A Genetic Algorithm Approach to Persistent UAV Surveillance in Probability-Guided Wildlife Monitoring

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Unmanned Aerial Vehicles (UAVs) have revolutionized wildlife monitoring through real-time, non-intrusive observation over vast and often inaccessible areas. However, persistent surveillance remains a challenge due to energy constraints and inefficient path planning. This paper proposes a Genetic Algorithm (GA)-based path planning framework designed to maximize surveillance efficiency in probabilistic environments where wildlife presence is spatially uncertain. By encoding UAV flight paths as chromosomes and optimizing for cumulative coverage of high-probability zones, the GA evolves adaptive trajectories that minimize redundant coverage and enhance monitoring efficacy. Simulated in a 10×10 probabilistic grid, the proposed method significantly outperformed the traditional lawn-mower sweep strategy, achieving higher probability coverage with fewer moves. The results validate the potential of evolutionary algorithms in developing intelligent, autonomous UAV systems capable of persistent, energy-aware surveillance. This framework lays the groundwork for scalable ecological monitoring solutions that can support conservation strategies in remote and sensitive environments.

Povzetek:

1 Introduction

Unmanned Aerial Vehicles (UAVs) have emerged as transformative tools in wildlife conservation, offering unprecedented capabilities for real-time, non-intrusive monitoring across vast and inaccessible terrains. Unlike traditional ground-based or satellite surveillance methods, UAVs can capture high-resolution imagery and thermal data with greater flexibility and lower operational costs, making them ideal for tracking endangered species, monitoring poaching activities, and assessing habitat changes. Their ability to cover large areas with minimal human presence significantly reduces disturbance to wildlife, thereby enhancing the accuracy of behavioral and population studies. As noted by [1], UAVs have been shown to outperform traditional wildlife monitoring techniques in terms of efficiency and data quality, demonstrating their potential to revolutionize conservation science in the 21st century.

UAVs have found diverse applications across multiple domains of wildlife conservation. One of the most impactful uses is in anti-poaching operations, where UAVs provide real-time surveillance of protected areas, significantly enhancing response capabilities against illegal activities [2]. They are also widely used for habitat mapping, enabling researchers to assess environmental changes, deforestation patterns, and land-use transitions with high spatial accuracy [3]. In addition, UAVs facilitate population census and behavioral monitoring of species that are difficult to observe from the ground, such as marine mammals, nesting birds, or forest-dwelling animals [4]. These capabilities allow conservationists to gather detailed ecological data with minimal intrusion, improving the precision and ethical standards of field research.

One of the most promising and obvious applications of UAVs in wildlife conservation is persistent aerial surveillance — enabling continuous monitoring of animal movements, poaching activity, and environmental changes in real-time. However, a major bottleneck to achieving true persistence is the limited battery capacity of most UAVs, which typically allows for only 30 to 60 minutes of flight time under standard payload conditions. This restricts the ability of drones to provide long-term coverage, especially in remote or wide geographic areas where recharging infrastructure is not available. As noted by Dhawde and Chakraborty (2025), the energy-intensive nature of continuous surveillance poses a substantial challenge, necessitating solutions like periodic charging or drone rotation models to maintain sustainable operations [5].

