

Optimization of Artificial Potential Fields by Genetic Algorithm for Autonomous Mobile Robot Navigation

Amina Nedjoua Benali ¹, Hocine Chebi ², Abdelakader Benaissa ³
Intelligent Control et Electrical Power System (ICEPS) 1,2,3

INTRODUCTION & AIM

Mobile robots play a crucial role in automating a wide range of tasks across various industries. To enable robots to navigate complex environments, effective collision-free path planning methods are essential. Path planning can be categorized into global and local approaches, depending on the level of environmental knowledge available to the robot.

Among local methods, Artificial Potential Fields (APF) provide a simple and efficient solution by combining attractive forces to guide the robot toward the goal and repulsive forces to avoid obstacles. However, APF faces challenges such as oscillations, local minima, and heavy dependence on manually tuned parameters, which can limit performance and reliability.

To address these limitations, we propose a hybrid approach incorporating a Genetic Algorithm (GA) to optimize APF parameters. Simulations demonstrate that this method enhances navigation smoothness and obstacle avoidance compared to traditional APF.

METHOD

The Artificial Potential Fields (APF) method, introduced by Khatib (1986), guides robots towards a target while avoiding obstacles by generating a potential field. The attractive potential field pulls the robot towards the goal and is defined as:

$$U_d(q) = \frac{1}{2} k_p (q - q_d)^2 \quad (1)$$

where q is the robot's position, q_d is the target, and k_p is the attractive gain. The repulsive potential field, which pushes the robot away from obstacles, is given by:

$$U_o(q) = \begin{cases} \frac{1}{2} \eta \left(\frac{1}{\rho} - \frac{1}{\rho_0} \right)^2, & \rho \leq \rho_0 \\ 0, & \rho > \rho_0 \end{cases} \quad (2)$$

where ρ is the distance to the obstacle, ρ_0 is the threshold distance, and η is the repulsive gain. The total potential field is the sum of these two components:

$$U_{do}(q) = U_d(q) + U_o(q) \quad (3)$$

The gradient of the total potential field determines the robot's reference velocity:

$$v_{do}(q) = -\nabla U_{do}(q) \quad (4)$$

Despite its efficiency, the APF method has limitations, such as stagnation at local minima, oscillations near obstacles, and difficulties navigating narrow corridors. These challenges can be addressed by fine-tuning the attractive (k_p) and repulsive (η) gains to ensure smoother navigation and reduced oscillations.

To further enhance APF performance, a genetic algorithm (GA) was used to optimize k_p and η . The GA begins with a randomly initialized population of gain pairs, evaluates their performance using a cost function based on navigation efficiency, and iteratively improves them through selection, crossover, and mutation. This process effectively identifies optimal parameters, improving the robot's ability to navigate complex environments safely and efficiently.

The figure below represents a diagram detailing the optimization process of artificial potential field parameters by the genetic algorithm :

