24 Minutes Wasted: How Autonomous Navigation Will Transform Space Exploration

Aarush Kejriwal

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Intern/Mentor

Dr. Melissa Kiehl

Abstract

Autonomous navigation systems are fundamentally transforming space exploration by reducing the limitations imposed by Earth-based control, communication delays, and the unpredictability of extraterrestrial environments. This research investigates how the integration of machine learning algorithms—particularly reinforcement learning and deep learning-based object detection—enhances the adaptability, accuracy, and operational efficiency of autonomous spacecraft. Through a meta-analysis of five recent peer-reviewed studies, mission reports from NASA, and two expert interviews, this study systematically compares traditional rule-based navigation with AI-powered approaches. The findings demonstrate that machine learning enables spacecraft to make real-time decisions, adapt dynamically to their surroundings, and function independently of constant human input. Evidence from missions such as NASA's Perseverance rover and the CAPSTONE spacecraft underscores the value of AI integration, revealing improvements in mission efficiency, navigation precision, and resilience in unexpected situations. These results suggest that continued development of adaptive AI systems is essential for expanding the capabilities and reach of robotic exploration in space, and that the future of deep-space missions will increasingly rely on robust, autonomous navigation solutions.

Introduction

Twenty-four minutes. That's how long it takes for a command to travel from Earth to Mars—twenty-four minutes of uncertainty, waiting for a rover to execute a single action. In deep-space exploration, where unpredictable terrains and communication delays present significant challenges, reliance on Earth-based control systems limits efficiency and mission success. Traditional navigation systems, which depend on human intervention, struggle to adapt to real-time environmental changes, increasing the risk of failure. Machine learning offers a transformative solution by enabling autonomous navigation systems to process data dynamically, improving decision-making, terrain navigation, and mission reliability. This research will explore how the integration of machine learning enhances the adaptability of autonomous spacecraft, the accuracy of navigation through deep learning-based object detection, and the overall efficiency of space exploration by reducing dependency on Earth-based interventions.

In recent years, significant advancements in autonomous navigation have revolutionized how spacecraft and rovers explore outer space. Autonomous navigation refers to the capability of these machines to navigate without direct human intervention. By processing real-time data, they can make independent decisions that are crucial for navigating the complex and unpredictable terrains found on other planets. Key to this advancement is the integration of machine learning techniques such as reinforcement learning (RL) and deep learning-based object detection. Reinforcement learning enables these autonomous agents to learn and adapt to their environments by interacting with them and maximizing a cumulative reward. Concurrently, deep learning algorithms, particularly

Convolutional Neural Networks (CNNs), enhance the capability of these systems to identify and classify objects within their visual field, improving terrain assessment and obstacle avoidance.

Definitions and Key Concepts

- Autonomous Navigation: This concept embodies the ability of spacecraft or rovers to operate independently, making decisions based on the data they collect without needing real-time instructions from Earth.
- Reinforcement Learning (RL): A branch of machine learning where an agent improves its performance by interacting with an environment to maximize some notion of cumulative reward. This technique is instrumental in autonomous navigation as it enables decision-making processes in environments that are constantly changing.
- Deep Learning-Based Object Detection: This involves AI-driven algorithms, such as CNNs, which are crucial for recognizing and classifying objects in visual data. By doing so, these systems can better assess terrains and avoid obstacles, thereby enhancing the autonomous navigating abilities of spacecraft.

Review of Literature

The ability of spacecraft to autonomously navigate and respond to unforeseen challenges in space is crucial for the success of deep-space missions. Traditional autonomous systems rely on pre-programmed commands and rule-based navigation, which lack the adaptability required to operate in unstructured environments. Machine learning addresses this limitation by enabling spacecraft to process real-time data, recognize patterns, and make independent decisions. This adaptability ensures that spacecraft can adjust their trajectories, avoid obstacles, and navigate dynamically changing environments without human intervention.

One of the most critical aspects of autonomous navigation is the ability to operate in environments where predefined navigation paths are impossible or inefficient. Machine learning models, particularly reinforcement learning (RL), allow spacecraft to self-learn optimal movement strategies by interacting with their surroundings. Mortensen et al. (2023) discuss how reinforcement learning models enable planetary rovers to navigate unpredictable terrains by adapting their movement strategies in real time. This adaptability is particularly beneficial in uncharted planetary surfaces like those found on Mars, the Moon, or asteroids, where terrain features cannot be fully mapped in advance.

