Integrating Tabu-Based Memory and Field Superposition in Swarm Robotics for Indoor Waste Collection

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Abstract. *Waste collection in indoor environments is challenged by spatial constraints and dynamic conditions, requiring adaptive and efficient solutions. In this context, swarm robotics combined with cellular automata has emerged as a promising decentralized approach. This work applies the Cellular Automata Ant Memory (CAAM) model using a state superposition perspective, integrating static and dynamic fields with tabu-based memory at the cell level. This unified representation enables agents to balance exploration and goal-oriented navigation. Experimental results show that the proposed integration improves efficiency and stability, reducing revisitation and enhancing environmental coverage. The findings highlight the potential of the model as a scalable solution for decentralized waste collection.*

Resumo. *A coleta de resíduos em ambientes internos é desafiada por restrições espaciais e condições dinâmicas, exigindo soluções adaptativas e eficientes. Nesse contexto, a robótica de enxame, combinada com autômatos celulares, tem emergido como uma abordagem descentralizada promissora. Este trabalho aplica o modelo Cellular Automata Ant Memory (CAAM) sob a perspectiva de superposição de estados, integrando campos estáticos e dinâmicos com memória baseada em lista tabu no nível das células. Essa representação unificada permite que os agentes equilibrem a exploração e a navegação orientada a objetivos. Os resultados experimentais demonstram que a integração proposta melhora a eficiência e a estabilidade do sistema, reduzindo revisitações e ampliando a cobertura do ambiente. Os achados destacam o potencial do modelo como uma solução escalável para a coleta descentralizada de resíduos.*

1. Introduction

Waste management has emerged as one of the primary contemporary environmental challenges, with a direct impact on the environment [Hussain et al. 2024, Oliveira and Guedes 2024], especially given the need to promote more sustainable cities and responsible consumption patterns in accordance with the Sustainable Development Goals (SDGs) [Fund 2015]. In the Brazilian context, marked by high urbanization, this problem intensifies in indoor environments, such as logistics centers, hospitals, and industrial facilities, where spatial constraints, obstacles, and variable operational dynamics demand adaptive and efficient solutions [Borges et al. 2019].

Given these limitations, decentralized approaches have gained prominence, particularly swarm robotics combined with cellular automata. This combination allows for a discrete representation of the environment and the coordination of multiple agents through local rules [Brasiel and Lima 2024, Lima and Oliveira 2019]. However, efficient coordination remains a challenge, primarily in balancing exploration and efficiency, while avoiding both redundant trajectories and congestion in critical regions. In systems based on local decisions, the absence of mechanisms that integrate factors such as movement history, proximity to destinations, and spatial constraints can compromise global performance, resulting in low coverage and increased execution time.

In this context, cellular automata offer a suitable framework for modeling discretized environments and local interactions between agents, allowing for a scalable representation of system dynamics. Models inspired by collective behavior, based on pheromones and local memory, have demonstrated potential in constructing distributed strategies [Lima and Oliveira 2017]. However, these approaches often treat decision-making factors in isolation, considering each variable independently rather than as part of an integrated system. This fragmented perspective makes it difficult to understand how multiple variables simultaneously interact and influence agent behavior in complex and dynamic environments. Additionally, such methods frequently lack a clear and explicit representation of how these factors are combined and processed at the cell level, limiting both interpretability and the effectiveness of decentralized coordination strategies.

To address this gap, this work presents the application of the Cellular Automata Ant Memory (CAAM) [Lima and Oliveira 2017] model for waste collection in indoor environments [Lima and Oliveira 2019], using a state superposition perspective. In this approach, each cell integrates variables such as the static field, dynamic field, and local memory, allowing for an explicit combination of the factors that influence collective behavior and contributing to greater efficiency and system understanding.

