SIMULATION OF EMPATHETIC ROBOT INTERACTION IN SWARM

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Abstract. Artificial empathy is key in enabling robotic agents to adapt, co- operate, and share knowledge in multi-agent systems. This study aims to develop an artificially empathetic decision-making framework implemented in Unity software to enhance robotic swarm interactions, leveraging prin- ciples from cognitive science, fuzzy logic, and imprecise cognition. The re- search focuses on improving decision-making in uncertain environments and exploring the benefits of empathy-driven collaboration over traditional ego- istic approaches.

Keywords: artificial empathy · artificial intelligence

1 Introduction

Artificial Intelligence (AI) and robotics have evolved rapidly, leading to complex autonomous decision-making systems. One of the most crucial areas of research within this field is the enhancement of multi-agent cooperation using artificial empathy [3, 1]. Artificial empathy allows agents to perceive, interpret, and respond to the emotional and cognitive states of others, fostering enhanced teamwork, knowledge sharing, and adaptation [4]. The primary aim of this study is to simulate empathetic robots in Unity and analyze how their interactions improve efficiency in collaborative swarm robotics environments.

Swarm robotics is an emerging field inspired by collective behaviours observed in nature, such as ant colonies and bird flocks. Swarm intelligence models typically employ decentralized control, local agent interactions, and simple behavioural rules to achieve complex group dynamics [10]. However, traditional approaches to swarm robotics often lack a mechanism for intuitive, experience-based knowledge sharing. By incorporating artificial empathy, agents can infer and predict the needs and intentions of other agents, enhancing cooperative efficiency.

Unlike traditional AI-driven collaboration, which follows pre-defined behavioural rules, artificially empathetic agents utilize subjective experience, fuzzy logic, and knowledge interpolation to infer intentions and optimize cooperative decision-making [5]. Neuroscience research has shown that humans learn from observing others via mirror neurons, a concept that can be applied to artificial systems to improve adaptive behaviour [6].

Imprecise cognition plays a crucial role in this model, as robots must operate in uncertain environments where communication is inherently noisy and information exchange is subjective [11]. This concept, drawn from psychology and AI research, allows agents to generalize observed behaviours and interpolate missing data to guide decision-making. This research aims to develop and implement a Unity simulation in which autonomous robotic agents interact using an artificially empathetic decision-making model.

2 Models and methods

Mathematically, the internal and external states of an agent are modelled as fuzzy sets:

$$\Psi_A = (X_A, Y_A), \tag{1}$$

where:

$$X_A = (x_{A1}, x_{A2}, ..., x_{An}), \quad Y_A = (y_{A1}, y_{A2}, ..., y_{Am}). \tag{2}$$

This representation allows for handling imprecise and uncertain knowledge when agents interact with their environment.

To evaluate how well an agent's state sequence aligns with the overall objective, we define the goal operator:

$$\omega(x) = \max(2(x - 0.5), 0), \tag{3}$$

where ω assigns weights to sequences based on their alignment with a predefined goal.

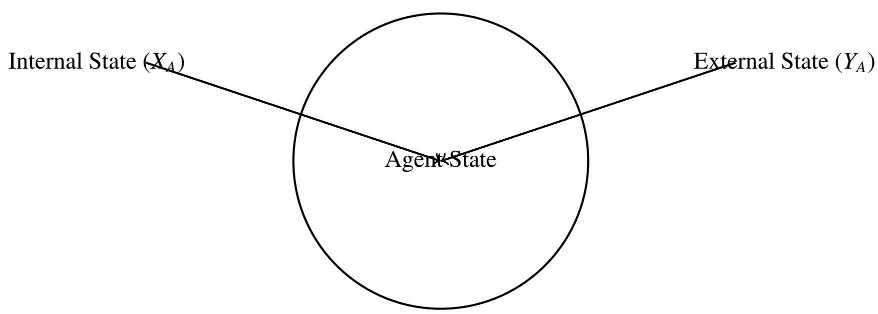

Fig. 1: Diagram of an agent's state representation using fuzzy logic. Source: Own research.

