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Characterization and commissioning of a mobile robot platform for swarm-oriented applications

Caracterización y comisionamiento de una plataforma robótica móvil para aplicaciones orientadas a enjambres

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Abstract:

Accurate sensing and reliable control are essential for the effective operation of autonomous mobile robots, particularly in constrained environments where navigation errors and detection failures can significantly affect performance. This work presents the characterization and commissioning of a mobile robot platform as a foundational stage toward swarm-based inventory localization strategies. The onboard infrared, light, and acoustic sensors were experimentally evaluated to determine their operational ranges, environmental sensitivity, and detection reliability. A Proportional-Derivative controller was implemented and tuned to enhance trajectory stability, while light-sensing calibration ensured robust operation under varying ambient illumination. Additionally, an acoustic detection mechanism was integrated to enable robot-to-robot detection without physical contact. Experimental results confirmed that thorough sensor characterization, combined with targeted control adjustments, improved navigation stability and detection robustness. These developments establish a solid technical basis for the subsequent implementation of swarm coordination and clustering behaviors in autonomous inventory localization applications.

Keywords: swarm robotics, autonomous navigation, mobile robots.

Resumen:

La detección precisa y el control fiable son esenciales para el funcionamiento de robots móviles autónomos en entornos restringidos. Este trabajo presenta la caracterización y puesta en marcha de una plataforma robótica móvil como etapa inicial hacia estrategias de localización de inventario basadas en enjambres. Los sensores infrarrojos, de luz y acústicos integrados fueron evaluados experimentalmente para determinar sus rangos operativos, sensibilidad ambiental y fiabilidad. Se implementó un controlador proporcional-derivativo y se calibró el sistema de detección de luz para mejorar la estabilidad de la navegación, mientras que un mecanismo acústico permitió la detección entre robots sin contacto físico. Los resultados evidencian que la combinación de caracterización exhaustiva y ajustes de control incrementa la robustez y el rendimiento del sistema, proporcionando una base sólida para la implementación futura de comportamientos de coordinación y agrupamiento en enjambre.

Palabras clave: robótica en enjambre, navegación autónoma, robots móviles.

INTRODUCTION

Inventory management plays a fundamental role in agricultural operations, where warehouse logistics directly influence productivity, sales, and overall profitability[1]. Despite its importance, maintaining accurate and efficient inventory control usually requires a considerable investment of human and material resources. Common problems, such as incorrect product placement, disorganization, or inefficient order flow, can cause delays, incomplete deliveries, and significant financial losses.

Conventional systems, including barcode scanners and transport mechanisms, have helped mitigate some of these drawbacks; however, they remain susceptible to human error and often require substantial infrastructure modifications. In this regard, more advanced approaches have been proposed, such as IoT-based frameworks, which are pillars of Industry 4.0 initiatives and seek to increase efficiency in industrial processes[2].

Radio Frequency Identification (RFID) technology has emerged as a more sophisticated solution, allowing real-time inventory tracking with greater accuracy[3]. However, its high implementation cost and the complexity of its deployment make it unviable in rural or small-scale agricultural contexts.

In response to these limitations, research has focused its efforts on mobile robotics as a flexible and scalable alternative for automating inventory processes. Autonomous robots are capable of moving in unstructured environments with minimal infrastructure and minimal human intervention [4][5][6]. However, the effectiveness of these systems largely depends on their perception and control capabilities, which must be robust, precise, and adapted to the characteristics of the work environment.

This article focuses on the characterization and commissioning of a low-cost mobile robot platform equipped with infrared, light and acoustic sensors. These components are evaluated to ensure their suitability for indoor navigation tasks and interaction within a controlled maze-shaped environment. The study constitutes a preparatory stage toward the development of swarm-based inventory localization strategies.

On this basis, future work will incorporate collaborative behaviors inspired by clustering algorithms, such as BeeClust [7], in which autonomous agents converge towards environmental incentives without the need for centralized coordination, offering advantages in scalability, robustness, and efficiency [8], [9].

