Multi-agent System for Reforestation Efforts

Project Report - Group 23
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ABSTRACT

Deforestation and habitat loss threaten climate change and biodiversity. This paper introduces a multiagent system of autonomous drones to optimize and coordinate reforestation. Our approach prioritizes resource efficiency and real-time reforestation monitoring. Expected contributions include a decentralized collaboration and communication mechanism among reforestation agents, which lead to efficient resource allocation.

KEYWORDS

Coordination, Communication, Drones, Multi-agent system, Reforestation

1 INTRODUCTION

The problem comes from the urgent need to reforest the Portuguese forest and therefore minimize the effects of deforestation. A multiagent system that improves the efficiency and coordination of reforestation projects can help achieve reforestation goals and reduce deforestation's environmental impacts. According to Quercus, Portugal has the fifth-biggest deforestation rate in the world, having lost between 2001 and 2014 280,122 hectares of forest area. [2]

Having outlined the motivation now we center our attention into the existing work on this topic. Siedler and Alpha [1] approach exactly the same problem with a collaborative multi-agent reinforcement learning setup. To effectively plant the maximum area possible, a Graph Neural Network was proposed as a communication mechanism between the autonomous tree-planting drones. Wei Meng et al. [3] developed a decentralized coverage base algorithm for the communication protocol between UAVs (Unmanned aerial vehicle) that derived optimal paths so that they could monitor multiple static targets while searching.

The primary challenge is to design and implement a multiagent system that optimizes the allocation of resources, monitors reforestation progress, and adapts strategies based on real-time feedback from the other agents. The agents must effectively coordinate between themselves their actions.

Reforestation projects, ecosystem restoration, climate change mitigation, and biodiversity conservation would all benefit greatly from a solution to this issue. Considering current trends in deforestation and the rising awareness of the issue worldwide, the implementation of such a system couldn't come at a better time.

Given the context we have given above, we propose the following objectives for the project:

(1) Design a multiagent system that facilitates efficient coordination and collaboration among various agents involved in reforestation efforts.
(2) Optimization of resource allocation and energy management.

2 APPROACH

Our project aims to simulate the reforestation process of a rural area using drone agents. The objective is to efficiently plant trees in every viable location (fertile land squares in Fig.1) within the shortest possible amount of time, while minimizing energy consumption. To achieve this, effective communication and coordination among the drones are essential. The task concludes once all fertile land squares have been planted or the maximum time-step established has been reached.

2.1 Environment

To begin, we will commence by establishing the parameters of our environment, which constitutes the initial phase in the process of system modeling. Our environment is depicted as a grid, comprising six distinct types of cells: fertile land, obstacles, a charging station, oak trees, pine trees, and eucalyptus (refer to Figure 1). The environment grid is randomly generated at each run. In the described environment, the charging station is not considered to be an agent, as it does not exhibit any decision-making behavior. However, it possesses a significant characteristic where only one drone can charge simultaneously at the station. For the purpose of our model, we will assume that the charging station has infinite seeds and never ending energy supplies.

Figure 1: Different types of environment cells.

Formally, we can describe our environment as **partially accessible**, as agents are unable to obtain complete and up-to-date information about the state of the environment due to their inability to observe the entire grid. Furthermore, it is **deterministic**,

AASMA Project, IST, 2022, Lisbon, Portugal

https://doi.org/

meaning that each action produces a singular guaranteed outcome. The environment is **static**, with a finite number of possible actions and perceptions. In terms of memory, we consider our environment as **episodic**, since the world we have defined can be divided into independent intervals. Consequently, the events occurring in one episode do not influence subsequent episodes.

2.2 Multi-agent System

Our agent drones are computer systems capable of **autonomous** actions in our environment in order to meet its design objectives, in this case the reforestation of the territory. The **utility function** of our agent drones is a mathematical representation that quantifies the value associated with different actions in the context of their reforestation task. It serves as a measure of the agents' preferences and guides their decision-making process by evaluating the expected benefits or costs of various choices. The utility function considers factors such as the number of planted squares, energy efficiency, collaboration, and seeds' availability. By maximizing the utility function, the agent drones aim to achieve optimal performance. We can affirm that our agent drones are **rational**, because they are able to act in a way that maximizes their utility function.

