Fault Diagnosis of Functional Circuit in Avionics System Based on BPNN

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Abstract—**Avionics system is one of the key systems involved in the safe operation of aircraft. Improving the fault diagnosis and testing capability of Avionics system is of great significance to the safe operation of aircraft. In this paper, fault simulation of avionics system is carried out by means of fault injection. We select the general processing module P2020 board of the avionics system, analyze and extract the sensitive parameters of the general processing module, extract the fault sensitive features and use BP neural network to data mining, to realize the fault diagnosis of the functional circuit level of the avionics system. The experimental results show that the fault diagnosis accuracy of this method is over 99% for the functional circuit level of avionics system. The research results of this paper have certain engineering application value for fault diagnosis of avionics system.**

Keywords—Avionicssystem;feature extraction; feature selection; BPNN; machine leaning.

I. Introduction

With the rapid development of electronic technology and computer technology, most modern avionics systems are highly digital, modular, integrated and intelligent equipment [1-2]. Highly integrated integrated avionics systems include a large number of digital computers, multi-channel transmission data bus, control display devices, sensors or airline replaceable parts. Avionics system has the characteristics of complex circuit, strong non-linearity, multi-level structure and non-linear coupling. At the same time, its failure modes are diverse, intermittent faults are frequent and difficult to recur. In order to improve the efficiency of fault elimination and shorten the time of fault elimination, it is necessary to carry out in-depth research on fault diagnosis, maintenance testing and fault elimination methods of avionics system.

Many scholars have carried out extensive research on the fault diagnosis technology of avionics system. Reggia of the University of Maryland proposed the theory of reduced cover set to realize knowledge-based intelligent diagnosis [3]. Zhang Peng has studied the fault diagnosis of complex avionics system of civil aircraft [4]. By using fault tree analysis method and symptom-based reasoning analysis method, the fault elimination scheme has been rationally optimized, which greatly reduces the aircraft parking cycle, improves the economic benefits of aircraft operation, and provides a feasible reference method for the fault diagnosis of complex avionics system of civil aircraft.Duan Rongyi et al. applied virtual instrument technology [5], which enabled the test system to realize automatic control of various test instruments, thus laying the foundation for the whole test system to realize automatic test, and applied database engine and fault diagnosis technology to realize the functions of system performance test information storage, fault location and diagnosis. Aiming at the intermittent fault diagnosis of electronic systems, Professor Lafortune S of the University of Michigan, USA, has studied the diagnosability of DESs by monitoring theory, that is, whether the fault can be diagnosed within a limited time delay, and put forward the concept of DESs diagnostic device at the earliest stage [6]. IhabSamy et al. applied EMRAN RBF network to sensor fault diagnosis of UAV, and studied the simultaneous and continuous occurrence of multiple faults [7]. Zhu Yaguang et al. took the aircraft avionics system as the research object, and took the equipment reliability data and expert experience as the data source, studied the multi-fault diagnosis technology of the avionics system based on causal network [8], which was used to improve the fault diagnosis efficiency of the avionics equipment and shorten the maintenance cycle.

This paper builds a fault injection and test simulation platform for avionics system. Fault simulation is carried out by means of fault injection. In this paper, we choose the general processing module P2020 board of the avionics system, analyze and extract the sensitivity parameters of the general processing module, extract the fault sensitive features and use BP neural network to data mining and analysis, so as to realize the fault diagnosis of the functional circuit level of the avionics system.

II. THEORY AND METHODOLOGY

A. Fault Diagnosis and Test Simulation Platform for Avionics System

At present, the development of avionics system is mainly based on Integrated Avionics system. The typical representatives are Airbus A380 and Boeing B787. They replace a large number of independent processors and LRUs with fewer and more centralized processing units. They have the advantages of less weight and less maintenance costs on the new generation of civil airliners, but they also bring many

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problems, such as resource sharing. The spread of resource shortcomings. Due to the high sharing of resources, the defects of a single resource will affect all the application functions using the resource and increase the scope of fault propagation. At the same time, functional errors caused by functional synthesis are complex cross-linking problems. Functional organization and cross-linking become more complex, which makes it more difficult to diagnose functional errors.

