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Satellite Cluster Fault Diagnosis and Detection Analysis Based on Neural Network

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Abstract: Due to the frequent occurrence of spacecraft failures and accidents, it will cause personal injury and economic loss, and will have a huge impact on the aerospace industry. Therefore, it is necessary to enrich the research on satellite constellation fault diagnosis and detection technology. In order to solve the shortcomings of existing research on fault diagnosis and detection of satellite swarms, this paper discusses the neural network fault diagnosis technology, satellite swarm fault diagnosis method and the functional equation of satellite swarm execution fault types. The fault samples and parameter settings of the group fault diagnosis detection application are briefly introduced. In addition, the work design and calculation process of satellite swarm fault diagnosis and detection relying on neural network are discussed. Finally, the application of neural network in satellite swarm fault diagnosis and detection is subjected to experimental comparison and analysis of the correct rate of fault diagnosis. The experimental data show that the algorithm proposed in this paper and Although the correct rate of fault diagnosis of the other two types shows a downward trend after the failure rate of 10%, the correct rate of the neural network algorithm proposed in this paper is significantly better than the other two algorithms, and the algorithm in this paper is in 50% to 200% of the satellites. In the group failure rate, the correct rate of diagnosis is stable at about 96%, while the correct rate of the other two algorithms is gradually lower than 90%. Therefore, it is verified that the satellite group fault diagnosis and detection relying on neural network has high use value.

1. Introduction

Due to the influence of the current spacecraft design level and economic cost constraints, the safety of each satellite system and the satellite group will be reduced, resulting in satellite group failure. Effective satellite group failure technology can monitor the operation status of the satellite group in real time.

Nowadays, more and more scholars pay attention to the research of various technologies and platforms in the fault diagnosis and detection of satellite constellations, and through practical research, they have also achieved certain research results. Hajipour P believes that the execution failure of various satellite systems has a huge impact on the life of the satellite. And one of the most common influencing factors of billing in satellite system is FW failure. Hajipour P therefore investigated the first step in using a data-driven approach to predict the service life of a satellite failure reaction wheel. Hajipour P uses an autoregressive fault monitoring model and a short-term memory recurrent neural network for satellite fault prediction. Both models can guarantee the monitoring accuracy of satellite faults under the condition of limited actual data [1]. Akyildiz IF believes that the completion of the mission can only be guaranteed when the satellite is in a stable state and safe operation, including the operation control subsystem. When a constellation fails, if proactive detection measures are provided, it can avoid constellation anomalies and improve constellation safety. Akyildiz IF introduces a fault diagnosis of algorithmic data for efficient fault detection of different faults in satellite operation control systems. The failure prediction accuracy of the vector machine support method proposed by Akyildiz IF is as high as 96.8% [2]. Asvm A proposed a model to detect power drop in satellite systems. The model is based on satellite irradiance data for satellite fault detection. Its detection time is more efficient and timely. In order to alleviate the error of satellite fault detection, Asvm A performs data calculation, calculates the fault data by setting the satellite irradiance lower limit, and determines the "calculated fault amount" according to the actual data of the fault. The fault detection parameters used by Asvm A were tested on 100 satellite constellations in normal operation and the data were calculated, and using the calculated data, 200 satellite constellations were analyzed with the proposed fault detection model. Experimental data demonstrate the accuracy and effectiveness of the model [3]. Although the existing research on high-proportion distributed energy grid-connected massive monitoring data is very rich, the research on cloud processing and intelligent decision-making technology application of high-proportion distributed energy grid-connected massive monitoring data is still insufficient.

Therefore, in order to solve the problems existing in the existing research on fault diagnosis and detection of satellite swarms, this paper firstly introduces the functional equation steps of satellite swarm execution fault types, the concepts of neural network fault diagnosis technology and satellite swarm fault diagnosis method, and then discusses the concept of relying on neural network. The fault samples and parameter settings of the satellite swarm fault diagnosis and detection application of the network, and finally designed the neural network satellite swarm fault diagnosis and detection calculation process architecture, and carried out experiments through the application of the neural network and the other two algorithms in the satellite swarm fault diagnosis and detection., the final experiments show the reliability of the neural network proposed in this paper in the application of satellite swarm fault diagnosis and detection.

