# 2D Pose Optimization with Genetic Algorithms and Particle Swarm Optimization: A Comparative Analysis for Robotic Localization

**Henrique Nunes Teixeira**[*,1], **Daniel do Carmo Silva Ribeiro**[1], **Eduardo Furtado de Simas Filho**[1], **Samara Maria Assunção de Souza**[2], **Fillipe Valente Braz**[2], **Tiago Silva e Silva**[2]
[1]Federal University of Bahia, DEEC, Salvador, Bahia, Brazil
[2]Federal University of Recôncavo da Bahia, CETENS, Feira de Santana, Bahia, Brazil
*Corresponding author: henrique.teixeira@ufba.br

**Abstract: Accurate localization of mobile robots—particularly under conditions of initial uncertainty, known as the Global Localization Problem (GLP)—remains a fundamental challenge in robotics, as it directly impacts autonomous navigation, precise mapping, and safe interaction with the environment. This paper presents a comparative study of two optimization metaheuristics—Genetic Algorithms (GA) and Particle Swarm Optimization (PSO)—applied to the scan-to-map matching problem for 2D localization with LiDAR sensing. A controlled simulation framework was developed, within which 150 independent experiments were conducted on a high-resolution synthetic occupancy map, employing a cost function based on a Euclidean distance field with penalties assigned to invalid poses. The methodology encompassed automated data generation, parameterized execution of the algorithms, and comprehensive statistical evaluation of key performance metrics, including position error, orientation error, computational time, and convergence behavior. The experimental results demonstrate that both algorithms achieve high accuracy in most trials, yet with notable differences. PSO exhibited faster convergence and attained a lower median angular error (0.18° versus 0.45° for GA), though it displayed a greater tendency to converge to local minima, occasionally resulting in substantial localization errors. In contrast, GA, while slower and with a higher median angular error, proved more robust in avoiding large-magnitude failures, thereby yielding more consistent solutions across the simulated scenarios. These findings suggest that the choice between GA and PSO should be dictated by application-specific requirements: PSO is preferable in domains where rapid convergence is essential, whereas GA is advantageous in safety-critical contexts demanding reliability and fault tolerance. Future directions include the design of hybrid approaches that combine the efficiency of PSO with the robustness of GA, as well as validation in real-world robotic systems, extension to 3D localization tasks, and integration with multi-sensor data.**

**Keywords: Mobile Robot Localization. Scan-to-Map Matching. Particle Swarm Optimization. Genetic Algorithms. Metaheuristics.**

**Abbreviations: GA, Genetic Algorithms. PSO, Particle Swarm Optimization.**

## 1 Introduction

Autonomous and precise localization of mobile robots is a cornerstone of modern robotics, serving as a prerequisite for tasks such as navigation, mapping, and safe interaction with the environment [1]. In many scenarios, localization becomes a critical challenge, particularly when the robot's prior pose is unknown or uncertain—a condition referred to as the Global Localization Problem (GLP). Unlike continuous localization, where the robot has an initial pose estimate that is refined over time, the GLP arises when the robot's initial pose is completely unknown or highly uncertain. This situation may occur, for example, after a system failure, a reset in an arbitrary location, or entry into a completely new environment without prior position information [6].

The challenges inherent to the GLP are multifaceted. First, the initial uncertainty requires the localization algorithm to explore a vast search space, which can be high-dimensional (position and orientation). Moreover, sensor noise (from LiDARs or cameras) and the dynamic nature of environments (with moving objects or structural changes) add further layers of complexity. The phenomenon of perceptual aliasing, where distinct locations in the map present similar sensory characteristics (e.g., long repetitive corridors), can cause the robot to misidentify its location, resulting in significant localization errors [7].

Robust resolution of the GLP is crucial for a wide range of real-world applications. In search-and-rescue operations, robots must localize rapidly in unknown and hazardous environments. Autonomous vehicles, when deployed in unmapped areas or after being transported to new locations, require effective solutions to the GLP before navigation can begin. Planetary exploration rovers, operating in GPS-denied environments, depend on autonomous and reliable methods to determine their absolute position. Failure to solve the GLP robustly can lead to collisions, mission loss, or safety risks [8].

