Fault Detection and Diagnosis for Spacecraft using Principal Component Analysis and Support Vector Machines

Yu Gao, Tianshe Yang, Nan Xing
State Key Laboratory of Astronautic Dynamics
Xi'an Satellite Control Center
Xi'an, P.R. China
gy615@163.com

Minqiang Xu
School of Astronautics
Harbin Institute of Technology
Harbin, P. R. China

***Abstract*—Development of intelligent fault detection and diagnosis technologies for spacecraft is one of important issues in the space engineering. In this paper, we present a new fault detection and diagnosis approach for spacecraft based on Principal Component Analysis (PCA) and Support Vector Machines (SVM). Firstly, PCA is used to extract features from input data and reduce the input data to low dimensional feature vectors. Then the method use a binary SVM to detect whether there is a fault or not. If the fault is detected, a multi-class SVM is used to identify fault type. The experimental results show that the method is efficient and practical for fault detection and diagnosis of spacecraft system.**

Keywords-fault detection; fault diagnosis; principal component analysis (PCA); support vector machine (SVM); spacecraft

I. INTRODUCTION

For any space mission, safety and reliability are the most important issues. Because of the complex structure of the spacecraft system and the harshness of the space environment, it is practically impossible to completely eliminate the possibility of anomalies or faults, even if we increase the reliability of the system components to the limit. In addition, the space is so distant from the earth that it is extremely difficult to directly repair or replace a damaged component. Therefore, fault detection and diagnosis for spacecraft system is significantly important.

Many approaches have been applied to fault detection and diagnosis for spacecraft system. Limit checking is the most fundamental and widely used technique. Its basic function is to check whether various telemetry parameters of the spacecraft system are within pre-defined upper and lower limits. Though the limit checking has an advantage that it is simple enough for human operators to implement a system, it lacks flexibility and can not check some small anomalies that occur without violating the limits on the variables.

To overcome the limitations of simple limit checking techniques, a number of intelligent monitoring system such as rule-based expert systems [1] or model-based reasoning methods [2, 3] have been developed. However, these approaches are heavily dependent on apriori knowledge on the system behavior for the spacecraft and have difficulties in acquiring accurate and complete models and knowledge of the spacecraft systems beforehand. Furthermore, these approaches may not be able to recognize faults that involve relationships among large numbers of parameters.

On the other hand, the spacecraft transmits multi-dimensional telemetry data to ground stations everyday. These telemetry data can contain a wealth of information about complex system behavior of the spacecraft. With the recent development of data mining and machine learning technologies, it is possible to examine this archived data and extract embedded information for the fault detection and diagnosis [4, 5]. These approaches can also been called the "data-driven" approaches [6, 7, 8]. They seek to build a model for the fault detection and diagnosis directly from vast archived spacecraft telemetry data, rather than building it based on human expertise. A significant advantage of these approaches compared with the expert systems and model-based approach is that it does not require complete and accurate expert knowledge or models.

In this paper, we propose a new fault detection and diagnosis approach for spacecraft based on Principal Component Analysis (PCA) and Support Vector Machines (SVM). In order to reduce the complexity and dimensionality of the input data, PCA is used to extract feature vectors from input data. Then the method use binary SVM to detect fault. After the fault is detected, a multi-class SVM is used to identify fault type.

The rest of this paper is organized as follows. In section 2, we give a brief overview of our approach. Section 3 describes the PCA for feature extraction. Section 4 describes binary SVM and multi-class SVM for fault detection and diagnosis. In section 5, we describe some results of an experiment. Finally, Section 6 concludes the paper and discusses some areas for future work.

II. OVERVIEW OF OUR APPROACH

In this section, we give a brief overview of our fault detection and diagnosis approach. The framework of our approach is shown in Figure 1. The approach has two main phases: the training phase and the real-time detection phase.

This work was supported by Postdoctoral Science Foundation of China (No. 201150M1539)

In the training phase, we use training dataset which are obtained from archived telemetry data or simulation data to calculate PCA matrix and train SVMs. The format of training data is shown in Table 1. The first column is fault mode. The mode “1” means normal State. The other columns are observed values of the telemetry parameters. The normal data and other fault data are used to train the Binary SVM which is used for fault detection. Then fault data of each mode are used to construct multi-class SVM for fault diagnosis.

In the real-time detection phase, the real-time telemetry data of the spacecraft system is processed. The approach first transforms the input data to a low dimensional feature space using PCA matrix and obtain feature vectors. These feature vectors then pass through the Binary SVM to detect whether there is a fault or not. If the fault is detected, these feature vectors continue to be sent into multi-class SVM which results into classification of different types of faults.