We classify our agent as a **deductive reasoning** agent because it demonstrates a commitment to preserving biodiversity by taking into account the presence of existing trees before deciding which tree to plant. This commitment can be characterized as a **blind commitment**, as it involves making choices based on a predetermined principle or rule without ever questioning it. By considering the existing trees and incorporating this information into the decision-making process, our agent demonstrates a conscious effort to respect and maintain biodiversity in the reforestation task.

2.2.1 ***Sensors and actuators:*** Considering the described environment, we decided that, at each time step, each agent should be able to perceive the following elements:

- Current location
- Current cell type
- Current seeds in inventory
- Current battery level
- Adjacent locations
- Adjacent cell types

In Fig. 2, the red rectangle symbolizes the cells within the drone's field of observation at each time step. These cells encompass the current and adjacent locations, along with their corresponding cell types. Assuming this is the initial stage of the simulation, the drone's perception is limited to the square inside the red rectangle, as illustrated in Fig. 3. As the drone progresses in each time step, its perception of the environment expands, incorporating additional cells into the map, as depicted in Fig. 4.

The agent drones have the following actions:

- **Move Up:** The agent moves up.
- **Move Down:** The agent moves down.
- **Move Left:** The agent moves left.
- **Move Right:** The agent moves right.
- **Move Up Right:** The agent moves diagonally to the upper right square.

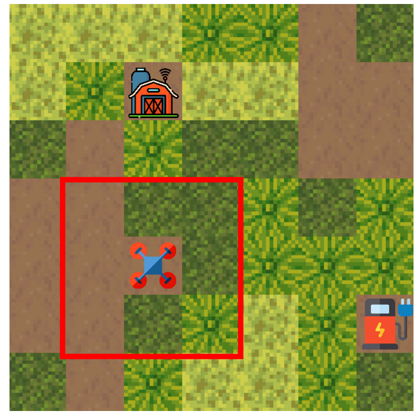

Figure 2: Simulated reforestation environment with the drones observation range.

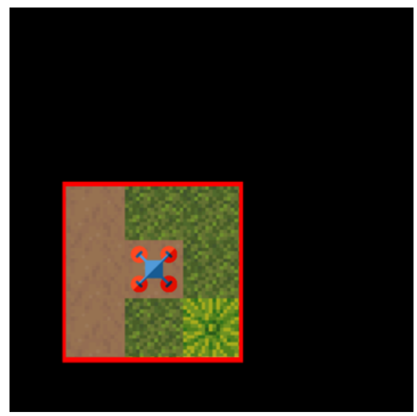

Figure 3: Drone's map in the first time step .

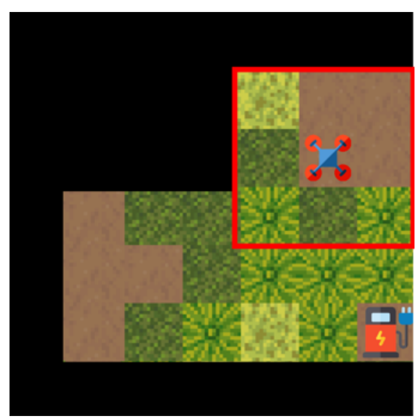

Figure 4: Drone's map after moving around the environment.

- **Move Up Left:** The agent moves diagonally to the upper left square.
- **Move Down Right:** The agent moves diagonally to the right square below.

- **Move Down Left:** The agent moves diagonally to the left square below.
- **Stay:** The agent stays in the same position.
- **Plant:** The agent tries to plant.
- **Charge:** The agent tries to charge.

Each drone agent has the capability to navigate within the environment by choosing one of the actions above. Additionally, drones have the option to perform specific actions such as planting and recharging. These actions will only have effect if the drone is positioned on a fertile land square or a charging station, respectively. Otherwise, the action is not successful.

2.3 Agent Architectures

It is important to note that, in every architecture, drones might overlap with each other, which means there can sometimes be multiple drones occupying the same location.

