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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.

1. INTRODUCTION

Inventory management plays a vital role in agricultural operations, where warehouse logistics directly influence productivity, sales, and overall profitability [1]. Despite its importance, maintaining accurate and efficient inventory tracking often demands significant human and material resources. Common issues such as product misplacement, disorganization, and inefficient order flow can lead to delays, incomplete deliveries, and substantial financial losses.

Conventional systems, including barcode scanners and conveyor mechanisms, have helped mitigate some of these challenges, yet they remain prone to human error and often require extensive infrastructure modifications. More advanced approaches such as IoT-based frameworks, which are central to Industry 4.0 initiatives, have also been proposed as alternatives to improve efficiency in industrial processes [2].

RFID (Radio Frequency Identification) technology has emerged as a more advanced solution, offering real-time inventory tracking with improved precision [3]. However, its high implementation cost and complex deployment make it less viable in small-scale or rural agricultural contexts.

In response to these limitations, research has increasingly turned toward mobile robotics as a flexible and scalable alternative for automating inventory processes. Autonomous robots are capable of navigating through unstructured environments with minimal infrastructure and reduced human intervention [4][5][6]. Nevertheless, the effectiveness of such systems relies heavily on their sensing and control capabilities, which must be robust, accurate, and adapted to the characteristics of the workspace.

This article focuses on 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 and interaction within a controlled maze-like environment. The study serves as a preparatory step toward developing of swarm-based inventory localization strategies.
Building on this foundation, future work will incorporate collaborative behaviors inspired by clustering algorithms such as BeeClust [7], where autonomous agents converge on environmental stimuli without centralized coordination, offering advantages in scalability, robustness, and efficiency [8], [9].

2. METHODOLOGY

2.1 Experimental Setup

The experiments were conducted in a controlled, scaled warehouse environment, to simulate real-world conditions. Unlike previous studies implementing the BeeClust algorithm, where robot swarms typically operate in open environments, this setup introduced a maze-like arena to assess robot behavior under spatial constraints. In open environments, robots move randomly until encountering a stimulus (e.g., light), responding to obstacles by turning at random angles and temporarily stopping upon detecting another robot, guided by captured luminosity.

The test area measured approximately 80 cm × 100 cm (see Fig. 1) and provided sufficient space for robot navigation, interaction, and clustering around a designated stimulus source, ensuring controlled and reproducible experimental conditions.

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

The robotic platform used for experimentation was the Formula AllCode robot, selected due to its compact dimensions (10 cm × 10 cm), integrated sensors, and suitable maneuverability for navigating constrained spaces.

2.2 BeeClust algorithm

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 distinct action, and predefined events or conditions trigger transitions between states. In this case, the FSM organizes the robot's behavior into three main states: FWD (move forward), RTT (rotation/turn), and WAIT (waiting) (see Fig. 2).

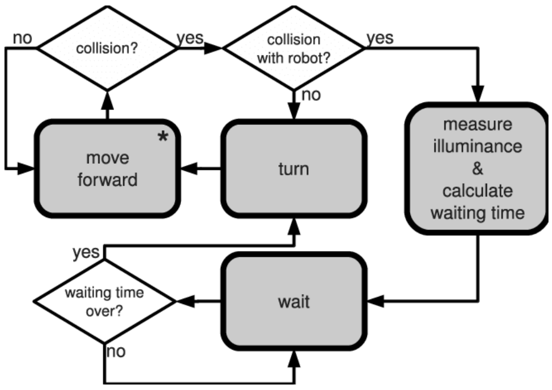

***Fig. 2.** Finite state machine of the BEECLUST algorithm.*
***Source:** [10]*

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

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

If the obstacle is another robot, the robot enters the WAIT state, where it remains idle for a duration proportional to the light intensity detected at its position, following the 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, $s(t)$ is the light intensity perceived by the sensor, and θ is the parameter regulating the slope of the curve.

After the waiting period, the robot returns to the RTT state. It is important to note that obstacle detection is only performed in the FWD state.

2.3 Robot Description

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

***Table 1.** Inputs and Outputs of the Robot 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 onboard 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 using Python, leveraging its readability and extensive library support. The interaction between the host computer and the robot was established via Bluetooth using an Application Programming Interface (API). This allowed for real-time command execution and system monitoring during experimental procedures.

2.4 Sensor characterization and control

A series of experimental tests were conducted under controlled conditions to determine the operational range and 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 sensing disc. However, only the front-facing sensors were considered for this study, given the maze-like structure of the testing environment, where frontal obstacle detection was prioritized.

The experimental setup involved placing various surfaces such as colored paper, cardboard, and rough-textured materials at predefined distances from the sensors. The analog output was recorded and then linearized to estimate approximate distances in millimeters. All tests were performed under consistent ambient lighting to minimize external interference. Although the manufacturer specifies a raw sensor output range from 0 to 4095 units, particular attention was given to signal behavior at very short distances, where saturation and noise were observed.

To complement the sensor characterization and enable stable navigation within the maze, a Proportional-Derivative (PD) controller was implemented exclusively for the FWD (forward) state. This control strategy was chosen for its simplicity, stability, and fast transient response, characteristics that matched the requirements of the experimental setup where integral action was unnecessary. In the forward motion phase, the PD controller continuously regulated the robot's trajectory by adjusting the outputs of the left and right motors according to its lateral deviation from the corridor center. The control law followed the standard discrete-time PD formulation (2).

