AUTONOMOUS AGENTS AND MULTIAGENT SYSTEMS

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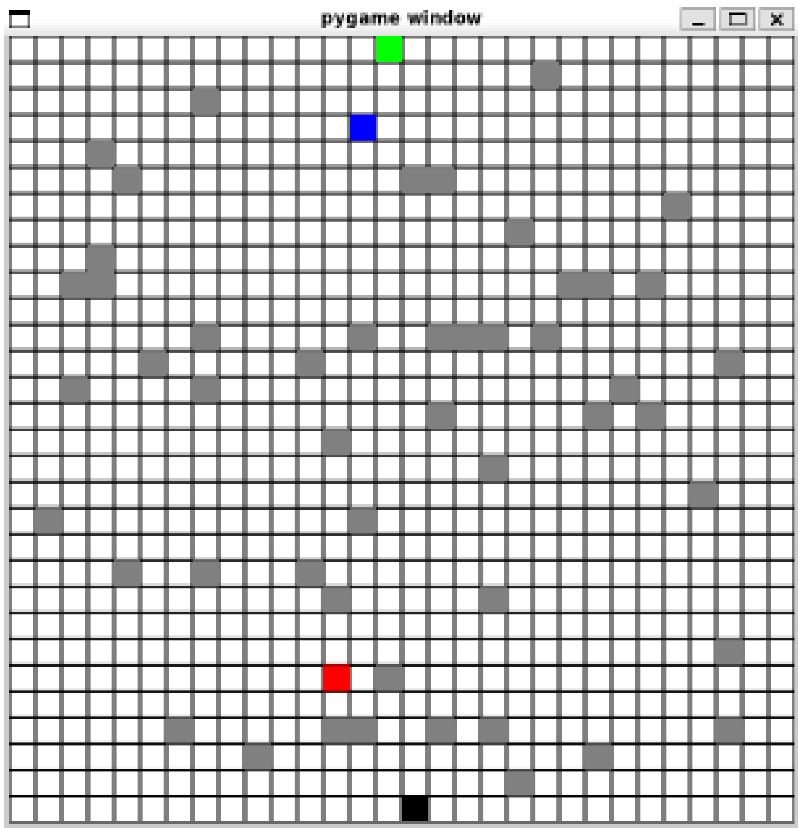

Figure 1: Game preview.

ABSTRACT

The proposed project involves the development of a cooperative hunter and prey game utilizing a multi-agent system. In this game, two preys agents navigate through a field of obstacles with the objective of reaching the exit, staying alive or killing the hunter, while facing challenges posed by the hunter agent. The gameplay is designed to incorporate cooperative mechanics, requiring the prey agents to work together to overcome obstacles and evade or confront the hunter agent. This project aims to offer an engaging gaming experience that emphasizes teamwork and strategic thinking.

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1 INTRODUCTION

This project introduces a cooperative hunter and prey game utilizing a multi-agent system. While existing games often focus on single-player experiences like the "World Hardest Game" by Snubby Land or "Pac-Man" by Namco, our game introduces a new dynamic where players must collaborate to navigate a field of obstacles, evade or confront a hunter agent, and reach the exit. This cooperative gameplay dimension aims to fill a gap in the gaming landscape by emphasizing teamwork and strategic coordination in overcoming challenges posed by an intelligent adversary.

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The relevance of this project lies in its potential to offer a unique gaming experience that promotes teamwork, problem-solving, and strategic thinking. Our objectives include designing and implementing game mechanics that facilitate cooperation, developing the multi-agent system with advanced decision-making capabilities, such as coordination mechanisms and learning techniques (e.g., reinforcement learning), and ensuring that the gameplay is engaging and challenging.

2 ENVIRONMENT

The environment consists of a field with various obstacles, represented by a 30x30 two dimensional grid . Two cooperative prey agents tasked with navigating the field, overcoming obstacles, and either evading or confronting the hunter agent to reach the exit. The hunter can kill both preys by catching them, however the preys can combine themselves into one stronger prey that can kill the hunter.

2.1 Problem definition

The problem definition involves creating a captivating gameplay experience that encourages cooperation between preys. By introducing a hunter agent as an obstacle, we add tension and urgency to the gameplay, requiring preys to strategize and coordinate their actions effectively. The objective is for both prey agents to reach the exit together, to do this, they must avoid the hunter, kill it, and reach the exit, thereby reinforcing the importance of teamwork and coordination.

Collaboration is essential since the probability of both agents independently reach the exit is very low. They must come together, becoming stronger, so they can kill the hunter and reach the final destination. This opens an interesting concept, since they can only try to kill the hunter after they both coordinate themselves to get together.

