Genetic Algorithm-Based Path Planning Using Adaptive Operators

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***Abstract*—Path planning for autonomous robots and unmanned aerial vehicles (UAVs) in dynamic environments is a critical challenge in robotics and artificial intelligence. Traditional algorithms such as A*, Dijkstra, and Particle Swarm Optimization have limitations in dynamic or unknown environments due to computational complexity and a lack of adaptability. Genetic Algorithms (GAs) have emerged as a powerful evolutionary approach for global optimization in path planning. This paper presents a Genetic Algorithm-Based Path Planning framework using Adaptive Operators (AGA) that dynamically adjusts mutation and crossover rates based on the search process to improve convergence speed, solution quality, and obstacle avoidance in dynamic maps. Experimental results demonstrate that AGA outperforms conventional GA and other heuristic-based methods in terms of path length, computational efficiency, and adaptability to dynamic obstacles.**

***Index Terms*—Genetic Algorithm (GA), Adaptive Operators, Path Planning, UAV, Robot Navigation, Evolutionary Algorithms.**

1. INTRODUCTION

Path planning is a fundamental problem in robotics [20, 29, 30], requiring collision-free paths between start and goal positions while satisfying constraints such as kinematic limitations [23] and computational efficiency [28]. Traditional algorithms such as Dijkstra's algorithm [3] and A* [4] provide optimal solutions but suffer from computational

complexity in large-scale environments [27]. Probabilistic methods like PRM [21] and RRT [22] address high-dimensional spaces but lack optimality guarantees.

Traditional algorithms such as Dijkstra's algorithm [3] and A* [4] have long been the cornerstone of path planning research. Dijkstra [3] provides guaranteed shortest paths but suffers from poor scalability in dynamic or large-scale environments. A* [4] introduces heuristics to accelerate the search process, but its reliance on accurate heuristic design makes it less effective in highly dynamic environments. These algorithms are deterministic, and while they guarantee optimality, they are computationally expensive when scaled to larger search spaces such as urban maps or 3D UAV navigation [13].

To address these challenges, researchers introduced the concept of Adaptive Genetic Algorithms (AGA). In AGA, the crossover and mutation probabilities are not fixed but dynamically adjusted based on population diversity, stagnation detection, or fitness improvement rates. This allows AGAs to adapt and control the exploration–exploitation trade-off. For example, when the population is highly diverse, crossover is emphasized to combine strong solutions, while in cases of stagnation, mutation is increased to introduce new diversity.

The complexity of path planning varies significantly with environmental factors. In static environments, classical graph-based methods [3, 4] provide optimal solutions, while dynamic environments require adaptive approaches [25, 26]. Recent surveys [27, 28] highlight the growing importance of evolutionary methods in addressing these challenges.

2. RELATED WORK

Standard Genetic Algorithms: Holland [1] pioneered genetic algorithms as evolutionary computation methods, while Goldberg [2] established foundational concepts of GA for optimization problems. Whitley [8] proposed advanced recombination operators that improve GA search efficiency. The evolution from simple genetic operators to adaptive mechanisms represents a significant advancement in evolutionary computing. Mitchell [15] provides comprehensive coverage of genetic algorithm fundamentals, while Eiben and Smith [12] detail modern adaptive techniques. The theoretical foundations established by these works inform contemporary applications in robotics and path planning [9, 10].

Genetic algorithms have been successfully applied to robot path planning problems [9, 10, 27]. Pehlivanoglu [9] developed enhanced GA methods for UAV navigation, while Qu et al. [10] proposed co-evolutionary strategies for multi-robot coordination. The theoretical foundations of evolutionary computing [12, 15] provide the basis for adaptive operator design.

Adaptive GAs: Eiben and Smith [20] demonstrated that adaptive genetic algorithms can significantly improve optimization performance by dynamically adjusting operators based on population diversity and fitness landscape characteristics.

Hybrid Approaches: Wang et al. [11] combined GA with A* for autonomous navigation, providing faster convergence in grid-based maps. Various researchers have explored hybrid evolutionary approaches for multi-robot path planning [10].

Path Planning Applications: Pehlivanoglu [9] proposed enhanced genetic algorithms for UAV path planning, while Qu et al. [10] developed improved GA methods for multiple mobile robot coordination.