In order to study the fault diagnosis of avionics system, we need to build a simplified simulation test platform in the laboratory. The hardware test platform of avionics system can be built by shelf products in the laboratory. It mainly includes three modules: data processing module, network switching module and power supply module. The fault diagnosis and test simulation test platform for avionics system built in our laboratory is shown in Figure 1.

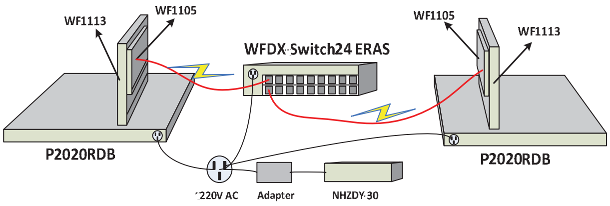

Fig. 1. Fault Diagnosis and Test Simulation Test Platform for Avionics System.

In this test platform, the data processing module is P2020RDB. P2020RDB-PCA is a highly integrated reference design board developed by Freescale. It is based on QorIQTMP2020E processor family and supports dual-core P2020E and single-core P2010E configurations. The P2020E processor family is based on dual E500 cores and is constructed with Power Architecture #technology. WFDX-Switch24 ERAS switch is used in network switching moduleWFDX-Switch24 ERAS is a 24-port aviation full-duplex switched Ethernet (AFDX) switch supporting 10/100 Mbps. It supports 4096 virtual links with virtual link numbers ranging from 0 to 65535, supports frame-based traffic filtering strategy and is fully compatible with ARINC664 protocol. ERAS uses natural heat dissipation and can be used as an independent product. The power module adopts NHZDY-30 PCB power supply NHWYS-30 series programmable DC power supply with constant voltage and current mode output, automatic cross-conversion, preset and view functions of constant voltage, constant current and overvoltage protection value. The three main modules constitute the experimental simulation platform for fault diagnosis and testing of the avionics system built in the laboratory.

B. Fault Injection and Test Design of Avionics System

The main instruments used in this experiment include fault injection hardware platform, P2020 experimental board, AFDX network protocol board and ADFX network switch. PXIe-8135 is the core control module of the fault injection platform, which controls PXI-5422 fault signal generation module to generate fault signal. The fault signal is injected into each test point of P2020 test board through PXI-25334*64 matrix card. The P2020 experimental board is connected with the column pins in PXI-2533 through multiple signal injection lines, so as to realize the injection function of fault signals at different positions of the P2020 experimental board after channel selection. The experimental fault injection platform is based on PXI data acquisition system and other discrete instruments. The structure of the platform is shown in Table 1.

Table 1. Hardware Composition of Simulation and Verification Platform.

Instrument Model	Explain
PXIe-8135	control module
PXIe-1062Q	Chassis
PXI-4110	Power Board Card
PXI-4461	Dynamic signal acquisition module
PXIe-6363	X Series Multifunctional Acquisition Card
PXI-4072	Digital multimeter
PXI-5124	Digitizer
PXI-5422	Arbitrary Waveform Generating Module
Dual Channel Copper AFDX PXI Interface from AIT	AFDXBus interface module
Channel 1553 PXI Interface Module from AIT	1553B interface module
PXI-2533	Matrix Switch
SCB-68	Relevant junction box

The fault injection platform of avionics system realizes the test of key pin/node parameters and functional interface parameters of hardware simulation test platform. Fault injection includes four functions: post-drive fault injection, voltage summation fault injection, signal-level real-time fault injection and protocol-level fault injection.

1）Rear Drive Fault Injection

wo kinds of faults are simulated, i.e. high and low faults, disconnected or interrupted connections, short-circuit between pins, short-circuit for battery voltage and short-circuit to ground on each channel.

The post-drive technology is a mobile fault injection of probes. It does not need to set the corresponding fault injection interface, as long as the fault injection probe contacts the pin of the injected device. The probe is in high resistance in the non-injection state and does not affect the normal operation of UUT. Instantaneous high current is injected or pulled out at the input stage of the device/circuit under test (the output stage of the former driver or circuit), forcing its potential to increase or decrease as required to simulate product failure.

