Wumpus World development and metrics with gama platform

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Abstract. This project focuses on creating and solving the Wumpus World problem using a multi-agent system implemented in the GAMA platform. By simulating an environment with two players, three Wumpuses, and two pits, we analyze the agents' behaviors and performance. Metrics such as total steps taken and danger avoidance are evaluated, supported by graphical analyses, including line and pie charts. The insights contribute to understanding agent decision-making and environment navigation strategies in multi-agent systems.

Keywords: Multi agent system · agents · Belief desire intent

1 State of the Art

Wumpus World is a classic problem in artificial intelligence, designed to test logical reasoning and decision-making capabilities of autonomous agents. Introduced as part of AI research, it involves navigating a grid-based world to locate treasure while avoiding hazards like Wumpuses and pits. Historically, this environment has been a benchmark for testing BDI (Belief-Desire-Intention) agent models, which simulate human-like decision-making processes based on beliefs (environmental knowledge), desires (objectives), and intentions (action plans).

Recent advancements in multi-agent platforms like GAMA have allowed more sophisticated simulations. GAMA facilitates the modeling of complex systems with dynamic interactions, making it ideal for Wumpus World experiments. Researchers have used GAMA to develop agents capable of learning and adapting strategies in real time, contributing to fields such as game theory, robotics, and risk management and much more.

2 Experimentation

2.1 Introduction

The experiment was conducted in a 20x20 grid-based Wumpus World environment (see Fig. 1). The key components of the environment included:

- **Players:** Two agents tasked with navigating the grid.
- **Wumpuses:** Three Wumpuses, each representing a lethal hazard.
- **Pits:** Two pits, adding an additional layer of risk.

The simulation aimed to test agent performance in terms of hazard avoidance and successful navigation toward the goal (treasure collection). The agents used a rule-based BDI model to make decisions based on their perceptions of the environment, such as detecting breezes near pits (breezeArea) or stenches (odorAreas) near Wumpuses.

2.2 BDI Implementation Overview

The BDI (Belief-Desire-Intention) model in this simulation involves three key components:

Beliefs: These represent the agent's knowledge about its environment, updated based on perceptions. For example:

Detecting a breeze or odor updates the belief about nearby dangers. Perceiving glitter creates a belief about the gold's location. Desires: Desires define the agent's goals or objectives:

patrol_desire: Default state where the agent explores the environment. go_back_desire: Activated when danger is perceived, prompting retreat. glitter_location: Activated when gold is detected, triggering the get_gold plan. Intentions: Intentions are plans the agent commits to, based on its current desires and beliefs:

When in danger, the agent commits to the goBack plan to ensure survival. When detecting glitter, it follows the get_gold plan to collect the treasure. In normal conditions, it patrols the environment. This BDI framework enables the agent to adapt its behavior dynamically, balancing exploration, danger avoidance, and goal-seeking to navigate the Wumpus World effectively.

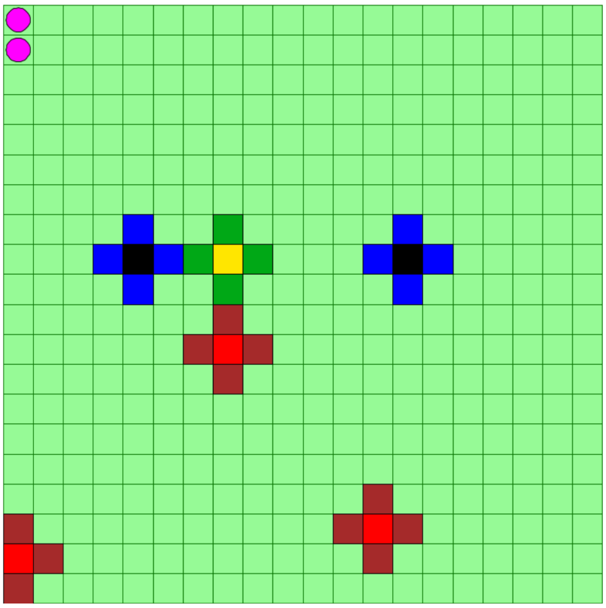

Fig. 1. Wumpus World with custom parameters (2 players, 2 pits, 3 wumpus)

2.3 Danger Avoidance Plan (go_back)

The go_back plan is designed to handle situations where an agent detects a dangerous environment, such as a pit or a Wumpus nearby. The plan works as follows:

Direction Adjustment: Depending on the current movement direction (mov), the agent reverses its heading:

If facing North (0°), it turns South (180°). If facing East (90°), it turns West (270°). If facing South (180°), it turns North (0°). If facing West (270°), it turns East (90°). Movement Execution: After changing direction, the agent moves one cell in the opposite direction to avoid the perceived danger.

Desire Management:

The go_back_desire is removed once the agent successfully moves away. The agent then reactivates the patrol_desire, returning to its default patrolling state. This plan ensures that the agent prioritizes immediate retreat from danger, contributing to its overall survival strategy.

