

Chapter 3

Multi-Cloud Path Planning of Unmanned Aerial Vehicles with Multi-Criteria Decision Making: A Literature Review



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3.1 Introduction

UAV denotes a pilotless aircraft which functions via a combination of technologies such as artificial intelligence, computer vision, object avoidance technologies, and what not. A UAV operates on ample levels of independency via remote control by a manual operation or a pre-programmed operation on board computers. Having experience significant levels of achievements on autonomous technologies, UAVs take a big chunk on wide versatility of applications, such as national security, talking of emergency situation, humanitarian aid and disaster management, conservation of resources, disease control and prevention, agriculture and forming, weather forecasting, urbanization, retail, manufactural establishment, nourishment of inventories, and upbringing of economies.

3.2 Classification of UAV

There is no one criterion when it arrives to the classification of UAV. They are categorized by aerodynamics, landing, weight, and range as shown in Fig. 3.1.

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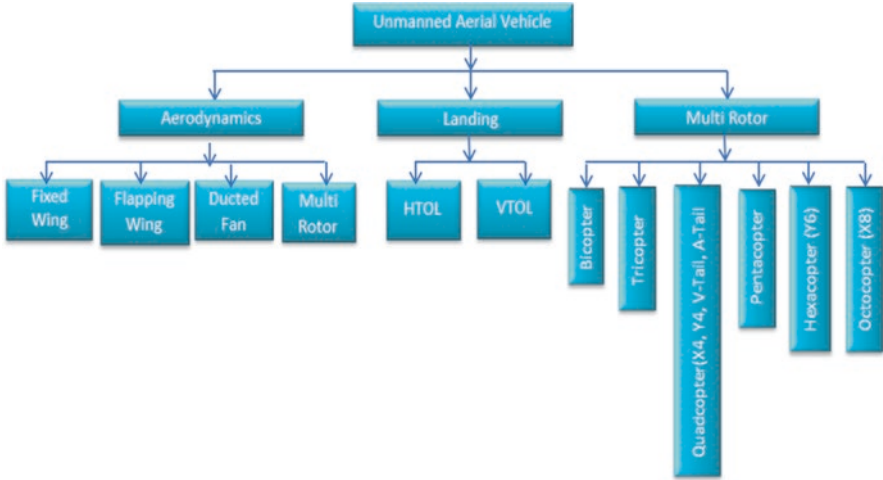


Fig. 3.1 Classification of UAV based on aerodynamics, landing, and multi-rotor

3.2.1 Based on Aerodynamics

Wide varieties of UAV systems have been worked upon, which includes the fixed wing aircraft [1], chopper [2], multi-copter [3], vertical aeration and piloting [4], details on various part in the making of UAVs, and getting the UAVs into the market.

Fixed wings are the key uplifting components which work on accelerating the current phase ahead. Lifts generated are systematically influenced by angulation of the UAVs along with its initial phase of aeration which influenced on fixed wings. A thrust-to-load ratio lower than one and higher is essential to get the most out of fixed wing drones when launching the flight [5]. It must be noted that fixed wing drones are higher in sophistication and does utilize appreciable amount of power when compared to multi-rotor on some of payload [6]. Controlling this aircraft does require roll, pitch, and yaw maneuvers. Direction, aeration, and positioning are taken cared by roll, pitch, and yaw, respectively. Yaw, roll, and pitch are angulated by rudder, ailerons, and elevators on the surface of aircraft shown in Fig. 3.2.

Given that fixed wing drones are getting higher popularity due to its sophistication and compatibility with larger lift-to-drag ratio (L/D ratio) and with sophisticated Reynolds number, they cannot aerate on low speed and also hover still. Being well observed the fact that the lift-drag points on lift generated by a trailing wing are counter generated, fixed wing drones are less valued for L/D. Small hummingbirds to large dragonflies [7] have been an inspiration for developing flapping wing drones. Not only the birds on the whole have been driven inspiration from but also the feathers of the above further helped in designing lightweight and flexible wings in aerodynamics. Although the inspiration came easy from the birds, it is a big technological challenge to work on accounting to the complexity in aerodynamic for creating flexible and weightless flaps [8].



Fig. 3.2 Pitch, roll, and yaw in an aircraft (NASA official: Tom Benson)

In a multirotor, main rotor sharp edge delivers a powerful push helping on aeration and piloting. Multirotor unmanned aerial vehicles aid **vertical** take-off and **landing** (VTOL) and also as a special feature of hovering still which unfortunately fixed wing aircraft are not capable of. Furthermore, the practice of flexible root bars as an alternative of universal joints significantly reduces the machinery complexity. Instead, the wing twist modulation model requires a specific wing design, whose lift force differs almost linearly with the root bar deformation [9]. The sole draw back with multirotor is they require ample amount of power to function. Abbott equations are used to numerate power and thrust requirements [10] where RPM (Revolutions per minute)

$$\text{Power } [w] = \text{Pitch} * (\text{Diameter})^3 * (\text{RPM})^2 * (10^{-10}) \quad (3.1)$$

$$\text{Thrust } [oz] = \text{Pitch} * (\text{Diameter})^3 * (\text{RPM})^2 * (10^{-10}) \quad (3.2)$$

