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UAV PATH PLANNING MODEL LEVERAGING MACHINE LEARNING AND SWARM INTELLIGENCE FOR SMART AGRICULTURE

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Abstract. Smart agriculture, through precision farming, is revolutionizing traditional farming methods by optimizing resource use and enhancing yields. With the integration of technology, especially the advent of Unmanned Aerial Vehicles (UAVs) or drones, modern agriculture has attained new heights in efficient crop management, real-time data collection, and sustainable practices. UAVs play a pivotal role, offering aerial insights into crop health, soil conditions, and targeted resource application, promoting sustainable farming. However, navigating UAVs efficiently across dynamic agricultural terrains presents challenges, particularly in path planning. While traditional grid-based models have their merits, the complexities of modern farms demand more adaptive models. This work introduces a hierarchical path planning framework for UAVs, combining the "Enhanced Genetic Algorithm using Fuzzy Logic" for global planning and the "Improved D* Algorithm" for real-time local adjustments. This dual-layered approach ensures efficient, safe, and energy-conserving UAV trajectories, marking a significant advancement in UAV-based smart agriculture.

Key words: Unmanned Aerial Vehicles, Precision Farming, Grid-Based Models, D* Algorithm, Smart Agriculture

1. Introduction. Smart agriculture has reshaped the way we perceive and practice traditional farming. Through the lens of precision farming, the nuances of crop management are being meticulously addressed, leveraging data-driven insights to optimize resource utilization and maximize yields. The influence of autonomous vehicles in this domain underscores the potential of technology to enhance and streamline agricultural operations, bringing about a seamless integration of mechanization and intelligence [11]. This synergy promises to lead the farm sector toward unprecedented efficiency and sustainability. Unmanned Aerial Vehicles (UAVs), commonly known as drones, have emerged as revolutionary tools in modern agriculture. Their ability to swiftly traverse vast expanses of land, capturing high-resolution imagery and providing real-time data, has redefined precision farming. UAVs can efficiently monitor crop health, assess soil moisture levels, and detect pest infestations, all from an aerial vantage point. This bird's-eye view enables farmers to make informed decisions, leading to reduced input costs and increased crop yields. Furthermore, UAVs facilitate targeted applications of pesticides and fertilizers, ensuring that resources are used judiciously, minimizing environmental impact [12]. The integration of UAV technology in agriculture optimizes farm management practices and paves the way for sustainable and environmentally-conscious farming, marking a significant stride toward the future of agriculture.

In the growing field of smart agriculture, integrating UAVs offers immense potential but is not without challenges. One of the paramount issues is the intricacy of path planning for UAVs. Given agricultural landscapes' diverse and dynamic nature, plotting an efficient and safe drone route necessitates advanced algorithms and real-time data processing [7]. Factors like varying crop heights, obstacles like trees or infrastructures, and changing weather conditions can significantly influence the UAV's trajectory. While the objective is to cover

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maximum ground efficiently to gather data, avoiding collisions and ensuring the UAV's energy conservation becomes equally vital. Therefore, a practical path planning mechanism is imperative not only for the operational success of UAVs in smart agriculture but also to ensure the safety and sustainability of their application in such a crucial sector.

In addressing the path planning challenge for UAVs in smart agriculture, several existing models have been proposed and explored. Traditional approaches have primarily revolved around grid-based methods, where the agricultural field is divided into uniform cells, and the UAV's path is determined by traversing these cells based on predefined algorithms. A* and Dijkstra are classic examples renowned for their efficiency in obstacle-free environments. However, the need for adaptive and dynamic models grew as agricultural terrains became more complex. Genetic Algorithms (GAs) and Particle Swarm Optimization (PSO) have been introduced as heuristic methods to navigate intricate landscapes [8]. These algorithms simulate natural processes and behaviors to find optimal or near-optimal paths, making them more resilient to dynamic environmental changes. More recently, machine learning techniques, particularly deep learning, have been incorporated to predict and adjust UAV paths in real-time, leveraging vast datasets from past flights. While these models have highlighted promising results, a comprehensive solution that seamlessly integrates responsiveness, accuracy, and efficiency remains a subject of ongoing research.

The challenge of UAV path planning in smart agriculture demands a model that is accurate and adaptive to the varying nuances of an agricultural landscape. To tackle this, this work introduces a novel, hierarchical framework. Firstly, the farm terrain is meticulously represented through a grid environment. This grid is formed by discretizing the field into a two-dimensional lattice, where distinct cells denote either navigable or obstructed zones. To enhance clarity and reduce computational overhead, morphological operations refine this grid, highlighting only essential path-planning elements. This dynamic grid adjusts to changing agricultural conditions, ensuring the UAV's viability throughout different agricultural phases. Following the grid formation, our model sequentially integrates two sophisticated algorithms to provide optimal UAV navigation.

The first phase involves "Global path planning", utilizing the "Enhanced Genetic Algorithm using Fuzzy Logic for Global Path Planning". This algorithm evaluates various pathways throughout the grid, identifying the most efficient route from the beginning point to the target by selecting the paths with the highest fitness values. This ensures that the UAV is provided with an efficient and energy-conserving trajectory. Following the global path planning, critical path nodes are extracted, marking significant waypoints or transitions in the path. Subsequently, the "Improved D* Algorithm for Local Path Planning" is applied in the second phase. This algorithm focuses on the UAV's immediate surroundings, adjusting its real-time trajectory based on detected obstacles or unforeseen environmental changes. By doing so, the UAV can adapt quickly to ensure safe and effective local maneuvering. The culmination of these two processes yields "The optimal trajectory", guiding the UAV seamlessly from its initial point to its destination. Once this trajectory is successfully followed, the model confirms Path finding success.