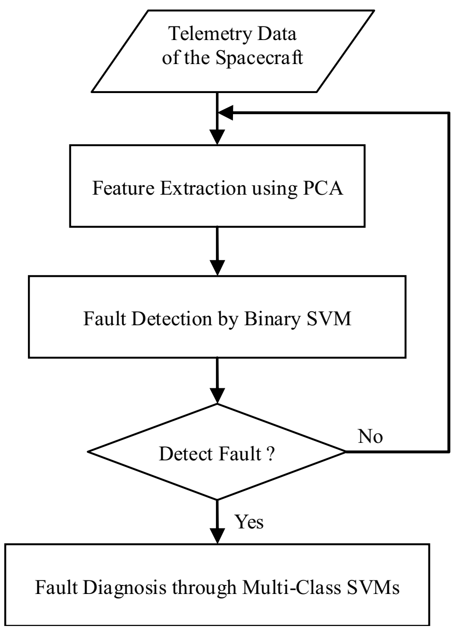

Figure 1. The Framework of Our Approach

TABLE I. FORMAT OF TRAINING DATA

Fault Mode	P_1	P_2	···	P_n
1	0.2	0.57	···	0.8

III. PCA FOR FEATURE EXTRACTION

Principal component analysis (PCA) is a mathematical technique which is derived from the applied linear algebra. It has been widely used in feature extraction and dimensional reduction [9, 10]. PCA finds a linear transformation Φ which reduces n-dimensional data to m-dimensional feature vectors (where m < n) in such a way that the information is maximally preserved in minimum mean squared error.

Suppose that $\{\mathbf{x}_t\}$ where t =1, 2, …, N are stochastic n-dimensional input data. The covariance matrix of $\mathbf{x}_t$ is defined by:

$$\mathbf{C} = \frac{1}{N}\sum_{t=1}^{N}(\mathbf{x}_t - \overline{\mathbf{x}}) \cdot (\mathbf{x}_t - \overline{\mathbf{x}})^T \tag{1}$$

Where $\overline{\mathbf{x}}$ is the sample mean. PCA solves the following eigenvalue problem of covariance matrix *C*:

$$\mathbf{C}\mathbf{v}_i = \lambda_i \mathbf{v}_i \tag{2}$$

Where λ_i (i =1, 2, ..., n) are the eigenvalues and $\mathbf{v}_i$ (i =1, 2, ..., n) are the corresponding eigenvectors.

To represent data records with low dimensional vectors, we only need to compute the m eigenvectors (called principal directions) corresponding to those m largest eigenvalues (m < n). It is well known that the variance of the projections of the input data onto the principal direction is greater than that of any other directions.

Let

$$\mathbf{\Phi} = \left[\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_m\right],\ \mathbf{\Lambda} = diag\left[\lambda_1, \lambda_2, \ldots, \lambda_m\right] \tag{3}$$

Then

$$\mathbf{C\Phi} = \mathbf{\Phi\Lambda} \tag{4}$$

The parameter v denote to the approximation precision of the m largest eigenvectors so that the following relation holds.

$$\frac{\sum_{i=1}^{m}\lambda_i}{\sum_{i=1}^{n}\lambda_i} \geq v \tag{5}$$

Based on (4) and (5) the number of eigenvectors can be selected and given a precision parameter v , the low-dimensional feature vector of a new input data $\mathbf{x}$ is determined by

$$\mathbf{x}_f = \mathbf{\Phi}^T \mathbf{x} \tag{6}$$

IV. SVMS FOR FAULT DETECTION AND DIAGNOSIS

A. *Binary SVM for Fault Dtection*

Support vector machine (SVM) is a classification technique based on statistical learning theory [11, 12]. It can be considered to find a linear separating hyper-plane in the feature space for a two class classification problem. The hyper-plane is defined by a number of support vectors, which are a subset of the training data available for both cases, and is used to define the boundary between the two classes.

