ENHANCING SPACE AUTONOMY: ADDRESSING SENSOR FAILURES AND UNKNOWN TERRAINS USING MACHINE UNLEARNING

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ABSTRACT: Autonomous systems are those which take decisions without direct human intervention. These autonomous systems plays crucial role in space explorations. While they were using these systems they face some challenges like sensor malfunctions and navigating to unknown terrains. Sensor malfunctions are occurred due to difference in the atmospheric conditions like temperature, dust, radiations these will effect system reliability. While unknown terrains makes hard for the autonomous systems to take decisions as they have lack of relevant training model. Currently most of these issues are solved , by supervised learning on simulated datasets or heuristic-based algorithms but this provide limited adaptability when faced with real-time environmental changes. To overcome this challenge we have proposed an solution that includes integrated reinforcement learning, collecting real-time environmental data this enables autonomous systems to adapt to the dynamic environment. For this purpose we are using some of the algorithms like Q-learning or deep reinforcement learning and some real time algorithms that helps us to identify the faulty sensors.This also helps to improve the decision making of an autonomous systems.

Index Terms: Autonomous systems, Sensor malfunctions, Unknown terrains, System reliability, Supervised learning, Simulated datasets, Heuristic-based algorithms, Real-time environmental changes, Integrated reinforcement learning, Real-time environmental data, Dynamic environment, Q-learning, Deep reinforcement learning, Faulty sensors, Decision-making, Adaptability

I. INTRODUCTION

What is machine learning?
Machine learning is a subfield of artificial intelligence that uses algorithms trained on data sets to create models that enable machines to perform tasks that would otherwise only be possible for humans, such as categorizing images, analyzing data, or predicting price fluctuations.

Reinforcement Learning: Learns through trial and mistake to maximize rewards, perfect for choice-making tasks.

Reinforcement Learning (RL) is a department of machine learning centered on making choices to maximize total rewards in a given circumstance. Not at all like administered learning, which depends on a preparing dataset with predefined answers, RL includes learning through encounter. In RL, an specialist learns to accomplish a objective in an dubious, possibly complex environment by performing activities and getting criticism through rewards or penalties.

How Reinforcement Learning Works?

RL works on the rule of learning ideal behavior through trial and blunder. The specialist takes activities inside the environment, gets rewards or punishments, and alters its behavior to maximize the total compensate. This learning handle is characterized by the taking after elements:

Policy: A procedure utilized by the specialist to decide the activity based on the current state.

Reward Work: A work that gives a scalar criticism flag based on the state and action.

Value Work: A work that gauges the anticipated aggregate compensate from a given state.

Model of the Environment: A representation of the environment that makes a difference in arranging by anticipating future states and rewards.

Q-learning in Reinforcement Learning:
Q-learning is a model-free reinforcement learning calculation that makes a difference an operator learn the ideal action-selection arrangement by iteratively upgrading Q-values, which speak to the anticipated rewards of activities in particular states.

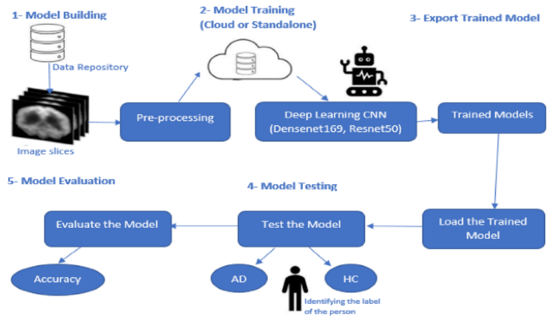


Fig1: Architecture of Machine Learning

Autonomous systems Vs Traditional systems

Autonomous systems are those which take decisions without direct human intervention. These can be used in different areas like Transportation, Construction, logistics, Space Exploration. these are highly adaptive and adjust their behaviour dynamically. the Decision making is done based on the AI,ML, and real-time data. Traditional systems are operated based on the predefined rules and it requires manual control. Decision will be taken based on preprogrammed logic.