It is important to note that the GLP is intrinsically related to the problem of Simultaneous Localization and Mapping (SLAM). While SLAM builds a map of the environment while simultaneously localizing within it, the resolution of the GLP is often a prerequisite or an essential component for initializing or recovering a SLAM system. A robust SLAM system must therefore be capable of handling the GLP to ensure continuous and reliable operation in challenging scenarios. Recent research continues to explore new approaches to GLP, aiming for higher accuracy and robustness in increasingly complex environments [9].

This work focuses on a central subproblem of localization: scan-to-map matching, which consists of aligning a sensor scan with a pre-existing map. Traditional methods such as Iterative Closest Point (ICP) are widely used, but they can be sensitive to local minima, particularly in environments with ambiguities or lacking distinctive features [4]. To overcome these limitations, metaheuristics such as Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) have emerged as promising alternatives [2, 5]. These algorithms are capable of performing global search in the solution space, increasing robustness and the likelihood of finding the correct pose [2].

This paper introduces a computational framework to compare the performance of GA and PSO in solving the scan-to-map matching problem for a robot equipped with a 2D LiDAR sensor. Using a controlled simulation environment, we investigate the effectiveness, accuracy, and computational cost of each approach, with the goal of determining which method provides the best trade-off between robustness and efficiency for global localization.

# 2 Methodology

The methodology of this study was designed to systematically evaluate and compare GA and PSO in the task of 2D pose optimization. The process involves constructing a simulated environment, defining a robust cost (fitness) function, and performing controlled executions of the optimization algorithms.

## 2.1 Scan-to-Map Matching Problem

The problem is formalized as the search for the pose $\mathbf{p} = (x, y, \theta)$ that minimizes a cost function, which quantifies the misalignment between a 2D point cloud, $\mathcal{S}$, obtained from a laser sensor, and a pre-existing occupancy map, $\mathcal{M}$. The pose $\mathbf{p}$ consists of a translation $(x, y)$ and a rotation $\theta$. The transformation of a point $\mathbf{s}_i \in \mathcal{S}$ into its map representation, $\mathbf{s'}_i$, is given by:

$$\mathbf{s'}_i = \begin{pmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{pmatrix} \mathbf{s}_i + \begin{pmatrix} x \\ y \end{pmatrix} \tag{1}$$

The objective is to find the optimal pose $\mathbf{p}^*$ that aligns all points in $\mathcal{S}$ with the occupied regions of $\mathcal{M}$.

## 2.2 Fitness Function

The evaluation of a candidate pose is carried out through the `scan_to_map_fitness` function, which is minimized. The efficiency and accuracy of this function are critical to the success of the optimization algorithms [3]. To accelerate computation, a Euclidean distance field is precomputed from the occupancy map. This field stores, for each free cell, the distance to the nearest obstacle, significantly improving performance by avoiding repeated searches.

The error (cost) of a pose $\mathbf{p}$ is computed as the sum of the distances obtained from the distance field for each transformed scan point, $\mathbf{s'}_i$:

$$\text{Cost}(\mathbf{p}) = \frac{1}{N} \sum_{i=1}^{N} \text{DistanceField}(\mathbf{s'}_i) \tag{2}$$

where $N$ is the number of points in the scan. A penalty is added for points that, after transformation, fall outside the map boundaries, discouraging invalid solutions. This approach is inspired by map-to-scan matching metrics such as Perfect Match.

## 2.3 Optimization Algorithms

Both GA and PSO were implemented to explore the three-dimensional search space $(x, y, \theta)$ and find the pose that minimizes the cost function.

### 2.3.1 Genetic Algorithm (GA)

GA is a metaheuristic based on the principles of natural evolution [1]. The population is composed of individuals, where each chromosome encodes a candidate pose. Evolution proceeds through genetic operators:

- **Tournament Selection:** Individuals are selected for reproduction based on their fitness value, where a lower error corresponds to a higher probability of selection.
- **Crossover:** Selected parents exchange genetic information (parts of their pose vectors) to generate offspring.
- **Mutation:** Small random perturbations are introduced into the offspring to preserve diversity and avoid premature convergence.
- **Elitism:** The best individuals of each generation are preserved and carried forward, ensuring the retention of the best solutions found.