This is a Markov Decision Problem, it can be described by the following elements:

- Discrete time t = 0,1,2,... which in this case are represented by each frame of the game.
- A discrete set of states s, which is all the possible combinations of the agents on the grid, considering the obstacles and the exit.
- A discrete set of actions a = {up, down, left, right}
- A stochastic transition model P(s'|s,a) representing how the world transitions stochastically to state s' when the agent takes action a at state s
- A reward function R, where an agent receives a reward R(s,a) when it takes action a at state s, in this case an agent receives 1 reward when reaching the exit, and 0.01 for getting further away from the hunter. All other rewards are zero.

2.2 Observations

To better suit their next action, agents must observe the environment and decide what to do. The prey agents know their own position, the position of the other prey, the position of the hunter, the target position on the grid, and the positions of obstacles on the grid. They also know the size of the grid, ensuring that their movements stay within its boundaries. Additionally, the prey agents are aware of their activity status, indicating whether they are still active in the game, as well as whether they have reached the target position. If the prey agents are acting together, they know whether the combined prey is active and, if so, the position of the combined prey. The hunter agent, knows its own position, the positions of both preys, and the positions of obstacles on the grid. The hunter also knows the size of the grid and the activity status of each prey. If the prey agents are acting together, the hunter is aware of the position of the combined prey.

2.3 Agents Behaviour

The agents must move up, down, left or right in order to achieve their objectives. The hunter catches the prey by moving towards them while avoiding obstacles. It calculates the optimal move to minimize the distance to the closest prey. The prey has five distinct strategies: random, alive, runner as the greedy, mixed as roles and killer. Each strategy influences how the prey decides its next move to evade the hunter or achieve specific goals.

3 EMPIRICAL EVALUATION

The empirical evaluation involves subjecting the multi-agent system to various scenarios and conditions within the game environment to evaluate its behavior, effectiveness, and efficiency. The evaluation will focus on assessing the system's ability to fulfill its primary objectives, which include the collaboration of two prey agents to navigate through the field, overcome obstacles, and achieve their goals while evading or confronting the hunter agent. As such, we have defined different metrics for the evaluation.

3.1 Success rate

The success rate metric provides insight into the effectiveness of the prey agents' strategies to overcome the challenges posed by the hunter agent and obstacles in the environment. A higher success rate indicates that the prey agents are more proficient at working together and achieving their goals, while a lower success rate suggests areas for improvement in their strategies or coordination.

3.2 Number of steps

The number of steps metric measures the efficiency of the prey agents' navigation through the game environment. It quantifies the total number of actions taken by the prey agents to achieve their objectives. A lower number of steps indicates that the prey agents were able to reach their goals with fewer actions, demonstrating efficient navigation and decision-making while, a higher number of steps may indicate inefficiencies in the agents' strategies or difficulties encountered in the environment.

4 APPROACH

In this section, we detail the various strategies employed by the prey agents to navigate the game environment and achieve their objectives. Each strategy is designed to explore different aspects of decision-making and cooperation within the multi-agent system.

4.1 Social Conventions

We adapted one social convention where the agents avoid going to the corners of the map to avoid them of getting trapped.

We also adapted a social convention where the agents avoid going to the place they were immediately before so they do not engage in repetitive loops.

4.2 Random Strategy

The prey moves randomly. There are no considerations on the next action.

4.3 Alive Strategy

With this strategy the preys try to keep themselves alive with the thought that they will, eventually find the path to the exit whilst running away from the hunter. The prey maximizes the distance from the hunter to stay alive. The prey calculates possible moves and selects the one that maximizes the distance from the hunter.

4.4 Runner Strategy

The main concern of the prey is to move toward the exit. However if the hunter comes too close it starts running away from him. It calculates possible moves and select the one that minimizes the distance to the end position while maximizing the distance from the hunter.

4.5 Mixed Strategy

In this strategy we applied roles where one prey behaves like the alive strategy and the other one behaves like the runner strategy. The preys switch roles depending on the distance to the hunter.

The nearest prey to the hunter calculates possible moves and selects the one that maximizes the distance from it, while the other prey selects the one that minimizes the distance to the end position, running away from the hunter if he gets too close. It's called mixed because one prey is trying to stay alive while the other is trying to reach the exit.

4.6 Killer Strategy

In this strategy the preys highly value combining themselves so they can defeat the hunter. The prey coordinates with the other prey to move together and potentially attack the hunter. If both preys are in the same position, they combine in a single powerful prey and move towards the hunter with the ability to kill it. If not together, the prey moves towards the other prey to coordinate their movements.