Similarly, Turan et al. (2022) explore how autonomous navigation techniques in deep space leverage machine learning to improve adaptability. Their study highlights that deep-space environments, characterized by low visibility, weak gravitational fields, and unpredictable celestial movements, require navigation systems that continuously adjust to changes in real time. Machine learning models process sensor inputs, including LiDAR and vision data, to assess the spacecraft's surroundings and dynamically modify its trajectory. This ability to adapt to extreme conditions ensures that spacecraft can continue operating safely and efficiently, even in environments where traditional rule-based algorithms would fail.

A key advantage of reinforcement learning is its ability to improve decision-making over time. Unlike traditional navigation systems, which follow fixed movement rules, RL agents continuously refine their models based on feedback from previous interactions with the environment. Bourriez et al. (2023) propose a reinforcement learning framework for collision avoidance in autonomous spacecraft, demonstrating how RL-based decision planning can predict and react to potential obstacles without human intervention. Their study highlights that by training reinforcement learning models in simulated environments, spacecraft can develop optimized avoidance strategies for real-world missions, reducing the risk of collision.

In addition, Song et al. (2023) discuss how deep learning techniques improve spacecraft relative navigation, allowing them to adjust their positioning based on changing environmental conditions. By integrating visual and sensor data, deep learning-based navigation models learn optimal motion strategies for interplanetary travel. These advancements ensure that autonomous systems can adapt their behavior in response to past experiences, improving navigation accuracy and reducing reliance on Earth-based corrections.

Another critical factor in spacecraft adaptability is situational awareness, which refers to a system's ability to accurately perceive and interpret its surroundings. AI-powered sensor fusion combines data from multiple sources, such as LiDAR, cameras, and inertial measurement units (IMUs), to provide a more comprehensive understanding of the environment. Li et al. (2008) analyze how terrain slippage impacts rover navigation and how sensor-based AI models help rovers adjust their movement in response to unexpected terrain conditions. Their research demonstrates that machine learning can analyze sensor feedback in real time, allowing spacecraft to modify their navigation strategy to prevent errors and improve stability.

Furthermore, NASA (2024) describes how the Perseverance rover's AutoNav system improved adaptability on Mars by integrating real-time obstacle detection and avoidance. Unlike previous rovers, which relied on pre-mapped routes, Perseverance uses AI-powered navigation models to assess terrain safety and make independent movement decisions. This development marks a significant step forward in spacecraft autonomy, enabling future missions to navigate more complex and uncharted landscapes without constant human oversight.

Several organizations have invested in the development and deployment of autonomous navigation systems in space exploration. Among these, NASA (National Aeronautics and Space Administration) and the European Space Agency (ESA) are at the forefront. Their missions leverage advanced AI technologies to improve the efficiency and safety of space exploration. Despite the advancements, autonomous navigation in space faces several challenges. The vast distances in space cause significant communication delays between Earth and spacecraft. This necessitates high-level autonomy in navigation to ensure timely decision-making. Machine learning enhances adaptability by allowing spacecraft to analyze their environment, learn from past experiences, and make independent decisions. However, adaptability alone is insufficient—accurate navigation is equally critical for mission success. The next section will examine how deep learning-based object detection improves the precision of autonomous navigation in space.

For autonomous navigation systems to be effective, they must accurately identify terrain features, obstacles, and celestial reference points. Deep learning, particularly Convolutional Neural Networks (CNNs), has significantly improved object detection, allowing spacecraft to navigate more precisely and reliably. By using AI-driven optical navigation and sensor fusion, spacecraft can self-localize, refine trajectory planning, and avoid hazards with greater accuracy.

Deep learning-based feature extraction allows spacecraft to analyze complex images and sensor data more effectively. Song et al. (2023) demonstrate how CNNs improve object recognition, enabling spacecraft to identify landmarks and celestial bodies with greater precision. CNNs process large datasets of visual and spectral information, extracting key features necessary for accurate navigation.

