

Research paper

Inventory Localization in Agriculture, a Swarm Intelligence Approach

Localización de inventario en agricultura, un enfoque de inteligencia de enjambre

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Abstract

Context. Locating lost inventory is a key challenge in agricultural logistics, as traditional tracking systems such as radio-frequency identification (RFID) and barcodes remain costly and infrastructure-dependent. Swarm robotics offers a decentralized alternative, and the BeeClust algorithm enables robots to self-organize around environmental stimuli without direct communication. This study validates a BeeClust-inspired approach for inventory localization in a warehouse-like maze.

Method. Formula AllCode robots equipped with light and distance sensors were programmed with an adapted BeeClust finite state machine including forward, rotation, and waiting states. Experiments evaluated the effects of workspace size, light source size, and light source position on clustering performance. Detection accuracy was also tested under different orientations and distances.

Results. Larger light sources accelerated clustering but produced dispersed formations, while smaller sources promoted compact clusters at the cost of longer convergence times. Mid-sized arenas yielded faster and more consistent aggregation than very small or very large spaces. The system achieved 96.67% accuracy in robot detection, while obstacle recognition was identified as an aspect requiring further improvement.

Conclusions. The findings confirm the feasibility of BeeClust-based swarm robotics for inventory localization in structured environments and provide experimental evidence that support future work on swarm scalability, enhanced perception, and validation in real agricultural facilities.

Keywords: BeeClust, Clustering algorithm, Swarm intelligence, Inventory localization

Resumen

Contexto. La localización de inventario perdido es un reto en la logística agrícola, ya que los sistemas de identificación por radiofrecuencia y códigos de barras dependen de infraestructura y generan altos costos. La robótica de enjambre ofrece una alternativa descentralizada, y el algoritmo BeeClust permite que los robots se agrupen en torno a estímulos ambientales sin comunicación directa. Este estudio valida un enfoque inspirado en BeeClust para la localización de inventario en un entorno tipo almacén.

Método. Se emplearon robots Formula AllCode con sensores de luz y distancia, programados con una máquina de estados finitos adaptada de BeeClust que comprendía los estados de avance, rotación y espera). Los experimentos evaluaron el efecto del tamaño y la posición de la fuente de luz y del espacio de trabajo sobre la agrupación. También se midió la precisión en la detección de robots y obstáculos en distintas orientaciones.

Resultados. Las fuentes grandes aceleraron la formación de clústeres pero produjeron agrupaciones más dispersas, mientras que las pequeñas favorecieron clústeres compactos con mayor tiempo de convergencia. Los espacios intermedios mostraron mayor rapidez y consistencia que las áreas muy pequeñas o muy grandes. El sistema alcanzó un 96.67% de precisión en la detección de robots, y el reconocimiento de obstáculos se identifica como un aspecto a mejorar.

Conclusiones. Los hallazgos confirman la viabilidad de un enfoque basado en BeeClust para la localización de inventario en entornos estructurados y aportan evidencia experimental que contribuye a cerrar la brecha entre simulaciones y pruebas reales, abriendo camino a investigaciones sobre escalabilidad y validación en instalaciones agrícolas.

Palabras clave: BeeClust, algoritmo de agrupamiento, inteligencia de enjambre

1 Introduction

In agricultural logistics, efficiently locating lost inventory is vital, as demand uncertainty and the consequent lost sales at storage and distribution points can magnify disruptions and drive-up total logistics costs. Reducing these losses is therefore critical to maintaining service levels and ensuring seamless operations [1]. Similar challenges are also evident in healthcare logistics, where supply chain research has emphasized the importance of performance, management approaches, and inventory administration for ensuring efficiency and service quality [2].

Traditional solutions such as conveyor belt systems, barcode scanners, and RFID (Radio Frequency Identification) have improved tracking accuracy but remain limited by infrastructure requirements, cost, and vulnerability to operational inefficiencies [3], [4]. Recent advances in mobile robotics offer a flexible and scalable alternative, enabling autonomous navigation in structured and semi-structured environments with minimal human intervention.

In addition to traditional navigation approaches, recent studies have explored alternative guidance and tracking strategies based on vision systems and ultra-wideband (UWB) positioning. Vision-based approaches enable environment perception and path extraction through image processing and machine learning techniques, offering rich environmental information and flexible deployment. However, their performance can be affected by lighting variability and occlusions in complex environments [5].

On the other hand, UWB-based positioning systems have demonstrated strong potential for high-precision indoor localization because of their robustness to signal interference and ability to operate in non-line-of-sight conditions. For instance, UWB-based navigation systems have achieved centimeter-level positioning accuracy and reliable path tracking in agricultural environments, particularly when combined with dynamic control strategies such as pure pursuit algorithms [6]. These approaches highlight the growing relevance of hybrid and alternative localization technologies for unmanned platforms operating in structured but challenging environments.

