L-Università ta' Malta
Faculty of Information & Communication Technology
Department of Artificial Intelligence

B.Sc. IT (Hons.) Artificial Intelligence

Autonomous Drone Control using Reinforcement Learning

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INTRODUCTION

This project aimed to develop a system for autonomous drone control that focused on the problem of drone obstacle avoidance. The successful development of such a system is crucial for ensuring the safe and efficient deployment of drones across various industries [1-2], including search and rescue operations, package delivery, and infrastructure inspections. The specific problem this thesis addressed is developing a reinforcement learning-based solution for unmanned aerial vehicles (UAVs) that enable drones to safely navigate through unmapped cluttered environments, including obstacles that are either static or moving.

AIM

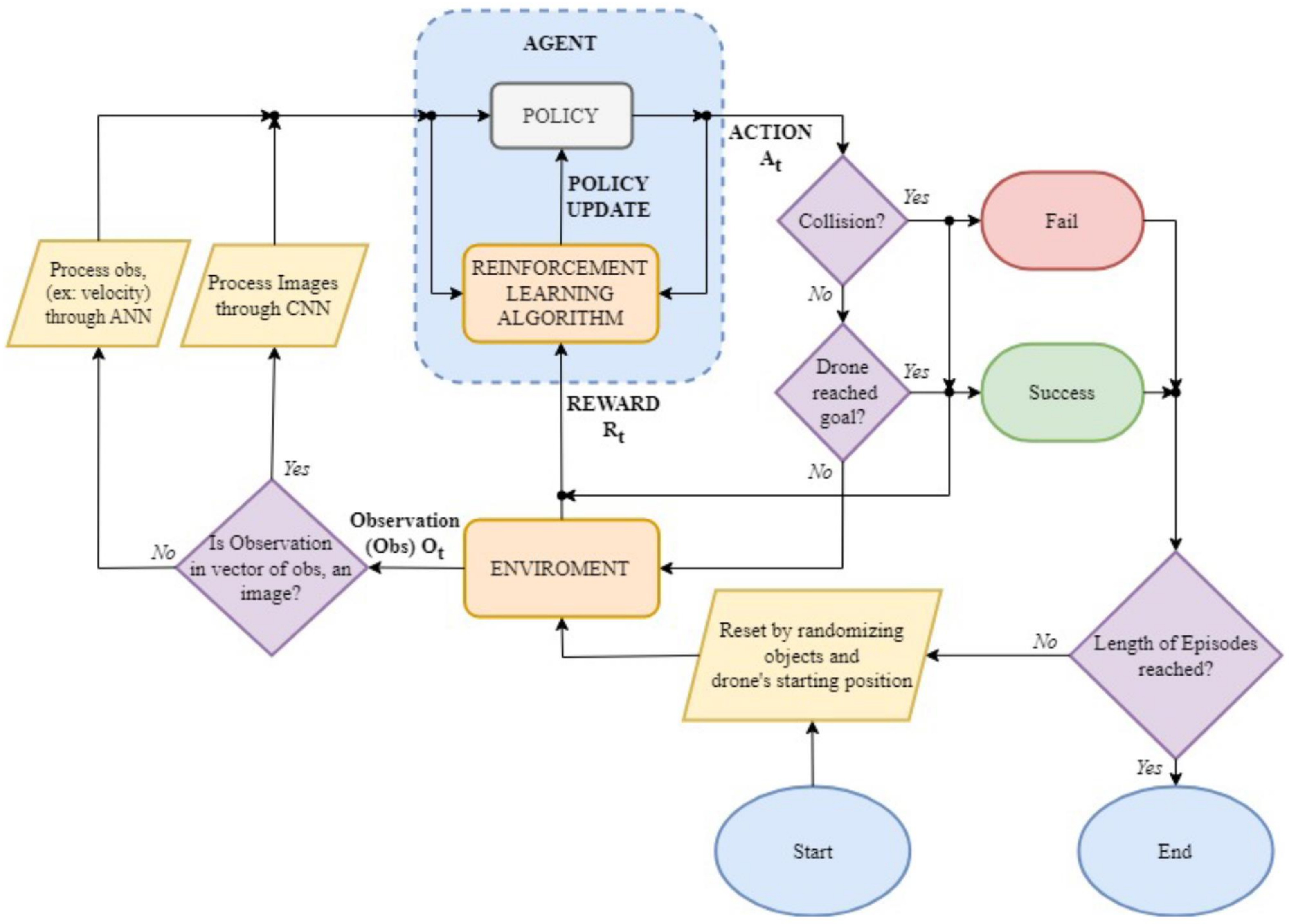
Objective 1: Integrate a drone environment simulator within a Reinforcement Learning framework such that the drone can be programmatically controlled.

