

Cops and Thieves

Project for the Agent Systems course

Tomasz Kawiak, Mateusz Mazur

Faculty of Electrical Engineering, Automation, Computer Science and Biomedical Engineering, AGH

Field of study: Computer Science and Intelligent Systems

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Introduction

Cops And Thieves (*cops and robbers*) is a strategic pursuit-and-evasion game where two opposing agent types operate in a shared environment. Thieves aim to evade capture, while cops patrol, chase, and arrest thieves to maintain order. The game mechanics involve agent coordination, pathfinding, and adaptive decision-making.

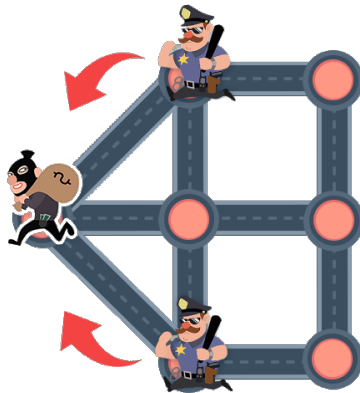


Figure 1: *Cops and Thieves* game depiction.
Source: *Catch The Thief: Help Police* by MicroEra

Comparison of other approach for a problem considered previously on engineering studies course *Development Workshop*. Our project – *Chase model* – was also implementation of the cops and thieves game. This project aims to hopefully improve our earlier attempt.

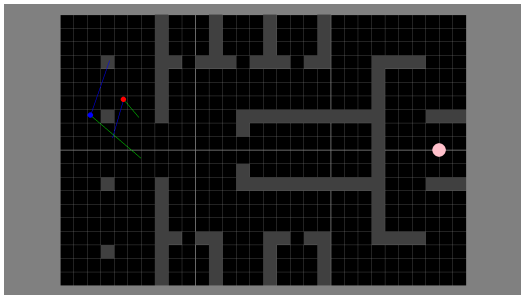


Figure 2: *Chase model* – game area.

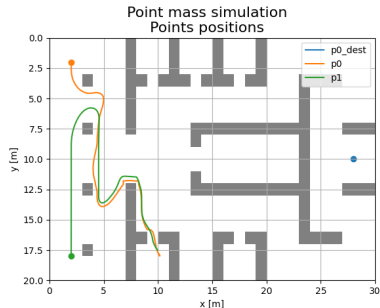


Figure 3: *Chase model* – movement chart.



WE ARE
BACK

Figure 4: We are back

As depicted in fig. 4, we are back to face the challenge of the cops and thieves problem, but this time with a different approach.

The main goal of this project is to train *environment-agnostic* agents:

- *Cops*: search and chase the thief.
- *Thief*: hide and try not to get caught.

A key aspect for both agents will be their ability to analyze their surroundings and act based on past observations. For our project we'll initially focus on only 2 agents (1 cop and 1 thief), with possibility of increasing the number of cop agents to observe cooperative behavior and more sophisticated search patterns.

We expect to achieve the following behaviors from agents:

Agent Type	Expected Description
<i>Cop</i>	Search and chase (if more cops, cooperation)
<i>Thief</i>	Evade capture and hide efficiently

In our project we intend to use the following frameworks:

- skrl (fig. 5) for MARL implementation.
- PettingZoo (fig. 6) to guarantee MARL environment standards.
- pymunk (fig. 7) as 2D physics engine, complemented by:
 - ▶ pygame (fig. 8) for visualization.



Figure 5: skrl logo



Figure 6: PettingZoo logo



Figure 7: pymunk logo



Figure 8: pygame logo

1st progress update

Agents

As stated in our first presentation, we have 2 agent types, namely, cops and thieves. Because this part is critical for our project to move forward, we have implemented agent functionality, which covers:

- observation space implemented using vision controller (ray casting),
- action space (enabling movement of our agents in 2D space),
- initial reward function.

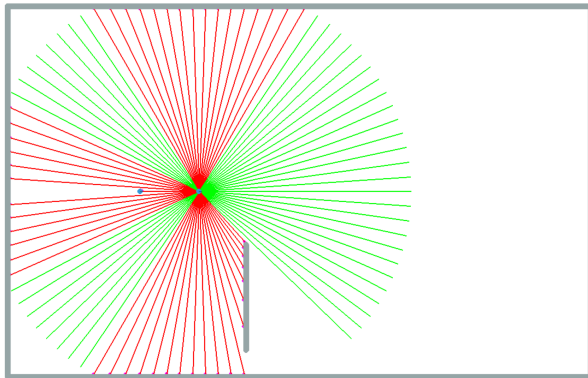


Figure 9: Visualization of vision controller

Environment

Using *PettingZoo* library we have implemented initial environment, compliant with `Parallel` API in order for all agents to simultaneously perform action and observations.

As part of this we have implemented:

- rendering together with map generation (explained in-depth later on).
- Basic methods needed for *Reinforcement Learning* algorithms (reset, step, etc.).
- Shared observation space:
 - ▶ needed for learning loop, where agents from the same category share a common observation that represents global information about the environment,
 - ▶ constructed based on their intrinsic priority (i.e. cops wanting to catch a thief), shared observation holds the most important information about their observations.

