Multi-Robot Traversal of 3D Terrain Using Adversarial Reinforcement Learning

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Abstract

Autonomous navigation of multi-robot systems in unstructured 3D terrain remains a critical challenge for search-and-rescue (SAR) operations. We present a novel adversarial reinforcement learning (ARL) framework that enables robust sim-to-real transfer for quadrupedal swarms traversing rubble-like environments. Our approach combines:

- A **multi-agent proximal policy optimization (MAPPO)** baseline with adversarial perturbations
- A **domain randomization engine** simulating debris variability (slope, friction, obstacle density)
- **Hardware-in-the-loop (HIL) validation** using ANYmal-C robots

Experimental results demonstrate a **92% success rate** in unseen terrains, outperforming classical SLAM-based methods by **37%**. This work bridges the sim-to-real gap for legged swarm robotics in disaster scenarios.

Keywords: Multi-Robot Systems, Adversarial RL, Sim-to-Real, Quadrupedal Locomotion, 3D Navigation

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1. Introduction

1.1 Problem Statement

Disaster environments feature highly irregular terrains (collapsed buildings, uneven rubble) where wheeled robots fail, and GPS-denied conditions preclude traditional navigation. Legged swarms offer mobility advantages but face:

- **Dynamic instability** in granular media
- **Inter-robot collisions** in dense formations
- **Sim-to-real transfer gaps** in physics modeling

1.2 Contributions

1. **First adversarial RL framework** for multi-quadruped 3D traversal, with:
   - Opponent policies generating terrain perturbations
   - Latent space invariance training
2. **Real-world validation** on 6 ANYmal-C units (Fig. 1)
3. **Open-source simulation toolkit** (PyBullet + ROS2)

2. Related Work

Approach	Limitations
Centralized MPC (Boston Dynamics)	Scalability issues
Decentralized RL (ETH Zurich)	Poor sim-to-real transfer
Classical SLAM (ORB-SLAM3)	Fails in featureless rubble

Our method uniquely combines **adversarial robustness** with **decentralized execution**.

3. Methodology

3.1 Adversarial RL Formulation

- **Agents**: N ANYmal-C robots with shared policy π_θ
- **Adversary**: Perturbation policy π_ϕ modifies:
  - Ground friction coefficients ($\mu \in [0.2, 1.2]$)
  - Debris height maps ($\pm 0.3m$ noise)
- Reward function
  - $R_t = 0.3R_{progress} + 0.2R_{stability}0.5 + 0.5R_{swarm}$

3.2 Sim-to-Real Pipeline

1. **Domain Randomization**: 200+ terrain variants in PyBullet
2. **Latent Space Alignment**:
   - Train VAE on real-world depth scans
   - Minimize KL divergence between sim/real features
3. **Hardware Deployment**:
   - Onboard computation: NVIDIA Jetson AGX Orin
   - Communication: ROS2 DDS over UWB

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4. Experiments

4.1 Simulation Benchmarks

Metric	Our (ARL)	MAPPO	SLAM
Success Rate	**92%**	68%	55%
Collisions/hr	1.2	4.7	N/A
Energy Efficiency (J/m)	480	620	-

4.2 Real-World Tests

- **Scenario**: Mock earthquake site (Fig. 3a)
- **Results**:
  - 89% success in transfer (vs. 51% for non-adversarial baseline)
  - 2.3× faster debris clearance vs. single-robot

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5. Discussion

5.1 Key Findings

- Adversarial training reduced sim-to-real performance drop from **41% → 8%**
- Swarm coordination emergent from **local LiDAR observations only**

5.2 Limitations

- Requires **>10,000 sim hours** for convergence
- UWB ranging errors >3m degrade performance

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6. Conclusion

We demonstrated that adversarial RL enables reliable multi-robot navigation in 3D disaster environments. Future work will:

- Integrate **neuromorphic control** for energy efficiency
- Develop **failure recovery** via robot-to-robot physical assistance

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