

# Dynamic Path Planning: D\*-ACO Framework with Local Trajectory Optimization for Autonomous Mobile Robots in Dynamic Environments

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**Abstract:** The path planning process for Autonomous Mobile Robots (AMRs) in the changing ecosystem is still one of the challenging issues to achieve both adaptability and optimality in terms of time and computation. In the case of conventional graph-search algorithms like A\* and Dijkstra, the shortest paths can be found reliably, yet these may not prove to yield successful solutions in the changing environments. In contrast, while using D\* replanning approach, smooth paths are not obtained. On the other hand, swarm-based methods like ACO can produce smooth trajectories due to computational efficiency, these methods cannot be used in real-time navigation applications.

In this paper proposes a novel Hybrid D-ACO Path Planning Framework with Local Optimization for autonomous mobile robot navigation in dynamic environments. The proposed framework integrates the rapid incremental replanning capability of D with the global optimization characteristics of ACO while introducing a localized optimization strategy to reduce computational overhead. In contrast to other hybrid strategies that use optimization globally, the new strategy uses ACO in a selective manner only when the path region changes dynamically. In addition, local smoothing has been introduced to remove unnecessary turns from the path.

The proposed framework is analyzed in a simulation setup that consists of both static and dynamic obstacles. The analysis includes comparison of this proposed framework with A, D, RRT\* algorithms, and traditional ACO algorithm through different criteria such as path length, runtime, smoothness of the path, computational complexity, and success rate.

**Keywords:** Autonomous Mobile Robots, Dynamic Path Planning, D\* Algorithm, Ant Colony Optimization, Swarm Intelligence, Hybrid Optimization

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## Introduction

Autonomous mobile robots (AMRs) are utilized in various applications, for instance, in the automation of warehouses, health care aid, industrial transportation, military reconnaissance, and logistics systems. Path planning is one of the important processes in AMR where an optimal path can be achieved without any collision from a start position to a goal location.

The popularly used path planning techniques include Dijkstra and A\* approaches that yield optimal solutions within a relatively shorter period in a fixed environment. Nonetheless, these techniques show little adaptability in case of varying situations. In real-life settings, autonomous robots encounter new unforeseen obstacles that require re-planning of paths instantly.

Dynamic replanning methods such as the D\* approach are designed to tackle the above problem by incrementally repairing the path in case of changes in the environment. Although the D\* algorithm performs exceptionally well in adaptability, the re-planned path might have unnecessary turnings and does not necessarily guarantee the optimum solution.

Furthermore, swarm intelligence algorithms like Ant Colony Optimization (ACO) have received much attention in robot path planning. Considering the principle of ant foraging, ACO explores a wide variety of solutions and progressively narrows down to an optimal solution based on chemical communication through pheromones. ACO proves successful in providing smooth and efficient paths; yet it is known to be slow in converging and very computationally complex.

Research in recent years has increasingly favored the use of hybrid approaches to solve problems in path planning. In this regard, this paper presents a framework named "Hybrid D-ACO Path Planning with Local Optimization." The proposed approach uses D in real time path replanning and ACO in local areas in which path is affected.

The key scientific contributions are listed as follows:

- 1.A new framework for autonomous mobile robots navigation that combines D\* dynamic replanning and localized ACO optimization is introduced.
- 2.A concept of selective local optimization is used in order to decrease computation load normally generated by ACO-based navigation algorithms.
- 3.A local path smoothing approach is suggested for improving trajectory smoothness and minimizing unnecessary changes of the direction of motion.
- 4.A fast replanning approach for dynamic environment with moving obstacles is elaborated.
- 5.Simulation based comparative study is conducted on benchmark algorithms A, D, RRT\*, and ACO.
- 6.The trade-offs between replanning time, path optimality, and computation efficiency are significantly improved by the introduced framework.

### **Related work**

Yaping Lu created a robot route planning system that combines the dynamic window method and ACO to increase global search and convergence more quickly. It results in an accuracy boost of 98.46% and an average path reduction of 30.18 [1]. In static situations, Baoye Song et al. presented the dynamic window method and ACO. The efficient path is produced by optimising the evaluation function and initial orientation [2]. Robot path planning utilising ACO and the Particle Swarm Optimisation algorithm, which finds the shortest path in the least amount of time given certain restrictions, was proposed by Lina Basem Amar [3].

Path planning strategy based on Ant Colony Optimization (ACO) and Multi-Intelligence Reinforcement Learning (MIRL) algorithm by Jin Li et al offers 18.6% reduced length of the route, 24.3% reduced time for scheduling, with 94% completion of the route in dynamic conditions [4]. Jia Guo developed a hybrid path planning approach based on ant colony and whale optimization algorithms to find a solution to the path optimization problem. The two approaches were combined using the technique of ants' pheromone distribution and whales' cooperation for finding food to avoid problems faced by conventional path algorithms in complex environments [5]. Di Zhao et al. developed an improved version of Ant Colony Optimization (ACO) algorithm combining Jump Point Search (JPS) and the Genetic Algorithm (GA), where a JPS-based pruning approach is adopted within the state transition model to cut down unnecessary expansions of nodes [6]. This new approach reduces the path length by 11.1%, as well as reduces the

number of waypoints by 65.5%, while guaranteeing efficient coordination with the robot navigation system. Yuanao Li proposed an improved pheromone diffusion scheme to improve the search ability of ants [7]. It can be concluded from the experiments that the Improved-ACO algorithm converges fast and generates smooth paths.