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

where $e(k)$ is the error signal, defined as the difference between the readings of the left and right infrared sensors, and Δt is the sampling period. The derivative term was approximated using 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. Controller gains were tuned 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).

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

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

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

This adjustment ensured that the robots only reacted to the intended light source, even under varying environmental lighting conditions.

To complement light-based sensing, robot detection was accomplished through an acoustic system that leveraged the robot's built-in speaker and microphone. The speaker emitted a 392 Hz tone (G4 note) lasting two seconds, while the receiving robot measured the corresponding sound levels using its microphone. Experimental tests were conducted under various emitter-receiver configurations including front-facing, 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 enables reliable identification of nearby robots while minimizing false positives caused by ambient noise or environmental interference.

3. RESULTS

The characterization of the infrared distance sensors revealed a clear influence of surface properties on detection performance. As shown in Fig. 3, maximum detection distances ranged from approximately 35 mm for rough surfaces and cardboard to about 90 mm for colored surfaces such as red, yellow, and green. At distances shorter than 25 mm, sensor readings remained stable at around 3000 units, whereas at greater distances the signal progressively decayed and exhibited increased noise.

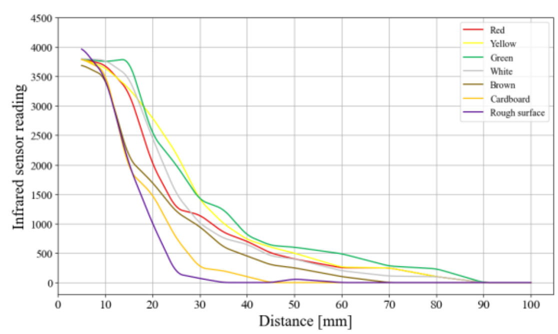

Fig. 3. *Infrared Sensor Range.*
Source: *own elaboration.*

Based on these observations, a reliable operational sensing distance of 20 mm was selected. This value ensures consistent obstacle detection, reduces measurement variability, and supports stable navigation within the maze environment.

With the sensing range established, attention was directed toward the robot's motion control strategy. Experimental tuning using the Ziegler–Nichols procedure resulted in controller gains of $K_p = 0.288$ and $K_d = 0.18$. 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 corridor center after deviations, demonstrating robustness across multiple trials. Calibration of the light detection system yielded an ambient light offset of 500 units. This value was incorporated into the WAIT function according to (5).

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

Incorporating this threshold successfully prevented false activations caused by background illumination, allowing the robots to respond exclusively to the target stimulus. This modification proved particularly effective in maintaining clustering performance under conditions where ambient light intensity fluctuated during the experiments.

Following the light-sensing calibration, the acoustic detection system was evaluated to determine its effectiveness in identifying nearby robots. The experimental sound detection tests revealed significant variability in microphone readings depending on the relative position of the emitter and receiver robots. As shown in Table 2, the highest values were recorded when the robots were aligned face to face, while configurations involving lateral or rear positioning resulted in lower signal intensities. Among all cases, the lowest readings were observed when the emitter was placed to the right of the receiver, likely 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 and receiver robot.*

Position	Sensor Readings				
Front to front	997	1069	1012	1047	998
Emitter behind 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.*

4. DISCUSSION

The results demonstrate that the sensor characterization and the 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 500-unit threshold significantly reduced false activations. Such performance enhancements, achieved through targeted parameter adjustments, are consistent with previous studies showing that controlled variations—such as changes in speed or waiting time—can improve the efficiency of the BeeClust algorithm [9].

In terms of motion control, implementing an optimized PD controller enabled stable and centered navigation along corridors, effectively reducing collisions and oscillations. This approach is consistent with previous work where specific control strategies and sensor calibration were applied to ensure precise trajectory tracking and minimize deviations in BeeClust-based systems [12].

The integration of an acoustic detection system into our BeeClust-based platform represents a distinctive innovation compared to classical versions of the algorithm, which traditionally rely on tactile collisions or light cues for aggregation. The system demonstrated high reliability in frontal positions; however, its reduced sensitivity on the sides and rear highlights the need for improvements, such as microphone arrays or spatial filtering algorithms, to enhance robustness under variable orientation conditions.

Previous studies have explored the use of sound sources as environmental stimuli to compare BeeClust with alternative cue-based aggregation strategies [9], yet these implementations employed sound merely as a global cue rather than incorporating advanced directional acoustic sensing. In contrast, our approach leverages a frontal sound detection module, a well stablished principle established in microphone array sound localization for mobile robots [13], to trigger BeeClust behaviors and enable proximity-based interaction without physical contact. While the system achieved reliable frontal detection, reduced sensitivity at the sides and rear suggests that incorporating a full microphone array, as explored in cooperative acoustic swarm navigation [14], could enhance directional awareness and robustness under variable orientation conditions. This advancement highlights the potential of integrating multimodal sensing into swarm algorithms, paving the way for more versatile and resilient collective behaviors in complex and dynamic environments.

5. CONCLUSIONS

The experimental evaluation of the onboard sensors confirmed that surface properties influence infrared detection performance, which led to the definition of an optimal operational range to ensure 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 environment. Calibration of the light detection system effectively filtered ambient illumination, preventing false activations and enhancing 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. While frontal detection demonstrated high reliability, the lower performance of lateral and rear configurations highlights opportunities for refinement 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 swarm coordination and clustering behaviors in inventory localization applications.

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