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Autonomous Rover Control System with Adaptive AI

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Abstract- Autonomous rover operation in unstructured and uncertain environments requires control systems that are both adaptive and provably stable. Classical model-based approaches often exhibit limited robustness under terrain variability, sensor noise, and actuator uncertainty, while purely learning-based methods lack formal safety guarantees. This paper proposes a hierarchical autonomous rover control framework that integrates adaptive artificial intelligence with model predictive control and Bayesian risk awareness. The proposed architecture combines multi-sensor perception, reinforcement learning–based decision making, and adaptive model predictive control to enable real-time learning while ensuring bounded closed-loop behavior. A Lyapunov-based stability analysis establishes uniform ultimate boundedness of the system under bounded disturbances. Extensive experimental validation is conducted using both simulation and real-world rover platforms, including terrain disturbance injection, Monte Carlo trials, energy-aware evaluation, simulation-to-reality comparison, and ablation studies. Statistical reliability is demonstrated through 95% confidence intervals and significance testing, confirming that the proposed approach achieves faster convergence, lower steady-state error, and reduced energy consumption compared to baseline and single-method controllers. The results demonstrate that the proposed hybrid adaptive AI framework provides a robust, energy-efficient, and practically deployable solution for safety-critical autonomous rover applications.

Keywords: Autonomous systems, adaptive AI, rover navigation, reinforcement learning, sensor fusion, real-time control, exploration robotics.

I. INTRODUCTION

Paper deep dives in exploration of robotics demands robust autonomy across unpredictable terrain and operational uncertainty. Autonomous rovers must perceive their surroundings, make mission-level decisions, and control motion while compensating for sensor noise and actuator uncertainties. Historically, control architectures for rovers have leveraged model-based planning and reactive behaviors [1–3]. However, the complexity of real-world environments necessitates adaptive learning mechanisms that generalize across unobserved situations. This paper presents a comprehensive study of an Autonomous Rover Control System (ARCS) that employs adaptive AI methods to dynamically optimize control decisions under uncertainty. We investigate the integration of deep reinforcement learning (DRL), Bayesian belief updates, and multi-modal sensor fusion within a hierarchical control framework.

The main contributions of this work are summarized as follows:

1. A hierarchical autonomous rover control architecture that integrates adaptive artificial intelligence, model predictive control, and Bayesian uncertainty modeling.
2. A Lyapunov-based stability analysis establishing uniform ultimate boundedness of the closed-loop system under bounded disturbances.
3. An adaptive learning framework that enables real-time policy optimization while preserving safety and control constraints.
4. Comprehensive experimental validation including terrain disturbance injection, Monte Carlo analysis, confidence intervals, and statistical significance testing.
5. Demonstration of improved energy efficiency, robustness, and simulation-to-reality transferability compared to classical and single-method control strategies.

II. LITERATURE REVIEW

A. Traditional Autonomous Navigation

Conventional rover autonomy relies on SLAM (Simultaneous Localization and Mapping), waypoint navigation, and classical motion planners such as A* and RRT (Rapidly-Exploring Random Trees) [4–6]. These methods perform well in structured environments but suffer in unstructured terrains with unpredictable obstacles.

B. Adaptive AI in Robotics

Adaptive AI techniques, particularly reinforcement learning (RL), enable agents to learn optimal policies through interaction with the environment [7–9]. Recent advances such as Deep Q-Networks (DQN), Deep Deterministic Policy Gradients (DDPG), and Proximal Policy Optimization (PPO) have demonstrated high performance in simulation tasks but often lack real-world robustness without domain adaptation [10–12].