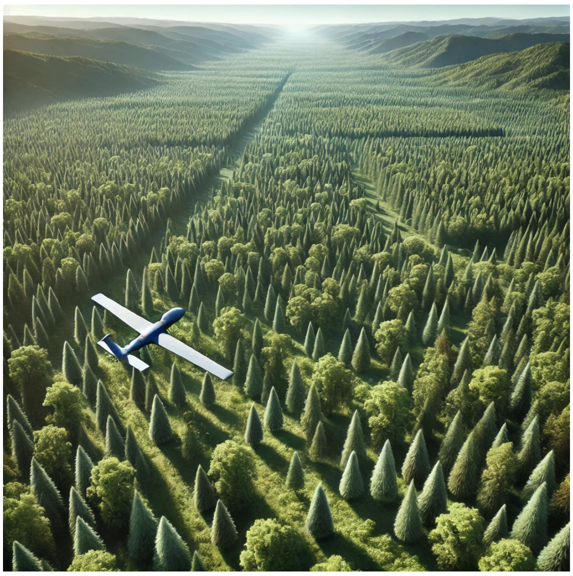

Figure 1: Futuristic UAV Surveillance in huge forest

While current battery limitations restrict the endurance of UAVs in wildlife surveillance, promising advancements in solar energy integration and battery technology are transforming the landscape. Solar-powered UAVs have demonstrated significant potential in extending flight duration without the need for frequent recharging, especially in open environments like savannahs and coastal regions [6]. Additionally, innovations in lithium-sulfur and solid-state batteries are enabling higher energy densities and longer lifespans, directly contributing to more persistent and autonomous flight capabilities [7]. These technological strides hint at a near future where persistent UAV surveillance becomes both practical and scalable — fostering real-time monitoring over extended periods without compromising energy constraints.

In the near future, advancements in battery technology, renewable energy harvesting, and data-driven modeling are poised to revolutionize wildlife monitoring. With battery constraints eliminated, UAVs could operate continuously, forming intelligent aerial networks capable of passive, real-time ecological observation. Fueled by large volumes of behavioral and spatial wildlife data—such as migratory routes and habitat usage—these systems will evolve into autonomous surveillance frameworks that require minimal human intervention. A vital first step in this transformation is intelligent path planning, guided by probabilistic models derived from historical wildlife patterns. By integrating these insights into UAV routing algorithms, surveillance efficiency can be maximized while minimizing redundant coverage and energy expenditure. Ultimately, such adaptive systems could autonomously detect threats like poaching or habitat disruption and alert authorities, creating a scalable, proactive, and non-invasive approach to conservation.

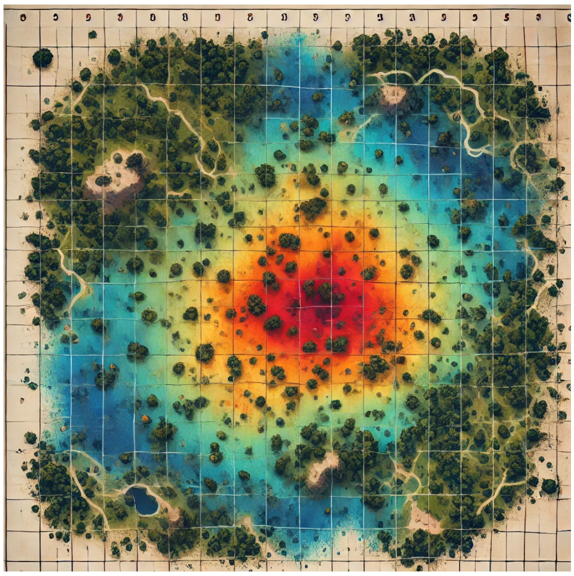

Figure 2: Probability map of animal presence in a forest

Numerous algorithms have been developed for UAV path planning, each with distinct advantages and limitations. Classical methods like A* and Dijkstra are known for their deterministic outcomes and simplicity but often struggle with real-time adaptability in dynamic environments. Heuristic and metaheuristic approaches such as Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Reinforcement Learning (RL) offer better scalability and adaptability but can be computationally intensive or require large datasets for training [8, 9]. Among these, Genetic Algorithms (GAs) have gained popularity due to their robustness in solving multi-objective optimization problems and their flexibility in handling complex constraints such as limited UAV energy, obstacle avoidance, and mission duration. GAs are particularly well-suited for wildlife surveillance, where flight paths must adapt to probabilistic animal presence and unpredictable terrain. Their ability to evolve optimal or near-optimal routes over generations makes them ideal for balancing coverage efficiency and energy usage in persistent monitoring tasks [10].

Therefore, we propose a Genetic Algorithm (GA)-based path planning method tailored to probabilistic surveillance environments. In our framework, UAV flight paths are represented as chromosomes—sequences of discrete moves through a grid—and are evolved over successive generations to maximize cumulative coverage of high-probability regions, where animal presence is statistically more likely. An adapted fitness function is employed to encourage the visitation of new, unobserved areas and to prioritize routes through zones with higher expected value.

