Spacecraft in Orbit Fault Prediction Based on Deep Machine Learning

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Abstract. Spacecraft is playing a more and more important role in military reconnaissance, environmental disaster reduction and other fields in China. The research on fault prediction technology based on deep machine learning will realize the transformation from traditional post-fault processing to prior system maintenance. In this paper, combined with different in-orbit fault modes of spacecraft and the complexity of the fault modes, multi-kind of prediction methods for single parameter and multi-parameter faults are proposed. Based on this, the in-orbit fault prediction system is constructed, and for the results of a typical in-orbit case show that the prediction results are good. In the future, it can be considered to further expand the fault prediction methods of the system, such as modeling the in-orbit data directly by the graph neural network algorithm, so as to further improve the prediction accuracy.

1. Introduction
Spacecraft is a landmark product of the progress of human science and technology. With the continuous development of science and technology, the structure of spacecraft has become complex and changeable, and its status is also increasing. However, the following problem is that the probability of fault occurrence and the complexity of diagnosis technology also increase. From the process and mechanism of fault generation, before the fault occurs, it is often accompanied by some characteristic signals or data trend to predict the occurrence of the fault. If these data information can be collected and judged timely and effectively, the effect of fault prediction can be achieved. According to the current or historical status of the system, the possible faults can be identified predictably to avoid the occurrence of unexpected serious accidents.

In the fault prediction of the in-orbit spacecraft, NASA added fault prediction technology to spacecraft equipment in 1960s, but its prediction technology is based on sensor technology, and artificial intelligence method is gradually introduced in the later stage. In the 1980s, the United States mainly carried out early fault diagnosis and prediction technology for major projects such as Hubble telescope, Gemini constellation and Apollo lunar exploration project [2]. Russian vasilchenko and others have developed a fault detection and prediction system for buran space shuttle; Germany's hotop [3] and other people have developed fault diagnosis expert system for D2 space laboratory. The European Space Agency completed the health testing system for launch vehicles by 2007. Ikawa and others in Japan have developed expert diagnosis system and health detection system for spacecraft. The grey prediction model and expert system proposed by Huang Wenhui, Jiang Xingwei and others [4] of Harbin Institute of Technology made China's aerospace engineering diagnosis technology move to another stage. With the development of artificial intelligence technology, fault prediction technology has made progress, but there are some shortcomings more or less. The error of traditional grey prediction model needs to be further improved, such as the optimal combination of fault prediction schemes, the determination of...
attribute weights in case diagnosis, and the similarity calculation when satellite data is missing. However, the established prediction system is only effective for a certain subsystem / single machine, or divorced from the actual needs of the project. And most of the existing fault prediction rely on human experience knowledge. For the incompleteness of limited fault samples and empirical knowledge, fault prediction is still difficult to have high accuracy and strong comprehensiveness, and has not achieved ideal effect in practical application. With the in-depth development of artificial intelligence, these limitations become more and more prominent. Therefore, it is still a hot issue whether a set of artificial intelligence system with fault prediction can be proposed based on data.

In this paper, based on the massive data of spacecraft in orbit telemetry data, test data, fault information and other massive data, this paper studies the machine deep learning theory under the big data environment, combines the fault mode, the design experience knowledge with intelligent self-learning, classifies the single parameter and multi parameter fault prediction methods, and proposes the machine deep learning based on this. It is of great significance to improve the ability of spacecraft fault prediction.

2. Analysis and classification of typical failure modes of spacecraft

2.1. Fault case analysis of spacecraft in orbit
Based on the actual fault case of spacecraft in orbit, the fault distribution and situation of spacecraft in orbit are analyzed, including fault name, equipment, effect, cause, etc. In general, the fault type can be classified into accumulation, wear, decline, burst, degradation, consumption, etc.

2.2. Formalization of typical failure modes of spacecraft in orbit
The typical in orbit fault cases of the whole satellite, subsystem and single product are selected as the research objects. The symptoms and the process of the in orbit faults are analyzed. The correlation between the input and output parameters of the fault is studied. The attribute items of the fault mode are summarized, and the formal representation of the fault mode is given by a series of attribute items, including fault mode name, subsystem, severity level, treatment measures, a set of characteristic parameters, fault process, change of characteristic parameters, etc.

| fault mode name | fault agreement level | fault severity level | fault treatment measures | a set of characteristic parameters | fault process | process correlation analysis |
|-----------------|-----------------------|----------------------|--------------------------|----------------------------------|---------------|-----------------------------|
| Bus short circuit | power subsystem | catastrophic | disconnect ion of bus parallel switch | bus voltage, bus current | ...... | input parameter | output parameter | change process | ...... | ...... | ...... | ...... |

2.3. Classification and analysis of typical failure modes of spacecraft in orbit
For the typical in orbit faults, two categories can be classified for prediction:
- Single parameter fault. For some faults whose mechanism is simple and whose input parameters only involve single parameter, the fault can be predicted by parameter prediction method.
- Multi parameter fault. For some complex faults, the input parameters of the fault may involve multiple subsystems and parameters. It is necessary to identify the main characteristic parameters of the fault mode from a large number of telemetry parameters, and use the training of in orbit telemetry data to obtain the fault model of the input and output parameters of the fault for multi parameter fault prediction.

