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AI-Driven Robotics in Space Exploration

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Abstract - *Artificial Intelligence (AI) and robotics are transforming the landscape of space exploration by enabling autonomous decision-making, adaptive mission planning, and resilient operations in extreme environments. This paper presents a consolidated review of recent advancements in AI-driven robotics, focusing on applications in optical experimentation, planetary surface exploration, spacecraft guidance, and mission optimization. The discussion integrates developments from five key research works: the OptoMate platform for automating free-space optics experiments using fine-tuned large language models (LLMs) and precision robotics; JAXA's deployment of autonomous rovers and pinpoint landing systems in asteroid and lunar missions; legal and governance analyses addressing the risks and liabilities of AI operations in space; deep reinforcement learning (DRL) frameworks for navigation, hazard detection, and resource allocation; and evolutionary optimization techniques for interplanetary trajectory design. The review identifies performance gains achieved in both simulated and real- world missions while highlighting limitations in explainability, simulation-to-reality transfer, and regulatory compliance. Future research directions include hybrid AI-human decision systems, legal-aware mission planning, and explainable AI for high- stakes operations. This synthesis aims to guide researchers toward more reliable, transparent, and accountable AI- driven space systems.*

Key Words: Artificial Intelligence (AI); Space Robotics; Autonomous Systems; Deep Reinforcement Learning (DRL); Planetary Exploration; Optical Experimentation; Large Language Models (LLMs); Evolutionary Optimization; Explainable AI (XAI); Spacecraft Guidance; Trajectory Design; AI Governance; Adaptive Mission Planning.

I.INTRODUCTION

Space exploration has come a long way— from the early days of fully human- controlled missions to today's use of smart, independent systems. Artificial Intelligence (AI) and robotics are now at the center of this change. They help spacecraft and rovers work on their own, make quick decisions, and adapt to unexpected problems. This is especially important for missions far from Earth, where communication delays can take several minutes and Conditions can change without warning. With AI, robots in space can plan their paths, avoid dangers, use resources wisely, and complete their goals without constant human instructions. In recent years, technologies like deep reinforcement learning (DRL), large language models (LLMs), computer vision, and evolutionary optimization have greatly improved what autonomous systems can do. For example, AI-powered robots can now design and set up complex optical experiments in a lab. DRL-based systems can help rovers find safer and faster routes on difficult terrain. Algorithms inspired by nature can also guide spacecraft along the best possible path while balancing fuel, time, and safety.

Space agencies like Japan's JAXA, Europe's ESA, and the United States' NASA have already shown how powerful these technologies can be. JAXA's Hayabusa-2 mission used small hopping rovers to explore an asteroid's surface without human control, and their SLIM lander demonstrated highly accurate landing technology. ESA and NASA are also testing AI for coordinating groups of satellites, servicing spacecraft in orbit, and navigating in dangerous planetary environments. These advances make missions more efficient and open the door for long-term projects like building a base on the Moon or exploring Mars. But as AI becomes more common in space missions, it brings new challenges. The rules and laws for space activities were written decades ago and don't fully cover AI's unique issues, like who is responsible if an autonomous system causes an accident, or how to handle massive amounts of space-generated data. This means engineers, scientists, and policy-makers need to work together to make sure AI systems are safe, trustworthy, and follow international space laws.

This paper reviews recent progress in AI- based robotics for space missions. It looks at five key areas: AI in optical experiments, robotics for planetary exploration, legal and policy issues, DRL-based mission planning, and advanced algorithms for spacecraft guidance. By studying these areas, we highlight the main achievements, the challenges that remain, and possible future directions to make AI systems for space more reliable, transparent, and ready for real missions.

I. Literature Review

Uddin et al. (2025) presented the OptoMate platform, a groundbreaking example of combining generative AI with robotics for the automation of free-space optical experiments. The system integrates a fine- tuned LLaMA3.1-8B-Instruct large language model with Quantum-informed Tensor Adaptation (QuanTA) to design optical setups that are both spatially and physically valid. OptoMate follows a design–assembly–verification loop, where the AI model first generates a detailed plan for an optical experiment, the instructions are sent to a 7-degree- of-freedom robotic arm, and a computer vision system verifies alignment and precision before proceeding. This feedback mechanism ensures that the physical implementation matches the AI- generated design, reducing assembly errors. In tests, OptoMate achieved 41.2% pre- validation accuracy, outperforming both prompt-engineered GPT-4o and zero-shot baselines. Uddin et al. emphasize the platform's potential for space missions, where autonomous optical systems could handle tasks like laser-based communication, interferometry, or adaptive optics without human supervision, especially in deep- space environments where communication delays are significant.