2. Neural Network Fault Diagnosis and Detection of Satellite Swarms

2.1. Neural Network Fault Diagnosis Technology

Neural network fault diagnosis technology is essentially the application of neural network technology in accident judgment. It can regard neural network as a new pattern recognition technology or a new data processing technology in the process of accident judgment [4]. There are three forms of fault diagnosis modes for neural network applications:

(1) From the aspect of pattern recognition, the neural network model is mainly used as a classifier for fault diagnosis [5].

(2) In terms of modeling, estimation and prediction, the neural network model is mainly used as a dynamic prediction and prediction model for fault diagnosis [6].

(3) From the perspective of the application of artificial intelligence theory, it mainly uses the

above two or more neural network reasoning, or neural network and other artificial intelligence theories combined [7]. Combination reasoning and decision-making process voting methods are used to diagnose faults in complex information systems [8].

2.2. Types of Satellite Constellation Execution Failures

The failure mode analysis of satellite swarm execution is divided into three types according to the impact of aircraft failure on the performance of the satellite swarm system during satellite swarm execution:

(1)Deviation failure occurs in the aircraft, that is, deviation failure [9]. Its mathematical model can be expressed as:

$$HE = \frac{1}{x}\sum_{u=1}^{x}\left|m_u - \hat{m}_u\right| \tag{1}$$

Among them, $g_{out}(k)$ and $g_{in}(k)$ represent the input and output data of the satellite constellation system, respectively, and $\mathrm{A}q$ is the fault data of the satellite constellation system, that is, the deviation fault value [10].

(2) The gain failure of the aircraft can be expressed as:

$$g_{out}(k) = q(u)\cdot g_{in}(k) \tag{2}$$

Among them, $g_{out}(k)$ and $g_{in}(k)$ represent the input and output signals of the system, respectively, and $q(u)$ is the fault data of the satellite constellation system, that is, the coefficient of gain fault [11].

(3) An aggregate fault occurs in the aircraft, that is, a deviation fault and a gain fault occur at the same time [12]. The mathematical model can be expressed as:

$$g_{out}(k) = q(u)\cdot g_{in}(k) + \mathrm{A}q \tag{3}$$

2.3. Fault Diagnosis Method of Satellite Constellation

Fault diagnosis research includes two types of diagnosis methods: analytical model diagnosis method, signal processing diagnosis method and knowledge diagnosis method:

(1) Analytical model diagnosis method

Based on the mathematical model of the system, the hardware redundancy is replaced by the analytical redundancy, and the residual error is generated and analyzed and decided, so as to realize the fault diagnosis [12].

(2) Signal processing diagnosis method

Corresponding redundant information can be obtained by processing the relationship between the data information, so as to analyze the working state of the satellite[13].

3. Investigation and Research on Fault Diagnosis and Detection of Satellite Swarms Relying on Neural Networks

3.1. Satellite Swarm Fault Diagnosis Relying on Neural Network to Detect Fault Samples

In order to verify the effectiveness of the neural network for fault diagnosis and detection of satellite swarms, the simulation constellation parameters shown in the following table are used in the experiment [14]. The FEO layer is composed of 6 high-orbit satellites (GEO) the orbits are connected by LOU, and the LEL is composed of polar orbit constellations [15]. As shown in Table 1:

Table 1. Failure samples

	LOU	LEL
Model	TDI	TRF
Track number	5	2
Number of satellites	50	4
Orbital inclination	85.9	0
Number of satellites in orbit	13	6
Highly	670m	2356km
The volume of the satellite	20cm×20cm×20cm	20cm×20cm×20cm