### 2.3.2 Particle Swarm Optimization (PSO)

PSO is inspired by the collective behavior of swarms [2]. Each particle in the swarm represents a candidate pose and adjusts its trajectory based on its own best experience (*pBest*) and the best experience of the group (*gBest*). The velocity and position of each particle are updated iteratively according to the following equations:

$$\mathbf{v}_{k+1} = w\mathbf{v}_k + c_1 r_1(\mathbf{pBest}_k - \mathbf{p}_k) + c_2 r_2(\mathbf{gBest}_k - \mathbf{p}_k) \quad (3)$$

$$\mathbf{p}_{k+1} = \mathbf{p}_k + \mathbf{v}_{k+1} \quad (4)$$

where $w$ is the inertia factor, $c_1$ and $c_2$ are the cognitive and social coefficients, and $r_1, r_2$ are random values. This dynamic allows the swarm to efficiently explore the search space.

## 2.4 Simulation Framework

To ensure reproducibility and a fair comparison, a simulation framework was developed:

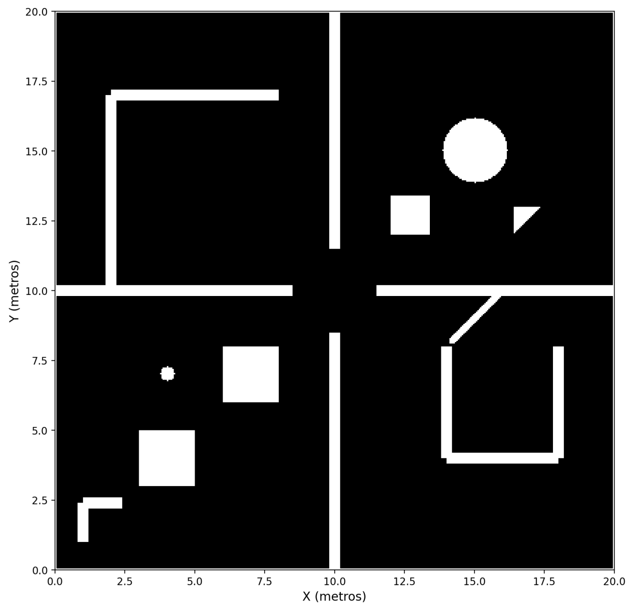
1. **Map and Data Generation:** A synthetic 20×20 meter occupancy map with 0.05 m/pixel resolution was created. Ground-truth poses were generated randomly within free-space regions of the map. For each pose, a 2D LiDAR scan was simulated using the function `simulate_scan_from_pose`, which casts rays from the pose and computes distances to obstacles, adding Gaussian noise of 0.01 m to emulate real sensor imperfections.

2. **Execution and Analysis:** A total of 150 independent experiments were conducted. In each run, a new ground-truth pose was sampled and a corresponding scan generated. GA and PSO were executed to optimize a randomly initialized pose using the simulated scan. Performance metrics such as position error, angular error, and runtime were recorded for comparative statistical analysis.

# 3 Results and Discussion

The performance evaluation of the algorithms was conducted on the simulated map developed in this work, presented in Figure 1. White areas represent obstacles, while black areas correspond to free navigable space. The map was designed to include a variety of elements, such as obstacles with different geometric shapes (e.g., circles, squares, and angled lines) and structural divisions that segment the environment into distinct regions. This configuration was intended to assess the robustness of the algorithms in scenarios with spatial diversity and moderate complexity.

Figura 1: Synthetic occupancy map used in the experiments.




## 3.1 Statistical Analysis of Position Error

Quantitative analysis of position error reveals similar mean performance between the algorithms. GA achieved a mean position error of $0.4408 \pm 0.7329$ m, while PSO obtained $0.4664 \pm 0.8069$ m. The Wilcoxon test confirmed the absence of a statistically significant difference between these distributions ($p = 0.1580$).
However, a more detailed analysis based on the median, which is less sensitive to outliers, provides clearer insight: the median position error was only 0.0536 m for GA and 0.0420 m for PSO. These values, shown in Figure 2, indicate that both algorithms are capable of achieving high accuracy in most runs. It is also notable that both algorithms exhibit low medians alongside outliers. The high means and standard deviations are therefore largely influenced by a limited number of runs in which the algorithms converged to local minima. The boxplot (Figure 2) also suggests that although the median error of PSO is slightly lower, the spread of its outliers (larger errors) is greater than that of GA, indicating a higher risk of large-magnitude errors.