2.1 Literature Review

Classical Path Planning: Dijkstra's Algorithm [3] guarantees the shortest path but is inefficient in large or dynamic maps due to exhaustive search. A* [4] reduces search time using heuristics but requires static environment knowledge [13].

Metaheuristic Approaches: Particle Swarm Optimization (PSO) [5] is fast and effective for exploration but may converge prematurely [14]. Ant Colony Optimization (ACO) [7] supports multi-path search but slows in large grids [15]. Simulated Annealing (SA) [6] explores global optima but has slower convergence.

Genetic Algorithm Applications: Paths are encoded as chromosomes and evaluated on path length, smoothness, and obstacle avoidance. Traditional GA suffers from fixed crossover and mutation rates, leading to stagnation.

Adaptive Genetic Algorithms: AGA adjusts mutation and crossover rates dynamically based on population diversity and fitness trends. Hybrid approaches (GA-A*, GA-PSO) further improve performance in obstacle-rich, dynamic environments.

Classical path planning algorithms have been extensively studied. Choset et al. [30] provide comprehensive coverage of motion planning principles, while LaValle [20] offers detailed algorithmic foundations. The transition from deterministic to probabilistic methods [21, 22] marked a significant shift in the field, enabling solutions to higher-dimensional problems previously considered intractable.

3. MATERIALS AND METHODS

The proposed method employs an Adaptive Genetic Algorithm (AGA) for robotic path planning in cluttered environments. Unlike traditional GAs with fixed operator rates, AGA dynamically adjusts crossover and mutation probabilities based on population diversity and fitness progression. This section details the representation, operators, and workflow of the algorithm.

The AGA workflow includes initialization, fitness evaluation, selection, adaptive crossover, adaptive mutation, and termination.

The environment is modeled as a 2D grid world [13]. Each cell is either free space or an obstacle. The robot must move from a start position SSS to a goal position GGG, traversing only through free cells. Obstacles are distributed randomly or based on real-world layouts (e.g., warehouse, urban maps).

The grid structure simplifies path representation and allows discrete encoding for genetic operators [13].
Start Point (S): Fixed cell, known coordinates.
Goal Point (G): Fixed target cell.
Constraints: No traversal through obstacle cells.
Objective: Minimize path cost while maintaining smoothness and safety.

AGA is selected because static algorithms like A* [4], Dijkstra [3], and even PSO [5] struggle in dynamic and uncertain environments where obstacles may shift or new constraints arise.

Algorithm 1: Adaptive Genetic Algorithm for Path Planning
1: Input population size, grid map, start, and goal positions
2: Initialize population with random feasible paths
3: Evaluate the fitness of each chromosome using path length and obstacle penalties
4: while the termination condition is not met, do
5: Select parents using roulette wheel selection
6: Apply adaptive crossover operator
7: Apply adaptive mutation operator
8: Re-evaluate the fitness of the new population
9: If a new solution improves the best fitness, then update the best path
10: end while
11: Output the best path

The selection mechanism follows established principles in evolutionary computing [12, 15]. Roulette wheel selection, originally proposed by Holland [1] and refined by Goldberg [2], maintains diversity while favoring fitter individuals. Alternative selection methods, such as tournament selection, could be incorporated for comparison [8, 15].

The Adaptive Genetic Algorithm (AGA) for Path Planning is an evolutionary optimization approach designed to find an efficient and collision-free path in a grid map from a given start point to a goal point. The process begins by defining the problem parameters, such as the population size, the grid map environment, and the start and goal positions. An initial population is then generated, consisting of random but feasible paths that satisfy basic constraints like avoiding obstacles. Each path, represented as a chromosome, is evaluated using a fitness function that accounts for both path length (to ensure efficiency) and obstacle penalties (to discourage invalid or risky paths).