We validate our approach through simulation in a 10×10 probabilistic grid environment, comparing the GA-evolved trajectories to a baseline lawnmower sweep strategy commonly used in fixed-wing UAV missions. Our results demonstrate that the GA-based planner consistently identifies higher-utility paths, achieving greater cumulative probability with fewer redundant movements.

This work serves as a foundational step toward building fully autonomous ecological UAV systems that integrate evolutionary optimization with environmental awareness. By coupling adaptive path planning with probabilistic modeling, we envision future UAV systems that can intelligently and independently monitor wildlife populations, adapt to behavioral patterns, and operate persistently across vast conservation areas with minimal human intervention. Such systems have the potential to significantly improve biodiversity data acquisition, support proactive management strategies, and enable continuous, non-intrusive monitoring in some of the planet's most sensitive and remote ecosystems.

2 Related Work

The use of Unmanned Aerial Vehicles (UAVs) for wildlife monitoring has been very prominent in recent years due to their ability to access remote areas and record high-resolution spatial and temporal information. Studies by[1, 3] have proved UAVs to be very effective for tracking large mammals, monitoring nesting sites, and conducting aerial surveys without disrupting wildlife. The systems usually utilize onboard RGB or thermal cameras and used to supplement or replace traditional monitoring tools like camera traps or manned aircraft.

The use of UAVs for wildlife monitoring is often faced with technical challenges based on finite battery life, unoptimized flight trajectories, and limited onboard processing[11]. The majority of existing UAV missions are based on pre-programmed flight plans, e.g., grid-based or lawn-mower sweeps [12], easy to deploy but inefficient in covering optimal areas of random animal densities or variable habitat occupation.

In dealing with path optimization, several algorithmic approaches have been used. Deterministic planners like A* and Dijkstra's algorithm are effective in shortest-path navigation and obstacle evasion but fall short in dynamic or probabilistic environments. Sampling-based approaches like Rapidly-exploring Random Trees (RRT) and Probabilistic Roadmaps (PRM) give mobility in high-dimensional spaces, though they typically do not have coverage-awareness and flexibility with evolving surveillance necessities.

On the other hand, bio-inspired metaheuristic algorithms such as Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), and Genetic Algorithms (GA) have shown promise in solving complex UAV path planning problems [13]. Genetic Algorithms, in particular, are valued for their capacity to manage large search spaces and evolve solutions over generations. GA has been used in previous studies for UAV navigation in dense obstacle environments [14], energy-efficient routing [15], and coverage path planning in agricultural and urban environments.

In the wildlife monitoring scenario, however, relatively fewer studies have examined GA-based approaches that account for spatial uncertainty—such as varying probabilities of animal presence across a region. The integration of probabilistic modeling and evolutionary planning is an open research problem. Our contribution fills this gap by developing a GA-based path planning algorithm that optimizes UAV flight trajectories to maximize expected coverage across a probabilistic distribution map of animals. The approach not only supports spatial uncertainty but also facilitates vision-guided autonomy for long-duration aerial surveillance missions.

3 Methodology

3.1 Problem Formulation

In practical applications, wildlife surveillance systems can be greatly enhanced using real-world statistics and historical probability data collected from tracking devices, camera traps, or ecological models. These data sources provide spatial and temporal patterns of animal presence, which can be translated into probability maps. For instance, cells with a higher frequency of sightings or movement paths would be assigned higher probability values. However, for the purpose of this study and to demonstrate the feasibility of our approach, we adopt a theoretical model where probability values are synthetically assigned to represent varying levels of animal activity across a designated area.

We model the surveillance space as a two-dimensional grid, with each grid cell representing a spatial unit of a national park or wildlife reserve. A probability value is associated with every grid cell, indicating the likelihood of animal presence—whether derived from real data in practice or predefined for simulation. The core objective is to compute an optimal UAV path that begins at a fixed initial position and traverses the grid in a way that maximizes expected coverage of high-probability areas, subject to a constraint on total path length. This path planning problem inherently requires balancing surveillance gain against travel limitations, making it ideal for optimization via intelligent algorithms such as Genetic Algorithms.

