Autonomous Drone Navigation for Unexploded Ordnance Localization

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About Me

- Master’s Student in Computer Science at Clemson University
  - Undergraduate
    - Software Development
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    - AI/ML research
    - Deep reinforcement Learning
    - Data mining
    - AI Receptive Software
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- Using Graph Neural Networks for Multi-Agent Path Planning Solutions in Unknown Environments

CLEMSON UNIVERSITY

Introduction

Source: Reuters

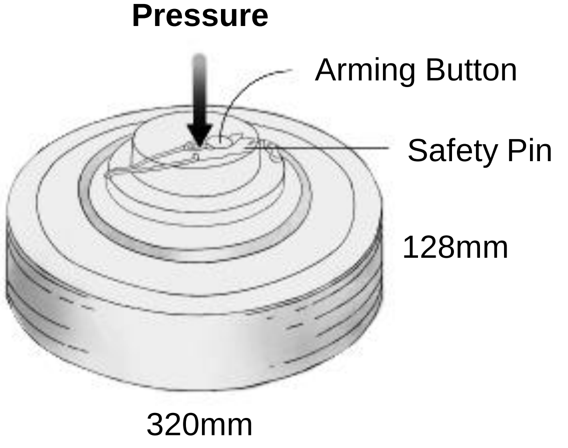
- **Feb 2022** –
  Russia invades Ukraine
- **Aug 2022** – 141 reported UXO incidents
- **June 2023** – Russia retreats leaving behind countless UXO

Introduction

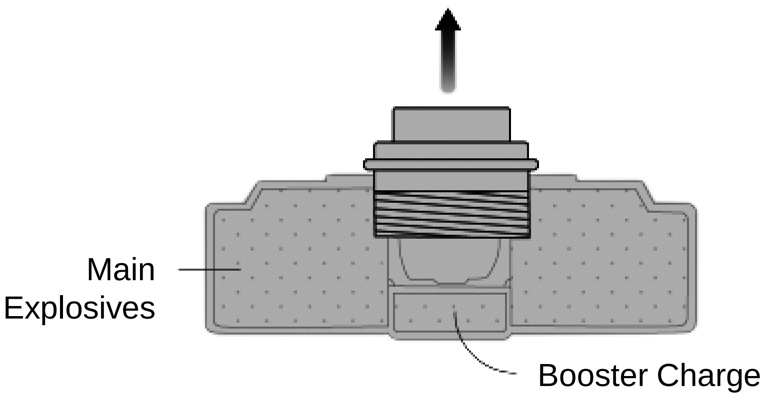
Classic Mine – TM-62 Series

This mine, deployed by both Russia and Ukraine, is designed to detonate when pressure is applied to the top of the device.

A weight exceeding 150 kg will trigger the fuse



Fuse section is unscrewed and removed during demining



Source: Reuters

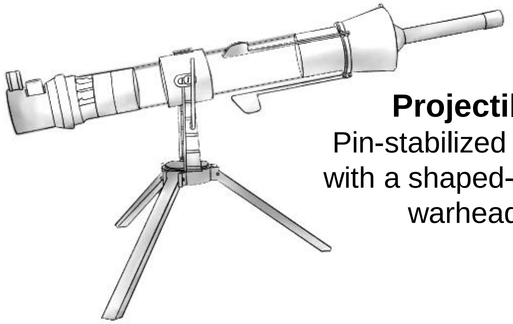
- Classic mines are designed to be hidden from the naked eye
- These mines can be easily detected through various means (metal detectors, ground penetrating radars etc.)

Introduction

PARM

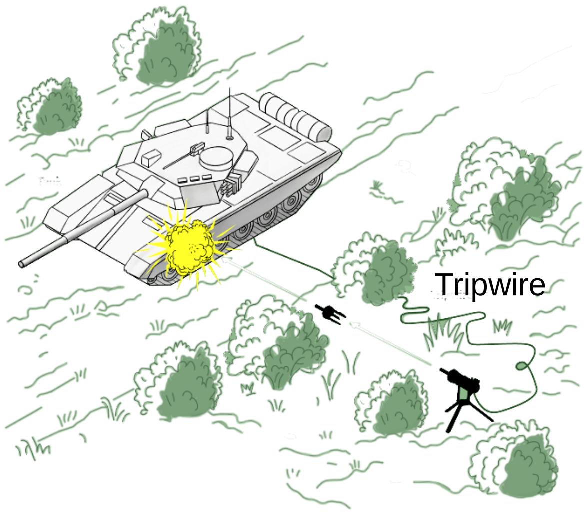
When triggered, this mine fires a rocket to pierce the armor of passing vehicles.

