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RESEARCH ON REAL-TIME MONITORING AND DATA ANALYSIS METHODS FOR ASTRONOMICAL PHENOMENA IN SPACE MISSIONS

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ABSTRACT
As space missions grow increasingly complex, real-time monitoring of astronomical phenomena plays a crucial role in mission planning, navigation, and scientific research. Due to communication delays, bandwidth limitations, and environmental challenges, traditional methods often fail to meet the demands of modern missions. This paper proposes an intelligent analysis model based on multi-source data fusion, integrating enhanced deep learning algorithms with real-time data processing techniques. [1] Experimental results demonstrate significant improvements in processing speed (194%), detection accuracy (95.3%), and resource utilization efficiency (43%). These advancements underline the proposed method's reliability and effectiveness in addressing challenges in space exploration.

Keywords: Space Missions, Astronomical Phenomena, Real-time Monitoring, Data Fusion, Deep Learning.

1. INTRODUCTION
With the advancement of space exploration, the demand for real-time monitoring of astronomical phenomena during space missions is becoming increasingly urgent. However, traditional monitoring methods are constrained by communication delays, bandwidth limitations, and complex environments, making it difficult to meet modern mission demands. Existing methods often rely on single data sources, which limit real-time capabilities and accuracy, rendering them inadequate for the complexity and uncertainty of the space environment.

To address these issues, this paper proposes an intelligent analysis model based on multi-source data fusion, combined with deep learning algorithms and real-time data processing technologies, enabling rapid identification and precise localization of astronomical phenomena. This approach not only enhances the real-time and accuracy of monitoring but also strengthens the reliability and stability of analysis through data fusion.

This research is of significant theoretical and practical value. Experimental validation reveals substantial improvements in processing speed, detection accuracy, and resource utilization efficiency, providing technical support for space mission execution and offering new avenues for scientific research. Hence, this study holds broad application prospects.

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2. METHODS

Improved Kalman Filtering Model

Model Background and Design

Traditional Kalman filters struggle with noisy space environments and high-dimensional data. This paper introduces an adaptive weighting mechanism based on the innovation e(k) (observed minus predicted value) to enhance filter performance and data fusion. The weight formula is:

w(k) = exp(-e(k)T R-1 e(k)) (3)[3]

where w(k) is the weight factor, and R(k) represents the observational noise covariance. This adjustment enhances estimation accuracy by suppressing outliers and optimizing noise response.

Application Process

The improved Kalman filter process involves initialization, state prediction, weight calculation, state update, and iteration. Simulated satellite data shows improved accuracy (position error reduced from 80m to 50m) and a 35% efficiency gain. Compared to EKF and UKF, this model performs better with nonlinear systems, non-Gaussian noise, and especially with sudden data anomalies.

Deep Learning Optimization Techniques

Model Design

To improve astronomical event recognition, a CNN-based multi-task optimization model is proposed. [2]It uses a multi-task loss function to optimize classification, regression, and spatial consistency:

L = λ1Lc + λ2Lr + λ3Ls (4)[5]

where Lc, Lr, and Ls are the classification, regression, and spatial consistency losses, respectively, and λ1,λ2,λ3 are the weight coefficients. Multi-task learning is chosen for its ability to enhance model generalization and learning efficiency by sharing underlying feature representations.

Attention Mechanism Application

To improve focus on critical data features, a spatial attention mechanism is integrated:

A(x) = softmax(Wx + b) (5)

where x is the feature map, and W and b are the weight matrix and bias. Attention weights are multiplied with the feature map, highlighting important regions. This improves focus on areas like solar activity in flare detection.

Implementation Details

Data preprocessing ensures consistency, and transfer learning leverages public datasets for pretraining, followed by fine-tuning with mission-specific data. GPU acceleration speeds up training 12-fold. The model achieved a 95.3% accuracy (up from 88.5%) and reduced false alarms to 0.8% (from 3.2%), outperforming traditional and other deep learning models in robustness and efficiency.

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3. RESULTS AND DISCUSSION

Current Status and Challenges of Real-Time Monitoring Technologies for Astronomical Phenomena

Advancements in telescope technology and data processing capabilities have enabled scientists to observe distant celestial bodies with unprecedented precision and resolution. Modern space telescopes, such as Hubble and James Webb, can capture faint signals from deep within the cosmos, unraveling the universe's mysteries. Ground-based telescopes, employing adaptive optics, have overcome atmospheric interference to achieve high-precision observations.

However, real-time monitoring technologies still face numerous challenges. Firstly, the vast diversity of celestial bodies, each with unique characteristics, makes their real-time monitoring highly complex. Scientists must continually develop new observational technologies and data processing methods to meet varied observational needs.

Moreover, real-time monitoring is limited by factors like observational equipment and environments. For instance, ground-based telescopes are affected by atmospheric interference, while space telescopes face threats such as cosmic radiation and micrometeoroids, adding to the complexity and uncertainty of real-time monitoring.

System Performance Comparison

To verify the effectiveness of the proposed method, it was compared with traditional approaches. The results are summarized in Table 1:

Table 1. Algorithm Performance Comparison.[6]

Metric	Traditional	Proposed	Improvement
Processing Delay(ms)	250	85	194%
Detection Accuracy(%)	88.5	95.3	7.7%
Memory Usage(MB)	1500	850	43%
Power Consumption(W)	180	95	47%
False Alarm Rate(%)	3.2	0.8	75%

Experimental Setup:

Tests were conducted on identical hardware and datasets to ensure fairness. The hardware platform consisted of a server equipped with an Intel Core i7 processor and NVIDIA GeForce RTX 3080 GPU. The dataset included multi-source data from simulated environments and real deep-space missions.

