

Summarization of Spacecraft Telemetry Data by Extracting Significant Temporal Patterns

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Abstract

This paper presents a method to summarize massive spacecraft telemetry data by extracting significant event and change patterns in the low-level time-series data. This method first transforms the numerical time-series into a symbol sequence by a clustering technique using DTW distance measure, then detects event patterns and change points in the sequence. We demonstrate that our method can successfully summarize the large telemetry data of an actual artificial satellite, and help human operators to understand the overall system behavior.

1 Introduction

In recent years, a lot of datamining techniques for time-series data such as similar pattern search[1],[2], pattern clustering[3],[4],[5], event detection[6],[7],[8], change-point detection[9],[10],[11], and temporal association rule mining[12] have been studied actively. These techniques have been successfully applied to various domains dealing with vast time-series data such as finance, medicine, biology, robotics, etc. In the meantime, telemetry data of spacecrafts or artificial satellites is also a huge time-series data set usually containing thousands of sensor outputs from various system components. Though it is known that the telemetry data often contains some symptoms prior to fatal system failures, the limit-checking technique which is ordinarily used in most space systems often fails to detect them.

The purpose of this paper is to propose a data summarization method which helps human experts to find the anomaly symptoms by extracting important temporal patterns from the telemetry data. The summarization process consists of symbolization of the originally numerical time-series and detection of event patterns and change-points. This data-driven approach to the fault detection problem is expected to overcome some limitations of other sophisticated approaches such as expert systems and model-based simulations which require the costly a priori expert knowledge. We also show some results of applying the method to a telemetry data set of an actual artificial satellite ETS-VII (Engineering Test Satellite VII) of NASDA (National Space Development Agency of Japan).

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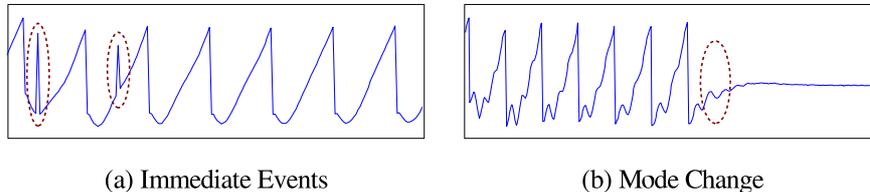


Figure 1: Examples of event and change patterns in time-series data

2 Proposed Method

2.1 Basic Idea

The purpose of our method is to make a summary of the telemetry (HK) data automatically by preserving only important information while discarding the other. This helps the operators to understand the health status of the systems, and hence increases the chance to find subtle symptoms of anomalies that could not be detected by the conventional techniques.

A non-trivial problem here is that we need to decide “what is important information” in the data beforehand. As to the HK data of spacecrafts, we judged that the following two kinds of information are especially important based on the investigation of past failure cases and interviews with experts.

1. Immediate events \cdots Patterns that are distinct from other neighboring parts
2. Mode changes \cdots Points where the characteristics of the time-series change

Fig. 1 shows examples of the event and change patterns. They are considered to have certain important information in that it corresponds to some actual events in the system such as “engine thrustings”, “changes of attitude control mode”, and so on. In the remainder of this section, we describe the ways of detecting the immediate events and mode changes from the data.

2.2 Detection of Immediate Events

The symbolization of the original HK data and detection of the immediate events are described as follows. First, each time-series in the HK data is divided into a set of subsequences with a fixed length. Then all the subsequences are grouped into clusters based on the DTW (Dynamic Time Warping) distance measure. Finally, each cluster is assigned a unique symbol, and the subsequences contained in “small” clusters are detected as event patterns.

Selecting the number of clusters is a common problem for all clustering methods. In the current implementation, although the system mostly recommends a proper value based on the MDL (Minimum Description Length) criterion, it is sometimes necessary for human operators to adjust the parameter in order to obtain a better result.

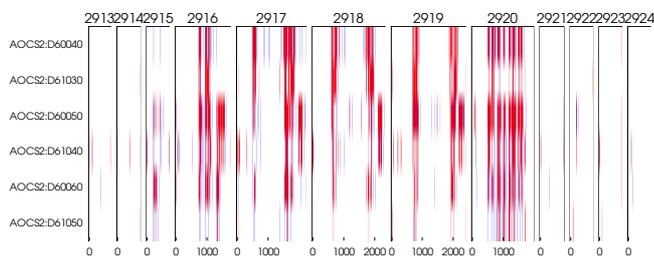


Figure 2: (Example 1) Co-occurrences of events and changes

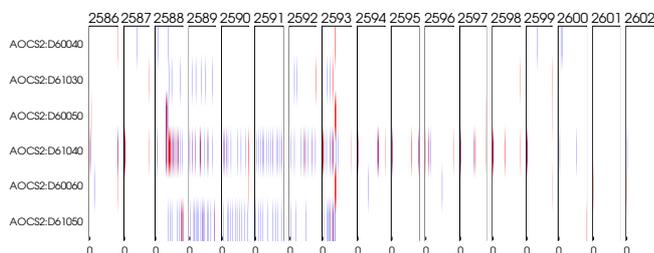


Figure 3: (Example 2) Association among events and changes of D60050, D61040, and D61050