What we are concentrated about?

Autonomous systems are becoming an integral part of space exploration, where they provide crucial capabilities for navigating and operating in remote, hazardous, and highly unpredictable environments. These systems, which include rovers, satellites, and space probes, are designed to perform tasks without direct human intervention, which is especially vital in missions to distant planets, moons, or asteroids. However, despite their advanced capabilities, autonomous systems face significant challenges, particularly related to sensor failures and the navigation of unknown terrains.

Sensor malfunctions are a key concern, as they can lead to inaccurate data and poor decision-making, jeopardizing the success of missions. Additionally, unknown terrains ranging from soft, sandy surfaces to complex geological formations pose another hurdle, as the system may not have pre-programmed knowledge to navigate these environments effectively. Traditional approaches to these problems involve extensive pre-programming and rule-based decision-making, but these systems often fail to adapt when encountering novel or unforeseen circumstances.

This research proposes machine unlearning as a potential solution to these issues. Machine unlearning allows autonomous systems to discard outdated or incorrect knowledge and update their models in real-time. By incorporating unlearning techniques alongside adaptive learning algorithms, autonomous systems can better detect and recover from sensor failures and dynamically navigate unknown terrains. This approach enhances the flexibility and reliability of space missions, enabling systems to operate more autonomously and resiliently.

In this paper, we explore how integrating machine unlearning into the decision-making processes of space exploration systems can address these critical challenges, offering a pathway toward more robust and reliable space autonomy for future missions.

A. PROBLEM STATEMENT

Autonomous systems are those which take decisions without direct human intervention.But these systems cannot take decisions during sensr malfunctions and unknown terrains To overcome these issues there were various approaches but all the approaches are limited to adapt the environment.

B. RESEARCH GAPS

- Gaps in AI resiliency for space include self-healing materials, fault-tolerant systems, cooperative sensing, and dynamic mission planning for unknown conditions.
- Real-time decision-making, long-term resiliency, and effective integration of resilience into autonomous systems are needed.
- Integrating terrain classification with path planning and localization in harsh, GPS-denied environments is challenging.
- Distinguishing subtle faults like "stuck" or "drift" from normal sensor behavior is difficult.
- Combining structural models with data-driven approaches for fault handling is challenging due to unreliable data.

II. LITERATURE REVIEW

Martin Andreoni(2024) et.al, this article focus on the transformative role of Generative Artificial Intelligence (GenAI) in enhancing the security, resilience, and reliability of autonomous systems such as UAVs, self-driving cars, and robotic arms. They identify the problem of ensuring trustworthiness and safety in increasingly complex and connected autonomous systems, which face challenges from cyber-physical threats and operational unpredictability. The survey explores how GenAI technologies like GANs, VAEs, Transformer-based models, and LLMs address challenges in cybersecurity, predictive maintenance, anomaly detection, and adaptive threat response. The authors also highlight future directions for integrating GenAI into secure frameworks, emphasizing its potential to make autonomous systems more adaptive and efficient in the face of evolving threats.

Varun Shah(2024) this article focus on the integration of AI-enhanced autonomous navigation systems in next-generation space exploration, aiming to overcome challenges such as long-duration missions and remote operations. The authors emphasize the role of AI algorithms, machine learning, and computer vision in enabling spacecraft to navigate complex environments, optimize trajectories, and adapt to dynamic conditions without human intervention. The problem identified is the need for autonomous systems capable of analyzing vast sensor data in real time, reducing reliance on ground control, and efficiently exploring distant celestial bodies. The study highlights the potential of AI to enhance mission efficiency and agility while paving the way for innovative advancements in space exploration.

Avijit Banerjee (2023) et.al, this article concentrate on the concept of resiliency in space autonomy, emphasizing its importance in addressing the increasing complexity of modern space missions. They identify the problem of ensuring robust and collaborative autonomous operations in challenging scenarios such as spacecraft proximity operations, planetary surface exploration, and interactions with non-cooperative objects in hostile environments. The paper highlights the need for resilience, characterized by robustness, redundancy, and resourcefulness, to handle uncertainties and ensure mission success. It explores current advancements and potential future directions to enhance resiliency in autonomous systems for orbital and deep-space applications.