METHODOLOGY

Experimental setup

The experiments were carried out in a controlled warehouse-scale environment in order to simulate real conditions. Unlike previous studies that implemented the algoritmo BeeClust, in which robot swarms typically operated in open spaces, in this case a maze-shaped environment was introduced to evaluate the behavior of the robots under spatial constraints. In open environments, the robots move randomly until they find a stimulus (for example, light), responding to obstacles by turning at random angles and stopping temporarily upon detecting another robot, guided by the perceived luminosity.

The test area had approximate dimensions of 80 cm × 100 cm (see Fig. 1), providing sufficient space for the robots to navigate, interact and form clustering around a designated stimulus source, which ensured controlled and reproducible experimental conditions.

The robot platform used in the experimentation was the Formula AllCode robot, selected for its compact dimensions (10 cm × 10 cm), its sensor integration and its adequate maneuverability for moving in restricted spaces.

Algorithm BeeClust



Fig. 1. *Arena.*
Source: own elaboration.

The BeeClust algorithm can be represented as a finite state machine (FSM). An FSM is a mathematical model used in systems theory and automation to describe the behavior of a system that can exist in a finite number of states and transition between them in response to external stimuli or internal conditions. Each state represents a specific action, and predefined events or conditions trigger transitions between states. In this case, FSM organizes the robot's behavior into three main states: FWD (forward), RTT (rotation/turn), and WAIT (standby) (see Fig. 2).

In the FWD state, the robot moves at constant speed while scanning its environment to avoid obstacles. Upon a collision, it must determine whether the obstacle corresponds to a wall or to another robot.

If the obstacle is a wall, the robot transitions to the RTT state, where it selects a random angle and performs a rotation movement. Once the rotation is complete, the robot returns to the FWD state[11][12].

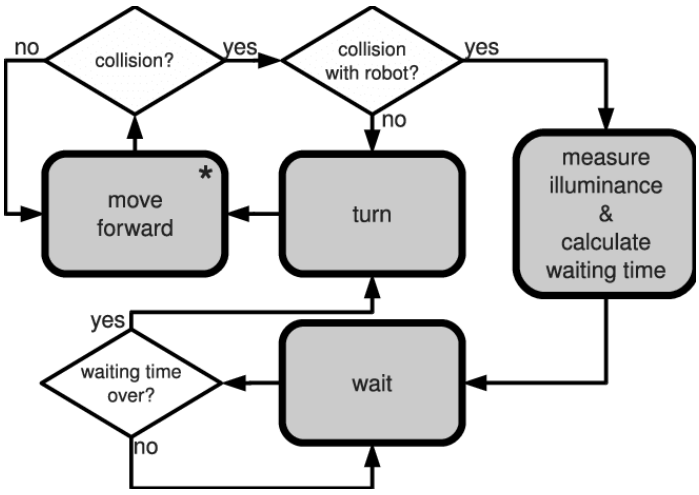

Fig. 2. *Finite state machine of the Beeclust algorithm.*
Source: [10]

If the obstacle is another robot, the latter enters the WAIT state, in which it remains inactive for a time proportional to the light intensity detected at its position, following equation (1).

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

Where $t_{\max}$ represents the maximum waiting time, $s(t)$ corresponds to the light intensity perceived by the sensor and θ is the parameter that regulates the slope of the curve.

After the waiting period, the robot returns to the RTT state. Obstacle detection is performed only in the FWD state.

Robot description

The Formula AllCode is a robotic platform designed for experimentation in autonomous systems, selected for its compact structure, integrated sensors, and adaptability to controlled environments. As shown in Table 1, the platform is equipped with various sensors and actuators that support environmental perception and mobility.