Stationary arming and firing mechanism



Projectile
Pin-stabilized rocket with a shaped-charge warhead

Tank



The PARM mine can be triggered by a fiber optic cable, infrared sensor or remote command.

Source: Reuters

Modern Mines

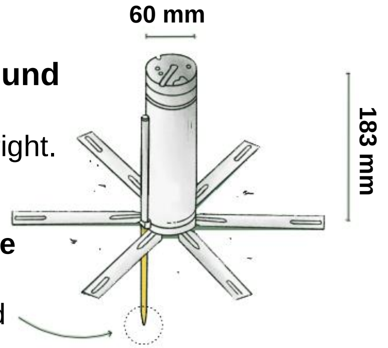
- In modern warfare, mines are being designed so that they can detonate before being detected from a safe distance
- These versions can be detonated from greater distances using more advanced motion detection methods

POM-3

This anti-personnel mine does not need to be touched to detonate.

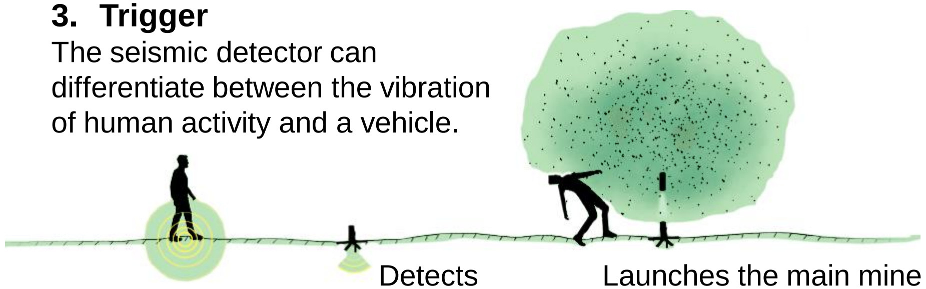
1. **Dropped from the Sky**
The POM-3 can be scattered using rockets and uses a small parachute to land softly.

2. **Fixed to the Ground**
Spring-loaded legs position the device upright.



Seismic sensor spike
The mine inserts a probe into the ground

3. **Trigger**
The seismic detector can differentiate between the vibration of human activity and a vehicle.



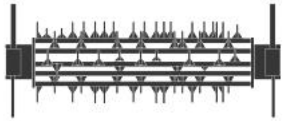
Source: Reuters

Detects footsteps nearby

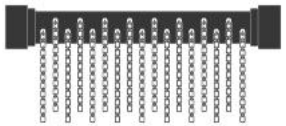
Launches the main mine 1 to 1.5 meters into the air.

Current Solutions and Associated Challenges

Vehicles Used for Surveying and Demining

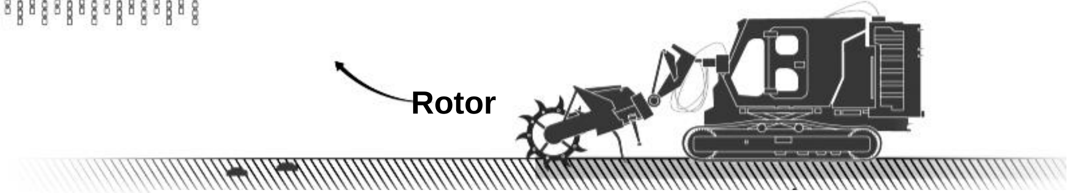


Tillers consist of steel alloy bits or teeth mounted on heavy rotating shafts.



Flails have revolving shafts with metal chains and hammers attached.

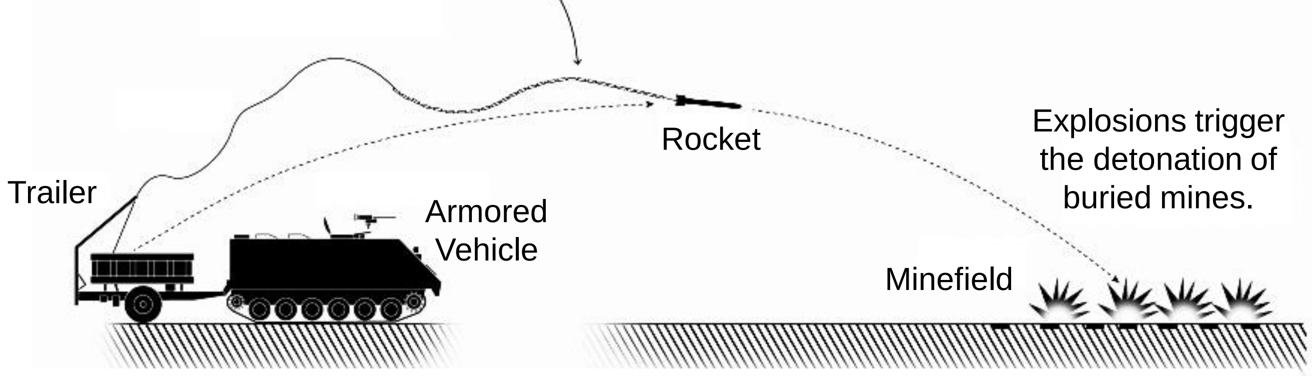
Armtrac 400
One of the vehicles used in Ukraine