Similarly, Andreis et al. (2023) describe an AI-powered image-processing pipeline that enables spacecraft to extract and analyze celestial body positions for autonomous navigation. Their study highlights how deep learning algorithms detect, track, and classify objects in real time, reducing navigation errors and dependency on Earth-based guidance systems. Deep learning is also transforming optical navigation, which relies on image-based localization. Mahendrakar et al. (2023) evaluate the performance of deep learning-based object detection algorithms, such as YOLOv5 and Faster R-CNN, for spacecraft navigation. Their findings indicate that AI-driven optical navigation significantly improves positioning accuracy, enabling spacecraft to adjust their location in real time. Furthermore, Biesiadecki et al. (2007) discuss the effectiveness of autonomous vs. directed navigation in Mars exploration missions. They conclude that autonomous optical navigation allows for faster and more efficient travel, eliminating delays caused by human intervention.

AI-driven sensor fusion combines data from multiple sensors to improve navigation accuracy. Beycimen et al. (2023) surveyed terrain-traversability algorithms that integrate LiDAR, cameras, and IMUs, demonstrating how these techniques enhance robotic mobility. Their study underscores the importance of real-time sensor integration in deep-space missions, where environmental conditions can change unexpectedly. Additionally, Rubio (2023) explains pathfinding algorithms, such as A and Dijkstra's algorithm, which are widely used in autonomous space navigation. These algorithms ensure that spacecrafts select the most efficient routes, improving overall mission efficiency.

While adaptability and precise navigation are essential, true autonomy in space requires minimizing reliance on Earth-based control, ensuring spacecraft can independently operate and make decisions in real time. This shift toward AI-driven autonomy is critical for the future of space exploration, especially as we venture farther into deep space, where communication delays make human oversight impractical. Machine learning not only enhances a spacecraft's ability to adapt and navigate but also improves the overall efficiency and resilience of space missions, fundamentally altering how we approach interplanetary and interstellar exploration. One of the most significant challenges facing deep-space missions is the severe communication delay between Earth and distant spacecraft. For example, a round-trip signal to Mars can take up to 48 minutes, making real-time control impossible during critical moments. AI-driven autonomous systems address this challenge by eliminating the need for constant human input, allowing spacecraft to evaluate their environment and make life-critical decisions on their own.

Turan et al. (2022) emphasize that autonomous navigation is no longer a luxury but a necessity in deep-space exploration, where communication delays make timely human intervention infeasible. They argue that AI enables spacecraft to manage their own trajectories, obstacle avoidance, and mission adjustments in environments that are highly unpredictable and dynamic. This capability is essential when operating on the surface of Mars, orbiting moons of Jupiter, or exploring the asteroid belt, where split-second decisions are necessary for mission success and survival. Similarly, Nesnas et al. (2021) provide a comprehensive review of past, present, and future advancements in spacecraft autonomy, showing how AI has progressively reduced the need for Earth-based oversight. Their analysis outlines how modern spacecraft, equipped with AI, can handle unexpected challenges such as terrain hazards or equipment malfunctions without waiting for instructions from Earth. This shift toward self-sufficiency not only makes missions safer but also enables the exploration of more remote and hazardous regions of space that would be inaccessible under human control alone.

Historically, space missions have depended on pre-planned routes and rigid sequences of commands uploaded to spacecraft before launch. While this method works for simple missions, it lacks the flexibility needed for dynamic environments, where unexpected obstacles or mission adjustments are common. AI and machine learning models address this limitation by allowing spacecraft to adapt their paths in real time, creating a more resilient and robust mission architecture. The CAPSTONE mission, as detailed by Advanced Space

(2024), is a pioneering example of this capability. CAPSTONE employed an AI-driven navigation system that allowed it to maneuver in cislunar space without continuous Earth-based input, demonstrating how autonomous navigation can maintain orbital stability and trajectory corrections independently. This level of autonomy not only ensures mission resilience but also allows for rapid adjustments in response to changing environmental conditions, such as gravitational perturbations or debris encounters.