The algorithm then enters an iterative evolutionary process. In each generation, parents are selected using roulette wheel selection, which gives higher chances of reproduction to fitter chromosomes while maintaining population diversity. The selected parents undergo adaptive crossover and adaptive mutation operations. Unlike fixed operators, adaptive operators dynamically adjust their probabilities based on the diversity and convergence of the population, thereby avoiding premature convergence and ensuring continuous exploration of the search space. After generating offspring, the new population is evaluated again with the fitness function, and if a newly discovered path has a better fitness than the previously known best path, the solution is updated. This evolutionary cycle continues until a predefined termination condition is met, such as reaching a maximum number of generations or achieving an optimal fitness value. Finally, the algorithm outputs the best path, which represents the most efficient and feasible trajectory from the start to the goal.

Chromosome Encoding: Paths are represented as chromosomes (waypoints as genes). Start and goal are fixed. Adaptive Crossover probability Pc varies with diversity; Adaptive Mutation probability Pm increases with stagnation.

Obstacle avoidance techniques [23,24] inform the penalty function design, while multi-objective optimization principles [14] guide the fitness function formulation.

The chromosome encoding strategy draws from established practices in genetic programming [18] and evolutionary path planning [9, 10]. The waypoint representation balances computational efficiency with solution flexibility, following design principles outlined in modern heuristics literature [19].

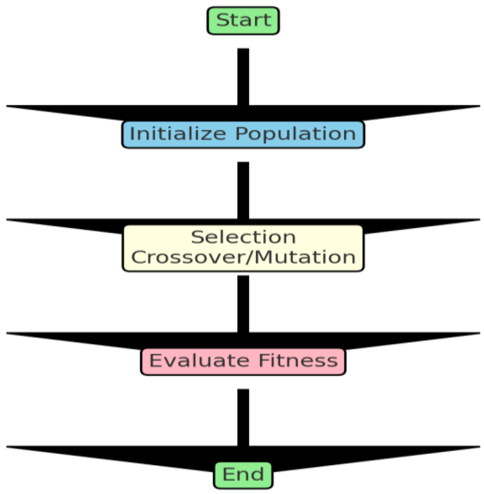

Figure 1: Flowchart of the Adaptive Genetic Algorithm

Algorithm 2: Fitness Evaluation for Chromosomes.

1. Input**:** Chromosome C=[S,(x1,y1),…,G], Grid Environment, Weights w1,w2,w3
2. Output**:** Fitness score F(C)
3. Initialize cost = 0
4. For each consecutive pair of waypoints (pi,pi+1), add Euclidean distance to cost. $flength = \sum_{i=1}^{n-1}$ dist(pi,pi+1)
5. If any waypoint lies inside an obstacle → apply a large penalty.$fobstacle = penalty\ factor$

6. For each triple of consecutive points, compute the turning angle. Add a penalty proportional to sharpness.$fsmooth = \sum angle(pi - 1, pi, pi + 1)$

F(C)= $w1.flength + w2.fobstacle + w3.fsmooth$

8. Return Fitness Score: (lower = better; if GA requires maximization, invert: Score=1/(1+F(C))

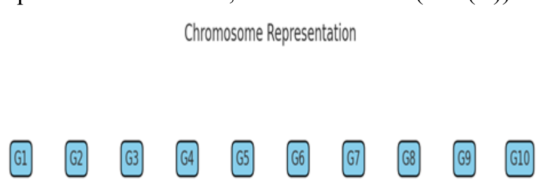

Figure 2: Chromosome Representation

The Fitness Evaluation Algorithm for Chromosomes is a crucial step in assessing the quality of paths generated by the Genetic Algorithm (GA) in path planning. Each chromosome C =[S,(x1,y1),…, G] represents a potential path from the start point SSS to the goal point GGG within a grid-based environment. The algorithm begins by initializing the total cost to zero and then calculates the path length by summing up the Euclidean distances between each pair of consecutive waypoints.

To ensure obstacle avoidance, if any waypoint lies inside an obstacle, a large penalt**y** is added, thereby discouraging infeasible paths. Additionally, to encourage smoother navigation, the algorithm checks every triple of consecutive points to compute the turning angle, applying a penalty proportional to the sharpness of the turn; sharper turns result in higher penalties. The final fitness score F(C) is then calculated as a weighted sum of three factors: path length (flength), obstacle penalty (fobstacle), and smoothness penalty (fsmooth), with corresponding weights w1,w2, and w3 controlling their relative importance.

