Postprint of Research on Intelligent Control Systems for Large Astronomical Optical Telescopes

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Abstract

Due to the high complexity and numerous influencing factors of large astronomical optical telescopes, traditional automatic control technologies struggle to guarantee autonomous, reliable, and high-efficiency operation. Therefore, there is an urgent demand to improve aspects such as telescope reliability and observation quality. This study constructs a control system supported by next-generation artificial intelligence technology through the organic integration of deep learning, intelligent agents, and other techniques. Supported by an artificial intelligence software experimental platform, the research and development of two application control systems—reliability management and observation quality optimization—are implemented. These two application systems will run on historical data from the Large Sky Area Multi-Object Fiber Spectroscopic Telescope (LAMOST), with verification and evaluation conducted through simulation. The research results will provide a pilot study for the intelligent development of China' s existing and next-generation telescope control systems.

Full Text

Preamble

Research on Intelligent Control Systems for Large Astronomical Optical Telescopes

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Figure 1

Figure 1: Figure 1

Abstract

With the continuous development of astronomical observation technology, the aperture of astronomical optical telescopes is increasing, and their structural complexity is rising accordingly. Traditional control methods face significant challenges in meeting the high-precision and high-stability requirements of modern large-scale telescopes. This paper investigates the application of intelligent control systems in large astronomical optical telescopes, focusing on the integration of advanced control algorithms and machine learning techniques to enhance system performance. By analyzing the dynamic characteristics of telescope structures and the impact of environmental disturbances, we propose an intelligent control framework designed to optimize tracking accuracy and pointing stability.

1. Introduction

Large astronomical optical telescopes are essential tools for exploring the universe and conducting fundamental astrophysical research. As scientific goals become more ambitious, the demand for higher resolution and sensitivity has led to the design of telescopes with larger primary mirrors and more complex optomechanical systems. These advancements, however, introduce significant control difficulties, such as structural resonances, wind-induced vibrations, and thermal deformations.

Traditional Proportional-Integral-Derivative (PID) control, while robust, often struggles to adapt to the non-linear and time-varying nature of these large-scale systems. Consequently, there is a critical need to transition toward intelligent control architectures. These systems leverage modern computational power to implement real-time adjustments, predictive modeling, and autonomous fault detection, ensuring that the telescope maintains peak performance under diverse operational conditions.

2. System Architecture and Modeling

The control system of a large astronomical telescope is a multi-layered architecture involving the mount control system (MCS), active optics (aO), and adaptive optics (AO). To achieve precise pointing, it is necessary to establish an accurate mathematical model of the telescope’ s mechanical structure.

The dynamic behavior of the telescope can be represented by the following state-space equation:

$$\dot{x}(t) = Ax(t) + Bu(t) + w(t)$$
$$y(t) = Cx(t) + v(t)$$

where $x

摘要

Large-scale astronomical optical telescopes are characterized by high complexity and are influenced by numerous variables. Consequently, traditional automatic control technologies struggle to guarantee autonomous, reliable, and high-efficiency operation. There is currently an urgent demand to enhance both the operational reliability and the observational quality of these instruments.

This research aims to construct a control system supported by next-generation artificial intelligence (AI) through the organic integration of deep learning and intelligent agents. Supported by an AI software experimental platform, the study focuses on the development of two specific application control systems: reliability management and observational quality optimization. These two systems will be executed and validated using historical data from the Large Sky Area Multi-Object Fiber Spectroscopic Telescope (LAMOST).

The performance of the proposed systems will be verified and evaluated through simulations. The results of this study will serve as a pilot study for the intelligent development of control systems for both existing and next-generation telescopes in China.

关键词

Telescope Control Systems

The telescope control system (TCS) serves as the core operational framework for modern astronomical observatories, responsible for the precise coordination of complex hardware components to achieve high-fidelity celestial observations. At its fundamental level, a TCS must manage the pointing and tracking of the telescope mount, the positioning of optical elements, and the synchronization of scientific instruments. As telescopes have evolved from manual instruments to massive, automated facilities, the requirements for control systems have shifted toward high-precision real-time performance, robust fault tolerance, and seamless integration with data acquisition pipelines.

System Architecture and Design

Modern telescope control systems typically employ a distributed hierarchical architecture to manage the diverse range of subsystems involved. This structure often consists of a high-level supervisory layer for scheduling and user interface, a middle layer for coordination and command distribution, and a low-level hardware abstraction layer for direct motor control and sensor feedback. By decoupling these layers, engineers can ensure that time-critical tasks—such as the servo loops required for sub-arcsecond tracking—are not interrupted by high-level computational processes. Common frameworks used in this domain include EPICS (Experimental Physics and Industrial Control System) and specialized middleware designed to handle the high-bandwidth telemetry generated by modern sensors.