Despite these advances in perception and localization, effectively coordinating multiple agents to exploit this information remains a key challenge. In this context, swarm robotics leverages the coordination of multiple simple agents to achieve collective objectives more effectively than single-robot systems, enhancing robustness, scalability, and resilience in complex tasks [7], [8]. This distributed approach allows simultaneous operations in different areas of a workspace, thus maximizing coverage and reducing task completion time [9], even in dynamic or partially known environments [10].

Within swarm robotics, environment-mediated aggregation, understood as the self-organized gathering of initially dispersed robots into one or more cohesive clusters [11], offers a robust means of coordinating autonomous agents. Among these approaches, the BeeClust algorithm—modeled after the thermotactic clustering behavior of young bees—enables robots to converge toward environmental stimuli without direct communication, supporting scalable, resilient, and fully decentralized control in dynamic settings [12]. Adaptive variants of BeeClust have further improved its aggregation performance under changing environmental conditions, reinforcing its potential for large-scale swarm deployments [13].

This study presents the development and experimental validation of a BeeClust-based clustering strategy for agricultural inventory localization. The approach integrates navigation

and detection algorithms to enable robots to identify and aggregate around a designated stimulus within a maze-like environment. Performance is evaluated under varying environmental conditions, including workspace size, light source position, and light source size. This provides insights into the adaptability and scalability of the system for real-world applications. To address these objectives, an experimental methodology was designed to evaluate the proposed BeeClust-based strategy under controlled yet representative warehouse-like conditions. The following section describes the experimental environment, control architecture, and validation procedures adopted in this study.

2 Materials and Method

2.1 Experimental Environment

The experiments were conducted in a scaled warehouse mock-up designed as a maze to evaluate swarm behavior under spatial constraints. The 80×100 cm arena allowed reproducible tests of robot interaction and clustering around a light stimulus (Fig. 1). The trials employed Formula AllCode robots, equipped with infrared distance sensors, a light sensor, and a microphone, enabling navigation, stimulus detection, and robot-to-robot interaction. The robots were programmed in Python and controlled via Bluetooth, which facilitated flexible communication and monitoring during the experiments. Initial tests with two robots served to validate the setup and assess scalability. With the experimental environment defined, the following subsection details the clustering strategy implemented on the robotic platform, including the finite state machine and stimulus-driven control logic.



Fig. 1. Experimental maze used for swarm robot navigation and clustering tests.

2.2 BeeClust clustering strategy

BeeClust can be modeled as a finite state machine (FSM), a systems-theoretic construct in which a process occupies one of finitely many states and transitions between them based on inputs or internal variables. Each state corresponds to a distinct action, and transitions occur when specified events or conditions are met. In this study, the finite state machine comprises three states: FWD for forward motion, RTT for rotation or turn, and WAIT for waiting, as shown in Fig. 2.

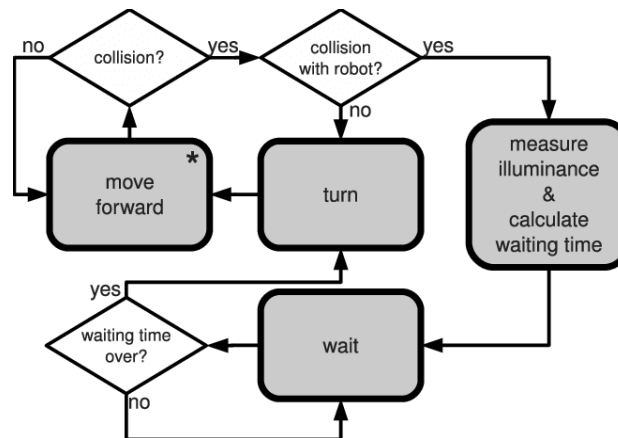


Fig. 2. FSM of BEECLUST algorithm. Source: [14]

The robot advances in FWD while scanning for obstacles. When contact occurs, it distinguishes walls from robots. A wall triggers a transition from FWD to RTT, where the agent samples a random heading change, executes the rotation, and then re-enters FWD [12], [15]. Contact with another robot triggers a transition from FWD to WAIT. As part of this transition, the robot measures the local light intensity and computes the corresponding waiting time using Eq. (1), after which it remains idle before resuming FWD.

$$t_{wait} = t_{max} \cdot \frac{s^2(t)}{s^2(t) + \theta} \quad (1)$$

In this context, t_{max} specifies the maximum allowable wait, $s(t)$ is the light intensity, and θ tunes the slope of the response. This formulation produces a nonlinear response in which the waiting time increases with light intensity and asymptotically approaches t_{max} , enabling longer interactions in highly illuminated regions. After the idle period, the system returns to RTT. Obstacle detection is restricted to the FWD state. Beyond the behavioral logic of the BeeClust algorithm, reliable perception and control are essential to ensure correct state

transitions and interaction events. For this reason, the sensing and control parameters were carefully tuned, as described below.

