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Data-driven Satellite Monitoring Method Applicable to Various Telemetry

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Abstract

It is difficult to detect signs of faults for the rule-based health monitoring systems currently installed on artificial satellites in principle, and manual monitoring of satellite telemetry is conducted. However, due to lack of human resources, much of the data is left not yet well reviewed. In this study, a systematic telemetry monitoring method that screens anomalous ones applicable to various time-series telemetry is proposed. The proposed method estimates the normal range of future telemetry values by focusing on quantile statistics of each telemetry. The demonstrative application results to the real telemetry data are also reported.

1. Introduction

Satellite use continues to grow, becoming an integral part of our daily life. It is important to maintain them in good condition and assure their continued operation as with other industrial equipment. To deal with the various types of faults that may occur, satellites are equipped with a system that detects faults (Fault Detection), identifies the type of fault (Identification), and automatically recovers from the fault (Recovery). This system is called an FDIR system. However, FDIR systems currently installed on satellites are based on primitive rules combining logical values, such as whether a value exceeds a certain predefined threshold. Such rule-based systems are suited for identifying the type of fault from many possible errors. However, the FDIR system can only detect errors that have already occurred in the sense of deviating from some rules, and the system is not suitable for detecting signs that a small change has begun to occur. On the other hand, it is desirable to detect anomalies at an early stage and deal with them before they become problematic. When a problem occurs in satellite operations, the satellite is shifted into a safety mode, where the first priority is to prevent the loss of the satellite. There is a demand to avoid the safety mode as much as possible, since it interferes with the mission execution. To achieve this, it is necessary to identify the signs of a trouble and take action as early as possible, i.e., before the FDIR system works.

In current satellite operations, various types of data transmitted from satellites, referred to as telemetry, are manually monitored to detect signs of faults. There are two main types of monitoring methods: monitoring by the satellite operator as telemetry is received, and the manufacturer review where examines longer-term trends. In practice, however, it is often the case that the presence of signs is revealed after a problem has occurred by detailed analysis. To avoid such a situation, satellite anomaly detection systems have been studied for the purpose of early detection of precursors and workload reduction for satellite operators (Takaki, Honda, Mizutani, & Hirose, 2009).

Research to automate satellite health monitoring still continues actively these days, with the development of machine learning techniques. Hundman, Constantinou, Laporte, Colwell, and Soderstrom (2018) and Tariq et al. (2019) independently proposed a method based on the prediction of future telemetry values using LSTM (long short term memory), a type of recurrent neural network. There have been other studies using feature values, such as one using the dictionary learning method (Pilastre, Boussouf, D'Escrivan, & Tourneret, 2020) and one assuming a generative model behind the observed telemetry values (Yairi et al., 2017). The concept of these studies is to find complex signs that cannot be detected by humans. This is because simple predictive signs were considered to be detected by satellite operators or satellite manufacturers. However, there is a limit to the amount of telemetry that can be checked manually since the number of operators and the time available for manufacturer reviews are limited. Consequently, there were cases where even simple precursors appeared, but were left undetected until the actual problem has arisen. These precursors were left undetected simply because they occurred outside of the monitored telemetries. They might have been detected if they had been monitored by a human. However, this would require a huge workload, and it is not realistic for a human to check all telemetry, which exists in the order of 1,000 to 10,000, one by one. In other words, such precursors can only be detected by a systematic process.

In this study, a data-driven change detection method for systematic monitoring of satellite telemetries is investigated. We limit the changes to be detected to simple ones, and instead, consider method that can target a wider range of telemetry. We also present the results of applying the method to actual telemetry data of a satellite operated by JAXA (Japan Aerospace Exploration Agency).

2. Strategy for Telemetry Monitoring

When we look at satellite telemetry over a time span of minutes to hours, the telemetry values vary widely, with a wide variety of waveforms and distributions. In order to predict the instantaneous values of such telemetry, a simulation that correctly simulates the satellite's behaviors is required. In principle, this is not realistic, since it is necessary to understand the operations to be performed and commands to be sent on each day, as well as to consider uncertain factors such as the radiation environment. On the other hand, for longer time spans, such as weeks or months, it is almost the case that there is no trend, or if there is a trend, it is slight or smooth.