Precision Tracking and Pointing

The primary objective of any TCS is to maintain the target object within the instrument' s field of view with extreme accuracy. This involves compensating for various physical phenomena, including atmospheric refraction, structural flexure due to gravity, and the Earth' s rotation. Advanced control algorithms, such as Proportional-Integral-Derivative (PID) controllers augmented with feed-forward models or state-space controllers, are utilized to minimize tracking errors. Furthermore, the integration of Global Positioning System (GPS) timing and high-resolution encoders allows for the precise synchronization of the telescope's axes, ensuring that the pointing model remains accurate over long-duration exposures.

Automation and Remote Operation

With the rise of robotic telescopes and large-scale survey missions, automation has become a critical component of telescope control. Modern systems are increasingly capable of autonomous decision-making, utilizing sophisticated scheduling algorithms to optimize observing time based on weather conditions, target priority, and instrument availability. Remote operation capabilities allow astronomers to conduct observations from anywhere in the world, necessitating robust cybersecurity measures and high-reliability communication protocols. These advancements not only increase the scientific throughput of the observatory but also enable rapid response to transient astronomical events, such as supernovae or gamma-ray bursts.

方法

Reliability Management

Reliability management is a systematic engineering discipline focused on ensuring that products, systems, or processes perform their intended functions without failure under specified conditions for a defined period. In the context of modern industrial engineering and systems design, reliability management encompasses the entire lifecycle of a product—from initial conceptual design and development to manufacturing, operation, and eventual decommissioning.

Core Objectives and Methodologies

The primary objective of reliability management is to minimize the probability of failure and mitigate the consequences when failures occur. This is achieved through a combination of quantitative analysis and qualitative management strategies. Key methodologies include:

- **Reliability Modeling and Prediction:** Utilizing mathematical models to estimate the expected performance and lifespan of a system based on component data and environmental factors.
- **Failure Mode and Effects Analysis (FMEA):** A proactive approach used to identify potential failure modes within a system, evaluate their impact, and prioritize risks for mitigation.
- **Fault Tree Analysis (FTA):** A top-down deductive failure analysis that employs Boolean logic to combine lower-level events to understand the causes of complex system failures.
- **Reliability Testing:** Conducting rigorous stress tests, such as Highly Accelerated Life Testing (HALT) and Reliability Growth Testing, to identify weaknesses and verify that the system meets its reliability requirements.

Lifecycle Integration

Effective reliability management requires integration across all organizational levels. During the **design phase**, engineers focus on redundancy, derating, and the selection of high-quality components to build inherent reliability into the system. In the **manufacturing phase**, the focus shifts to process control and quality assurance to ensure that the physical product matches the design specifications. Finally, during the **operational phase**, reliability management involves condition monitoring, predictive maintenance, and the collection of field data to inform future design improvements.

Data-Driven Reliability

With the advent of Industry 4.0 and the proliferation of sensors, reliability management has become increasingly data-driven. Machine learning and deep learning techniques are now frequently employed to analyze vast amounts of telemetry data, enabling predictive maintenance strategies that can anticipate failures before they occur. This transition from reactive to proactive management significantly reduces downtime and lifecycle costs while enhancing safety and performance.

In summary, reliability management is not merely a technical requirement but a strategic necessity. By systematically addressing potential failures throughout the product lifecycle, organizations can ensure the safety, quality, and economic viability of their systems in increasingly complex operational environments.

方法

Observation Quality Optimization

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Abstract

In the field of astronomical observation and satellite tracking, optimizing observation quality is fundamental to ensuring the accuracy of orbital determination and the reliability of data analysis. This paper explores systematic approaches to enhancing the precision and efficiency of observational data. By analyzing the primary sources of error—including atmospheric turbulence, instrumental noise, and geometric dilution of precision—we propose a multi-layered optimization framework. This framework integrates advanced machine learning algorithms for real-time signal processing with robust statistical models for error correction. Experimental results demonstrate that the proposed optimization strategies significantly reduce the variance in observational residuals and improve the overall consistency of the data across different observation windows.

1. Introduction

The rapid expansion of space exploration and the increasing density of satellite constellations have placed unprecedented demands on the quality of ground-based and space-based observations. High-quality observational data is the cornerstone of space situational awareness, celestial mechanics research, and deep-space navigation. However, the process of capturing high-fidelity signals is often compromised by a variety of environmental and technical constraints.

Observation quality optimization involves the systematic refinement of the entire data acquisition pipeline, from initial sensor calibration to final post-processing. Traditional methods often rely on static filtering techniques, which may fail to adapt to the dynamic nature of observational environments. This study aims to bridge this gap by introducing adaptive optimization techniques that respond to real-time changes in observation conditions.

2. Factors Influencing Observation Quality

To effectively optimize observation quality, it is necessary to categorize and quantify the factors that degrade signal integrity. These factors can be broadly classified into three categories:

1. **Environmental Factors:** These include atmospheric refraction, scintillation, and background light pollution. For ground-based optical observations, the seeing conditions dictated by atmospheric turbulence are often the limiting factor for angular resolution.
2. **Instrumental Factors:** Noise characteristics of the detector (such as dark current and readout noise), optical aberrations, and tracking jitter

Figure 1

Figure 2: Figure 1

of the telescope mount contribute significantly to the error budget.

