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Anomaly detection for satellite power subsystem with associated rules based on Kernel Principal Component Analysis

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ABSTRACT

The paper presents an implementable method of anomaly detection for satellite power system. Specifically, a data-driven anomaly detection method for sensor data integrated Kernel Principal Component Analysis (KPCA) and association rule mining is demonstrated. Establishing associated rules among sensor monitoring data sets, this approach analyses the structure of measure space via its Eigen matrix with KPCA, and identifies the anomaly. Especially, different anomalies from satellite system and sensors can be distinguished with the changes of association rules. The effectiveness of the method is proved on sensor data from Feng-Yun satellite power subsystem.

1. Introduction

The power supply sub-system provides sustainable and reliable energy for satellite in order to ensure the normal operation. The performance of power supply subsystem will directly affect the other subsystems and dominate their performance of the satellite. Hence, it is significant to detect anomalous states of the power subsystem to ensure the system health [1,2]. Moreover, anomaly detection is the basic function of prognostics and health management (PHM) which has been applied widely in space engineering [3–5].

In general, the in-orbit anomaly detection of satellite requires detailed analysis of the large-scale data by monitoring sensors. However, the sensor is one of the elements or units with high failure risk, as the sensor anomaly on spacecraft may lead to state estimation error and false alarm. Thus, the anomaly detection method for satellite power subsystem must have the capability of anomaly identification. For a complex system (e.g. satellite power subsystem), a single sensor is incapable of collecting enough information for accurate condition monitoring. Multiple sensors are needed in order to complete this task [6,7]. The relationship between the multiple sensor monitoring data is often complex and nondeterministic. While detecting anomaly with monitoring sensor data, large amount of sensor data as multiple time series is redundant and correlative. Thus, the system and sensors can be described more comprehensively. It should be noticed that, the relationship between the multiple sensor monitoring data can no longer keep constant when sensor anomaly occurred. Therefore, it is quite critical to isolate and locate the sensor anomaly and system anomaly via the associated rules between sensor data.

In this work, we propose a novel anomaly detection method for satellite power subsystem based on Kernel Principal Component Analysis (KPCA) and association rule mining. After establishing associated rules between multiple monitoring data, the structure of measure space is analysed via its Eigen matrix through the KPCA algorithm, and the root of anomaly is therefore determined whether the associated rules are changed. Different anomalous modes are simulated on the basis of sensor data from actual power subsystem of Feng-Yun meteorological satellite. Comparing with the typical method, the experimental results demonstrate that the proposed method can effectively improve the performance of anomaly detection and distinguish the anomalies from space system and sensors.

2. Satellite power subsystem description

In this study, we use the satellite power subsystem as objective system to illustrate our work. The architecture of a typical satellite power subsystem is shown as Fig. 1.

The main elements of power subsystem include solar cell array (solar charging array and solar supply array), battery set, and Battery Charging Controller (BCC), Battery Discharge Regulator (BDR), Shunt Regulator (SHUNT), Main Error Amplifier (MEA) and capacity array.

The satellite power subsystem is the uniform bus alignment system through direct energy conversion (DET). It includes a uniform bus with three region (shunt region, charge region and discharge region) control.

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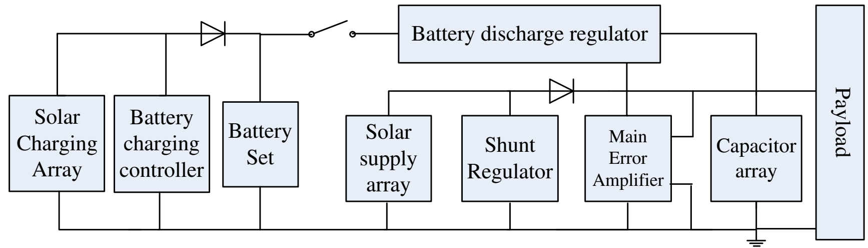

Fig. 1. Diagram of the satellite power subsystem and its sensor deployment.

It is power supplied by the solar charging array and solar supply array. During the light period, the solar array generates electrical energy, and supplies power to the payloads and charges batteries, under SHUNT and BCC modules controlling together. During the shadow period, battery pack supplies power to the payloads by BDR. To meet the instantaneous high power requirements, battery discharges and solar array must be combined for the load supply adjusted by MEA and BDR.