Source: Reuters

Line Charges
Cluster of small explosives attached to the rocket on a line.

Clearing a Path
Ropes are fired into a minefield and detonated, triggering mines.



Challenges with Current Solutions

- Do not currently have a method for surveying an area
- Significant casualties using current approach (~1305 over 2 year period*)
- Cost of operations > $100,000
  - Vehicles could be lost since they are going in blind
- Takes a long time to survey and demine a large geographic area
- Form factor of current vehicles limit areas that can be surveyed for undetonated ordnances

*ACLED, accessed 7/17/2024

Proposed Solution for Surveying a Region

Consumer-Style Drone Swarms

- Cost from $50–$500
- Small and easy to store and replace
- Fully autonomous solution
- Drones can act cooperatively to cover much larger areas in less time
- Due to their small size drones can also operate in areas where vehicles cannot (forests, mountains, residential areas)

Overall Steps of Proposed Solution

1. By leveraging modern object detection techniques, drones can analyze captured images to identify and pinpoint the precise coordinates of potential threats

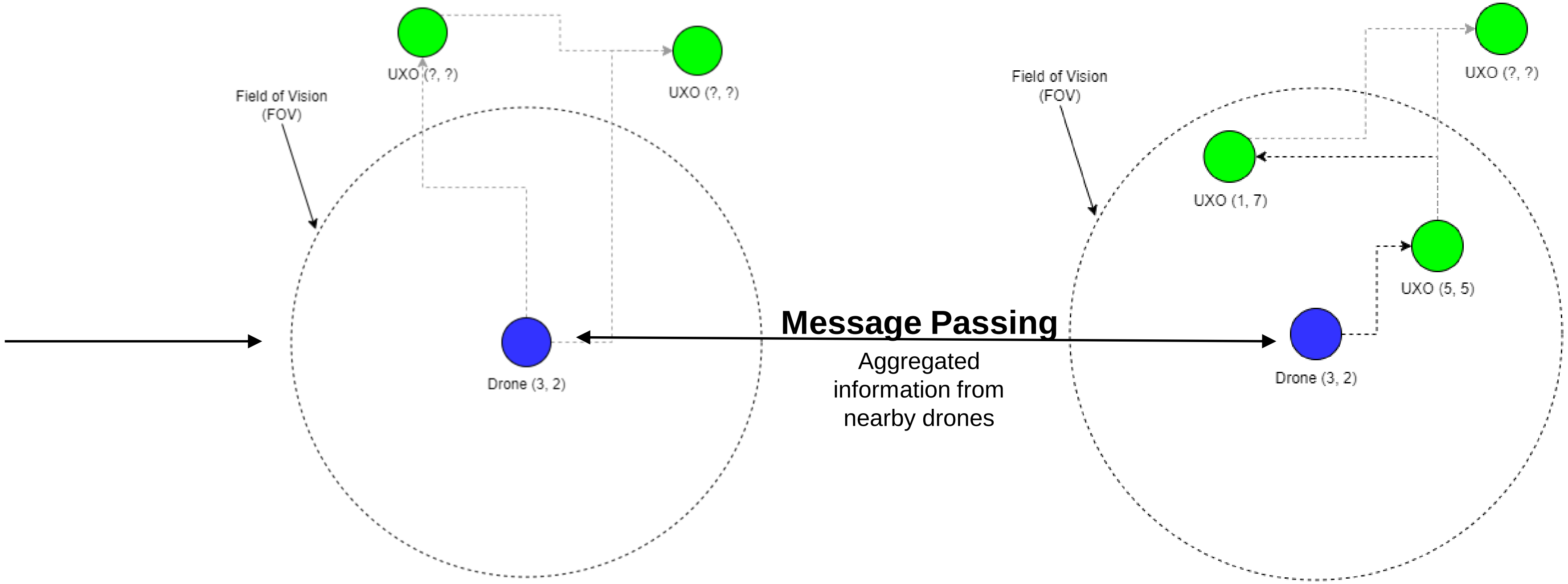
2. Once this data is collected we can then employ a path finding algorithm that navigates drones to each detected object or to continue searching

