

A Sensor Waveform Conversion Management System

Ying ZHANG ^{a,b,1}, Tuo WANG ^{a,b}, Cunsheng JIANG ^{a,b}, Hongqian WANG ^c and Li FENG ^{a,b}

^aBeijing Institute of Aerospace Automatic Control, Beijing, 100854 China

^bState Key Laboratory of Aerospace Intelligent Control Technology, Beijing, 100854 China

^cBeijing Institute of Technology, Beijing, 100081 China

Abstract. The management system consists of a sensor waveform conversion system, a fault handling detection system, and a switching execution system. In this paper, the integration circuit is used for waveform transformation, the elimination of the offset voltage of the amplification circuit, and the integration compensation in feedback control. And we collect data from each state of the system under test, and use the redundant fault-tolerant system to manage and warn the system status to verify the effectiveness of the model. Combined with the waveform generation circuit and the waveform transformation circuit, the output of the signal generator is connected to the input of the integration circuit. The function of the waveform transformation system is to transform one waveform into another waveform, which can convert the square wave into a triangular wave. The redundant fault tolerance model proved to be effective on this management system, that is, the redundant fault-tolerant system has good generalization and can be implemented in the aerospace scene.

Keywords. Sensor, waveform, conversion

1. Introduction

The management system adopts a heterogeneous scheme in each processing module [1-3], which is composed of a sensor waveform conversion system, a fault handling detection system and a switching execution system [4-8]. Aiming at the application of artificial intelligence in redundant fault-tolerant systems, the management system proposes a health assessment method based on deep learning for the problems of traditional redundant fault-tolerant systems [9-12] that cannot quantify equipment reliability and predict failures, and uses dual heterogeneous algorithm modules in fault handling detection systems [13-14] to improve system reliability. The system sensor generated by the sensor waveform transformation system is used to monitor the state data, complete the codec network training of the algorithm module, construct the state feature space of the intelligent algorithm, and measure the degree of degradation of the health state by using the characteristic vector of the measured data and the spatial

¹ Ying Zhang, Corresponding author, Beijing Institute of Aerospace Automatic Control, Beijing, 100854 China. State Key Laboratory of Aerospace Intelligent Control Technology, Beijing, 100854 China; E-mail: zhangying_@pku.edu.cn.

distance of the health state feature as shown in figure 1. Obtain the real-time health of the measured data, select the high health module to put into work, and output one to the execution system, so as to achieve redundancy and fault tolerance of the system [15-18].

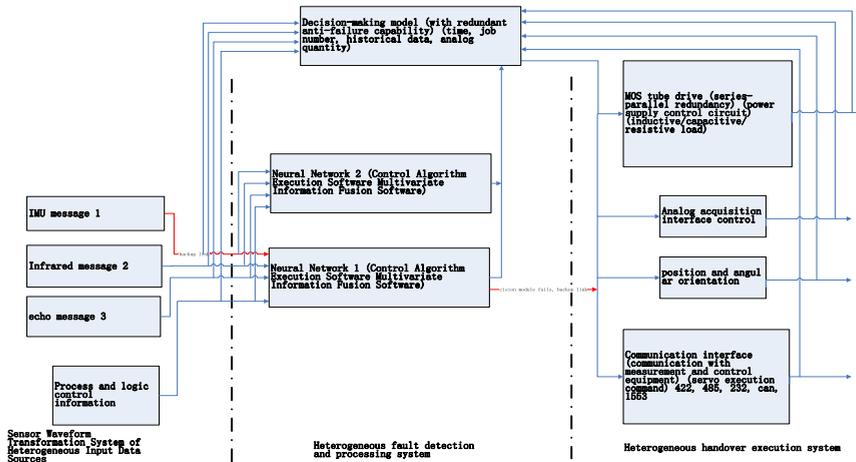


Figure 1. System composition diagram.

2. Model Implementation

A model implementation technical state diagram is shown in figure 2. By collecting monitoring data from the object system, then through the relevant data processing and analysis process, diagnostic and predictive analysis is formed, and finally, the degree of performance degradation of the target system is given, thereby providing decision-making information for the maintenance plan.

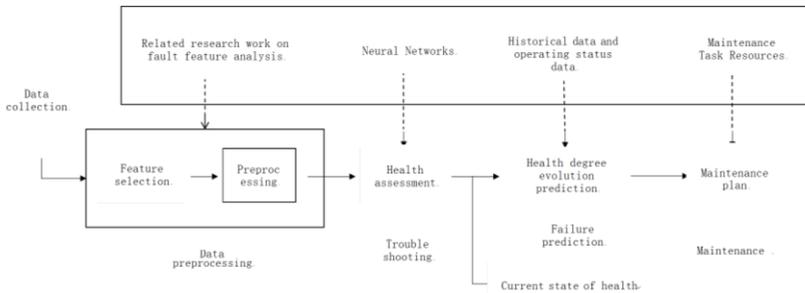


Figure 2. The model implements a technical state diagram.

The data of this system should have the following five-point properties: timing, floating-point, nonlinear, multidimensional, and coupled. Time series means that the data should be time series related data; floating-point refers to the data type should be floating-point numbers; nonlinear because most complex systems in real-world applications are nonlinear systems, which should be characterized by nonlinear data; multidimensional exponential data should have multiple dimensions, that is, the working state of the system is reflected through multiple feature spaces; coupling

means that there should be a certain correlation between the dimensions, by calculating dimensionality data A measure of the correlation coefficient between. Therefore, a waveform transformation system is used.