2. Related Work

Cellular automata-based models have been widely used to represent discrete and dynamic systems, where global behavior emerges from local interactions [Ferreira et al. 2022]. These models are suitable for simulating structured environments and applications in multi-agent systems, particularly in environmental [Lima and Lima 2014] and logistical scenarios with spatial constraints [Ferreira et al. 2025].

In the context of swarm robotics, decentralized approaches based on local rules and indirect communication, such as the use of pheromones, are widely employed in exploration, foraging, and collection tasks, standing out for their robustness, scalability, and adaptability [Brasiel and Lima 2024]. Various models have been proposed for agent coordination, incorporating floor fields, probabilistic heuristics, and memory mechanisms. In this scenario, CAAM [Lima and Oliveira 2017] integrates a static field, a dynamic field, and tabu search-based memory, promoting efficient exploration and return in discretized environments.

Park et al. [Park et al. 2021] propose a bio-inspired system with stigmergy and probabilistic adjustment, allowing for the reorganization of trajectories in dynamic environments. Similarly, Obute et al. [Obute et al. 2022] utilize adaptive digital pheromones in both simulation and real-world testing, achieving improved accuracy and reduced collection time. Despite these advancements, many models do not explicitly state in an integrated manner how variables such as distance to the goal, movement history, and local memory are combined in the decision process, highlighting the need for more unified approaches.

3. Proposed Model

This section presents the model adopted for the simulation of indoor waste collection, based on the *Cellular Automata Ant Memory* (CAAM). The model is described considering its implementation in a discretized environment and its representation through the superposition of states in cellular automata, allowing for the integration of different variables into the agents' decision-making process.

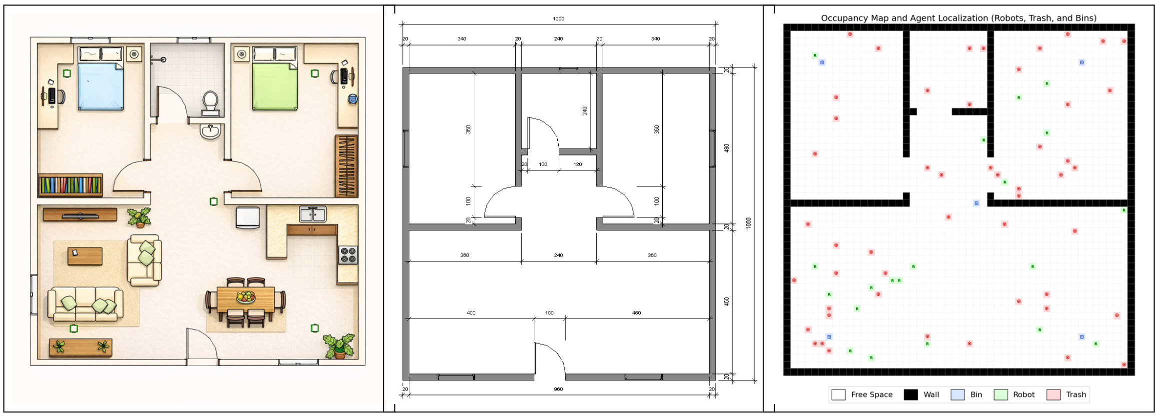
3.1. Environmental representation

The simulated environment is modeled as a discrete two-dimensional lattice of 50×50 dimensions, in which each cell represents a physical region of approximately $20\,\text{cm} \times 20\,\text{cm}$, resulting in a total space of about $10\,\text{m} \times 10\,\text{m}$. This space is compatible with indoor scenarios such as residences, industrial environments, and small-scale logistics spaces. Each cell can assume different functions, including free space, obstacles, nests, and regions containing waste, in addition to storing dynamic information relevant to the model, such as static field values, dynamic fields, and states associated with visitation memory. The simulation agents are *e-puck* mobile robots, approximately $7\,\text{cm}$ in diameter, such that each robot occupies a single cell of the lattice, ensuring coherence between the computational modeling and the physical scale. Considering the dimensions of the *e-puck* robots, the proposed approach targets small and lightweight indoor waste items compatible with the platform scale. The simulations were implemented in Python using a discrete cellular automata-based framework.