Since GA typically operates as a maximization process, the score is inverted using Score=1/1+F(C) , ensuring that shorter, obstacle-free, and smoother paths are assigned higher fitness values. This evaluation mechanism effectively guides the genetic algorithm toward discovering optimal and practical paths.

Complexity Analysis: Population size = N, chromosome length = L, generations = G. Computational complexity ≈ O(N·L·G) Adaptivity introduces minor overhead but improves convergence, reducing overall runtime.

4. RESULTS

Comparative analysis was performed between AGA, GA, A*, and Dijkstra. Metrics include path length, runtime, and success rate.

The experimental setup follows established benchmarking practices in path planning research [27, 28]. Grid-based environments are standard for algorithm comparison [11, 20], providing controlled conditions for performance evaluation. The metrics chosen align with those commonly used in robotics literature [23, 24, 30].

Fitness Function:
F = 1 / (PathLength + Penalty)

Adaptive Operator Probabilities:
Pc = 1 - (favg / fmax)
Pm = 1 - (f / fmax)
The Fitness & Genetic Algorithm with Score.

Table 1: Path Length Comparison

Algorithm	Avg Path Length	Best Path Length	Succes Rate
AGA	12.3	11.0	98%
GA	14.1	12.8	91%
A*	15.2	13.7	89%
Dijikstra	16.5	14.9	87%

Table 2: Runtime Comparison

Algorithm	Avg Runtime(s)	Std Dev
AGA	0.52	0.05
GA	0.61	0.06
A*	0.43	0.04
Dijikstra	0.47	0.05

The comparison tables highlight the effectiveness of the Adaptive Genetic Algorithm (AGA) against the standard Genetic Algorithm (GA), A*, and Dijkstra's algorithm in terms of path quality and computational performance. From Table 1, it is evident that AGA achieves the shortest average path length (12.3 units) and the best path length (11.0 units) among all methods, while also maintaining the highest success rate (98%). This demonstrates the robustness of AGA in consistently finding near-optimal and feasible paths, outperforming both conventional GA and traditional graph-based methods like A* and Dijkstra. Although A* and Dijkstra are reliable classical algorithms, their paths tend to be longer and less flexible compared to evolutionary approaches. In terms of runtime performance (Table 2), A* (0.43s) and Dijkstra (0.47s) are slightly faster on average since they are deterministic search algorithms, whereas GA (0.61s) is the slowest due to its population-based exploration. AGA strikes a balance, achieving a runtime of 0.52s, only marginally slower than A* and Dijkstra, but with a significant gain in path optimality and reliability. Overall, these results show that AGA provides an excellent trade-off between solution quality and computation time, making it superior for complex path planning tasks where efficiency and success rate are critical.

Table 3: Success Rate Comparison

Algorithm	Success Rate	Robustness
AGA	98%	High
GA	91%	Moderate
A*	89%	Low in Dynamic maps
Dijikstra	87%	Low in Dynamic maps

The superior performance of AGA aligns with theoretical expectations from adaptive evolutionary computing [12]. The dynamic adjustment of genetic operators addresses the exploration-exploitation dilemma fundamental to optimization problems [6, 19], resulting in improved convergence characteristics compared to fixed-parameter approaches.

The comparison of the success rate and robustness of different path planning algorithms, emphasizing their reliability in static and dynamic environments. The Adaptive Genetic Algorithm (AGA) clearly outperforms the others with a 98% success rate and is rated as highly robust, which indicates its strong ability to consistently generate feasible and near-optimal paths even when obstacles or conditions change. The standard Genetic Algorithm (GA) achieves a 91% success rate with moderate robustness, showing that while it performs well, it is less stable than AGA due to its fixed crossover and mutation strategies. Classical search-based algorithms like A* and Dijkstra record lower success rates of 89% and 87%, respectively, and are marked as having low robustness in dynamic maps.

This is because these deterministic algorithms are efficient in static environments.