3.2 Probability Map Generation

To simulate spatial uncertainty in wildlife presence, we construct a probabilistic heatmap that represents the static spatial distribution of animal activity across the surveillance area. The environment is discretized into a two-dimensional grid, where each cell corresponds to a fixed geographic unit, such as a square meter or hectare within a national park. Each grid cell is assigned a discrete probability value reflecting the estimated likelihood of an animal being present at that location. Specifically, we define three probability levels: high (0.8), medium (0.4), and low (0.2), which are randomly distributed across the grid to introduce environmental variability and uncertainty.

This simulated heatmap serves as the static input for the path planning process, representing areas of varying surveillance value. High-probability regions indicate zones of greater ecological interest—such as water sources, grazing fields, or migratory routes—while low-probability regions may correspond to less frequented or inaccessible areas. By abstracting real animal movement data into a controlled probability distribution, the model provides a simplified yet effective environment to evaluate UAV routing strategies. This approach enables the development and testing of optimization algorithms under controlled conditions before deployment with real ecological data.

3.3 Path Encoding and Chromosome Representation

Each candidate solution is encoded as a chromosome in the Genetic Algorithm (GA), representing a possible UAV surveillance path. A chromosome is defined as a fixed-length sequence of discrete movement commands (genes), where each gene belongs to a predefined set of allowable UAV moves. In this implementation, the UAV operates within a discrete 2D grid, and the set of available moves includes:

$$\text{MOVES} = \{(0,1),(1,0),(0,-1),(-1,0)\}$$

These correspond to movements in the four cardinal directions: right, down, left, and up, respectively. Each gene in the chromosome thus instructs the UAV to move from its current grid position to an adjacent cell in one of these directions.

Figure 3: Genetic representation of path(Chromosome)

As illustrated in Figure 3, the chromosome does not store absolute coordinates but instead encodes relative transitions between cells. Starting from a known initial position (typically the top-left corner of the grid), the UAV sequentially applies the movements defined by the chromosome to trace out a path.

The length of the chromosome determines the number of UAV steps (i.e., the mission duration or maximum flight moves). This constraint implicitly models the UAV's flight time or battery capacity. Importantly, the algorithm ensures that movements stay within the bounds of the grid, and invalid moves that would lead the UAV outside the map are either skipped or ignored during fitness evaluation.

This encoding scheme is highly flexible and well-suited for evolutionary optimization. It enables crossover and mutation operations to be applied naturally: crossover exchanges sub-paths between parent chromosomes, while mutation randomly replaces individual moves to introduce behavioral diversity in the population.

Additionally, by using relative motion, this representation generalizes across grid sizes and is scalable to larger environments. It also simplifies the application of penalties or rewards during fitness evaluation based on the specific locations visited, such as high-probability zones, revisited cells, or forbidden regions.

In summary, this encoding provides a compact, mutation-friendly representation of UAV trajectories, supporting the evolutionary search process in identifying optimal surveillance paths within probabilistic environments.

3.4 Fitness Function

The fitness function plays a central role in guiding the evolutionary process of the Genetic Algorithm (GA). In the context of probabilistic UAV path planning for wildlife monitoring, the fitness function evaluates how well a candidate path performs in terms of surveillance utility. Specifically, it measures the total cumulative probability collected by the UAV as it traverses the environment.

Each cell in the 2D grid is associated with a probability value $P(x, y)$, representing the likelihood of animal presence at coordinates (x, y). As the UAV visits grid cells along its path, it accumulates the probability values of the cells it observes. To prevent redundant surveillance of the same location, only the first visit to a cell contributes to the fitness score. This encourages spatial exploration and coverage diversity.

Let a candidate path be defined as a sequence of n movements, and let $S = \{(x_1, y_1), (x_2, y_2), \ldots, (x_k, y_k)\}$ denote the set of unique grid cells visited during this path. Then, the fitness function is defined as:

$$\text{Fitness}(path) = \sum_{(x,y)\in S} P(x,y)$$

This equation ensures that the fitness score is proportional to the cumulative probability of the visited locations, incentivizing the UAV to prioritize high-reward regions in the environment.

To compute this score, the algorithm simulates the UAV's movements starting from a fixed initial position. At each step, the move encoded in the chromosome is applied, resulting in a transition to a new position (if valid). If the new position has not been visited before and lies within the grid bounds, its associated probability value is added to the total fitness score.