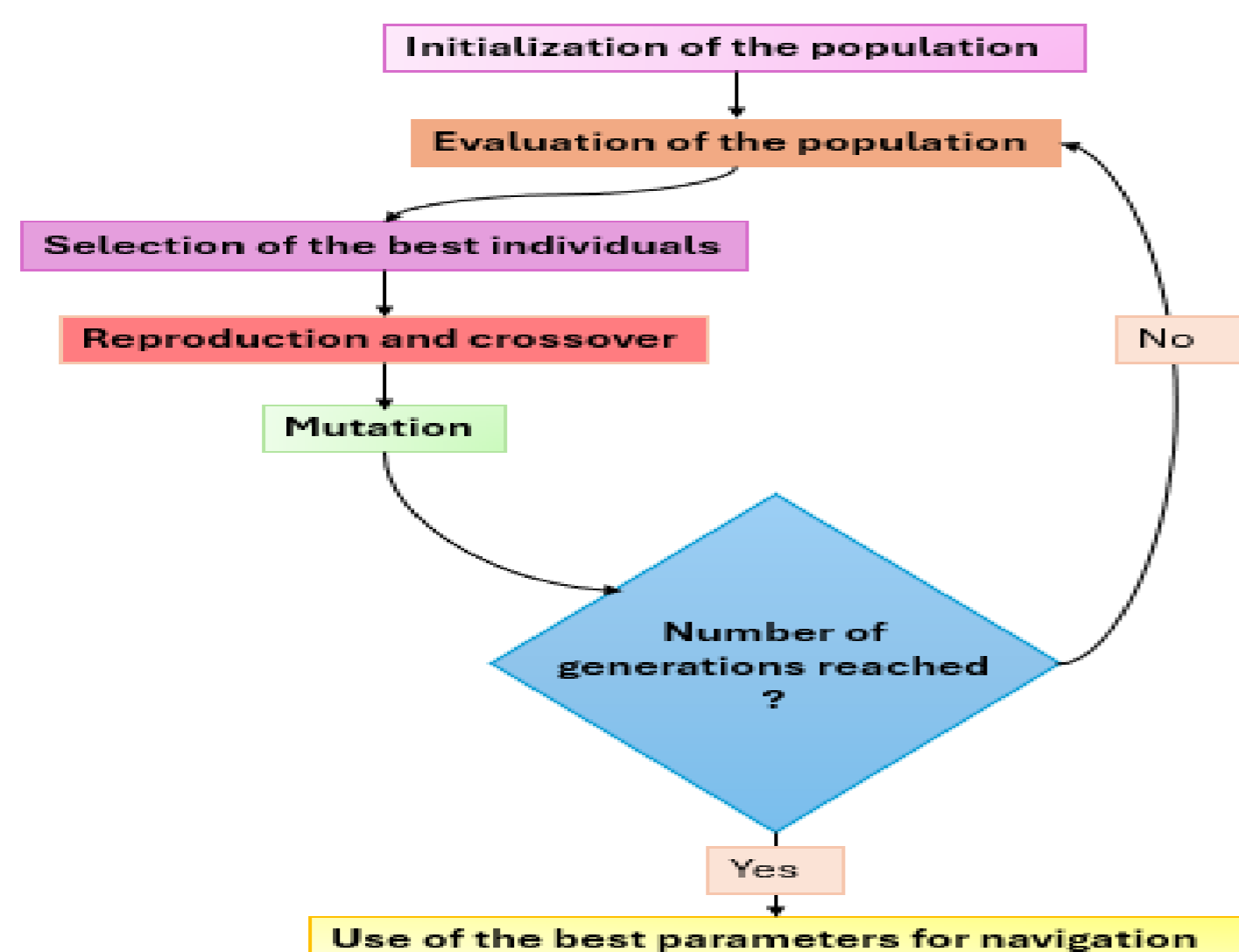
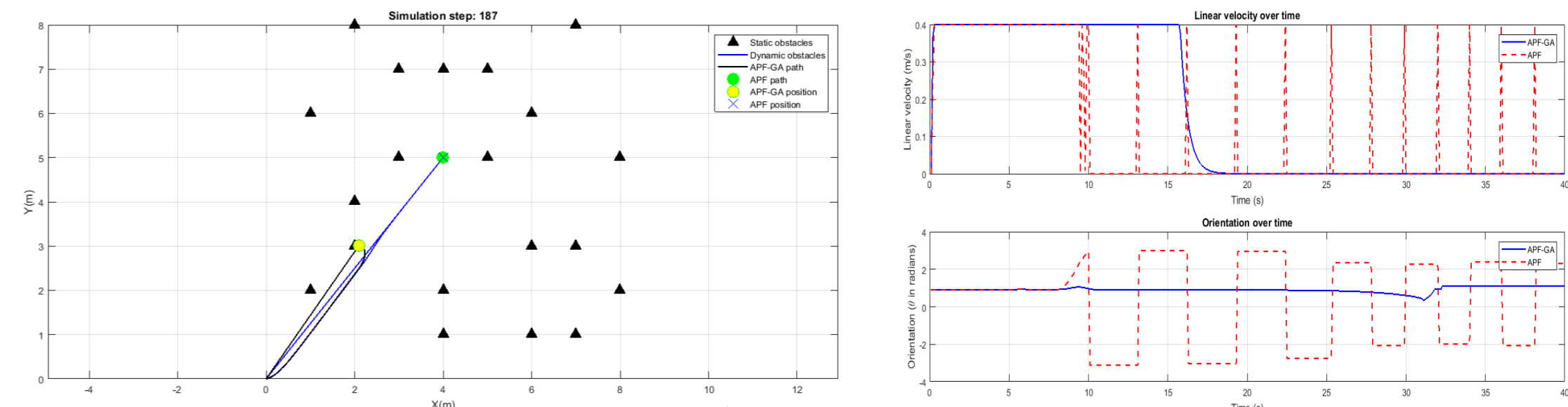


