Scalable Computing: Practice and Experience, ISSN 1895-1767, http://www.scpe.org
© 2025 SCPE. Volume 26, Issues 2, pp. 503–516, DOI 10.12694/scpe.v26i2.3969

MODELING AN INTELLIGENT FRAMEWORK FOR OPTIMIZING UAV PATH PLANNING AND ANTI-COLLISION IN AGRICULTURE

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Abstract. Unmanned aerial vehicles (UAV) are increasingly utilized for monitor expansive farming to their effectiveness in observation and data gathered. Efficient path planning and collision prevention are critical for optimizing UAV operation in such settings. The efficiency can be controlled by the quality and declaration of UAV sensed data, as well as the difficulty of real world ecological variables that could impact path optimization and collision prevention. This research introduce a novel technique, the customizable dung beetle search tuned random forest (CDBS-RF) method, designed to improve UAV route planning. The CDBS-RF method integrated the dung beetle search (DBS) algorithm, known for its robust optimization capabilities, with random forest (RF) to enhance optimal path security and effectiveness. This method dynamically adjusts path safety and effectiveness. This approach dynamically adjusts path planning parameter to make sure optimal route selection and collision prevention. The suggested technique was evaluated utilizing UAV-sensed data and implement in python based virtual environment. Experimental consequences demonstrate that the CDBS-RF approach considerably enhances UAV path planning performance, provide safer and more efficient navigation for self and more efficient navigation for self-sufficient tarp monitoring. The performance evaluation techniques include the planning time (0.789) and path length (21.526). By utilize advanced optimization and anti-collision algorithms, this technique offer a promising solution for improving UAV operations in agricultural surveillance.

Key words: Agriculture, UAVs (unmanned aerial vehicles), path planning, obstacles, anti-collision, customizable dung beetle search-tuned random forest (CDBS-RF)

1. Introduction. Unmanned aerial vehicle s(UAVs) are suitable additional established and utilized in several different sectors, such as profitable deliveries, farming, and emergency relief. worldwide, there have been a lot UAV flying operation. The anti-collision approaches of UAVs have garnered important attention because of their wide utilizes, to avoid UAVs from collide with other objects [1].

1.1. UAVs Path Planning. UAVs are superior demand between civilians for uses such as aerial investigation, search and rescue operations, and military uses. According to, UAVs have shown to be quite helpful in the agricultural sector, particularly for monitoring palm oil plantation, which gives farmers on how to supervise their plantation [2]. One additional advantage of using UAVs is that they can equipped with a range of measuring devices that can assist in eliminating fixed position constraints and enable real-time, unrestricted measurement in three dimensions.

The quick expansion of many aircraft types, particularly UAVs has been fueled by the increasing liberalization of low-altitude airspace and the quick growth of the general aviation sector [3].UAVs are becoming an important part of the worldwide commercial industry. Depending on their intended applications, civilian drones can be classified as patrol, agricultural, meteorological, exploratory, or disaster relief drones. Based on this, nations substantial sums of money have been invested globally in the study and creation of UAVs with

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greater integration, improved processing efficiency, and faster reaction times [4].

1.2. Advancements in Agricultural UAV Applications. Plant protection, farmland information, precision agriculture, and agricultural insurance UAV use is increasing in businesses that include pesticide spraying, fertilization, and seeding. UAVs are currently being used to monitor and control illnesses and pests in local areas and are encouraged by the governments of various countries since agriculture is becoming more and more popular. Plant protection UAVs provide several benefits over traditional pesticide spraying methods, including superior labor efficiency, excellent mobility, consistent and modest pesticide dose per unit area and a vertical takeoff and landing capability [5].

Robotic systems have become more and more common in the past ten years as a means of handling laborious agricultural jobs in field operations. Numerous robotic systems have been created to address the complexity of agricultural field tasks, including harvesting, spraying, fertilizing, sowing, weeding, and harvesting [6].Civilizations centered on trees for many nations, europea L. represent a significant source of income. The quality of the product is affected when the fly female deposits in the fruits that developing larvae eat. Pesticides are used to combat this type of infestation, but environmental issues and the resulting financial expenses make the development of innovative strategies to minimize their usage necessary [7].Recent technical breakthroughs regarding farming have led to a rise in the usage of Robots in the industry. A cheap alternative is provided by the UAV, a mobile robot for conventional detecting technologies and data analysis methods. UAVs come in a range of variety, and inexpensive UAVs are competent of gathering high-resolution images from a lot of location in space. Even while UAVs aren't at the present utilized in the majority of accuracy farming application, are becoming additional concerned in the business in terms of beneficial and sustainable farming techniques. The UAV, which is utilized in farming, offers dimension accuracy and drastically lower the need for human resources. When the data from the UAV are appropriately assessed and analyze, they can increase crop efficiency and develop crop yield [8].

UAVs have a great possible to enhanced crop, water, and pest management effectiveness, and they can be especially useful for precision agricultural applications.They are also capable of doing a variety of agricultural tasks, such as monitoring soil health, applying fertilizer, and analyzing weather. A UAV with a camera and agile motions can supplement human labor in scenario evaluation and surveillance tasks by offering basic assistance. Additionally, the UAV may utilize numerous sensors at once, and sensor fusion can boost analysis. Farmers may continually monitor crop variability and stress levels by using UAVs to obtain vegetation indicators [9].