Table 1. Inputs and outputs of the robotic clustering system

Type	Sensor/Actuator	Location/Function
Input	8 infrared distance sensors	Front, left, left side, right side, right, rear right, rear, rear left
Input	Light sensor	Ambient light detection
Input	Microphone	Sound detection
Output	Motor 1	Right motor
Output	Motor 2	Left motor
Output	Buzzer	Acoustic signal

Source: Own elaboration.

The integrated dsPIC microcontroller manages all sensor inputs and actuator outputs, processing both analog and digital signals. It generates pulse-width modulation (PWM) commands to control the motors and communicates with external devices. The robot was programmed in Python, taking advantage of its readability and the broad library support available. The interaction between the host computer and the robot was established via Bluetooth using an Application Programming Interface (API), which allowed commands to be executed in real time and the system to be monitored during the experimental procedures.

Sensor and Control Characterization

A series of experimental tests were carried out under controlled conditions to determine the operational range and the response behavior of the infrared sensors integrated into the Formula AllCode robot. These sensors are distributed around the perimeter of the chassis, forming a 360-degree detection disk. However, for this study only the front sensors were considered, since the maze-like structure of the experimental environment prioritized frontal obstacle detection.

The experimental setup consisted of placing different surfaces, such as colored paper, cardboard and rough materials, at predefined distances in front of the sensors. The analog output was recorded and subsequently linearized to estimate approximate distances in millimeters. All tests were carried out under constant ambient illumination conditions to minimize external interference. Although the manufacturer specifies a raw output range of the sensors between 0 and 4095 units, special attention was paid to the behavior of the signal at very short distances, where saturation and noise were observed.

To complement the characterization of the sensors and enable stable navigation within the maze, a Proportional-Derivative (PD) controller was implemented for exclusive use in the FWD (forward) state. This control strategy was selected for its simplicity, stability and fast transient response, characteristics consistent with the requirements of the experimental setup, where integral action was not necessary.

In the forward movement phase, the PD controller continuously regulated the robot's trajectory by adjusting the right and left motor outputs according to its lateral deviation from the center of the corridor. The control law followed the standard discrete-time PD formulation(2).

$$u(k) = K_p e(k) + K_d \frac{e(k) - e(k-1)}{\Delta t} \quad (2)$$

Where$e(k)$is the error signal, defined as the difference between the readings of the left and right infrared sensors, andΔt corresponds to the sampling period. The derivative term was approximated by means of finite differences. The proportional gain$K_p$determines the magnitude of the response to the error, while the derivative gain$K_d$compensates for rapid variations in$e(k)$, improving stability. The controller gains were adjusted experimentally using the Ziegler–Nichols method, applying a sequence of step inputs and observing the dynamic response until oscillatory conditions were reached. The resulting controller output was applied to the differential drive system according to(3).

$$\begin{aligned} V_L &= V_{base} - u[k] \\ V_R &= V_{base} - u[k] \end{aligned} \quad (3)$$

In addition to the PD control, the WAIT function used to regulate the robot's stationary behavior in response to a detected stimulus was modified to take ambient light into account. The original implementation assumed a completely dark environment($s(t)=0$); however, the experimental space had a measurable background illumination. To avoid false clustering responses, an ambient light compensation value, obtained through calibration, was incorporated into the equation as the lower detection threshold, see(4).

$$t_{wait} = t_{\max} \cdot \frac{(s(t) - offset)^2}{(s(t) - offset)^2 + \theta} \quad (4)$$

This adjustment ensured that the robots reacted only to the intended light source, even under variable ambient illumination conditions.

To complement light-based detection, robots were identified using an acoustic system that took advantage of the speaker and microphone integrated into the platform. The speaker emitted a 392 Hz tone (note G4) lasting two seconds, while the receiving robot measured the corresponding sound levels with its microphone. Experimental tests were carried out under different emitter-receiver configurations, including frontal, rear, and lateral positions, to evaluate the impact of relative orientation on signal reception. These measurements were then used to establish a detection threshold that would allow reliable identification of nearby robots while minimizing false positives caused by ambient noise or interference from the environment.