Figure 1 presents the simulation environment with dimensions of 10×10 meters, modeled from a residential floor plan and discretized into a two-dimensional grid, enabling its representation via cellular automata within the CAAM context. In Figure 1a, the floor plan is shown with the arrangement of furniture, providing greater realism to the scenario. Figure 1b presents the same structure without furniture, highlighting only the architectural configuration used in the discretization. This approach allows for the incorporation of real spatial constraints, such as walls, rooms, and passages, into the agents' navigation process.

The initial configuration of the environment includes five nests distributed across the space, fifty waste units, and ten robots operating in a decentralized manner. This setup allows the evaluation of system behavior in a controlled scenario, maintaining a balanced relationship between agents, resources, and destinations, while also supporting future transfer to real-world applications.

Figure 1c illustrates the occupancy map of the simulation environment used in the CAAM model, where space is discretized into a two-dimensional grid. Each cell represents a region of the environment and can assume different states, enabling its modeling through cellular automata. The environment consists of walls (black), which delimit rooms and restrict movement, and free cells (white), which represent navigable areas. Robots (green) are distributed throughout the space as agents responsible for search and



(a) House floor plan with furniture.

(b) House floor plan without furniture.

(c) Occupancy Map and Localization.

Figure 1. Simulation environment of 10×10 meters based on a residential floor plan.

collection, while objects (red) represent the targets to be collected. Nests (blue) indicate the deposit points to which robots return after collection. This configuration combines obstacles and open regions, creating challenges for navigation and coverage, and enabling the analysis of collective behavior in terms of exploration, dispersion, and efficiency in collection and return.

3.2. Agents and state machine

The agents operate in a decentralized manner, making decisions based on local information and their internal state. Individual behavior is modeled as a finite state machine composed of four main states: *searching*, *grabbing*, *homing*, and *depositing*. In the *searching* state, the robot agent explores the environment in search of waste, prioritizing less-visited regions and avoiding excessive revisitation. Upon finding an object, it enters the *grabbing* state, performs the collection, and changes its internal state to transport. Subsequently, in the *homing* state, the robot agent returns to the nest guided by the static field and, upon reaching the destination, enters the *depositing* state, where it unloads the waste and restarts the cycle.

Figure 2 illustrates the state machine of the agents in the proposed model. The cycle begins with environmental perception, followed by the searching state (*searching*), in which the robot explores the space for objects. Upon detecting and locating an item within the environment, the agent transitions from its exploratory behavior into a dedicated capturing phase, referred to as the (*grabbing*) state, in which it securely acquires the object. After successfully capturing the item, the agent initiates a navigation process back toward the nest by entering the *homing* state, typically guided by environmental cues or internal memory representations. Once the agent reaches the nest location, it proceeds to the *depositing* state, where the collected object is released and incorporated into the storage area. After completing this sequence of actions, the agent resets its internal state and restarts the operational cycle, returning to exploration in search of new items to collect. Transitions occur reactively based on local conditions and the agent's internal state, characterizing a decentralized behavior guided by simple rules. This organization allows for a clear separation between exploration and return behaviors, enabling the combination of distinct strategies within a single agent. As a result, the system alternates between

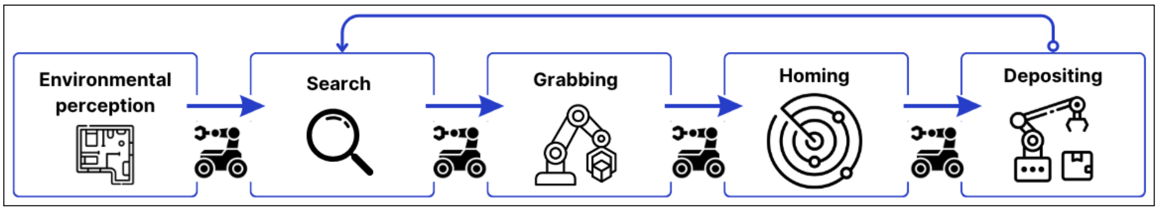


Figure 2. Agent state machine in the CAAM model.

distributed search and oriented navigation, favoring global efficiency.