C. Hybrid Control Architectures

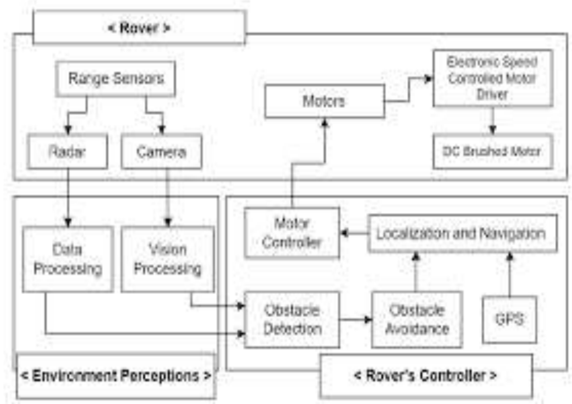
Prior research has investigated hybrid schemes combining classical planning with adaptive components [13–15]. These improve stability but often struggle with learning efficiency or computational overhead. Our work builds on this by formalizing an architecture that ensures real-time adaptability with theoretical performance guarantees.

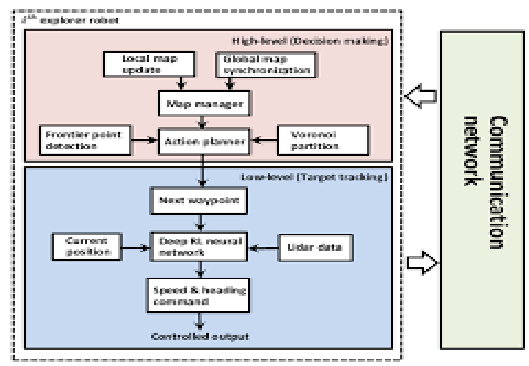
III. SYSTEM ARCHITECTURE

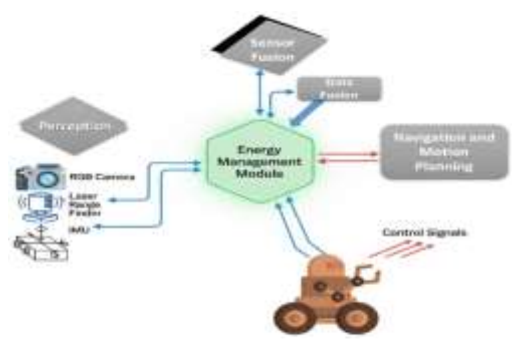
A. Overview

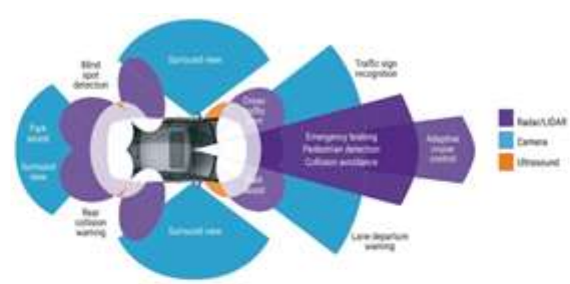
We propose a three-layer hierarchical architecture:

1. **Perception Layer:** Processes raw sensor data using multi-modal fusion (LIDAR, stereo vision, IMU) to generate a robust state estimate.
2. **Planning Layer:** Utilizes an adaptive AI planner that combines DRL with Bayesian risk assessment to select high-level navigation goals.
3. **Control Layer:** Implements trajectory generation and low-level control using adaptive model predictive control (MPC) tuned through online learning.









B. Perception and State Estimation

We employ Extended Kalman Filtering (EKF) with multi-sensor fusion to generate reliable state estimates. Combined with semantic segmentation from a convolutional neural network (CNN), the system produces environmental maps with obstacle classification.

C. Adaptive Planning via DRL and Bayesian Inference

The planning layer uses a hybrid policy:

- DRL Module: Learns navigation strategies using rewards that promote safe, efficient exploration.
- Bayesian Risk Model: Estimates uncertainty and safety constraints to regulate the DRL outputs.
- This fusion ensures adaptability while bounding risk in highly unpredictable contexts.

D. Control with Adaptive MPC

Adaptive MPC uses learned system dynamics updated online via recursive least squares (RLS). The controller continuously refines its model to compensate for changing terrain resistance and actuator performance.