The similarity of different state sequences is computed using the fuzzy similarity measure:

$$sim(S_A, S_B) = \sup_{S_A \in L_c(S_A), S_B \in L_c(S_B)} \bigotimes_{i=1}^{c} s(X_{A_i}, X_{B_i}) \odot s(Y_{A_i}, Y_{B_i}), \tag{4}$$

where $\bigotimes$ and $\odot$ are aggregation operators and *sim* is a similarity measure for comparing fuzzy sets.

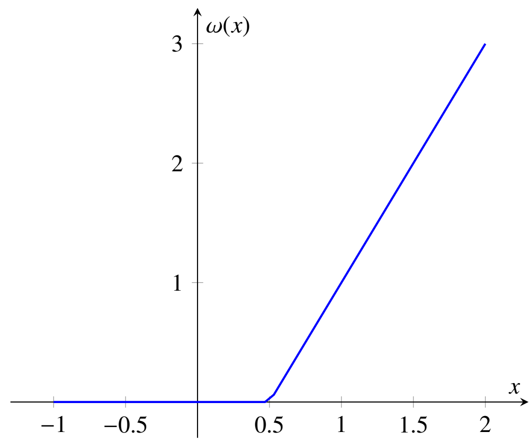

Fig. 2: Graphical representation of the goal operator. Source: Own research.

3 Simulation research

The Unity simulation is structured around a robotic swarm performing collaborative tasks in an environment where agents must make real-time decisions. The key components of the implementation include:

1. Agents use sensors (simulated cameras and distance sensors) to detect objects and other agents.

2. Each robot has an internal knowledge base, storing state-reward pairs, which guide actions based on predicted outcomes.

3. Robots evaluate the needs of their neighbours and decide whether to act independently or assist others based on reward projections [12]. The decision is based on the evaluation of three key reward values:

$$R_A(X_A, Y_A), \quad R_A(X_Bi, Y_Bi), \quad R_A(X_A, Y_Bi) \tag{5}$$

   Where R is a reward function, assigning the highest reward to the maximal fuzzy similarity between the evaluated state and the goal. The agent selects the highest reward among these options to decide between egoistic or empathetic behaviour.

4. Agents broadcast state information, allowing others to interpolate missing knowledge and adapt their behaviour accordingly.

5. The simulation evaluates how:

   – robots handle incomplete or imprecise knowledge when making decisions [7].

   – cognitive empathy and similarity measures influence cooperative actions [8].

   – agents modify actions based on experience and states of others [9].

– Evaluate whether empathetic agents perform better in achieving shared goals than traditional, egoistic agents [3].

The simulation model performs the following algorithm steps:

1. **Goal of the Test**
   – The objective of this simulation is for the robots to successfully find the food source.
   – Robots must either find the food source independently or learn about it from other robots.
2. **Robot Colors and States**
   – Each robot starts with a **basic blue color** (`searchingColor = blue`), indicating it is searching for food.
   – If a robot **finds the food**, it changes to **green** (`foundFoodColor = green`).
   – Robots in empathetic mode can also turn **green** when they detect another robot that has found food.
3. **Start Searching for Food**
   – Each robot continuously checks for food by calling `DetectFood()`.
   – If a robot does not find food, and if `useEmpatheticBehavior` is `true`, it calls `DetectNearbyRobots()` to learn from others.
4. **Calculate Own Fuzzy State**
   – with `GetCurrentFuzzyState()` function, where:
     - **Internal Value:** battery level or another internal factor.
     - **External Value:** A normalized measure of how far the robot is from the food source.
5. **Detect Nearby Robots**
   – with `Physics.OverlapSphere()`, within a given range.
   – Check if any robot has already found food.
6. **Compare Fuzzy States for Empathy**
   – If a robot detects the fuzzy state of a nearby robot spotting food, it calculates the similarity between its own state and the successful robot's state using `CalculateFuzzySimilarity()`.
   – The similarity is measured between 0 (no similarity) and 1 (full similarity). If similarity is above the threshold (0.7), the robot considers the other robot's success as relevant and:

- Learns from the other robot (copies its food location).
- Changes color to green to indicate food has been found.
- Stops searching and moves toward the learned food position.