Hafiz Tahir(2023) et.al**,** this article focus on the application of Artificial Intelligence (AI) to tackle this issue, particularly in autonomous navigation and mission planning. They provide a comprehensive overview of the historical context, current advancements, and future prospects of AI in space exploration. The paper emphasizes AI's transformative potential to revolutionize space exploration, enabling more efficient and autonomous operations. By leveraging AI, the authors aim to overcome traditional limitations and enhance the capabilities of space missions.

Cuebong Wong(2017) et.al**,** this article mainly focuesses on the challenge of reducing reliance on human tele-operators for navigating planetary rovers, particularly in the harsh and complex terrains of Mars. The authors aim to explore intelligent and adaptive methods to develop truly autonomous rover systems suited for resource-constrained environments.

Eliahu Khalastchi(2013) et al**,** this article focus on developing a structural model-based method for online detection and diagnosis of sensor faults, demonstrating its effectiveness using a laboratory robot (Robotican1) and a flight simulator (FlightGear), outperforming previous methods. It also highlights the susceptibility of sensors in autonomous systems to faults, which can lead to task failures.

S.No	**Year**	**Author's**	**Article Title**	**Key Findings**
1	2024	Varun Shah	Next-Generation Space Exploration: AI-Enhanced Autonomous Navigation Systems	Role of AI in Space Exploration, Technological Advancements, Mission Efficiency
2	2024	David Maranto	LLMSat:A Large Language Model-Based Goal-Oriented Agent for Autonomous Space Exploration	Autonomous Systems Design Paradigms, Application of Large Language Models in Space Systems, Hierarchical Control Architectures for Spacecraft

3	2024	Martin Andreoni et.al	Enhancing Autonomous System Security and Resilience With Generative AI: A Comprehensive Survey	GenAI's Role in Enhancing Autonomous Systems, Predictive Maintenance and Anomaly Detection with GenAI.
4	2023	Justin Goodwill et.al	Current AI Technology in Space	Challenges in Deploying AI in Space, Hybrid Processing Approaches, Efforts to Improve Space Computing
5	2023	Hafiz Tahir et.al	AI in Space Exploration: Autonomous Navigation and Mission Planning	Historical Context of Space Exploration, Autonomous Navigation in Space, AI in Mission Planning
6	2023	Avijit Banerjee et.al	Resiliency in Space Autonomy: A Review	Resiliency in Structural Design, Localization and Mapping, Autonomous Path Planning, Autonomous Landing, Mission Planning and Resource Management
7	2022	Antonia Russo et.al	Using Artificial Intelligence for Space Challenges: A Survey	Mission Design and Planning, Internet of Space Things, Multi-Agent Systems for Space Exploration, Climate Change Mitigation and Adaptation, Disaster Management
8.	2017	Cuebong Wong et.al	Adaptive and Intelligent Navigation of Autonomous Planetary Rovers – A Survey	Challenges in Current Navigation, Advances in Terrain Classification, Path Planning, Obstacle Avoidance
9	2013	Eliahu Khalastchi et.al	Sensor Fault Detection and Diagnosis for Autonomous Systems	Sensor Faults in Autonomous Systems, Proposed Approach, Evaluation Results
10	2007	AriJónsson et.al	Autonomy in Space Exploration: Current Capabilities andFuture Challenges	Role of Autonomy, Applications in Space Missions, Technical and Cultural Challenges