The article is framed as follows: Section 2 presents the literature review, Section 3 presents the proposed model, Section 5 presents the experimental analysis, and Section 6 presents the conclusion of the work.

2. Literature Review. The arena of UAV path planning has seen extensive research and development in recent years, focusing primarily on optimization, collision avoidance, and adaptability to the varying complexities of the UAVs' environment. Aggarwal *et al.,* comprehensively analyzed various path-planning techniques used for UAVs over the years [1]. They broadly classified these techniques into representative, cooperative, and non-cooperative, emphasizing the path's optimality, shortness, and collision-free nature. An essential contribution of their work is the exhaustive comparative tables and identification of open research problems in UAV path planning, emphasizing factors such as energy efficiency, time efficiency, and robustness.ents.

Bai *et al.,* proposed a path-planning algorithm harmoniously integrated with the A∗ and DWA algorithms [2]. Their approach gave prominence to global path optimization while considering UAVs' security and speed requirements. By preprocessing the map for obstacles, they addressed inherent limitations of the standard algorithms, ensuring the UAV path is efficient and safe. Delving into the potential of reinforcement learning in UAV path planning, Tu *et al.,* highlighted its application in aquaculture cage detection [13]. They employed the Q-learning algorithm, comparing it with the SARSA algorithm. Their use case underscored the importance of energy conservation and efficiency, given the vast expanse of the sea and the scattered nature of net cages.

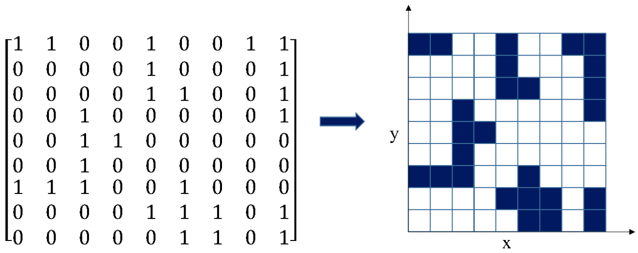

Fig. 3.1: Grid Representation

Chen *et al.,* addressed challenges in agricultural irrigation by introducing an intelligent irrigation robot [3]. Their work is pivotal for its emphasis on precision in irrigation using an improved path planning algorithm leveraging Bayesian theory. They aimed for full irrigation coverage in the complex agricultural environment, ensuring no area was inspected. Li *et al.,* brought forward an innovative integration of the improved artificial fish swarm algorithm with Bézier curves for mobile robot path planning and smoothing [6]. Their method promises enhanced planning accuracy and path continuity, meeting the kinematic demands of mobile robots.

Highlighting the potential of reinforcement learning in multi-layered path planning, Cui *et al.,* introduced a unique algorithm that assimilated local and global information for superior performance [4]. Their approach utilized B-spline curves for real-time path smoothing, proving its efficacy through various simulations. Qu *et al.,* proposed a hybrid algorithm, HSGWO-MSOS, by combining the strengths of the simplified grey wolf optimizer and the modified symbiotic organism's search [9]. Their algorithm emphasized efficiency in exploration and exploitation, offering an enhanced route for UAVs that is feasible and effective. Yan *et al.,* ventured into Deep Reinforcement Learning (DRL) for UAV path planning in dynamic and potentially threatening environments [14]. Their model simulated the UAV's survival probability against threats like missile attacks, using the D3QN algorithm for improved performance. Shao *et al.,* tackled the issue of autonomous UAV formation system path planning, proposing a comprehensively enhanced particle swarm optimization technique [10]. Their methodology emphasized rapidity and solution optimality, addressing terrain and threat constraints. Lastly, Han *et al.,* concentrated on UAV indoor path planning in complex environments [5]. They introduced a set of grid-optimized algorithms that considerably reduced computational complexity, efficiently tackled dead zone airspaces, and assured efficient and flyable path planning in intricate 3D indoor airspace.

3. Proposed Model.

3.1. Task Model. In configuring the computational representation of the agricultural terrain for UAV path planning, a meticulous grid structuring process is undertaken. This grid acts as a virtual model, aiding the UAV in discerning navigable paths from obstructed zones within the agricultural landscape. The field is discretized into a two-dimensional grid, G, where each cell, C_{ij}, corresponds to a specific area in the farmland. Cells that represent obstacles are assigned a value of O, indicating areas that are off-limits for the UAV. In contrast, cells expressing free space are assigned a value of 1, delineating safe flight zones (Figure 3.1). The binary values create a stark contrast on the grid, forming a map of passable and impassable regions for the UAV.

To ensure the UAV path planning model does not become overburdened by environmental intricacies, a combination of morphological operations, specifically dilation and erosion, is applied. These operations facilitate feature extraction, resulting in a refined grid, G', which highlights critical path planning information while negating redundant details. For the UAV to accurately locate itself within the grid, each cell is indexed with a unique coordinate pair, (x_i, y_j). The relationship between a cell's linear index, k, and its two-dimensional coordinate pair is governed by EUQ (3.1) and EQU (3.2)

$$x_i = \left\lfloor \frac{k-1}{N_x} \right\rfloor + 1 \tag{3.1}$$

$$y_j = ((k-1) \bmod N_y) + 1 \tag{3.2}$$

where N_x and N_y represent the total number of rows and columns in the grid, respectively. The functions $[\cdot]$ and mod denote the floor operation and modulus operation, instrumental in mapping the linear index to the grid coordinates. The grid environment, G', is designed to be dynamic, accommodating changes in agricultural conditions, such as seasonal crop growth or temporary obstructions like farming equipment. This dynamic aspect ensures that the path planning model remains viable throughout varying stages of the agricultural lifecycle.

