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One-Dimensional Management with Neural Network Data Generation Method

Ying ZHANG [a,b,1], Tuo Wang [a,b], Cunsheng JIANG [a,b], Hongqian WANG [c] and Li FENG [a,b]

[a] *Beijing Institute of Aerospace Automatic Control, Beijing, 100854 China*
[b] *State Key Laboratory of Aerospace Intelligent Control Technology, Beijing, 100854 China*
[c] *Beijing Institute of Technology, Beijing, 100081 China*

Abstract. This paper proposes a data generation method for one-dimensional aircraft simulation neural network, which is used for data preprocessing of aircraft real-time control health design, which is the basis of aircraft intelligent health prediction algorithm. According to the methodological research needs, this method generates data of different health levels, and the data generator adjusts the health degree of the data by changing the weight, changing the noise size, changing the frequency, etc.; the recognition ability of the redundant fault-tolerant model for the singularity data is studied, and the experimental results show that the system will not ignore the singularity, and the occurrence of singularity will significantly affect the health of the data. Experimental results show that the model can work effectively under the premise that at least one dimension is a fault feature. The intelligent system trained through this data has a better effect.

Keywords. AI, neural networks, health predictions, aerocraft

1. Introduction

At present, the aircraft control system [1,2] under research and the simulation preprocessing technology [3,4] have the following two difficulties at the data level. First, since most of the current aircraft simulation [5] intelligent diagnosis system research work is for complex military [6] equipment, it is difficult for many physical models, experimental data and performance evaluation standard systems of many actual systems to be collected and widely used by developers [7,8]. Both deep learning-based health assessment and data-based failure prediction are based on big data [9,10], which requires a lot of data to conduct research. However, the lack of data in the space scene and the high cost of acquisition urgently require the generation of aircraft simulation data and the construction of data sets.

On the other hand, in engineering applications, in the process of product development, experimentation, production and use [11,12], various maintenance methods are used to minimize the occurrence of failures [13,14], thereby greatly reducing the probability of various types of failures. As a result, there is a problem of insufficient failure mode samples and failure verification environments, resulting in a

[1] Ying Zhang, Corresponding author, Beijing Institute of Aerospace Automatic Control, Beijing, 100854 China; E-mail: zhangying_@pku.edu.cn.

lack of realistic environments and conditions for adequate analysis and verification of failure modes.

In this paper, a data generation and dataset construction method is studied in the absence of experimental data and fault data, which is the research basis of the aircraft simulation intelligent system [15-18]. The data generated by the dataset generation system is used to discuss the methodological evaluation of the health assessment of aircraft simulation and its effectiveness, which provides a research basis for the subsequent application of aircraft system intelligence.

2. Generation of Data on Different Levels of Health

The system uses a real-time evaluation method of device health status based on deep learning, and its basic idea is: using normal data to fit an encoding and decoding network model, abnormal data will have a large error when encoded and decoded through the network model, thereby triggering abnormal alarms. The basic method used is to establish a feature space for the normal state data, quantify the degree of degradation by measuring the degree of difference between the measurement data and the normal state sample space, and then convert it to a percentage system of health. Therefore, depending on the application requirements, the data generation system should be able to generate data with different levels of health.

Data of different health levels mainly refer to the data in the health state of the system and the data in the state of serious failure of the system, in order to better characterize the process of early degradation of the health state of the system, this paper also generates a class of minor failure data. A minor fault state refers to the fact that the system behaves normally on the external output at this time, that is, the system can still work normally, but the internal health state has degenerated early, which is a critical state before the system fails. In practical application, the system mainly identifies the health state of the system and the state of severe failure, and the minor fault state is an additional supplement to meet the research needs.