1.3. The challenges of path planning and collision avoidance. It is a critical challenge in UAV operations, particularly in complex agricultural environments. UAV must navigate dynamic and cluttered landscape, which can include varying terrain, tall vegetation, and unpredictable weather conditions. Effective path planning involves not only finding the most efficient route but also dynamically adjusting to obstacles that can appear suddenly such as other UAV. Collision avoidance further complicated the task by requiring real-time detection and response to potential threats, which can be hindered by limited sensor range oorr processing power. Additionally, the need to balance optimal path efficiency with safety considerations adds another layer of complexity. Recent advancements in algorithms and sensor technologies are addressing these challenges, but achieving robust and reliable performance remains a significant hurdle. As UAV are increasingly deployed for agricultural tasks, developing sophisticated path planning strategies and collision-avoidance systems is essential for enhancing operational safety and effectiveness [10].

Aim of the study. The principal aim of this undertaking is to produce a path collision avoidance and path planning system for a UAV that will be used to check apple fly traps.This study aims to improve an online adaptive method of UAV route planning based on the Customizable dung beetle search-tuned random forest (CDBS-RF) approach.

The remainder of the paper. Section 2 contains related works. There was a comprehensive methodology within Section 3. An analysis of the findings is provided in Section 4, and a conclusion is provided in Section 5.

2. Related work. According to the author [11]examined the variety of navigation situations with increasing complexity and static obstacle density are applied to evaluate two of the most popular search path planning methods for geometrical simulations: the (A* and D*) algorithms. It executes intricate situations with outstanding outcomes in terms of computation time, collision avoidance abilities, and length of path.

Study [12] explored the safe Blockchain-based communication between UAVs and wireless unmanned aerial vehicles (WUAV).Because the position is subjected to change in an unexpected environment, base station transfer will be delayed. UAVs are more likely to be the target of security breaches. The use of a flocking control method inspired by starling behavior, a large-scale UAV swarm working in a dynamic and unpredictable three-dimensional environment can increase the efficacy, security, and dependability of obstacle avoidance [13]. The motion model is constructed by examining the systematic and quick obstacle avoidance behavior of the starlings. Current examples of RF data transfer and visual processing to integrate leader-follower UAVs are provided in this study. This system uses embedded electronics, visual processing, and controls to provide the simple deployment of several quadrotor UAVs under the control of a single operator in search and rescue scenarios [14].According to [15] the paper provided a thorough overview of UAV anti-collision systems. To prevent collisions at the policy level, we must propose legislation and regulations on UAV safety. Furthermore, from the standpoint of quick obstacle detection and quick wireless networking in UAV anti-collision technology are discussed. The coverage issues that might come up while monitoring and when implementing agro-technical interventions are in this article [16]. The proposed method, mhCPPmp, utilizes a genetic algorithm to plan flight paths for various UAV types while they are refueling and charging on a moving ground platform. The suggested multigene, enhanced anti-collision RRT* and Iterative Adaptive Configuration-Rapidly Exploring Random Tree (IAC-RRT*) algorithms modify the probability of mutation and crossover. UAVs can efficiently cut down on energy use and task completion time because of their multigene and IAC-RRT* algorithms [17].

Study [18] suggested a way for autonomously assigning tasks and making decisions for numerous cooperative quad copters to design a coverage path. The best solution for the given issue was found by applying the Sequential Quadratic Programming (SQP) approach. Next, using the Stateflow approach, MATLAB Graphical User Interfaces (GUIs) construct a simulation platform, and numerous the real flying experiments were carried out using ZY-UAV-680 quadrotor UAVs . Article [19] proposed the use of an intelligent logistics UAV as a courier substitute for minor goods deliveries. The quad copter was controlled by a mobile application that was linked with a webcam and an ultrasonic ground proximity warning system (GPWS). Improved PID (proportion-integral-derivative) controllers and LQR(linear quadratic regulator) were used in its light control system. The article employs the ant colony method and dynamic route planning, which could quickly determine the ideal path of a UAV in challenging terrain when compared to the classic an algorithm and artificial potential field technique. Study [21] examined the use of ML techniques to predict crop yields using a large dataset from Indian agriculture that includes variables such as soil composition, seasonal variations, and fertilizer use. Ten machine learning methods were evaluated for performance. The paper examined the vital topic of enhancing agricultural decision-making and guaranteeing food security, which are essential components of the sustainable development goal (SDG).

2.1. Problem statement. The problem addressed in the reviewed studies is the optimization of path planning, collision avoidance, and efficient communication for UAV operating in dynamic and complex environments. The examination of various navigation algorithms, such as A* and D* reveals their effectiveness in different scenarios, yet challenges remain in enhancing computation time and collision avoidance capabilities. UAV face increased risks of security breaches and operational delays due to their variable positioning and environmental unpredictability. To address these issues, several advanced approaches are explored flocking control inspired by starling behavior to improve swarm coordination, integration of RF data transfer and visual processing for leader- follower UAV systems, and multi gene algorithms for optimizing flight path and reducing energy consumption. Additionally autonomous task assignment and converge path planning are achieved through sequential quadratic programming (SQP) and real flight experiments. The use of intelligent logistics UAVs for small deliveries highlights the need for improved route optimization to overcome challenging terrain and enhance overall UAV performance.