2.3 Detection of Mode Changes

In the proposed method, detection of the mode change points in the HK data is realized by finding an optimum segmentation of the symbolized time-series. Suppose a sequence of symbols $[s_1, \dots, s_t, \dots, s_N]$ is divided into M segments. Then we model each segment by a 0-order Markov model, and evaluate the goodness of this segmentation by the sum of *modelling losses* for the segments. We search for the best segmentation that minimizes the sum of modelling losses, and define the borders of segments as the mode change points.

This change-detection process also has an open problem of how to decide the number of segments M , which is similar to the decision problem of number of clusters in the symbolization process. In the current implementation, the subtle adjustment is up to the operators.

3 Case Study

We implemented the methods described above and applied it to the HK data of ETS-VII for four years. In this case study, we picked up 6 time-series relating to the AOCs (Attitude & Orbit Control Subsystem). Their brief descriptions

Table 1: List of time-series in ETS-VII's HK data chosen for this case study

ID	Explanation
D60040	Drive signal of AOCS reaction wheel (Roll)
D60050	Drive signal of AOCS reaction wheel (Pitch)
D60060	Drive signal of AOCS reaction wheel (Yaw)
D61030	Incremental angle of IRU (Roll)
D61040	Incremental angle of IRU (Pitch)
D61050	Incremental angle of IRU (Yaw)

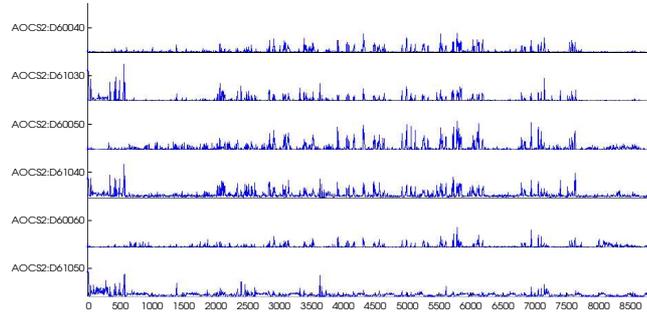


Figure 4: (Example 3) Transition of relationship among event frequencies

are given in Table 1.

Fig. 2 shows an example of the occurrence pattern of the events and changes in the 6 time-series for one day. We can easily notice the associations among the series. Fig. 3 also gives a summary of events and changes for another day. In this figure, we can see a characteristic association pattern among the series. That is to say, D61030, D61040 and D61050 become suddenly active right after an event occurs in D60050 (access period 2588), and then become inactive again, responding to the simultaneous events in D60040, D60050 and D60060 (period 2593). Fig. 4 is a summary of the 4 years' data in a more abstract way. It shows the transition of frequencies of the events and changes in each series per day. We can browse the global trend of the system activities and associations among the series. Fig. 5 shows an example of anomalous patterns detected in D61050 by the proposed method.

4 Conclusion

In this paper, we presented a method to summarize spacecraft telemetry data and to visualize most important information in it for monitoring the health status of the spacecraft systems. It focuses on two kinds of temporal patterns – “event” and “change” in the time-series, and extracts them by combining

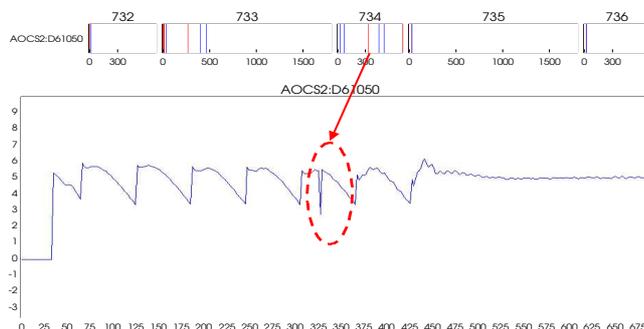


Figure 5: (Example 4) Detection of an event or distinctive pattern

techniques of pattern clustering and change-point detection.

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