Even for the real satellite operators, it is hardly possible to follow all the detailed values of each telemetry in their evaluations. What they do first is to visualize each telemetry as a time-series graph. By looking at the visualized graph, they seek for major changes such as changes in long-term trends, waveforms, and the range of the value. By doing this, they screen for anomalous telemetry, i.e., telemetry that requires a more detailed review. Such a screening is an inductive, data-driven method that does not use any knowledge of satellite structure and operation deductively, which is an unsupervised anomaly detection itself. We considered imitating this procedure as an systematic algorithm in the proposed method.

It is assumed that distribution of values crucially characterizes the time series telemetry data in such screening. Carlton, Morgan, Lohmeyer, and Cahoy (2018) propose to perform a statistical test on whether the current distribution is different from the previous one or not. However, their method is sensitive to insignificant changes and the interpretation of the results is difficult. As quantities related to the distribution of telemetry values, upper and lower limits are specified for many telemetries. Hence, the concepts of upper and lower limits are expected reasonable for satellite operators. This study focuses on the range of telemetry values instead of the whole distribution. This concept is similar to that of Yairi et al. (2004)

The most naive features for evaluating the range of telemetry values are the maximum and minimum values within a certain time window. However, satellite telemetry often contains noise with extremely large or small values. The noise is due to radiation and other factors, and is unrelated to the actual physical values. Thus, the maximum and minimum values would be the meaningless values of the noise, and simply using these values lead to the meaningless result. Alternatively, one may use the mean and standard deviation as a parametric characterization of the distribution of the telemetry values. For example, if the data follow a normal distribution, almost all (99.7%) of the samples shall fall within the range of ± 3 standard deviations from the mean. However, the shape of the distribution of telemetry data varies widely, and it is rather rare for the distribution to be normal or even bell-shaped. The use of more complex parametric distributions such as Gamma distribution is also possible, but estimating parameters from a large number of data points is computationally demanding.

As an alternative to these methods, this study uses quantiles as features. Quantiles are not affected by the extreme outlier-like noise, and it is possible to obtain the rough shape of the distribution from some quantile values, especially the values at the edges of the distribution. In addition, since quantiles are calculated in a nonparametric manner, the distribution does not need to have a specified shape, e.g., bell-shaped. Another advantage over parametric methods is that quantiles are not computationally expensive because they can be obtained simply by performing a sort.

3. Proposed Method

In this section, *Quantile Gaussian Process Regression (Q-GPR)*, a change detection method using quartiles as features, is proposed as an example that achieves wide-range systematic telemetry monitoring. The procedure of the Q-GPR is shown in Figure 1. The length of the data processing interval, w, is determined by considering the time interval when communication with the satellite can be established and other factors. For simplicity, let us assume that $w = 1$ day. For a given telemetry series, let us denote the i-th interval (i.e., day) of the series as Day i, and denote the telemetry series of Day i as $\boldsymbol{x}^i$. Suppose that we have already obtained the data from the satellite from Day 1 to Day N. We now consider the

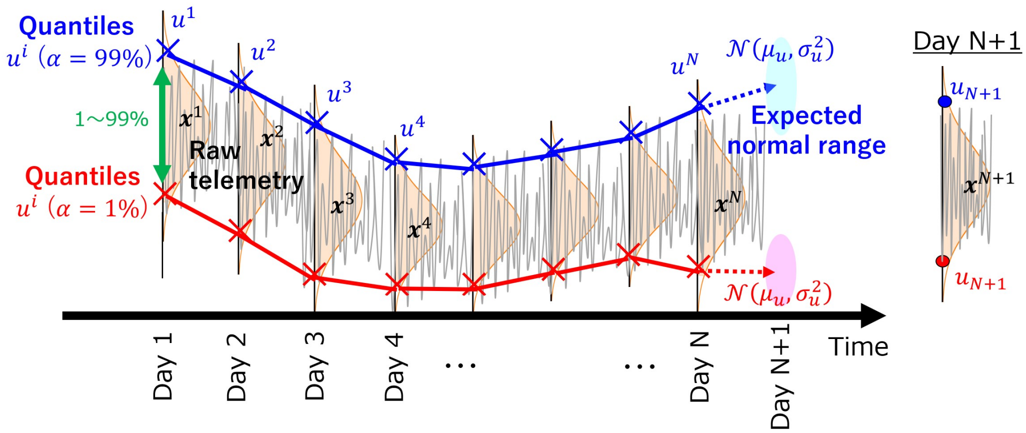

Figure 1. Sketch of the proposed change detection method, Q-GPR.

case where the data $\boldsymbol{x}^{N+1}$ for Day $N + 1$ comes down, and we are interested in determining whether this is an anomalous or not.