3. Methods. The quality and resolution of UAV sensed data, together with the complexity of real-world environmental factors that may affect path optimization and collision avoidance, might limit the efficacy. In order to improve UAV route planning, this research presents a unique method called the customizable dung beetle search tuned random forest (CDBS-RF) the technique displayed in Figure 3.1.

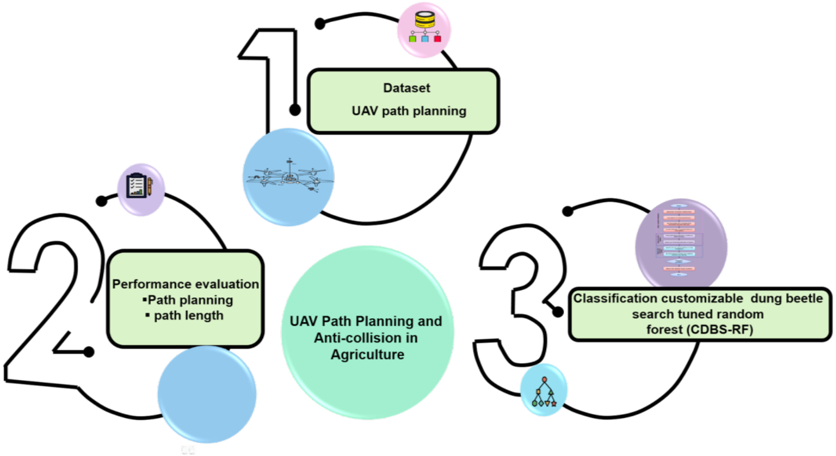

Fig. 3.1: Block schematic illustrating the intended workflow

3.1. Dataset. A UAV is utilized to images the fly traps that are attached to the tree crop along a growing zone to perform an apple as part of the fly trap inspection procedure. Due to its unstructured nature, this type of space needs the ability to identify and prevent collisions to ensure process security. An image of a region used for apple cultivation. To obtain the trap images, the UAV has to fly at a height that falls between the tree crops that is not much higher than the mean of the tree diameters.

The intricate flying zone, with a few branches that reach beyond the tree canopy, is depicted in the illustration. When the UAV is moving, other dynamic objects in this area, such as people, animals, and vehicles that can be seen. In certain cases, the flight controller must intervene to prevent them. This image depicts the UAV's possible behavior during its relocation to arrive at a point of inspection. The UAV makes use of light detection and ranging (LIDAR) to its surroundings as it travels toward its goal after obtaining the route program. Upon arriving at the trap location, the UAV takes an image before moving on to the next target point. The following criteria are used to evaluate the proposed solution in this paper: There are five traps per tree, arranged in a random pattern across the areas

- The minimum distance required to take an image of the trap is 3.0 meters.
- The UAV's planar LIDAR, which has a360-degree scanning angle, can be used to identify obstructions in space.
- Every trap has a preset position that is utilized to provide the route planner with target locations.

The LIDAR scanning methodology led the UAV to decide against using the vertical collision avoidance. Since the UAV lacks an integrated sensor to recognize objects on the aircraft's upper side, it would be difficult for the algorithm to work if vertical detection was included. To ensure a trajectory free of collisions, the RF will create the path between the rows of apple trees. The robot is believed to be able to cohabit with other robots, farm people, shifting tree branches, etc. when faced with dynamic impediments. The proposed CDBS-RF can handle extremely dynamic and time-varying situations while achieving a map exploration speed.

3.2. Quadrotor model design. The four fundamental motions were controlled by four separate cascaded proportional-integral (PI) controllers as shown in Figure 3.2. The inner loop and outer loop are two types of PI controllers. When disturbances impact a quantifiable secondary variable input in the middle that is directly related to influences the main outcome that has to be managed, there are benefits to this type of cascaded controller.

Disorders that reach the second variable can have an unwanted effect that the cascaded control system can lessen. This system's outer loop works at a lower frequency than the inner loop to manage the system bandwidth. Reference position data is received by the position control PI loop, and output data is received by the PI loop for speed control. The speed loop generates the command to drive the motors. The inertial

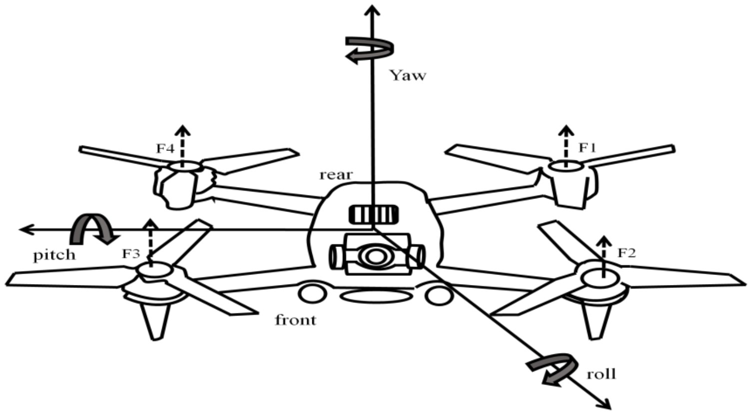

Fig. 3.2: Structure of UAV Quadrotor

measurement unit's (IMU) gyroscope provides instantaneous feedback to the speed loop. The controller's is to change the four propellers' speeds to obtain the intended quad-rotor orientation. One used a cascading connection to connect the foundations (1), where l is the separation between the rotors that are in opposition to one another.