Kubota (2020) offered an in-depth overview of the Japan Aerospace Exploration Agency's (JAXA) AI-enabled robotics programs, focusing on asteroidand lunar missions. In the Hayabusa-2 mission, the deployment of MINERVA-II rovers marked a significant achievement in autonomous planetary robotics. Unlike traditional wheeled rovers, these compact robots moved by hopping—a design choice dictated by the asteroid Ryugu's extremely low gravity, which renders wheels ineffective. Operating autonomously, the rovers navigated hazardous terrain, captured over 600 high-resolution images, and transmitted them to Earth. The mission also deployed a Small Carry-on Impactor (SCI) to create an artificial crater, enabling the study of subsurface material composition. Kubota also discusses the Smart Lander for Investigating the Moon (SLIM), which uses AI-assisted visual navigation and hazard detection to achieve pinpoint landings within 100 meters of the target site. These innovations demonstrate how AI can improve landing accuracy, reduce operational risks, and enhance surface exploration efficiency in resource- limited environments.

Gal et al. (2023) shifted the focus to governance, policy, and legal challenges associated with AI in outer space. They critically analyze how the current international space law framework— primarily the Outer Space Treaty (1967) and the Liability Convention (1972)—fails to address scenarios involving autonomous decision-making systems. Three primary challenges are identified. First, liability ambiguity, where determining responsibility for AI-caused damage or collisions remains unclear, particularly if the AI acts unpredictably. Second, data governance, as AI-driven missions generate massive datasets that raise questions about ownership, privacy, and equitable access. Third, accountability, since AI decisions are often based on complex algorithms that are not easily interpretable, making post- incident investigation difficult. Gal et al. argue for integrating AI governance models into space law to ensure transparent decision-making, traceability, and fair accountability, especially as more commercial actors enter the space domain.

Santwani and Rani (2024) provided a detailed study of Deep Reinforcement Learning (DRL) techniques for enhancing the autonomy of space robotics. DRL enables robots to learn optimal strategies through trial-and-error interactions with the environment, making it well-suited for unpredictable planetary terrains. They introduce AlphaNavNet, an adaptive path-planning system that learns to navigate partially known terrains by balancing safety and efficiency. AstroPlannerNet is presented as a mission scheduling system that optimizes resource allocation under strict time and energy constraints. StellarRL, a multi-agent DRL framework, coordinates fleets of robots for collaborative tasks such as asteroid mining. A notable contribution is the integration of Explainable AI (XAI) methods, ensuring that decisions—such as hazard avoidance maneuvers—can be explained and verified by human operators. Simulation results showed StellarRL improving multi-robot coordination efficiency by more than 20% compared to conventional approaches, suggesting strong potential for real-world deployment in cooperative space missions.

Izzo et al. (2018) reviewed the application of evolutionary algorithms and AI-based optimization techniques in spacecraft guidance and control. They compared the performance of algorithms such as Differential Evolution (DE), Particle Swarm Optimization (PSO), and Covariance Matrix Adaptation Evolutionary Strategy (CMA-ES) in solving complex trajectory design problems. CMA-ES was found to outperform DE and PSO in multi-objective optimization scenarios, particularly when trade-offs between fuel consumption, travel time, andmission risk had to be considered. The study also examined Monte Carlo Tree Search (MCTS) for sequential decision- making and discussed hybrid approaches that combine traditional astrodynamics with AI optimization. These hybrid methods not only improved solution quality but also reduced computational time, making them highly applicable for designing interplanetary transfer trajectories and rendezvous maneuvers under tight mission constraints.

Taken together, these studies illustrate the breadth of AI's role in modern space exploration, spanning laboratory automation, planetary surface mobility, spacecraft guidance, and the legal frameworks that govern their use. They show that AI is not just a technical enhancement but atransformative force that impacts both the operational capabilities and the governance of space missions. The literature indicates a clear trend toward greater autonomy, improved adaptability, and interdisciplinary integration, setting the stage for the methodologies and results discussed in the subsequent sections.

II. Methodology

The reviewed studies collectively employ a range of artificial intelligence techniques, robotics architectures, and optimization strategies to enhance autonomy, precision, and decision-making in space exploration systems. While the individual applications vary—from laboratory automation to planetary landing and trajectory optimization—they share common methodological principles that can be integrated into a unified operational framework.

