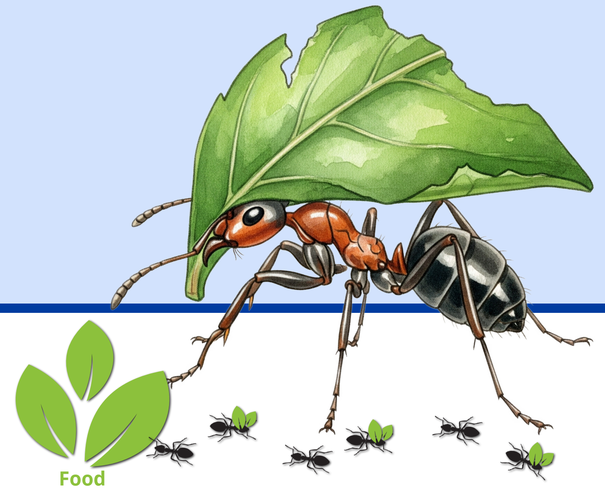
HAW HAMBURG

MARS GROUP
Multi-Agent Research & Simulation

Flexible Simulation Platform for Ant Colonies

Modeling of Emergent Behavior through Biologically Inspired Multi-Agent Systems

Sebastian Wewer
www.haw-hamburg.de
sebastian.wewer@haw-hamburg.de
www.mars-group.org



1. Motivation & Problem Statement

Ant colonies solve complex tasks through collective intelligence and emergence, a key principle for robotics and logistics. They are the subject of numerous research efforts and studies. However, existing simulations are often limited to specific aspects. A unified, flexible platform for investigating various behaviors in dynamic environments is missing.

The goal of this work is the design and implementation of such a simulation platform based on the MARS Framework to systematically research emergent behavior.

2. System Architecture

The MARS platform is based on a modular multi-layer architecture to enable a realistic simulation:

Vector Layer for Agents & Objects: Agents move freely in a continuous space. The environmental geometry, including obstacles and food sources, is created using QGIS as a GeoJSON file and loaded into the layer as a precise polygon structure.

Grid Layer for Pheromones: Independent of the agents' free movement, pheromone information is stored in an underlying grid layer. This grid enables a very performant simulation of pheromone propagation (diffusion) and evaporation.

Layer Interaction: The core of the simulation lies in the interplay between the layers. Agents in the vector layer continuously read the pheromone values from the grid cells beneath them to make their movement decisions. At the same time, they leave behind pheromone trails by modifying the values in the grid layer.

3. Behavioral Modeling

The emergent behavior of the colony is based on three biologically inspired core mechanisms:

State-Based Control: A Finite State Machine (FSM) controls the behavior of each ant (e.g., exploring, following). Navigation in the vector layer is accomplished through steering vectors that account for polygon obstacles.

Stigmergy & Pheromone Simulation: Coordination occurs indirectly. Agents in the vector layer leave pheromone trails in the underlying grid layer. Other ants follow these trails by aligning their steering vectors with the pheromone gradient.

Information Exchange & Emergence: When two agents meet in the vector layer, they can exchange status information (e.g., food source found). This can trigger a state change in the FSM and directly adapt the behavior.

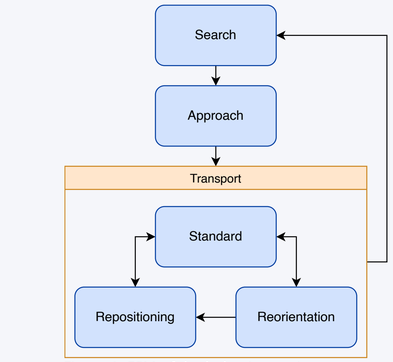


Figure 1: FSM of the behavior engine

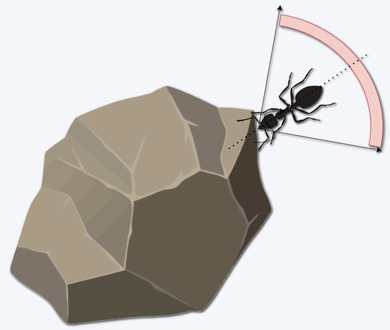


Figure 2: Reorientation

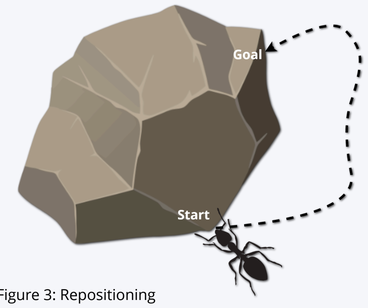


Figure 3: Repositioning

Figure 1: The states of the FSM that controls an individual ant's behavior. **Figure 2:** In case of resistance, the ant changes its body orientation without letting go and pulls from a different angle. **Figure 3:** If reorientation fails, the ant lets go, moves to a new position, and starts the process again.