The proposed method takes the daily $\alpha\%$ quantile values as features. The quantile values can be obtained by sorting data points contained in $\boldsymbol{x}^i$ and referring to the value at the $\alpha\%$ position. The value of α is an appropriate value to characterize the distribution of the telemetry. For example, a value of 99% for α allows us to identify the upper border of the value range, while a value of 1% allows us to identify the lower border. The median value ($\alpha = 50\%$) may also be used to evaluate a rough trend of the telemetry. Let u^i denote the $\alpha\%$ quantile for Day i.

Expected normal range for u^{N+1} is predicted by using the data up to Day N. When the telemetry of Day $N + 1$ is acquired, the actual u^{N+1} is calculated, and if it is not within the expected normal range, the telemetry is judged to be anomalous. *Gaussian Process Regression (GPR)* is used to predict the expected normal range. GPR is a nonlinear regression model with a background of stochastic processes. It is characterized by its ability to smoothly connect given training data points, making it a particularly powerful model for low-dimensional regression such as univariate time-series prediction. This paper does not go into the details of GPR, as there are many literatures available on the subject (e.g. Rasmussen and Williams (2005)). There are also many libraries for implementation, and GPy (GPy, since 2012) is used in this research. GPR predicts the distribution of u^{N+1} from the quantile points from Day 1 to Day N. The predictive distribution by GPR will be a normal distribution, so it can be expressed in terms of mean and variance as follows:

$$P(u^{N+1} \mid u^1, \ldots, u^N) = \mathcal{N}\left(\mu_u, \sigma_u^2\right) \tag{1}$$

The expected normal range of u^{N+1} shall be the range of $\mu_u \pm 3\sigma_u$, using the parameters of the predictive distribution. If the actual u^{N+1} deviates from this range, the telemetry is alerted as anomalous.

3.1. Advantages and Limitations

One of the major advantages of the proposed method is that the objective in Q-GPR, range of telemetry values, is intuitively clear and easy to interpret for satellite operators unfamiliar with data-driven analysis. Interviews with satellite operators indicated that existing methods have interpretability problem. This problem in principle arises because their focus is on finding complex signs of anomaly that cannot be found manually. The proposed method solves this problem by redefining the research objective to just imitating manual monitoring. This redefinition of the research objective lead the proposed method widely applicable, and also solved another limitation in previous study that they are variable-specific and difficult to transfer to other components. In addition, while GPR and other complex machine learning techniques offer high performance, their large computational complexity is often a problem. Q-GPR solves this problem by reducing the number of data points used in regression by summarizing the daily telemetry data into a quantile statistic. This is important when considering the use of the proposed method on a satellite's onboard computer for autonomous operation of the satellite.

Next, the limitations of the proposed method are discussed. First, since quantiles in Q-GPR focuses only on the distribution of telemetry values, they cannot capture changes in waveforms where the distribution remains the same. A possible solution to this issue is to monitor some additional feature values derived from the shape of the waveform, such as those proposed by Barreyre, Boussouf, Cabon, Laurent, and Loubes (2019). Also, Q-GPR cannot detect faults that occurs smoothly and continuously, such as equipment deterioration. This is the logical reflection of the fact that Q-GPR is capable of following and predicting smooth continuous changes. Other algorithms, such as out of limit detection using a threshold value, should be used to address this point. Operating several algorithms together as a powerful algorithm is consistent with the idea of ensemble learning in the field of machine learning. Although some other limitations may be stated, such as the absence of a focus on multivariate relationships and multiple satellite modes, the most limitations can be summarized as the difficulty of capturing complex changes due to the simplicity of the method. Hence, the proposed method is suitable for the main objective of this study, which is to offer simple additional systematic screening for unmonitored telemetries.

4. Demonstration with Real Satellite Telemetry

To demonstrate the effectiveness of the proposed method, we applied the proposed method to actual satellite telemetry data. The target of application is the satellite for geospace exploration named *"Arase" (ERG)*, which is currently in operation at the Institute of Space and Astronautical Science (ISAS) of JAXA. Numeric data (i.e., not categorical data, etc.) in health monitoring telemetries for a certain 90-day period during actual operation were used. No anomalous behavior of the satellite was observed during this period, and the required behavior of the change detection algorithm is that it does not detect any anomaly. The initial period up to Day 30 was dedicated to the training period, and no change detection was performed. After $N > 30$, the change detection with Q-GPR was performed on a daily basis. The values of α were set to 1% and 99%, in order to check the edges of the telemetry value range. The parameter w was set to 1 day for all telemetry, regardless of the sampling rate or the timing of the acquisition of signal (AOS). Although this period length does not coincide with the orbital period of the satellite, different values were purposely chosen to demonstrate that the effect of w is small.