3.2. Parameter Settings for Fault Diagnosis and Detection of Satellite Swarms Relying on Neural Networks

In order to experimentally test the effectiveness of neural networks for fault diagnosis detection of satellite swarms [16]. In this paper, the parameters of the neural network in the fault diagnosis and detection of satellite swarms are designed, in which 10%, 12%, and 14% of white Gaussian noise are added to the three-axis attitude sensor of the satellite respectively [17]. Sensor failures are observed through a recurrent neural network observer. The neural network consists of an input layer, a hidden layer and an output layer [18]. The specific neural network satellite group fault diagnosis and detection parameter settings are shown in Table 2:

Table 2. Neural network parameters

Learning parameters	$\mu_1 = 0.1, \quad \omega_1 = 10^{-6},$
HW matrix	$B = -2I_{3\times3}$
Input time	200
Time slice length	2
The number of iterations	300
Number of layers of neural network	5
Number of neurons	30、60、90
Connection of neurons	0.5

4. Application Research on Fault Diagnosis and Detection of Satellite Swarms Relying on Neural Networks

4.1. Process Design of Satellite Swarm Fault Diagnosis and Detection Algorithm Relying on Neural Network

Due to the complexity of satellite constellation fault diagnosis to detect the surrounding environment, this paper reduces the complexity of satellite constellation fault diagnosis by utilizing a layered neural network. The fault diagnosis and detection of satellite swarms are carried out in the neural network structure, and the neural network hierarchical structure needs to be decomposed and executed according to the level. For satellite swarm fault diagnosis and detection, the input network of neural network and the decomposition of training set are practical. Therefore, this paper designs the algorithm flow of fault diagnosis and detection of satellite swarms of hierarchical neural network, and its specific calculation flow is shown in Figure 1:

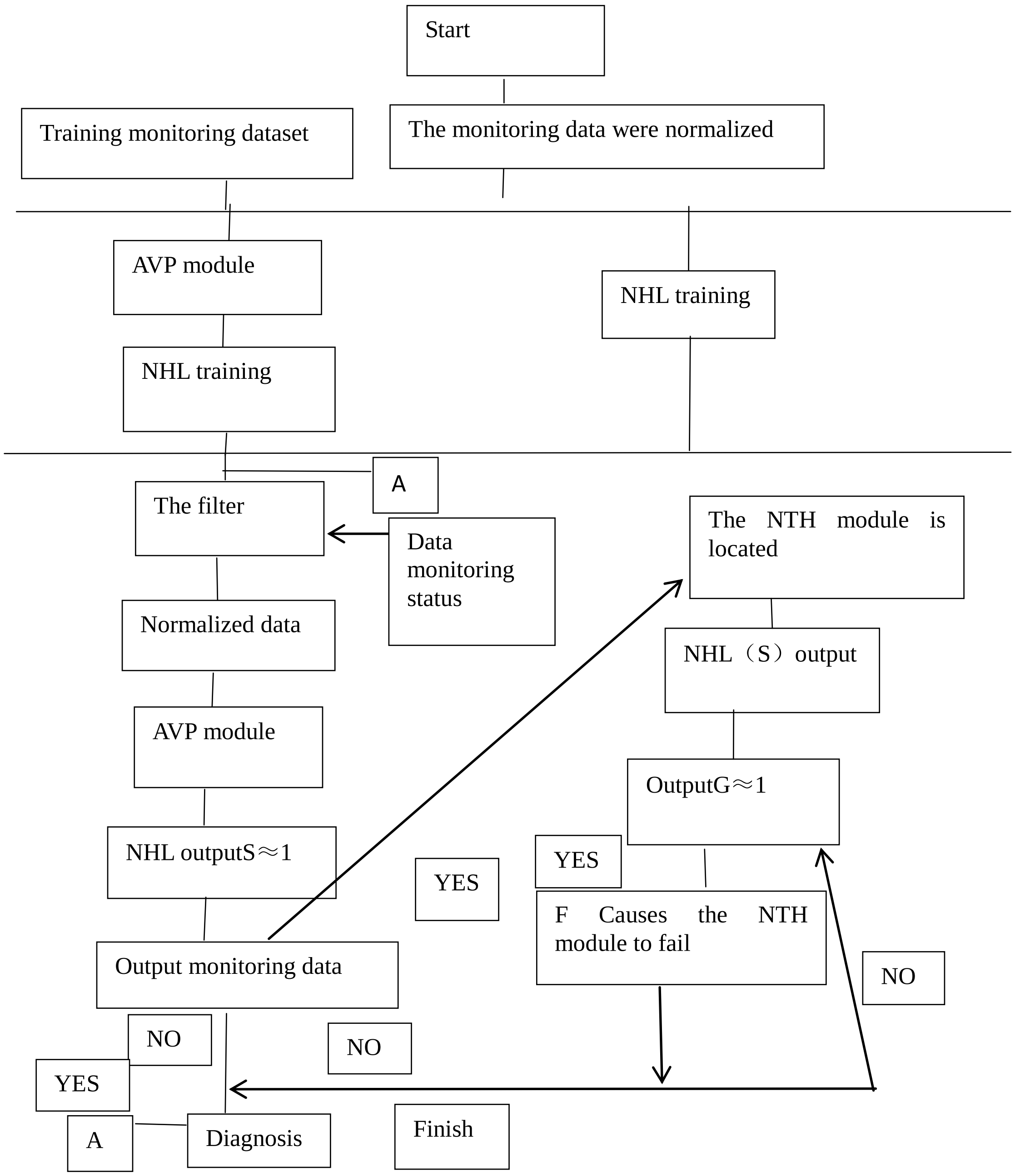

Figure 1. Shows the algorithm flow of the hierarchical neural network diagnosis system

The specific calculation process is as follows:

(1) In the training data preparation stage, normalize the fault diagnosis and detection data of the satellite constellation.

(2) In the training process of NHL, the normalized data set is converted, the main features of fault diagnosis and detection data are extracted, and the data is simplified.

(3) After the data is preprocessed, the data enters the NHL network. The value (S) of the output neuron specifies the structural module in which the abnormal condition exists.

(4) If the corresponding output reaches the expected value of fault diagnosis, that is, $S \approx 1$, for example, $S=0.5$, then an abnormal situation is considered to have occurred.

(5) If the value S≈1 of the NN-HL neuron output or exceeds the set fault diagnosis limit, the corresponding NHL(S) is activated.

(6) After NHL(S) is activated, the Nth neuron of the output gives a fault abnormal signal, indicating that this situation (S) is caused by fault F.

4.2. Application of Satellite Swarm Fault Diagnosis and Detection Relying on Neural Network

In order to verify the effectiveness of the neural network proposed in this paper in fault diagnosis and detection of satellite swarms, this paper uses the neural network algorithm and the other two algorithms (CFD) and (SLD) constellation fault diagnosis algorithms to diagnose correctly when satellite nodes fail. Using the proposed neural network algorithm and (CFD) and (SLD) diagnostic algorithms, the failure rate of the satellite constellation is in five progressive failure rates of 10%, 50%, 100%, 150%, and 200%. Calculate to test. The simulation experiment is repeated 150 times to obtain the average value of the correct rate of the three algorithms in the fault diagnosis of the satellite constellation. The specific accuracy data of the three algorithms are shown in Table 3:

Table 3. Algorithm accuracy data

Algorithm	The neural network	CFD	SLD
10%	100%	100%	100%
50%	98%	90%	92%
100%	97%	89%	90%
150%	96%	87%	89%
200%	97%	86%	88%