Figura 2: Distribution of final position error.

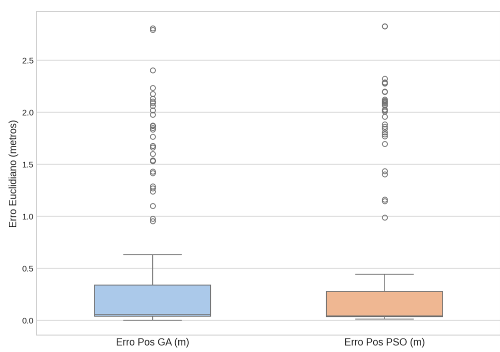


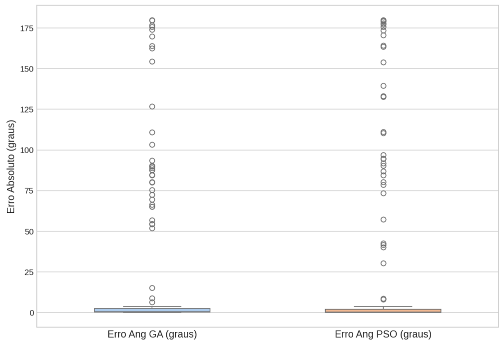
Tabela 1: Statistical summary of position and angular errors.

| Metric | GA | | PSO | |
|---|---|---|---|---|
| | Position (m) | Angle (°) | Position (m) | Angle (°) |
| Mean | 0.4408 | 23.6882 | 0.4664 | 24.3806 |
| Standard Deviation | 0.7329 | 47.9431 | 0.8069 | 52.0710 |
| Median | 0.0536 | 0.4476 | 0.0420 | 0.1822 |
| Minimum | 0.0011 | 0.0184 | 0.0127 | 0.0028 |
| Maximum | 2.8100 | 179.9788 | 2.8284 | 179.9386 |

## 3.2 Statistical Analysis of Orientation Error

For orientation error, the Wilcoxon test indicated a statistically significant difference ($p = 0.0187$). Examining the data in Table 1 and Figure 3, we observe that PSO achieved a median angular error of $0.18°$, considerably lower than GA's $0.45°$. This suggests that, in typical scenarios, PSO demonstrated superior capability in correctly aligning the robot's orientation. The statistical significance, combined with a lower median, supports the conclusion that PSO was more accurate in terms of orientation. Similar to position error, outliers with high angular errors were observed in both algorithms, representing a risk factor to be considered.

Figura 3: Distribution of final orientation error.

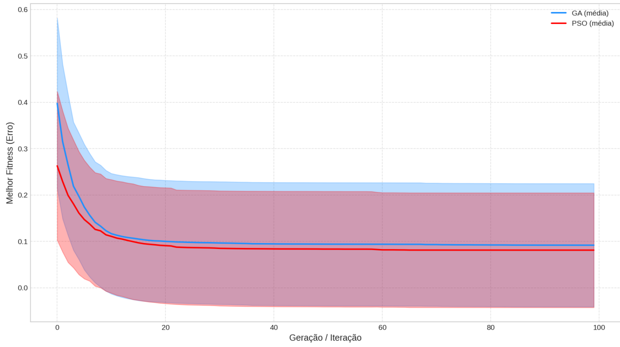



## 3.3 Convergence and Computational Cost Analysis

Figure 4 shows that PSO exhibits faster initial convergence, reaching lower fitness values in fewer iterations. GA, in contrast, displays a more gradual convergence, but its mean error curve concludes with smaller variability (standard deviation shadow), suggesting greater stability and consistency across runs in the later generations.

In terms of computational cost, mean execution times were 13.77s for GA and 13.64s for PSO. The absence of a significant difference indicates that, for the parameters used, the choice between the two should not be based on computational efficiency but rather on their accuracy and robustness profiles.