Examples of the results are shown in Figures 2–4. In each figure, the raw telemetry values and 1% and 99% quantile points for each day are shown. The expected range of the quantile predicted by GPR is also shown. In telemetry A shown in Figure 2, the raw telemetry value oscillates up and down irregularly, and it is difficult to accurately predict the raw values. If the telemetry highly reflects satellite operation, it is in principle impossible to predict the value without the knowledge of the operation in the next day. However, the 1% and 99% quantile values were settled within a certain range. This makes it possible to estimate the rough range using a relatively simple method such as GPR. This is a simple demonstration of the advantage of using quantiles. For telemetry A, the 1% and 99% quantiles on Days 30–90 were within the expected normal range predicted by GPR in each preceding day, and no anomaly alerts were raised at all. Since the satellite was operated normally as mentioned, this is an ideal result. If there were to be any changes with a deviation from the expected normal range, an alert would be raised for that event. It is clear what changes in the telemetry shall be detected.

A similar observation can be made for telemetry B shown in Figure 3. Telemetry B is characterized by a peaky waveform that appears on the upper side. The timing and length of this waveform vary, making it difficult to predict the raw value. In the proposed method, such events that require individual assessment for each telemetry are eliminated by use of quantiles. The statistical process simplifies the structure to a relatively simple one in which the 1% quartile remains almost constant and the 99% quartile has a distribution according to the variation in the length of the peaks. This is consistent with human intuitive understanding. The proposed method successfully stated that there are no peculiar changes in the given period.

Telemetry C in Figure 4 is characterized by a peaky component extending up and down. In addition, the range where most of the values are concentrated has some long-term trends. Referencing the quantiles successfully removed the influence of the unpredictable peaky component. On the other hand, the smooth global trends could be captured by the series of quantile values. Since the GPR prediction can follow smooth changes, the predicted normal range changed smoothly, and the prediction was consistent with our general human perception. However, although the prediction itself appeared to work well, a few minor deviations from the predicted normal range were judged anomalous for both the 1% and 99% quantiles. This is mainly due to the effect of quantization in digitizing telemetry value, which causes large stepwise changes in telemetry values at one time. This step-like change is a unique characteristic of satellite telemetry, which needs to conserve data volume due to communication capacity constraints.

It was demonstrated that the proposed Q-GPR technique is applicable regardless of waveforms, and can be applied uniformly regardless of what the telemetry measures. It could be applied to many telemetry items in the same way, indicating that the proposed method can be used as a systematic screening method. However, the current algorithm yields some false alarms, while a system that generates too many alerts will not be trusted. Appropriate adjustment of the width of the expected normal range, including the elimination of the effect of quantization, is an important issue. The value of α also needs further consideration.

5. Conclusion

In the health management of satellites, a systematic monitoring method of telemetry is proposed to deal with the limitation of human resources. The proposed method, Q-GPR, monitors the range of telemetry values and detects anomalous deviations by focusing on quantile statistics. The simplicity of the strategy makes the proposed method uniformly applicable to many types of telemetry. The uniform applicability of the proposed method is demonstrated by applying it to real telemetries with various waveforms.