The general process begins with mission objective definition, where requirements such as navigation accuracy, task allocation, or experimental setup are translated into formal problem statements. For laboratory- based automation tasks, large language models (LLMs) are fine- tuned using domain-specific adaptation methods to generate experimental designs that adhere to spatial and physical constraints. These models produce step-by- step assembly instructions, which are executed by multi- degree-of-freedom robotic arms equipped with precise motion control algorithms. Computer vision modules are used to verify the physical implementation, employing image recognition, edge detection, and geometric validation to ensure component alignment and correct configuration. This closed-loop control system integrates feedback from the vision module to the AI planner, allowing iterative refinement until the setup meets the required specifications.

For planetary exploration missions, the methodology incorporates autonomous mobility algorithms capable of operating in low-gravity and unpredictable environments. Instead of relying solely on wheeled locomotion, hopping and other alternative mobility mechanisms are deployed, supported by onboard visual navigation systems. These systems process terrain images in real time, using feature extraction and hazard detection algorithms to identify safe landing zones or movement paths. Advanced guidance, navigation, and control (GNC) systems integrate AI-based terrain recognition with preloaded surface maps, enabling pinpoint landings and obstacle avoidance. Hazard detection operates in both pre- landing and in-motion phases, allowing robots or landers to adjust their trajectories dynamically.

For decision-making and adaptive control, Deep Reinforcement Learning (DRL) plays a central role. DRL agents are trained in simulated environments that model the gravitational, visual, and physical characteristics of target celestial bodies. Architectures such as convolutional neural networks (CNNs) are used for processing visual input, while recurrent neural networks (RNNs) handle temporal dependencies in decision-making. In multi- robot scenarios, policy-sharing and decentralized coordination frameworks enable cooperative behavior, with each agent learning to optimize its actions for collective mission success. Explainable AI components are integrated into the decision pipeline, generating interpretable visualizations and reasoning traces that mission operators can review for transparency and trust.

In spacecraft guidance and control, evolutionary optimization algorithms— including Differential Evolution (DE), Particle Swarm Optimization (PSO), and Covariance Matrix Adaptation Evolutionary Strategy (CMA-ES)—are applied to multi-objective trajectory design problems. These algorithms iteratively refine solutions by exploring large, nonlinear search spaces, balancing objectives such as fuel efficiency, travel time, and mission safety. Monte Carlo Tree Search (MCTS) is employed for sequential maneuver planning, particularly in missions requiring multiple gravity assists or complex rendezvous sequences. Hybrid methods combine AI optimization with traditional orbital mechanics models, ensuring that computationally derived solutions remain physically valid.

Finally, a governance and compliance layer is included in the methodological framework to ensure alignment with international space laws and ethical AI principles. This involves mapping operational AI capabilities to regulatory requirements, defining accountability measures, and establishing traceability mechanisms for autonomous decision-making processes.

Overall, the methodology is characterized by the integration of AI-based planning and control algorithms with domain-specific robotics and aerospace engineering models, supported by closed-loop feedback systems, simulation-to-reality transfer, and explainable decision- making tools. This combination ensures that autonomous space systems are both technically capable and operationally trustworthy, capable of functioning effectively in the challenging and unpredictable conditions of space exploration.

III. Results and Discussion

The application of AI-powered automation in laboratory- based optical experiments produced notable improvements in precision and repeatability. By combining fine-tuned large language models with robotic arms and computer vision verification, experimental setups achieved alignment accuracy within sub-millimeter tolerances. This closed-loop process reduced configuration errors and assembly time when compared to manual methods, demonstrating strong potential for autonomous optical calibration in space applications such as laser communication and astronomical instrumentation.

In planetary surface exploration, AI- enhanced mobility systems provided superior navigation capabilities in low- gravity and irregular terrain environments. Robots equipped with hopping mechanisms were able to traverse asteroid and lunar surfaces more effectively than traditional wheeled designs. Real-time visual navigation, supported by hazard detection algorithms, allowed autonomous identification of safe paths and landing zones, improving operational safety and reducing reliance on ground control instructions.

Pinpoint landing technologies also showed significant advancements. By integrating AI-assisted terrain recognition with preloaded surface maps, landing systems achieved high positional accuracy, often within 100 meters of target coordinates. These systems dynamically adapted during descent to avoid hazards such as slopes, large rocks, or shadowed areas, ensuring a safer and more reliable landing process in unpredictable environments.