3.2. Objective Function Formulation. In smart agriculture, the path-planning model aims to blend global and local methodologies to derive an optimal trajectory for UAVs. The quantification of this trajectory's optimality is captured in the objective function, F_{obj}.

Formally, this function is given by EQU (3.3)

$$F_{obj}(P) = w_1 \cdot L_{\text{global}}(P) + w_2 \cdot E_{\text{global}}(P) + w_3 \cdot T_{\text{local}}(P) - w_4 \cdot C_{\text{local}}(P) \tag{3.3}$$

where:

- P represents the UAV's path.
- $L_{\text{global}}(P)$ signifies the total length from the global path planning perspective.
- $E_{\text{global}}(P)$ corresponds to the energy consumed during the global path traversal.
- $T_{\text{local}}(P)$ denotes the time taken to focus on finer, local path intricacies.
- $C_{\text{local}}(P)$ captures the coverage of specific areas of interest from a local planning standpoint.
- w_1, w_2, w_3, and w_4 are weighting coefficients reflecting the relative significance of each component to the holistic path planning objectives.

The optimal path, while considering both global and local aspects, should satisfy the following constraints:

- *Safety Constraints:* The UAV's trajectory must bypass obstacles, notably the 0value cells in the grid environment.
- *Flight Dynamics Constraints:* Considering the UAV's inherent physical capabilities, the path is limited by its turning radius and maximum flight speed.
- *Coverage Constraints:* Ensuring complete and detailed coverage of agricultural areas is pivotal, especially zones marked for close monitoring. The route must minimize overlaps and redundancies.

3.3. Optimization Strategy. For the global path planning phase, a fuzzy-based Genetic Algorithm (GA) is employed to navigate the broader aspects of the agricultural terrain. The GA's intrinsic evolutionary process, when enhanced with fuzzy logic, provides a robust mechanism to discern optimal paths by considering the global dynamics of the agricultural landscape. In the local path planning phase, Swarm Intelligence is utilized. Swarm Intelligence, inspired by the collective behavior of decentralized systems, excels in refining trajectories. It accounts for intricate details and unexpected hindrances in the agricultural setting, ensuring the UAV can navigate tighter spaces and rapidly adjust its trajectory when faced with unforeseen challenges. Formally, the proposed model optimizes the objective function F_{obj} using these methods, targeting the following goal:

$$P^* = \arg\min_P F_{obj}(P) \tag{3.4}$$

With this optimization strategy, the hierarchical UAV path planning model seeks to determine the best possible trajectory. This trajectory balances the broad strokes of global path planning with the finer nuances of local planning, ensuring the UAV meets the demands of smart agriculture. The emphasis is firmly on precision, efficiency, and adaptability.

3.4. Proposed Enhanced Genetic Algorithm Using Fuzzy Logic for Global Path Planning. In UAV-based smart agriculture, achieving comprehensive field coverage while minimizing energy consumption and traversal time is paramount. The Genetic Algorithm (GA) has been a popular method for this task due to its inherent ability to search vast solution spaces efficiently. However, to better address an agricultural field's dynamic and often uncertain environment, integrating fuzzy logic into GA can offer significant advantages.

3.4.1. Representation and Initial Population. For the given agricultural grid, denoted as G, of dimensions $M \times N$, each chromosome in the GA represents a potential path P that the UAV can follow. This path starts at a designated point S and ends at a predetermined destination D. Utilizing the principle of random walks, we initialize our population of chromosomes. In this approach, each UAV path is generated by letting it 'walk' randomly across the grid from the start point S to the destination D, ensuring it stays within the boundaries and constraints of the grid. Through this stochastic method, many diverse pathways are conceived, providing a broad spectrum of starting solutions for the GA to refine and optimize. These random walks, while unguided, produce routes that capture the vast complexities of the agricultural landscape, laying a strong foundation for the subsequent genetic algorithm optimization.

3.4.2. Fuzzy-based Fitness Evaluation. The fitness of each path is determined by several factors: path length L(P), energy consumed E(P), and the agricultural area covered A(P). Instead of rigid thresholds, fuzzy logic can handle the imprecision in measurements. This includes the unpredictability of dynamic obstacles that may suddenly block the path, uncertain wind conditions affecting energy consumption, and varying crop heights impacting the coverage assessment. The fuzzy-enhanced fitness function may be expressed as (3.5)

$$F_{\text{fitness}}(P) = w_1 \times \mu_{\text{length}}(L(P)) + w_2 \times \mu_{\text{energy}}(E(P)) + w_3 \times \mu_{\text{area}}(A(P)) \tag{3.5}$$

Here, μ denotes the membership function in fuzzy logic, defining the degree of truth of each component.