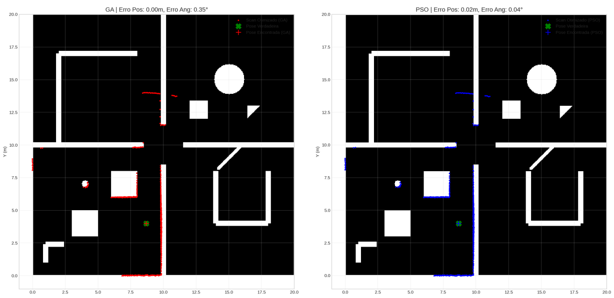
Figura 4: Average fitness convergence with standard deviation.




## 3.4 Qualitative Alignment Analysis

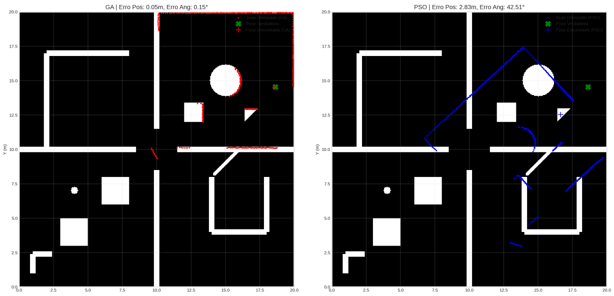
Alignment error analysis provides further insight into the robustness of the algorithms. Figure 5 illustrates the best-case scenario, in which both methods correctly identified the true pose with minimal residual errors, validating their ability to reach the global optimum.

Figura 5: Alignment in the best-case scenario.



The most revealing scenario, however, is the worst-case outcome (Figure 6). In this experiment, GA maintained an accurate solution (error of 0.054 m), whereas PSO converged to an incorrect local minimum, resulting in an error of 2.83 meters. This finding highlights a fundamental trade-off: PSO's accelerated convergence, which favors speed and lower median angular error, also increases its vulnerability to failures. GA's broader exploration, although slower, proved more robust in avoiding this specific failure mode.

Figura 6: Alignment in the worst-case scenario.




### 3.5 General Discussion and Conclusions

The results indicate that there is no absolute winner, but rather a trade-off—namely, a balance between speed, accuracy, and robustness. PSO stood out for its faster convergence and statistically superior median angular accuracy, making it an attractive choice for applications where computational efficiency is a priority. However, this efficiency comes at the cost of reduced robustness, as PSO demonstrated vulnerability to significant localization errors when converging to incorrect local minima.

In contrast, GA, although slower in its convergence, proved to be more robust, avoiding the large-magnitude errors observed with PSO in the constructed test scenario. This characteristic positions GA as a safer alternative for high-integrity systems, where preventing critical errors takes precedence over optimization speed.

The choice between the algorithms, therefore, depends on the application domain. Systems that can tolerate and recover from occasional failures may benefit from the efficiency of PSO. Conversely, safety-critical systems may require the more cautious and robust exploration provided by GA. Future work could investigate hybrid or adaptive techniques that dynamically adjust the search strategy, aiming to combine the efficiency of PSO with the robustness of GA.

## 4 Conclusion

This work presented a comparative analysis of Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) for the *scan-to-map matching* problem, a fundamental component of mobile robot localization. Through a simulation framework, we demonstrated that both metaheuristics are effective tools for 2D pose optimization, overcoming the limitations of local search methods.

The main conclusion of this study is not the absolute superiority of one algorithm over the other, but the identification of a clear trade-off between accuracy, speed, and robustness. PSO distinguished itself by its faster convergence and statistically superior median angular accuracy, making it an attractive option for applications where computational efficiency is paramount. However, this efficiency comes at the cost of reduced robustness, with PSO showing vulnerability to localization failures when converging to incorrect local minima.

On the other hand, GA, although slower in convergence, proved to be more robust, avoiding the large-magnitude errors observed with PSO in the proposed test scenario. This characteristic positions it as a safer alternative for high-integrity systems, where preventing significant failures outweighs optimization speed.

For future work, the investigation of hybrid approaches that combine the stable exploration of GA with the aggressive convergence of PSO represents a promising direction. Additionally, validating these results with experimental data from robots in real environments and extending the framework to 3D localization are natural next steps in the evolution of this research. Parameter optimization of the algorithms for different types of environments and the incorporation of more sophisticated evaluation metrics also constitute important directions for future contributions.

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