2.4 Random Agent Architecture

Our random agents operate solely on reactive principles, devoid of any reliance on their past actions or internal state. Their decision-making process is solely based on the current state, where they randomly select an action that may or may not yield success. For instance, they may attempt to plant a cell that is already occupied by oak trees, resulting in the action failing and the agent remaining in the same cell. To achieve success in their task, random agents must be situated on a fertile land square and make a random decision to perform the planting action. Another example of a successful operation would be if a random agent happens to be positioned at the charging station and chooses to recharge its battery. Also, it is important to note that sometimes the drone appears to be stuck on the corners of the grid, but in reality it is deliberately choosing actions that would take it outside the grid, and therefore remains in the same position.

2.5 Greedy Agent Architecture

The Greedy Agent Architecture involves drones that prioritize searching for the closest available fertile land square and planting seeds there. This approach is our first improvement over the baseline agent type. Unlike Random agents, our 'path-based' agents won't easily run out of battery, since they ensure they have enough battery to return to the charging station at each step. However, a major issue with this implementation arises when multiple drones fly over each other, causing them to move in sync and reducing the benefits of having multiple drones. This problem is only prevalent in small grids and can be mitigated by increasing the window size for our graphical interface. This issue will not arise in a real world setting where the reforestation will take place in several acres of land. It is worth mentioning, our agents are also considered greedy because they decide to go to the charging station as soon as they have their energy equal to the distance plus one (to account for charging). This is considered greedy because they assume that once they arrive there, they will be able to charge, which may not necessarily be true. This will, unintentionally, lead to some drones running out of battery. Additionally, if our maximum battery capacity is low, the drones may be unable to leave the charging station and reach the distant fertile land squares due to insufficient battery power for a round trip.

2.6 Communicative Agent Architecture

As mentioned previously, our drones begin their mission with a map that is initially devoid of any information, with all cells being unknown. This poses a significant challenge for our agents, as they must explore the terrain while also fulfilling their planting objectives. If operating individually, drones would only possess knowledge about the cells they have already visited, making it difficult to gain a comprehensive understanding of the environment, which is crucial for making informed planting decisions. To overcome this obstacle, our architecture enables the drones to communicate with one another, sharing their observations at each time step.

To optimize their performance and maximize efficiency, several strategies have been developed:

(1) **Cooperative Charging:** Drones engage in cooperative charging by assessing their energy levels and collectively determining priority. In this approach, they communicate with each other to identify which drone is in greater need of charging and should take precedence. By collaborating and sharing resources, drones can effectively manage their energy requirements.

To facilitate seamless information exchange following those strategies, various types of messages have been defined:

- **MapUpdateMessage:** Provides updates on the map, allowing drones to stay informed about changes in the environment.
- **EnergyAndSeedLevelsStatusMessage:** Shares information about the energy levels and seed quantities of each drone, aiding in coordination and resource management.
- **ChargingStatusMessage:** Communicates the charging status of drones, enabling others to plan their charging activities accordingly.
- **DronePlantingMessage:** Conveys information about planned or completed plantings, ensuring efficient allocation of planting efforts.
- **DroneLocationMessage:** Shares the location of each drone, enabling better coordination and avoidance of collisions.

Furthermore, our drone agents are coordinated to manage their access to the charging station, which serves as the source of energy required for them to plant in new fertile land squares. Coordination, in this context, involves managing the interdependencies between their activities. In this case, they must share access to a resource in the environment that cannot be simultaneously used by multiple drones: the energy provided by the charging station. The charging station has a predefined maximum capacity for accommodating a certain number of drones.

To ensure the success of the negotiation process among the drones for accessing the charging station, we have designed a protocol. This protocol guarantees that agreement will eventually be reached, as only one drone can charge at a time. To optimize the efficiency of the negotiation participants and minimize waiting times, we have implemented a "first in, first out" rule. This rule ensures that each drone spends the least amount of time waiting

Map size	15 * 15 squares
Ratio of fertile land	0.7
Battery capacity for the drones	45
Number of seeds in inventory for each tree type	7

to be charged, thereby maximizing the overall utility of all participants involved in the negotiation. We have prioritized simplicity in defining this rule, as we believe a "simple" protocol is one that provides clear and easily followed strategies for the negotiation participants.