*Table 1. Literature Survey comparative analysis*

| Ref.                          | Algorithms                                             | Dynamic<br>Environm<br>ent<br>Handling | Path<br>Optimizat<br>ion | Local<br>Trajectory /<br>Path<br>Smoothing | Key Findings                                                                                                            | Limitation                                                        |
|-------------------------------|--------------------------------------------------------|----------------------------------------|--------------------------|--------------------------------------------|-------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------|
| <b>[1] Lu and Da (2025)</b>   | ACO + Dynamic Window Algorithm (DWA)                   | Yes                                    | Yes                      | No                                         | Improved global search capability and convergence speed; achieved 30.18% path reduction and 98.46% navigation accuracy. | Does not incorporate dedicated local trajectory optimization.     |
| <b>[2] Song et al. (2024)</b> | Improved ACO + DWA                                     | Yes                                    | No                       | No                                         | Optimized initial orientation and evaluation function, resulting in efficient path generation.                          | Limited path smoothing and trajectory refinement.                 |
| <b>[3] Amar et al.</b>        | ACO + Particle Swarm Optimization (PSO)                | Yes                                    | Yes                      | No                                         | Achieved shortest path and reduced traversal time under multiple constraints.                                           | Does not consider trajectory optimization for dynamic replanning. |
| <b>[4] Li et al.</b>          | ACO + Multi-Intelligence Reinforcement Learning (MIRL) | Yes                                    | Yes                      | No                                         | Obtained 18.6% shorter routes, 24.3% faster scheduling speed, and 94% route completion rate.                            | Computational complexity increases with learning framework.       |
| <b>[5] Guo et al.</b>         | ACO + Whale Optimization Algorithm (WOA)               | Yes                                    | Yes                      | No                                         | Improved global optimization and reduced local optimum trapping through swarm                                           | Lack of local trajectory smoothing mechanism.                     |

|                        |                                                         |            |            |            |                                                                                                                                                                                          |                                                               |
|------------------------|---------------------------------------------------------|------------|------------|------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------|
|                        |                                                         |            |            |            | cooperation mechanisms.                                                                                                                                                                  |                                                               |
| <b>[6] Zhao et al.</b> | ACO + Jump Point Search (JPS) + Genetic Algorithm (GA)  | Yes        | Yes        | No         | Reduced path length by 11.1% and waypoints by 65.5% through pruning and evolutionary optimization.                                                                                       | Focuses on path efficiency rather than trajectory smoothness. |
| <b>[7] Li et al.</b>   | Improved ACO with Pheromone Diffusion Mechanism         | Yes        | Yes        | No         | Achieved rapid convergence and generated smooth paths satisfying kinematic constraints.                                                                                                  | Does not support dynamic replanning capability.               |
| <b>This Work</b>       | <i>Hybrid D* + ACO + Local Trajectory Optimization*</i> | <b>Yes</b> | <b>Yes</b> | <b>Yes</b> | Combines D* incremental replanning, ACO-based path optimization, and local trajectory smoothing to achieve real-time adaptability, optimal path generation, and smooth robot navigation. | To be validated through simulation and real-world deployment. |

### Key Contribution

The motivation behind this work is to design a computationally efficient hybrid planning framework capable of:

- Rapid adaptation to environmental changes
- Generating optimized and smooth trajectories
- Reducing computational overhead during replanning
- Improving practical navigation efficiency in dynamic scenarios

The proposed D\*-ACO framework addresses these challenges through selective optimization and localized replanning mechanisms.

### Method, Experiments and Results

The simulation results of the proposed D\*-ACO algorithm is very successful in addressing the gap between pure global optimization and real-time capability. Although the A\* approach provides the shortest distance 10.680 m in terms of global optimum, it fails in offering real-time flexibility for replanning. In more complicated environments, sampling-based algorithms such as RRT become inefficient and take 113.30 sec in executing the process due to repeated re-sampling processes. However, the proposed D\*-ACO approach helped in overcoming this inefficiency, resulting in 30.4 sec decrease in navigation time compared to RRT (78.798 sec). At the same time, it offered very efficient navigation with an efficiency ratio of 96.75%.