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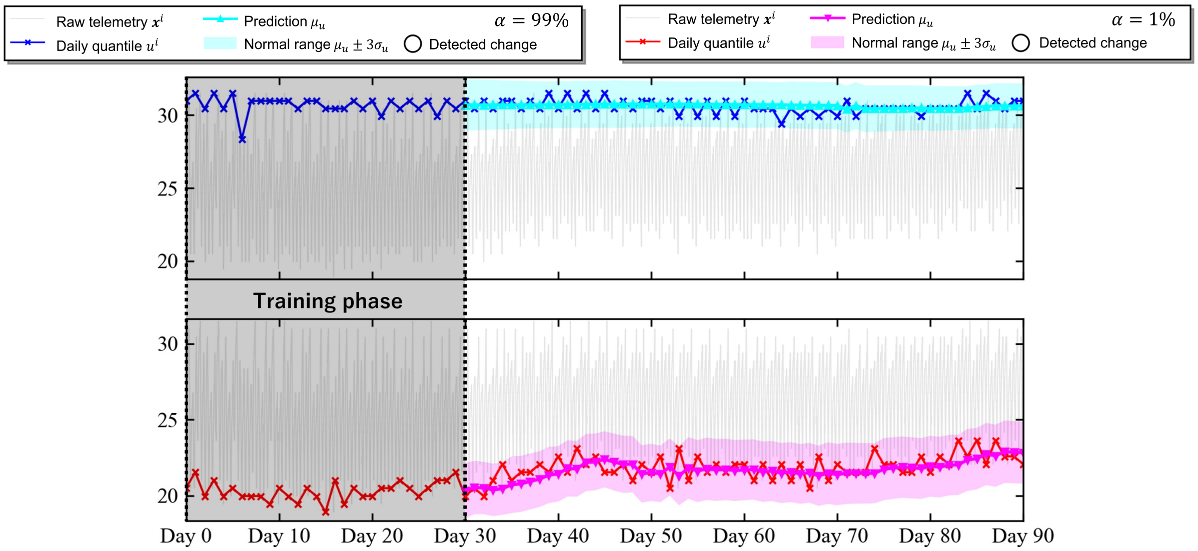

Figure 2. Results of proposed change detection for telemetry A.

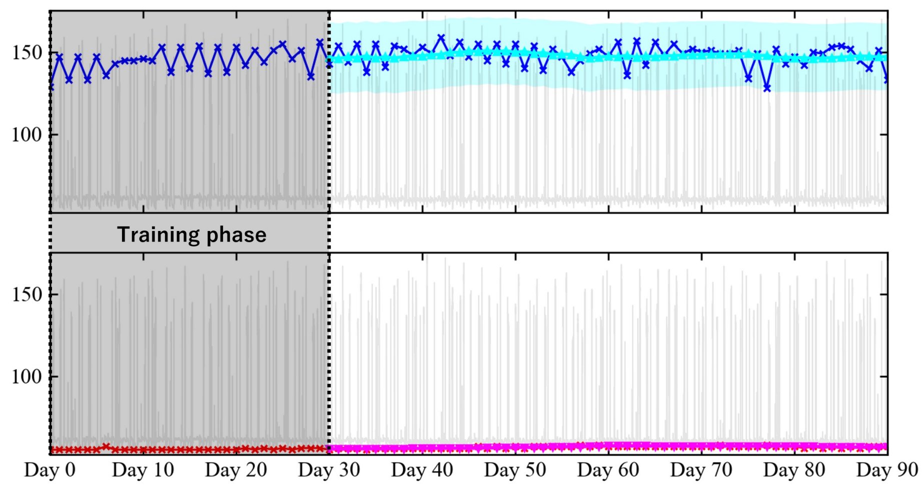

Figure 3. Results of proposed change detection for telemetry B. (Legend is the same as Figure 2.)

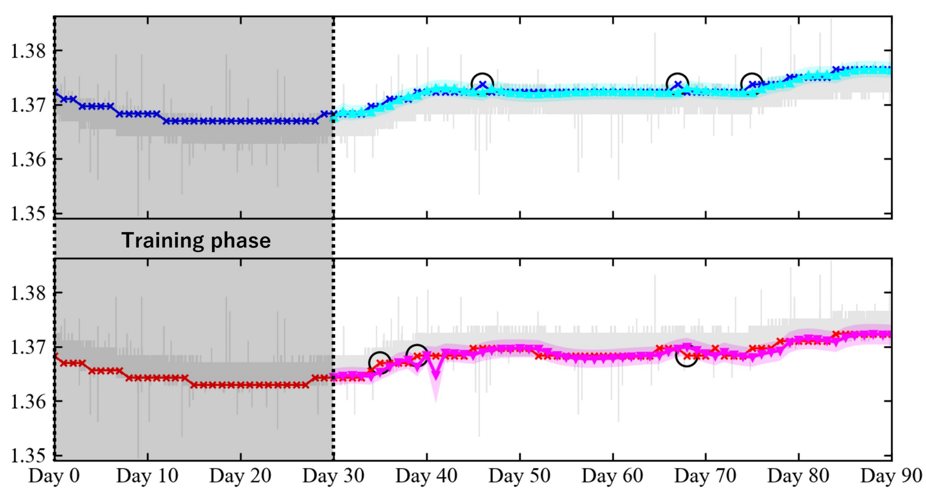

Figure 4. Results of proposed change detection for telemetry C. (Legend is the same as Figure 2.)