Objective 2: Identity what sensor information to use for the observations and evaluate which algorithms and configurations perform obstacle detection accurately.

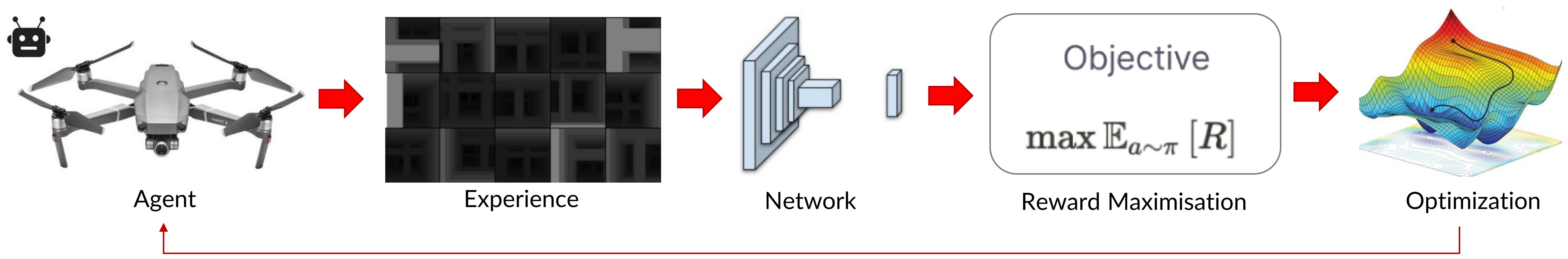
Objective 3: Train four RL algorithms to navigate environments with static obstacles, with two algorithms using discrete actions and two algorithms using continuous actions and evaluate them by the number of successful runs without collision.

Objective 4: Train the best two RL algorithms on environments with dynamic obstacles, using adapted observations and rewards to capture obstacle movement information.