3.3. Static floor field

The static floor field S is a scalar field defined over the lattice, in which each cell possesses a fixed value corresponding to the distance to the nearest nest [Alizadeh 2011]. This field is pre-calculated before the simulation and remains constant throughout the execution, being used exclusively to represent the structure of the environment and to guide the agents' return. The calculation is performed via propagation from the nests, which receive minimum values, expanding to the other cells with distinct costs for orthogonal and diagonal movements, while obstacles receive high values or are treated as inaccessible regions.

During the *homing* state, agents tend to select cells with lower S values, following the field gradient toward the destination. However, since all agents share this same gradient, congestion may occur near the nests, which justifies the need for complementary mechanisms.

3.4. Dynamic pheromone field

The dynamic field is modeled as an inverted pheromone, responsible for representing the collective memory of the system. Unlike attraction-based approaches, this mechanism acts repulsively, making recently visited regions less attractive and promoting swarm dispersion. During the *searching* state, all agents share this field, which is initially null, subsequently avoiding regions with higher pheromone intensity and, consequently, prioritizing unexplored areas, see Equation 1.

$$D(x, y, t + 1) = D(x, y, t) + \delta(x, y, t) \tag{1}$$

The field update occurs at each time step through two complementary processes. In the deposition with diffusion stage, the visited cell receives an increment δ (increase $+\delta(x, y, t)$), while neighboring cells receive an attenuated increment δ' (increase $+\delta'(x, y, t)$), forming a local region of influence. Subsequently, evaporation occurs, controlled by the parameter β (decrease $-\beta(x, y, t)$), uniformly reducing the field values over time. This mechanism prevents environmental saturation and allows for the re-exploration of previously visited regions.

3.5. Individual memory based on Tabu search

The model incorporates a short-term individual memory based on tabu search, implemented through a queue Q associated with each robot. This structure stores the last positions visited by the agent, defined as a limited-size FIFO (first-in, first-out) queue, which maintains only a recent movement history. During the movement decision, cells belonging to Q are temporarily avoided, reducing the revisitation of recent states. If all available options are contained within the memory, the mechanism can be relaxed, allowing the selection of previously visited positions.

At each time step, the new position is inserted into Q and, when necessary, the oldest position is removed, characterizing a sliding memory. This mechanism contributes to avoiding local cycles and improving environmental coverage. Together with the pheromone field, a balance is established between individual and collective memory, in which the agent's recent history complements the global information of the environment, favoring efficient exploration.

3.6. Representation by state superposition

In the adopted model, each cell of the cellular automaton is represented by a vector of states that coexist simultaneously. Formally, the state of a cell (x, y) at time t is given by Equation 2.

$$\mathbf{C}(x,y,t) = \big(S(x,y), D(x,y,t), T(x,y,t)\big) \tag{2}$$

where S represents the static floor field, D corresponds to the dynamic pheromone field, and T indicates whether the cell belongs to the agent's recent memory queue Q. This representation allows the integration of structural, collective, and individual information into a single cellular state.

3.7. Agent decision rule

The movement of the agents is determined by the evaluation of neighboring cells using a decision Equation 3.

$$Score(x,y,t) = -\alpha \cdot S(x,y) - \beta \cdot D(x,y,t) - \gamma \cdot T(x,y,t) \tag{3}$$

where α, β, and γ control the relative influence of each component. This formulation allows the agent to balance exploration and return adaptively.