3.5 Genetic Algorithm Design

The path planning problem is solved using a classical Genetic Algorithm with the following components:

- **Initial Population:** A set of randomly generated paths, each with a fixed number of steps.
- **Selection:** Top individuals are selected based on fitness using elitism and roulette wheel methods.
- **Crossover:** One-point crossover is applied to recombine parent chromosomes and generate offspring.
- **Mutation:** With a mutation rate of 10%, individual moves are randomly altered to maintain diversity.
- **Elitism:** A subset of top individuals is directly passed to the next generation to retain high fitness solutions.

The GA iteratively evolves the population over several generations, and the best-performing paths are tracked.

Algorithm 1 Pseudo-code of the Genetic Algorithm for UAV Path Planning

Require: N: Population size, P_c: Crossover rate, P_m: Mutation rate
Ensure: Best evolved UAV path

```
t ← 0
Initialize population P(t) randomly
while termination condition not met do
    Evaluate fitness of P(t)
    Select parents from P(t)
    Apply crossover to produce offspring
    Apply mutation to offspring
    Form new population P(t + 1)
    t ← t + 1
end while
```

3.6 Baseline Strategy: Lawn-Mower Sweep

For comparison, a deterministic lawn-mower pattern is employed. This simulates the traditional fixed-wing UAV coverage strategy, where the UAV traverses the grid in back-and-forth straight lines. While easy to implement, this method is not highly adaptable to probabilistic spatial properties and can cause wasteful coverage.

3.7 Implementation Details

The default parameters used for the simulation are:

Parameter	Value
Grid Size	10×10
Start Position	$(0, 0)$
Path Length	50 steps
Population Size	2000 individuals
Generations	1000
Mutation Rate	0.1
Elitism Count	400

Table 1: Implementation Details

4 Results and Discussion

4.1 Experimental Setup

The experiment was conducted on a 10×10 grid of a smaller-scale wildlife monitoring region. The probability value was assigned randomly to each grid cell based on the probability of animal presence, with high (0.8), medium (0.4), and low (0.2) values dispersed in the grid. The UAV was initiated at the top-left corner of the grid at location $(0, 0)$ and was restricted to travel on a preassigned fixed length of 50 moves. The Genetic Algorithm was run for 1000 generations with 2000 in population and a mutation of 0.1. The optimum solutions were saved every 10 generations to analyze.

4.2 Performance of the Genetic Algorithm

The Genetic Algorithm showed optimal convergence behavior throughout generations. As can be seen in Fig. 4, the fitness value — as the aggregate probability amassed by the UAV — increased steadily throughout initial generations and leveled off as populations converged on a best collection of paths. This indicates successful population adaptation to regions of high value in the environment.

The final path identified by the algorithm consistently navigated through high-probability zones while avoiding unnecessary revisits. The path's smooth

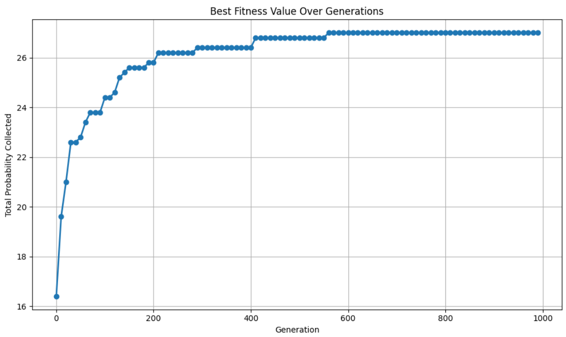

Figure 4: Best fitness value over the generations

structure and targeted movements are indicative of the algorithm's ability to evolve both spatial awareness and efficiency.

4.3 Comparison with Lawn-Mower Strategy

To evaluate the efficacy of the evolved paths, a lawn-mower sweep pattern was implemented as a baseline strategy. This deterministic pattern covers the grid row by row without considering the probability distribution.

Table 2 shows a comparison between the GA-based approach and the lawn-mower strategy in terms of total probability collected:

Strategy	Total Probability
Genetic Algorithm(Best)	27.0
Lawn Mower Sweep	17.19

Table 2: Performance Comparison: Genetic Algorithm vs Lawn-mower

The GA approach outperformed the lawn-mower strategy by a significant margin, demonstrating its advantage in selectively covering regions of high interest rather than uniformly sweeping the entire area. This is especially relevant in wildlife monitoring, where animal presence is sparse and non-uniform.