3. At each location an image is captured to later be surveyed by military personnel

Coordinates: (37.43, 244.87)

Overall Steps of Proposed Solution

Path Planning w/ Graph Neural Network (GNN)



How it works:

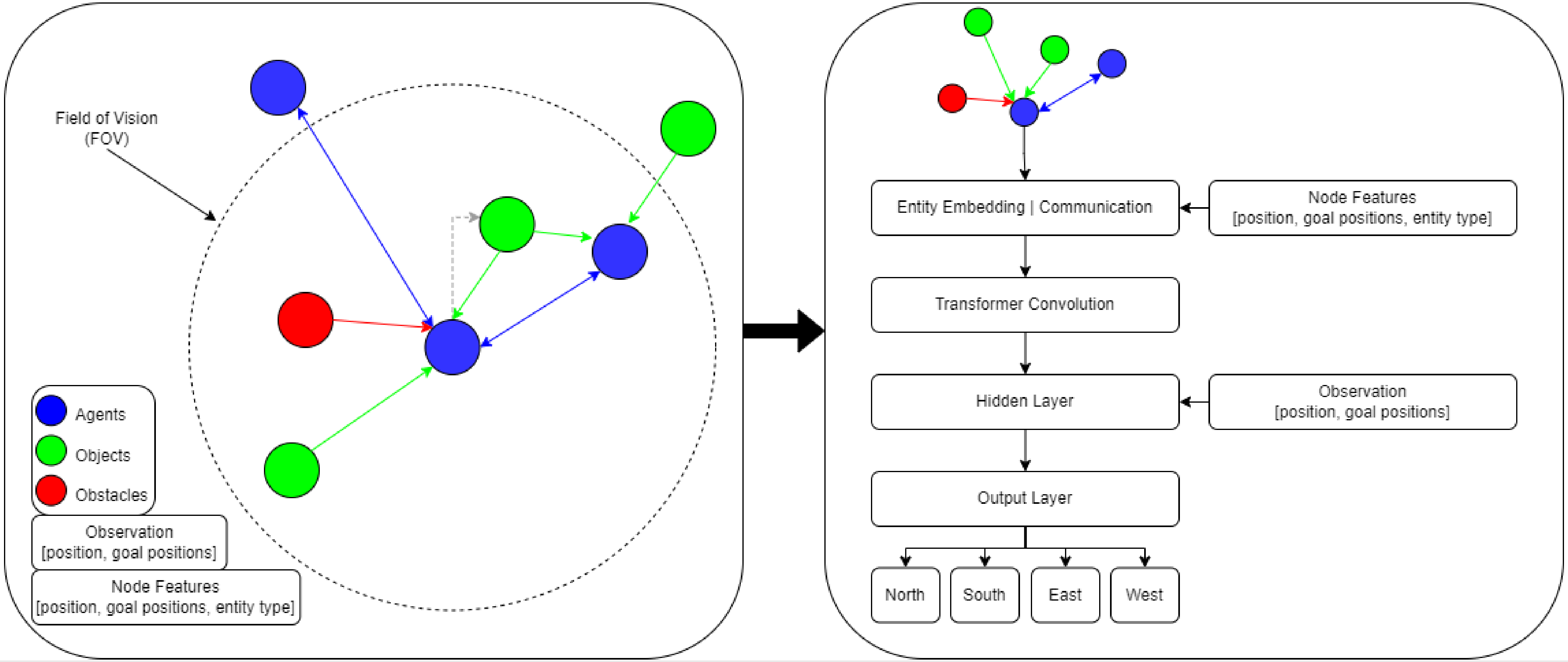
1. The GNN acts as a path planning solution that balances traveling to detected objects and exploring more of the field
2. Each drone detects potential threats in its field of view using object detection
3. Then passes information about object locations to other nearby drones
4. Using both their immediate observation and aggregated information from other drones in the area, the GNN then calculates an optimal route

Why a GNN?

