Fault diagnosis for space utilisation

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Abstract: The space application task is to carry out various scientific experiments and applied research by using the ability of space experiment of spacecraft. In the past 20 years, >50 space application studies have been carried out in Chinese manned space flight application system, >500 units have been involved in the previous flight missions, and fruitful results have been achieved. The white paper ‘Chinese spaceflight in 2016’ pointed out that in the next 5 years, Chinese satellite system will enhance the level and basic ability to construct the satellite system. Chinese manned space station project is scheduled to be completed ∼2022 and it will plan to operate >10 years. The space station, based on the world-wide integrated information network, has a large number of payloads and will become a national space laboratory. Space activities are full of risks and challenges. On the basis of a great deal of literatures, the method of avoiding space risk in the field of spaceflight is discussed. Aiming at the fault diagnosis task for space utilisation, the intelligent methods of deep learning including deep belief network, convolutional neural network and generative adversarial network are discussed.

1 Introduction

The space application task is to carry out various scientific experiments and applied research by using the ability of space experiment of spacecraft. This task is very practical, and it is closely related to people’s life and environment. With the development of space technology, the space application research becomes more and more important in the space field. Space applications include the ability to accelerate getting information, high-speed transmission of information, to carry out various test in order to produce new products and new materials in space environment, to seek efficient method, to utilise energy and access to new energy. It is a long-term goal of space applications to acquire information efficiently, to develop new materials and acquire new energy from space.

Over the past 20 years, >50 space science and application studies have been carried out in Chinese manned space flight system, and >500 units have been involved in the previous flight test missions. In the multiple fields such as space communication and application of new technology, earth observation and the global environment monitoring, life science and biological technology, material science in space, microgravity fluid physics, space detection, astronomical observation, and space environmental detection, lots of experiments and research have been carried out, and fruitful results are achieved. It is the most extensive research activities in the field of space science and application in China.

The white paper [1] ‘Chinese spaceflight in 2016’ pointed out that in the next 5 years, Chinese satellite system will enhance the level and basic ability to construct the satellite system, including remote sensing, satellite communications, satellite navigation, and to construct the integrated information network in order to promote the development of space application industry.

Chinese manned space station project is scheduled to be completed ∼2022 and it plans to operate >10 years. The space station, based on the world-wide integrated information network, has a large number of payloads and will become a national space laboratory.

Space station laboratory can also be connected with the Internet. The Payload Operation and Application Center on ground can send command through the integration network of satellite and ground network in order to control the process of science and application task of space station.

Space activities are full of risks and challenges. Normally, we need to invest large amount of fund, and face the huge risks. There have been serious space accidents in American history, resulting in huge economic losses and casualties [2].

In January 1967, Apollo-1 failed during the routine launch test, resulting in the death of three astronauts. The accident forced NASA to suspend the space race with the Soviet Union and to improve the design of safety.

In January 1986, the Challenger space shuttle disintegrated in 73 s after launch, seven crew members died. After 5 months, the cause of the accident was found. The accident of space shuttle was because of the fault of two ‘O’ rings during the launch.

Just a few months later after the accident of Challenger, the most expensive space disaster occurred in the history of the United States. On 18 April 1986, NASA planned to use the Titan 34D-9 KH9-20 rocket to bring photographic reconnaissance satellites into space, which might be worth to billions of dollars. Only 8 s after the launch, it exploded.

On 1 February 2003, Columbia entered the atmosphere at the location between Texas and Louisiana, and it was going to complete its 28th task. At this time, the accident occurred. The accident also caused seven astronauts lost their life. The space shuttle was suspended for 2 years thereafter. Investigators drew a conclusion that during the launch of the space shuttle, the insulation of the fuel tank fell off which caused the left-wing damaged, resulting in hot air went through the space shuttle, and eventually it disintegrated.

The most serious space accident in Chinese history occurred on 15 February 1996. Chinese newly developed Long March III B rocket launched with international 708 communication satellite. However, 2 s after the launch of the rocket, it began to tilt, 22 s later it was completely out of control, and crashed on the hillside 1.85 km away from the launch tower. Then violent explosion occurred, both satellite and rocket were ruined. In this accident, 6 people died and 57 people was injured. The cause of the accident was subsequently identified as the quality of the welding of the...
The spacecraft is expensive and the system is made up of multiple subsystems. For our space scientific application task, from the view of application, we can concentrate on the sub-system of space communication and payload by the support of spacecraft platform.