3.8. System dynamics

The evolution of the system occurs in discrete time steps, following a synchronous update. In each iteration, all agents evaluate their possible actions, select movement intentions, have their conflicts resolved, and then execute their movements. Subsequently, internal states are updated, and the dynamic field is recalculated. The process continues until all waste is collected or a stopping criterion is met, resulting in emergent collective behavior from simple local rules.

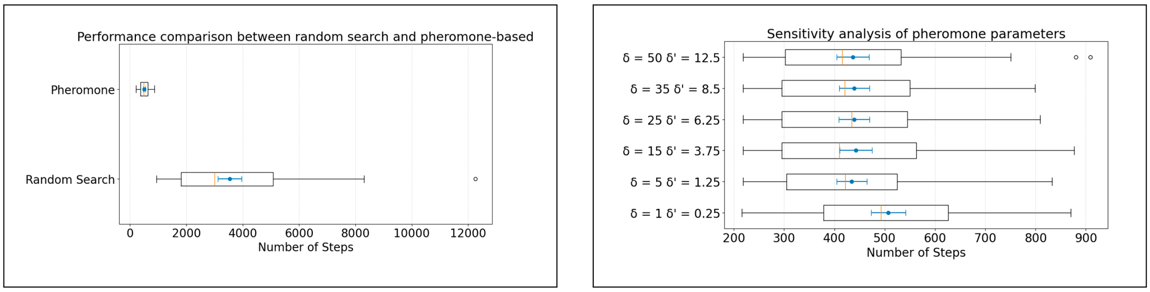
4. Experiments

This section presents the experimental evaluation of the proposed model, focusing on the analysis of the impact of its primary components on system efficiency and stability. The investigation covers the use of the pheromone field, the variation of its parameters, the influence of tabu search-based memory, the effect of the number of agents, and, finally, a qualitative analysis of the emergent exploration pattern.

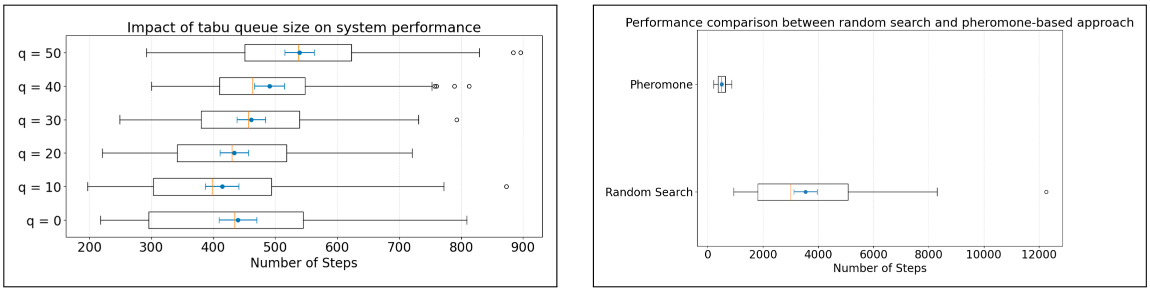
4.1. Evaluation of the pheromone field

An experiment was conducted comparing two search strategies: random search and pheromone-guided search, both without the use of tabu memory, in an environment containing 50 waste units, 10 robots, and 5 nests, across 100 independent simulations. In the pheromone model, the parameters $\delta = 1.0$ (robot's position) and $\delta' = 0.25$ (robot's radius vision) were adopted.

Figure 3a presents the results obtained. It is observed that the utilization of the pheromone field results in a reduction of both the mean and the variability of the number of steps, indicating simultaneous gains in efficiency and consistency. In contrast, the random search exhibits high dispersion and a significant presence of outliers, evidencing lower predictability and inferior performance.



(a) Random search versus pheromone. **(b) Pheromone parameters δ and δ'.**



(c) Tabu queue size q. **(d) Number of robots.**

Figure 3. Boxplots of steps: random vs. pheromone (a), δ and δ' (b), q (c), and number of robots (d).