$$\begin{bmatrix} \Omega_1^2 \\ \Omega_2^2 \\ \Omega_3^2 \\ \Omega_4^2 \end{bmatrix} = \begin{bmatrix} \frac{1}{4c}V_1 - & \frac{1}{2cl}V_3 - & \frac{1}{4d}V_3 \\ \frac{1}{4c}V_1 - & \frac{1}{2cl}V_2 + & \frac{1}{4d}V_3 \\ \frac{1}{4c}V_1 + & \frac{1}{2cl}V_3 - & \frac{1}{4d}V_3 \\ \frac{1}{4c}V_1 + & \frac{1}{2cl}V_2 + & \frac{1}{4d}V_3 \end{bmatrix} \tag{1}$$

3.3. Path planning using Customizable dung beetle search-tuned random forest (CDBS-RF). The Customizable dung beetle search-tuned random forest (CDBS-RF) is a path planning method that combines the CDBS algorithm's adaptive exploration capabilities with RF robust predictive modeling. This method optimizes navigation in complex environments by dynamically adjusting the search strategy based on environmental feedback. The algorithm refines path predictions through decision trees and accommodates real-time adjustments to changing conditions, resulting in a more accurate, resource-efficient, and adaptable path planning solution, offering significant improvements over traditional methods in computational efficiency and accuracy in dynamic and complex scenarios.

3.3.1. Customizable Dung Beetle Search (CDBS). The fundamental CDBS is population-based and principally inspired by the actions of the dung beetle including thieving, rolling balls, dancing, scavenging, and procreating. Four kinds of search agents little dung beetles, brood balls, ball-rolling dung beetles, and thieves—are used by the CDBS to divide the population. More specifically, every search agent has a unique set of updating guidelines. Figure 3.3 displays the CDBS flow chart.

A. Ball-rolling dung beetle. To maintain a straight course for the rolling dung ball, dung bugs must adhere to astronomical signals. Consequently, the rolling dung beetle's location has been modified and can be expressed as follows:

$$W_j\left(s+1\right) = W_j\left(s\right) + \alpha \times l \times W_j\left(s-1\right) + a \times \triangle w \tag{2}$$

$$\triangle w = \left|W_j\left(s\right) - W^x\right| \tag{3}$$

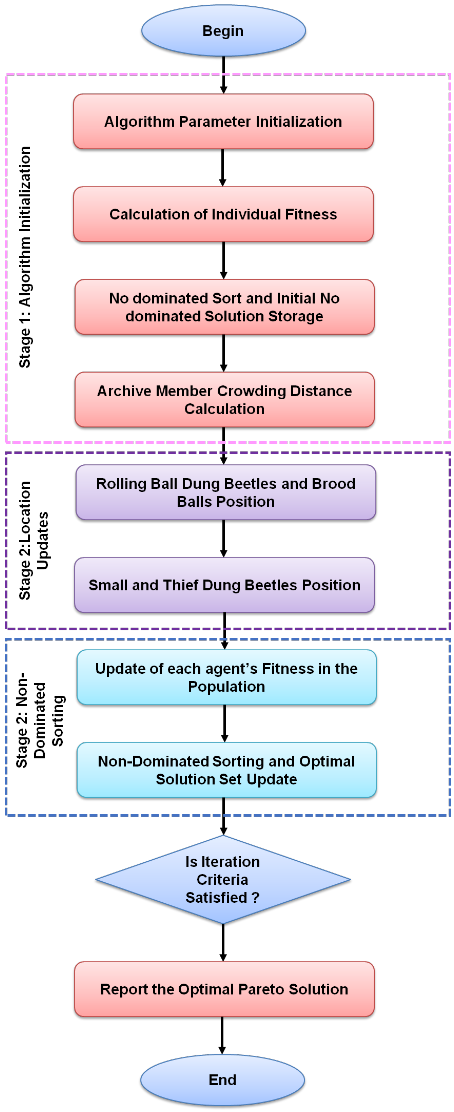

Fig. 3.3: Flow diagram of CDBS

where $s$is the number of iterations at this time$w_j(s)$is the location data of the j^{th}dung beetle across the t^{th} iteration, $a$is a fixed value that is a part of (0,1), $l \in$ (0, 0.2]If the deflection coefficient represented by a constant value, $\alpha$is given a natural coefficient to 1 or -1, $W^x$is the worst position in the world, and $\triangle w$ mimics variations in light intensity.

When faced with obstacles that prevent from moving forward, a dung beetle will employ dance to discover a new route. A tangent function provides a rolling direction by imitating the dance behavior. Thus, this is the ball-rolling dung beetle was last seen:

$$W_j\left(s+1\right)=W_j\left(s\right)+tan(\theta)\left|W_j\left(s\right)-W_j\left(s-1\right)\right| \tag{4}$$

where $\theta \in [0, \pi]$ is the angle of deflection.