2.3 Perception System Tuning and Control Strategy

An operational sensing distance of 20 mm was established to ensure reliable obstacle detection within the maze environment. Navigation control was implemented using a Proportional-Derivative (PD) scheme tuned via the Ziegler–Nichols method, while the WAIT function was adjusted to account for ambient light by incorporating a 500-unit offset, which represents the ambient light level measured experimentally in the absence of the stimulus. Robot-to-robot detection was achieved using the onboard microphone and speaker, with a threshold of 918, corresponding to the microphone signal level. This threshold represents the minimum signal level reliably detected experimentally, obtained as the average of the lowest detected values across different robot-to-robot spatial configurations, to ensure robust detection while minimizing sensitivity to background noise.

2.4 Experimental Validation

To ensure the reliability of the proposed system, a series of experimental validations were conducted under controlled conditions. The validation focused on three key aspects: waiting time estimation, robot detection accuracy, and the influence of environmental factors on clustering behavior.

Waiting Time Validation. The waiting time estimation was validated by comparing the computed values from the algorithm's equation with real-time measurements. Controlled tests were performed using different light intensities, and the system's response was analyzed to assess whether the computed values aligned with the expected theoretical model.

Robot Detection Accuracy. To evaluate the system's ability to distinguish robots from static obstacles, detection tests were conducted under different relative positions, including frontal alignment, lateral placements, and rear positioning. Microphone readings were recorded under each scenario to determine the most effective detection threshold.

Environmental Variable Testing. The system's performance was further assessed under varying environmental conditions to determine the influence of specific factors on clustering dynamics. Three experimental series were conducted, considering the following factors:

- **Workspace Size.** The effect of arena size was evaluated using four configurations corresponding to 100%, 75%, 50%, and 25% of the total area. In all cases, the light source was fixed at the center to ensure that any observed variations were attributable solely to changes in available space rather than stimulus positioning.
- **Light Source Position.** The light source was placed in different locations, including the center, corners, and randomly selected points within the arena. This variation was intended to determine how stimulus placement affects robot convergence rates and cluster formation dynamics.
- **Light Source Size.** The light source diameter was adjusted to represent 1/2, 1/4, and 1/8 of the arena area. This series of tests examined the relationship between illumination area and both clustering speed and cohesion. Two main metrics were analyzed: clustering time and the average distance between robots, providing a comprehensive understanding of how stimulus size influences aggregation behavior.

3 Results

Based on the experimental protocol described above, the following results are presented to assess both the internal consistency of the proposed system and its response to key environmental variables affecting clustering performance.

3.1 Waiting Time Based on Light Intensity

Experimental Verification of Waiting Time. The results of the validation of the waiting time calculated using the adjusted algorithm equation are presented in Table I.

Table I
Experimental Verification of Waiting Time.

Light Intensity (a.u.)	Calculated Time [s]	Actual Time [s]	% Error
1489	29.6964	29.6969	0.0017
1475	29.6877	29.6894	0.0057
4001	29.9755	29.9765	0.0033
3977	29.9752	29.9768	0.0053
524	1.6339	1.6354	0.0918
1847	29.8356	29.8365	0.003
3951	29.9748	29.9761	0.0043
1215	29.4244	29.4256	0.0041
1752	29.8098	29.8108	0.0034

829	27.4628	27.4635	0.0025
734	25.3672	25.3684	0.0047
905	28.2761	28.2766	0.0018
847	27.6995	27.7004	0.0032
3176	29.9582	29.9595	0.0043
937	28.5072	28.5087	0.0053

Note: Light intensity values are expressed in arbitrary units (a.u.) corresponding to sensor readings.

The average differences between the calculated and actual times are minimal, with percentage errors below 0.01%. This indicates that the algorithm aligns with theoretical values under controlled conditions. The relatively higher error observed at a light intensity of 524 a. u, corresponding to $s = 524$ in Eq. (1), suggest greater sensitivity near the minimum threshold.

Impact of Parameter θ on System Behavior. The test results presented in Fig. 3 illustrate the influence of θ on the clustering behavior of the robots. The graph shows that for low values of θ , the curves display a steeper slope, causing the calculated time to quickly approach the maximum allowed value (30 s). This behavior results in low variability in waiting times, reducing the system's sensitivity to differences in light intensity.