3.4.3. Fuzzy-enhanced Selection. Given a set of chromosomes $C = \{c_1, c_2, \ldots, c_n\}$, each chromosome c_i has an associated fitness value $F_{\text{fitness}}(c_i)$. In the fuzzy-enhanced GA, a fuzzy membership function $\mu_{\text{suitability}}(c_i)$ evaluates the suitability of chromosome c_i for selection. The uncertain factor, such as obstacle, is represented as ω. If the challenges are uncertain, the adjusted fitness can be defined as EQU (3.6)

$$F'_{\text{fitness}}(c_i) = F_{\text{fitness}}(c_i) + \alpha \times \mu_{\text{wind}}(\omega) \tag{3.6}$$

where α is a factor determining the effect of obstacle uncertainty.

3.4.4. Fuzzy-enhanced Selection. For two parent chromosomes c_p and c_q, the compatibility for a crossover at a gene g_i is given by $\mu_{\text{compatibility}}(c_p[g_i], c_q[g_i])$.

The crossover point(s) X is determined as EQU (3.7)

$$X = \arg\max_i \mu_{\text{compatibility}}(c_p[g_i], c_q[g_i]) \tag{3.7}$$

This ensures that genes around point X have the highest compatibility between parents.

3.4.5. Fuzzy-enhanced Selection. For a chromosome c_i, the mutation likelihood for a gene g_j is determined by $\mu_{\text{effectiveness}}(c_i[g_j])$. If the mutation threshold is θ, a gene g_j is mutated if: $\mu_{\text{effectiveness}}(c_i[g_j]) > \theta$. This ensures targeted mutations based on the effectiveness of individual genes in the chromosome.

3.4.6. Optimization and Convergence. Optimization and Convergence: Let the optimal path after k generations be P^* and the fuzzy-adjusted path quality be $Q(P)$ considering the specific challenges and requirements of smart agriculture. As the generations progress, the optimal path is refined as EQU (3.8)

$$P^{k+1^*} = \arg\max_{P \in C^{k+1}} Q(P) \tag{3.8}$$

The algorithm converges when the quality difference between consecutive generations is below a predefined threshold, EQU (3.9)

$$\left| Q\left(P^{k^*}\right) - Q\left(P^{k+1^*}\right) \right| < \epsilon \tag{3.9}$$

The following algorithm presents the steps in the proposed enhanced GA algorithm.

Algorithm 1: Enhanced Genetic Algorithm (EGA) using Fuzzy Logic
Inputs:

- Agricultural grid G of dimensions $M \times N$.
- Start point S.
- Destination point D.
- Population size: PopSize.
- Maximum number of generations: MaxGen,
- Crossover probability: P_c.
- Mutation probability: P_m.
- Convergence threshold: ε.

Output: Optimal path P^*.
Algorithm:

1. **Initialization**
   (a) Set generation to 0.
   (b) Initialize an empty set Population.
   (c) For i from 1 to PopSize:
      i. Generate a path P_i using random walks from S to D within grid G. 1.3.2
      ii. Add P_i to Population.
2. **Evaluation**
   (a) For each path P_i in Population:
      i. Compute the fitness value:

$$F_{\text{fitness}}\left(P_i\right)=w_1 \times \mu_{\text{length}}\left(L\left(P_i\right)\right)+w_2 \times \mu_{\text{energy}}\left(E\left(P_i\right)\right)+w_3 \times \mu_{\text{area}}\left(A\left(P_i\right)\right)$$

3. **Selection**
   (a) For each chromosome c_i in Population:
      i. Evaluate the suitability using $\mu_{\text{suitability}}\left(c_i\right)$.
      ii. Adjust fitness considering uncertain obstacles:

$$F_{\text{fitness}}^{\prime}\left(c_i\right)=F_{\text{fitness}}\left(c_i\right)+\alpha \times \mu_{\text{obstacle}}(\omega)$$

4. **Crossover**
   (a) For two parent chromosomes c_p and c_q :
      i. Determine compatibility for crossover at a gene g_i by $\mu_{\text{compatibility}}\left(c_p\left[g_i\right], c_q\left[g_i\right]\right)$.
      ii. Choose crossover points X maximizing compatibility.
5. **Mutation**
   (a) For Each chromosome c_i :
      i. Determine mutation likelihood for a gene g_j by $\mu_{\text{effectiveness}}\left(c_i\left[g_j\right]\right)$.
      ii. If $\mu_{\text{effectiveness}}\left(c_i\left[g_j\right]\right)>\theta$, mutate gene g_j.
6. **Optimization and Convergence**
   (a) Determine the optimal path after k generations as P_k^* and the fuzzy-adjusted path quality as $Q(P)$.
   (b) Refine the optimal path:

$$P_{k+1}^*=\arg \max _{P \in \text { Population }_{k+1}} Q(P)$$

   (c) Check for convergence: If $\left|Q\left(P_k^*\right)-Q\left(P_{k+1}^*\right)\right|<\varepsilon$, end the algorithm.

4. Improved D* Algorithm for Local Path Planning. In the context of UAV-based smart agriculture, while global path planning designs an optimal route for comprehensive field coverage, local path planning adapts to dynamic obstacles and sudden environmental changes. The traditional D* algorithm has been effective for this purpose, but we propose an enhanced approach incorporating refined UAV safety distance determination.