The data generation formula for the data generation system as shown in figure 1.

$$F_1(t) = \mathrm{random}(t) + w_1 a^t + w_2 \sin(2\pi f_1 t + \varphi_1) + w_3 \cos(2\pi f_2 t + \varphi_2) + \cdots$$

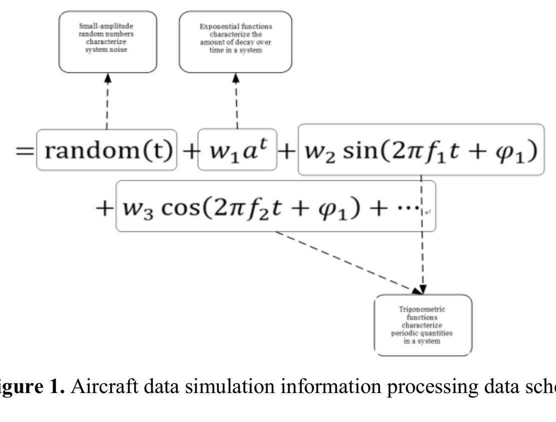

Figure 1. Aircraft data simulation information processing data schematic diagram.

The idea of constructing datasets of different health levels is to form a reference function, that is, the first dimensional health data, and then construct minor fault data and serious fault data by means of noise reinforcement and fine adjustment. When constructing a datum function, three types of components are used: random quantities, decay quantities, and periodic quantities. Because the datum function is healthy data, the amplitude of the random quantity should be smaller than the total data amplitude to characterize the presence of noise in the system in a real-world scenario but does not affect the normal operation of the system. In order for the amount of decay to run through the system cycle, the exponential t of the exponential function should be multiplied by a smaller coefficient to slow down the decay of the function. The frequency and number of trigonometric functions in periodic quantities can be valued according to the system functions of the real-world system.

This article uses the following function as the benchmark function, that is, the health data is:

$$F_1(t) = \mathrm{random}(-0.25,\ 0.25) + 0.9^{0.0001\cdot t} + 10\cdot\sin\left(2\pi\cdot 15\cdot t + \frac{\pi}{6}\right) + 3 \cdot\cos\left(2\pi\cdot 10\cdot t + \frac{\pi}{4}\right)$$

At the same time, by increasing the early degradation of the noise simulation system, minor failure data is constructed. The formula for generating minor failure data is:

$$F_2(t) = \mathrm{random}(-3.5,\ 3.5) + 0.9^{0.0001\cdot t} + 10\cdot\sin\left(2\pi\cdot 15\cdot t + \frac{\pi}{6}\right) + 3 \cdot\cos\left(2\pi\cdot 10\cdot t + \frac{\pi}{4}\right)$$

Critical failure data should be greatly changed on the basis of healthy system functions, such as louder noise, system frequency component changes, etc., this article uses the following functions to generate critical failure data:

$$F_3(t) = \mathrm{random}(-3.5,\ 3.5) + 0.95^{0.0001\cdot t} + 8\cdot\sin\left(2\pi\cdot 18\cdot t + \frac{\pi}{6}\right) + 2.5 \cdot\cos\left(2\pi\cdot 10.5\cdot t + \frac{\pi}{4}\right) + 2.5\cdot\cos\left(2\pi\cdot 30\cdot t + \frac{3\pi}{4}\right)$$

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 below.

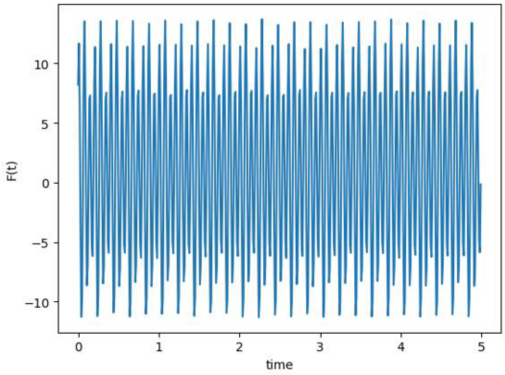

Figure 2. Health data.

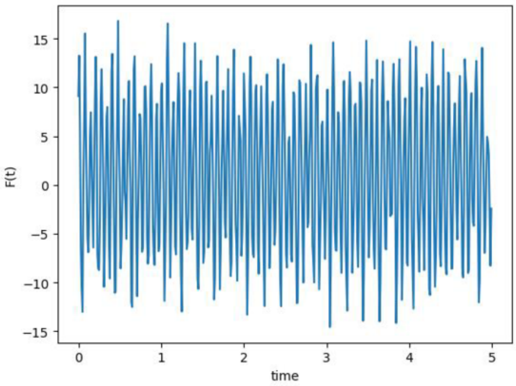

Figure 3. Minor failure data.