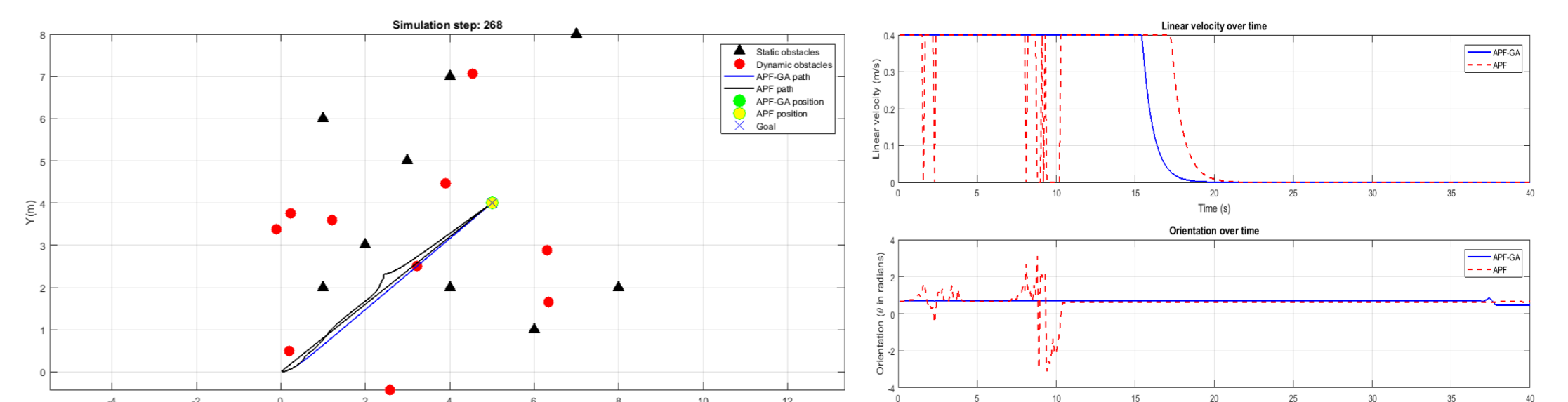
Figure 1. Diagram of the APF Parameter Optimization Process by Genetic Algorithm (GA).