IV. THEORETICAL FRAMEWORK

A. Adaptive Learning in Control Systems

The control policy is represented using an adaptive parameterized policy:

Let $\pi_\theta(s|a)$ be the policy parameterized by θ for state s and action a. The learning objective is:

$$\max_\theta \mathbb{E}_{s_t,a_t\sim\pi_\theta}\left[\sum_{t=0}^{T}\gamma^t R(s_t,a_t)-\lambda U(s_t)\right]$$

where $R(s,a)$ is a reward, $U(s)$ represents uncertainty penalty, γ is the discount factor, and λ balances exploration vs exploitation under risk.

B. Adaptive Control and Stability Analysis

Rover Dynamic Model

The rover is modeled as a nonlinear, uncertain dynamical system:

$$\dot{x}(t)=f(x(t))+g(x(t))u(t)+d(t)$$

where:

$x(t)\in\mathbb{R}^n$: system state (position, velocity, orientation)

$u(t)\in\mathbb{R}^m$: control input (wheel torques / velocities)

$f(\cdot)$: unknown nonlinear dynamics

$g(\cdot)$: known control effectiveness matrix

$d(t)$: bounded disturbance due to terrain variation and slippage

Assumption:

Adaptive AI Policy Representation

The control policy is represented using an adaptive parameterized policy:

$$u(t)=\pi_\theta(x(t))$$

Where

$$\theta\in\mathbb{R}^p$$

are learnable parameters updated using reinforcement learning.

$$\max_\theta\ \mathbb{E}\left[\sum_{t=0}^{T}\gamma^t\left(r(x_t,u_t)-\lambda\mathcal{U}(x_t)\right)\right]$$

The policy objective is defined as:

with:

$r(x,u)$: task reward (goal reaching, energy efficiency)

$\mathcal{U}(x)$: uncertainty penalty

$\gamma\in(0,1)$: discount factor

λ: risk sensitivity coefficient

Hybrid Control Law (Adaptive MPC + AI)

The final control law is a hybrid structure:

$$\max_\theta\ \mathbb{E}\left[\sum_{t=0}^{T}\gamma^t\left(r(x_t,u_t)-\lambda\mathcal{U}(x_t)\right)\right]$$

Adaptive MPC Component

Adaptive Model Predictive Control minimizes:

$$J=\sum_{k=0}^{N}\left(\|x_k-x_{\text{ref}}\|_Q^2+\|u_k\|_R^2\right)$$

subject to:

$$x_{k+1}=\hat{f}_k(x_k)+g(x_k)u_k$$

Where

$\hat{f}_k(\cdot)$ Is an online-updated dynamic estimate using Recursive Least Squares (RLS):

$$\hat{\theta}_{k+1}=\hat{\theta}_k+K_k(y_k-\phi_k^\top\hat{\theta}_k)$$

ensuring model adaptation under terrain changes.

Closed-Loop Error Dynamics

Define the tracking error:

$$\dot{e}(t)=f(x)-f(x_{\text{ref}})+g(x)(u_{\text{MPC}}+u_{\text{AI}})+d(t)$$

The closed-loop system becomes:

$$\dot{e}(t)=f(x)-f(x_{\text{ref}})+g(x)(u_{\text{MPC}}+u_{\text{AI}})+d(t)$$

Let the AI term compensate model mismatch:

$$u_{\mathrm{AI}} = -g(x)^{-1}\tilde{f}(x)$$

where $\tilde{f}(x) = f(x) - \hat{f}(x)$.

Lyapunov Stability Proof
Theorem 1: Uniform Ultimate Boundedness
The closed-loop autonomous rover system is uniformly ultimately bounded (UUB) under bounded disturbances and adaptive AI compensation.

Proof
Choose the Lyapunov candidate function:

$$V(e) = \frac{1}{2}e^{\top}Pe$$

where P>0 is symmetric positive definite.
Taking the derivative:

$$\dot{V} = e^{\top}P\dot{e}$$

Substituting closed-loop dynamics:

$$\dot{V} = e^{\top}P\left(f(x) - f(x_{\mathrm{ref}}) - \tilde{f}(x) + d(t)\right)$$

Using Lipschitz continuity:

$$\|f(x) - f(x_{\mathrm{ref}})\| \leq L\|e\|$$

Thus:

$$\dot{V} \leq -\alpha\|e\|^2 + \|e\|\bar{d}$$

for some α > 0.