1. GNNs have a built in Message Passing functionality that facilitates information sharing between drones
2. This makes the solution resilient to drone malfunctions within the swarm and allows the drones to work cooperatively without scaling the networks complexity

Overall Steps of Proposed Solution

Graph Neural Network & Deep Q-Learning

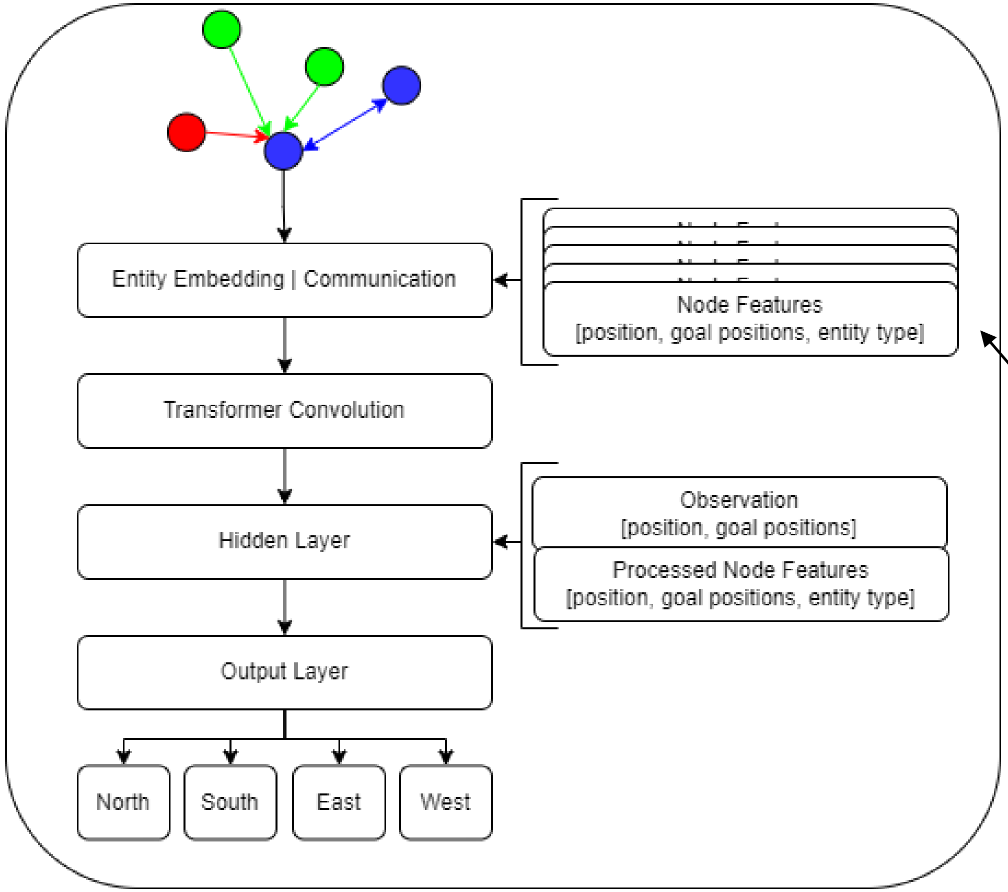


Each drone receives information about entities within its FOV in the form of node feature vectors.

These node features capture the relevant attributes of the entities (coordinates), enabling the drones to make informed decisions based on its local & shared observation.