5 COMPARATIVE ANALYSIS

In this section, we analyze the results obtained from the different strategies implemented by the multi-agent system. We compare the performance of the prey agents across various scenarios using the defined metrics: success rate and number of steps. This comparative analysis will highlight the strengths and weaknesses of each strategy, providing insights into their effectiveness and efficiency in different game environments. For each strategy the values were obtained after 100 episodes.

5.1 Random Strategy

Figure 2 shows the success rate for the random strategy, which, as expected, performed the worst with no successful attempts. By choosing the next step randomly, the prey agents were unable to win a single time, as the hunter consistently caught them both. There were still a few times where one of the preys managed to achieve the exit. The preys also did not manage to combine themselves.

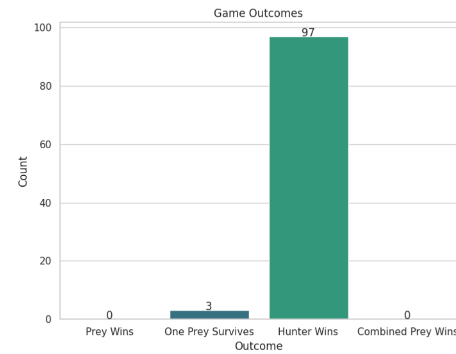

Figure 2: Success Rate in random strategy.

Figure 3 shows the average number of steps for the random strategy, which reflects the inefficiency of the prey agents' movements.

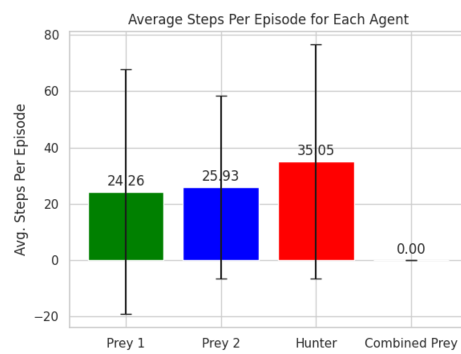

Figure 3: Average number of steps in random strategy.

5.2 Alive Strategy

The alive strategy was better than anticipated, as we can analyze in Figure 4 that shows the success rate for the alive strategy. While running away from the hunter, the preys eventually reach the exit. With both preys managing to reach the exit one in four tries, and almost half of the times at least one prey would reach the exit. With this strategy, the preys were able to combine themselves a few times, defeating the hunter.

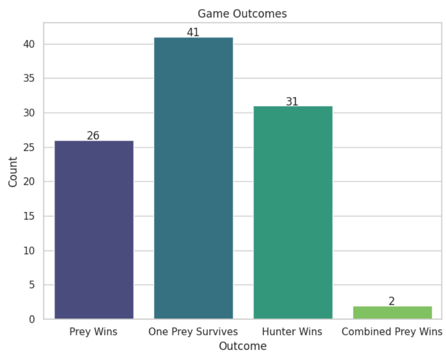

Figure 4: Success Rate in alive strategy.

Figure 5 shows the average number of steps for the alive strategy. Here we can see an increase of the steps, this happens because the preys are only running away, not actively looking to win.

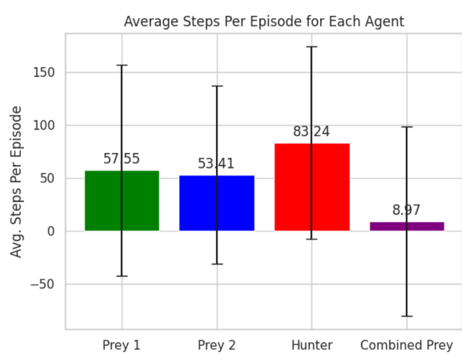

Figure 5: Number of steps in alive strategy.

5.3 Runner Strategy

The runner strategy revealed itself as a success, with the preys winning almost half of the times, with the hunter only being able to catch both preys one in ten times. The preys also managed to combine themselves a few times. Figure 6 shows the success rate for the runner strategy.

Figure 7 shows the average number of steps for the runner strategy. As expected, this is the strategy with the fewest steps, as the primary goal of the preys is going to the exit.

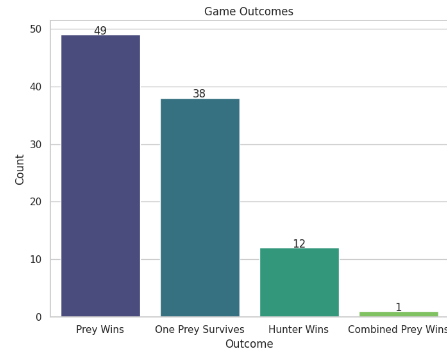

Figure 6: Success Rate in runner strategy.