3. **Geometric Factors:** The relative geometry between the observer and the target, often quantified by the Dilution of Precision (DOP), affects the sensitivity of the measurements to random errors.

3. Optimization Methodology

We propose a comprehensive optimization strategy that utilizes both hardware-level adjustments and software-level algorithmic enhancements.

3.1 Adaptive Signal Processing Using machine

1 引言

Introduction

With the continuous advancement of astronomy, the performance requirements for astronomical telescopes have become increasingly demanding. The development trends toward larger apertures, more remote observation sites, and increasingly complex functionalities pose significant challenges to telescope control systems. Large astronomical optical telescopes, in particular, face high system complexity and numerous factors that can degrade observation quality, indicating that current control systems still have substantial room for improvement.

Years of operational experience with the Large Sky Area Multi-Object Fiber Spectroscopic Telescope (LAMOST) have highlighted an urgent need to further enhance equipment reliability and observational data quality. Research into intelligent control systems for astronomical optical telescopes is driven by the pressing practical demand to improve the observational performance of large-scale instruments, ensure their stable operation, and facilitate continuous upgrades. Innovative telescope solutions that integrate artificial intelligence (AI) technologies are poised to drive transformative developments across the field of astronomy.

In this study, we developed a highly automated and intelligent control system for large astronomical optical telescopes by constructing an AI-driven software experimental platform. This system integrates AI technologies to conduct reliability management research, enabling real-time fault monitoring for the telescope. Furthermore, the system optimizes observational quality by improving the internal dome environment and streamlining operational workflows, ultimately leading to enhanced imaging quality. This work provides technical support for transitioning existing telescope control systems from automation to intelligence and offers a practical foundation for the application of intelligent operations in telescope systems.

2.1 望远镜可靠性管理

The fault semi-physical simulation platform constructed in this study.

The fault simulation system, as described in the *Acta Astronomica Sinica*, consists of two primary components: a fault simulation module and a fault analysis and self-healing system. This system enables the prediction and diagnosis of multiple types of faults. It incorporates a maintenance decision-making mechanism based on life prediction models and utilizes big data analysis to formulate emergency response plans. The specific framework is illustrated in the "Reliability management framework for telescopes." Within this fault simulation semi-physical platform, the telescope drive system serves as the core component of large-scale astronomical instruments. Although the frequency of failures in actual operation is relatively low, any occurrence can significantly degrade observation quality or lead to direct interruptions of observational tasks. This study utilizes the telescope drive system' s semi-physical simulation platform to simulate and evaluate various fault-handling algorithms. This process allows for the acquisition of critical data regarding the telescope' s direct-drive system. The mechanical structure of the fault simulation semi-physical platform utilizes the UMAC (Universal Machine and Automation Controller) hardware, which is a Eurocard-standard system-level controller designed for precision motion control and automation applications.

Research on Intelligent Control Systems for Large Astronomical Optical Telescopes: The fault simulation semi-physical simulation platform effectively and accurately simulates various potential telescope fault phenomena through the integration of hardware and software, producing analog outputs consistent with actual fault conditions. It employs a universal network interface to achieve comprehensive real-time communication and system monitoring. The system maintains flexibility by allowing for the continuous addition of new fault modes based on operational experience. Regarding the software system of the fault simulation semi-physical platform, this study developed a dedicated host computer software based on the Microsoft Foundation Classes (MFC) framework. This software facilitates real-time communication between the host computer and the telescope drive system simulation platform, providing a foundation for the research of unintended state recognition algorithms and evaluation mechanisms for telescope direct-drive systems.

2.2 望远镜观测质量优化

Atmospheric seeing is a critical factor affecting imaging quality. Based on the physical environment of the observation station, providing optimal adjustments for the optical system and the telescope state—specifically by improving the internal dome environment and optimizing telescope operations—constitutes a framework for enhancing observational quality. Seeing prediction is based on the time series of atmospheric seeing at the station. In this study, we utilize the temperature difference within the dome and other atmospheric environmental parameters, combined with various sequence prediction algorithms, to predict atmospheric seeing for the next 20 minutes. The core architecture of the proposed model, SeeRocket, consists of an organic integration of a feature extractor utilizing a large number of fixed convolutional kernels and a tree-based model. The SeeRocket model primarily comprises differential processing, feature extraction, and prediction modules. Comparative analyses were conducted regarding model training time, prediction latency, the number of convolutional kernels, and their relationship with the accuracy of the seeing prediction model to support the research.

The primary functions of the telescope reliability management system include the operation and communication of the operational controllers and the real-time status monitoring of the dual motors on the simulation platform. This monitoring encompasses information such as position, speed, current, voltage, acceleration, and following error. The collected data are synchronized and stored in a local database to ensure data integrity and traceability. The system also integrates a torque sensor serial module to implement the reading and closing of the control serial port, providing multi-dimensional information. The telescope reliability management system offers comprehensive data research support for the platform' s operation. Through precise data monitoring, the reliability of telescope operations is improved.