B. Brood ball. For dung beetles to give their young secure environment, selecting an appropriate spawning place is essential. To replicate the female dung beetle spawning region, a boundary selection approach is suggested in CDBS and is described as follows:

$$lb^* = max(W^* \times (1 - Q)\,, lb) \tag{5}$$

$$ub^* = min(W^* \times (1 - Q)\,, lb \tag{6}$$

where $lb^*$and ub^* indicate the spawning area's top and bottom bounds, and W^* represents the best spot in the area at the moment:$R = \ 1 \ - s/S_{max}$ where $S_{max}$is the most iterations that can be made Lb and $Ub$are, respectively, the upper and lower bounds of the search space.

$$A_j\,(s+1) = W^* + a_1 \times (a_j\,(s) - lb^*) + a_2 \times (a_j\,(s) - ub^*) \tag{7}$$

where a_1 and $a_2$are two separate, size-dependent random vectors $1 \ \times C$;$C$is the size$a_j\,(s)$represents the j^{th} sphere's location at the s^{th} iteration

C. Tiny dung beetles. A special kind of adult dung beetle that burrows into the earth in quest of food is the tiny dung beetle. The following factors determine the boundaries of the optimal feeding region for little dung beetles:

$$lb^* = max(W^b \times (1 - Q)\,, lb) \tag{8}$$

$$ub^* = min(W^b \times (1 - Q)\,, ub \tag{9}$$

where Lb^a and $Ub^a$are the top of the perfect foraging area and lower bounds, correspondingly. andW^a is the ideal location on the planet. The little feces beetles have relocated to this area.

$$w_j\,(s+1) = W_j\,(s) + D_1 \times \left(W_j\,(s) - lb^b\right) + D_2 \times \left(W_j\,(s) - ub^b\right) \tag{10}$$

where $D_1$is a normal distribution applied to the random number, $D_2$is the arbitrary vector that falls between (0,1), and $w_j(s)$ is the location of at the s^{th} iteration the j^{th} dung beetle.

D. Thief. Some bugs pilfer other bugs' excrement balls; these are called thieves. The ideal food supply is W^a, as can be shown from Equation (5). $W^a$is the best place for competing food, therefore let's assume so. The following is an update to the thief's position information during the iteration process:

$$w_j\,(s+1) = W^a + T \times h \times ((W_j\,(s) - x^*| + |W_j\,(s) - x^b|) \tag{11}$$

There T is a fixed figure, h is a chance vector with a size of $1 \ \times C$ that is subject to a normal distribution, and $w_j(s)$ discloses the location of the j^{th} thief at the s^{th} repetition.

3.3.2. Random forest (RF). RF is an algorithm that uses random sampling searches inside a predetermined state space. Ensemble learning is the term used to describe the application of many models to a single classification issue. When it comes to RF, the forecasts are made by a voting procedure over the results and flow chart of RF as show in Figure 3.4

Each tree chooses at random a subset of the characteristics that are present in the data to produce different distributions in the models, as well as random samples taken from the dataset. The Gini Index (GI) produces greater precision in the experiments that are carried out, to assess the significance of the characteristics before generating a new node

$$GI = 1 - \textstyle\sum_{j=1}^{D} o_j^2 \tag{12}$$

where o_j, the probability of class j, is determined by its frequency of presence on the split under consideration, and d is the number of classes. Using a Grid Search approach yields the RF architecture for training. We construct a set of potential parameters for each job (landing and mid-range flights), and we use all conceivable

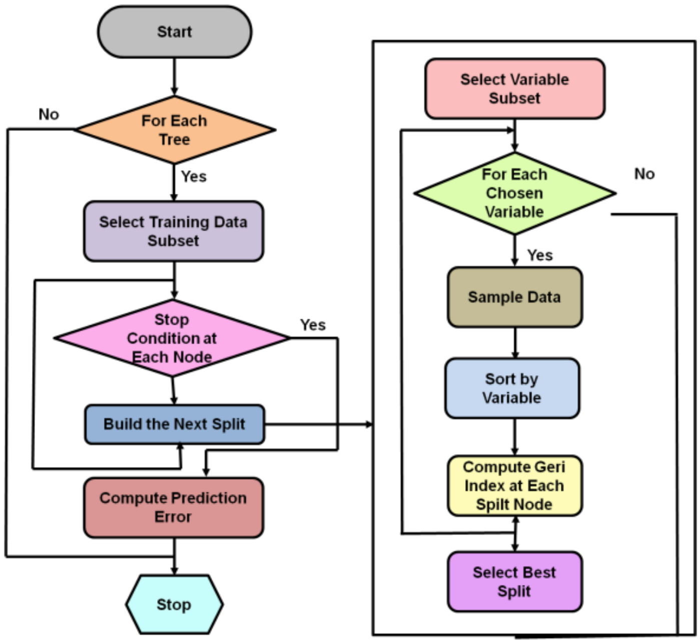

Fig. 3.4: Structure of the RF

combinations to generate distinct forests. Every forest undergoes evaluation using a subset of the training data, known as the validation set and the optimal parameter configuration is kept for the whole training process.

By combining the clever navigational techniques of dung beetles with cutting-edge machine learning algorithms, CDBS-RF path planning effectively plans routes and implements anti-collision procedures as shown in Algorithm 1.