Public statistics showed that in China there are 25 satellites on orbit and 97 times failures in 2006. Public statistics in 2011 showed that according to the fault location onboard, the percentage of the payload sub-system failure events was 24.2%. According to the type of satellite, the percentage of communication satellite failure events was 40.9% [3]. As can be seen from the statistics, the space application activities has high proportion in the space incident. To carry out the diagnosis research in space application task can ensure the safety and reliability for the long term operation of task.

The system of applications become more and more complicated. It is impossible to have sufficient test on ground because of the complex environment of space, such as sunspot radiation, ionospheric disturbances, anomaly magnetic field environment in south Atlantic. In addition, space environment is open and distributed environment. The spacecraft in space communication and payload by the support of spacecraft platform. In recent years, business data transmitted by satellites is increasing very fast and satellites become the mature object of network attack. According to Bloomberg, a draft of the annual report of the US and China Economic and Security Review Commission pointed that from October 2007 to July 2008, the Landsat-7 of United States was disturbed up to 12 min. In June 2008, hackers also interfered with Terra AM-1, an earth observation satellite of NASA, and the interference lasted 2 min. In October 2008, the satellite's control password was once hacked, and the satellite was disturbed again for >10 min, resulting in system abnormalities. As for network hackers, they can attack the hardware itself in space, resulting in completely damage to satellite nodes. They can also attack the control system satellite and control the tasks of satellite application tasks. This can lead to system fault, resulting in the failure of the mission.

There are great differences between different systems and operation mode, so the fault diagnosis methods in different fields are not the same. Different fault diagnosis methods have their own characteristics. A fault diagnosis method that is often applied to a particular field or system maybe is not applicable to another field or another system. Although in the industrial process, fault diagnosis technology has more mature application. However, in the field of space application tasks, research is relatively few, and achievements are not mature enough. Therefore, it is necessary to develop various fault diagnosis techniques for space applications.

2 Development of fault diagnosis in aerospace

Fault diagnosis technology originated in the United States. In 1960s, when NASA began to implement the Appollo project, they met a series of intractable fault of equipment. The mechanical failures prevention group of the US Naval Research Department started to research on special fault diagnosis technology. As an important means to improve system reliability and security, fault diagnosis technology has become a key technology in the plan of space developing [4, 5]. In 1960s, only simple status monitoring was performed. In 1970s, fault diagnosis was based on Algorithm. In 1980s, the knowledge-based fault diagnosis become popular. At present, the fault diagnosis technology is in the stage of intelligent diagnosis, which is characterised by the application of artificial intelligence technology [including machine learning, expert systems, fuzzy logic (FL) etc.] to the field of fault diagnosis. In recent years, with the development of artificial intelligence technology, intelligent fault diagnosis has been paid more and more attention in the field of fault diagnosis and has been more prominent in large complex non-linear system. For the problems of uncertainty and complexity that the traditional fault diagnosis methods are not easy to solve, intelligent diagnosis technology shows great advantages. There are several basic direction based on intelligent diagnosis such as expert system based on rules and models, FL, neural network (NN).

NASA has developed a series of fault diagnosis tools, mainly based on model and reasoning diagnosis. It contains Livestonel, Livestonel2, HYDE (hybrid dynamic inductive engine and so on). Livestonel was part of the remote intelligent control experiment and was applied to deep space-1 [6] in 1999. The Livestone diagnostic system mainly consisted of two parts: general inference engine and domain-specific modelling. When installed on different aircraft, the general inference engine need not change. Livestone used qualitative expression and propositional logic to model the target system. The target system can be physical system, such as aircraft hardware, or a logical system, such as aircraft software. The Livestone diagnostic system utilised models to estimate the state of target system. Comparing with the measured value, if the difference was found then a conflict would be generated. It is necessary to look for the component pattern or possible semantic translation that matched the measured value of conflict. The model-based diagnosis and recovery team created a second version [7] based on Livestonel, that was Livestone2 (L2). L2 was applied to EQ-1 (Earth observation 1) on 2004 [8].

HYDE [9] is model-based fault diagnosis reasoning engine developed by Ames Research Center of NASA. It uses the difference between the hybrid system model prediction and sensor observation value to diagnose system. HYDE is the mixed reasoning engine that uses the relational model for reasoning and determines the possible reasons. This model captures dependency relationship between multiple model entities, including the relationship between components, operating mode, and component variables.