3. Single parameter fault prediction based on machine deep learning
Based on the analysis of typical in orbit faults, the key parameters related to the fault are clear and the correlation of other parameters is low, so the single parameter fault prediction can be carried out only
based on this parameter, without considering the influence of other parameters. The methods of single parameter fault prediction include periodic parameter prediction method, asymmetric interval prediction method and theme pattern mining based prediction method. The three methods complement each other and carry out auxiliary verification at the same time.

- The prediction method of periodic parameters is suitable for the parameters with obvious periodic change law.
- The asymmetric interval prediction method is suitable for the parameters which have great influence on the future parameter changes due to the change of parameters in the previous time or a period of time.
- The prediction method based on motif pattern mining is suitable for continuous data, data without mutation and few change rules, but it is not suitable for the data with more or less obvious parameter change rules, so the asymmetric interval prediction method can only be used. The following three prediction methods based on telemetry data are introduced in detail.

3.1. Periodic parameter prediction method based on time series decomposition

With the seasonal change, illumination and other factors, the satellite telemetry parameters will change according to the fixed period, some telemetry parameters are annual cycle changes, for example, the variation of the total output current of the North solar array in a year is a saddle curve, the lowest point is in summer solstice, the second low point is in winter solstice, the highest point is in spring equinox, and the second high point is in autumn equinox; some telemetry parameters are daily variation, such as some temperature telemetry parameters. Considering the characteristics of periodic parameters and based on the idea of "divide and conquer", the scheme of "decomposition, prediction and consolidation" is adopted. The time series YT is decomposed into several orthogonal factors, including trend factor TT, periodic factor PT and random factor RT. The trend factor (TT) represents a kind of continuous upward or downward steady change of complex system in a long time. This trend can be linear or nonlinear. The periodic factor (PT) is repeated changes that occur at intervals. The random factor (RT) changes are uncertain factors caused by accidental events.

3.2. Prediction of complex parameters based on asymmetric interval

The asymmetric interval prediction method uses extreme learning machine for data training, and then uses differential evolution algorithm to optimize the parameters of the extreme learning machine. When the prediction results of the learning machine are partitioned, the proportion coefficient of the proportion coefficient method is optimized. Finally, the interval prediction index measurement method is used to evaluate the prediction interval. If the evaluation results are satisfied, the end of the prediction is completed. If not, the prediction interval should be determined again.

3.3. Time series mining prediction method based on theme pattern

The goal of motif pattern extraction is to find two or more similar subsequences in temporal data. Most of the existing algorithms for motif pattern extraction use sliding window to segment the original sequence into a set, and then calculate the theme pattern, which results in the neglect of the subject sequence with small matching number, and it is difficult to effectively solve the trivial matching problem. In addition, the spacecraft telemetry data has periodicity, and the rigid segmentation method of sliding window will lead to some subsequences containing different periods of data, but these subsequences can’t reflect the working mode of spacecraft, which leads to the distortion of the main mode. In order to solve these problems, a penalty based global average sequential thematic pattern extraction method is proposed, and a prediction method based on thematic pattern mining is proposed.
4. Research on multi parameter correlation fault prediction method for spacecraft

4.1. Multi parameter prediction method based on least squares support vector regression

On the basis of principal component analysis, the appropriate embedding dimension and delay time are selected to reconstruct the phase space of multi parameter chaotic time series. With the same time delay, the embedding dimension of each parameter time series is calculated. The input samples and output samples of each parameter are determined respectively, and the embedded delay vector combination of each parameter is taken as the input sample of the prediction model, and the output sample combination of each parameter is taken as the output sample of the prediction model. The prediction model based on least squares support vector regression (LS-SVR) is established, and the parameters of the model are optimized. The trained optimal model is used to make one-step prediction. The multi-step prediction can be realized by enriching the one-step prediction value into the original sequence, removing the oldest data.

4.2. Multi parameter association mining and prediction method based on closed pattern

Closed pattern mining is an improvement of traditional pattern mining. It only mines the maximum frequent sequence with the same support degree, and compresses the result set without loss of information. The task of closed pattern mining is to find all closed sequences which satisfy the minimum support threshold in a given sequence set. Firstly, all frequent 1-sequences are found in the database, and each frequent sequence is extended by depth first sequence to generate candidate closed frequent sequence set, and then closed sequence set is generated by excluding unclosed sequence. When extending the depth first sequence, we need to judge whether the current sequence needs to be expanded, which involves heuristic pruning. If it can be extended, the extended sequence with support greater than the threshold is generated, and then recursively called.