- **Enhanced Cost Function:** While the basic D relies on a static cost between nodes, our improved model integrates dynamic costs influenced by numerous factors:
- **Energy Cost:** Borrowing from our global path planning model, the energy E required to traverse a path segment is included in the cost function.
- Safety Cost: Given that a UAV requires a safe distance from obstacles, especially in unpredictable agricultural terrains, a cost component S that penalizes paths too close to detected obstacles is introduced. This is determined as EQU (4.1)

$$S = k \times e^{-d} \tag{4.1}$$

where k is a constant, d is the distance from the obstacle, and e is the base of the natural logarithm. This ensures a higher cost for paths closer to blocks and vice versa. The final cost C for an edge can be represented as EQU (4.2)

$$C = w_1 \times L + w_2 \times E + w_3 \times S \tag{4.2}$$

where w_1, w_2, and w_3 are weighting factors, and L denotes path length.
- **UAV Safety Distance Determination:** The safety distance determination ensures that the UAV maintains a safe distance from obstacles (Figure 4.1). This involves geometric calculations to determine the distance between the UAV's path and nearby obstructions.
Given:
  - Coordinates of a current node P are (x_p, y_p).
  - Coordinates of the destination node Q in its path are (x_q, y_q).
  - Coordinates of an obstacle node R are (x_r, y_r).

The projection of obstacle R onto the path segment PQ is denoted by R'. The ycoordinate, $y_{r'}$ of this projection can be determined as EQU (4.3)

$$y_{r'} = \frac{(y_q - y_p)}{x_q - x_p}(x_r - x_p) + y_p \tag{4.3}$$

The angle θ between the path segment PQ and the x-axis can be found as EQU (4.4)

$$\theta = \arctan\left(\frac{y_p - y_q}{x_p - x_q}\right) \tag{4.4}$$

Now, the distance s from the obstacle R to its projection R' on the path, PQ is EQU (4.5)

$$s = |y_r - y_{r'}| \tag{4.5}$$

- **Safety Threshold and Path Consideration**: A predefined safety threshold, T, is essential. If s is less than T, the path might be too close to the obstacle and should be reconsidered. However, considering environmental factors and UAV specifications, a dynamic adjustment factor, Δ, is introduced. This adjustment factor modifies the safety threshold based on real-time data, EQU (4.6)

$$T' = T + \Delta \tag{4.6}$$

Now, if $s < T'$, the UAV should reconsider the path. Otherwise, it can continue on the path PQ. The above equation, Δ, represents the dynamic adjustment factor influenced by UAV speed, wind conditions, and obstacle mobility. For instance, the safety threshold should be increased if an obstacle moves.
- **Path Smoothing Optimization**: One of the challenges with any path planning algorithm is that the generated path might not always be smooth. Sharp turns or zigzag patterns may be introduced in the path, especially when navigating through dense obstacle environments. Such paths are inefficient

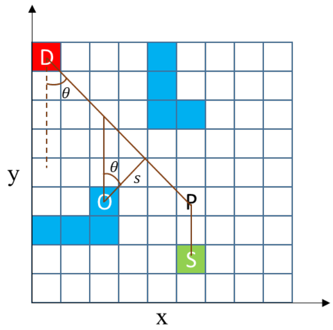

Fig. 4.1: Determining Safety Distance

for a UAV, leading to rapid battery drain, instability, and reduced safety. Thus, path smoothing optimization ensures that the UAV's path is as streamlined as possible, reducing unnecessary movements and providing a more efficient trajectory.
Bezier curves are a mathematical tool in computer graphics designed to generate smooth curves. By employing Bezier curves, we can transform a series of linear segments into a smooth curve that preserves the original waypoints and reduces inflections. Given two control points A and B and two endpoints, P_0 and P_1, the Bezier curve $B(t)$ is defined as EQU (4.7)

$$B(t) = (1-t)^3 P_0 + 3(1-t)^2 tA + 3(1-t)t^2 B + t^3 P_1 \tag{4.7}$$

where $0 \leq t \leq 1$. A cost function can be defined to evaluate the smoothness of a path. The cost is higher for paths with sharp turns or abrupt changes in direction. Given a path segment s, the cost $C(s)$ could be related to the derivative of the path concerning distance, squared, EQU (4.8)

$$C(s) = \int_{\text{path}} \left(\frac{d^2 s}{dt^2}\right)^2 dt \tag{4.8}$$

The goal is to minimize $C(s)$ to achieve the smoothest path. Often, a single pass of optimization might not yield the best results. Iterative refinement involves running the smoothing algorithm multiple times, tweaking parameters, and adjusting waypoints as needed until a desired level of smoothness and efficiency is achieved.

- **Collision Check after Smoothing:** Path smoothing optimizes UAV trajectories, eliminating abrupt changes and ensuring energy-efficient movement. However, as trajectories are modified, the risk of infringing upon safety margins around obstacles may inadvertently increase. Thus, postsmoothing collision checks are indispensable. A UAV operating in a cluttered environment may encounter multiple obstacles, static (e.g., infrastructure) and dynamic (e.g., other UAVs). As the UAV's path undergoes smoothing, ensuring that it remains collision-free at every point becomes paramount. To this end, we introduce a distance function, D. For any point p on the UAV's trajectory, D calculates the shortest distance to the closest obstacle, facilitating instantaneous hazard proximity assessment. Let O denote the set of all obstacles in the environment, and $d(p, o)$ represent the Euclidean distance between point p and obstacle o. Then, the distance function $D(p)$ is articulated as, EQU (4.9)

$$D(p) = \text{Min}_{o \in o}\, d(p, o) \tag{4.9}$$

To ensure safety, for all points p on the smoothed path: $D(p) > R_{\text{safe}}$; where R_{safe} is not merely a predefined radius. Instead, it is dynamically computed based on the UAV's relative positioning to nearby obstacles, considering both distance and angular considerations.