The workflow of the SeeRocket model's seeing prediction framework is as follows: The SeeingData-30s dataset is used as the input time series. This input is sent to the differential processing module, which handles feature differentiation on the spatial axis and first-order differentiation on the temporal axis, respectively. The processed time series is then fed into the feature extraction module, where a large number of variable-stride convolutional kernels are used to transform the sequence into a high-dimensional vector. This high-dimensional vector is then input into the downstream predictor to obtain the predicted seeing value for the next time point. Seeing optimization techniques involve selecting appropriate optimization operations based on the internal and external dome environments. Seeing and telescope performance are improved through means such as cooling, ventilation, and dehumidification. By utilizing accumulated data on imaging quality changes, scores for each operation are provided, as shown in the [FIGURE: Interface diagram of human-machine interaction for upper computer software].

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The full names and meanings of each feature are as follows: Dome monitoring module seeing (Differential Image Motion Monitor, DIMM); Elevation of Primary Mirror Assembly (Ma1-evi); Focus of Primary Mirror Assembly (Ma1-Focal); and Front of Secondary Mirror Assembly (Front of Secondary Mirror Assembly, ···).

Output: Predicted Output Downstream Predictor Feature Extraction Convolutional Kernel Transformation First-Order Difference Differential Processing Temperature Sensor Position Information Input:

Grouped Differencing of Temperature Features. Schematic diagram of the SeeRocket seeing prediction framework. A reinforcement learning-based method for dome seeing optimization: the optimization process iteratively updates a deep neural network to improve accuracy, utilizing the network to approximate value functions and provide evaluations for specific operations. Key components include the Back of Secondary Mirror Assembly (M_b front - M_b back) and the Secondary Mirror Stop (Stop of Secondary Mirror Assembly, Back of Secondary Mirror Assembly, M_b stop - M_b back).

Ultimately, the features influencing imaging quality are derived, revealing key factors across multiple dimensions. The Imaging Quality Model, built upon a deep neural network, includes modules for atmospheric seeing prediction, the relationship between imaging quality and the internal/external dome environment, and the impact of operational optimization on the dome environment. Based on real-time environmental states monitored by sensors, this method evaluates the effectiveness of different optimization actions through the deep neural network. It automatically selects the optimal operation to improve seeing. When an action is executed, it represents a specific operation with a corresponding score. These scores are aggregated into the table on the right, providing a basis for the system' s final action selection. The specific architecture is as follows:

2.3 人工智能软件实验平台

The artificial intelligence software experimental platform is based on a microservice architecture and Docker, integrating various data management and processing methods, machine learning, and deep learning models. It provides functions for the publication and management of AI services, offering technical support for the reliability management and observation quality optimization of telescopes. The overall architecture of the platform is designed as an Observation Quality Optimization Dynamic Closed-Loop framework.

Research on Intelligent Control Systems for Large Astronomical Optical Telescopes

The platform supports the modeling of multi-source operational data, including structured and text data. Structured data consists of monitoring data collected by various sensors (such as current and voltage) and internal/外部 environment data (such as temperature, humidity, and atmospheric pressure). Unstructured text data primarily comprises telescope-related knowledge documents, including design documents, manuals, and maintenance logs. For structured data, data labeling is completed across three dimensions: equipment failure types, remaining useful life, and observational seeing. For unstructured text data, a text labeling scheme has been designed to facilitate knowledge extraction.

Data Management Layer

The platform supports the uploading of various telescope operational data and employs a two-layer data management framework. This facilitates the convenient import of structured data files, unstructured text files, and astronomical databases, ensuring unified management of raw data for subsequent processing.

Intelligent Algorithm Layer

The platform supports the modeling of telescope operational data. The logical structure of the intelligent algorithm layer is designed to implement core functions such as the evaluation and prediction of telescope seeing, as well as fault detection and identification. The algorithm layer can dynamically capture the temporal features and periodic patterns of the data based on the relationship between observed values and future predictions. By mining textual information such as technical specifications and maintenance records, a maintenance knowledge graph is constructed to assess the failure risks of specific equipment or components, thereby providing decision support for preventive maintenance.

[FIGURE: Importance of features affecting imaging quality, including Feature Importance, Mal-Focal surface, stop altpos, humidity, DIMM seeing, pressure, dewpoint, day/year, and mirror temperatures (Mb stop-Mb back, Mb front-Mb back)]

[FIGURE: Optimization framework for dome visibility based on reinforcement learning, illustrating the closed-loop process: Input -> Model (training) -> Choose/Optimize -> Change Dome State/Manual Action -> Output]

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Model Management Layer

This layer performs life-cycle management of models, including training, evaluation, tuning, version control, permission management, and deployment. It supports the automated tuning and modification of model parameters and provides image-based management and custom configurations for models.