RESULTS & DISCUSSION

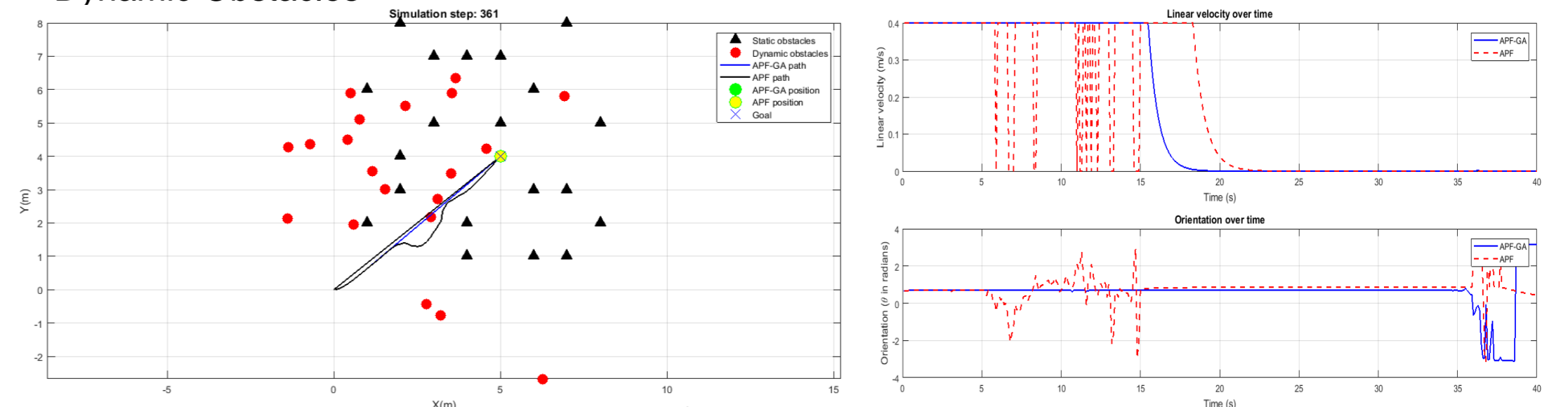
The APF-GA method was evaluated and compared to the traditional APF in environments with static and dynamic obstacles. Simulations were conducted in a 10x10 m environment with three configurations: (1) 20 static obstacles, (2) 10 static and 10 dynamic obstacles, and (3) 20 static and 20 dynamic obstacles. Using MATLAB, the APF-GA method optimized the attraction (k_p) and repulsion (η) constants through a genetic algorithm with a population of 50 individuals over 100 generations.



a) Performance Comparison of APF and APF-GA in an Environment with 20 Static Obstacles



b) Performance Comparison of APF and APF-GA in an Environment with 10 Static and 10 Dynamic Obstacles



c) Performance Comparison of APF and APF-GA in an Environment with 20 Static and 20 Dynamic Obstacles

Figure 2. Performance Comparison of APF and APF-GA Across Different Obstacle Configurations

Environment	Metric	APF-GA	APF
20 Static Obstacles	Time to Goal (s)	16.1	NaN
	Total Distance (m)	6.4354	4.2932
10 Static and 10 Dynamic Obstacles	Time to Goal (s)	16.1	18.8
	Total Distance (m)	6.4343	7.6135
20 Static and 20 Dynamic Obstacles	Time to Goal (s)	16.2	22.3
	Total Distance (m)	6.4524	8.1522

Table 1: Comparison of Performance Between APF and APF-GA Methods

The results demonstrate that APF-GA significantly outperforms traditional APF by providing smoother and more direct trajectories while improving obstacle avoidance, especially with dynamic obstacles.

CONCLUSION

This study highlights the effectiveness of integrating a genetic algorithm (GA) to optimize the parameters of artificial potential fields (APF) for autonomous robot navigation. Compared to traditional APF, the APF-GA method significantly improves trajectory smoothness, efficiency, and safety, particularly in complex environments. The optimized attractive (k_p) and repulsive (η) gains resolve common APF limitations, such as stagnation at local minima and oscillations in narrow corridors, while ensuring robust and adaptive navigation.

FUTURE WORK / REFERENCES

Future work will focus on testing the APF-GA approach in real-world applications, including automated warehouses, urban navigation, and rescue missions.

[1] Abu, N. S., Bukhari, W. M., Adli, M. H., et al. (2023). Optimization of an autonomous mobile robot path planning based on improved genetic algorithms. *Journal of Robotics and Control (JRC)*, 4(4), 557-571.

[2] Szczepanski, R. (2023). Safe artificial potential field - novel local path planning algorithm maintaining safe distance from obstacles. *IEEE Robotics and Automation Letters*. Advance online publication.