In the context of cooperative multi-robot missions, deep reinforcement learning architectures improved efficiency and adaptability. Simulations of asteroid mining operations demonstrated that multi-agent frameworks completed task allocations more than 20% faster than baseline approaches. Decentralized policy-sharing allowed robots to respond to local changes without compromising coordinated mission objectives, increasing overall system resilience.

Explainable AI components added value to these operations by providing clear justifications for decision-making processes. Operators were able to review visual and analytical reasoning for route choices, hazard avoidance maneuvers, and task assignments, which increased transparency and trust in autonomous decision- making systems. This capability is particularly valuable for missions requiring human oversight despite high levels of autonomy.

Spacecraft trajectory design and control also benefited from advanced optimization methods. Covariance matrix adaptation evolutionary strategy delivered the most balanced results in multi-objective optimization tasks, effectively managing trade-offs between fuel efficiency, travel time, and mission safety. Hybrid approaches that combined AI optimization with classical astrodynamics reduced computation times while maintaining physically valid and mission-feasible trajectories. Monte Carlo tree search proved especially effective for sequential maneuver planning in missions involving complex gravity assist sequences.

IV. Future directions

Future work should focus on improving AI models for space exploration by training them with more mission- specific datasets. Combining simulated and real operational data will help these systems make better decisions in unstructured and unpredictable environments.

Planetary mobility could benefit from hybrid systems that combine hopping, rolling, and legged locomotion in a single robot. AI-driven adaptability would allow dynamic switching between movement types depending on the terrain, improving mission efficiency and durability.

Precision landing technologies can be enhanced through multi-sensor fusion, integrating visual data with LiDAR, radar, and thermal imaging. This would increase reliability in low-light or dust-heavy environments such as lunar poles and shadowed craters. For multi-robot missions, decentralized learning and swarm intelligence can enable large fleets to operate effectively with minimal communication. This will be particularly useful in deep-space missions where communication delays are unavoidable.

Explainable AI should be advanced to provide clearer, real- time reasoning for autonomous decisions. This would increase trust from mission operators and improve post- mission analysis.

Spacecraft trajectory planning could explore quantum- enhanced optimization for faster and more accurate solutions. Real- time adaptive corrections onboard could allow spacecraft to respond to changing conditions without waiting for ground commands

V. Conclusion

This study reviewed advancements in artificial intelligence, robotics, and optimization techniques that are redefining the capabilities of modern space missions. Across the five referenced works, a clear trend emerged—AI is transitioning from a support tool to a mission-critical component, enabling greater autonomy, precision, and operational efficiency in both terrestrial test environments and real extraterrestrial applications.

Research on automated laboratory optical systems demonstrated how large language models, when fine- tuned with domain- specific adaptations, can work alongside robotic arms and computer vision to achieve sub-millimeter assembly accuracy. Such closed-loop automation has immediate applications in space-based optical systems, where autonomous alignment and calibration are vital for communication and scientific instrumentation.
Planetary exploration studies showcased the benefits of AI- enhanced mobility and landing systems, particularly in low-gravity or hazardous terrains. Hopping mechanisms, AI- based hazard detection, and terrain recognition combined with preloaded maps achieved safe and precise landings within meters of targets. These methods reduced human intervention requirements, making operations more efficient and resilient.

Deep reinforcement learning approaches for multi-robot coordination proved effective in simulated asteroid mining scenarios, enabling faster task allocation and adaptability through decentralized decision-making. The addition of explainable AI improved transparency, allowing human operators to trust and verify autonomous decisions in critical missions. Similarly, spacecraft guidance research revealed that evolutionary optimization algorithms— especially covariance matrix adaptation evolutionary strategy—can produce efficient, balanced trajectories, while hybrid methods improved computation times without compromising physical accuracy.

Finally, governance-oriented analysis emphasized that while technical advancements are significant, regulatory frameworks lag behind. Current space law does not adequately address liability or accountability for AI-driven systems operating independently. Addressing these gaps will be critical for safe and responsible mission deployment.

In summary, the collective findings of these studies confirm that AI-driven systems offer substantial improvements in autonomy, adaptability, and performance across the space mission lifecycle. However, technical progress must be matched by legal and operational safeguards to ensure that these systems can be deployed responsibly, sustainably, and effectively in the next generation of space exploration.

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