Suppose we have a data set ($\mathbf{x}_1, y_1$), . . . , ($\mathbf{x}_k, y_k$), where, $\mathbf{x} \in R^m$ denotes the input vector and $y \in \{-1,+1\}$. The key ideas of the SVM is finding out a optimal hyper-plane as in Figure 2:

$$y = f(\mathbf{x}, \mathbf{w}) = \langle \mathbf{w} \cdot \mathbf{x} \rangle + b \quad (7)$$

where, $\mathbf{w} \in R^m$ and $b \in R$ are the weighting factors, $f : R^m \rightarrow \{-1, +1\}$, which can maximize the class margin not only reduces the empirical risk but also controls the generalization capacity. Using the soft margin concept, the problem is equivalent to solve the following optimization problem:

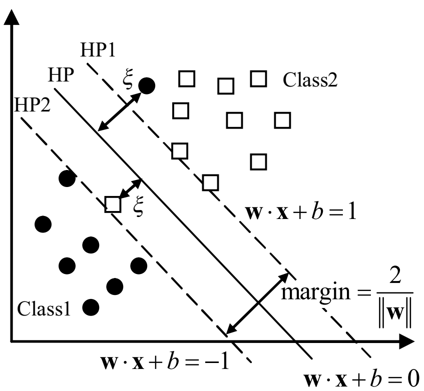

Figure 2. Optimal Hyper-Plane in SVM Classification

$$\min_{w,b,\xi} \ \frac{1}{2}\langle \mathbf{w} \cdot \mathbf{w} \rangle + C\sum_{i=1}^{m} \xi_i = \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i=1}^{m} \xi_i \quad (8)$$

$$\text{s.t.} \quad y_i(\langle \mathbf{w} \cdot \mathbf{x}_i \rangle + b) \geq 1 - \xi_i$$

$$\xi_i \geq 0$$

$$i = 1, 2, \ldots, k$$

where $C > 0$ is a penalty parameter, and ξ_i denotes positive slack variables. This represents a quadratic optimization problem that can be solved using Lagrange multipliers. Therefore, the hyper-plane decision function can be written as:

$$f(\mathbf{x}) = sign(\langle \mathbf{w} \cdot \mathbf{x} \rangle + b) = sign(\sum_{i=1}^{k} a_i y_i \langle \mathbf{x}_i \cdot \mathbf{x} \rangle + b) \quad (9)$$

In practice, the data is often not linearly separable. However, one can still implement a linear model by transform the data points via a non-linear mapping to another higher dimensional space (feature space) such that the data points will be linear separable. This mapping is done by a kernel function K.

The nonlinear decision function of SVM is given by the following function:

$$f(\mathbf{x}) = sign(\sum_{i=1}^{k} a_i y_i K(\mathbf{x}_i, \mathbf{x}) + b) \quad (10)$$

where $K(\mathbf{x}_i, \mathbf{x})$ is the kernel function.

B. Multi-Class SVM for Fault Diagnsis

SVM is designed for the classification of two classes. The fault diagnosis, however, has to deal with multi-type faults. To comply with these practical problems, two types of approaches have been introduced to construct multi-class SVM. One approach is realized by combining several binary SVMs, i.e., implementing multi-class classification based on binary classification. The other approach is implemented by direct multi-class classification. The first approach includes "One against One" [13], "One against All" [14] and DAG-SVM (Directed Acyclic Graph SVM) [15] methodologies.

In this paper, OAA is used as the main fault diagnosis approach. OAA strategy consists of constructing a SVM per class. This means that one binary support vector classifier is utilized to separate members of a specific class from members of other classes. Therefore, if there are N class fault mode, the OAA method must construct N+1 SVM models (1 nomal mode and N fault mode). As a result, the k-th SVM is trained for the k-th class, allocating positive labels for the relevant class members while other class members are indicated by negative label. These SVMs could be designed with a hierarchical architecture illustrated as Figure 3. In the first layer, the corresponding SVM detects the fault occurring efficiently. If people only want the system to implement fault detection, the task then is finished by here. Otherwise, the real-time data will be transferred to the second layer in abnormal case for the fault isolation. The second layer's SVM is designed to identify only one particular fault from the others. Consequently, same operation was implemented on the following layers, each layer will isolate one kind of fault from the left. Therefore, the diagnosis procedure keeps towards till the type of fault is determined.

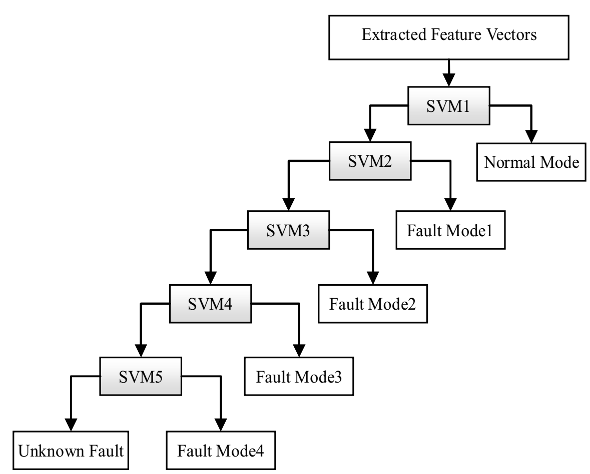

Figure 3. Fault Diagnosis based on Multi-Class SVM

V. EXPERIMENTS

We have implemented the approach described above and verified it using data from actual in-orbit satellite and simulated by Matlab/Simulink. In Matlab/Simulink environment, we simulate the control subsystem of an actual in-orbit satellite. The normal data is the telemetry data of actual in-orbit satellite. The fault data is obtained by fault injection. As shown in Table