3 EMPIRICAL EVALUATION

3.1 Metrics

To empirically evaluate our multi-agent system, we focused on three different metrics:

(1) Percentage of planted squares at the end of each simulation
(2) Average distance traveled by a drone to identify fertile land
(3) Average energy used per planted tree

We also take into account the number of drones that ran out of energy during the simulation, the average distance traveled by the drones, as well as the number of steps needed to complete the reforestation task.

The first metric stated above measures the effectiveness of the reforestation process by calculating the percentage of land squares that have been successfully planted with trees. It provides an overall assessment of the system's ability to achieve its objective. A higher percentage indicates a more successful reforestation effort. The second one quantifies the efficiency of the drone agents in identifying fertile land squares. By calculating the average distance traveled by a drone to find viable planting locations, we can assess the effectiveness of the system in minimizing unnecessary movements and optimizing the exploration process. A lower average distance implies more efficient drone operations. Finally, our last metric focuses on the energy consumption efficiency of the system. By calculating the average energy used per planted tree, you can evaluate the sustainability of the reforestation process. It helps identify whether the system efficiently utilizes energy resources, minimizing waste and maximizing the number of trees planted per unit of energy consumed.

These metrics were chosen because they provide comprehensive insights into different aspects of the multi-agent system's performance. The percentage of planted squares evaluates the overall success of reforestation, while the average distance traveled and energy used metrics focus on the efficiency and sustainability of the system's operations.

3.2 Variable Number of Agents

In this evaluation, we analyze the performance of various architectures using a variable number of agents. To ensure a balanced comparison, we test the architectures with 1, 3, 5 and 10 agents along with the following metrics

3.2.1 Percentage of planted squares at the end of each simulation. As the number of agents increases, we anticipate observing a higher

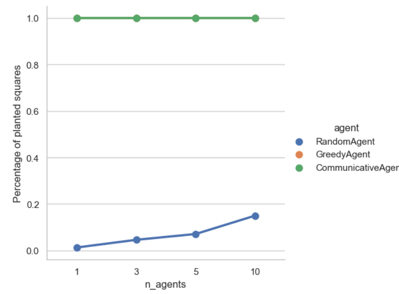

Figure 5: Percentage of planted squares at the end of each simulation.

percentage of planted squares in our system. We expected our random agents to have a truly lower performance compared to our greedy and communicative agents, which was in fact verified with Figure 5. We observed that both the Greedy and Communicative agents achieved a 100% planting rate (both curves overlap, refer to Figure 5) in the environment, regardless of the number of drones employed. This was not the case for the Random Agent, which could only achieve a maximum of 15% of planted squares, even though the planting rate increased proportionally with the number of drones used. The greedy agents prioritize immediate gains, while the communicative agents leverage shared knowledge about available resources and potential obstacles. By contrast, the random agents' reliance on purely random actions limits their ability to make strategic choices and achieve optimal outcomes. Consequently, their planting rate is significantly lower compared to the greedy and communicative agents. This demonstrates the importance of strategic decision-making and collaboration in achieving higher performance in the planting task.

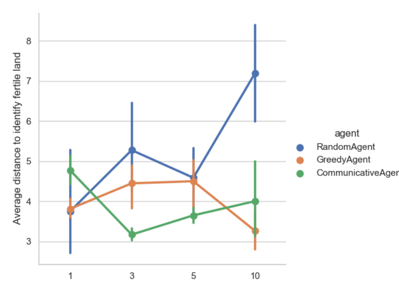

Figure 6: Average distance traveled by a drone to identify fertile land.

3.2.2 Average distance traveled by a drone to identify fertile land. Note that the goal is for the drones to cover the minimum land possible to plant, which means the best performance according to this metric corresponds to the lowest average distance traveled by a drone to identify fertile land. This strongly depends on the random position in which the drones started off during the simulation. This explains the great variation of results we can see in Figure 6, even though we can distinguish a better performance for the communicative and greedy agents. The enhanced level of coordination and collaboration for 3 and 5 communicative agents contributes to their superior performance compared to the random and greedy agents.