GUI & Visualization

Apart from a command line interface (CLI) “visualization” (suited for training the agents), we have also implemented a graphical user interface (GUI) that allows us to visualize the environment and the agents’ actions. The GUI is presented in fig. 10.

Environment map generation

We have implemented a simple map generation tool that allows us to create a *map* file based real-world data from OSM. It generates obstacles for all the buildings in the area and places agents in given locations. Moreover, it generates a *png* file with a depiction of the area to be used as a background for the GUI. Figure 10 presents a screenshot of the GUI with a map of the AGH University of Science and Technology in Kraków, Poland.

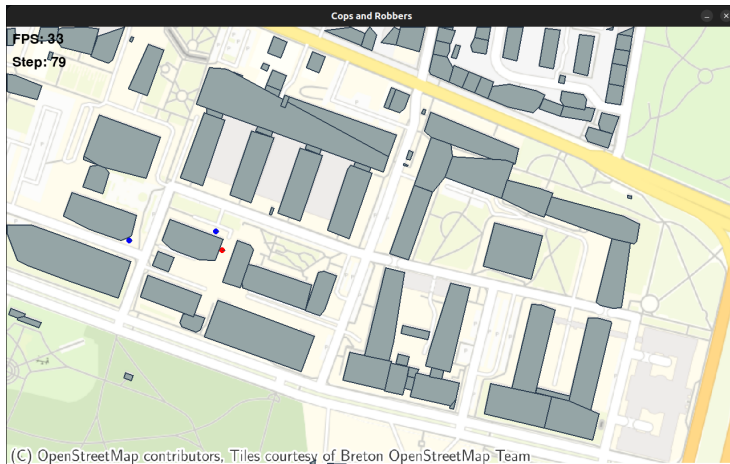


Figure 10: GUI of the application

2nd Progress Update

Environment

Since the last report, we have undertaken significant refactoring and bug-fixing efforts to ensure compliance with the skrl framework.

skrl & RL Algorithm

For our Multi-Agent Reinforcement Learning (MARL) task, we have chosen to utilize MAPPO (Multi-Agent Proximal Policy Optimization) due to the cooperative nature of our environment.

This phase involved:

- Introducing new spaces: *shared observation space* and *state space*
- Restructuring the observation and action spaces to fully leverage PyTorch tensors

Agents

On the agent side, we implemented minor fixes and further optimizations in the vision controller.

We are also addressing ongoing challenges with the reward function, where agents are exploiting the reward mechanism, leading to unintended behaviors during episodes.

For the MAPPO implementation, we developed both policy and value networks. Both networks use a Multi-Layer Perceptron (MLP) architecture with two hidden layers. The policy network outputs the best possible action for a given state, while the value network serves as a critic, estimating the expected return for the agent's actions.

Policy Network

Utilizes CategoricalMixin base skrl class due to its stochastic nature, and because of the categorical action space.

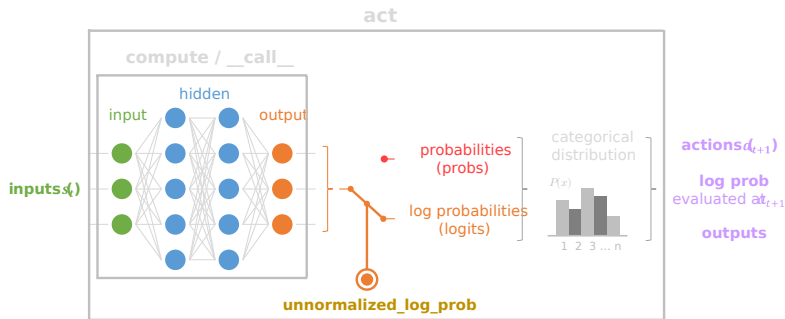


Figure 11: Concept of policy network. Source

Value Network

Utilizes DeterministicMixin base skrl class. Takes the global state of the environment.

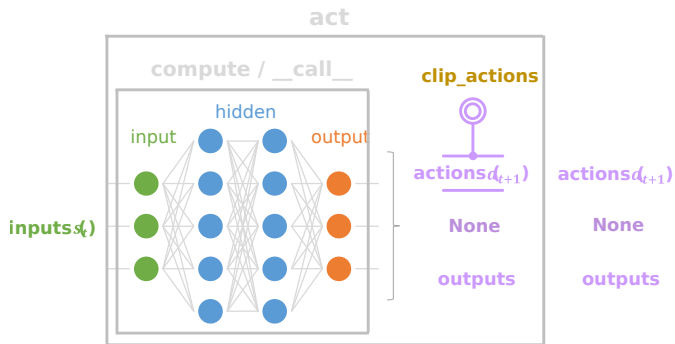


Figure 12: Concept of value network. Source

Thank you for your attention

Questions?