II, there are 1 normal mode and 4 fault mode in our experiments. For each mode in Table II, we get 5000 points of data. So there are totally 25000 points of data. Each point of these data contains 12 parameters relating to the control subsystem of the satellite, which is shown in TABLE III.

TABLE II. FAULT MODE AND OUTPUT ID

ID	Fault Mode
1	normal
2	roll axis of earth sensor fault
3	roll axis of gyroscope fault
4	pitch axis of gyroscope fault
5	pitch axis of infrared sensor fault

TABLE III. PARAMETER CONTAINED IN TEST DATASET

Parameter	Descriptions
P_1	Output of roll axis of earth sensor
P_2	Output of pitch axis of earth sensor
P_3	Output of yaw axis of earth sensor
P_4	Output of roll axis of gyroscope
P_5	Output of pitch axis of gyroscope
P_6	Output of yaw axis of gyroscope
P_7	Output of roll axis of controller
P_8	Output of pitch axis of controller
P_9	Output of yaw axis of controller
P_{10}	Output of roll axis of momentum wheel
P_{11}	Output of pitch axis of momentum wheel
P_{12}	Output of yaw axis of momentum wheel

We verified our approach in two case:

Case 1: All 25000 points of data are as training data. After the training, we used the same data as test data to verify the performance of our approach.

Case 2: The 25000 points of data are divided into two sets by cross-extraction. The first set is as training data. The second set is as test data.

The performance analysis of our approach is shown in Table IV. From the table we can see that the classification accuracy of case 1 is high. This is because we use the same data as training data and test data. For Case 2, the classification accuracy is also satisfactory.

TABLE IV. PERFORMANCE ANALYSIS OF OUR APPROACH

	Case 1	Case 2
Classification accuracy	99.2%	97.4%
Training time (s)	36.2	19.5
Test time (s)	11.2	5.8

In our experiments, we also analyzed how to select appropriate number of principal components. As shown in Figure 4, when the number of principal components is less than 4, the classification accuracy can not meet the requirements of application. When the number of principal components is more than 8, the classification accuracy change slowly, but the training time has a relatively larger increasing. So the appropriate number of principal components is between 6 to 8.

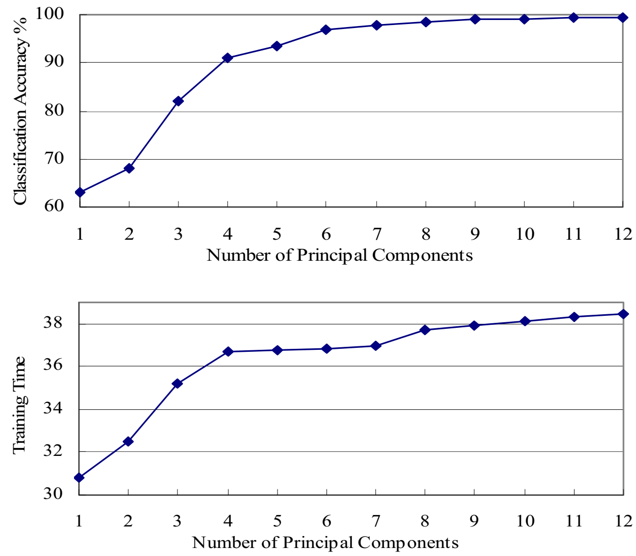

Figure 4. The Relationship between Number of Principal Components and Classification Accuracy and Training Time

Finally, we compared our approach with the neural network based classification method [16]. From table V we can see that for case 1, the classification accuracy of SVM and neural network are close. But for case 2, our SVM based approach is well than neural network. This is because that SVM is a pattern recognition approach based on small sample data and has better generalization than neural network. When the training data and test data is not the same, it has the better performance.