RESULTS

The characterization of the infrared distance sensors showed a clear influence of surface properties on detection performance. As shown in Fig. 3, the maximum detection distances ranged from approximately 35 mm for rough surfaces and cardboard to nearly 90 mm for colored surfaces such as red, yellow, and green. At distances below 25 mm, the sensor readings remained

stable at around 3000 units, whereas at greater distances the signal decayed progressively and the noise level increased.

Based on these observations, a reliable operational detection distance of 20 mm was selected. This value ensures consistent obstacle detection, reduces variability in the measurements, and favors stable navigation within the maze-type environment.

Once the detection range was established, attention focused on the robot's motion control strategy. Experimental tuning using the Ziegler–Nichols procedure resulted in controller gains ofK_p=0.288andK_d=0.18. With these values, the PD controller maintained smooth and stable forward navigation within the maze, effectively minimizing wall collisions and reducing oscillations in the robot's trajectory. The system consistently returned to the center of the aisle after deviations, demonstrating robustness in multiple tests. Calibration of the light detection system yielded a compensation value of 500 units. This value was incorporated into the WAIT function according to(5).

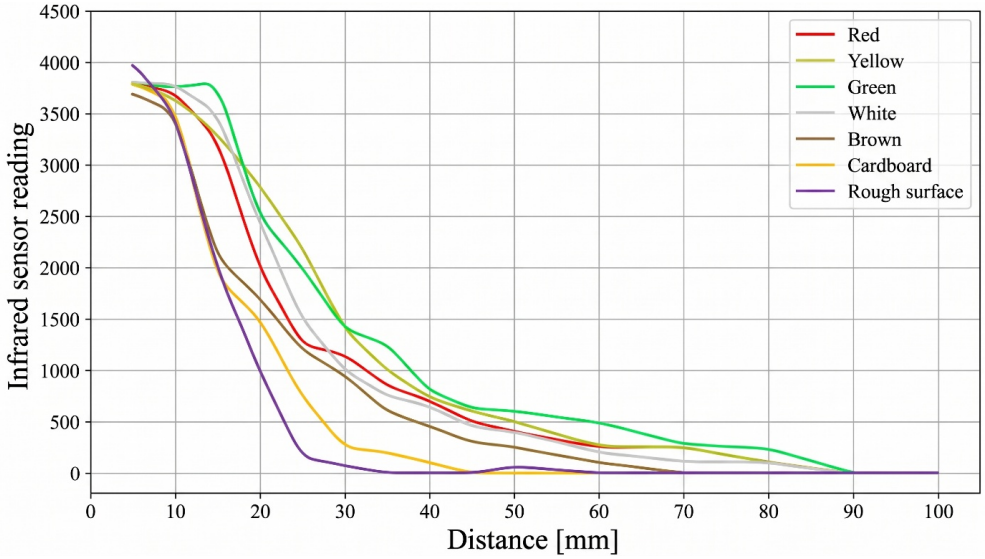

Fig. 3. *Infrared sensor range.*
Source: own elaboration.

$$t_{wait} = t_{\max} \cdot \frac{(s(t) - 500)^2}{(s(t) - 500)^2 + \theta} \quad (5)$$

The incorporation of this threshold successfully prevented false activations caused by background lighting, which ensured that the robots responded only to the target stimulus. This modification proved particularly effective in maintaining clustering performance under conditions where ambient light intensity fluctuated during the experiments.

After the calibration of the light-sensing system, the acoustic detection system was evaluated to determine its effectiveness in identifying nearby robots. The experimental tests of sound detection revealed significant variability in the microphone readings depending on the relative position between the emitter robot and the receiver. As shown in Table 2, the highest values were recorded when the robots were aligned face to face, whereas configurations involving lateral or rear positions resulted in lower signal intensities. Among all cases, the lowest readings were observed when the emitter was located to the right of the receiver, probably due to angular displacement and partial occlusion. Based on these results, a detection threshold of 918 units was established, providing a balance between sensitivity to nearby robots and robustness against ambient noise.