NASA has built an advanced diagnostic system called ADS for the space station flight system (ISS). The ADS project is a modelling and reasoning tool for the fault detection, isolation and recovery of international space station. Providing anomaly solutions of aircraft, mission management, and critical decision support, the ADS system establishes a computational model for each subsystem of the space station. The core of ADS system is the integration, demonstration and expansion of ISS domain expert knowledge including avionics software engineers, systems engineers and flight control engineers. ADS developed the space station diagnosis model to solve the problem of several subsystems, including the power supply system based on physical modelling, and thermal control system, electronic system, communication system, instruction system and logic interaction model etc. The instruction and data processing system of ADS consisted 30 taskers which formed three levels of networks. It is responsible for the instruction and data acquisition of the space station (ISS), including propulsion, electronics, life systems, and navigation systems.

In addition, NASA has also established the international space station diagnostic data service system DDS, which used data mining technology to detect early warning of faults. Although advanced diagnostic methods were proposed, NASA proposed the concept of health management [10–12]. According to the characteristics of weak faults signals, the possible future failures will be predicted, and the maintenance according to the health state will be carried out according to the situation, so as to avoid the occurrence of huge losses in time.

3 Analysis of fault diagnosis for space application task

Comparatively, we have relatively few studies for fault management of spacecraft on orbit of space application tasks. Under the background of space station and integrated SIN in our country, it is necessary to carry out more research on space application task and fault diagnosis. The success of space applications task requires the support of all aspects. The ground transportation control centre transmits the application task commands through the spatial communication
network. The communication system on the spacecraft receives the commands and sends it to the integrated information processing system onboard. The integrated information processing system distributes the command to each payload of application task. Payload works according to the commands, and the application data produced is packed by the comprehensive information processing system. The application data is transmitted to the ground command centre through the SIN. At the same time, the comprehensive information processing system will pack satellite telemetry data and send them back to the ground command centre also by SIN.

As far as the application task itself is concerned, its normal operation means two aspects. (i) the application of spacecraft or satellite node is normal and (ii) the SINs work normally.

Spacecraft and communication satellites are expensive. The design is never too elaborate, but the mission of space system is so complex and huge, and no matter how hard people try, it is so difficult to ensure that there is no fault at all.

There are several kinds of methods to define the types of fault. For example, according to the scope of the fault, it can be divided into system hardware failure and system software failure. According to the intention of the fault, it can be divided into malicious fault and non-malicious fault; because SINs play an important role in space exploration, electronic reconnaissance and global information acquisition, it is easy to attract space attack and result in disaster. The unconventional attack, including cyber attacks and even physical destruction, can lead to malicious fault. The defects of system design, improper operation of personnel, which result in fault can be called non-malicious fault.

The main reasons for the fault of space application tasks include payload failure and SIN failure. Therefore, in this paper, we mainly aim at the fault scenarios including: (i) SIN failure and (ii) application task failure of payloads.

3.1 Fault detection of SIN

With the development of modern science and technology, the reliability of satellite nodes is more and more higher, but in the complex outer space, the environment is bad, and the satellite nodes are prone to various faults. At the same time, the SINs occupy an important position in space exploration, global communications, military applications and other fields, it is vulnerable to various attacks and even be destroyed.

The fault of the SINs generally refer to the complete damage, partial function failure of a satellite node or the satellite node cannot establish intersatellite links in some directions.

The difficulty of fault detection for SIN is that the topological structure of space satellite network changes rapidly, and it is difficult to obtain the feature information of satellite nodes in real time. At present, the protocol of SIN is not perfect. Space malicious attack is difficult to avoid, and the attack form is difficult to predict. Therefore, the fault model of SIN is difficult to predict ahead of time.

The SIN is shown in Fig. 1, consisting of GEO, MEO, and LEO. The spacecraft, space station and the aircraft constitute access network that communicates with ground stations and ground users.

While the SIN is still not perfect, the research on fault detection of SIN is based on the diagnosis technology of ground network. The fault diagnosis techniques used on the ground include alarm correlation, NN, and system level fault diagnosis method.

Comparatively, the fault diagnosis method based on system level is more suitable for the diagnosis of SIN. System level diagnosis theory [13] was first proposed by Preparata et al. in 1967. It is originally used to analyse complex failures of multiprocessor system, and it corresponded to circuit-level diagnosis. The idea is to test each other according to certain strategies. The fault state of processor node is analysed according to the test structure. Although it is a fault diagnosis method for multiprocessors, it is also suitable for the fault diagnosis of SIN. For the SIN, the biggest problem is that the diagnostic model is a dynamic model. Satellite or spacecraft orbits have different relative speeds, which results in the dynamic change of topological structure of SIN. This results in the dynamic entry or exit the topology structure of the satellite or spacecraft, which bring difficulties for modelling system-level fault diagnosis. The anomaly detection of SIN can refer to the idea of controlling the hce network topology [14] and establish the cluster management mechanism [15, 16]. Here we can see how to model the anomaly detection framework of dynamic system of SIN and the selection of anomaly detection algorithm.

