

# Deep Reinforcement Learning for Autonomous Inspection System

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# Deep Reinforced Learning for Autonomous Inspection System



Authors: Romita Biswas, Aditya Chakraborty, Cassidy Friedrich, Yug Rao



## Abstract

The objective of the group is to investigate the application of Deep Reinforcement Learning to create a drone that autonomously inspects damages on buildings after natural disasters. Deep learning is a technique through which computers can identify complex patterns like detecting cracks in large amounts of data like a video stream. By applying Reinforcement Learning and Deep Convolutional Neural Networks, the drone will be trained to perform building inspections without scanning the whole structure. The need for such an autonomous system comes from:

- Safety issues that prevent a human inspector from investigating the damaged state of an impacted building
- Demand for reliable and cost-effective systems to perform building inspections in settings dangerous to humans.

## Algorithms

- Proposed Model is **A3C framework** with two parallel branches similar to the UNREAL agent [3].
- One branch will focus on control tasks for the navigation of the drone and the other will focus on reward tasks to process inspection images.
- To train our reward task branch we use Proximal Policy Optimization (PPO) since there are multiple objectives. There are very few extrinsic rewards in our environment, so our agent analyzes other targets in the stream of images [1].
- The UNREAL agent uses a mechanism to focus representation upon extrinsic rewards so learning can be focused on tasks most relevant [3].
- The agent can engage in a behavior by knowing the end goal and focusing the stream to achieve it.
- The architecture incorporates a long short-term memory (LSTM) architecture to approximate policy and value functions given the recent history of experience as inputs.

## System

- A **reward branch** focuses on pixel control. For the pixel control function we wish to detect changes in the stream, indicating building issues being detected. In order to learn in parallel, we will train off-policy by Reinforcement Learning.
- A **task branch** focuses on the navigation of our drone. It is taught to fly off-policy using negative data since there are no large data-sets for learning to fly [2]. We will employ deep learning networks here with multiple convolutional layers with RELU applied. This branch will make predictions based off the most recent previous frames as a sequence [3].

## Future Work

As of now, we have a design for our system. Our future goals include:

- Training the reward branch of our system on image streams including building inspection by a drone.
- Once the reward branch has been trained to identify building damage we will invest in a drone and teach it to fly autonomously by applying a Deep Learning Network.
- Building the two branches in parallel, we will attempt to train the task branch by flying and processing images. This would improve the drones ability to locate damage in an optimal manner.
- Finally, we will conduct a thorough testing and improvement phase to optimize our networks
- Once the control algorithm is finalized, a metric will be developed for quantifying or classifying the structural integrity of buildings based on severity of the cracks
- A proposal for full scale deployment in disaster areas will be discussed