Given the UAV's position as p_{UAV}, and the angle $\alpha\left(p_{UAV}, o\right)$ between its heading direction and an obstacle o, we compute distances and angles to all obstacles, EQU (4.10) and EQU (4.11)

$$D(o)=d\left(p_{UAV}, o\right) \forall o \in O \tag{4.10}$$

$$\mathrm{A}(o)=\alpha\left(p_{UAV}, o\right) \forall o \in O \tag{4.11}$$

This work introduces weighting factors, w_d and w_α, which dictate the significance of distance and angular considerations. R_{safe} is then defined as EQU (4.12)

$$R_{\text{safe}}=\frac{\sum_{o \in O} w_d \cdot D(o)+w_\alpha \cdot \mathrm{A}(o)}{|O|} \tag{4.12}$$

This approach ensures that the UAV maintains an adaptive safety radius, considering its distance from and orientation to potential obstacles. Should any point on the smoothed path breach the condition mentioned above, the path is deemed unsafe and requires further refinement. This rigorous framework guarantees that the UAV's route is not only visually smooth but also technically secure for traversal. The following steps present the proposed local path algorithm.

Algorithm 2: Improved D* for Local Path Planning

Inputs:

- Start node S
- Goal node G
- Global Path Planning Model
- Weights w_1, w_2, w_3
- Safety factor k
- Safety threshold adjustment Δ

Output:

- The smoothed path from S to G or "UNSAFE" notification.

Steps:

1. **Initialization:**
   (a) Current node $\leftarrow S$
   (b) Initialize open_list = {} and closed_list = {}
2. **Enhanced Cost Function:**
   (a) Compute E, which represents the energy from the Global Path Planning Model.
   (b) Calculate the safety cost as: Safety_Cost $(n)=k \times \exp$ (distance to nearest obstacle (n))
   (c) Determine the path length from node n to the goal node: Path_Length $(n)=\operatorname{distance}(n, G)$
   (d) Return $w_1 \times$ Path_Length $(n)+w_2 \times EE+w_3 \times$ Safety_Cost (n)
3. **UAV Safety Distance Determination**
   (a) Calculate Safetv $_{\text{a Distance}}$ (P, Q, R) :

$$\begin{aligned} & R^{\prime}=\text{ projection of R onto segment PQ} \\ & s=\underline{\text{ distance }(\mathrm{R} \text{ to } R^{\prime})} \end{aligned}$$

   (b) Return s
4. **Safety Threshold and Path Consideration:**
   (a) Check_Safety_Threshold (s, T):

$$T^{\prime}=\mathrm{T}+\Delta$$

   (b) If $s<T^{\prime}$ Then return "UNSAFE"
   (c) Else, return "SAFE".
5. **Path Smoothing Optimization:**

(a) Bezier Smoothing(path):
   i. For each segment s in the path: Apply Bezier curves using control points and endpoints If C(s) (based on the derivative) is too high, refine segment s
   ii. Return smoothed path

6. **Collision Check after Smoothing:**
   (a) Collision Check (path):
      i. For each point p in the path:
      Calculate $D(p)$ as the shortest distance to the closest obstacle If $D(p) < R_{\text{safe}}$, return "UNSAFE"
      ii. Return "SAFE"
7. **Path Planning Procedure:**
   (a) While current node is not goal node:
   (b) Find neighbors of current node
   (c) For each neighbor:
      i. Calculate cost using Calculate Cost_Cost
      ii. Calculate safety distance using Calculate Safettocos _Distance
      iii. Check safety threshold using Check_Safety_Threshold
      iv. If the node is safe and has a reasonable cost, add to opena list
   (d) Move current node to closed list
   (e) Set the node with the lowest cost in open list as current node
8. **After Reaching Goal_Node:**
   (a) Traceback path from goal node to start node
   (b) Apply Bezier. Smoothing to the path
   (c) Conduct Collision Check on the smoothed path
   (d) If the path is "UNSAFE", reiterate path planning or refine the smoothing
   (e) Else, execute the path.

Having delved into the intricacies of both the Enhanced Genetic Algorithm using Fuzzy Logic for global path planning and the Improved D* Algorithm for local path planning, it is crucial to understand their harmonized implementation in UAV navigation. The Enhanced Genetic Algorithm using Fuzzy Logic, renowned for its adeptness in combining genetic algorithms with fuzzy logic principles, sketches an optimal path from the start point to the goal by evaluating multiple routes and selecting the best fitness value. This provides the UAV with a broad overview of its trajectory, ensuring efficient and energy-conservative navigation. However, the ever-changing nature of real-world scenarios requires a more adaptive approach to immediate obstacles and dynamic environments. This is where the Improved D* Algorithm comes into play. It operates in the UAV's immediate surroundings, dynamically adjusting its real-time trajectory based on the sensed obstacles and environmental changes. By rapidly updating the robot's path as the environment changes, the Improved D* Algorithm ensures safe and adaptive local maneuvering. When these two algorithms are sequentially integrated, the UAV benefits from the foresight of the Enhanced Genetic Algorithm using Fuzzy Logic for long-range planning while relying on the agility and responsiveness of the Improved D* Algorithm for short-range adjustments. The synergy of these algorithms equips the UAV with a comprehensive and adaptable navigation blueprint, ensuring safe and efficient flight.