2）Voltage summation fault injection

In the input stage or output stage of analog circuit, product faults are simulated by changing node voltage by cascading probes and signal generators. Taking the fault injection of operational amplifier as an example, the principle of voltage summation is shown in Fig. 2. By changing the input of Vin2, the output of Vout can be changed, thus the fault injection of analog circuit can be realized. The probe is in high resistance in the non-injection state and does not affect the normal operation of UUT. The stress of fault injection is voltage, and the quantification form is how much voltage is injected. The applied stress types include voltage drift, voltage overshoot, noise superposition, etc. The applied mode can be typical values, step-by-step or random extraction, such as injection voltage from 0 to 5 V with 0.2V step size.

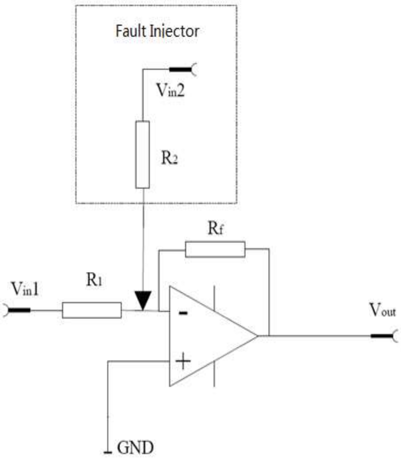

Fig. 2. Schematic diagram of voltage summation fault injection.

3）Signal-level Real-time Fault Injection

After real-time acquisition and analysis of the signal to be input, fault injection based on signal processing, such as adding noise, changing the relevant level, or modifying to other arbitrary signals, and then signal input, needs to improve real-time (ns level).

4）Fault Injection in Protocol Layer

Through open programming, equipment testing, simulation, monitoring and analysis MIL-STD-1553, AFDX aviation bus, simulation protocol fault, programmable Bit coding (Manchester code, NRZ, RZ, etc).

C. Back Propagation Neural Network

Artificial neural network does not need to determine the mathematical equation of the mapping relationship between input and output beforehand. It only learns some rules through its own training, and obtains the results closest to the expected output value when given the input value. As an intelligent information processing system, the core of the function of artificial neural network is algorithm. BP neural network is a multi-layer feedforward network trained by error back propagation. Its algorithm is called BP algorithm. Its basic idea is gradient descent method. Gradient search technology is used to minimize the mean square error between the actual output value and the expected output value of the network.

BP algorithm includes forward propagation of signal and reverse propagation of error. The error output is calculated in the direction from input to output, while the weight and threshold are adjusted in the direction from output to input. In forward propagation, the input signal acts on the output node through the hidden layer, and generates the output signal through non-linear transformation. If the actual output does not match the expected output, the reverse propagation process of the error will be introduced. By adjusting the connection strength between input node and hidden layer node, the connection strength between hidden layer node and output node, and the threshold, the error decreases along the gradient direction. After repeated learning and training, the network parameters (weights and thresholds) corresponding to the minimum error are determined, and the training is stopped. The trained neural network can process the input information of similar samples and the output information with the least error through non-linear transformation.

III. FAULT DIAGNOSIS EXAMPLE

In this section, we choose one of the general processing module P2020 board through the fault injection and test simulation platform of the avionics system built in the laboratory. By monitoring the monitoring parameters related to the fault, we can realize the fault diagnosis of the functional circuit level of the general processing module. Here we choose the function of the general processing module of the FPGA as the research object. The AC value of power supply voltage, GND and clock frequency of GPGA functional area are collected. In the process of fault injection, we inject different amplitudes, different frequencies of noise, square, sine and other interference signals into the fault through GND of Ethernet, simulate the abnormal clock frequency of the output of the functional circuit of the FPGA, the abnormal power supply of the FPGA, and the GND noise of the circuit of the FPGA. At the same time, we also collected data samples in the normal working state of the system. First, in order to effectively utilize the information of data sets, we need to standardize the original data sets. Here, we normalize the data by mean and variance. The distribution of the values is shown in Figure 3.

The data set contains 8000 samples. We have set fault labels for three types of faults and normal data. Each type of fault includes normal data with 2000 samples. Since the original monitoring parameters we collected are all time-domain data, we need to extract features from the data. The data of each physical parameter are divided into 10 groups. Meanwhile, the average value, peak value, absolute value, standard deviation, kurtosis and root mean square of the data are extracted. Then, we merge the feature samples of three fault parameters and get a sample matrix of 33 features. According to the feature ranking results of mRMR feature selection, the top 10 ranking features are selected, which are 4, 24, 2, 13, 5, 6, 7, 8, 9 and 11 features respectively. Finally, the first 10 features selected by the mRMR method are analyzed by principal component analysis, and the first four principal components (the cumulative contribution rate is 97.41%) are extracted, as shown in Figure 4.

