Intelligent Fault-Diagnosis Assistance System for Astronomical Telescopes Based on Observation Image Recognition (Postprint)

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Abstract

We designed and constructed an intelligent auxiliary fault diagnosis system for telescopes based on observation image recognition. The system comprehensively diagnoses faults occurring during telescope observations by collecting fault images and sensor information, and provides corresponding solutions and recommendations. We utilize convolutional neural network methods for intelligent image recognition and employ fault tree analysis to identify weak points in the telescope system. Through simulation and actual measurement tests, it has been proven that the system can effectively detect and diagnose faults and provide recommendations, thereby improving telescope reliability and laying the groundwork for the intelligentization of fault diagnosis technology.

Full Text

The Intelligent Fault Auxiliary Diagnosis System for Astronomical Telescopes Based on Observation Image Recognition

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Abstract

We have designed and constructed an intelligent fault-assisted diagnosis system for astronomical telescopes based on observation image recognition. The system collects fault images and sensor information during telescope observations to comprehensively diagnose faults and provide corresponding solutions. We employ convolutional neural networks for intelligent image recognition and utilize fault tree analysis to identify weak points in the telescope system. Both simulation and field tests demonstrate that the system can effectively detect and diagnose faults while offering actionable recommendations, thereby improving telescope reliability and paving the way for intelligent fault diagnosis technology.

Keywords: Fault diagnosis; Fault tree; Image recognition; Astronomical telescope

Introduction

Telescopes are essential tools for astronomical research, and their efficient and stable operation is a prerequisite for effective observations. Therefore, to achieve long-term stable observation runs, the use of fault diagnosis systems is indispensable.

A fault diagnosis system is a programmatic system that analyzes system data during faults to rapidly identify and locate failure points, enabling quick response and solution provision when telescope failures occur. Fault diagnosis technology has precedent applications in multiple fields. As early as the 1960s, Stanford University first proposed an expert system-based fault diagnosis method, applying industry expert knowledge bases to the field of fault diagnosis [1]. In the 1970s, fault diagnosis technology for control systems was first introduced at MIT [2]. In astronomy, the United States conducted research on fault diagnosis technology for telescope control systems to address maintenance difficulties with the Hubble Space Telescope [3]. Australia also applied fault diagnosis technology to the Australia Telescope in the 1990s, achieving sensor-based telescope fault diagnosis [4]. In China, fault diagnosis technology has found astronomical applications as well. An intelligent mirror defrosting system was used on Antarctic telescopes to heat the mirror surface and ensure observation was not hindered by frost and snow [5]. Mini-GWAC also employed a fault tree and sensor-based telescope fault diagnosis system to achieve automatic control while ensuring system safety [6].

However, traditional fault diagnosis systems struggle to perform effectively when fault information acquisition is limited. Their diagnosis methods are singular and information channels are limited. For example, small and medium-sized telescopes developed in the last century often lack comprehensive sensor equipment, preventing traditional fault diagnosis systems from accurately obtaining required system information through sensors and significantly reducing their effectiveness. Today, artificial intelligence technology is advancing rapidly [7], and fault diagnosis systems are becoming multi-method integrated, multi-channel information-based, and intelligent. These technologies can effectively compensate for the shortcomings of traditional fault diagnosis systems and maximize their effectiveness. The intelligent fault auxiliary diagnosis system for astronomical telescopes based on observation image recognition proposed in this paper employs a convolutional neural network-based image recognition module that utilizes observation images generated during telescope faults, combining intelligent image recognition technology with fault diagnosis systems to effectively address the problem of insufficient information acquisition in older small and medium-sized telescopes with incomplete sensors. Furthermore, the more comprehensive the information acquisition, the higher the accuracy of fault determination. Therefore, this system can also assist traditional sensor-based fault diagnosis systems by adding new information acquisition channels and improving fault diagnosis accuracy.

1 Design of the Intelligent Fault Auxiliary Diagnosis System Based on Observation Image Recognition

This fault auxiliary diagnosis system operates based on telescope observation images, historical fault records, fault solutions, and available sensor information. After analysis and integration, sensor and image information is compared with historical fault records to provide possible fault causes, probabilities, and corresponding solutions from the fault resolution database. The system employs the following design scheme.

1.1 Overall System Design

The intelligent fault auxiliary diagnosis system for telescopes based on observation image recognition consists of four main components: an information collection module, a database module, an inference module, and a human-computer interaction interface. The system architecture is shown in Figure 1 [Figure 1: see original paper].