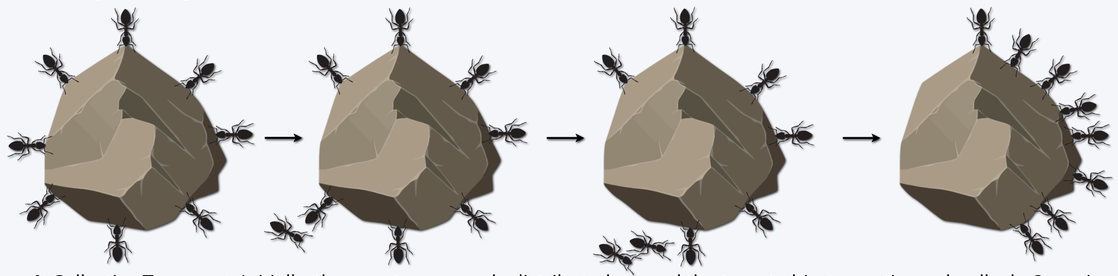


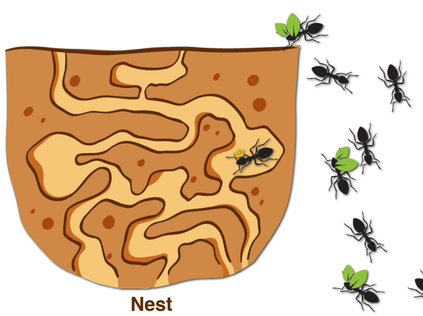
Figure 4: Collective Transport. Initially, the agents are evenly distributed around the target object, creating a deadlock. Over time, the ants break the deadlock through reorientation and repositioning, and the combined force moves the object.

4. Validation Scenarios & Visualization

The platform is validated in test scenarios; the analysis of emergent paths is conducted using kepler.gl.

Dynamic Pathfinding: The colony is expected to autonomously find efficient paths around interactively placed obstacles, thereby demonstrating its adaptive self-organization.

Strategy Comparison: The investigation of explorative vs. pheromone-driven colonies is intended to demonstrate the "Exploration-Exploitation Trade-off" (efficiency vs. resilience).



5. Outlook and Next Steps

The developed platform can serve as a basis for further research:

Implementation of more complex behaviors: Investigating collective transport, brood care, or competition between colonies to probe the limits of emergence.

Use of Reinforcement Learning: Agents could independently develop optimal strategies through machine learning that go beyond hand-coded rules.

Quantitative Validation: Comparing the simulation results with real tracking data from ants could further enhance the scientific validity of the model.

6. References

[1] Xiang, W., Ren, J., Wang, K., Deng, Z., & Jin, X. (2019). Biologically inspired ant colony simulation. Computer Animation and Virtual Worlds, 30(3-4), e1867. https://doi.org/10.1002/cav.1867

[2] Cristín, J., Fernández-López, P., Lloret-Cabot, R., et al. (2024). Spatiotemporal organization of ant foraging from a complex systems perspective. Scientific Reports, 14(1), 12801. https://doi.org/10.1038/s41598-024-63307-1

[3] Guo, S., Wang, M., Notman, G., Chang, J., Zhang, J., & Liao, M. (2017). Simulating collective transport of virtual ants. Computer Animation and Virtual Worlds, 28(3-4), e1757. https://doi.org/10.1002/cav.1779

[4] Zhang, Wei-guo & Lu, Tian-yu. (2012). The Research of Genetic Ant Colony Algorithm and Its Application. Procedia Engineering. 37. 101–106. http://dx.doi.org/10.1016/j.proeng.2012.04.210

www.mars-group.org/