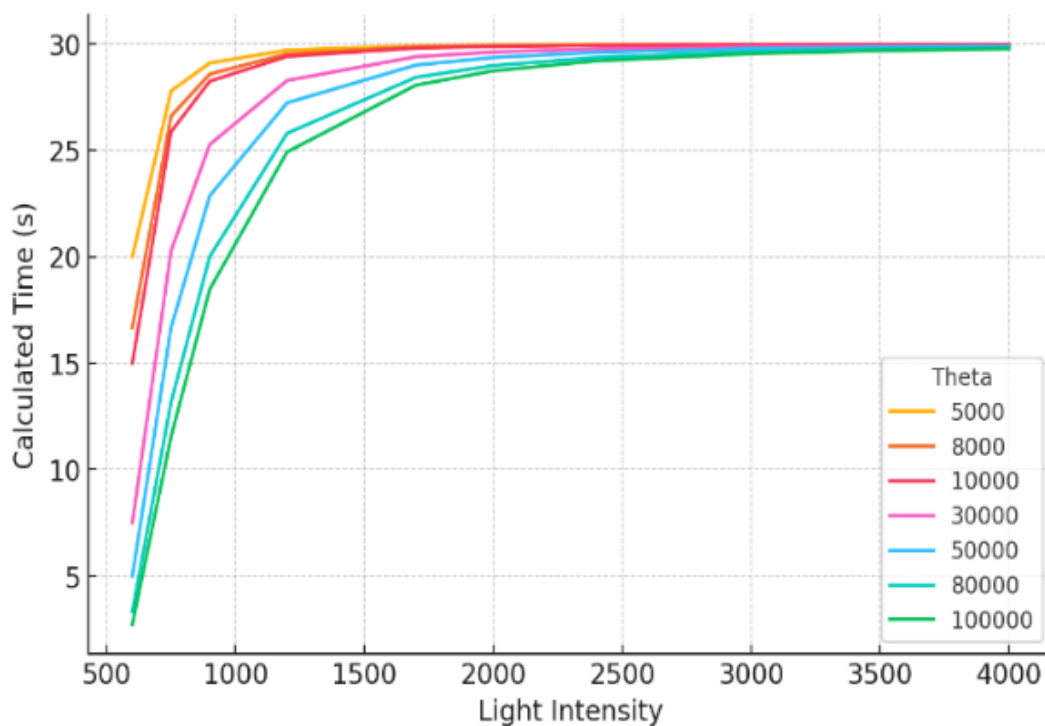


Fig. 3. Relationship Between Light Intensity and Calculated Time for Different θ Values.

Conversely, as θ increases, the curves become flatter, introducing greater variability in the calculated times. This enables robots to exhibit more diverse responses when exposed to intermediate and low light intensities, making the system more adaptive to environmental changes. Having validated the stimulus–response mechanism governing robot waiting behavior, the next step was to assess the reliability of robot perception, which directly affects interaction and aggregation dynamics.

3.2 Robot Detection Accuracy

The detection capability of the robots was evaluated across multiple scenarios involving varying orientations, distances, and types of obstacles. The results of these experiments are summarized in Fig. 4 and Fig. 5. For robot-to-robot detection, the system achieved an accuracy rate of 96.67%, demonstrating robust performance and reliability in recognizing peer robots—a crucial factor for effective swarm coordination. However, accuracy decreased significantly to 65.00% for obstacle detection, indicating limitations in differentiating between robots and static objects. Detection errors in obstacle scenarios (35.00%) highlight the system’s challenge in distinguishing stationary obstacles, especially under certain positional conditions and environmental constraints.

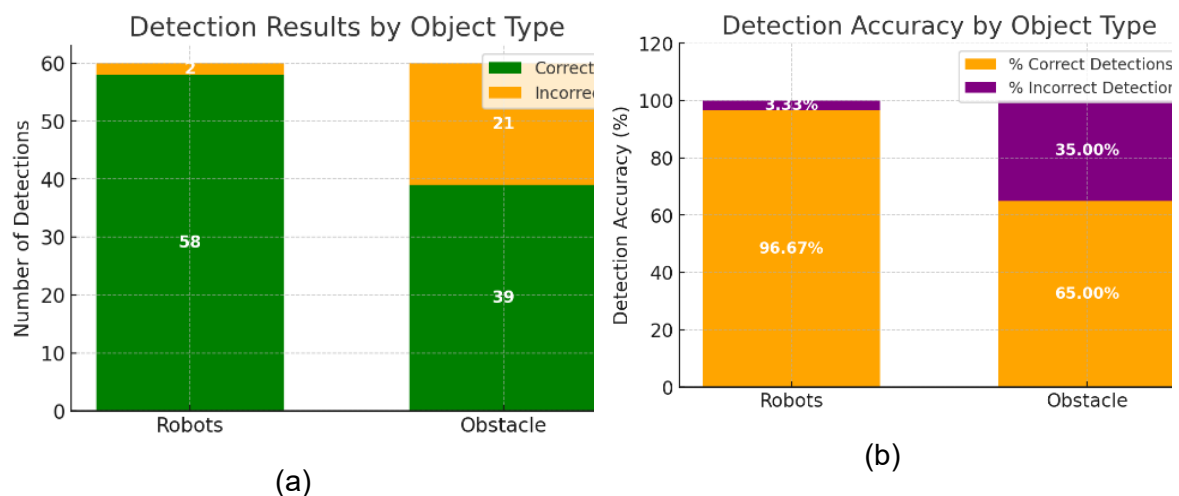


Fig. 4. Detection results for robots and obstacles. (a) Counts. (b) Accuracy (%).