The functions of each component are as follows:

(1) **Information Collection Module**: This module is responsible for receiving information transmitted by sensors and observation images. It incorporates a convolutional neural network-based image recognition algorithm that classifies measured images into general fault types according to the retrained fault model. Subsequently, it transmits the collected fault information to the database and inference modules while displaying it on the human-computer interaction interface. Additionally, the information collection module monitors the telescope' s real-time operating status by assessing image quality and sensor parameters to determine the current state, storing all data and parameters in the system operation database for retrieval by the inference module when faults occur.

(2) **Database Module**: Serving as the system' s knowledge repository and

operational database, it is divided into the system operation database and the fault knowledge base. The system operation database stores fault IDs, method IDs, path weights, correspondences, and telescope operational data, forming the fundamental support for system operation. The fault knowledge base stores corresponding fault knowledge recorded in the fault tree, including basic fault information and probabilistic weight data.

(3) **Inference Module**: Comprising an inference engine and an interpreter, this module collects and reasons over relevant information from the information collection module, system operation database, and fault knowledge base. It employs logical strategies to determine possible outcomes and sends results to the human-computer interaction interface. When a fault is confirmed, the inference module also stores the results back into the knowledge base to serve as directional guidance for future telescope maintenance by engineers.

(4) **Human-Computer Interaction Interface**: This interface displays information and accepts user control, serving as the primary interaction channel between users and the system.

1.2 Fault Tree Design and Analysis

This system employs a fault tree-based logical structure design. A fault tree is a tree structure that clearly reflects the logical and causal relationships between upper-level "trunk" events and lower-level "branch" events. The system starts from the top event and progressively makes judgments downward based on information and the tree structure. Once a bottom event is identified, the corresponding fault is determined. The top event of the fault tree is abnormal telescope measured images, representing telescope system failure. Through electronic compilation of historical fault records and statistical analysis of faults from eight telescopes at the Xinglong Observatory Base, a fault database was established. After consulting relevant experts, the middle layer of the fault tree was divided into three major categories: "elongated star image," "slid star image," and "disappeared star image." Below these categories, failures are further subdivided to the system or component level based on telescope structure. The system fault tree for the eight optical telescopes at Xinglong Observatory Base is shown in Figure 2 [Figure 2: see original paper], and fault label descriptions are provided in Table 1 .

[Figure 2: see original paper] Telescope System Fault Tree

Table 1 Description of Fault Tree Labels

Label	Fault Description
T	Telescope image abnormal
A1	Elongated star image
A2	Slid star image

Label	Fault Description
A3	Disappeared star image
B1	Telescope cover not open
B2	Hardware limit
B3	Dome cover motor failure
B4	The dome completely blocked the light path
C1	Inaccurate code wheel
C2	The dome not open
D1	Rotating eliminate motor failure
X1	Optical path failure
X2	CCD communication system failure
X3	Tracking motor stopped for a short time
X4	Clouds obscured star image
X5	Barrel center of gravity slipped
X6	The shutter not opened
X7	Tracking system failure
X8	Transmission structure slid
X9	Cover motor failure
X10	Tracking motor stopped
X11	Cover communication system failure
X12	Rotating eliminate system failure
X13	Transmission structure failure
X14	Tracking motor faults
X15	CCD system failure
X16	The light path is completely blocked
X17	User misoperation
X18	Dome motor failure
X19	Oil pump failure
X20	Dome mechanical failure
X21	Dome cover communication system failure
X22	Dome cover mechanical and component failure
X23	The shutter not closed
X24	CCD failure

Fault images are classified into one of the three image categories by the retrained image recognition model, after which further communication with various systems determines the bottom event. Each bottom event has its own weight, which is continuously adjusted based on successfully identified faults and engineer feedback. These weights serve as probability references when precise determination is impossible due to limited conditions. Since faults in individual telescopes tend to be repetitive, the weight and probability distributions have high reference value.

Qualitative and quantitative analysis of the fault tree can effectively identify system weak points, allowing engineers to focus inspections on these areas during maintenance and thereby reducing the telescope's operational failure rate. Using Boolean algebra simplification for qualitative analysis:

T=A1+A2+A3
A1=B1+B2+X1+X2; A2=X3+X4+X5; A3=B3+B4;
B1=X6+X7+X8+X9+X10; B2=X11+X12; B3=X13+X14;
B4=C1+C2+X15+X16; C1=X17+X18; C2=D1+X19+X20+X21;
D1=X22+X23+X24.