Service Management Layer

This layer links model training with model services to ensure effective deployment and operation. It features automatic resource scaling based on load and automated construction for service publication and maintenance. Access to specific service resources is governed by user access control policies, while the layer also collects, monitors, and analyzes service performance.

[FIGURE: Data processing and algorithm selection workflow: Upload selection -> Processing selection (Normalization, Discretization, Imputation, Outlier Detection) -> Algorithm Selection (Support Vector Machine (SVM), Neural Network)]

Com- ponent Unit Fault State

User Interface Layer

Based on the functional layers described above, the platform provides a comprehensive intelligent modeling user interface that covers the entire lifecycle of model development. This includes data uploading, data selection, data processing, task selection, algorithm selection, model training, model management, service publishing, and service management. The interface allows users to initiate various intelligent modeling tasks and provides the flexibility to manage these tasks throughout their execution.

As the primary entry point for artificial intelligence services, the user interface layer displays all external services currently running on the platform. It provides essential operational controls, including entry points for starting, stopping, and monitoring the status of these services. Key modules within this layer include Model Management, Service Publishing, and Service Management, as well as parameter configuration tools for fine-tuning runtime performance.

Model Training

Selection Recurrent Neural Convolutional Neural Network (RNN) Network (CNN) Transformer Perfor -mance Characteri -zation Perfor- mance Failure Perfor- mance Testing Linear Regression Transformer Missing Value Decision Forest Overall architecture of telescope artificial intelligence software experimental platform Testing ponent Failure

Research on Intelligent Control Systems for Large Astronomical Optical Telescopes

Introduction

The development of large astronomical optical telescopes represents a pinnacle of precision engineering and observational science. As the aperture size and structural complexity of these instruments increase, traditional control methods face significant challenges in maintaining the required pointing accuracy and tracking stability. This research focuses on the implementation of an intelligent control system designed to optimize the performance of next-generation telescopes through advanced modeling and data-driven strategies.

Modeling Tasks

The core of the intelligent control system is built upon three primary modeling tasks, each addressing a critical aspect of telescope operation:

- **Modeling Task 1: Structural Dynamics and Environmental Compensation.** This task involves creating high-fidelity models of the telescope' s mechanical structure. It accounts for gravitational deformation, thermal expansion, and wind loading, which are the primary sources of pointing errors in large-scale optical systems.

- **Modeling Task 2: Precision Servo Control and Non-linear Friction.** This task focuses on the electromechanical drive systems. By modeling non-linear effects such as "stick-slip" friction and backlash in the gear assemblies, the system can implement predictive compensation to ensure smooth tracking at sub-arcsecond scales.
- **Modeling Task 3: Adaptive Optics and Wavefront Sensing.** This task integrates the optical performance into the control loop. It involves modeling the atmospheric turbulence and the corresponding response of deformable mirrors to achieve real-time diffraction-limited imaging.

Dataset Architecture

To support these modeling tasks and train the underlying machine learning algorithms, a comprehensive multi-tier dataset has been established.

Dataset 1: Environmental and Structural Monitoring This dataset contains long-term telemetry from sensors distributed across the telescope structure. * **Dataset 1.1: Thermal and Meteorological Data.** Includes ambient temperature, humidity, wind velocity vectors, and localized temperature gradients within the telescope dome. * **Dataset 1.2: Strain and Vibration Profiles.** Records high-frequency data from accelerometers and strain gauges to capture the structural resonance modes during various pointing maneuvers.

Dataset 2: Control System Performance This dataset focuses on the operational characteristics of the telescope' s motion control units. * **Dataset 2.1: Drive Motor Telemetry.** Contains current, voltage, and encoder feedback from the azimuth and elevation axes, providing a baseline for power consumption and torque requirements. * **Dataset 2.2: Error Logs and Tracking Residuals.** A collection of historical

3.1 望远镜故障模拟

1. Simulation and Data Acquisition

Simulation experiments are conducted using a hardware-in-the-loop (HIL) platform, utilizing various signal types including analog, digital, and switching signals. Based on the theory of multi-stage business processes, we develop a formal hierarchical model for astronomical instruments using the Transformer architecture. This approach integrates expert knowledge and empirical experience regarding the target system to perform comprehensive analysis on historical data.

To facilitate supervised learning, information labels are appended to each equipment monitoring record. We specifically filter equipment monitoring data corresponding to fault states to generate simulated fault datasets. Each fault category encompasses multiple distinct fault modes, which are classified as follows:

The simulated fault types include: - Fault Increase - Fault Fluctuation - Fault Stabilized After Increase - Fault Torque Fluctuation - Fault Torque Deviation

2. Feature Engineering and Modeling

The system is supported by a feature engineering algorithm framework integrated within the modeling platform. This framework processes the raw monitoring signals to extract high-dimensional features that characterize the operational state of the astronomical instruments. By leveraging the hierarchical Transformer model, the system can capture long-range dependencies and multi-stage transitions within the instrument' s operational lifecycle, ensuring high fidelity in fault representation and diagnostic accuracy.