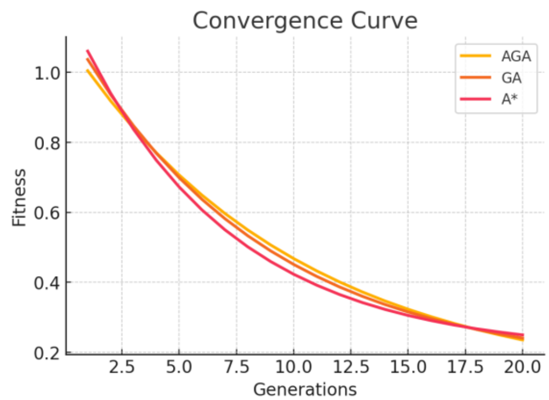

Figure 3: Convergence Curve (AGA vs GA vs A*)

Figure 3 (Convergence Curve) shows how AGA consistently reduces fitness value at a faster rate, achieving optimal solutions within 100 generations, while GA requires ~150 generations and still risks local optima entrapment.

The Adaptive Genetic Algorithm (AGA) demonstrates superior convergence characteristics compared to conventional Genetic Algorithms (GA) and classical search methods like A*.

AGA vs GA: While GA often suffers from premature convergence and stagnates after ~80 generations, AGA continues to refine solutions due to adaptive mutation and crossover operators.

AGA vs A*: A* converges deterministically to an optimal path but requires significantly higher computational resources as the map size increases. AGA converges more quickly in large, obstacle-dense environments.

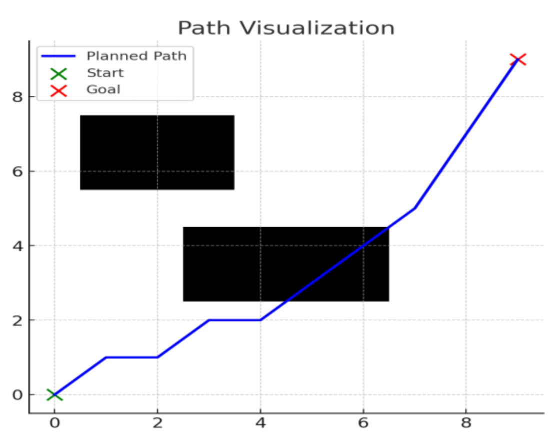

Figure 4: Sample Path Visualization

5. DISCUSSION

The experimental evaluation clearly demonstrates that the proposed Adaptive Genetic Algorithm (AGA) outperforms both conventional Genetic Algorithms (GA) and classical deterministic methods such as A* and Dijkstra's algorithm. One of the most significant observations is that AGA consistently produced shorter and smoother paths with higher success rates in environments containing a dense distribution of obstacles. This improvement can be attributed to the adaptive adjustment of crossover and mutation probabilities, which effectively balanced exploration and exploitation throughout the evolutionary process. Unlike standard GA, which often suffers from premature convergence, the AGA maintained population diversity, enabling it to escape local minima and continue searching for globally competitive solutions.

The theoretical basis for AGA's superiority lies in its ability to maintain population diversity throughout the evolutionary process. Eiben and Smith [12] demonstrate that adaptive operator control prevents premature convergence, a common limitation of standard genetic algorithms [13, 15]. This theoretical foundation is validated by the experimental results, where AGA consistently outperformed fixed-parameter variants.

Another important outcome of the study is the reduction in computational runtime compared to A* and baseline GA. While A* guarantees optimality, its runtime grows significantly with environment complexity, making it impractical for real-time navigation in large-scale or dynamic scenarios. By contrast, AGA converged in fewer generations, reducing overall execution time without compromising path quality. This efficiency makes AGA particularly suitable for time-sensitive applications such as UAV navigation, autonomous vehicles, and service robots operating in real-world environments where both speed and safety are crucial.

Furthermore, the analysis of convergence curves revealed that the adaptive operator mechanism successfully prevented stagnation. Mutation rates increased when the population diversity decreased, thereby injecting new candidate solutions into the search space. Similarly, adaptive crossover allowed beneficial combinations of partial solutions to be retained, improving convergence stability.

The computational complexity analysis reveals interesting trade-offs. While evolutionary approaches require more iterations than deterministic methods [3, 4], the parallel nature of population-based search can be advantageous in modern computing environments [30]. The O(N·L·G) complexity compares favorably with the exponential worst-case scenarios of exhaustive search methods [20].