Algorithm 1: CDBS-RF
Initialize parameters:
Define the number of UAVs (N)
Define the environment map ($grid\_size$, $obstacles$, $waypoints$)
Set the maximum number of iterations (max_iter)
Initialize DBS parameters ($e.g.$, $population\_size$, $search\_radius$)
Initialize RF parameters ($e.g.$, $number\_of\_trees$, max_depth)
Generate initial population of paths:
For $i = 1$ to N:
Generate random path ($start\_point$ to end_point)
Evaluate path using RF model to calculate safety and efficiency
Perform DBS optimization:
For $iteration = 1$ to max_iter:
Evaluate fitness of each path in the population using the RF model
Update the best path based on fitness evaluation
Update paths using DBS algorithm:
Move each path based on Dung Beetle Search rules (e.g., attraction to better paths)
Apply random adjustments to paths for exploration
Refine paths using RF model:
For each path in the population:
Tune path parameters using RF model to optimize safety and efficiency

Table 4.1: Experimental setup

Category	Component	Details
Hardware	Operating System	64-bt Ubuntu18.04 bionic
	CPU	2.7 Ghz core-i5-5200
	RAM	8GB
	Desktop environment	LXDE
Software	Python version	Python 3.10
	Simulation software	Gazebo
	Description of software	Gazebo is comprehensive simulation software that enables the creation of realistic environments with dynamic features like gravity and wind, enabling the addition of visual components.

Choose the optimal course of action:
Select the route from the ultimate demographic that has the highest fitness score
Output the optimal path:
Display or save the best path for UAV navigation
End

With this novel method, dung beetle search patterns' flexibility and random forest models' predictive capacity are combined to create a system that can safely navigate over obstacles while dynamically adapting to changing circumstances. Through the imitation of natural navigation skills and the utilization of artificial intelligence's processing power, CDBS-RF provides a strong solution for efficient path planning in intricate situations, improving autonomy and security in self-governing systems.

4. Results and Discussion.

4.1. Configuration of Environment and Hardware. The Table 4.1 summarizes the hardware and software used for the simulations, including the specific versions and functionalities relevant to the experiments.

4.2. Simulation Resullts. The authors experimented with several CDBS-RF models, including the one recommended by others, to improve results for an environment where $[0, 0, 0] \leq Z \leq [10, 10, 10]$ and M=15. Model 3 has a steady reaction than others, as can be seen in Figure 4.1.Compared to the previous models, Model 3 appears to have a consistent reaction. Its exploration factor among the lowest, nevertheless. Though it differs significantly throughout the exploitation phase, Model 1 produces almost equal outcomes. The model is still exploring close states at that point.

These comparisons are explained, and a comparison based on the overall mean average is as shown in Figure 4.2. The model's performance is shown by the black line following eight training cycles, the blue line marking the violet line indicating modifications at the conclusion of the exploration phase in the stage of discovery during the utilization phase. Based on their Total Mean Reward and Exploration Phase End event, three models are compared in the table that is presented. At the twentieth exploration phase, Model 1 produced a Total Mean Reward of -10.26. Model 2 had lengthier exploration duration, as seen by its lower reward of -10.30 at the 800th phase. With a payout of -10.20 at the 60th phase, Model 3 landed in the middle.

It is crucial to remember that the CDBS-RF algorithm's path may not be collision-free because it knows information about static objects. The suggested approach accomplishes the goal in every experiment. The difference between the angular coefficient of CDBS-RF pathways and the header UAV angle throughout the validation testing is shown in Figure 4.3. These deviations, on average, range from -1^0 to 1^0, and they deviate when the agent must avoid moving impediments. The suggested technique was verified by the authors through a run-time comparison experiment between the CDBS-RF model and alternative path-planning algorithms.

4.3. Performance evolution. The suggested performance metrics for the CDBS-RF algorithm are shown in the Table 4.2. With a score of 90, the algorithm shows good path efficiency and successful route optimization. With a notable high of 95 for collision avoidance, it demonstrates its capacity to reduce impediments during