Table 2. Microphone readings for different relative positions between the emitter robot and the receiver.

Position	Sensor readings
Face to face	997, 1069, 1012, 1047, 998
Emitter behind the detector	954, 1079, 1112, 978, 1114
Emitter on the left side	977, 1188, 994, 910, 991
Emitter on the right side	938, 1000, 1255, 812, 906

Source: Own elaboration.

DISCUSSION

The results show that sensor characterization and adaptation of the BeeClust algorithm enabled efficient clustering behavior

in controlled environments with spatial constraints. Setting the infrared detection range to 20 mm and calibrating the light detection system with a threshold of 500 units significantly reduced false triggers. These performance improvements, achieved through specific parameter adjustments, are consistent with previous studies showing how controlled variations such as changes in speed or wait time can improve the efficiency of the BeeClust algorithm[9].

Regarding motion control, the implementation of an optimized PD controller allowed stable and focused navigation along the aisles, effectively reducing collisions and oscillations. This approach aligns with previous work applying specific control strategies and sensor calibration to ensure accurate trajectory tracking and minimize deviations in BeeClust-based systems[12].

Integrating an acoustic detection system into our BeeClust-based platform is a distinctive innovation compared with the classic versions of the algorithm, which traditionally rely on tactile collisions or light stimuli for clustering. The system demonstrated high reliability in frontal positions; however, its lower sensitivity on the sides and at the rear highlights the need for improvements, such as the use of microphone arrays or spatial filtering algorithms, that increase robustness under conditions of variable orientation.

Previous studies have explored the use of sound sources as environmental stimuli to compare BeeClust with aggregation strategies based on alternative signals[9]; however, these implementations used sound only as a global stimulus, without incorporating advanced directional acoustic detection techniques. In contrast, our approach leverages a frontal sound detection module, a well-established principle in locating acoustic sources through microphone arrays in mobile robots[13]to enable BeeClust behaviors and enable proximity-based interaction without physical contact. While the system achieved reliable frontal detection, the lower sensitivity on the sides and back suggests the incorporation of a full microphone array, as explored in cooperative navigation of acoustic swarms[14], could improve directional awareness and robustness under variable orientation conditions. This breakthrough highlights the potential to integrate multimodal perception into swarm algorithms, paving the way for more versatile and resilient collective behaviors in complex and dynamic environments.

CONCLUSIONS

The experimental evaluation of the onboard sensors confirmed that surface properties influence the performance of infrared detection, which made it possible to define an optimal operational range to guarantee stable and consistent obstacle detection.

The implementation and tuning of the PD controller resulted in smoother and more stable navigation, significantly reducing collisions and oscillations within the maze-type environment. The calibration of the light-sensing system proved effective in filtering ambient illumination, preventing false activations and improving the reliability of stimulus-based responses.

Integrating an acoustic detection system further enhanced the platform's sensing capabilities by enabling robot-to-robot detection without physical contact. Although frontal detection showed high reliability, the lower performance of the lateral and rear configurations points to opportunities for improvement in future designs.

Overall, the characterization and commissioning of the mobile robot platform significantly improve the performance and robustness of the system in constrained environments, establishing a solid technical foundation for future implementations of coordination and clustering behaviors in swarms aimed at inventory localization applications.

REFERENCES

[1] P. N. Hutapea and M. Siallagan, "Predictive Analysis for Inventory Management of Coconut Warehouse (Case Study: Banio Lahewa)," *International Journal of Current Science Research and Review*, vol. 06, no. 11, Nov. 2023, doi: 10.47191/ijcsrr/V6-i11-44.

[2] N. S. Sandoval Carrero, N. M. Acevedo Quintana, and L. M. Santos Jaimes, "LINEAMIENTOS DESDE LA INDUSTRIA 4.0 A LA EDUCACIÓN 4.0: CASO TECNOLOGÍA IoT," *REVISTA COLOMBIANA DE TECNOLOGIAS DE AVANZADA (RCTA)*, vol. 1, no. 39, pp. 81–92, Jul. 2023, doi: 10.24054/rcta.v1i39.1379.