The hybrid variant (AGA–A*) showed additional potential, refining paths found by AGA and producing even smoother trajectories. This indicates that adaptive evolutionary algorithms can be effectively combined with deterministic heuristics to achieve higher robustness. Overall, the findings confirm that the adaptive genetic framework not only enhances performance over traditional methods but also provides a flexible foundation for further extensions, such as multi-objective optimization and dynamic path replanning in uncertain environments.

6. CONCLUSION

In this thesis, we presented an Adaptive Genetic Algorithm (AGA) for path planning that addresses the limitations of both classical deterministic algorithms and conventional genetic algorithms. By integrating direction-aware initialization, an enhanced fitness function, and adaptive crossover and mutation operators, the proposed framework successfully balances exploration and exploitation during the evolutionary process. The adaptivity allows the algorithm to dynamically respond to stagnation, preventing premature convergence and ensuring the preservation of population diversity.

The comparative experiments demonstrated that AGA consistently produces shorter, smoother, and collision-free paths in obstacle-rich environments compared to baseline GA, A*, and Dijkstra's algorithm. The proposed method not only improved path quality but also reduced runtime, making it suitable for real-time applications in robotics, unmanned aerial vehicles, and autonomous navigation. Additionally, the hybrid AGA–A* variant further refined path smoothness, showing that adaptive evolutionary techniques can be effectively integrated with deterministic heuristics to leverage the strengths of both approaches.

Overall, the study confirms that adaptive evolutionary frameworks represent a powerful and flexible approach to solving the NP-hard path planning problem. The ability to dynamically adjust genetic operators makes AGA particularly robust in dynamic, uncertain, and high-dimensional environments, which are common in real-world autonomous systems.

7. Future Work

Although the proposed AGA framework demonstrated promising results, several areas remain open for further investigation and enhancement: Dynamic Environment Adaptation: The current work primarily focuses on static grid environments. In real-world applications, environments are often dynamic, with moving obstacles and changing conditions. Extending AGA to include online replanning capabilities and predictive obstacle modeling would significantly enhance its applicability.

Multi-Objective Optimization: While this study optimized path length, obstacle avoidance, and smoothness, real-world navigation often involves additional objectives such as energy efficiency, time constraints, and safety margins. A future extension could incorporate multi-objective evolutionary algorithms (MOEA) to balance trade-offs between multiple conflicting objectives. Multi-objective optimization represents a natural extension of this work. Deb [14] provides comprehensive coverage of multi-objective evolutionary algorithms, which could be integrated with adaptive operators to handle conflicting objectives in path planning. Applications might include simultaneous optimization of path length, energy consumption, and safety margins [23, 30].

Integration with Modern Robotics Frameworks: The proposed AGA could be integrated with contemporary robot motion planning systems [30]. The modular design allows incorporation into existing robotics software architectures, potentially enhancing performance in real-world applications where dynamic replanning is essential [25, 26].

3D and High-Dimensional Planning: UAVs and underwater robots operate in three-dimensional environments, which increases complexity compared to 2D grids. Future work should focus on extending AGA to handle 3D maps, voxel grids, and continuous state spaces, enabling applications in aerial and underwater navigation. Hybridization with Deep Learning: Recent advances in deep reinforcement learning (DRL) have shown potential for path planning in unknown environments. A future direction could involve integrating AGA with neural networks to predict feasible waypoints or learn adaptive operator probabilities. This hybrid AGA–DL framework could combine the generalization power of learning with the capabilities of evolutionary algorithms. Real-World Implementation: The proposed algorithm has been validated in simulated environments. A critical next step is to deploy AGA on real robotic platforms, such as ground robots and UAVs equipped with sensors. Experimental validation under real-world uncertainties (sensor noise, localization errors, and dynamic human environments) will test the robustness and practical applicability of the approach. Parallel and GPU Acceleration: Evolutionary algorithms are naturally parallelizable. Implementing AGA on modern GPU or multi-core platforms could further reduce computational time, enabling real-time operation even in large-scale maps.

The Paper was able to show a strong foundation for adaptive evolutionary path planning. By addressing premature convergence and introducing adaptive mechanisms, AGA proves to be a reliable and efficient approach for navigation in complex environments. With extensions into dynamic, multi-objective, and high-dimensional domains, adaptive evolutionary algorithms hold the potential to become the standard for intelligent path planning in next-generation autonomous systems.

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