Key Insights:

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1. False Positive Rate and Accuracy:
    - The proposed method reduced the false positive rate by 75% (from 3.2% to 0.8%) and improved detection accuracy by 7.7% (from 88.5% to 95.3%), significantly enhancing system reliability.
    - Reasons for False Positive Rate Reduction: The adaptive weight adjustment in the Kalman filter effectively mitigated noise impact. Attention mechanisms in the deep learning model improved critical feature recognition, reducing misclassifications.
    - Reasons for Accuracy Improvement: Deep learning's ability to learn complex features and the multi-task learning framework's generalization capability contributed to higher recognition accuracy.

2. Resource Utilization:
    - Memory usage decreased by 43% (from 1500MB to 850MB), and power consumption decreased by 47% (from 180W to 95W), optimizing computational efficiency and extending mission lifetimes.
    - Reasons for Memory Usage Reduction: Optimized deep learning models with techniques such as pruning and quantization reduced parameter count and memory footprint. Data structure and algorithm improvements further enhanced memory efficiency.
    - Reasons for Power Consumption Reduction: Hardware acceleration using GPUs improved computation efficiency while reducing energy requirements. Optimized algorithms lowered computational complexity.

Energy Efficiency: Lower power consumption is crucial for deep-space missions, extending the operational lifespan of probes and enabling longer observation periods. For example, reduced energy demands on Mars rovers or deep-space probes allow extended missions and additional scientific data collection.

Flexibility in Resources: Reduced memory demands free up bandwidth, enabling advanced operations such as real-time planetary mapping or high-resolution image processing.

Navigation and Positioning

To evaluate the method's performance in navigation and positioning tasks, a series of simulated experiments were conducted. Results demonstrate the following accuracies:

- Position Accuracy: <50 meters
- Velocity Accuracy: <0.05 m/s
- Attitude Accuracy: <0.008°

Experimental Setup:

Simulated scenarios of deep-space probes in different orbits and environments were generated using high-precision simulation software. Observational data was processed using the proposed method and compared against reference trajectories.

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Analysis:
The results confirm the proposed method's ability to provide high-precision navigation and positioning, meeting the stringent requirements of deep-space missions. High accuracy in navigation and positioning is critical for mission success, ensuring probes adhere to planned trajectories and accurately reach their target destinations.

Case Study: Deep-Space Mission

To further validate the practical application of the proposed method, it was deployed in a 180-day deep-space mission focusing on the close observation and data collection of an asteroid.

- Mission Description: The probe autonomously performed orbital maneuvers, attitude adjustments, data acquisition, and transmission. It also monitored asteroid activity in real time, responding to potential threats promptly.
- Application Outcomes:
    - Data Processing Accuracy: 95.3%—ensuring high-quality data for scientific research.
    - Resource Utilization Efficiency: Improved to 78%, optimizing memory and power usage through algorithm and hardware improvements.
    - Real-Time Response: Achieved response times below 150 milliseconds, satisfying real-time monitoring requirements.

Case Analysis:

During the mission, the probe detected an asteroid surface material ejection event. The proposed method quickly identified the event and guided the probe to adjust its attitude, enabling detailed observation of the ejection process. These observations provided critical data for studying asteroid activity mechanisms.

Summary of Advantages:

The method's application in the mission demonstrated its strengths in real-time monitoring, data analysis, and navigation, improving mission success rates, data quality, and operational efficiency while reducing costs.

4. CONCLUSION

This paper presented a framework for intelligent real-time monitoring and data analysis in space missions. Integrating an improved Kalman filter and deep learning techniques enables fast and accurate astronomical event identification and localization. Experiments, both simulated and using real mission data, demonstrate significant improvements in processing speed, detection accuracy, and resource utilization.

Key Contributions:

- Adaptive Kalman Filter: Improves state estimation accuracy, reducing position error from 80m to 50m.
- Multi-task Deep Learning Model: Achieves 95.3% detection accuracy and 0.8% false alarm rate, significantly enhancing reliability.
- Optimized Resource Use: Reduces processing latency by 66%, memory usage by 43%, and power consumption by 47%, extending mission lifespan.
- Validated in Real-World Mission: Demonstrated 95.3% data processing accuracy, 78% resource utilization, and sub-150ms response times in a 180-day mission.

This work provides effective tools for deep space exploration challenges, improving mission success, data quality, and cost-effectiveness.

Future Work

Further research directions include:

- Quantum Computing Integration: Exploring quantum computing for enhanced data fusion and simulation efficiency. Addressing challenges in space-based quantum computing, such as environmental adaptability and hardware reliability.
- Hardware Innovation: Developing high-resolution sensors and low-power processors tailored for deep learning to improve data acquisition and processing.
- Advanced Architectures: Investigating edge computing, distributed networks, and autonomous learning systems for increased adaptability and resilience in complex space environments. Addressing challenges related to radiation hardening, thermal control, and deep space communication limitations.

5.SUMMARY

The proposed method effectively addresses real-time monitoring and data analysis challenges in deep-space exploration. Future research will explore quantum computing, hardware advancements, and innovative system architectures to meet the increasing demands of deep-space missions, advancing our understanding of the universe and pushing the boundaries of human knowledge.

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