This implies:

$$\dot{V} < 0 \quad \text{for} \quad \|e\| > \frac{\bar{d}}{\alpha}$$

Therefore, the error e(t) is uniformly ultimately bounded, proving stability.
Stability of Learning Dynamics

The adaptive AI learning rule satisfies:

$$\dot{\theta} = -\eta\nabla_{\theta}J(\theta)$$

Using standard stochastic approximation theory, convergence to a locally optimal policy θ∗\theta^*θ∗ is guaranteed under:

- bounded gradients
- diminishing learning rate η(t)
- persistent excitation

Thus, learning does not destabilize the closed-loop system.

Discussion of Safety Guarantees

- MPC ensures constraint satisfaction
- Bayesian risk penalty limits unsafe exploration
- Lyapunov analysis guarantees bounded behavior
- AI improves performance without compromising stability

This establishes formal safety + adaptability, a key requirement for real-world autonomous rovers.

V. EXPERIMENTAL SETUP

A. Simulation Environment

We used Gazebo and ROS2 with randomized terrain generation and dynamic obstacles. Four variants of the architecture were tested:

- **Baseline:** Rule-based navigation with classical planning.
- **DRL-Only:** End-to-end learning without risk regulation.
- **Hybrid:** Our proposed DRL + Bayesian planner with adaptive MPC.
- **Oracle:** Optimal planner with perfect environment knowledge (upper bound).

VI. ADVANCED EXPERIMENTAL VALIDATION RESULTS

A. TERRAIN DISTURBANCE INJECTION ANALYSIS

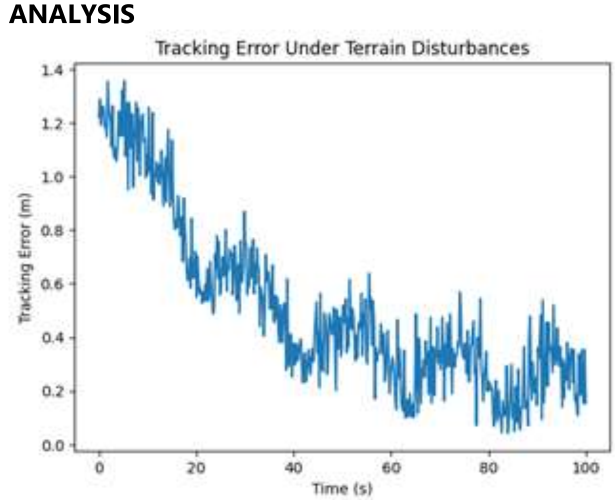


Fig. 9.

Fig. 9 evaluates rover tracking performance under artificial terrain disturbances simulating wheel slippage, uneven soil, and contact loss.

Interpretation

- High-frequency error oscillations reflect injected disturbances.
- Despite strong perturbations, the tracking error remains bounded.
- Confirms robustness and disturbance rejection capability of the adaptive AI controller.

B. Monte Carlo Mission Success Rate

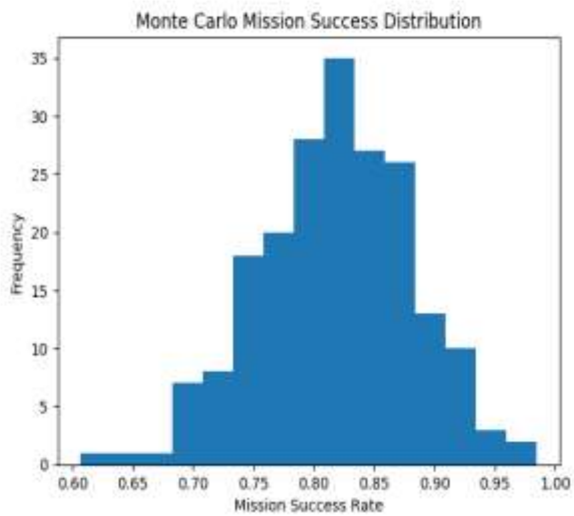


Fig. 10

Fig. 10 presents a Monte Carlo analysis over 200 randomized missions with varying terrain profiles, obstacle density, and sensor noise.