3.2 望远镜视宁度预测

Prediction of Astronomical Seeing Using Historical Data from the LAMOST Telescope

We utilize authentic historical data from the Large Sky Area Multi-Object Fiber Spectroscopic Telescope (LAMOST) to perform astronomical seeing predictions. For this study, we selected several representative time-series prediction models, categorized into five distinct types: traditional statistical models, tree-based models, classical deep learning models, specialized deep learning models for time series, and derivative models from the Rocket series.

1.1 Model Selection and Methodology

The performance of these models was evaluated based on their ability to capture the complex temporal dynamics of atmospheric turbulence at the telescope site. Traditional statistical models provide a baseline for linear dependencies, while tree-based models offer robustness in handling non-linear feature spaces. Classical deep learning architectures, such as Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks, were employed to model long-term dependencies. Furthermore, we integrated specialized deep learning models designed specifically for high-dimensional time-series data and advanced Rocket-based derivatives, which utilize random convolutional kernels to achieve high computational efficiency and accuracy.

1.2 System Monitoring and Fault Diagnostics

In addition to seeing prediction, the operational stability of the telescope is monitored through an online service management interface. This system tracks critical hardware performance and logs various operational anomalies. Key diagnostic parameters include:

- **Load Fault**: Monitoring mechanical stress and weight distribution issues within the telescope structure.
- **Readhead Fault**: Detecting errors in the precision positioning sensors used for tracking.
- **Motor Torque Output Fault**: Identifying inconsistencies or failures in the drive systems responsible for telescope movement.

By integrating these diagnostic metrics with environmental seeing predictions, we aim to optimize the observation schedule and improve the overall data quality of the LAMOST survey.

Readhead Tilt Fault Readhead Vibration Fault

Simulate fault mode types

Comparative Experiments of Prediction Methods

To evaluate the performance of the proposed methods, comparative experiments were conducted using a variety of established models. The full names of the models involved are: AutoRegressive Integrated Moving Average (ARIMA), Facebook' s Prophet time-series forecasting model, Extreme Gradient Boosting (XGBoost), Light Gradient Boosting Machine (LightGBM), Long Short-Term Memory (LSTM), Deep AutoRegressive (DeepAR), Long Short-Term Series Network (LSTNet), Temporal Convolutional Network (TCN), the Transformer time-series forecasting model, and the Long-sequence Time-series Forecasting model (Informer).

Additionally, the study includes the Seeing Adaptive Temporal Convolutional Recurrent Network (SeeATRCN), the Random Convolutional Kernel Transform (Rocket), Mini Random Convolutional Kernel Transform (MiniRocket), and Multi Random Convolutional Kernel Transform (MultiRocket). Finally, we evaluate the SeeRocket series of derivative models, which are specifically customized and optimized for astronomical seeing prediction tasks in this research. Regarding the core scale of the models, SeeRocket-50k is an optimized version utilizing 50,000 adaptive seeing feature convolutional kernels, while SeeRocket-30k is a lightweight version utilizing 30,000 adaptive seeing feature convolutional kernels. Both are improved models independently proposed in this paper, differing only in the number of convolutional kernels, feature extraction dimensions, and parameter magnitudes.

The experiments utilize Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE) as the core quantitative evaluation metrics. MAE reflects the average magnitude of the absolute deviation between predicted and true values. MSE amplifies larger prediction deviations through its squaring term, making it more sensitive to outliers. RMSE maintains the same units as the original data, providing an intuitive reflection of the discrete deviation of predicted values. MAPE eliminates the influence of data scale on error evaluation, thereby measuring the relative accuracy of the predictions.

Based on these four metrics, the prediction accuracy of each model was assessed. Among them, SeeATRCN demonstrated the fastest training speed and the highest prediction accuracy, achieving the lowest MAE for seeing prediction tasks.

MiniRocket 0.1422 0.0375 0.1937 0.0409

Based on time-series data of atmospheric seeing at the station, this study utilizes parameters including the temperature difference within the dome, atmospheric seeing, and other atmospheric environmental variables to predict atmospheric seeing over a 20-minute horizon. We employ and compare a variety of sequence prediction algorithms, including the Autoregressive Integrated Moving Average (ARIMA) model, the Facebook Prophet time-series forecasting model, Extreme Gradient Boosting (XGBoost), Multilayer Perceptron (MLP), Long Short-Term Memory (LSTM) networks, Gated Recurrent Units (GRU), and the Transformer model. By integrating these diverse modeling approaches, we obtain optimized atmospheric seeing predictions.

3.3.1 运行可靠性管理可视化系统

Reliability Management and Visualization System for Telescope Equipment Failure Prediction and Diagnostic Models.

Research on Intelligent Control Systems for Large Astronomical Optical Telescopes

The operational reliability management visualization system is designed to configure critical failure information predicted by the model and display detailed diagnostic results. The system' s main interface includes historical failure statistics and integrates with the telescope' s fault monitoring system. It performs real-time fault diagnosis for each failure mode across various time granularities. By invoking external fault classification services, the system achieves automated categorization of fault signals, which are then presented through a rolling table display.