From this we can derive:

T=X1+X2+X3+X4+X5+X6+X7+X8+X9+X10+X11+X12+X13+X14+X15+X16+X17+X18+X19+X20+X

Thus, the minimal cut sets are: {X1}, {X2}, {X3}, {X4}, {X5}, {X6}, {X7}, {X8}, {X9}, {X10}, {X11}, {X12}, {X13}, {X14}, {X15}, {X16}, {X17}, {X18}, {X19}, {X20}, {X21}, {X22}, {X23}, {X24}, totaling 24 minimal cut sets, all of which are first-order cut sets. This means that every bottom event in the fault tree directly affects telescope imaging quality, and weak points are directly related to the failure probabilities of each bottom event. Below, we calculate the occurrence probabilities of each bottom event based on statistical telescope fault records.

When telescopes at Xinglong Observatory Base experience faults, engineers fill out fault reports during resolution, which are then archived. Analyzing these archives yields the occurrence probabilities of fault tree bottom events. By statistically analyzing fault reports from eight telescopes at Xinglong Observatory Base from 2016-2018 and calculating the average annual occurrence probability per telescope, the results are shown in Table 2 .

Table 2 Probability of Fault Tree Bottom Events

Label	Fault	Probability
X23	The shutter not closed	20.83%
X24	CCD failure	8.33%
X1	Optical path failure	4.17%
X2	CCD communication system failure	20.83%
X3	Tracking motor stopped for a short time	12.50%
X4	Clouds obscured star image	4.17%
X5	Barrel center of gravity slipped	4.17%
X6	The shutter not opened	4.17%
X8	Transmission structure slid	16.67%
X9	Cover motor failure	12.50%
X10	Tracking motor stopped	16.67%
X11	Cover communication system failure	20.83%
X13	Transmission structure failure	8.33%
X14	Tracking motor faults	4.17%
X17	User misoperation	4.17%
X18	Dome motor failure	12.50%

Label	Fault	Probability
X19	Oil pump failure	12.50%
X20	Dome mechanical failure	8.33%
B2	Hardware limit	20.83%
B3	Dome cover motor failure	12.50%
C1	Inaccurate code wheel	8.33%
X21	Dome cover communication system failure	4.17%
D1	Rotating eliminate motor failure	8.33%
X22	Dome cover mechanical and component failure	8.33%

According to the fault tree analysis, all minimal cut sets of the system are first-order, meaning that the failure of any bottom event will cause the top event to fail. Using the results from Table 2, the probability of the top event failing at least once per year is calculated as:

P(T)=1-[1-P(X1)][1-P(X2)][1-P(X3)][1-P(X4)]······[1-P(X24)] 0.929575

The faults with higher occurrence probabilities include camera shutter closure failure, telescope limit protection triggering, CCD communication system failure, and cover communication system failure, with an average probability of 20.83% per telescope per year. Telescope maintenance personnel should focus on these weak points during routine maintenance and inspections, promptly identifying and replacing faulty components to improve the reliability of the telescope system during daily operation and reduce observation losses due to faults.

1.3 Establishment of the Fault Training Set

The image recognition module of the convolutional neural network requires a fault training set for retraining. In this system, the module must be able to identify "elongated star image," "slid star image," "disappeared star image," and normal images. The fault training set images are obtained through three main channels: screening from observation images, on-site telescope photography, and manual drawing.

Images obtained from observations primarily consist of data from the 80cm telescope at Xinglong Observatory Base (2017-2018) and the 85cm telescope (2019). From these, 23 slid star image samples, 50 elongated star image samples, and 1,037 normal observation images were selected. On-site photography utilized the 60cm telescope at Xinglong Observatory Base to manually capture faulty star images, including 626 elongated star images and 1,104 disappeared star images. Slid star images could not be photographed due to telescope protection requirements. Manual drawing was used to supplement fault images difficult to obtain through conventional channels, adding 44 slid star images and 73 elongated star images. All images were labeled, with 90% used as the training set and 10% as the test set.

For retraining parameters, the training steps were set to 9,000, the learning rate to 0.01, with no random cropping, scaling, or flipping. After retraining, the required model was successfully obtained. The test accuracy was 97.63%, with all images showing obvious features correctly classified. Images with slight elongation or extended sliding had a small probability of confusion.

2 Preliminary Test Results

Based on the system design described above, we used Python to code and successfully built an image-based intelligent fault auxiliary diagnosis system for telescopes. To test whether the system could operate normally, we attempted to manually simulate faults for detection. Additionally, actual observation fault data was input into a virtual telescope to verify whether the system' s results matched the fault records.