4.2. Pheromone field parameters

To analyze the sensitivity of the model to the dynamic field parameters, different values of δ were evaluated, assuming $\delta' = 0.25\delta$, such that the term δ' represents an attenuated propagation of the pheromone into neighboring cells. Figure 3b demonstrates that the configuration with $\delta = 1$ exhibits the poorest performance, characterized by high dispersion and a greater number of high-cost executions, indicating that the pheromone signal is insufficient to adequately guide the agents.

For $\delta = 5$ and $\delta = 15$, a significant improvement in performance is observed, with a reduction in both the mean and median. However, right-skewed tails persist in the distributions, indicating the occurrence of less efficient executions. The optimal balance is observed at $\delta = 25$ and $\delta' = 6.25$, a configuration showing greater stability, lower variability, and a more concentrated distribution. For higher values ($\delta = 35$ and $\delta = 50$), a saturation effect is noted, where increasing the parameter does not yield additional relevant performance gains. Thus, the configuration $\delta = 25$ proved to be the most suitable, providing a balance between signal intensity and the system's adaptive capacity.

4.3. Tabu queue size

Figure 3c illustrates the impact of the tabu queue size on system performance. It is observed that the introduction of tabu search-based memory results in a significant improvement compared to the absence of memory ($q = 0$), reducing the revisitation of recent states and increasing exploration efficiency. The best performance is obtained at $q = 10$, a configuration that exhibits the lowest mean and median, as well as the highest data concentration, indicating greater stability across executions. As the queue size increases ($q = 20$ to 50), the gains cease to be significant and, in some cases, an increase in dispersion and the presence of outliers are observed.

This behavior suggests that high values of q introduce excessive constraints on agent movement, limiting their adaptive capacity and reducing exploratory flexibility. Thus, the value $q = 10$ proved to be the most appropriate, balancing the prevention of revisitations with the maintenance of exploratory freedom.

4.4. Number of agents

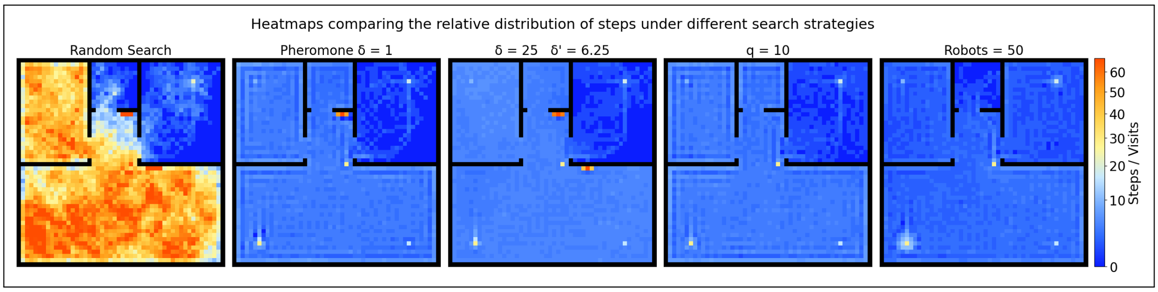
Figure 3d presents the impact of the number of agents on system performance. It is observed that configurations with 10 and 20 robots exhibit higher variability and poorer average performance, which can be attributed to insufficient environmental coverage. As the number of robots increases, there is a progressive improvement in both the efficiency and stability of the system. The configuration with 50 robots yields the best results, with the lowest dispersion and fewer inefficient executions. This behavior indicates that increasing agent density favors environmental coverage and reduces the time required for complete waste collection, resulting in more robust collective performance. , such density would also introduce real-world kinematic challenges, including congestion and collision avoidance delays, which may be partially mitigated by the discrete abstraction of the cellular automata model.