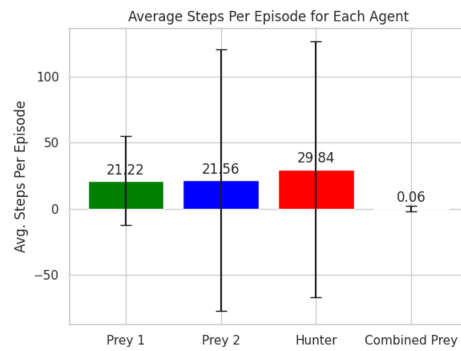

Figure 7: Number of steps in runner strategy.

5.4 Mixed Strategy

The mixed strategy was expected to have one of the best results. However, the preys only managed to win one in five times, combining themselves a few times. One interesting observation on this strategy is that the hunter was unable to catch both preys, with 95% of the times at least one of the prey running away. Figure 8 shows the success rate for the mixed strategy.

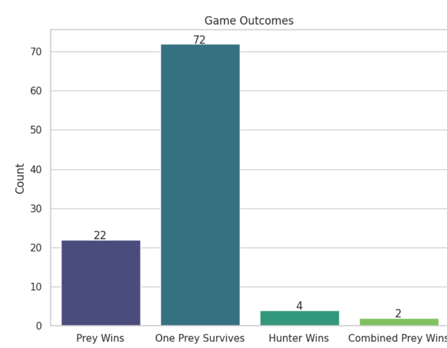

Figure 8: Success Rate in mixed strategy.

Figure 9 shows the average number of steps for the mixed strategy, as we would expect from the combination of the alive strategy with the runner.

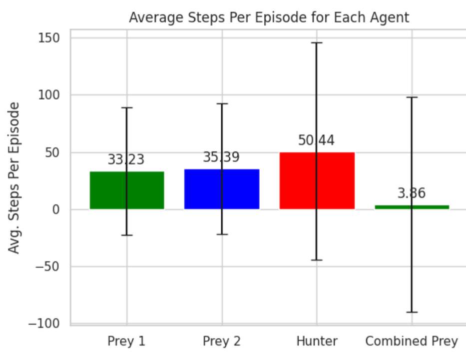

Figure 9: Number of steps in mixed strategy.

5.5 Killer Strategy

This strategy revealed interesting results, with the preys managing to combine almost half of the times. Unfortunately, ultimately achieving failure when not able to combine themselves. Figure 10 shows the success rate for the killer strategy.

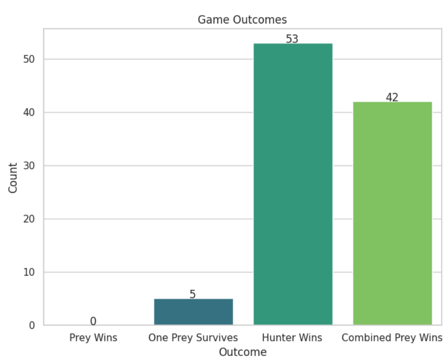

Figure 10: Success Rate in killer strategy.

Figure 11 shows the average number of steps for the killer strategy. We can see a lower prey1 and prey2 steps derived from the fact they would combine themselves, starting to count combined prey steps.

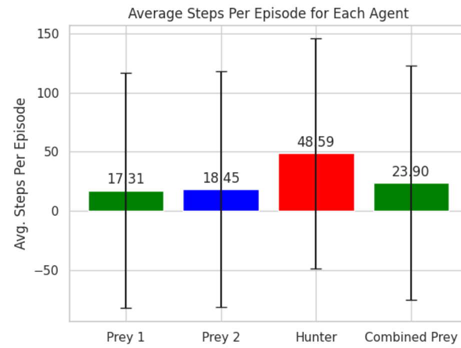

Figure 11: Number of steps in killer strategy.

6 CONCLUSION

In this paper, we developed and analyzed a cooperative hunter and prey game using a multi-agent system. Through implementing and testing various strategies for the prey agents, we gained insights into the effectiveness and efficiency of different decision-making approaches in achieving the game objectives.

Our empirical evaluation showed that the random strategy was the least effective, with no successful attempts recorded. In contrast, the runner strategy demonstrated the highest success rate, with prey agents winning nearly half of the games. The alive strategy and mixed strategy also performed reasonably well, with significant success rates and instances of prey agents combining to overcome the hunter. The killer strategy, while effective in combining the prey agents, ultimately resulted in failure when combination was not achieved.

Overall, the results emphasize the importance of strategic planning and cooperation in multi-agent systems, particularly in adversarial environments. Future work could explore more advanced coordination mechanisms and adaptive strategies, potentially incorporating machine learning techniques to further enhance the agents' performance.

This project not only contributes to the field of multi-agent systems but also provides a foundation for developing cooperative gameplay mechanics that can be applied to various gaming and simulation scenarios.