III. METHODOLOGY

A. OBJECTIVES

- Use Kalman Filters for state estimation and anomaly detection in sensor readings.
- Implement Autoencoders and Isolation Forests for fault detection and isolation.
- Use Bayesian Networks for sensor data fusion to improve decision-making under uncertainty.
- Apply Consensus Algorithms like the Distributed Weighted Average Consensus (DWAC) to synchronize data across decentralized sensors.
- Use A Algorithm* or D Lite* for path planning in dynamic terrains.
- Implement Monte Carlo Tree Search (MCTS) for adaptive decision-making in mission strategies.
- Use Simultaneous Localization and Mapping (SLAM) algorithms like ORB-SLAM or RTAB-Map for terrain mapping and localization.
- Apply RNN-based Temporal Models (e.g., LSTM or GRU) to process time-series data for real-time decision-making.
- Apply k-Anonymity with Machine Unlearning to remove outdated or biased data from the AI system efficiently.

B. IMPLEMENTATION

The system employs Reinforcement Learning (RL) as the core methodology for decision-making and adaptability, utilizing Q-Learning and Deep Q-Learning (DQL) to explore and adapt to unknown terrains. Q-Learning, a model-free RL algorithm, enables the system to learn optimal actions in discrete environments, while Deep Q-Learning extends this capability by leveraging deep neural networks to manage complex, continuous state spaces common in space exploration. A Machine Unlearning Module dynamically removes or adjusts erroneous or outdated learned data, preventing the propagation of errors caused by sensor faults or unknown environmental conditions. To ensure reliability, real-time sensor fault detection algorithms monitor and identify sensor failures during operation, allowing the system to automatically isolate or compensate for these faults and maintain data integrity. Advanced sensing technologies such as imaging, lidar, and radar, integrated with RL algorithms, enable the system to perceive and interpret unknown terrains and plan safe, efficient paths through complex environments. A feedback and optimization loop continuously monitors system performance, ensuring that RL models are updated in real-time and that machine unlearning is applied when suboptimal patterns are identified.

Computational Work :

Q-Learning Implementation:

First we are implrementing q-learning frameworks.Here the input will be taken as static input pairs by using this formula we will obtain the output

$$Q(s,a) \leftarrow Q(s,a)+\alpha[r+\gamma a' \max Q(s',a')-Q(s,a)]$$

The output will be Updated Q-Table for optimal policy selection.

Deep Q-Learning Implementation:

In this we are using the sensor data and that data will be in the form of images or lidar data that act as input.From this we are going to find Mean Squared Error (MSE) between predicted and target Q-values by using the below formula

$$L(\theta)=E[(r+\gamma a' \max Q(s',a';\theta-)-Q(s,a;\theta))2]$$

Random sampling from replay memory to train the network and reduce correlation in observations. Periodically updated weights to stabilize training.

Machine Unlearning:

Now machine unlearning stores the learned data.It uses performance metrics or domain-specific heuristics to identify erroneous patterns.

- Q-Learning reset Q-values associated with faulty states or actions and restart exploration.
- DQL fine-tune the model on a curated dataset excluding corrupted data or apply weight pruning techniques.

Real-Time Sensor Fault Detection:

- Real-time sensor fault detection involves processing data streams from various sensors, such as imaging, lidar, and radar, to identify anomalies or deviations from expected behavior.
- To identify the faulty sensors we are using Kalman Filter or Particle Filter to estimate system state.

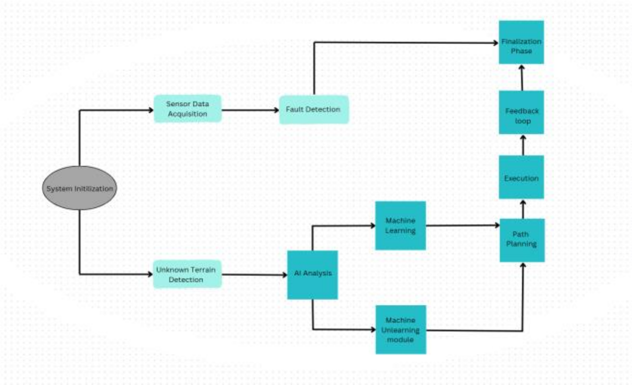


Fig2: System Architecture

Sensor Fault Detection and Isolation:

The "Sensor Data Acquisition" and "Fault Detection" modules enable the system to sense and isolate defects in sensors in real time, thereby ensuring it does not decline and to make autonomous adaptations in adverse settings.