NASA's Perseverance rover offers another compelling case. According to NASA (2024), Perseverance reduced the workload on mission operators through autonomous decision-making, using its AutoNav system to navigate challenging Martian terrains. AutoNav enabled the rover to assess terrain hazards, select routes, and avoid obstacles in real time, freeing mission control from micromanaging its every move. The ability to act independently means that future missions could explore more dangerous and complex environments, pushing the boundaries of scientific discovery without requiring constant human direction.

In addition to improving resilience and adaptability, AI-driven autonomy also has significant implications for reducing the operational costs of space exploration. Traditional missions require large teams of engineers and mission operators to constantly monitor and guide spacecraft, incurring high labor costs and resource commitments. AI-based systems alleviate much of this burden by allowing spacecraft to self-monitor and make decisions, thereby reducing the need for extensive human oversight. Forbes (2024) highlights how AI reduces the cost of deep-space mission control, streamlining operations and enabling missions to last longer and travel farther than was previously economically feasible. By removing the bottleneck of human control, AI allows space agencies to deploy more missions simultaneously and increases the pace of exploration. This cost efficiency is crucial as humanity begins to plan for long-term lunar bases and Mars colonization, where autonomous systems will need to manage habitat maintenance, scientific research, and resource extraction independently. Moreover, as Ekelund et al. (2024) discuss, the development of lightweight AI models optimized for limited onboard computational resources is making it increasingly feasible to deploy these technologies on small spacecraft and rovers. Their research shows how localized AI learning algorithms enable spacecraft to update and improve their behavior in situ, even with bandwidth constraints limiting communication with Earth. This ability to adapt and learn locally without relying on large, Earth-based data centers expands mission capabilities, especially for long-duration explorations where constant Earth contact is not possible. AI autonomy, therefore, unlocks new types of missions, such as small satellite constellations for asteroid mining or autonomous probes for exploring Europa's icy surface, all without requiring a continuous link to Earth.

The future of space exploration depends on the development and deployment of fully autonomous navigation systems capable of adapting to unknown environments, making independent decisions, and operating without the need for constant Earth-based control. Through the integration of machine learning, spacecraft are no longer confined to rigid, pre-programmed instructions but can learn and evolve in real time, enabling them to tackle the unpredictable challenges of deep-space exploration.

Machine learning has proven to be a transformative force—enhancing the adaptability of spacecraft through reinforcement learning, improving navigation accuracy via deep learning-based object detection, and dramatically increasing mission efficiency by reducing dependency on Earth. These technological advancements signal a fundamental shift in space exploration, moving from human-led remote operations to truly autonomous robotic missions capable of independent scientific discovery. However, despite these breakthroughs, significant challenges remain. AI systems must continue to evolve to handle limited computational resources, maintain reliability in unknown environments, and address ethical concerns around fully autonomous decision-making in space. Robust testing frameworks, hybrid AI architectures, and fail-safe mechanisms must be part of ongoing research to ensure these systems operate safely and effectively.

Looking forward, AI-powered autonomous navigation will be the cornerstone of humanity's next era of space exploration—enabling interstellar probes, robotic colonies, and missions to distant worlds where human presence may never reach. From navigating the dangerous cliffs of Mars to exploring the ice-covered oceans of Europa. As space agencies like NASA, ESA, and private companies like SpaceX continue to push the boundaries of what is possible, it is imperative for global scientific and engineering communities to invest in and prioritize the development of autonomous systems. The world must continue to support this research to ensure that when we reach for the stars, our machines can think, decide, and act on their own—without waiting 24 minutes or more for permission from Earth.

Methods and Data Collection

The primary research question driving this study was: How does the integration of machine learning algorithms enhance the performance and reliability of autonomous navigation systems in space exploration? The hypothesis proposed that embedding machine learning into these navigation frameworks would significantly improve the spacecraft's adaptability to real-time changes, enhance decision-making, and lead to more efficient, autonomous missions. To address this question, I adopted a meta-analytic and systematic review methodology, synthesizing quantitative data and qualitative insights from both the latest published research and firsthand professional experiences. Five scholarly articles were carefully selected based on their relevance to the use of machine learning in autonomous space navigation, covering topics such as reinforcement learning for planetary rovers, deep learning-based terrain interpretation, real-world AI deployment on Mars, and comparative studies of object detection algorithms. Additionally, two expert interviews—one with Dr. Umesh Patel of NASA Goddard and another with Dr. Naghmeh Karimi at UMBC—provided practical perspectives on the current state, challenges, and future directions of AI-driven space navigation. Each source was reviewed for its methodology, subject population (including both simulated and real-world missions), data collection instruments (such as onboard sensors, machine learning frameworks, and telemetry logs), and reported results. This dual approach, combining secondary data analysis with original qualitative interviews, allowed for a comprehensive understanding of both theoretical advancements and operational realities. The meta-analysis was designed to identify patterns, highlight areas of convergence, and address outliers, ensuring a nuanced evaluation of how machine learning is being implemented in the field. Through this rigorous methodology, I was able to connect empirical findings to the broader context of space exploration and draw meaningful conclusions relevant to current and future missions.

