Unanticipated Fault Detection Technology for Tip/Tilt Mirror Control System of Large Aperture Telescope

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Abstract. Large Aperture telescopes are usually placed in some special environment. Once a malfunction occurs, it’s inconvenient for maintenance. This paper presents those unanticipated failures in tip/tilt mirror control system of large aperture telescopes, and tries to propose a detection strategy based on BP neural network. Firstly, the paper analyses the failure mechanism of the software and the hardware of the tip/tilt mirror control system. Then the known fault data are used to train the BP neural network in order to obtain an accurate detection model. Finally, the unanticipated data are mixed into the known fault data, and the model is used to detect unanticipated faults. The simulation results show that the model can be used to detect the unanticipated fault in tip/tilt mirror control system effectively.

1. Introduction

Large optical/infrared telescopes are necessary for revealing the essence of the universe and exploring the origin of the universe. The 12m large optical /infrared telescope (LOT) to be planned can better meet the needs of astronomers to explore faint celestial bodies and major cosmic phenomena.

In order for large astronomical telescopes to give full play to their optical performance, they are generally built in the inaccessible plateau areas. However, once the telescope failed, it is difficult to resume its normal activities, which affects the astronomical observations greatly. So fault diagnosis research is very important for the telescope [1].

The structure of LOT is shown in Figure 1.
The tip/tilt mirror system of a large optical telescope determines the imaging quality of the CCD, and plays a vital role in stabilizing the optical path. The mechanical vibration caused by the movement of the telescope and the optical path jitter caused by the atmospheric disturbance would lead to the interference to the imaging of stars. In this case, the tip/tilt mirror control system of the telescope can effectively correct these jitter errors, so as to meet the requirements of optical performance of the telescope. The supporting actuator of the tip/tilt mirror control system is generally a piezoelectric ceramic actuator. If one of the actuators fails, it will seriously affect the imaging quality of the CCD. Therefore, it is necessary to study the malfunction of the tip/tilt mirror control system of the large telescopes.

2. BP Neural Network Theory
In the development of artificial neural networks, the research of perceptron learning models (PLM) has occupied an important position. With the deepening of the research, the study on PLM can’t help to solve the complex nonlinear model problems. So the researchers used a hidden layer between the input layer and the output layer to form a multilayer feed forward neural network, which effectively solved the problem. In the mid-1980s, Rumelhart and others proposed an error back-propagation algorithm, referred to as the BP neural network algorithm [2]. This algorithm system solves the problem of hidden layer connection weights and some problems that cannot be solved by the simple perceptron.

The BP neural network does not need a clear mathematical relationship. Its structure is divided into an input layer, a hidden layer, and an output layer. The signal propagates from the input layer to the output layer through forward propagation. And the error propagates from the output layer to the input layer through back propagation. Through the gradient descent method and the error back propagation, the weights and thresholds between the layers can be continuously adjusted to make the model more accurate [3].

The network model diagram is shown in Figure 2.

![Figure 1. LOT structure diagram](image)
3. Fault analysis of the tip/tilt mirror control system

Fault analysis is divided into two parts: hardware and software.

3.1. Hardware failure analysis

The hardware part of the experimental platform built in this paper mainly includes the main control computer, CCD camera, piezoelectric ceramic drivers, piezoelectric ceramic actuators (PZT), ambient temperature sensor, ambient humidity sensor. Its control flowchart is shown in Figure 3.

The optical path stabilization control of the tip/tilt mirror system uses a four-point support control method. Four PZTs are placed at the four corners of the mirror mechanism. The group of PZT1 and PZT4 and the group of PZT2 and PZT3 are moving at the same time, which represents the X-direction movement of the pendulum mirror. The group of PZT1 and PZT2 and the group of PZT3 and PZT4 are moving at the same time, which represents the Y-direction movement of the pendulum mirror. The actuator placement is shown in Figure 4.
3.2. Software failure analysis