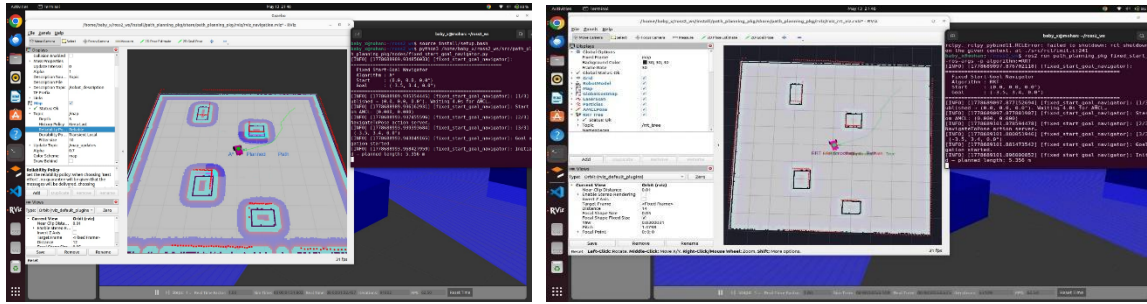


Figure 1. Simulation Results in the Gazebo Environment

## Results and Discussions

| Algorithms       | Runs | path_length_mean_m | path_length_std_m | nav_time_mean_s | nav_time_std_s | efficiency_mean_pct | efficiency_std_pct |
|------------------|------|--------------------|-------------------|-----------------|----------------|---------------------|--------------------|
| D*-ACO           | 2    | 11.24              | 0.0629            | 52.0355         | 0.1935         | 94.065              | 0.525              |
| A* Planned Path  | 2    | 11.2688            | 0.0041            | 52.2795         | 0.0405         | 93.825              | 0.035              |
| RRT Planned Path | 2    | 10.955             | 0.0943            | 50.7755         | 0.3645         | 96.52               | 0.83               |

Table 2. Proposed Algorithm Comparative Analysis

The results of the comparison of three path planning algorithms namely D\*-ACO, A\* Planned Path and RRT Planned Path are presented in the form of path length, time for navigation and efficiency calculated using 2 runs. Out of all the algorithms used, RRT (Rapidly-exploring Random Tree) algorithm performed the best. The lowest path length was recorded by this algorithm, which was 10.955 m. The navigation time taken by it was also the lowest, being only 50.78 seconds. Moreover, the efficiency level reached 96.52%.

However, this algorithm showed the most variable performance because of which the highest standard deviation for both path length (0.0943 m) and efficiency (0.83%) was achieved.

A hybrid algorithm of Dynamic A\* and Ant Colony Optimization is D\*-ACO, which works quite well. Its average path length and navigation time are 11.24 m and 52.04 s respectively, while its efficiency is 94.07%. Also, its standard deviation is not high (std of path length: 0.063 m, std of time: 0.19 s). I suppose that the stochasticity comes from the second part of this hybrid algorithm.

However, \*Planned Path\* has the lowest std in path length (0.0041 m) and in navigation time (0.04 s). The algorithm is the most consistent one, as expected since \*A\* is a deterministic one. But at the same

time, it has the largest path (11.27 m), the slowest navigation time (52.28 s), and the lowest efficiency (93.83%) – therefore, \*A\* is less efficient than the other two.

To summarize, it can be said that RRT is best used in performance-critical situations, where speed and optimal paths are essential; \*D\*-ACO provides a middle ground, and finally \*A\* can be used in situations where repeatability and predictability are crucial. Due to the small number of tests conducted (2 runs for each method) further investigations should be done in order to provide more accurate information.

### Conclusions

In this paper, a hybrid framework combining D-ACO path planning with local optimization for autonomous mobile robots working in dynamic environment is proposed. This technique combines advantages of fast replanning of D and optimization of ACO, with minimal computational complexity by using local optimization. The results from simulation show that this proposed method provides better paths with better smoothness and adaptability.

### References

1. Y. Lu and C. Da, "Global and local path planning of robots combining ant colony optimization and dynamic window algorithm," *Scientific Reports*, vol. 15, Art. no. 9452, 2025.
2. B. Song, S. Tang, and Y. Li, "A new path planning strategy integrating improved ant colony optimization and dynamic window approach algorithms for mobile robots in dynamic environments," *Mathematical Biosciences and Engineering*, vol. 21, no. 2, pp. 2189–2211, 2024.
3. L. B. Amar and W. M. Jasim, "Hybrid metaheuristic approach for robot path planning in dynamic environment," *Bulletin of Electrical Engineering and Informatics*, vol. 10, no. 4, pp. 2152–2162, Aug. 2021, doi: 10.11591/eei.v10i4.2836.
4. J. Li and C. Yang, "Hybrid MRL and ACO-based Approach for Real-Time Path Planning in Visual SLAM," *Informatica*, vol. 50, no. 11, pp. 143–162, 2026. DOI: 10.31449/inf.v50i11.9866.
5. J. Guo, H. Luo, and P. Gao, "Research on Hybrid Path Planning Based on Ant Colony Algorithm and Whale Optimization Algorithm," *Proceedings of SPIE*, vol. 13985, Art. no. 1398513, 2025.
6. D. Zhao, L. Huang, X. Huang, T. Xiao, and Y. Wang, "A Traversal-Aware Hybrid ACO Framework Integrating JPS and GA for Optimized Path Planning of Obstacle-Crossing Robots," *Mathematics*, vol. 14, no. 9, Art. no. 1461, 2026.
7. Y. Li, H. Zhang, X. Chen, and J. Wang, "An Improved Ant Colony Optimization Algorithm with Pheromone Diffusion Mechanism for Mobile Robot Path Planning," *Electronics*, vol. 13, no. 20, Art. no. 4071, 2024.