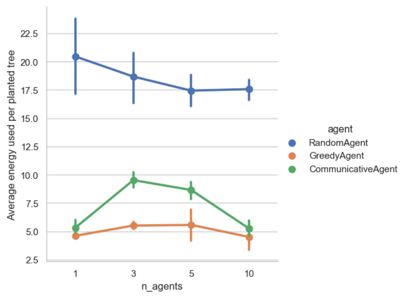

Figure 7: Average energy used per planted tree.

3.2.3 *Average energy used per planted tree.*

Furthermore, as predicted, both the Greedy and Communication agents exhibit notable enhancements compared to the Random Team. However, it is important to acknowledge that both the Greedy and Communicative Agents demonstrate significant variability when the number of drones increases to 5 or 10, primarily due to the random nature of the problem, resulting in diverse episodes with distinct characteristics. Some episodes are more likely to involve situations where the agents are widely dispersed and consistently target different fertile land squares, while in other episodes, they may move in proximity to one another and converge on the same square.

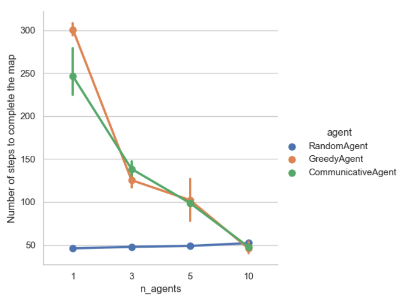

Figure 8: Number of steps needs to complete the reforestation process.

3.2.4 *Number of steps needs to complete the reforestation process.*

During the evaluation of our system, we imposed a limit on the number of time steps per episode. We observed that the required number of time steps to complete the reforestation process decreases as the number of agents increases for the Greedy and Communicative Agent. However, it is crucial to note that this reduction in time steps for the random agent is not due to their ability to replant all fertile land squares more efficiently than the other architectures. Instead, the reason for the stable number of steps for the random agent is that the drones eventually run out of battery, leading to the termination of the simulation when all drones become inactive or "dead". Otherwise, the curve would approach infinity, as the random agents rarely succeed in completing the reforestation task.

4 CONCLUSION

Based on this analysis, it is evident that the Greedy and Communicative architectures consistently outperform the Random approach, suggesting that the latter is not well-suited for addressing this problem. Overall, these observations highlight the advantages of the greedy and communicative architectures in terms of higher planting rates, reduced travel distance, and improved energy efficiency. The random agent's reliance on randomness limits its performance, reinforcing the significance of strategic decision-making and collaboration in achieving optimal outcomes in the reforestation task.

5 FUTURE WORK

There are several potential improvements that could enhance our research. One interesting avenue to explore would be testing a similar environment that includes multiple charging stations instead of just one. This modification could have a positive impact on various metrics, as it would allow drones to cover shorter distances by utilizing the closest charging station when necessary. Consequently, energy consumption could be reduced.

In the next phase of our research, it would be valuable to simulate natural events such as tree decay or potential fires that could destroy the trees. This dynamic system would require cyclic maintenance, operating within a continuous environment where our agent drones would function continuously without distinct episodes or breaks. The environment would no longer remain static, introducing additional requirements for our drones, as they would need to actively monitor and respond to changes in their surroundings.

Another strategy employed by drones that could be developed is a fertility focused strategy that prioritize areas with higher fertility levels in its planting decisions. Rather than solely focusing on the closest available location, drones evaluate the surrounding fertile land. By considering the quality of the land and optimizing their planting choices accordingly, drones can enhance overall vegetation growth and productivity. At last, we also discussed but did not implement the Consensus Decision-Making strategy, where drones engage in consensus a decision-making when determining the optimal planting locations. They communicate and deliberate among themselves to reach an agreement on where to plant. By collectively deciding on the most suitable areas based on shared information, drones can achieve better distribution of plantings and maximize environmental coverage.

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