4.5. Qualitative analysis of exploration

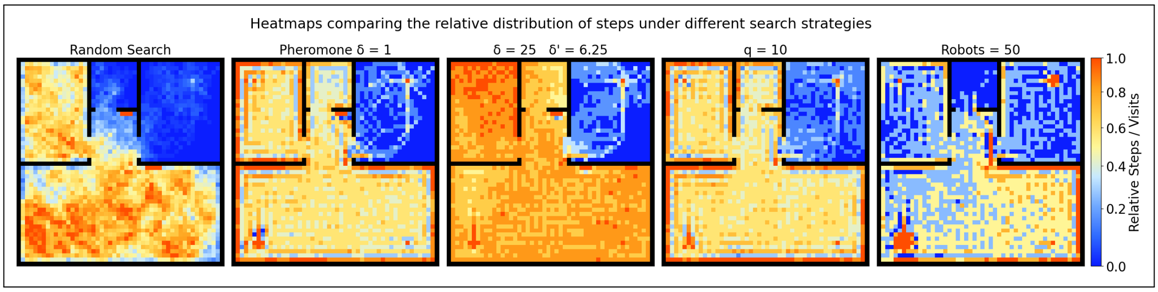
An experiment was conducted to analyze the spatial distribution of visits performed by the robots under different search strategies. Five configurations were considered: random search, pheromone with $\delta = 1$, parameter adjustment ($\delta = 25$ and $\delta' = 6.25$), inclusion of memory ($q = 10$), and an increase in the number of agents (50 robots). For each configuration, visitation matrices were recorded, representing the frequency of cell exploration.

Figure 4 presents the visitation matrices in two forms. In 4a, without normalization, the impact of the absolute scale is observed: random search concentrates higher values, with warm tones predominating, while the other configurations are compressed into the lower range of the scale, making comparison difficult. In 4b, after normalization, the patterns become more evident. Random search exhibits irregular coverage, $\delta = 1$ shows slight organization, $\delta = 25$ presents a more uniform distribution, the inclusion of memory ($q = 10$) reduces revisitations, and the configuration with 50 robots results in the most homogeneous coverage, indicating greater system efficiency.

In general, the results demonstrate that model performance depends on the balance between exploration and orientation mechanisms. In this context, the combination



(a) Without normalization.



(b) With normalization.

Figure 4. Heatmaps of visit matrices under different search strategies: (a) without normalization; (b) normalized heatmaps highlighting exploration patterns and coverage differences.

of $\delta = 25$, $\delta' = 6.25$, $q = 10$, and 50 robots proved to be the most efficient, providing high levels of performance and stability.

5. Final Considerations

This work presented the application of the CAAM model to indoor waste collection using a state superposition approach in cellular automata. The proposal integrates key factors influencing agent behavior — static field, dynamic field, and individual memory — providing a more structured understanding of decision-making in decentralized systems. It also considers environmental characteristics such as spatial constraints, obstacles, and dynamic conditions that affect navigation and task execution. By embedding this information into the cellular representation, agents better adapt to local conditions, improving efficiency, reducing revisitations, and enhancing coverage. This integration strengthens the robustness and applicability of the model in complex indoor scenarios.

Experimental results evidenced that system performance is directly related to the balance between exploration and orientation mechanisms. The use of pheromones proved essential for reducing variability and improving trajectory organization, while tabu search-based memory contributed to minimizing revisitations and expanding environmental coverage. Furthermore, the analysis of the number of agents demonstrated that increasing density favors collective efficiency, resulting in a lower number of steps and greater system stability.

Overall, the appropriate combination of dynamic field parameters, individual memory, and agent quantity yielded a more efficient, robust, and consistent collective behavior. These results reinforce the potential of models based on cellular automata and swarm robotics for applications in real-world waste collection and management scenarios. Future work includes increasing environmental complexity with dynamic obstacles and extending the model to outdoor scenarios in order to evaluate its generalization and applicability under more realistic conditions.

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