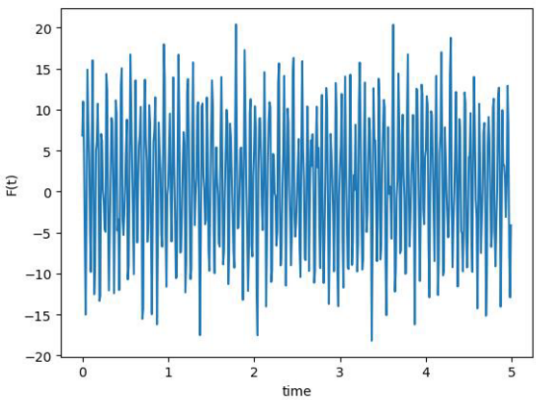

Figure 4. Critical failure data.

As can be seen from the figures 2 to 4, the generated time series meets the timing, floating-point, coupling, and nonlinear characteristics required by the subject. And the frequency, range and fluctuation law of the generated data are controllable, and can be adjusted according to the needs in practical application, so the data generated in this article can reflect the data characteristics of the space scene as a whole. There are small differences between health data and minor failure data in the fluctuation law and numerical range, while the numerical range and fluctuation law between the serious failure data and the health data are quite different, which is in line with the research needs of this article.

The 20,000-21,000 items of these three sets of data were taken separately, and a total of 1,000 data were used for health assessment to verify whether the health assessment model could effectively distinguish between different health level data. After data preprocessing, self-coding network training, feature space construction, and health calculation, the health assessment model outputs three sets of data health curves as shown in figure 5:

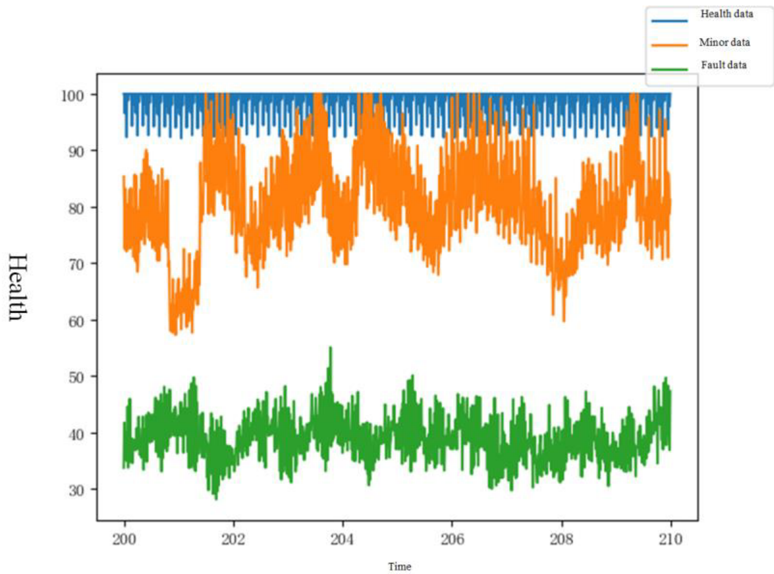

Figure 5. Unsormalized data health curve.

As can be seen from figure 5, among the three sets of data, the health data and the health of the serious fault are clearly separated, and the minor fault data and the health data are slightly intersected. Health data health is mostly 90-100, minor failure data health is mostly 60-90, and serious failure data health is mostly below 50. Health data and serious failure data can be completely distinguished through the health assessment model, which is in line with the characteristics of the data itself and the expected research effect of the topic.

3. Summary

This article conducts methodological research in the absence of data, so it is necessary to build a data generation system. Data generation systems need to not only meet the needs of methodological research, but also characterize the real data of practical applications as much as possible. Experimental results show that the data meets the intelligent data processing requirements of the aircraft simulation, and the model can work effectively.

References

[1] Zhang Y, Zhang X, Cao J, Shi H. Processor free time forcasting based on convolutional neural network. Proceedings of the 37th Chinese Control Conference, CCC 2018. 2018; Wu Han: IEEE, 7: 9331-9336. EI: 20184606054895.

