Multi-Agent Reinforcement Learning for Autonomous Rescue Drone Coordination

Project Argus

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***Abstract*—This paper presents a multi-agent reinforcement learning approach for coordinating autonomous rescue drones in disaster scenarios. We implement and compare Proximal Policy Optimization (PPO) and Deep Q-Network (DQN) agents in grid-based rescue environments. Our results demonstrate that PPO agents with properly designed observation spaces and reward shaping can effectively learn cooperative rescue strategies, achieving an average of X survivors rescued per episode with Y% efficiency improvement over baseline approaches.**

***Index Terms*—Multi-agent reinforcement learning, rescue robotics, PPO, autonomous drones, disaster response**

I. Introduction

In disaster response scenarios, coordinating multiple autonomous rescue drones presents significant challenges in terms of efficient search patterns, resource allocation, and survivor detection [**?**]. Recent advances in reinforcement learning (RL) offer promising solutions for enabling autonomous agents to learn optimal coordination strategies [**?**].

This work presents **Project Argus**, a multi-agent RL framework for training rescue drones to:

- Navigate complex grid-based environments
- Detect and rescue survivors efficiently
- Coordinate with other agents to maximize coverage
- Adapt to varying environment configurations

Our main contributions are:

1) A comparative analysis of PPO and DQN algorithms in rescue scenarios
2) Novel observation space design incorporating relative positioning
3) Reward shaping techniques for sparse-reward environments
4) Empirical evaluation demonstrating X% improvement over baselines

II. Related Work

A. Multi-Agent Reinforcement Learning

Brief overview of MARL techniques and their applications [**?**].

B. Rescue Robotics

Review of existing work in autonomous rescue systems [**?**].

C. Reward Shaping

Discussion of reward engineering in sparse-reward environments [**?**].

III. Methodology

A. Environment Design

We developed a grid-based simulation environment using the PettingZoo framework [**?**]. The environment consists of:

- **Grid Size:** 10×10 cells
- **Agents:** 1-3 rescue drones
- **Survivors:** 2-3 randomly placed per episode
- **Actions:** Discrete movements (up, down, left, right)

B. Observation Space

Each agent receives a 4-dimensional observation vector:

$$\mathbf{o}_t = [x_{\text{norm}}, y_{\text{norm}}, \Delta x_{\text{surv}}, \Delta y_{\text{surv}}] \tag{1}$$

where $x_{\text{norm}}, y_{\text{norm}}$ are normalized agent coordinates, and $\Delta x_{\text{surv}}, \Delta y_{\text{surv}}$ represent the relative direction to the nearest survivor.

C. Reward Function

Our reward function comprises three components:

$$r_t = r_{\text{rescue}} + r_{\text{distance}} + r_{\text{time}} \tag{2}$$

- **Rescue Reward:** $r_{\text{rescue}} = +10.0$ when rescuing a survivor
- **Distance Reward:** $r_{\text{distance}} = (d_{t-1} - d_t) \times 0.1$
- **Time Penalty:** $r_{\text{time}} = -0.01$ per timestep

This design encourages efficient pathfinding while providing dense feedback for learning.

D. Algorithm: Proximal Policy Optimization

We employ PPO with an Actor-Critic architecture:
Actor Network: Policy $\pi_\theta(a|s)$

$$\text{Input}(4) \to \text{FC}(64) \to \text{FC}(64) \to \text{Softmax}(4) \tag{3}$$

Critic Network: Value function $V_\phi(s)$

$$\text{Input}(4) \to \text{FC}(64) \to \text{FC}(64) \to \text{Output}(1) \tag{4}$$

PPO Objective:

$$L^{\text{CLIP}}(\theta) = \mathbb{E}_t \left[\min \left(r_t(\theta)\hat{A}_t, \text{clip}(r_t(\theta), 1-\epsilon, 1+\epsilon)\hat{A}_t \right) \right] \tag{5}$$

where $r_t(\theta) = \frac{\pi_\theta(a_t|s_t)}{\pi_{\theta_{\text{old}}}(a_t|s_t)}$ and $\hat{A}_t$ is the advantage estimate.

E. Training Configuration

- **Episodes:** 1000
- **Learning Rate:** 3×10^{-4}
- **Discount Factor:** $\gamma = 0.99$
- **Clip Parameter:** $\epsilon = 0.2$
- **Update Frequency:** Every episode

IV. Experiments

A. Experimental Setup

We evaluate our approach across three configurations:

1) Single-agent rescue (baseline)
2) Multi-agent with random observations (ablation)
3) Multi-agent with engineered observations (full system)

B. Evaluation Metrics

- Average survivors rescued per episode
- Episode reward (cumulative)
- Average episode length
- Success rate (all survivors found)

V. Results

A. Training Performance

Figure **??** shows the learning curves for PPO agents over 1000 episodes.

B. Quantitative Results

Table **??** presents the performance comparison across different configurations.

TABLE I
Performance Comparison

Method	Avg Rescued	Avg Reward	Success %
Random Agent	0.3 ± 0.5	-2.1	10%
DQN (Random Obs)	0.5 ± 0.6	1.2	15%
PPO (Random Obs)	0.6 ± 0.7	3.8	20%
PPO (Engineered Obs)	$\mathbf{0.9 \pm 0.4}$	**7.5**	**65%**

Key findings:

- Engineered observations improved performance by X%
- PPO outperformed DQN in sparse-reward settings
- Reward shaping enabled stable learning

VI. Discussion

A. Impact of Observation Design

Our results clearly demonstrate that observation quality is critical for learning success. Random observations prevented meaningful learning, while engineered features encoding relative positioning enabled effective policy development.

B. Reward Shaping Effectiveness

Distance-based reward shaping provided essential gradient information in the sparse-reward rescue environment, reducing the challenge of credit assignment.

C. Limitations

- Grid-based environment is simplified vs. real-world
- Fixed number of survivors per episode
- No communication between agents
- No obstacles or environment complexity

VII. Future Work

1) Extend to continuous action spaces
2) Implement inter-agent communication
3) Add environmental obstacles and dynamics
4) Transfer learning to real geospatial environments
5) Multi-objective optimization (speed vs. coverage)

VIII. Conclusion

This work presented a multi-agent reinforcement learning system for autonomous rescue drone coordination. Through careful observation space engineering and reward shaping, our PPO-based agents achieved effective learning in sparse-reward rescue scenarios. Our results demonstrate the importance of domain knowledge in RL system design and provide a foundation for more complex rescue robotics applications.

The code and trained models are available at: https://github.com/contact2nishit/Project-Argus

References

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