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.

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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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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 BCC 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.

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.

\[
TS_1 = [x_1^1, x_2^1, \ldots, x_n^1]
\]
\[
TS_2 = [x_1^2, x_2^2, \ldots, x_n^2]
\]
\[
\vdots
\]
\[
TS_m = [x_1^m, x_2^m, \ldots, x_n^m]
\]

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 \(|L_P| > \min_n\) where \( \min_n \) 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 \( [\bar{x}_1, \bar{x}_2, \ldots, \bar{x}_{n'}] \).

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

PAA method has only one parameter, the down-sampling factor \( \delta s = n/n' \). 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

![Diagram of the satellite power subsystem and its sensor deployment.](image-url)
symbolized from each set of subsequence. The close patterns are primitive and independent so that the redundant patterns must be removed.

Segmental-DTW is initially applied to find out whether the two similar segments in the input signal. Here, we utilize it to segment the most similar sequences of the multiple time series. The specific process of the algorithm is as below.

- Step1, each sensor data in the data set is segmented using equal length and overlapping time windows $T_m$. For example, the $n'$ length of time series is divided into $k$ segments, that is $[s_1, s_2, ..., s_n] = [v_1, v_2, ..., v_k]$.
- Step2, we pairwise compare the segments by Segmental-DTW to find the most similar candidate segment $CP$. Note that the diverse candidate segment can be obtained by controlling the minimum search length $L_0$ of Segmental-DTW.
- Step3, we use native 1-motif-find algorithm to get the number of the candidate segment occurrences. If $|C_k| > \min_0$ this candidate segment will be added into a set of frequent patterns. The procedure is repeated from Step2 to Step3 for generating frequent patterns.
- Step4, we remove redundant frequent patterns to obtain a more compact set of patterns. A frequent pattern is considered as redundant if it is covered by other patterns which have the same number of occurrences.

Thirdly, similar patterns are grouped into pattern clusters with hierarchical clustering with DTW distance.

We use the hierarchical clustering algorithm based on DTW distance to group similar patterns. The hierarchical clustering algorithm repeatedly selects the most similar pair of clusters and adds them to a new cluster until there is one cluster containing all objects. We give the hierarchical clustering procedure a stopping criterion to produce a set of clusters such that the minimum DTW distance $md_{ij}$ between sets of patterns.

Finally, Temporal Association Expansion (TAE) [11] is employed to discover frequent temporal associations of multiple block pattern clusters.

3.3. Kernel Principal Component Analysis

The principal components are a smaller set of the uncorrected variables of which the directions demonstrate the maximum variance in the raw data. However, PCA [12] is built on hypothesis of the linear relationships between the raw variables. Kernel PCA using the kernel is derived from PCA as a nonlinear feature extraction using kernel trick. KPCA maps the original data into a high Hilbert space using a nonlinear function $\phi(x)$.

$$\phi : c_i \in \mathbb{R}^d \rightarrow \phi(c_i) \in \mathbb{R}^k, k = 1, 2, ..., l$$ (3)

Note that the dimension of high Hilbert space $h$ can be any size, or even infinite, and the original data can almost always be linearly separated in $h \geq d$ dimensions.

Since we generally try to avoid direct computing nonlinear function $\phi(x)$. We can create the l-by-l kernel to get the nonlinear mapping.

$$K(c_i, c_j) = \phi(c_i)^T \phi(c_j). i, j = 1, 2, ..., l$$ (4)

The characteristic nonlinear mapping can be produced by kernel function. Using KPCA method, the mapping space is partitioned into two orthogonal kernel space: principal component space and residual space.

$$X = TP^T + E = T_1(p_{m1})^T + ... + T_n(p_{mn})^T + E_{n+1}$$ (5)

where $TP^T$ represents the principal sources of variability in the process, $E$ represents the variability corresponding to process noise, and $n$ is set to be the number of principal components.

After the KPCA is established, the measurement residual can be computed. For measurement vector $x_k$, the residual $\epsilon$ and squared predication error (SPE) are defined as.

$$\epsilon = x_k - x_kPP^T = x_k(I - PP^T)$$ (6)

$$SPE = \epsilon^T \epsilon = ||\epsilon||^2.$$ (7)

SPE is applied for anomaly detection through analysing of the new measurement data. The amount of information from this data sample can be measured with SPE, which cannot be described by KPCA model. Accordingly, SPE can indicate the consistency of the data sample with the KPCA model.