5. Experimental Analysis. The principal simulation platform for our experimental analysis was configured around an Intel® Core $^{\text{TM}}$i7 – 9700 K CPU @ 3.60GHz with Windows 10 as the operating system. The algorithm's performance was evaluated using MATLAB simulation tools. We designed a comprehensive path planning domain measuring 90 km by 90 km. The environment is partitioned into cells, each encompassing a 10 km by 10 km area. This results in a grid configuration of 9×9 cells.

Key simulation parameters were adjusted as follows:

- The UAV's maximum permissible turning angle was set to $\pi/6$ to account for a more agile flight profile, enhancing the fidelity of the simulation in representing the dynamic maneuvering capabilities of contemporary UAVs.
- The grid granularity was established with a resolution of N = 0.5 km, improving the precision of our

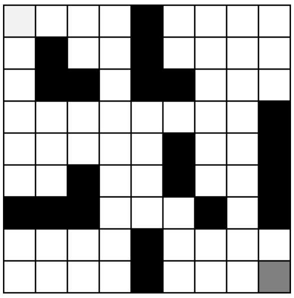

Fig. 5.1: Initial airspace setup

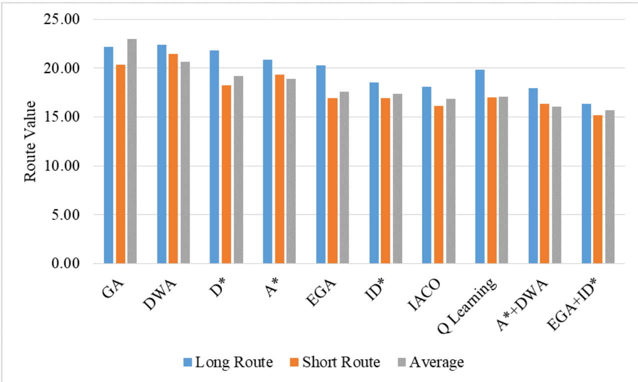

Fig. 5.2: Route length analysis

spatial analysis and the solution of the path-planning process.

- A safety margin was defined at 1 km, ensuring a conservative operational envelope for the UAV to prevent potential collisions with obstacles.
- The UAV's initial and target coordinates were plotted at $(10, 10)$ and $(90, 90)$, respectively, providing a diverse range of trajectory planning scenarios across the simulation space.

These simulation adjustments have been carefully chosen to test the boundaries of the proposed UAV path planning model, ensuring robustness, adaptability, and a high degree of environmental fidelity. Through this altered configuration, the model is subject to a wider range of test scenarios representative of complex agricultural terrains. Figure 5.1 shows the UAV's simulated airspace.

From Figures 5.2, 5.3, and Table 5.1, When the performance of the algorithms is compared using the average route values, the EGA+ID* approach emerges as the better standard, serving as our reference point. Relative to this, the Particle Swarm Optimization (PSO) method exhibited routes that were approximately 51.73% longer. Following closely, the Ant Colony Optimization (ACO) generated paths that were 47.48% longer than the EGA+ID*. The Genetic Algorithm (GA) trailed slightly behind, with 46.59% more extended paths than the proposed combined approach. The Dynamic Window Approach (DWA) displayed a marked improvement over the previous algorithms but still had routes approximately 31.57% longer than the EGA+ID*. When we consider other conventional algorithms, the disparity in performance becomes even more palpable: D* exhibited routes that were 22.34% longer, while A* demonstrated paths that were 20.39% more extended. When considering the state-of-the-art models, the Improved Ant Colony Optimization (IACO) and Q Learning had 7.80% and 9.20% longer routes, respectively. Impressively, the fusion of A^* with the Dynamic Window Approach (A*+DWA) came remarkably close to the top-performing model, with only a 2.49% increase in path length over the EGA+ID*.