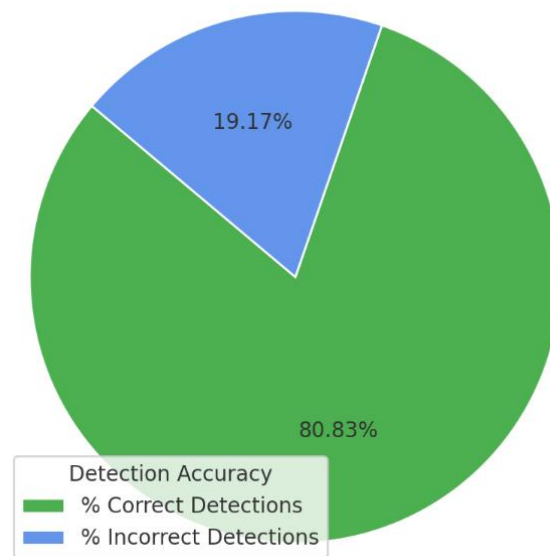


Fig. 5. Mean detection accuracy

The system achieved a mean detection accuracy of 80.83%, calculated as the average of robot (96.67%) and obstacle (65.00%) detection accuracies. The high accuracy in robot detection may be attributed to the system's ability to correctly process signals from the sensors, influenced by the swarm design characteristics. However, the results indicate difficulties in identifying obstacles, possibly due to environmental interference, sensor noise, or the configuration of the experimental environment. While perception accuracy defines the reliability of local interactions, clustering performance also depends strongly on external environmental conditions. Accordingly, the following experiments analyzed how spatial constraints and stimulus configuration influence aggregation behavior.

3.3 Response to External Variables

Arena Size. As the workspace size decreases, the average clustering time also reduces, reflecting the shorter distances robots must travel in smaller areas, which leads to faster clustering (see Fig. 6). However, this reduction does not necessarily imply greater consistency. In larger areas (100% and 75%), clustering times exhibit higher variability, with wide interquartile ranges and outliers, indicating inconsistent performance. In contrast, the smaller areas (50% and 25%) show more compact distributions, suggesting greater stability in clustering behavior.