The imaging quality optimization visualization system utilizes historical monitoring data from LAMOST, along with dome seeing optimization decision models and seeing prediction models. This system facilitates the prediction and optimization of imaging quality during the telescope' s observation process. It presents historical and real-time meteorological data from the observation site—such as temperature and wind speed—using various formats including curves and graphs. Data collected from various sensors deployed inside the telescope, along with their operational status, are monitored; the system triggers alarms for various data types based on preset thresholds. Key features include real-time environmental information and seeing prediction functions. The main interface integrates models such as ARIMA, Prophet, XGBoost, and Transformer to predict imaging quality parameters both inside and outside the dome. By calling external seeing prediction services, the system forecasts observational seeing and provides optimization decision suggestions, such as activating cooling systems, ventilation, or opening side windows.

Acta Astronomica: Imaging Quality Optimization Visualization System

The control system for large astronomical optical telescopes developed in this study relies on the cutting-edge cross-disciplinary integration of astronomy and artificial intelligence. By integrating advanced AI algorithms into the control system of large astronomical optical telescopes and leveraging an AI software experimental platform, we have implemented two primary applications: reliability management and observation quality optimization.

Using LAMOST as an experimental case study to verify the feasibility of this research, the system predicts observational parameters and dynamically adjusts the observation workflow to improve imaging quality. It provides real-time monitoring of the telescope' s key performance indicators, identifying and diagnosing potential equipment failures to ensure the continuity of observation tasks and the integrity of data collection. The AI software experimental platform developed in this study addresses general issues in optical telescope control systems, facilitating the transition from automation to intelligence. By providing essential services and decision support, this work promotes the intelligent development of large-scale, complex astronomical instrumentation.

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A Fault Injection Method for Control Systems Based on Signed Directed Graphs

1. Introduction

Fault injection is a critical technique for evaluating the reliability and resilience of control systems. By deliberately introducing faults into a system, researchers can observe the resulting behavior and assess the effectiveness of diagnostic and recovery mechanisms. This paper proposes a novel fault injection method based on Signed Directed Graphs (SDG), which provides a structured and systematic approach to modeling fault propagation within complex control architectures.

2. Methodology

The proposed method utilizes the qualitative modeling capabilities of Signed Directed Graphs to represent the causal relationships between various system variables. In an SDG, nodes represent system variables, and directed edges

Figure 1

Figure 3: Figure 1

represent the influence of one variable on another, labeled with a sign (+ or -) to indicate the direction of the influence.

2.1 SDG Modeling of Control Systems To implement fault injection, we first construct an SDG model that captures the nominal behavior of the control system. Let the system be represented by a set of variables $V = \{v_1, v_2, \dots, v_n\}$. The relationships between these variables are defined by the set of edges E, where an edge $e_{ij} \in E$ exists if variable v_i directly influences v_j. The sign of the edge, $s(e_{ij}) \in \{+, -\}$, indicates whether the influence is positive or negative.

2.2 Fault Injection Mechanism Faults are injected by modifying the states of specific nodes or the properties of the edges within the SDG. We define a fault injection operator $\mathcal{F}$ that acts on the graph $G = (V, E)$. The injection can take several forms:

1. **Node Faults:** Forcing a variable v_i to a specific value or adding an offset δ, such that $v_i' = v_i + \delta$.
2. **Edge Faults:** Altering the gain or the sign of the relationship between two variables, representing a degradation in sensor accuracy or actuator performance.

The propagation of the injected fault is then analyzed using the reachability properties of the SDG. If a fault is injected at node v_{inject}, the set of potentially affected nodes $V_{affected}$ is determined by the directed paths originating from v_{inject}.

3. Implementation and Analysis

The implementation of the fault injection process follows

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Abstract

In the context of modern manufacturing, the integration of advanced computational techniques has become essential for optimizing complex production

Figure 1

Figure 4: Figure 1

processes. This paper explores the application of machine learning and deep learning methodologies within the framework of Computer Integrated Manufacturing Systems (CIMS). By leveraging high-dimensional data analytics and robust algorithmic structures, we demonstrate significant improvements in operational efficiency and predictive maintenance accuracy. Our findings suggest that the synergy between intelligent algorithms and integrated manufacturing architectures provides a critical foundation for the next generation of industrial automation.

Introduction

The rapid evolution of industrial technologies has transitioned traditional manufacturing into a data-driven paradigm. Computer Integrated Manufacturing Systems (CIMS) represent a holistic approach to production, where every stage —from design to distribution—is interconnected through digital networks. As the complexity of these systems increases, the demand for sophisticated analytical tools grows proportionally. Machine learning has emerged as a transformative force in this domain, offering the capability to identify patterns and optimize decision-making processes that were previously managed through manual or heuristic methods.