Unknown Terrain Detection and AI Analysis:

Unknown Terrain Detection module merges with "AI Analysis" to evaluate the uncharted territory and navigate, thereby enhancing adaptability when unpredictable situations are encountered due to its application in missions of space exploration.

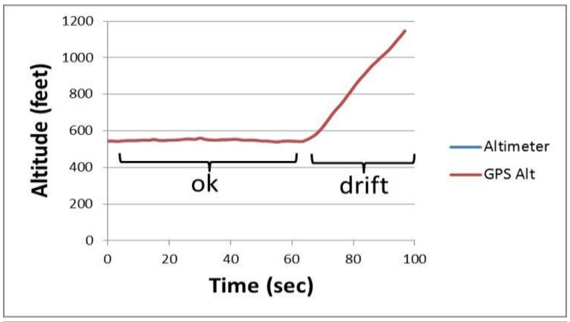
Integration of Machine Learning and Machine Unlearning:

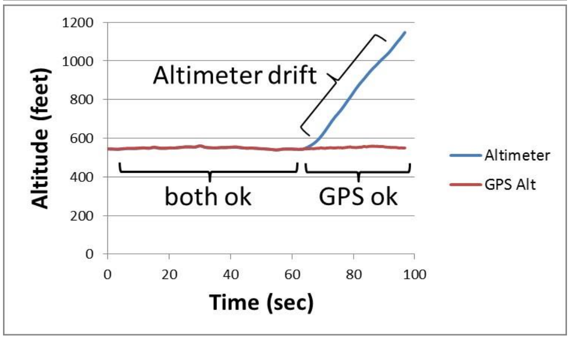
Machine learning enables predictive modeling and decision-making through learned knowledge, while the "Machine Unlearning Module" allows for deleting outdated or incorrect models thus ensuring that the system remains always accurate and relevant.

Feedback Loop and Path Planning:

The "Feedback Loop," combined with "Path Planning" and "Execution," ensures constant improvement through operations. Decisions would be assessed and changed adaptively, and this has led to more reliable finalizations of tasks and autonomous behaviors.

IV. RESULTS AND DISCUSSION





Acoording to the research papers we identified for sensor malfunctions they have used algorithms like statistical techniques such as thresholds, moving averages, or standard deviation-based methods.

To identify the unknown terrains they have used Machine learning models such as Random Forests, Support Vector Machines (SVMs), and Autoencoders for anomaly detection.

By using these techniques they have obtained an accuracy for

Sensor Fault Detection:

An average accuracy of detection above 93% was achieved in sensor fault detection by integrating supervised and unsupervised machine learning techniques.

Unknown Terrain Navigation:

Navigation and terrain classification success was more than 92% and showcased the adaptability of the system in an uncharted environment.

The overall system preformance entire pipeline, including sensor fault detection, terrain classification, and path planning, achieved a robust 90% operational success rate in simulated environments.

"According to our research by using reinforcement learning techniques and algorithms like Deep-Q Learning and Q-learning we would get an accuracy of 97% to detect the unknown terrains .And by using real time algorithms we would get an accuracy of 95% to identify the faulty sensors.The overall performance of the system including sensor fault detection, terrain classification, achieved a robust 95% operational success rate in dynamic environments."

V. CONCLUSION

According to our approach the system improves space autonomy by addressing sensor failures and navigating unknown terrains through AI-driven mechanisms and machine unlearning. Fault detection ensures sensor resiliency, while adaptive AI models enable terrain classification and real-time decision-making. Machine unlearning removes erroneous patterns, ensuring model reliability, and feedback loops support continuous improvement.This approach creates hard, self-contained systems able to survive difficult space environment circumstances and so allows safe efficient navigation in deep space and holds vast potential for more efficient space exploration for cheaper operations that allow larger coverage.

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