The waveform generator uses a square wave generator and an RC bridge oscillation circuit. Among them, the square wave generator circuit diagram is shown in figure 3, which is composed of a hysteresis comparator and an RC oscillator. It can be calculated from the circuit diagram that the oscillation frequency and amplitude of the waveform it produces are respectively

$$f_0 = \frac{1}{2R_f C_f \ln(1 + \frac{2R_2}{R_1})}$$

$$U_{om} = \pm U_z$$

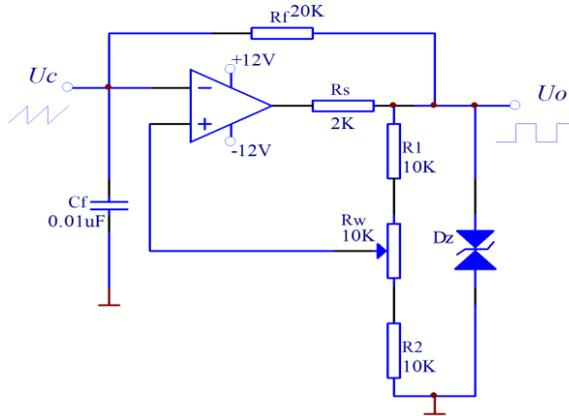


Figure 3. Square wave generator circuit diagram.

The RC bridge oscillation circuit is shown in figure 4. RC series and parallel circuits form positive feedback branches, and at the same time, components such as frequency selection network, and diodes constitute negative feedback and amplitude stabilization links. By adjusting the potentiometer, the negative feedback depth can be changed. Amplitude stabilization is achieved by using the nonlinear characteristics of two reverse parallel diodes and forward resistors. It is to weaken the effects of diode nonlinearity to improve waveform distortion. By changing the parameter C or R of the frequency selection network $R_1 R_2 R_w R_w D_1 D_2 R_3$, the oscillation frequency can be adjusted. The frequency of oscillation of the circuit is

$$f_0 = \frac{1}{2\pi RC}$$

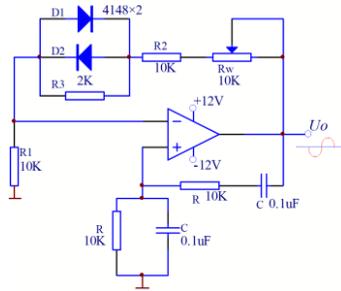


Figure 4. RC oscillation circuit structure diagram.

When building the dataset, 1 million pieces of data of each type of data are generated, with the first 800,000 pieces as the training set and the last 200,000 pieces as the test set. The sampling rate of health data, minor fault data, and critical fault data is 100Hz, and the figure for the first 5 seconds is shown as figure 5 and figure 6.

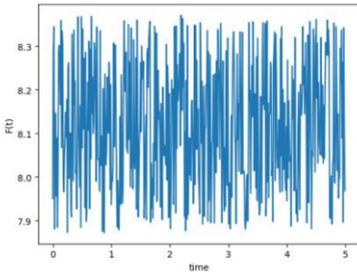


Figure 5. Health data.

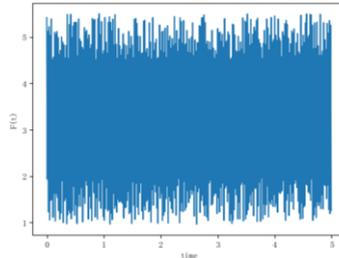


Figure 6. Fault data.

Therefore, the input and output of the data system is the characteristic of the smallest system containing the most fault information, and the acquisition is simple, and the system health can be obtained by analyzing the input and output of the system.

3. Summary

Through a large number of experiments, the feasibility of the proposed system is verified, and the system can be built as a redundant fault-tolerant system in the following scenarios.

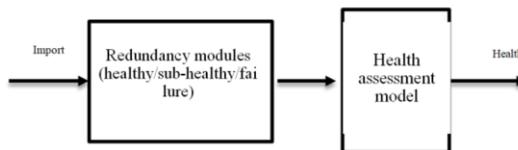


Figure 7. Redundant modules build redundant fault-tolerant systems.

As shown in figure 7, using redundant modules with different health levels, the health assessment model evaluates the redundancy modules of the three health levels and outputs the corresponding health curves. Observe whether the health curve conforms to the health level of the module to verify whether the health assessment model is valid.

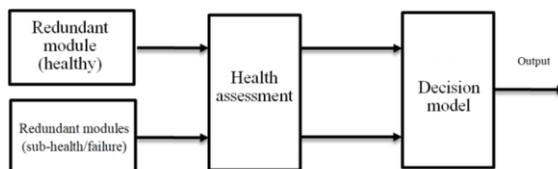


Figure 8. Redundant modules build redundant fault-tolerant systems.

As shown in figure 8, using a health redundancy module and a redundancy module with a degraded degree of health, the input decision model determines which module to use after the health assessment. Observing the output verifies the effectiveness of the decision model, that is, the fault tolerance of the redundant fault-tolerant system.

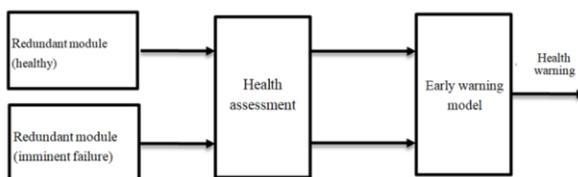


Figure 9. Redundant modules build redundant fault-tolerant systems.

As shown in figure 9, a redundant module that is about to fail is used, including: a redundant module that continues to decline in health, a redundant module that rapidly decreases in health at a certain time, and a redundant module that is always in a sub-healthy state. After the health assessment, you can enter the early warning model and observe whether the early warning model can issue a health warning, which can verify the effectiveness of the early warning model.

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