## Architecture

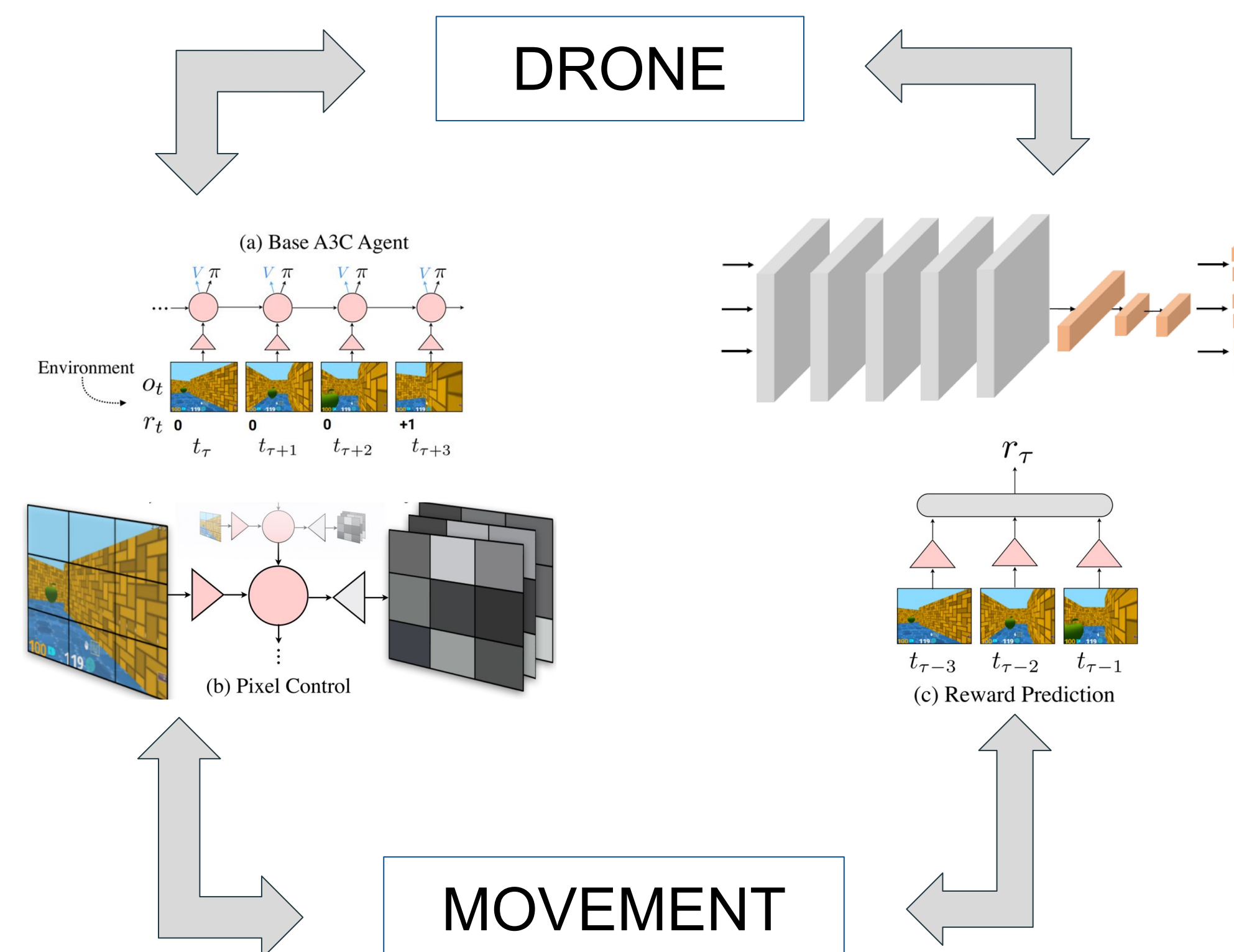
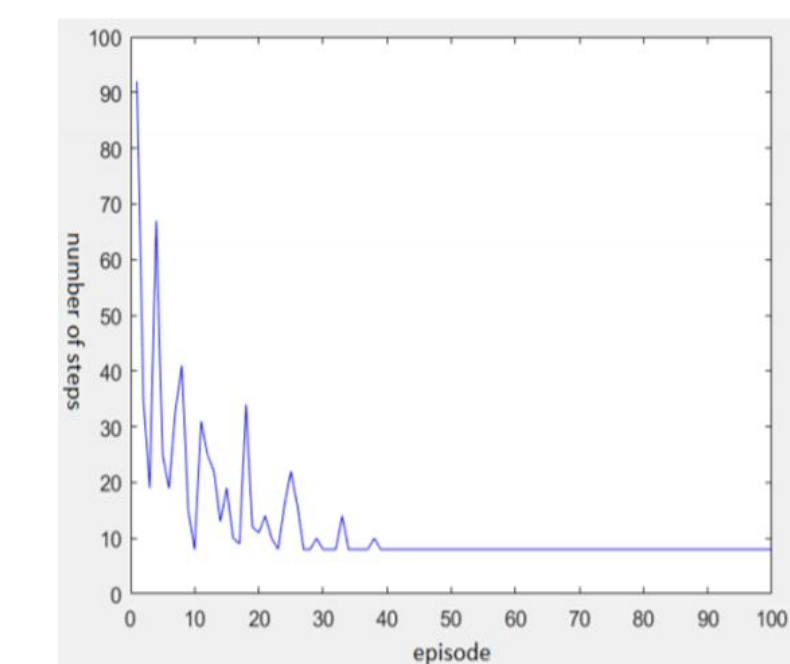


Figure 1: Architecture of Autonomous Inspection System [2][3]

Figure 2: Expected Plot to reach the most optimal movement during crack detection in a small environment



## References

1. Achiam, Edwards, Amodei, & Abbeel. (2018, July 26). Variational Option Discovery Algorithms. Retrieved from <https://arxiv.org/abs/1807.10299>
2. Gandhi, Dhiraj, Pinto, Gupta, & Abhinav. (2017, April 27). Learning to Fly by Crashing. Retrieved from <https://arxiv.org/abs/1704.05588>
3. Reinforcement learning with unsupervised auxiliary tasks. (n.d.). Retrieved from <https://deepmind.com/blog/reinforcement-learning-unsupervised-auxiliary-tasks/>
4. L. Aprville, Y. Roudier and T. J. Tanzi, "Autonomous drones for disasters management: Safety and security verifications," 2015 1st URSI Atlantic Radio Science Conference (URSI AT-RASC), Las Palmas, 2015, pp. 1-2