7. **Memory and Exploration**
   - When in empathetic mode, robots also:
     - Mark no-food areas when they explore but do not find food.
     - Avoid revisiting these areas, improving search efficiency.
8. **Behavior When Empathy is Disabled**
   - When `useEmpatheticBehavior = false`, the robot:
     - Ignores `DetectNearbyRobots()`.
     - Relies only on `DetectFood()`.
     - Does not share or receive information from other robots.

3.1 Testing Methodology and Results

To evaluate the effectiveness of artificially empathetic decision-making in swarm robotics, we conducted a series of test in a simulated environment. The test scenario required robots to locate a food source within a dynamically changing environment. Each experiment was repeated with different initial conditions, altering the map layout and the position of the food source. Additionally, the robots were spawned at random locations in each simulation, and the food source was repositioned to ensure varied starting conditions, testing the adaptability of both behavioural models. To assess the impact of artificial empathy, two sets of experiments were conducted:

- **Empathetic Behavior**: Robots utilized artificial empathy to share knowledge and predict the needs of other agents, allowing for cooperative decision-making. They actively communicated information about food locations and adjusted their paths based on the experiences of their peers.
- **Egoistic Behavior**: Robots operated independently, without knowledge sharing or anticipating the actions of other agents. Each agent relied solely on its own exploration capabilities, leading to potentially redundant searches and inefficient movement.

Each configuration was tested multiple times, and completion times for locating the food source were recorded. The following table compares the fastest empathetic trials and the slowest egoistic trials, demonstrating the significant efficiency gains achieved through cooperative decision-making.