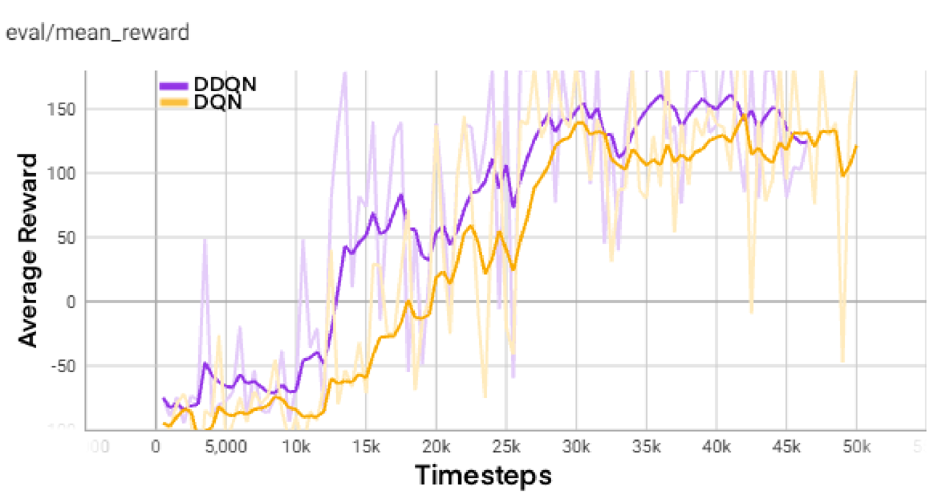
ARCHITECTURE DESIGN



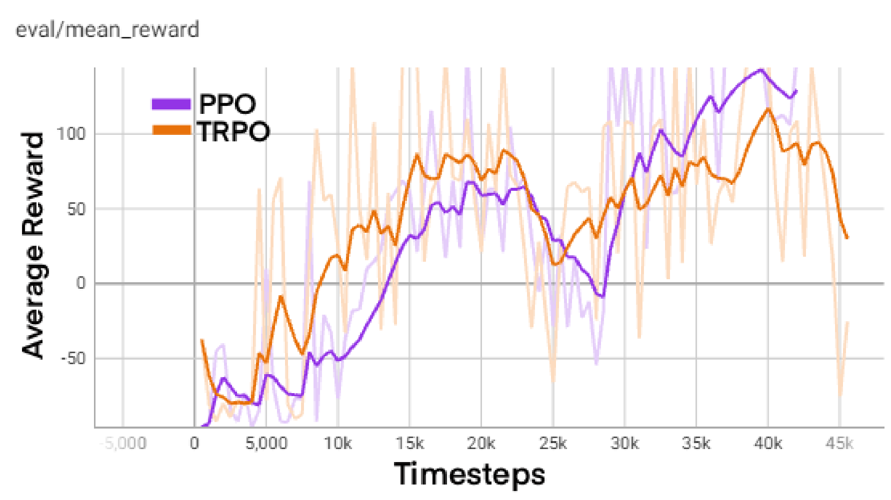
METHODOLOGY



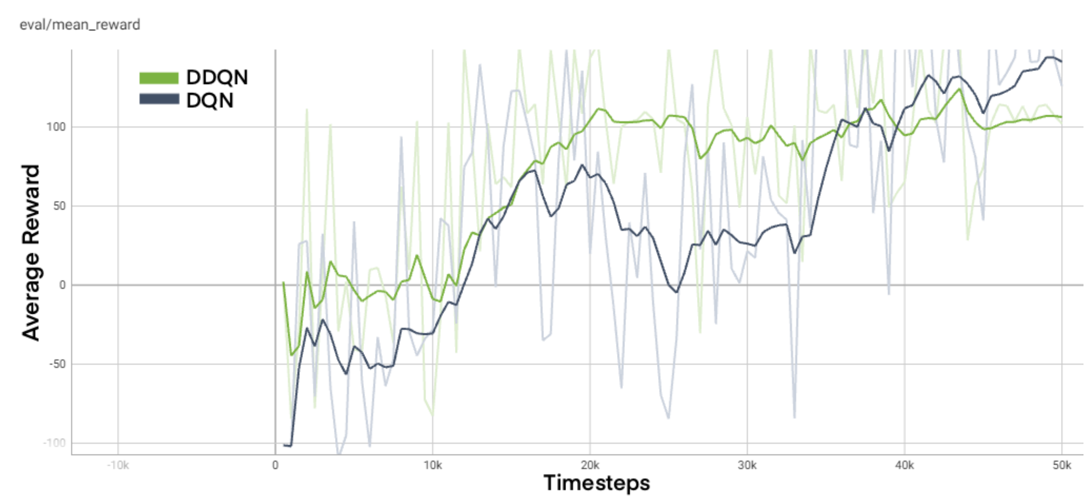
RESULTS



Accumulating Rewards: Discrete RL Algorithms Trained in a Static Environment



Accumulating Rewards: Continuous RL Algorithms Trained in a Static Environment



Accumulating Rewards: Best two RL Algorithms Trained in a Dynamic Environment

CONCLUSIONS AND FUTURE WORK

Ultimately, each objective set out for this project was achieved chronologically with a total of six trained agents that can navigate through complex environments utilizing a depth sensor to retrieve observation data about the surrounding unmapped environments.

For future work on this project, we limited the evaluation of our policies to the AirSim Simulation. This can be extended with real-life scenarios which have been replicated and tested within the simulation. For instance [3] proposed a high-level controller that can direct a UAV to track and pursue another UAV in a real-life pursuit-evasion scenario. This approach could be leveraged to test the effectiveness of our policies in a more realistic and challenging setting.

REFERENCES

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2. S.-Y. Shin, Y.-W. Kang, and Y.-G. Kim, "Obstacle Avoidance Drone by Deep Reinforcement Learning and Its Racing with Human Pilot," Applied Sciences, vol. 9, no. 24, 2019, ISSN: 2076-3417. DOI: 10.3390/app9245571
3. M. A. Akhloufi, S. Arola, and A. Bonnet, "Drones Chasing Drones: Reinforcement Learning and Deep Search Area Proposal," Drones, vol. 3, no. 3, 2019, ISSN: 2504-446X. DOI: 10.3390/drones3030058.