be predicted with a pre-learnt model. Last but not least, we believe that this approach can also be generalized to using the commands records in the logbook (if available). Under this approach, the pre-learnt model can help verifying the commands and ensuring the satellite performance in a more promptly manner.

4 Summary

Unsupervised anomaly detection is common in SHM research but lacks practicality. Aiming to solve this problem, we explore several ways to perform supervised learning despite the lack of the anomaly labels. We first propose a tree-based algorithm to learn the limits of continuous HK data from the status HK data. This algorithm co-learns the thresholds for a group of signals, and the thresholds are adaptive to the multimodality of the satellite HK data. Second, aiming for auto-verification and auto-generation of logbook events, we propose to learn a supervised model to predict logbook events from the continuous HK data.

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References

[Abdelghafar *et al.*, 2019] S. Abdelghafar, A. Darwish, A. E. Hassanien, M. Yahia, and A. Zaghrout. Anomaly detection of satellite telemetry based on optimized extreme learning machine. *Journal of Space Safety Engineering*, 6(4):291–298, December 2019.

[Ahn *et al.*, 2020] H. Ahn, D. Jung, and H. Choi. Deep generative models-based anomaly detection for spacecraft control systems. *Sensors (Basel, Switzerland)*, 20(7):1–20, April 2020.

[De'ath, 2002] G. De'ath. Multivariate regression trees: A new technique for modeling species-environment relationships. *Ecology*, 83(4):1105–1117, April 2002.

[Hundman *et al.*, 2018] K. Hundman, V. Constantinou, C. Laporte, I. Colwell, and T. Soderstrom. Detecting spacecraft anomalies using LSTMs and nonparametric dynamic thresholding. In *Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery Data Mining*, pages 387—-395, 2018.

[Pilastre *et al.*, 2020] B. Pilastre, L. Boussouf, S. D'Escrivan, and J. Tourneret. Anomaly detection in mixed telemetry data using a sparse representation and dictionary learning. *Signal Processing*, 168:1–10, September 2020.

[Takeishi and Yairi, 2014] N. Takeishi and T. Yairi. Anomaly detection from multivariate time-series with sparse representation. In *Proceedings of the IEEE International Conference on Systems, Man, and Cybernetics*, pages 2651–2656, 2014.

[Yairi *et al.*, 2004] T. Yairi, M. Nakatsugawa, K. Hori, S. Nakasuka, K. Machida, and N. Ishihama. Adaptive limit checking for spacecraft telemetry data using regression tree learning. In *Proceedings of the IEEE International Conference on Systems, Man and Cybernetics*, pages 5130–5135, 2004.

[Yairi *et al.*, 2012] T. Yairi, T. Tagawa, and N. Takata. Telemetry monitoring by dimensionality reduction and learning Hidden Markov Model. In *Proceedings of the International Symposium on Artificial Intelligence, Robotics and Automation in Space*, pages 1–7, 2012.

[Yairi *et al.*, 2017] T. Yairi, N. Takeishi, T. Oda, Y. Nakajima, N. Nishimura, and N. Takata. A data-driven health monitoring method for satellite housekeeping data based on probabilistic clustering and dimensionality reduction. *IEEE Transactions on Aerospace and Electronic Systems*, 53(3):1384–1401, June 2017.