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Fault detection of flywheel system based on clustering and principal component analysis

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Abstract Considering the nonlinear, multifunctional properties of double-flywheel with closed-loop control, a two-step method including clustering and principal component analysis is proposed to detect the two faults in the multifunctional flywheels. At the first step of the proposed algorithm, clustering is taken as feature recognition to check the instructions of "integrated power and attitude control" system, such as attitude control, energy storage or energy discharge. These commands will ask the flywheel system to work in different operation modes. Therefore, the relationship of parameters in different operations can define the cluster structure of training data. Ordering points to identify the clustering structure (OPTICS) can automatically identify these clusters by the reachability-plot. K-means algorithm can divide the training data into the corresponding operations according to the reachability-plot. Finally, the last step of proposed model is used to define the relationship of parameters in each operation through the principal component analysis (PCA) method. Compared with the PCA model, the proposed approach is capable of identifying the new clusters and learning the new behavior of incoming data. The simulation results show that it can effectively detect the faults in the multifunctional flywheels system.

1. Introduction

Fault detection plays a key role in improving the reliability of spacecraft system and preventing the serious damage of operation units. Due to the increase of interactions of operation units and instruments, the dynamics and kinematics mathematical modeling of spacecraft system becomes more and more difficult. In addition, there are divergences between theory, functions and environment of the system on the orbit and restrictions of reusing models of the past systems. Therefore, it is a challengeable job to extract and organize the knowledge of spacecraft system. As a result, the traditional qualitative models (such as transition system model (TSM),[1] expert system,[2] fault tree[3] and signed directed graph (SDG)[4,5]) are becoming more difficult to detect the faults of spacecraft as the number of operation modes and component interactions grows. Data-driven monitoring techniques have been proposed to solve these difficulties by automatically clustering data and deducing the normal system behavior in the statistical theory. The performance of system components and instruments can

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be timely monitored by a statistic estimated variable named the scoring index. The fault detection index is defined by comparing real-time operation data with these nominal indices, measuring the abnormal deviations from the normal conditions or assessing the extent of damage caused by system faults.

The advantage of data-driven methods is that they can automatically extract the system features and timely update fault detection indices more accurately and reasonably. Clustering techniques have been applied to a wide variety of research problems, especially for the pattern recognition and feature extraction. The clustering methods are provided to characterize typical system behavior by extracting general classes of nominal data without any prior knowledge of the spacecraft. And the statistical techniques are used to define the threshold of scoring indices. Therefore, the building model for data-driven methods is able to automatically identify these normal classes or clusters and score the historical data during the normal operations. The complex systems are usually monitored by comparing real-time data with these classes or checking the scoring results whether beyond or within the corresponding thresholds. The system operation is off nominal if a particular set of input value is not consistent with these classes or the corresponding scoring index exceeds the threshold. In some situations, the high-dimensional data may contain manifestations of previously unknown anomalies and failures or contain additional information that can be used to better differentiate and isolate known failures before they cause extensive damage. Data-driven techniques cannot only extract patterns and models from the low-dimensional dataset, but also manage as effectively with the high-dimensional data as they do with a few. The new features and patterns can be supplemented by updating the testing data. However, the more unknown a new feature is, the more necessary is it that the data-driven methods should be somewhat punctilious in learning from the training data generally. Hence, the data grouping should be as accurate as possible in order to discover the tiny faults from the normal fluctuations.

Several data-driven fault detection methods have been successfully applied to aerospace engineering applications by analyzing either archived data or real-time data. Adaptive limit checking[6] method can automatically predicts the intervals for each lower and upper limits of sensor measurement by analyzing the historical telemetry data of an artificial satellite. The two-stage radial basis function (RBF) neural network[7] is effective to learn the nonlinear control system behavior from the training data and detect the faults from the testing data. Considering the engine's health degradation, a bank of Kalman filters[8] can be used to track the conditions of engine and detect the faults of aircraft engine sensors based on on-line data. Inductive monitoring system (IMS)[9,10] usually uses a K-means or density clustering technique to analyze archived system data and characterize nominal allowable intervals of these data vectors including the chosen parameters. The clusters of predefined vectors are stored in a knowledge base that can be used for on-line system monitoring and analysis of historical incidents. Principal component analysis (PCA)[11] can be used to extract variable correlation from the input data set including a large number of parameters in spacecraft systems and reduce data dimensional space.