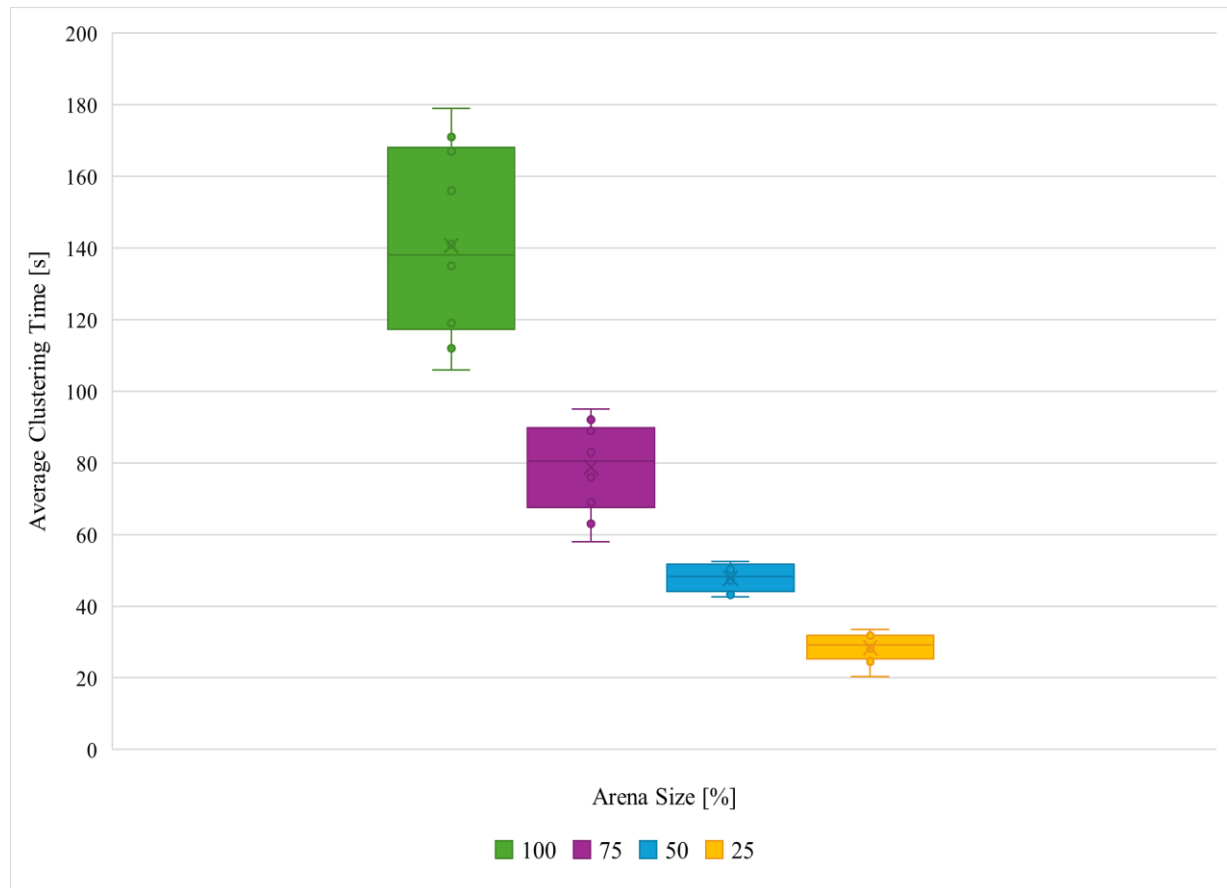


Fig. 6. Time Distribution by Workspace Size.

Light Source Location Within the Arena.

Table II presents the quantitative results of clustering time, dispersion, and variability for each evaluated light source position. The data indicate that corner positions (upper-left and upper-right) result in shorter clustering times and lower dispersion compared to both the center and a randomly placed light source. This suggests that the corners serve as natural confinement areas, effectively guiding the robots toward the light source and promoting faster, more consistent clustering. Furthermore, corner positions not only reduce clustering time but also enhance result consistency, reinforcing the findings of this analysis (see Fig. 7). This behavior aligns with existing literature, which identifies corners as natural boundaries that limit movement and thereby facilitate faster and more stable convergence toward the light source.

In contrast, the randomly placed light source leads to the longest average clustering time (114.49 s) but also the lowest coefficient of variation (CV) (14.3%), indicating that while the robots eventually converge, the process is slower due to their initial dispersion relative to

the light source. Similarly, the center position exhibits an intermediate behavior, with an average clustering time of 97.06 s and the highest standard deviation (19.51 s). This suggests that although robots successfully form clusters, their movement patterns may be less predictable due to the symmetry of the open space.

Table II.
Results of the Light Source Position in the Arena.

Position	Average Time [s]	Standard Deviation [s]	Coefficient of Variation
Center	97.06	19.51	20.1%
Upper-left corner	84.48	15.43	18.3%
Upper-right corner	74.72	13.92	18.6%
Random Point 1	114.49	16.35	14.3%