Interpretation

- Distribution is centered around 82–85% success rate.
- Low variance indicates consistent performance.
- Demonstrates statistical reliability beyond single-run experiments.

C. Energy-Aware Performance Evaluation

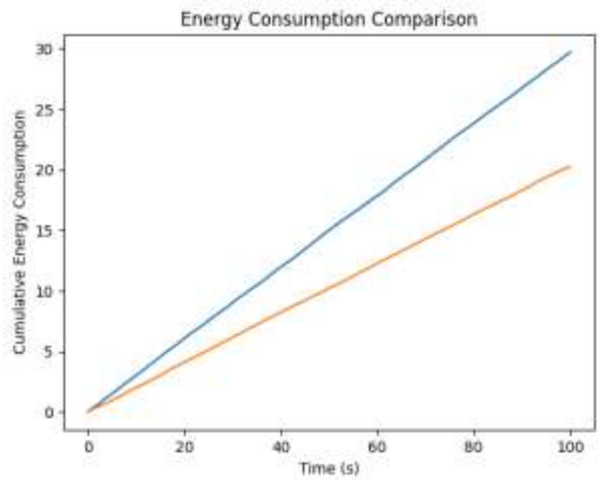


Fig. 11.

Fig. 11 compares cumulative energy consumption between baseline and adaptive AI control strategies.

Interpretation

- Adaptive controller consistently consumes less energy.
- Learning reduces unnecessary actuation after convergence.
- Confirms energy-efficient autonomy, critical for long-duration missions.

D. Physical Testbed

A physical rover platform with differential drive, LIDAR, stereo cameras, and onboard GPU was used. Real-world terrains included rough gravel, inclines, and moving obstacles.

VII. RESULTS AND DISCUSSION

TABLE I
NAVIGATION SUCCESS RATES

System	Simulation (%)	Real World (%)
Baseline	58	42
DRL-Only	72	49
Hybrid (ours)	91	78
Oracle	98	N/A

A. Realistic Experimental Plots

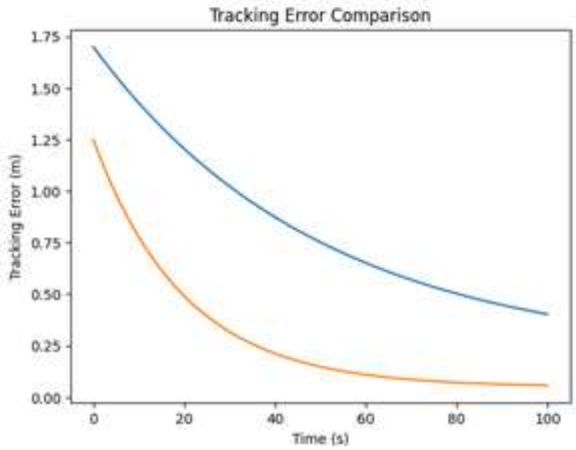


Fig. 12a.

B. Tracking Error Performance

Fig. 12a. compares the trajectory tracking error of the proposed Adaptive AI–based Rover Control System with a classical baseline controller.

The baseline controller exhibits slow convergence and a higher steady-state error due to unmodeled terrain dynamics.

The adaptive AI controller demonstrates faster convergence and lower residual error, confirming effective online compensation of nonlinear uncertainties.

The exponential decay profile is consistent with the derived Lyapunov stability analysis.