[2] Li Y, Zhang Y, Xie WC. Joint transmit-receive subarray sythesis optimization for Hybid MIMO phased-array radar. Proceedings of 2017 10th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics, CISP-BMEI 2017. 2017; v2018, p1-6. EI: 20182205244490.

[3] Zhang Y, Cao J, Tao LY, Xu SW, Wei MF, Zhang X. A redundant fault -tolerant aviation control system based on deep neural network. Lecture Notes in Electrical Engineering. 2020; 594: 344-351.

[4] Zhang Y, Cao J, Tao LY, Xu SW, Wei MF, Zhang X. An improved deep q-learning for intelligent transmitter control system. Lecture Notes in Electrical Engineering. 2020; 594: 344-351.

[5] Chang YX, Zhang Y, Li L, Cao J, Yang D. IP Softcore for a bubbling convolutional accelerator in a neural network. Electronics World. 2019; 125(5): 34-37.

[6] Zhang Q, Cao J, Zhang Y, Zhang SG, Zhang Q, Yu DS. FPGA implementation of quantized convolutional neural networks. Proceeding of International Conference on Communication Technology. ICCT 2019. 2019; Shanxi: IEEE; 6: 1605-1610. EI: 20200408089807.

[7] Zhang Y, Zhao Q, Tao LY, Cao J, Wei MF, Zhang X. A real-time online aircraft neural network system. International Workshop on Future Computing, ICCASIT 2019. 2019; Hang Zhou: IEEE; 12, p. 1-6. EI: 20202208717224.

[8] Zhang Y, Tao LY, Wei MF, Cao J, Xu SW, Zhang X. An intelligent unmanned control method for redunant moving agent. Proceedings of the 2019 IEEE International Conference on Unmanned Systems, ICUS 2019. 2019; Beijing: IEEE; 10. p. 649-654. EI: 20201008261383.

[9] Zhang SG, Cao J, Zhang Q, Zhang Q, Zhang Y and Wang Y. An FPGA-based reconfigurable CNN accelerator for Yolo. Proceeding of 2020 IEEE 3rd International Conference on Electronics Technology, ICET 2020. 2020; Chengdu: IEEE. p. 74-78. EI: 20202808913866

[10] Feng S, Cao J, Luo YB, Dai ZY, Zhang Y and Wang Y. Compression for text detection and recognition based on low bit-width quantization. Proceeding of International Conference on Signal and Image Processing. 2020; Nanjing: IEEE. v10, p. 313-317. EI: 20210809970607.

[11] Zhang Q, Cao J, Zhang SG, Zhang Q, Zhang Y and Wang Y. Efficient FPGA implementation of softmax layer in deep neural network. Proceeding of International Conference on Signal and Image Processing. 2020; Nanjing: IEEE. v10, p. 935-939. EI: 20210809970579

[12] Cui AY, Zhang Y, Dong W and Wang CY. Intelligent health management of fixed-wing UAVs: A deep-learning-based approach. Proceeding of international Conference on Control, Automation, Robotics and Vision, ICARCV 2020. 2020; Shenzhen: IEEE. v12, p. 1-6. EI: 20210509860007

[13] Zhang Y, Wei MF, Wang SH, Tao LY, Cao J, Zhang X. Aircraft reinforcement learning multi-mode control in orbit. Journal of Xidian University. 2020; 47(2): 75-82.

[14] Zhang Y, Tao LY, Cao J, Wang SH, Zhao Q and Zhang X. Real-time low power consumption aircraft neural network. Computer Science. 2021; 48(3): 196-200

[15] Zhang Y, Wei MF, Gao XY, Wang SH, Cao J, Zhang X. A neural network prediction method for aircraft health. Aerospace Control. 2019; 55(12): 24-28.

[16] Zhao XY, Qi HX, Wang SH, Zhang Y. Research on calibration of SINS by Kalman filter. Aerospace Control. 2017; 35(6): 14-18.

[17] Zhang Y, Tian F, Chen W, Li R. Space detector health prediction based on online neural network. Journal of Physics: Conference Series. 2022; 11-16.

[18] Zhang Y, Ma Z, Niu ZC and Feng L. High level integrated system of space detector network integration. Journal of Physics: Conference Series. 2022; 1-6.