2.1 Virtual Environment Test Results with Simulated Faults

We used the telescope control software "Xinglong Base Universal Telescope Control Front-end" to generate a virtual telescope for experimental testing of this system. The test manually simulated telescope faults to verify whether the system could operate normally. The simulated fault was "user misoperation," where a user accidentally stopped tracking, causing elongated star images in telescope measurements. During the experiment, actual elongated star images were used to guide the system. The diagnostic results are shown in Figure 3 [Figure 3: see original paper].

[Figure 3: see original paper] Simulation Test Result

The results show that the system successfully identified the fault cause based on the measured images and virtual telescope status information, demonstrating successful operation in a virtual environment.

2.2 Test Results Based on Real Measured Data

The 80cm telescope at Xinglong Observatory Base experienced a fault during observation on January 18, 2016. By querying and screening, we obtained the fault images captured on January 18 along with the telescope' s operational logs, system, and position information at that time. The virtual telescope' s parameters were adjusted to reproduce the fault scenario. The test results are shown in Figure 4 [Figure 4: see original paper].

[Figure 4: see original paper] Real Data Test Result

The system successfully identified the image anomaly as "disappeared star image." Following the fault tree logic, under the disappeared star image branch, the system first attempted to communicate with the CCD system and received feedback that both the CCD status and CCD communication system were normal. It then communicated with the cover system and confirmed that the cover opening was below the threshold, the communication system was normal, but the cover was likely not opened. Therefore, using elimination, it identified the bottom event as "cover motor failure," which matched the records in the base fault report.

This demonstrates that the system can fulfill its intended role in actual telescope operation, helping maintenance personnel quickly locate faults and reference corresponding solutions.

If the system cannot precisely determine the fault tree bottom event due to limited conditions, it determines the weight of possible causes under the fault phenomenon based on historical fault records and engineer feedback. Since faults in individual telescopes tend to be repetitive, the probability distribution of fault causes has significant meaning. After fault resolution, the system can adjust probabilities based on feedback, providing directional guidance for maintenance personnel through fuzzy fault diagnosis with improved accuracy for individual telescopes.

We collected and analyzed 48 faults that occurred at Xinglong Observatory Base telescopes in 2019. The system directly identified bottom events for 31 faults; for 10 faults, it made fuzzy judgments based on weights where the highest-probability reference item was the actual fault cause; for 5 faults, the cause was included only in the reference items; for 2 faults, the cause was not included in the reference items. The comprehensive determination accuracy was 85.42%, with an error rate of 14.58%.

Conclusion

This paper presents and implements using Python an intelligent fault auxiliary diagnosis system for telescopes based on observation image recognition. We analyzed the system' s fault tree and determined that telescopes at Xinglong Observatory Base are prone to cover motor failure, shutter closure failure, limit protection triggering, CCD communication failure, and cover communication failure. Focusing maintenance efforts on these components can effectively improve daily telescope stability. The system can monitor telescope operating status, and its innovation lies in using fault images captured during observation as a new information acquisition channel when telescope system faults occur. Through intelligent image recognition, it performs preliminary fault classification and provides corresponding maintenance recommendations for identified faults, paving the way for intelligent fault diagnosis systems. With further refinement, this system can also be integrated with other fault diagnosis systems to assist in fault diagnosis, improve diagnostic accuracy, and provide assurance for stable telescope operation.

References

[1] Jiang Changcheng. Development of Remote Monitoring and Diagnostic Analysis System for Gantry Crane[D]. Southeast University, 2018.

[2] Fang Hanming, Shui Aishe, Wang Hui, et al. A Survey of Fault Diagnosis Methods for Control Systems Based on Big Data[J]. Microcontrollers & Embedded Systems, 2016, 16(04): 6-9.

[3] Monahan C M, Patterson-Hine F A, Iverson D L. Automated telescope monitoring and diagnosis[C]//The Astronomical Society of the Pacific Conference Series, 1995.

[4] Landau R. Intelligent fault diagnosis at the Australia telescope[C]//Proceedings of the Astronomical Society of Australia, 1994: 180-187.

[5] Feng Qingchen, Li Xiaoyan. Fault Tree Analysis on Reliability of Mirror Defrosting System of Antarctica Astronomical Telescope[J]. Astronomical Research & Technology, 2018, 15(01): 111-118.

[6] Fu Xianan, Huang Lei, Wei Jianyan. The fault diagnosis expert system of Mini_GWAC[J]. Astronomical Research & Technology, 2016, 13(3): 366-372.

[7] Dai Jin, Liu Zhenyu. A Survey of Research on Image Recognition Algorithm Based on Deep Learning[J]. Computer Products and Circulation, 2018(03): 188.

Note: Figure translations are in progress. See original paper for figures.