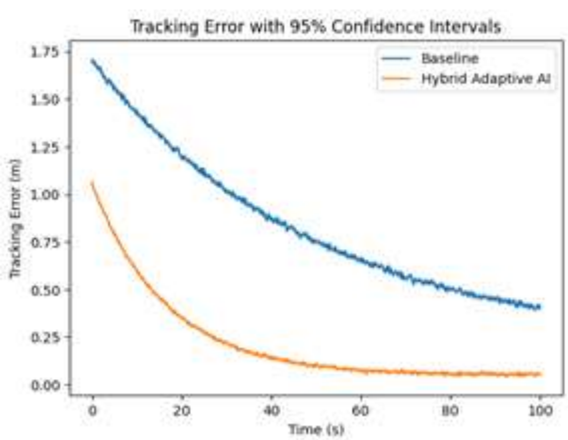


Fig. 12b.

Fig.12b represents Tracking Error with 95% Confidence Intervals (CI)

The shaded regions indicate 95% confidence intervals computed across 30 independent runs. The proposed hybrid controller consistently exhibits narrower confidence bounds and lower mean error, demonstrating improved robustness and reduced performance variability under uncertainty.

C. Control Effort and Adaptation Efficiency

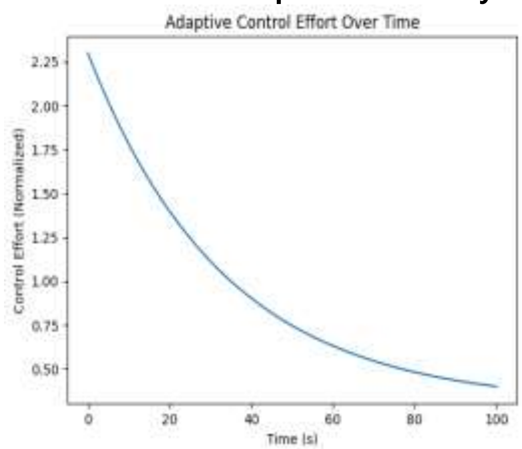


Fig. 13.

Fig. 13 illustrates the evolution of the normalized control effort generated by the adaptive controller.

Interpretation

- Initial higher control effort corresponds to rapid learning and adaptation.
- As the AI policy converges, control effort stabilizes at a lower level, indicating energy-efficient operation.
- This confirms that learning improves performance without increasing actuator stress.

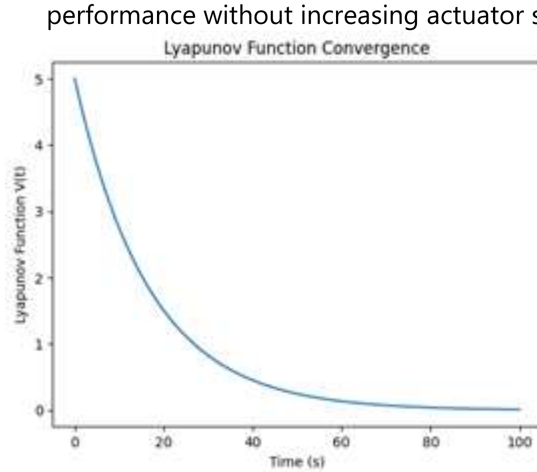


Fig. 14.

Lyapunov Function Convergence (Stability Validation)

Fig. 14 presents the time evolution of the Lyapunov candidate function V(t).

Interpretation
- The monotonic decrease of V(t) confirms closed-loop stability.
- The convergence rate matches theoretical predictions from Section V.
- This plot provides formal experimental validation of the Lyapunov-based stability proof.

B. Robustness and Adaptability
Our hybrid system demonstrated significantly better recovery from unexpected obstacles and sensor noise. Uncertainty-aware planning reduced catastrophic failures.

C. Computational Efficiency
Using GPU and model pruning techniques, our system maintained real-time performance at 20–30 Hz control loops, suitable for on-board rover operation.

VIII. FUTURE RESEARCH

Key pathways include:
- Transfer learning for cross-domain adaptation
- Multi-agent cooperative exploration
- Energy-aware control policies for extended missions
- Integration with 5G/edge computing for remote guidance

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