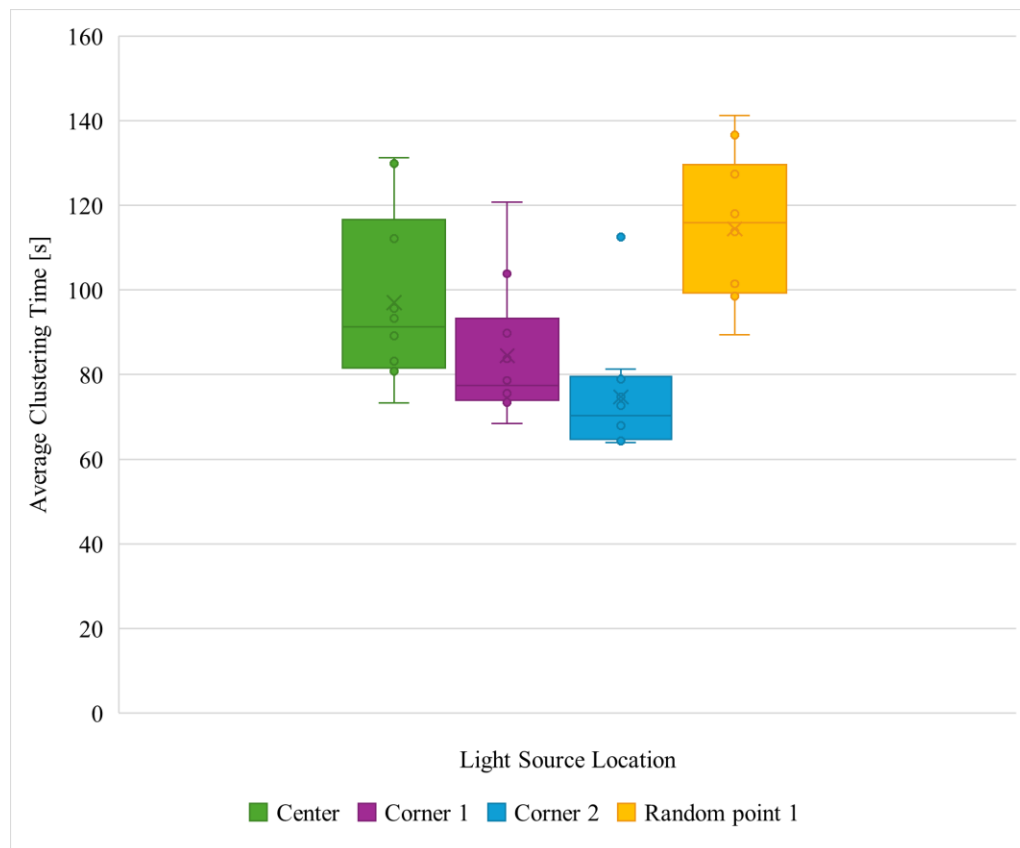


Fig. 7. Clustering Time Distribution by Light Source Position.

Light Source Size. Table III summarizes the results for clustering time and average inter-robot distance, along with their respective CV. The data reveal an inverse relationship

between light source size and cluster cohesion: larger sources reduce clustering time but increase the average distance between robots, leading to more dispersed formations. Conversely, smaller sources extend clustering time yet promote more compact groupings. This trend is illustrated in Fig. 9.

Table III.
Results of the Light Source Size Analysis.

Light Source Size	Time [s]		Distance [mm]	
	Mean	Coefficient of Variation	Mean	Coefficient of Variation
0.5	15.827	9.5%	306.3	17.26%
0.375	25.522	22.3%	225	16.78%
0.25	49.549	12.9%	125.5	17.77%
0.125	56.624	16.2%	58.2	11.16%

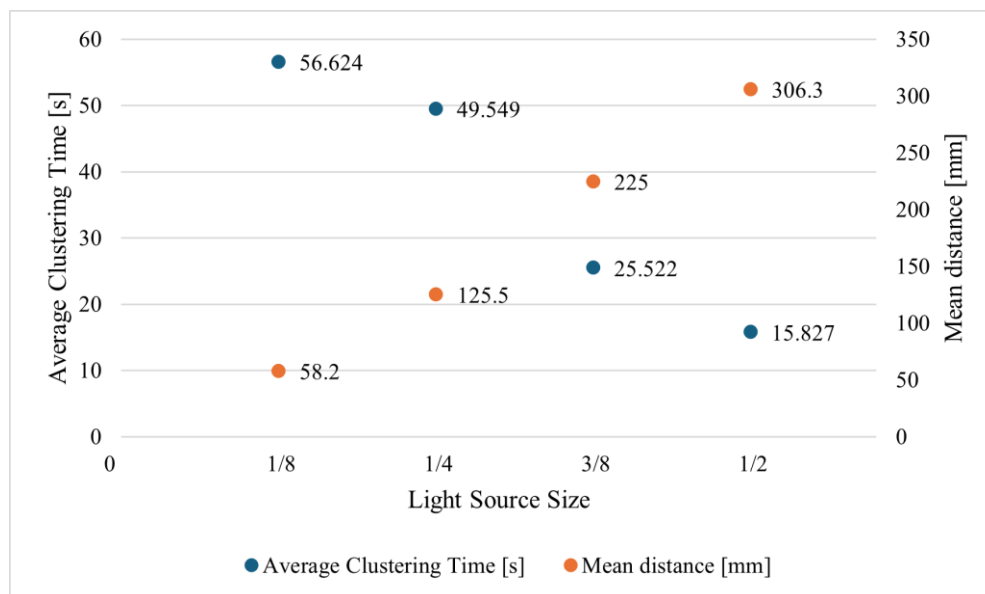


Fig. 8. Relationship Between Light Source Size and Average Time/Distance.

4 Discussion

Building on the experimental results presented above, this section interprets the observed clustering behaviors in terms of underlying mechanisms, environmental influences, and their implications for real-world inventory localization. The results demonstrate that the BeeClust-inspired clustering strategy is not only functional under controlled conditions and exhibits

interpretable and mechanism-driven behavior when environmental variables are modified. The close agreement between calculated and experimental waiting times confirms that the stimulus–response mapping operates as intended, ensuring that local light intensity effectively modulates robot behavior. This validation is critical, as stimulus-dependent waiting constitutes the core mechanism through which BeeClust amplifies local interactions into global aggregation.

The influence of light source size reveals a clear mechanistic explanation for the observed trade-off between clustering speed and cohesion. Larger light sources accelerate aggregation by increasing the spatial region in which robots experience high stimulus intensity and thus long waiting times. However, this expanded high-intensity area reduces spatial discrimination, allowing robots to remain distributed across the illuminated region rather than converging toward a single nucleus. Conversely, smaller light sources concentrate longer waiting times within a limited area, forcing robots into closer proximity and producing more compact clusters, albeit with longer convergence times. This behavior is consistent with aggregation dynamics reported in environment-mediated swarm systems, where stimulus geometry strongly conditions equilibrium cluster structure [11] [13] .