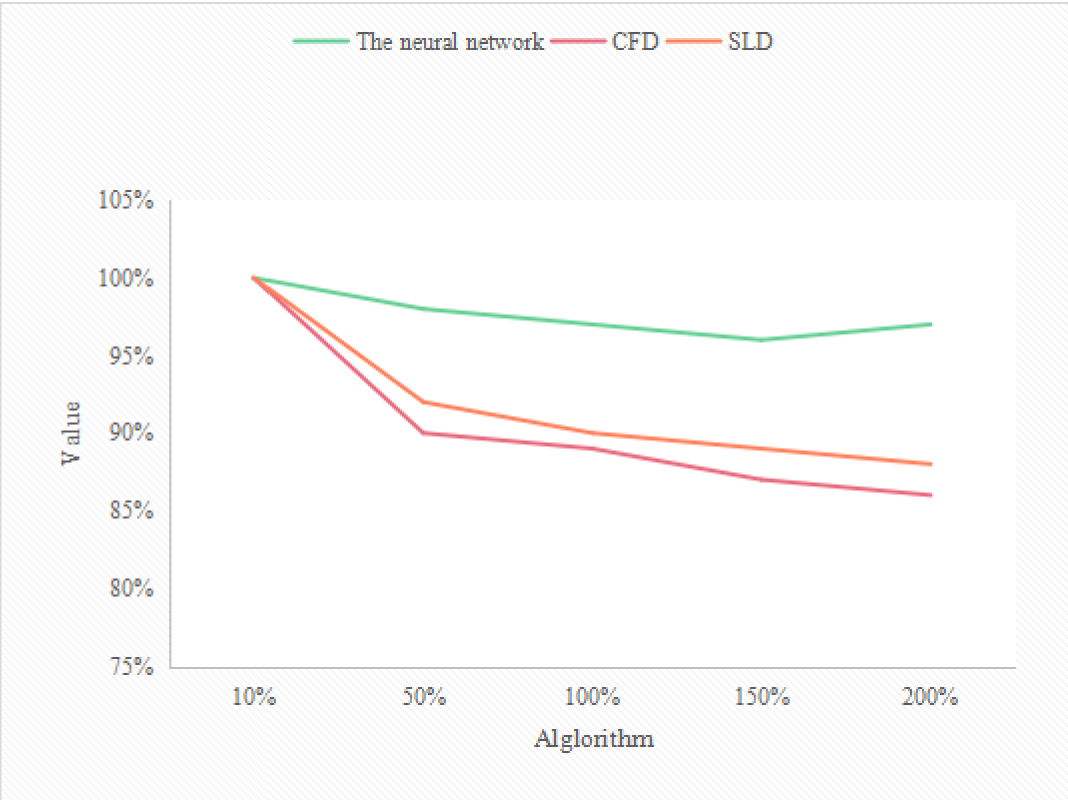

Figure 2. Algorithm accuracy comparison

From the comparison of the correct rates of the three algorithms in the satellite fault diagnosis algorithm in Figure 2, it can be seen that when the fault rate is lower than 10%, the three algorithms have a correct rate of 100% in the satellite network fault diagnosis big difference. When the satellite failure rate is above 10%, the neural network algorithm proposed in this paper has obvious advantages over the other two algorithms, and its correct rate is higher than the other two algorithms. When the failure rate is about 50%, the three algorithms Compared with the other two algorithms, the neural network algorithm proposed in this paper has a relatively stable decline in the diagnostic accuracy rate, and can maintain about 96% when the failure rate is above 100% diagnostic accuracy. Therefore, it can be shown that the neural network algorithm has a higher recognition rate for satellite fault diagnosis, and is better than the other two algorithms.

5. Conclusion

Therefore, in order to enrich the research on fault diagnosis and detection of satellite swarms relying on neural networks, this paper first briefly introduces the functional equation steps of satellite swarm execution fault types, the concepts of neural network fault diagnosis technology and satellite swarm fault diagnosis methods. Based on the analysis and discussion of satellite swarm fault diagnosis and detection technology, the fault samples and parameter settings of satellite swarm fault diagnosis and detection application relying on neural network are investigated and designed. Secondly, design and analyze the computing process architecture of the satellite swarm fault diagnosis and detection application relying on neural network, and finally analyze the experimental data for the application of the computing process architecture designed in this paper. The final experimental results verify the neural network-dependent satellite swarm fault diagnosis and detection in this paper Advantages of the application.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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