Actually, we can use SPE to detect whether there is an anomaly in the multiple sensor data. However, we cannot identify the sensor anomaly or the system anomaly only with the SPE. Thus, the temporal associations discovered in previous step can help to accomplishing anomaly.

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identification. Specifically, while anomaly occurs, two kinds of states can be obtained as follows.

- Change of the measured data matrix is due to anomaly in the subsystem. The sensor data keeps the associated rules within them, and do not change the original measurement space redundancy.
- Change of the measured data matrix is due to anomaly in the sensors. Under this circumstance, the fault sensor and normal sensor are considered to be independent to each other. Thus, they no longer satisfy the associated rules, and the measurement matrix no longer maintains redundancy.

Following the steps above, we can establish the KPCA model of the satellite power subsystem with associated rules, which can be regarded as an expected mathematical model with some correlation constraints. Therefore, by handling the monitoring data with the above model, we can achieve anomaly detection and identification.

4. Experimental results and analysis

4.1. Sensor data description

As introduced in Section 2, multiple sensors are utilized to monitor the operation status of satellite power subsystem. The normal sensor data is sampled from the actual satellite platform. With these real data, we simulate data by fault injection. The experiments are conducted under two typical sensor anomalies, including sensor deviation and sensor accuracy decrease.

We utilize the sensor data set \( MTS_{5000\times 63} \) from Feng-Yun satellite power subsystem to discover the frequent temporal associations. Then, this sensor data set is divided into training subset and testing subset. The training subset includes 3000 samples of 63 parameters which are used to establish KPCA model. The testing subset includes the up-to-date data and anomalous samples generated by anomaly injection.

The \( d_{ps} \) is set to 0.3 for the PAA, \( T_{ew} \) is set to 35, \( m_{in} \) is set to 20, \( m_{do} \) is set to 0.6, \( L_{c} \) is selected from group \( \sigma = [5, 10, 15, 20, 25] \).

4.2. Analysis for Associated Rules Mining

With the parameter settings above, we can discover 113 associations with multiple sensor data from satellite power subsystem.

Due to the fact that satellite sensor data has strong association and pseudo periodic characteristics, we first discover the associations between the sensor data that almost keep the linear relationship. Then, we find the temporal association rules from multiple sensor data. Figs. 4 and 5 present two typical cases.

Fig. 4 shows the first ranked association and the second association between temperature of solar cell and current of solar cell. Fig. 5 shows the association between current of battery charging A and battery charging current B. Those associations reflect the redundancy between sensors to be applied in anomaly identification.

4.3. Analysis for anomaly detection

4.3.1. Anomaly detection with standard KPCA

In order to detect the sensor anomaly, we add deviation to the normal data set and then calculate the residual. The first seven principal components contribute 94% for the covariance. Therefore, the first seven principal components are used to establish the system's KPCA model. Fig. 6 indicates the evolution of SPE with anomaly on a current sensor.

The first half of the data in the curve shows that training and normal process is all located below the confidence limit. The latter half of the data indicates that another residual of an abnormal data with a deviation of 1A integrated into current sensor of SHUNT. We can also find that when the sensor anomaly occurs, the residual increases significantly correspondingly.

4.3.2. Anomaly detection with associated rules

According to correlation relationship between multiple sensor data and nonlinear principal components, the contribution of each sensor data can be calculated to obtain the contribution plots [13]. Fig. 7

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shows the evolution of SPE contribution with anomaly on four temperature sensors of battery pack. Based on association rule mining, we find that the four temperature sensors have high correction and redundancy. Fig. 7(a) shows that the anomaly occurred in the battery pack as the original measurement space redundancy keeps unchanged. Comparatively, Fig. 7(b) shows that anomaly occurred with the sensor 3, and the measurement matrix no longer keeps redundancy.

5. Conclusion and future work

This paper proposes a new anomaly detection method for satellite power subsystem based on two different kinds of techniques: association rule mining and KPCA method. In this work, typical closed patterns are extracted from single time series, and then temporal relationships among those patterns in multiple time series are explored and obtained in the form of association rules. KPCA algorithm is used to build the principal component model by analysing the main element space and the residual space. Combined with the set of association rules, the KPCA model can be adopted for detecting and identifying system or sensor anomalies. Comparing with the typical method, this approach achieved better performance for anomaly identification.

In the future, we will expand the proposed method in two aspects. On one hand, we will realize the on-line anomaly detection with FPGA or other embedded platform to facilitate the actual applications. On the other hand, quantitative analysis will be implemented to the association rules to achieve the sensor data reconstruction to recover from certain circumstances.

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References


Fig. 7. SPE contribution plots for temperature sensors.