To monitor the operating condition of satellite power subsystem, several different types of sensors are utilized, such as temperature, voltage, current and digital I/O. Multiple sensors are installed and deployed in different components of the power subsystem, mainly involving the solar cell array voltage, current and temperature, MEA voltage, bus voltage and current, shunt controller temperature and current, battery pack voltage and current, temperature, digital I/O of BBC and BDR, etc.

A total of 70 sensors deploying distributed in the satellite power subsystem are shown in Table 1 in detail.

3. Anomaly detection algorithm

3.1. Overview

Basically, the proposed method consists of three main procedures:

- Extracting pattern from multiple sensor data, then mining association rules among the typical pattern existing in multiple time series.
- Analysing the structure of measure space via its Eigen matrix by the KPCA with temporal associated rules, and discover the cause of anomaly by tracking the change of the rules.
- Monitoring real-time sensor data from satellite power subsystem and detecting anomaly using KPCA method and associated rules.

The first two procedures are performed on the data accumulated in the ground station during the initial operation phase right after the launch of the spacecraft. The last procedure, on the other hand, is applied to the real-time data tested in-orbit from the power subsystem in order to detect anomalies appearing in sensor data. Fig. 2 illustrates the framework of the proposed method as well as the three parts.

Table 1
Description of sensor distribution.

Sensor type	Distribution	Numbers
Voltage	Solar cell array	10
Voltage	Battery array	10
Voltage	Payload	10
Voltage	Bus	1
Voltage	BCC	4
Voltage	MEA	1
Current	Solar cell array	3
Current	Shunt	2
Current	Bus	2
Current	BCC BDR	4
Temperature	Solar cell array	5
Temperature	Shunt	1
Temperature	BCC BDR	2
Temperature	Battery array	8
Digital I/O	Shunt	2
Digital I/O	BCC BDR	4
Digital I/O	Instruction	1

Definition 1 (Multivariate time series). Multivariate time series consist of m individual time series where each time series has an ordered sequence of n real values.

$$\begin{aligned} TS_1 &= [x_1^1, x_2^1, \ldots, x_n^1] \\ TS_2 &= [x_1^2, x_2^2, \ldots, x_n^2] \\ &\ldots \\ TS_m &= [x_1^m, x_2^m, \ldots, x_n^m] \end{aligned} \tag{1}$$

Definition 2 (Frequent pattern). A pattern P is a short sequence of time series TS, where $|P|$ is the length of the pattern. A frequent pattern is a pattern with its number of occurrences $|L_P| > \min_o$, where $\min_o$ is the threshold required for frequent pattern.

Definition 3 (Closed pattern). The frequent pattern P' is defined to be closed pattern if there is no pattern P having the same number of occurrences $|L_p| = |L_{p'}|$ and containing the pattern P' [8].

Based on the above definitions, we describe each of the detailed procedures in the rest of this section.

3.2. Temporal associated rule discovery

In industrial processes, sensor data as multivariate time series often encapsulate complex relations among time series with time delays. According to pattern clustering and association rule mining, we can build the system and sensor behaviour models in the form of a set of rules. This work contributes to detect anomaly and identify the anomaly of system or sensors. Fig. 3 presents an overview of temporal association rule mining. Note that the purpose of pattern extraction is to discover patterns in a single time series, and the purpose of pattern clustering is to group similar patterns between multiple time series.

Firstly, using linear segment representation, sensor data is divided into numbered discrete linear subsequence.

We adopt Piecewise Aggregate Approximation (PAA) [9], a linear segment representation method in time series mining, to reduce data dimension. The single time series TS of dimension n is represented in n' dimensions by a vector $[\bar{x}_1, \bar{x}_2, \ldots, \bar{x}_{n'}]$.

$$\bar{x}_i = \frac{n'}{n} \sum_{j=\frac{n}{n'}(i-1)+1}^{\frac{n}{n'}} x_j \tag{2}$$

PAA method has only one parameter, the down-sampling factor $dsf = n/n'$, PAA will down-sample the original time series of length n to n' $(n > n')$.

Secondly, searching the frequent pattern with Segmental Dynamic Time Warping (Segmental-DTW) [10], similar pattern is extracted and