The BP neural network fault diagnosis model is established based on four kinds of data of normal state and fault injection state of principal component.

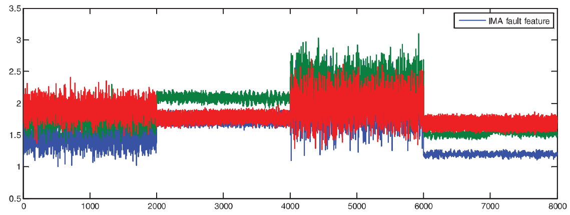

Fig. 3. Sample set normalized by mean and variance for original data samples.

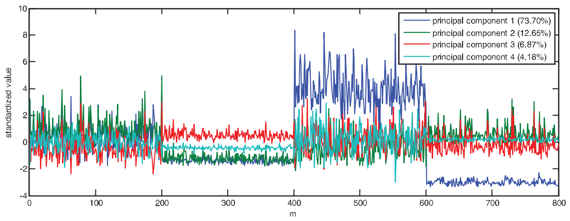

Fig. 4. Sample set after feature processing.

Firstly, we build a two-layer BP neural network, which consists of a hidden layer of three neurons and an output layer of four neurons. The activation functions of logsig and purelin are used in the implicit layer and the output layer respectively. The epochs is set to 500 and the learning rate is set to 0.01. The training function uses gradient descent adaptive learning rate training function.

We use random initialization weights and thresholds for training. The model is trained with 400 training sample sets and validated with 400 test samples. Finally, the BP network model with better convergence is saved. Fig. 5 and Fig. 6 are the error convergence and gradient and learning rate curves of the neural network model in the training process, respectively. For this two-layer network, the fault recognition rate of the BP neural network model is 91.25%.

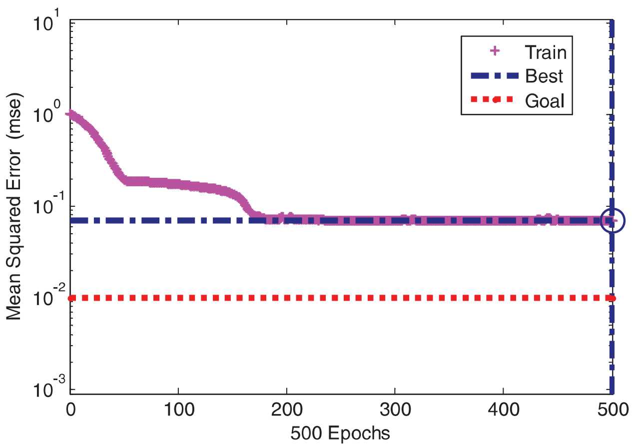

Fig. 5. Error Convergence in the Training of Two-Layer Neural Networks

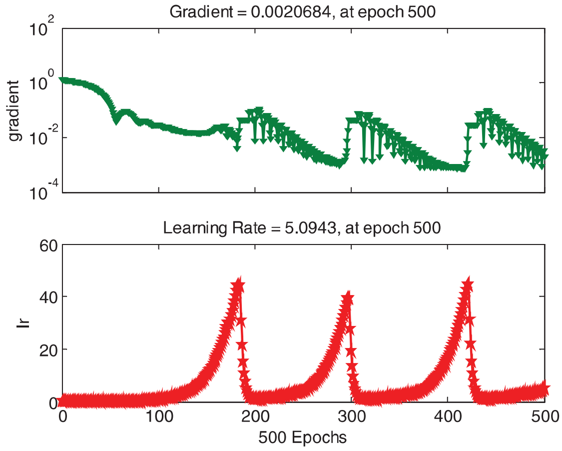

Fig. 6. Gradient and Learning Rate Change in the Process of Two-Layer Neural Network Training.