Results and Data Analysis

The results of this study provide strong evidence that machine learning algorithms, when incorporated into autonomous navigation systems, offer substantial improvements over traditional rule-based approaches in terms of adaptability, efficiency, and mission resilience. Across the peer-reviewed articles and mission reports, several key trends emerged. First, reinforcement learning (RL) models were shown to enable robotic spacecraft and planetary rovers to navigate unpredictable or unstructured environments, learning optimal strategies through continuous interaction with their surroundings. For instance, the “teacher-student” RL framework highlighted by Mortensen et al. (2023) allowed for successful transfer of navigation skills from simulation to real-world planetary rover operations, demonstrating robust adaptability in the presence of environmental noise and uncertainty. Deep learning-based object detection, as discussed by Song et al. (2023) and Mahendrakar et al. (2023), significantly enhanced the ability of spacecraft to recognize terrain features, avoid obstacles, and precisely localize themselves using visual data. In real missions, these technologies translated into tangible outcomes: NASA’s Perseverance rover, with its AutoNav system, autonomously charted efficient paths across Martian terrain, reducing travel time by 12 sols and increasing overall mission output. Similarly, the CAPSTONE spacecraft’s AI-powered navigation system executed successful orbit corrections and localization tasks in cislunar space without requiring constant ground intervention. The comparative analysis charted in this study highlighted a consistent pattern: AI integration led to faster decision-making, improved safety, and a marked reduction in human workload, supporting the hypothesis that machine learning dramatically boosts mission autonomy. Expert interviews underscored the practical challenges of translating these results to embedded hardware, especially with limited computational resources, but agreed that ongoing advancements in lightweight AI models are rapidly bridging this gap. One unexpected discovery was the rapid transition of AI navigation from simulation and lab environments to operational spacecraft, with successful outcomes already being reported from recent missions—demonstrating not just theoretical promise but immediate, real-world impact.

Discussion and Conclusion

The findings of this study are well aligned with the existing literature, providing compelling evidence that machine learning is a transformative force in the realm of autonomous navigation for space exploration. Both the peer-reviewed research and expert interviews support the conclusion that reinforcement learning and deep learning techniques enable spacecraft to operate with far greater independence, resilience, and scientific effectiveness than traditional methods. This shift toward AI-powered autonomy reduces the need for continuous ground control, enables faster adaptation to dynamic or unforeseen hazards, and allows exploration of more remote, hazardous, or scientifically valuable regions. However, several important limitations were also identified. While some of the studies reviewed were based on real-world mission data, others relied on simulations, which, although sophisticated, may not capture all the complexities of space environments. There remain ongoing challenges in deploying advanced machine learning models on spacecraft with limited processing power and energy resources. The interviews, while valuable for context, represent only a subset of professional perspectives and might not encompass all operational realities. Validity and reliability were supported by the convergence of findings across multiple sources and the use of real mission outcomes, but further large-scale, in-situ field studies are necessary to fully generalize these results. The study suggests future research should focus on the development of energy- and memory-efficient AI models, hybrid navigation architectures, and robust testing frameworks that can validate AI performance under true space conditions. Societally, the results indicate that investment in autonomous systems should be prioritized by both public and private space agencies, as these technologies have the potential to dramatically expand the horizons of human knowledge and capability. In summary, the integration of machine learning into autonomous navigation is not just an incremental upgrade—it is a paradigm shift that is redefining what is possible in the exploration of our solar system and beyond.

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