Overall Steps of Proposed Solution

Graph Neural Network & Deep Q-Learning

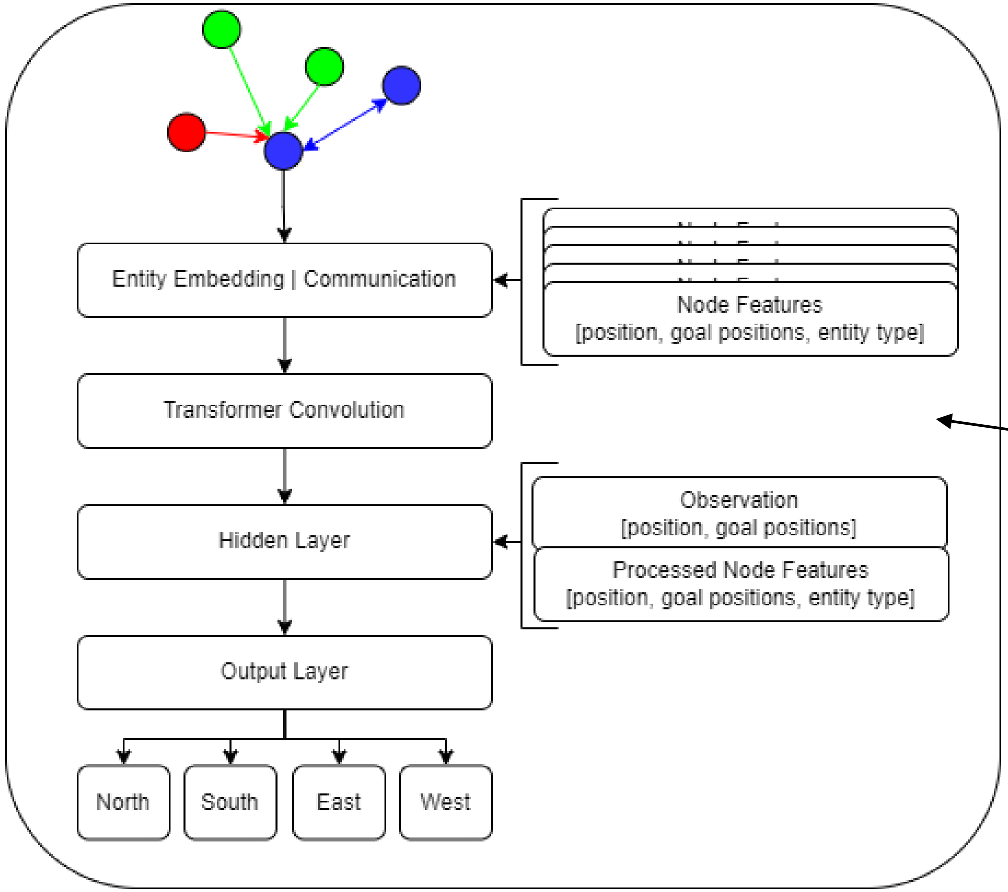


Entity Embedding/Message Passing Process

1. Node features of all entities within the drone's field of view (FOV) are collected.
2. Entity types are extracted from the node features to create entity-specific embeddings for each type (drones, objects, obstacles).
3. The remaining node features (positions/object positions) and edge attributes (magnitude).are concatenated and then processed through a series of linear layers to learn a hidden representation that captures the relationships and interactions between the nodes.
4. The processed feature vectors are aggregated from the neighboring nodes to update the representation of each node in the graph.

Overall Steps of Proposed Solution

Graph Neural Network & Deep Q-Learning

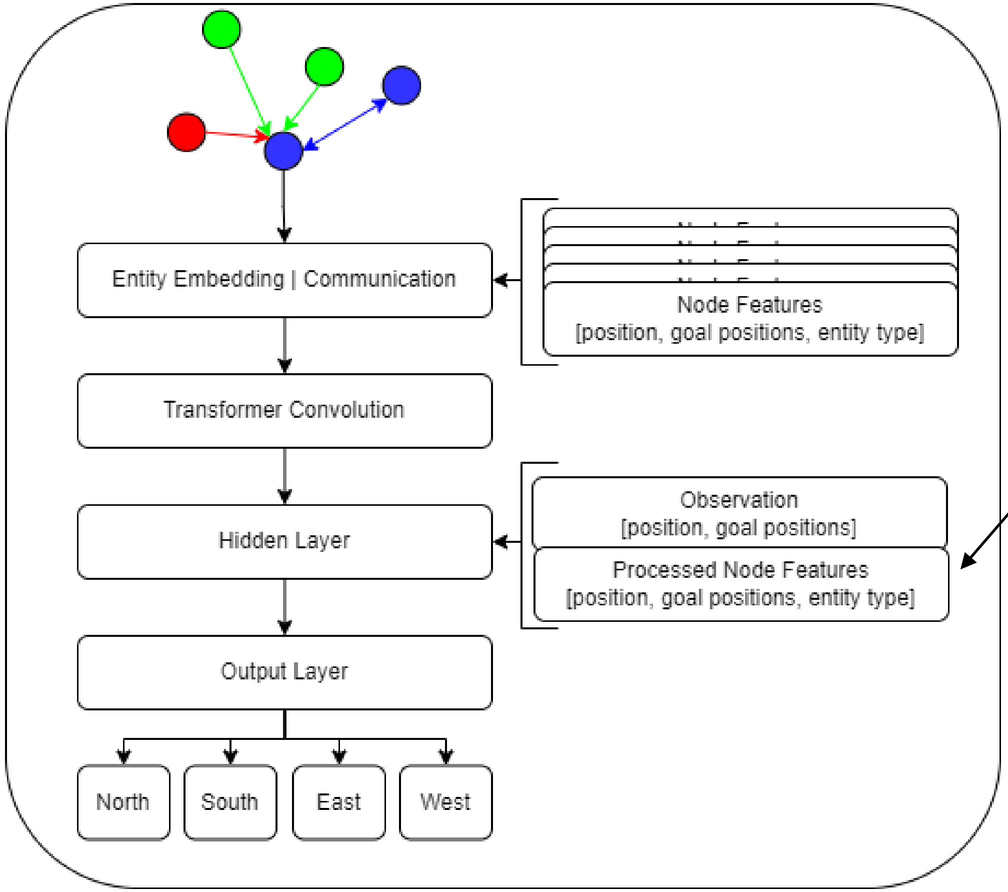


Transformer Convolution Process

1. The output from the entity embedding and communication layer undergoes convolutions using a Transformer-based architecture.
2. The transformer convolution layer learns which node features to weigh more than others through its self-attention mechanism. This allows the model to dynamically compute attention scores that determine the importance of each node's features.
3. The transformer convolution layer helps to further understand the hidden relationships between nodes in the graph