We increase the number of layers of BP network and use three layers of neural network to model the sample set. The number of neurons in each layer of the neural network is 5, 3 and 4 respectively, which is one more hidden layer of 5 neurons than the first model. In this new model, the activation functions in the form of logsig and purelin are used in the two hidden layers, while the activation functions in the output layer are logsig. As in the previous example, epochs is set to 500 and learning rate is set to 0.01. The training function uses gradient descent adaptive learning rate training function. The model is trained and tested, and the fault recognition rate of the three-layer BP network diagnosis model is 99.25%. Fig. 7 is the error convergence curve of the neural network model in the training process. Compared with the first model, the accuracy of this model has been improved.

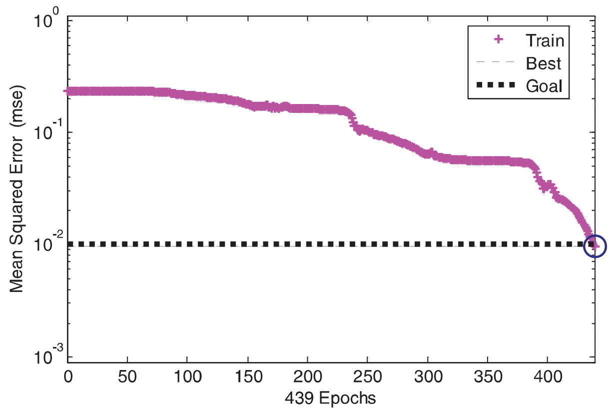

Fig. 7. Error Convergence in the Training of Three-Layer Neural Networks

Subsequently, we keep the number of layers of the neural network unchanged, but adjust the number of neurons in the first hidden layer to 10 and the number of neurons in the second layer to 6. At this time, the number of neurons in each layer of the network is 10, 6 and 4 in turn. The activation functions of the three layers network are logsig, purelin and logsig. Epochs is set to 400, and the learning rate is set to 0.01. The training function uses gradient descent adaptive learning rate training function. Through training and testing, the fault recognition rate of the model reaches 99.75%. This is a satisfactory accuracy. We also apply this model to more test data and get more than 99% recognition rate. Fig. 8 is the error convergence curve of the neural network model in the training process.

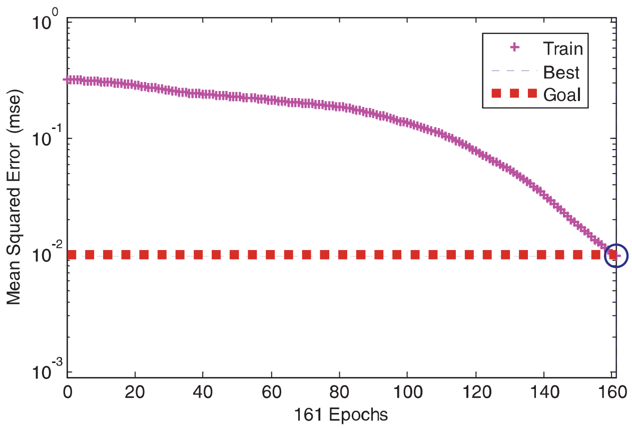

Fig. 8. Error Convergence in the Training Process of the Corrected Three-Layer Neural Network

In addition, we try to use more layers of networks, such as four hidden layers with 3, 3, 3, 5 neurons and one output layer with 5 neurons. But as a result of training, the diagnostic rate of the model was only 71.5%. This is mainly due to the insufficient number of samples in the sample set and the inability to train the weights and thresholds adequately.

IV. CONCLUSION

The development of avionics system mainly focuses on Integrated Avionics system, which brings about the spread of resource defects caused by resource sharing. Functional organization and cross-linking become more complex, which makes it more difficult to diagnose functional errors. In order to study the fault mode diagnosis of avionics system, a simple simulation platform of avionics system is built in the laboratory, and real faults are simulated by injecting faults. We select the data of three functional circuit-level faults and normal states of the general processing module of avionics system, extract the time-domain characteristics of the relevant state parameters, reduce the dimension of features by using maximum correlation, minimum redundancy and principal component analysis, and on this basis, we use BP neural network technology to realize the functional circuit-level fault diagnosis of avionics system. The experimental results show that the fault diagnosis accuracy of this method is over 99%. The method proposed in this paper has certain practical value and application prospects for the research of fault diagnosis and testing of avionics system.

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