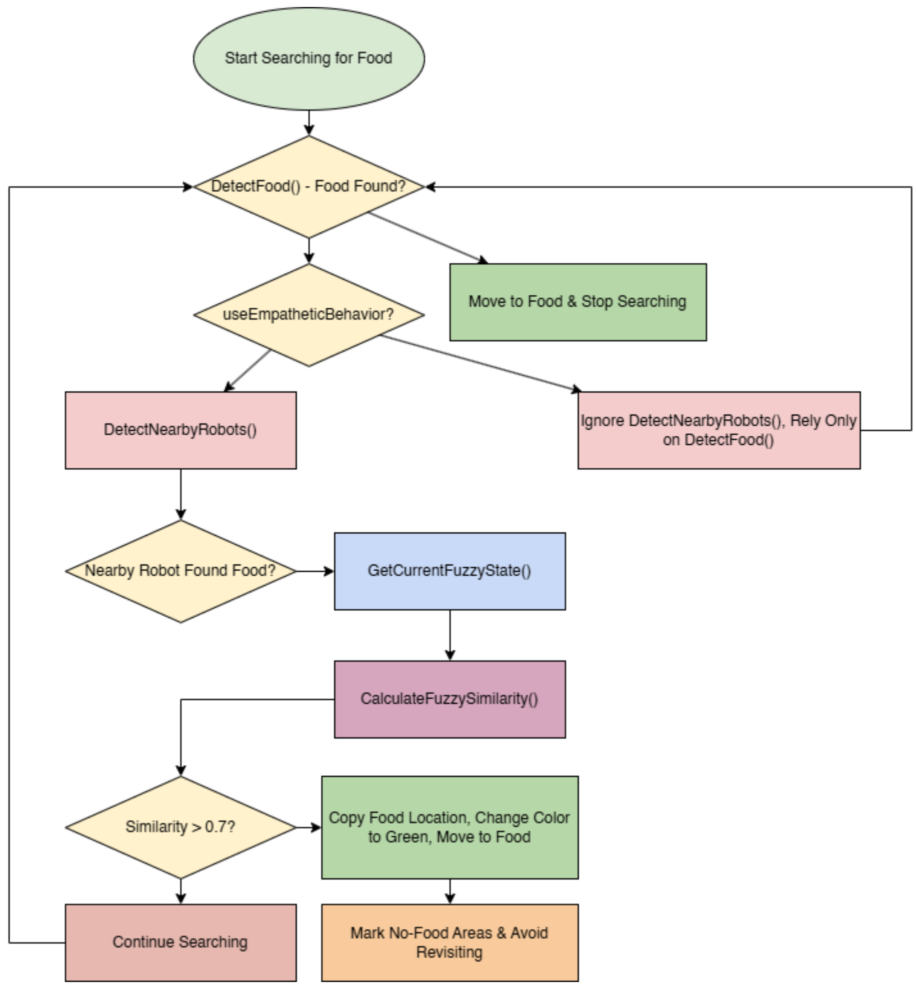

Fig. 3: Flowchart of the Food Searching Behavior in Robots. Source: Own research

From Table 1, it is evident that empathetic robots consistently outperformed egoistic robots in locating the food source. The threshold value of 0.7 was chosen based on empirical testing and prior literature in fuzzy similarity measurements. This threshold applies to the **fuzzy state similarity** between robots, determining whether one robot should trust and adopt another's information. A value above 0.7 ensures that only sufficiently similar states influence decision-making, preventing the robot from following misleading or irrelevant information. This balance prevents excessive reliance on uncertain data while still allowing for cooperative behavior. The fastest empathetic trials showcased significantly reduced search times due to effective communication and cooperation between agents. In contrast, egoistic robots required much longer to complete the task, often exceeding three times the duration of the fastest empathetic trials.

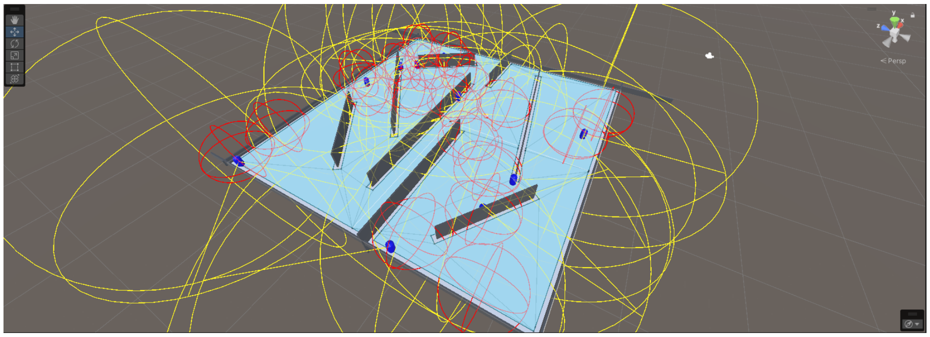

Fig. 4: Empathetic Behavior model simulation in Unity.

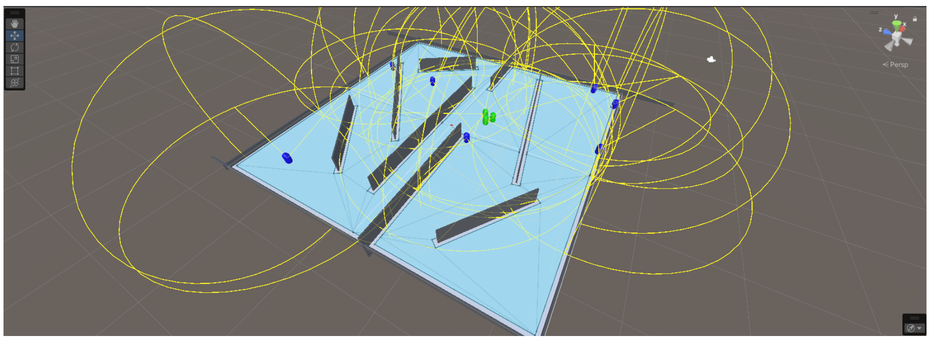

Fig. 5: Egoistic Behavior model simulation in Unity.