In this paper, the backbone network consists of high orbit, medium orbit and low earth orbit. How to identify the dynamic system and the static system according to the time slice is the main question. The idea of clustering [17] is dividing the satellites into several clusters, and the satellites in the same cluster can entry and exit the topology network in the same time slice. An anomaly detection algorithm for malicious and non-malicious faults in SINs is studied. The schematic diagram of the STK test simulation is shown in Fig. 2.

3.2 Machine learning techniques of fault diagnosis for payloads

Besides the fault of SIN, the failure of payload nodes may also lead to the failure of application task. The space application task system is so complex and large, and it is very difficult to diagnose the fault of payload nodes.

There are many types of faults: the system consists of hundreds of system components. The operation mechanisms of different subsystems are not the same, which result in many kinds of faults. There are influences between the parameters, and it is extremely difficult to locate and isolate the faults of payloads.
There are many types of parameters: thousands of parameters types, including telemetry parameters, engineering parameters and scientific experimental parameters.

Setting up abnormal data modelling is difficult: in order to maintain the robustness and high reliability of system operation, there are always multiple components redundancy as back-up. Most of the downlink data are normal. The amount of abnormal data available for fault diagnosis is rather small.

We have studied the current popular artificial intelligence and machine learning fault diagnosis techniques. Including the rule-based reasoning (RBR), case-based reasoning (CBR), NN, FL, genetic algorithm (GA), rough set, Bayesian network, multi agents, support vector machine, reinforcement learning (RL), and deep learning (DL). In all the abovementioned fields, DL is a promising direction.

4 DL for fault diagnosis

DL is a new field in machine learning, and it is currently the mainstream learning method. DL was proposed by Hinton [18] in 2006, which aimed to build simulation of the human brain. DL has not matured in the field of fault diagnosis, but it has also made some progress.

Tran et al. adopted the deep belief network (DBN) [19], using multilayer structure Restricted Boltzmann Machine (RBM) and the layer-rise greedy algorithm, to diagnose and classify the fault of round-trip air compression valve and achieve good effect. Tamilselvan et al. used DBN to establish the health status classification model [20]. Chen et al. establish a gear fault diagnosis network [21] by using multilayer NNs of DL model. Lin et al. adopted a DBN to establish engine component fault model, which proved that the diagnosis accuracy is better than that of BP NN and support vector machine (SVM) [22].

Xie [23] utilised DBN to train the train vibration signal in the process of walking. Zeng extracted time-frequency images of vibration signals of vehicle transmission failures [24] and used the DL algorithm of convolutional neural network (CNN) to classify the faults of the automobile transmission. Lei [25] utilised the CNN and DBN model to establish power diagram recognition model of the oil well and designed a complete fault diagnosis scheme of oil well system.

DL is one of the best agnostic algorithms. Before DL becomes the first choice of machine learning algorithms, the complexity of DL and the demand for large amounts of data remain to be resolved. DL methods can be divided into supervised learning and unsupervised learning. Among them, supervised learning model includes Multilayer Perception [27–30] and CNNs [31–34]. Unsupervised learning models include DBNs [35], Auto Encoder [36], Denoising Encoder [37], Sparse Encoder [38] and the hot topic of generative adversarial network (GAN) in recent years [39].

A DBN stacked by RBM is shown in Fig. 3. The output of the lower RBM is used as the input of upper layer, and the supervised BP NN can be used in the last layer for training. We can choose other classification algorithms as needed. The RBM structure is shown in Fig. 3. It consists of a visual layer V and an implicit layer H. Visual layer is data input layer. All the nerve cells in different layers connect each other, but they did not connect in the same layer, so it is called RBM.

Let \(v = (v_1, v_2, \ldots, v_n)\), \(h = (h_1, h_2, \ldots, h_n)\). The weight coefficient between the implicit layer and the visible layer is \(W\). The energy function is as follows:

\[
E(v, h | \theta) = -v^T Wh - a^T v - b^T h
\]

\[
= -\sum_{i=1}^{n} \sum_{j=1}^{m} v_i W_{ij} h_j - \sum_{i=1}^{n} a_i v_i - \sum_{j=1}^{m} b_j h_j,
\]

\(a_i\) denotes the bias of the i\(^{th}\) unit, \(b_j\) denotes the bias of the j\(^{th}\) unit, and \(W_{ij}\) denotes the weight coefficient between the i\(^{th}\) visual unit and the j\(^{th}\) implicit unit.