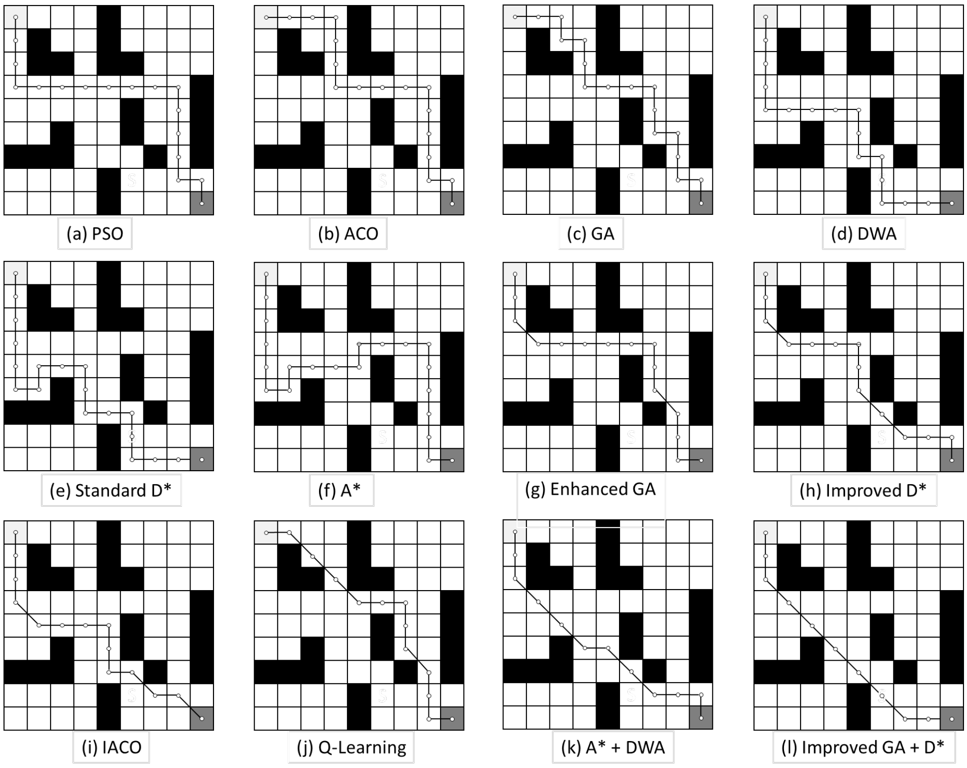

Fig. 5.3: Path planning results

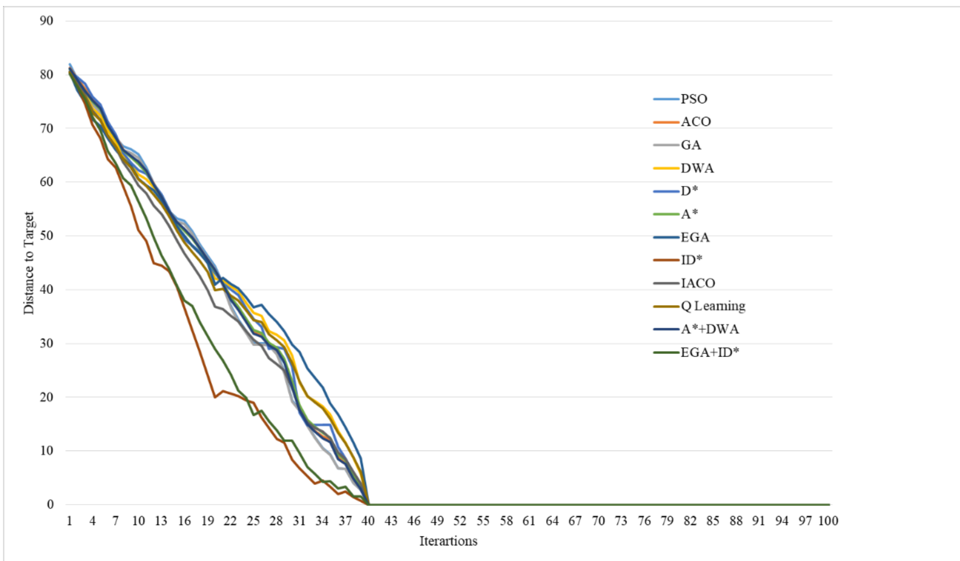

Fig. 5.4: Distance to target analysis

Table 5.1: Performance analysis of the compared models

Algorithms	Inflection Count	Time (s)	Accuracy
PSO	16	12.35	48.7
ACO	15	10.8	46.6
GA	15	11.63	48.3
DWA	15	10.46	45.5
D*	17	8.93	58.8
A*	17	9.02	56.4
EGA	12	8.83	74.1
ID*	11	9.57	74.83
IACO	13	7.96	73.36
Q Learning	12	7.07	81.23
A*+DWA	10	6.86	84.6
EGA+ID*	9	5.54	91.1

The data reveals a fascinating interplay between inflection count, time efficiency, and accuracy of various path-planning algorithms. The combined EGA+ID* model distinguishes itself as a frontrunner, completing its tasks in a mere 5.55 seconds and achieving an impressive accuracy of 91.1%. This superior performance is realized with a minimal inflection count of 9, implying a trajectory with fewer directional changes and a smoother path. In contrast, the D^* and A^* algorithms, despite having the highest inflection counts of 17, manage to hold their own. Specifically, D* highlights a respectable accuracy of 58.8%, slightly edging out A^*. On the other end of the spectrum, algorithms like PSO and ACO, while being relatively faster than some counterparts, lag in accuracy, hovering around the mid-40s range.

Meanwhile, the $A*$ +DWA fusion strikes a commendable balance, ensuring quick path planning in 6.863 seconds and delivering an accuracy of 84.6% with a mere 10 inflections. Overall, the results underscore the process of integrating global and local pathplanning models, as demonstrated by the unmatched efficiency and accuracy of EGA+ID*. The distance to the target for each iteration is displayed in Figure 6. Starting at 59.18 in the initial iteration, EGA+ID* demonstrates a steady decrease in distance values, reflecting its effective optimization capability. Compared to other algorithms, EGA+ID* maintains consistent performance, converging closer to the target as iterations progress. This pattern displays the efficiency and potential of the EGA+ID* model in optimization tasks, making it a promising choice for such applications.

6. Conclusion. The rapid evolution of smart agriculture, underpinned by the convergence of technology and traditional farming practices, underscores a transformative shift in the agricultural domain. Unmanned Aerial Vehicles (UAVs), central to this transformation, change how agricultural operations are visualized and executed. While their potential is undeniable, ensuring their efficient and safe operation in the dynamic environment of a farm presents considerable challenges. The key lies in the intricate process of path planning. Our proposed hierarchical framework, which amalgamates the strengths of the "Enhanced Genetic Algorithm using Fuzzy Logic" for broad trajectory planning and the "Improved D* Algorithm" for nuanced, real-time adjustments, is a step forward in addressing this challenge. This integrated approach not only guarantees efficient navigation but also bolsters the safety and energy conservation of UAVs in real-world agricultural settings. As we look to the future, the fusion of such sophisticated algorithms with UAV technology holds the promise of further elevating the standards of smart agriculture, driving the sector towards heightened sustainability and productivity.

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