The improved efficiency of empathetic robots can be attributed to their ability to share learned information about the environment. When one robot found the food source, it broadcasted this information, allowing others to adjust their search patterns accordingly. This prevented redundant searches and led to optimized movement strategies. In contrast, egoistic robots acted independently, resulting in unnecessary exploration and suboptimal resource allocation.

4 Discussion

The integration of artificial empathy into swarm robotics has gained significant attention, leading to various innovative approaches aimed at enhancing communication and cooperation among robotic agents. Several studies have proposed frameworks to incorporate artificial empathy, behaviour-based communication, and cognitive prediction into multi-agent systems. However, our approach extends these concepts by providing a more robust and adaptable model that addresses imprecise communication and enhances predictive capabilities.

Empathetic Behavior		Egoistic Behavior	
Simulation	**Completion Time [s]**	**Simulation**	**Completion Time [s]**
Simulation 1	39.80	Simulation 1	246.54
Simulation 2	22.82	Simulation 2	207.77
Simulation 3	59.85	Simulation 3	260.91
Simulation 4	92.51	Simulation 4	58.59
Simulation 5	64.45	Simulation 5	165.27
Simulation 6	81.18	Simulation 6	184.78
Simulation 7	1.20	Simulation 7	393.51

Table 1: Comparison of completion times for empathetic vs. egoistic behavior. Source: Own research

In contrast to these studies, our approach advances the concept of artificially empathetic decision-making by integrating fuzzy logic, decentralized communication, and real-time cognitive prediction. Our model offers several advantages:

- **Enhanced Predictive Capabilities**: Unlike previous studies that rely on predefined behavioural rules, our method leverages fuzzy similarity measures and knowledge interpolation to improve state prediction and decision-making.
- **Decentralized Communication**: Our framework reduces reliance on explicit information exchange, mitigating potential bottlenecks and enhancing the scalability of the swarm.
- **Continuous Learning Mechanism**: Agents update their knowledge bases in real-time, learning from both direct experiences and observed behaviours of other agents, leading to improved adaptability.
- **Robust Cooperation Strategies**: By incorporating cognitive empathy, our approach allows agents to assess the needs and intentions of peers dynamically, optimizing cooperative behaviours beyond simple task execution.

While prior research [13–15] has laid the foundation for integrating artificial empathy into swarm robotics, our method provides a more advanced and adaptable framework. By addressing the complexities of imprecise communication and enhancing cognitive predictive capabilities, our approach presents a superior solution for achieving efficient and resilient cooperation in robotic swarms.

5 Conclusions

This study has introduced an artificially empathetic decision-making framework for robotic swarms, implemented and tested in a Unity-based simulation environment. By leveraging cognitive science principles, fuzzy logic, and imprecise cognition, our approach demonstrates that artificial empathy enhances decision-making, knowledge-sharing, and cooperative behaviours in multi-agent systems.

Our research highlights several key advantages of incorporating artificial empathy into swarm robotics. The results indicate that empathy-driven decision-making improves overall swarm performance by fostering better adaptation to dynamic environments and enabling more efficient collaboration. Compared to traditional egoistic strategies, our approach allows agents to anticipate and respond to the needs of their peers, ultimately leading to more effective task completion and resource allocation.

Furthermore, the simulation experiments and physical robot trials reveal that artificial empathy enables agents to make decisions under uncertainty by utilizing fuzzy similarity measures and interpolating missing knowledge. This adaptability is crucial in real-world applications, where communication constraints and unpredictable scenarios require flexible decision-making models.

In conclusion, our study contributes to the growing field of AI-driven cooperation by demonstrating that artificial empathy provides a viable path for improving swarm intelligence. The findings suggest that integrating empathetic decision-making into robotic swarms can lead to more efficient and resilient multi-agent systems, paving the way for further advancements in AI-driven collective behaviour.

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