4.4 Visualization and Path Evolution

Fig. 5 and 6 illustrates the final evolved UAV path overlaid on the probability heatmap. The UAV effectively prioritized high-probability zones while maintaining a compact and efficient trajectory.

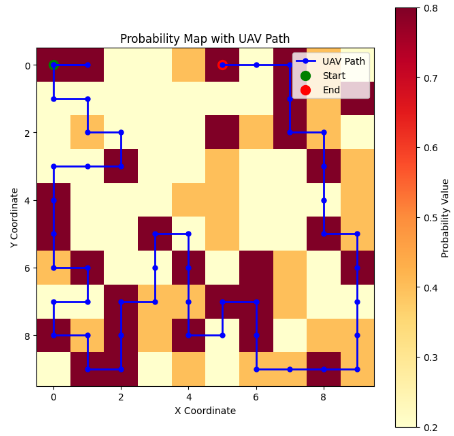

Figure 5: Path generated by genetic algorithm

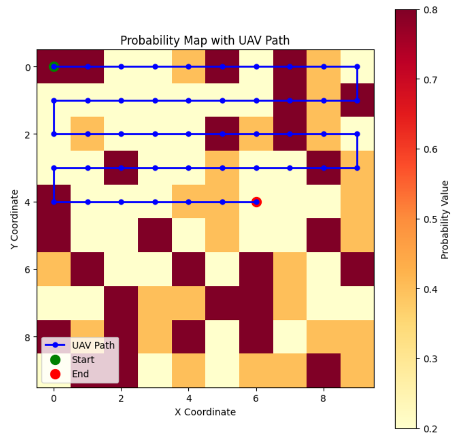

Figure 6: Path generated by lawn-mower method

4.5 Implications for Wildlife Monitoring

The results suggest that a GA-based planner can significantly enhance the efficiency of UAV surveillance missions in large-scale conservation areas. Unlike deterministic strategies, this method allows for adaptive path generation in the presence of spatial uncertainty — a common feature in real-world animal tracking scenarios. Furthermore, the evolved paths avoid redundant coverage, making them ideal for battery-constrained, long-endurance UAVs envisioned for future autonomous wildlife monitoring missions.

5 Conclusion

In this study, we presented a Genetic Algorithm (GA)-based path planning framework tailored for Unmanned Aerial Vehicle (UAV) surveillance in probabilistically modeled wildlife habitats. Leveraging historical data on animal presence, the proposed algorithm dynamically evolves UAV trajectories to prioritize high-probability regions, thereby maximizing coverage while minimizing redundant flight. Simulation results demonstrated that the GA-based method significantly outperformed traditional sweep patterns by offering adaptive, targeted surveillance rooted in ecological data.

The probability-driven fitness function, combined with evolutionary operators, enabled effective exploration and exploitation of the solution space across generations. Visualizations of path evolution further confirmed the algorithm's convergence behavior and practical applicability. These results underscore the potential of bio-inspired optimization in enhancing UAV-based monitoring strategies.

6 Future Work

While this study provides a foundational demonstration of probabilistic UAV path planning using theoretical probability distributions and a Genetic Algorithm approach, several avenues exist for future research. First, integrating real-world wildlife tracking data—such as GPS collar data, camera trap statistics, or remote sensing imagery—would enhance the ecological validity of the probability maps and improve path optimization outcomes.

Additionally, future work may explore the incorporation of dynamic environmental variables, such as changing weather conditions, animal movement patterns, or terrain constraints. These factors could be modeled in real-time to enable adaptive path planning strategies. The expansion from single-UAV systems to coordinated multi-UAV frameworks also presents a promising direction, where swarm intelligence or decentralized optimization techniques can be used to collaboratively cover larger areas and balance energy efficiency.

Finally, coupling this approach with onboard AI capabilities such as real-time image processing, anomaly detection, or event-triggered surveillance can lead to the development of fully autonomous, intelligent conservation systems that require minimal human intervention while providing continuous, data-rich environmental monitoring.

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