According to the joint distribution between the visual unit \(v\) and the hidden unit \(h\), and the conditional independence of each hidden layer node, given visual layer node state, the probability that the hidden layer node \(j\) be activated is as follows:

\[
P(h_j = 1 | v) = \sigma \left( \theta_j + \sum_{i=1}^{n} v_i W_{ij} \right),
\]

\(\sigma(x)\) is active function and it is Sigmoid function. At the same time, the probably of the i\(^{th}\) visual unit be activated is

\[
P(v_i = 1 | h) = \sigma \left( \theta_i + \sum_{j=1}^{m} W_{ij} h_j \right).
\]

The traditional RBM learning method is maximum likelihood method, using Markov chain and Monte Carlo method to learn parameters, but its convergence speed is not stable and training time is long. Hinton proposed a method of contrast divergence for RBM training, which not only guaranteed the accuracy but also improved the speed of operation greatly.

During training, DBN adopts layer-rise greedy training method, and the RBM error spreads up layer by layer, which cannot be corrected by itself. The BP NN of the top layer can reduce the error of RBM by means of error back propagation.

The difficulty of DBN lies in its training process, including the process of unsupervised training of RBM and the supervised training process of the whole DBN. The weight coefficient needs to
be adjusted continuously during training, which has great influence on the performance of the whole system. Besides DBN, CNNs are also used in the field of computer vision and speech recognition. Relevant results have been adopted by Google and Microsoft. DL has been studied in the field of information retrieval, natural language processing. In the field of fault diagnosis, researchers have tried to use this technology to carry out fault detection and classification. Janssens et al. used CNN for the fault detection [31] of rotating machines. They used CNN to automatically acquire diagnostic features, which is much better than manual fault feature extraction. Lee et al. adopted CNN for fault classification and diagnosis in semiconductor manufacturing process [32]. Sun et al. used CNN for fault detection of freight train [33]. Guo et al. adopted a graded CNN method for fault diagnosis of bearing [34].

A typical CNN is shown in Fig. 4. It contains convolutional layers, pooling layers, and a full connectivity layer. The convolutional layers scan the images and get result by convolutional cores. Pooling layer is used to reduce the connection between the convolutional layers. It can be seen as data aggregation, by using the method of average or maximum pooling to obtain results. There are many different styles of pooling, such as random pooling and LP pooling. The full connection layer stacks up the results of the convolutional layer and the pooling layer as input to the classifier of last layer.

The CNN can be improved in the aspects of layer design, the selection of activation function and loss function, regularisation and optimisation methods. Among them, we need to have a great deal of technology and experience on choosing the learning rate, the size of the convolution kernal and the number of layers. Still a lot of improvements needed for the structure design of CNN.

GAN was proposed by Goodfellow in 2014, and GAN is one of the most popular directions of machine learning research in recent years. The idea is minimax game. A generator is used to estimate the potential distribution of real data samples and to generate false data simulating real samples based on the distribution. The discriminator differentiate the false data samples generated by the generator and the real data. The optimisation goal of GAN is to find the Nash equilibrium between generator and discriminator, so that the sample distribution estimated by generator can be close to the true sample distribution at maximum extent. The design framework of GAN is quite flexible, and various types of loss functions can be integrated into the GAN model.

In order to solve the problems of small training samples and difficult to obtain fault samples in space application tasks, GAN can be used to generate fault samples for data training.

5 Conclusion
In this paper, the fault diagnosis characteristics of space applications are discussed. The typical application scenarios are SINs and payloads. On the basis of a large number of literatures, the previous fault diagnosis technology are summarised. Including the typical technology used by NASA, such as Livestone, HYDE, ADS, and DDS. In the intelligent diagnosis technology [40] of RBR, CBR, NN, FL, GA, rough set, Bayesian network, multi agents, SVM, RL, and DL, we focus on DL. It is the promising technology in machine learning field and it can also be extended to the field of fault diagnosis. We are going to adopt the DL for fault diagnosis of space utilisation in China.

6 Acknowledgements
I would like to thank my colleagues for their selfless help. I also want to thank ISTAI to give me this chance to share my idea.
7 References

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