3.2.1. Image stabilization PID. The image stabilization system of the pendulum mirror is controlled by the PID algorithm. By comparing the advantages and disadvantages of the incremental PID algorithm and the position PID algorithm at the same time, the study found that the position PID algorithm has a large amount of calculation, and the error results of its previous calculation would accumulate. And the incremental PID algorithm controls the increase and decrease of the control variable, meanwhile the error is only related to the previous calculations [4]. Therefore, an incremental PID algorithm is selected in the image stabilization system. The mathematical expression of the algorithm PID is:

\[ \Delta u = u_n - u_{n-1} = K_p \left( (e_n - e_{n-1}) + \frac{r}{T_i} e_n + \frac{r_d}{T} (e_n - 2e_{n-1} + e_{n-2}) \right) \]  

(1)

The image stabilization of the built simple optical path system was performed. The given optical path disturbance was selected as a sine wave with 0.5Hz amplitude, 0.2V amplitude, 93.8mV offset, and CCD processing frequency of 82Hz.
Figure 6. PID

The image data detected by the CCD without PID adjustment is shown in Figure 5. The image data after PID adjustment is shown in Figure 6.

Based on the feedback information of CCD, the pixel data obtained are analysed. And it is found that this method can effectively simulate the actual image stabilization control of the telescope, which is of great help to correctly analyze the software fault mechanism of the whole control system.

3.2.2. Software Failure Mechanism Analysis. By analysing the software failure mode, the selected software features are: (1) displacement parameter of piezoelectric actuator 1 (2) displacement parameter of piezoelectric actuator 2 (3) displacement parameter of piezoelectric actuator 3 (4) The piezoelectric actuator 4 has a displacement parameter (5) CCD detects X-direction pixels (6) CCD detects Y-direction pixels.

Synthesizing the failure mechanisms of software and hardware, a total of 13 failure features are selected as the input layer nodes of the BP neural network. They are: (1) supply voltage parameter (2) PZT1 driver voltage parameter (3) PZT2 driver voltage parameter (4) PZT3 driver voltage parameter (5) PZT4 driver voltage parameter (6) PZT1 actuator displacement parameter (7) PZT2 actuator displacement parameter (8) PZT3 actuator displacement parameter (9) PZT4 actuator displacement parameter (10) CCD detects X-direction pixels (11) CCD detects Y-direction pixels (12) auxiliary temperature parameter (13) auxiliary humidity parameter.

4. Mode Building and Data Analysis

4.1. Mode building

According to the number of input layer nodes determined in Section 3, it can set the number of output layer nodes to one, and then use the empirical formula (2) to determine the number of hidden layer nodes.

\[ L = \sqrt{m + n + a} \]  

\( L \) is the number of the hidden layer node. \( m \) is the number of the input layer node. \( n \) is the number of the output layer node. \( a \) is the number for 1~10 tuning parameters [5]. Through the constant adjustment of the experiment, the number of the hidden layer node is finally determined to be 14.

Due to the large data span of the selected input layer parameters, there are large parameters of the input voltage and multi-micron displacement parameters of the PZTs. If the neural network model is carried out directly, the training speed of the model will be extremely slow. Data must be normalized, and the formula of data normalization is formula (3).
When data is normalized to between -1 and 1, the transfer function adopted is a bipolar Sigmoid formula, so Logsig function is selected. With the output transfer function Purelin function, the curve can be simulated with high precision. In this paper, the training times are 5000, the global minimum error is 0.003, and the learning efficiency is 0.02.

4.2. Data analysis

4.2.1. Expected data analysis. In this paper, 5 fault features are selected as the detection of expected fault, and 1 fault is selected as the detection of unexpected fault. First, the expected fault of the model is detected, then the unexpected fault is detected, and finally, the expected fault and the unexpected fault are mixed for the unexpected fault detection again. The expected output value is defined as 1. And the validity of the model is verified by observing the deviation between the output value and the expected value of the model.

For the fault data used for training, the expected faults were first detected, and five sets of fault data used for detection were put into the model to obtain the actual output values in table 1.