[3] A. A. Ali, R. A. Rashid, N. M. Abdikadir, A. A. Mohamed, and M. M. Ahmed, "IoT Based Warehouse Management System Leveraging On RFID and Cloud Platform Technologies," in 2024 IEEE International Conference on Advanced Telecommunication and Networking Technologies (ATNT), IEEE, Sep. 2024, pp. 1–4. doi: 10.1109/ATNT61688.2024.10719252.

[4] V. Casamayor-Pujol, M. Morenza-Cinos, B. Gastón, and R. Pous, "Autonomous stock counting based on a stigmergic algorithm for multi-robot systems," *Comput Ind*, vol. 122, p. 103259, Nov. 2020, doi: 10.1016/j.compind.2020.103259.

[5] M. Vogrin, M. Stefanec, and T. Schmickl, "Social Distancing in Robot Swarms: Modulating Exploitation and Exploration Without Signal Exchange," in 2020 IEEE Symposium Series on Computational Intelligence (SSCI), IEEE, Dec. 2020, pp. 2233–2240. doi: 10.1109/SSCI47803.2020.9308502.

[6] T. Schmickl et al., "Get in touch: cooperative decision making based on robot-to-robot collisions," *Auton Agent Multi Agent Syst*, vol. 18, no. 1, pp. 133–155, Feb. 2009, doi: 10.1007/s10458-008-9058-5.

[7] S. Kernbach, R. Thenius, O. Kernbach, and T. Schmickl, "Re-embodiment of Honeybee Aggregation Behavior in an Artificial Micro-Robotic System," *Adaptive Behavior*, vol. 17, no. 3, pp. 237–259, Jun. 2009, doi: 10.1177/1059712309104966.

[8] L. Bayındır, "A review of swarm robotics tasks," *Neurocomputing*, vol. 172, pp. 292–321, Jan. 2016, doi: 10.1016/j.neucom.2015.05.116.

[9] F. Arvin, A. E. Turgut, F. Bazyari, K. B. Arikan, N. Bellotto, and S. Yue, "Cue-based aggregation with a mobile robot swarm: a novel fuzzy-based method," *Adaptive Behavior*, vol. 22, no. 3, pp. 189–206, Jun. 2014, doi: 10.1177/1059712314528009.

[10] M. Bodi, R. Thenius, T. Schmickl, and K. Crailsheim, "How Two Cooperating Robot Swarms Are Affected by Two Conflictive Aggregation Spots," 2011, pp. 367–374. doi: 10.1007/978-3-642-21314-4_46.

[11] O. Acevedo, Y. Y. Rios, J. Duque, E. Gomez, and L. García, "A Software for Simulating Robot Swarm Aggregation," 2022, pp. 386–399. doi: 10.1007/978-3-031-20611-5_32.

[12] O. Acevedo, Y. Y. Rios, L. Garcia, and D. Narvaez, "A study of the Beeclust algorithm for robot swarm aggregation," in 2022 IEEE International Conference on Machine Learning and Applied Network Technologies (ICMLANT), IEEE, Dec. 2022, pp. 1–6. doi: 10.1109/ICMLANT56191.2022.9996514.

[13] J.-M. Valin, F. Michaud, J. Rouat, and D. Letourneau, "Robust sound source localization using a microphone array on a mobile robot," in Proceedings 2003 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS 2003) (Cat. No.03CH37453), IEEE, pp. 1228–1233. doi: 10.1109/IROS.2003.1248813.

[14] M. Itani, T. Chen, T. Yoshioka, and S. Gollakota, "Creating speech zones with self-distributing acoustic swarms," *Nat Commun*, vol. 14, no. 1, p. 5684, Sep. 2023, doi: 10.1038/s41467-023-40869-8.

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