Overall Steps of Proposed Solution

Graph Neural Network & Deep Q-Learning

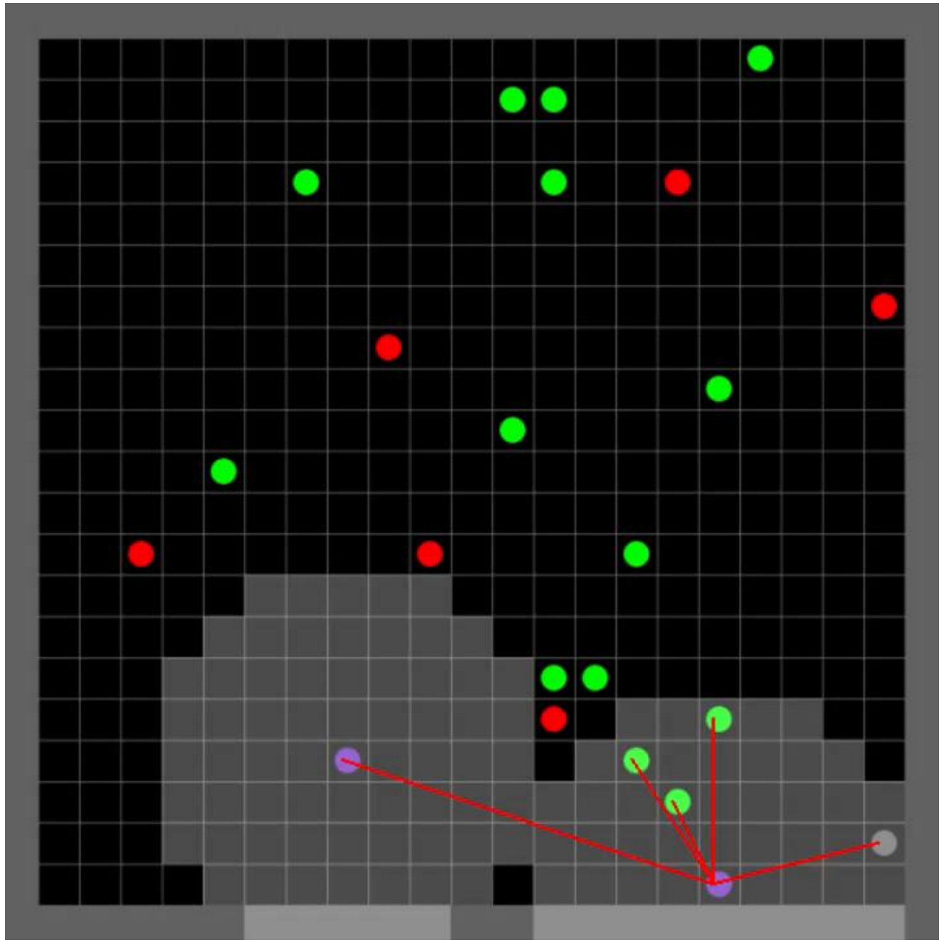


Output Process

1. The output of the transformer is concatenated with the drone's own observation vector. This combined representation is then further processed through additional linear layers.
2. After processing, the reinforcement learning algorithm, Q-Learning, estimates the expected cumulative reward for each of the drone's available actions (north, south, east, west).
3. Over the course of training, ~2,000,000 steps in the environment, the network's weights are iteratively updated using backpropagation techniques. The goal is to minimize the difference between the networks predicted Q-values and the actual rewards obtained by the drone to improve the network's ability to make optimal decisions at any state.

Simulation Environment

Graph Neural Network & Deep Q-Learning



MiniGrid (Python Library)