Recent advancements in deep learning have further expanded the possibilities within CIMS. By utilizing multi-layered neural networks, manufacturers can now process vast amounts of unstructured data, such as sensor logs and high-resolution imagery, to monitor equipment health and product quality in real-time. This paper aims to synthesize current research trends and present a novel framework for implementing these intelligent technologies within existing manufacturing infrastructures.

Methodology

Data Acquisition and Preprocessing

The effectiveness of any machine learning model in a manufacturing environment depends heavily on the quality of the input data. In this study, we collected data from a variety of sources, including Programmable Logic Controllers (PLCs), IoT sensors, and Enterprise Resource Planning (ERP) systems. The raw data often contains noise and missing values, necessitating a rigorous preprocessing phase. We applied normalization techniques to ensure that features with different scales, such as temperature and pressure, contribute equally to the model' s performance.

Let $\mathcal{D} = \{x_i, y_i\}_{i=1}^{n}$ represent our dataset, where x_i denotes the feature vector and y_i represents the target variable. To handle the temporal dependencies inherent in manufacturing sequences, we utilized a sliding window approach to transform the time-series data into a supervised learning format.

Model

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Research on Intelligent Control Systems for Large Astronomical Optical Telescopes

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Abstract

Due to high structural complexity and numerous external influencing factors, traditional automatic control technology struggles to ensure the autonomous, reliable, and efficient operation of large astronomical optical telescopes. Consequently, there is an urgent need to enhance both the operational reliability and the observation quality of these instruments. This study constructs a control system framework supported by a new generation of artificial intelligence technology through the organic integration of deep learning, intelligent agents, and other advanced methodologies. Supported by an artificial intelligence software experimental platform, we have developed two primary application control systems: reliability management and observation quality optimization. These two systems are executed using historical data from the Large Sky Area Multi-Object Fiber Spectroscopic Telescope (LAMOST) and are validated and evaluated through simulation. The results of this research provide pioneering insights for the intelligent development of both existing and next-generation telescope control systems in China.

Keywords: instrumentation: telescope control systems, methods: reliability management, methods: optimization of observation quality, techniques: artificial intelligence

1 Introduction

Modern large-scale astronomical optical telescopes are highly complex opto-mechatronic systems. As the aperture of telescopes continues to increase and scientific goals become more demanding, the requirements for control precision, environmental adaptability, and autonomous operation have grown exponentially. Traditional control methods, which largely rely on predefined mathematical models and manual intervention, often fail to account for the non-linearities, time-varying parameters, and unpredictable environmental disturbances inherent in large-scale astronomical observations.

To address these challenges, this research explores the application of a new generation of artificial intelligence (AI) technologies to telescope control. By leveraging deep learning for pattern recognition and intelligent agents for decision-making, we aim to transition telescope operations from traditional automation to true intelligence. This shift is essential for maximizing the scientific output of expensive astronomical facilities and ensuring their long-term operational stability.

2 System Architecture and Methodology

The proposed intelligent control system is built upon a multi-layered architecture designed to integrate seamlessly with existing telescope hardware while providing advanced analytical capabilities. The core of the system is an artificial intelligence software experimental platform that serves as the foundation for specialized application modules.

2.1 Intelligent Agent Framework

We utilize intelligent agents to manage the complex decision-making processes required during an observation night. These agents are capable of monitoring system states in real-time, perceiving environmental changes, and executing control strategies that optimize for both safety and data quality. By employing reinforcement learning, these agents can refine their control policies over time based on historical performance metrics.

2.2 Deep Learning for System Modeling

Deep learning models are employed to handle high-dimensional data from various sensors across the telescope structure. These models are particularly effective at predicting structural deformations and atmospheric turbulence effects

Figure 3

Figure 5: Figure 3

Figure 12

Figure 6: Figure 12

that are difficult to model using classical physics-based approaches. By training on vast repositories of historical telemetry, the system can anticipate potential failures and performance degradation before they impact observations.

3 Application Control Systems

The research focuses on two critical domains of telescope operation: reliability management and observation quality optimization.

3.1 Reliability Management System

The reliability management system is designed to transition maintenance from a reactive or scheduled approach to a predictive one. By analyzing historical data from LAMOST, the system identifies early signatures of component wear or impending failure. This proactive monitoring ensures that the telescope maintains high availability and reduces the risk of catastrophic failures during critical observation windows.

3.2 Observation Quality Optimization System

Observation quality is often degraded by factors such as tracking errors, thermal instability, and atmospheric seeing. The optimization system uses intelligent algorithms to dynamically adjust control parameters in response to real-time feedback. This includes optimizing the active optics system and the precision of the fiber positioning units to ensure that the maximum amount of light is captured and correctly processed by the spectrographs.

4 Validation and Simulation

To validate the effectiveness of the proposed intelligent control framework, we utilized historical data from the LAMOST project. LAMOST, as a large-scale spectroscopic survey telescope, provides a rich dataset of operational parameters and

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Figures

Source: ChinaXiv —Machine translation. Verify with original.

Figure 15

Figure 7: Figure 15

Figure 16

Figure 8: Figure 16