2.4 Gold Collection Plan (get_gold):

The get_gold plan enables the agent to navigate towards and collect gold when it perceives glitter, indicating proximity to a gold piece. The process involves:

Directional Control: The agent adjusts its movement based on a short flag, alternating between reversing its direction and selecting a random new heading:

If short is true, the agent reverses its current direction. Otherwise, it selects a random direction from predefined movement options. Movement Execution: The agent moves one step in the determined direction, progressively narrowing its search for the gold.

Goal Focus: This plan is triggered by the glitter_location belief, ensuring that the agent only executes this behavior when gold is detected nearby.

This strategy balances systematic search with reactive movement, increasing the likelihood of successful gold collection. There is a video available in google drive of the experiment execution in this link.

3 Metrics and Results

Key metrics evaluated in this experiment included:

- **Total Steps:** The number of steps (time measure) both agent took to complete the task or until termination.
- **Danger Avoidance:** Measured by the number of times agents successfully avoided hazardous cells.

3.1 Graphical Analysis

Line Chart: Displays the frequency of danger avoidance over time (steps). This graph illustrates the agents' learning curve and responsiveness to environmental hazards (see Fig. 2).

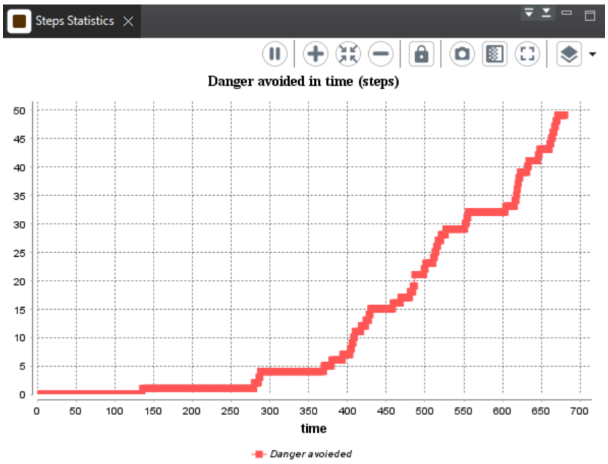

Fig. 2. Avoided dangers over time (steps)

Pie Charts:

- **Environment Composition:** Shows the distribution of Wumpuses, pits, and players, highlighting the dynamic configurability of the environment. This diagram is very useful to understand how the concrete aspects of the particular experiment are distributed (see Fig. 3).

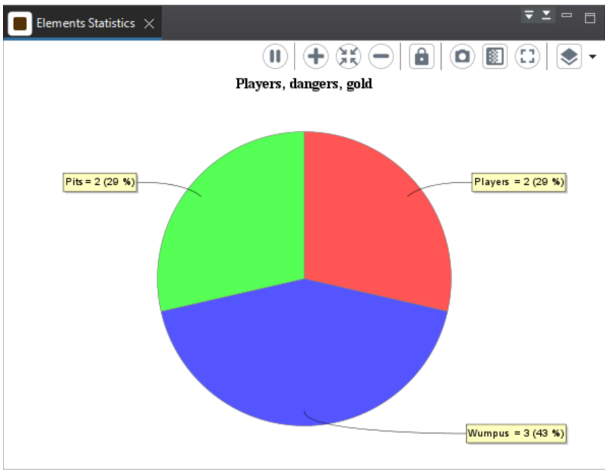

Fig. 3. Environment Composition with custom parameters (2 players, 2 pits, 3 wumpus)

- **Avoided vs. Existing Dangers:** Compares the total number of dangers avoided to the total number of hazards (sum of Wumpuses and pits), indicating the agents' efficiency (see Fig. 4).

4 Conclusion

The implementation and analysis of the Wumpus World in GAMA demonstrate the effectiveness of multi-agent systems in solving complex navigational challenges. The metrics and graphical results provide valuable insight into agent performance (see Fig. 5) , particularly in hazard avoidance and decision-making efficiency. Future work could explore larger environments, more sophisticated agents, and adaptive learning strategies to further enhance performance.

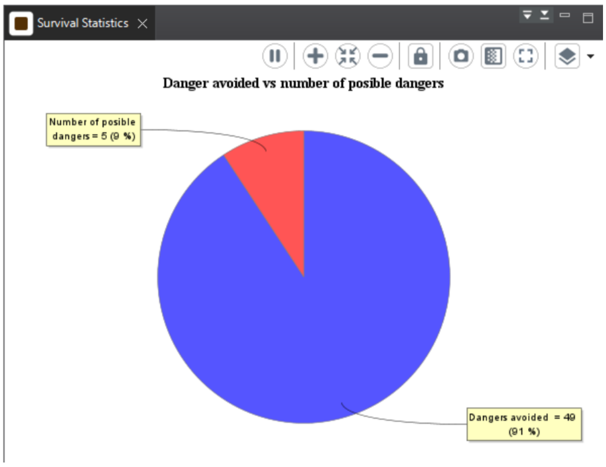

Fig. 4. Avoided vs. Existing Dangers (pits + Wumpuses)

Fig. 5. Wumpus World with custom parameters (2 players, 2 pits, 3 Wumpus)