Entities:
- Drones
- Objects
- Obstacles

Actions:
← Left
↑ Up
→ Right
↓ Down

1. As the drones move around the environment they form connections (edges) with entities in their FOV

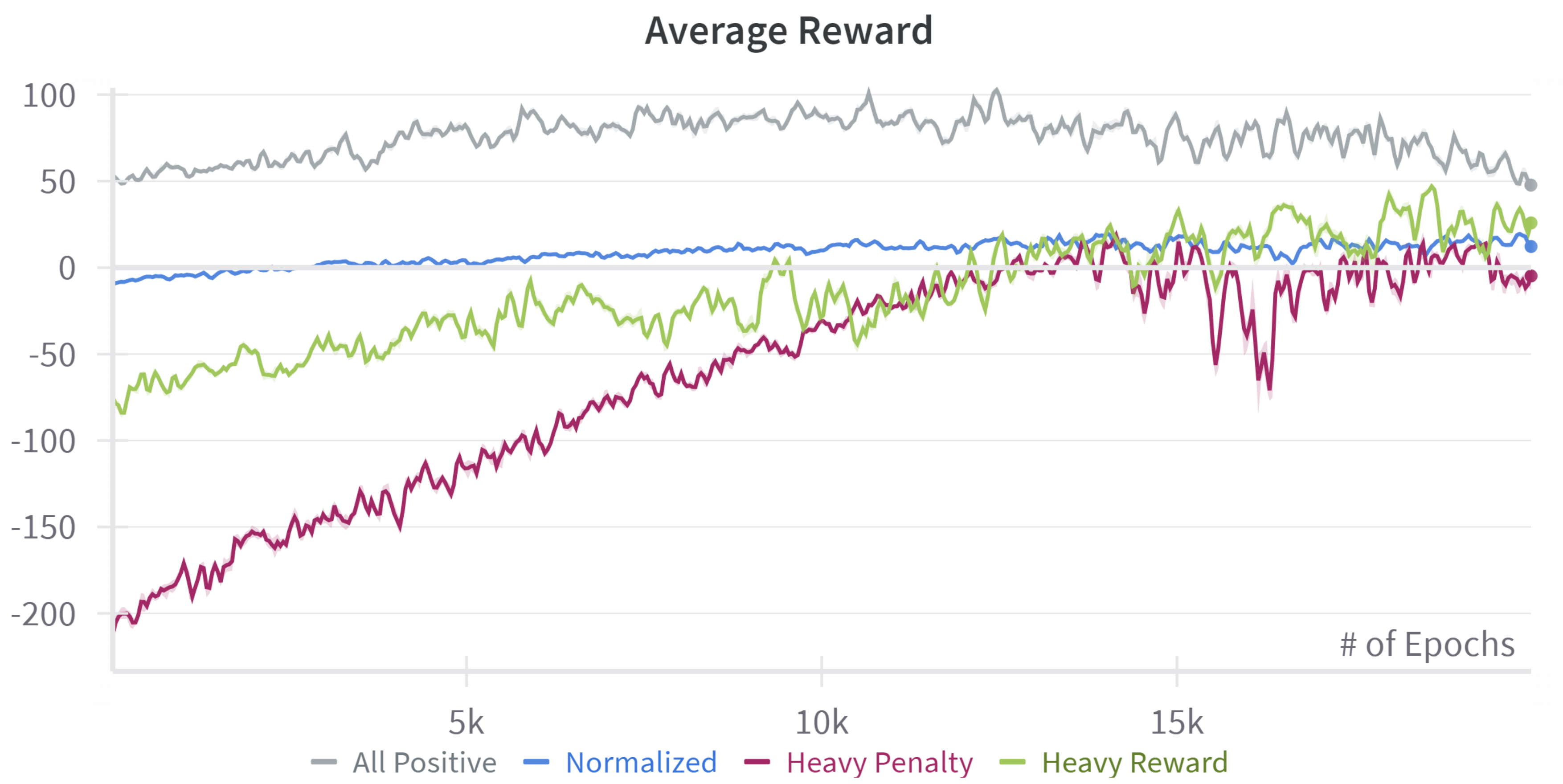
2. At each step in the environment the drones aggregate node features from each entity its connected to as well as nearby drones

3. This processed information combined with the agents original observation forms the networks state representation

Rewards: ✓
1. Visiting objects of interest
2. Exploring unvisited areas

Penalties: ✗
1. Collisions with obstacles and other agents
2. Exiting the field's boundary
3. Revisiting detected objects

Current Results



1. Testing different reward functions under the current architecture for about 2-3 weeks

2. While the networks architecture is showing promising results we have yet to converge on an optimal policy

Best Performance Metrics:

1. **Objects surveyed: ~95%**
2. **Map Coverage: ~83%**

Future Work

Optimization

1. Fine-tuning reward function to balance exploration & exploitation
2. Reducing stored information in the replay buffer
3. Switch to relative coordinates as opposed to actual

Scaling

1. Each node feature vector would include an additional coordinate for a 3D implementation
2. The action space would expand from 4 to 6 to account for vertical movement

Acknowledgements

Rahul Amin
John Lam
Laura Kellel
Nora Smith
Evelyn Bennet
Donna Rosati
Ashlee Rice-Bladykas

End

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Resources

[Reuters Graphics]
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