The data-driven methods mentioned above are effective. But the existing methods mostly focus on the assumption that each system component can have only one function. There is a lack of relevant researches on the fault detection of multifunctional system. On the one hand, it is popular to decrease the payload of spacecraft by integrating multiple functions into one subsystem or instrument. On the other hand, it is difficult to obtain the corresponding prior knowledge and failure mechanism for the multifunctional systems. Furthermore, the spacecraft usually switches subsystem's multifunction which leads to the normal fluctuations indistinguishable from the tiny faults. In summary, it is difficult to propose a useful method which can detect the tiny faults of multifunctional system. In order to solve this problem, a data driven method is studied on the fault detection of multifunctional system by combining clustering techniques with PCA model.

This paper is organized as follows: based on the principle of energy storage and attitude control of flywheels, Section 2 analyzes the basic topologies of multifunctional flywheels and applies them in a satellite used for charge, discharge and attitude control, respectively. Section 3 briefly presents the general principle of PCA method and clustering techniques including ordering points to identify the clustering structure (OPTICS) and K-means. Section 4 is devoted to offering the necessary parameter settings of flywheels and amenable mission constrains, and the effectiveness and accuracy of the proposed method can be verified by the detection results in simulations. Section 5 summarizes the conclusions.

2. Topology of multifunctional flywheels

The small satellites will pay enough attention to the multifunctional systems. And the multifunctional flywheels will attract a particular attention because they can storage energy and realize the attitude control. In recent years, data driven fault detection methods have obtained rapid developments. Due to the requirements of confidentiality, it is impossible to use the real-time telemetry data collected from the satellite system in this paper. In order to verify the effectiveness and accuracy of proposed algorithm, the required data is produced by the Simulink model. The Simulink model is built according to the fundamental principle of multifunctional flywheels.

Traditionally, the flywheel[12] becomes more and more popular and useable in satellites because it can work as an attitude control actuator without consuming nonrenewable fuel. As an important actuator, the closed-loop control will ensure that a flywheel can accurately produce the responsive angular momentum with strong anti-interference.[13] However, the closed-loop control will decrease the abnormal deviations and the alarm rate for the high accurate flywheel.[14] In addition, a high-speed flywheel can store a great deal of kinetic energy which can be used as an energy conversion device by accelerating and decelerating the flywheel. The multifunctional flywheels are constructed by two counter-rotating flywheels. And the corresponding flywheel system is controlled by a mathematical equation:

$$\begin{cases} \begin{bmatrix} \dot{\boldsymbol{I}}_{\mathrm{m}} \\ \dot{\boldsymbol{\omega}} \end{bmatrix} = \begin{bmatrix} G_{\mathrm{d}}\omega_{\mathrm{d}}(\psi_1(\boldsymbol{I}_{\mathrm{m}},\boldsymbol{\omega}) - \psi_3(\boldsymbol{\omega})) - \omega_{\mathrm{d}}\boldsymbol{I}_{\mathrm{m}} \\ \frac{1}{J}(k_{\mathrm{t}}\boldsymbol{I}_{\mathrm{m}} - \boldsymbol{\tau}_{\mathrm{c}}\psi_2(\boldsymbol{\omega}) - \boldsymbol{\tau}_{\mathrm{v}}\boldsymbol{\omega}) \end{bmatrix} + \begin{bmatrix} G_{\mathrm{d}}\omega_{\mathrm{d}} \\ 0 \end{bmatrix} V_{\mathrm{com}} \\ \boldsymbol{\tau}_z = k_{\mathrm{t}}\boldsymbol{I}_{\mathrm{m}} \end{cases} \tag{1}$$

where k_{t} is the motor torque constant coefficient, J the motor moment of inertia, $\boldsymbol{I}_{\mathrm{m}}$ the motor current, $\boldsymbol{\omega}$ the motor angular