From an application perspective, this speed–cohesion trade-off has practical implications for inventory localization in warehouse-like environments. Rapid but dispersed clustering may be advantageous for coarse localization tasks, where the goal is to quickly identify the general region of interest. In contrast, compact clustering is preferable when precise localization or cooperative actions around a specific inventory item are required. These results suggest that stimulus design—or adaptive control strategies—can be tuned according to operational priorities, rather than assuming a single optimal configuration.

The experiments on light source position further highlight the role of environmental constraints in shaping swarm behavior. Corner placements consistently produced faster and more stable clustering than central or random positions. This effect arises because boundaries reduce escape directions and increase encounter rates, effectively reinforcing the positive feedback loop underlying BeeClust aggregation. While boundary effects are often treated as experimental artifacts, in logistics environments they represent a realistic and exploitable feature, as aisles, shelves, and walls can naturally guide swarm convergence.

Regarding perception performance, the achieved robot-to-robot detection accuracy of 96.67% is competitive within the context of minimalist swarm robotics systems. Comparable platforms relying on infrared or acoustic sensing typically require error management or accept non-negligible uncertainty in relative detection and localization [9], [12]. In this sense, the reported accuracy is sufficient to reliably trigger the interaction events that drive aggregation. However, the lower obstacle detection accuracy (65.00%) indicates a limiting factor for deployment in cluttered environments, where misclassification may slow exploration or weaken clustering dynamics. Future work could therefore explore more advanced perception strategies, such as sensor fusion approaches combining acoustic, infrared, or vision-based sensing, as well as application-oriented detection mechanisms (e.g., visual markers or RFID-assisted cues), to improve robustness and discrimination in more complex scenarios.

In this context, previous studies on multi-robot exploration have shown that increasing the number of robots can reduce task completion time due to parallelization effects [16]. Nevertheless, this relationship does not necessarily extend to aggregation-based strategies such as BeeClust. In the proposed system, a higher robot density may increase the frequency of inter-robot encounters, thereby extending cumulative waiting times and potentially slowing overall convergence. This suggests the existence of a non-linear relationship between swarm size and clustering performance, in which, beyond a certain point, additional robots may degrade efficiency rather than improve it. Investigating this effect represents an important direction for future work.

Given these considerations, the observed clustering times are consistent with experimental BeeClust studies reported in the literature [9], [13]; however, competitiveness must be interpreted in light of differences in system scale and experimental conditions. This study employed a small swarm in a constrained arena, focusing on physical validation rather than large-scale optimization. As swarm size and environmental complexity increase, convergence time, dispersion, and sensing reliability are expected to evolve. Consequently, future work should prioritize scaling experiments, improving obstacle discrimination, and validating the approach in real or semi-real agricultural facilities to fully assess its performance and practical applicability in real-world scenarios.

5 Conclusions

Based on the experimental findings and their interpretation discussed in the previous section, the following conclusions summarize the main contributions of this study and outline directions for future work.

The maze-based experimental setup, inspired by logistics environments, provided a controlled yet representative framework to evaluate swarm-based inventory localization. By introducing spatial constraints similar to those found in warehouse settings, the proposed environment enabled a realistic assessment of navigation, detection, and clustering behavior under conditions that more closely resemble practical environments than idealized open arenas.

Experimental validation demonstrated that the BeeClust-inspired strategy effectively reproduces key swarm aggregation behaviors under varying light intensity, spatial configuration, and stimulus size. The results confirm the system's capacity to adapt to environmental changes, supporting its suitability for inventory localization tasks in confined and structured environments.

Although the current implementation was limited to a small number of robots and a controlled setting, the obtained results establish a solid foundation for future research. Extending the system to larger swarms, improving perception capabilities, and validating performance in real or semi-real agricultural facilities are natural next steps toward practical deployment and broader impact in inventory management applications.

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Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Artificial Intelligence Statement

Generative AI tools (ChatGPT and Grammarly) were used solely to support language editing of the manuscript (e.g., grammar correction, clarity improvements, and sentence rephrasing). These tools were not used to generate results, data, analyses, or conclusions.

The authors fully reviewed and edited the final text and take full responsibility for the accuracy, originality, and integrity of all content.

Author contributions

Hernán D. Sánchez-Restrepo: Data curation, Investigation, Writing – original draft, Writing – review & editing. Y. Yuliana Rios: Conceptualization, Software, Validation, Funding acquisition, Writing – review & editing. Manuel del Jesús Martínez: Methodology, Formal analysis, Supervision, Writing – review & editing.

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