**Table 1.** Expected fault output value

| Fault 1 | Fault 2 | Fault 3 | Fault 4 | Fault 5 | Desired Output |
|---------|---------|---------|---------|---------|----------------|
| 0.0152  | 0.046   | 0.0287  | 0.0213  | 0.0322  | 00000          |
| 0.9834  | 0.0133  | 0.04   | 0.0475  | 0.0383  | 00001          |
| 0.0678  | 0.9688  | 0.0609  | 0.0498  | 0.0481  | 00010          |
| 0.002   | 0.0071  | 0.9528  | 0.099   | 0.0523  | 00100          |
| 0.0217  | 0.0027  | 0.0077  | 0.9111  | 0.1083  | 01000          |
| 0.0098  | 0.0153  | 0.0511  | 0.1191  | 0.9005  | 10000          |

In table 1, the expected output is in binary code form, corresponding to the expected output values of fault 1~5 respectively from right to left. When the fault-free data samples are tested, the expected output is 0, while the actual output is not far from 0. When the fault is detected from 1 to 5, the actual output value is 0.98, 0.96, 0.95, 0.91 and 0.90 respectively, which is not far from the expected output value of 1.

4.2.2. Unexpected data analysis. Only the unexpected data fault 6 was put into the model for detection, without any expected fault data mixed in. And the actual output value was shown in table 2.

**Table 2.** Unexpected fault output value

| Fault 1 | Fault 2 | Fault 3 | Fault 4 | Fault 5 | Fault 6 |
|---------|---------|---------|---------|---------|---------|
| 0.0066  | 0.0082  | 0.0080  | 0.0563  | 0.0555  | 0.9119  |

The actual model output of unexpected fault data 6 is 0.9119. It can be seen that the actual output value of the unexpected fault is not far from the expected output value of 1. We can consider this model to be effective in detecting unexpected fault data.

4.2.3. Mixed data analysis. We mixed the randomly selected data of fault 2 and fault 3 with the unexpected fault data 6. Then data were put into the model for detection. The actual output of the model is shown in table 3.
Table 3. Mixed fault output value

| Fault 1 | Fault 2 | Fault 3 | Fault 4 | Fault 5 | Fault 6 |
|---------|---------|---------|---------|---------|---------|
| 0.0046  | 0.9894  | 0.9893  | 0.0586  | 0.0355  | 0.9049  |

The detected value of unexpected fault 6 is basically unchanged. It is not far from 1. And the detected value of expected fault is not far from the output value of 1. Through the verification of the mixed data, it is proved that the model is effective in detecting unexpected faults.

5. Conclusion

Based on the analysis of the hardware and software failure mechanism of the tip/tilt mirror control system, the data are analyzed and integrated. 13 fault characteristics were selected to construct BP neural network model. By analyzing the test data, it is found that the model can effectively detect the data of unexpected faults. It is verified that the actual output of detecting unexpected fault data and mixed fault data does not differ much from the expected output. This method can be applied to the control system of the tip/tilt mirror for the future 12-meter optical/infrared telescope. The fault analysis also has certain reference significance in the other tip/tilt mirror control systems.

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References

[1] Shihai Yang, Yun Li, Dandan Xu, and Jiajia Wu "Design of semi-physical fault simulation platform for Antarctic telescopes", Proc. SPIE 10700, Ground-based and Airborne Telescopes VII, 1070024 (6 July 2018)

[2] Wen Jin, Zhao Jia Li, Luo Si Wei and Han Zhen, "The improvements of BP neural network learning algorithm," WCC 2000 - ICSP 2000. 2000 5th International Conference on Signal Processing Proceedings. 16th World Computer Congress 2000, Beijing, China, 2000, pp. 1647-1649 vol.3.

[3] Ying Chen, and Ji Liu. "An improved BP neural network algorithm and its application." Metallurgical and Mining Industry 3 (2015): 175-181.

[4] Aström, Karl Johan, Tore Hägglund, and Karl J. Astrom. Advanced PID control. Vol. 461. Research Triangle Park, NC: ISA-The Instrumentation, Systems, and Automation Society, 2006.

[5] Zhang, X. H., and Yong LEI. "Application of BP neural network in mechanical fault diagnosis." Noise and Vibration Control 5 (2008): 95-97.