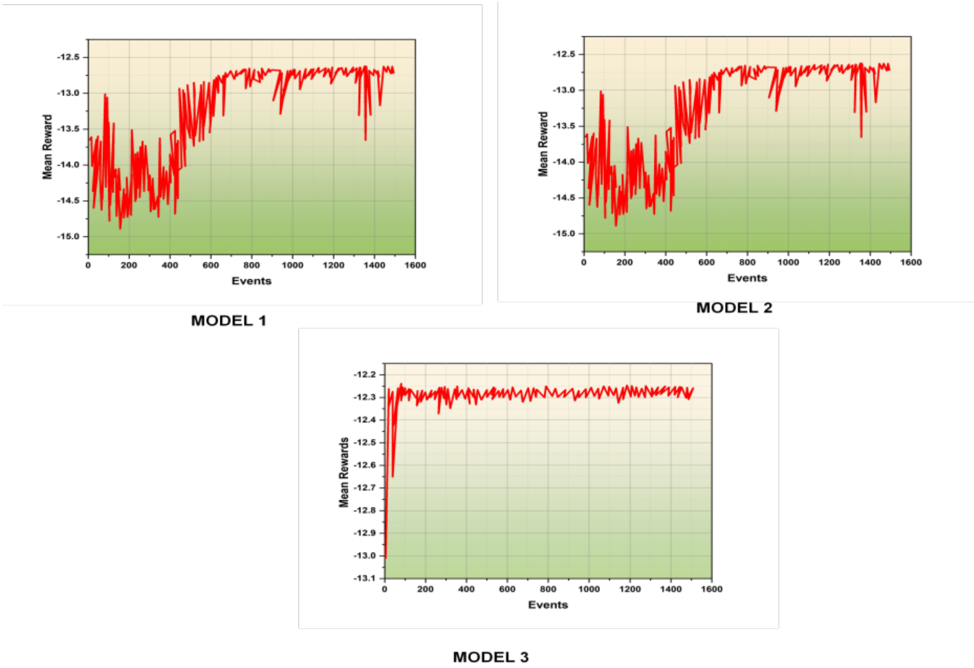

Fig. 4.1: Returns on investment for several models of CDBS-RF with 1500 events and 0.001 learning rate

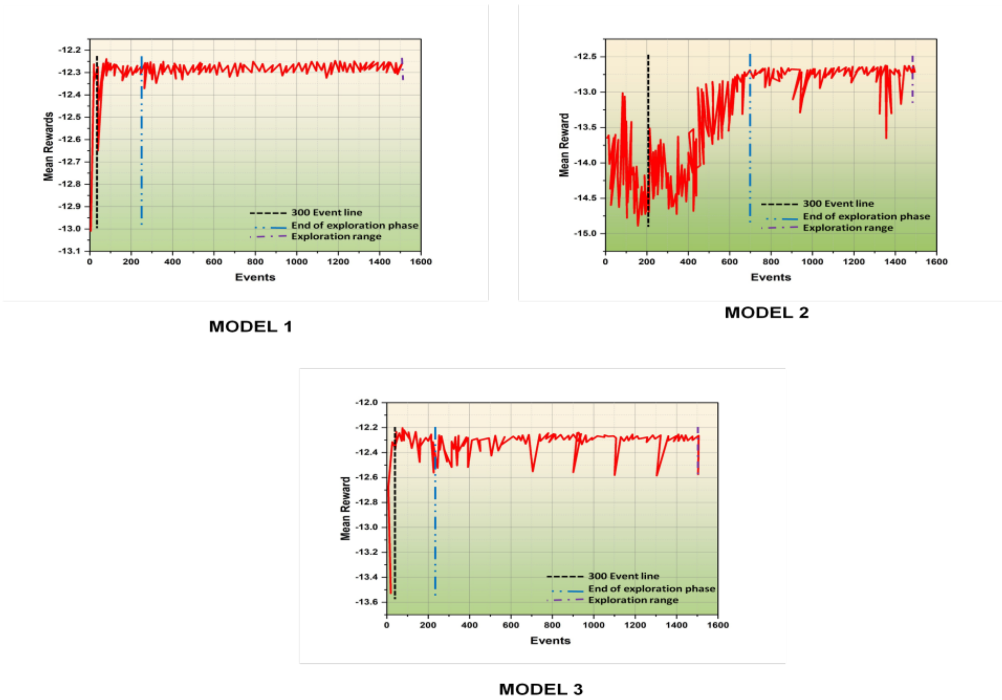

Fig. 4.2: Evaluating the top three models' performances in comparison

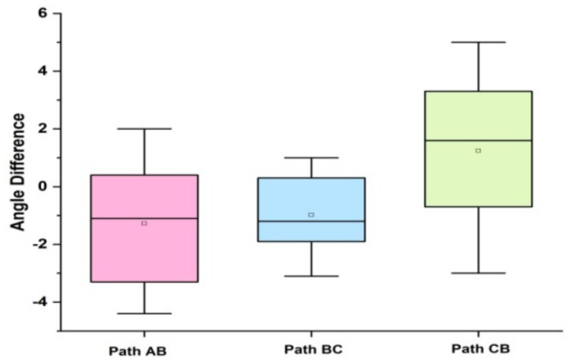

Fig. 4.3: Disturbance in angle between UAV header and CDBS-RF route

Table 4.2: Outcomes of performance

Evaluation parameter	**CDBS-RF [Proposed]**
Path Efficiency	**90%**
Collision Avoidance	**95%**
Computational Efficiency	**80%**
Accuracy	**92%**
Adaptability	**85%**

path planning. With an 80 score, computational efficiency indicates a well-balanced utilization of execution time and processor power. With a score of 92, accuracy emphasizes how precisely the algorithm produces correct results. The algorithm's strong performance in adapting to dynamic and changing surroundings is indicated by its adaptability score of 85. These numbers show the overall efficacy and dependability of the CDBS-RF algorithm across a range of assessment criteria.

4.4. Comparison phase. From the starting sites to the final location, the route that A* path planning algorithm creates often follows the edges of obstacles as it moves across the scene. It evaluates the performance of the CDBS-RF with existing methods like Optimized RRT [20], Generalized Wave front [20], and A* [20] Metrics like planning time and path length are used for assessment.