TABLE V. COMPARE BETWEEN SVM AND NEURAL NETWORK

		Case 1	Case 2
SVM	Classification accuracy	99.2%	97.4%
	Training time (s)	36.2	19.5
	Test time (s)	11.2	5.8
neural network	Classification accuracy	99.13%	92.6%
	Training time (s)	39.5	18.2
	Test time (s)	10.3	6.5

VI. CONCLUSION AND FUTURE WORK

This paper proposed a novel fault detection and diagnosis method for spacecraft based Principal Component Analysis (PCA) and Support Vector Machines (SVM). The method uses

PCA to extract feature vectors and can reduce the complexity and dimensionality of the input data. Binary SVM is used to detect fault and Multi-class SVM is used to identify fault type. The result shows that the method is efficient and practical for fault detection and diagnosis of spacecraft system.

There are some directions for future works. In this paper, we use PCA to extract features from input data. PCA is a linear method and is not suited for nonlinear systems. However, some components of the spacecraft system are nonlinear. In future work, we plan to use nonlinear PCA (for example, KPCA) for feature extraction.

ACKNOWLEDGMENT

This work was supported by the Postdoctoral Science Foundation of China (No. 201150M1539).

REFERENCES

[1] C. Chang, et al. “Satellite Diagnostic System: An Expert System for Intelsat Satellite Operations,” Proc. of IVth European Aerospace Conference (EAC), 1992: 321–327.

[2] A. Fijany, et al. “An Advanced Model-Based Diagnosis Engine,” Proc. of International Symposium on Artificial Intelligence, Robotics and Automation in Space (iSAIRAS), 2003.

[3] P. I. Robinson, et al. “Applying Model-Based Reasoning to the Fdir of the Command and Data Handling Subsystem of the International Space Station,” Proc. of International Symposium on Artificial Intelligence, Robotics and Automation in Space (iSAIRAS), 2003.

[4] L. David, Iverson. “Inductive System Health Monitoring,” Proc. of The 2004 International Conference on Artificial Intelligence, 2004.

[5] R. Fujimaki, T. Yairi, K. Machida. “An Approach to Spacecraft Anomaly Detection Problem Using Kernel Feature Space,” Proc. of 9th Pacific-Asia Conference on Knowledge Discovery and Data Mining. August 21-24, 2005, Chicago, Illinois, USA: 401-410.

[6] Quan Li, et al. “Anomaly Detection and Fault Diagnosis Technology of Spacecraft based on Telemetry-mining,” Proc. of 3rd International Symp. on Systems and Control in Aeronautics and Astronautics (ISSCAA’ 2010), June 8-10, 2010, Harbin, P.R.China: 233-236.

[7] T. Yairi, et al. “Telemetry-mining: A Machine Learning Approach to Anomaly Detection and Fault Diagnosis for Space Systems,” Proc. of the 2nd IEEE International Conference on Space Mission Challenges for Information Technology (SMC-IT 2006), July 17-20, 2006, Pasadena, California, USA.

[8] R. Fujimaki, T. Yairi, K. Machida. “An Anomaly Detection Method for Spacecraft using Relevance Vector Learning,” Proc. of 9th Pacific-Asia Conference on Knowledge Discovery and Data Mining. August 21-24, 2005, Chicago, Illinois, USA: 785-790.

[9] I. T. Jolliffe, “Principal Component Analysis,” 2nd Ed., Springer-Verlag, NY, 2002.

[10] A. Sophian, G. Tian, D. Taylor, J. Rudlin. “Feature Extraction Technique based on Pricipal Component Analysis for Pulsed Eddy Current NDT”. NDT&E international 36 (2003): 37-41.

[11] S. Poyhonen, Antero Arkkio, P. Jover, H. Hyotyniemi. “Coupling Pairwise Support Vector Machines for Fault Classification,” Control Engineering Practice, 2005, 13(6): 759-769.

[12] W.W. Yan, H. Shao. “Application of support vector machine nonlinear classifier to fault diagnoses,” Proc. of the fourth world congress intelligent control and automation. Shanghai, China; 2002: 2697-70.

[13] S. Knerr, L. Personnaz, G. Dreyfus. “Single-layer learning revisited: a stepwise procedure for building and training a neural network,” In: Fogelman J, editor. Neurocomputing: algorithms, architectures and applications. New York: Springer-Verlag; 1990.

[14] Hsu CW, Lin CJ. “A Comparison of methods for multiclass support vector machines,” IEEE Transactions on Neural Networks 2002;13(2):415-425.

[15] J.C. Platt, N. Cristianini, J.S. Taylor. “Large margin DAG’s for multiclass classification,” Advances in neural information processing systems, vol. 12. Cambridge, MA: MIT Press; 2000: 547-553.

[16] B. Samanta. “Gear fault detection using artificial neural networks and support vector machines with genetic algorithms”, Mechanical Systems and Signal Processing, v 18, n 3, pp. 625-644, May 2004.