5. System structure

Spacecraft in orbit fault prediction is one of the important parts of the ground management system. The system based on machine deep learning mainly realizes the extraction of current state characteristics of various functional components on the satellite and the prediction of future fault trend. The system consists of data receiving module, data preprocessing module, feature extraction module, prediction model module, prediction processing module and storage module. The system structure is shown in Figure 1.
• Data receiving module. The data receiving module receives telemetry data, including telemetry data and ground test data at each historical time point or time period of each satellite in orbit, and forwards them to the data preprocessing module.

• Data preprocessing module. The data preprocessing module checks the validity of the data, filters the abnormal or invalid data due to channel noise and other reasons, and forwards the extracted effective data to the feature extraction module.

• Feature extraction module. According to the functional and structural characteristics of the system, the parameters that can represent the health / fault status (or sensitive to system fault) of the system and its subsystems are stored. According to the classification principle of telemetry data, the key telemetry parameters are classified, and the classified data are sent to the prediction model module.

• Prediction model module. The prediction model module contains various prediction algorithms, and selects different fault prediction models or algorithms for different types of key characteristic parameters. By continuously learning the predicted object, new prediction model or algorithm can be injected at any time to improve the prediction processing ability. According to the characteristics of telemetry data, the prediction model module uses different machine learning methods to obtain the fault prediction model.

• Prediction processing module. On the basis of the data information of a series of characteristic parameters, the key telemetry parameters are predicted by the selected prediction model, the prediction results are given, the prediction curve is drawn, and the prediction error is calculated and analyzed.

• Prediction and decision module. According to the error analysis, the prediction results are evaluated and judged, and the state change trend of relevant equipment in a period of time in the future is given, and reasonable suggestions are put forward.

• Storage module. The storage module is used to store the predicted output results and prediction models (algorithms). The predicted output results include: prediction curve of key characteristic parameters, prediction results of key feature state, prediction error analysis, etc.

6. Experimental analysis
For the periodic parameters, the experimental results are analyzed. The prediction method based on time series is adopted. Firstly, the center moving average method is used to extract the trend term TT in the whole sequence, and then the trend term is eliminated. According to the period size, the value under the same frequency in each cycle is averaged to obtain the periodic term PT. Obviously, the random term can be obtained. The trend term TT obtained by the decomposition of telemetry parameters reflects the long-term and potential changes of spacecraft. It can be used for trend analysis and has the characteristics of gentle monotony. It can be predicted by general models, such as residual correction GM model. The random fluctuation sequence belongs to stationary sequence, which can be predicted by ARMA model with better order.

For period prediction of power supply (PW), the data after noise reduction sequence (NRS) is obtained. The period of PW is calculated by wavelet variance of different frequencies, and then time series decomposition is performed to obtain the trend term TT, periodic term PT and random term RT, as shown in Fig. 2. For the trend term, GM model is selected for prediction, ARMA (1, 2) is used for random term prediction, and the final prediction value is obtained by adding periodic term with additive model. Compared with other methods, the prediction error and comparison are shown in table 2.
Figure 2. Decomposition results of time series addition model

Table 2. Prediction error comparison of different methods

| Method                  | MRPE (E-05) | ARIMA (2,1,1) | Residual correction GM(1,1) | Seasonal linearity ARMA | Seasonal index ARMA | wavelet Neural network | SVM  |
|-------------------------|-------------|---------------|----------------------------|-------------------------|---------------------|------------------------|------|
| Proposed Method         | 3.37        | 9.58          | 47.20                      | 55.21                   | 407.40              | 15.70                  | 14.39|
| ARIMA (2,1,1)           | 0.14        | 4.82          | 19.35                      | 21.20                   | 161.13              | 0.58                   | 0.49 |
| Residual correction GM(1,1) | 19.12        | 93.86         | 109.76                     | 781.14                  | 31.41               | 29.77                  |      |
| Seasonal linearity ARMA |             |               |                            |                         |                     |                        |      |
| Seasonal index ARMA     |             |               |                            |                         |                     |                        |      |
| wavelet Neural network  |             |               |                            |                         |                     |                        |      |
| SVM                     |             |               |                            |                         |                     |                        |      |

Note: MRPE is the average relative percentage error, RMSE is the root mean square error, and NMSE is the standard mean square error.

It can be seen from table 2 that the proposed decomposition and combination prediction method is significantly better than other methods, especially the wavelet neural network and SVM with strong nonlinear fitting ability. Although the above experiments are only preliminary verification, we speculate that the scheme is feasible for the analysis and prediction of periodic parameters.

7. Conclusions

In this paper, the prediction methods of single parameter and multi parameter faults are given based on the different in orbit fault modes of spacecraft. Based on this, the in orbit fault prediction system is constructed, and for the periodic parameters in orbit data, it is verified that the prediction results are good. In the future, it can be considered to directly model and analyze the in orbit graphic data. For example, by using the graph neural network algorithm, the input, processing and output of the data are gradually changed from coding to directly processing the map data, and then used in telemetry data prediction to avoid errors caused by data conversion and coding, and further improve the prediction accuracy.

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