4.4.1. Planning time (s). The amount of time needed for any method to calculate a path for UAVs, representing its efficiency, is referred to as planning time. The planning timeframes for the different strategies are compared in Table 4.3 and Figure 4.4. The suggested CDBS-RF, A*, Generalized Wavefront, and Optimized RRT and the outcomes show that CDBS-RF is the most efficient in creating pathways rapidly, with the least planning time of 0.789 seconds. It shows the path created by the suggested method CDBS-RF is smoother and significantly farther from obstructions.

4.4.2. Path length (M). The distance of the route produced by each method for UAV navigation is represented by path length (M). The path lengths for the various techniques optimized RRT, Generalized Wavefront, A*, and the suggested CDBS-RF are displayed in Table 4.4 and Figure 4.5. According to the data, CDBS-RF produces the shortest path length (21.526 meters), suggesting a more direct, effective, and obstacle-avoidance method. It shows the path created by the suggested method CDBS-RF is smoother and significantly farther from obstructions.

Table 4.3: Results ofplanning time (S)

Methods	**Planning time (S)**
Optimized RRT [20]	0.857
Generalized Wavefront [20]	1.008
A* [20]	1.685
CDBS-RF [Proposed]	0.789

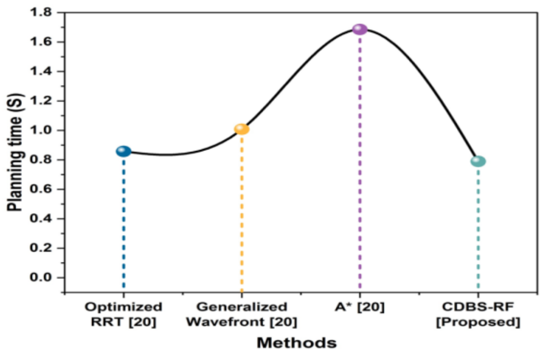

Fig. 4.4: Comparison of planning time (S)

Table 4.4: Path length (M)

Methods	**Path length (M)**
Optimized RRT [20]	27.85
Generalized Wavefront [20]	23.892
A* [20]	26.845
CDBS-RF [Proposed]	21.526

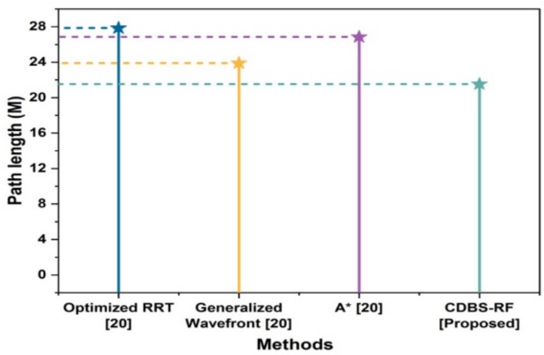

Fig. 4.5: Comparison of Path length (S)

4.5. Discussion. The limitations of the optimized RRT, generalized wave front, and A* algorithms are primarily related to their path efficiency and computational complexity. Optimized RRT, while effective for high dimensional spaces, can produce suboptimal paths that can be longer and less smooth, generalized wave front offers smooth paths but can be computationally intensive and slow, especially in complex environments, A* is known for its optimally and completeness but can suffer from high computational costs and slower performance in large-scale or dynamic environments. Each algorithm faces challenges in balancing path length, smoothness, and computational efficiency, impacting their overall effectiveness in practical applications. The CDBS-RF method addresses these issues by integrating dung beetle search optimization with RF techniques, which enhances path efficiency and smoothness while reducing computational complexity. This approach ensures shorter, smoother paths with faster planning times compared to traditional algorithms.

5. Conclusion. The primary aim of the study was to optimize UAV path planning and collision avoidance in agricultural surveillance by introducing a novel technique, the CDBS-RF method. The objective was to enhance UAV route planning by integrating the DBS algorithm with the RF model, thus improving path safety and operational efficiency. The proposed method dynamically adjusted path planning parameters to ensure optimal route selection and effective collision avoidance, thereby addressing the complexities of real-world environmental variables that impact UAV operations. The CDBS-RF technique was implemented in a python based virtual environments and evaluated using UAV sensed data. Experimental results demonstrated that this approach significantly improves UAV path planning performance, leading to safer and more efficient navigation. The integration of advanced optimization and anticollision algorithms within the CDBS-RF framework offers a promising solution for enhancing UAV operations in agricultural surveillance, particularly in monitoring large, complex agricultural landscapes. The performance evaluation techniques include the planning time (0.789) and path length (21.526).

5.1. Limitations and future scope. *Limitations:* Despite the promising results, the study faced limitations related to the quality and resolution of UAV sensed data, which could constrain the effectiveness of the CDBS-RF technique in real-world applications. Additionally, the model performance can be influenced by environmental variability that was not fully captured in the virtual testing environment.

Future scope: Future research should focus on validating the CDBS-RF method in diverse real-worls agricultural settings with varying environmental conditions to assess its robustness and adaptability. Further improvements could involve integrating more advanced sensors and data fusion techniques to enhance data quality as well as exploring Ml models beyond RF to potentially increase path planning precision and collision avoidance capabilities.

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Edited by: Vadivel Ayyasamy
Special issue on: Internet of Things and Autonomous Unmanned Aerial Vehicle Technologies for Smart Agriculture Research and Practice
Received: May 18, 2024
Accepted: Dec 19, 2024