Alteration in acceleration and deceleration of thrusting propeller/motor elements are used in functioning of multicopter. It is categorized into various classes keeping number and positioning of motors as sole components; every peculiar mission is specialized by a particular class. Because of which many number of configuration take birth, such as Bicopter, Tricopter (Y3, T3), Quadcopter (X4, Y4, V-Tail, A-Tail), Pentacopter, Hexacopter (Y6), and Octocopter (X8) [10].

3.2.2 Based on Landing

Horizontal take-off and landing (HTOL) are worked upon further from fixed wing aircraft as they happen to have a well-appreciated phase in its cruise and a smooth landing to end the aeration. Vertical take-off and landing (VTOL) cruise speed is a main detaining factor for vertical take-off and landing (VTOL) drones even though they are well versed in flying, landing, and vertical hovering [10]. Various automatic landing systems based on the GPS (global positioning system), INS (inertial navigation system), ILS (instrument landing system), and tracking radar may not be applicable due to the complexity and operational environment costs/limitations. The vision-based landing proved to be attractive as it is passive and inexpensive and

does not require special equipment other than a camera and on-board vision processing unit. An uncalibrated camera is utilized to generate high-precision position information for automatic landing on the runway with a speed sensor because air-speed is very important during landing. The superior distinctive of this method is that neither a calibrated camera is required nor the recognition of special points of the track and its 3D location must be experimented.

3.2.3 Based on Weight and Range

Engineers find weight and range as a solid parameter for classifying drones as listed in Table 3.1. Top 10 best value drones under 7100 ₹ in India 2020 are shown in Fig. 3.3. The best drones for 2020 are shown in Fig. 3.4.

3.3 Hardware Design and Challenges

Unmanned aerial system design involves a link between UAV and user and vice versa, and also components such as stations for ground controlling are involved. The design of UAV has head to tail programs for aerial vehicle as it can start from vehicle framing to aeration of the vehicle. The crucial task begins in picking up of elements such as airframe, controller, propellers motor, and power supply. The need of in-depth knowledge on mathematical designs to program a UAV for a particular operation is vital. Figure 3.5 labels the subsystems and also modules for programming an UAS.

(1) Aircraft design: The challenge begins when the complexity of the type of application used limits the reporting area phase and climbing rate. The key strings of an aircraft subsystem are assessment of inertia, motors, airframe, propellers, central processing unit, and receiver [10]. Alloys, aluminum, and titanium are the most

Table 3.1 Classification of UAV based on weight and range

Type	Range (km)	Weight (kg)
Nano-sized	<1	<0.025
Micro-sized	<10	<5
Mini	<10	<20
Close range	10–30	25–150
Short range	30–70	50–250
Medium range	70–200	150–500
Minimal altitude low endurance	>250	250–2500
Minimal altitude high endurance	>500	15–25
Marginal altitude low endurance	>500	1000–1500
Maximal altitude low endurance	>2000	2500–5000



Fig. 3.3 Top 10 best value drones under 7100 ₹ in India 2020

Drone Model	DJI Mavic 2 Pro	DJI Inspire 2	DJI Mavic Air 2	DJI Mavic 2 Pro	DJI Inspire 2	DJI Mavic Air 2	Anel Robotics EVO	DJI Mavic 2 Zoom	Parrot Anafi	DJI Spark	Ryze Tello	DJI Mavic Mini
Dimensions	3.3 by 3.6 by 8.4 inches	12.5 by 16.7 by 15.7 inches	3.3 by 3.8 by 7.1 inches	3.3 by 3.6 by 8.4 inches	12.5 by 16.7 by 15.7 inches	3.3 by 3.8 by 7.1 inches	5.5 by 5.5 by 10 inches	3.3 by 3.6 by 8.4 inches	2.5 by 2.6 by 9.6 inches	2.2 by 5.6 by 5.6 inches	1.6 by 3.9 by 3.6 inches	2.2 x 3.2 x 5.5 inches
Weight	2 lb	7.3 lb	1.3 lb	2 lb	7.3 lb	1.3 lb	1.9 lb	2 lb	11.3 oz	10.6 oz	2.8 oz	0.8 oz
Rotors	4	4	4	4	4	4	4	4	4	4	4	4
Obstacle Detection	✓	✓	✓	✓	✓	✓	-	✓	-	✓	-	-
Integrated Camera	Integrated with Gimbal	Integrated with Gimbal	Integrated with Gimbal	Integrated with Gimbal	Integrated with Gimbal	Integrated with Gimbal	Integrated with Gimbal	Integrated with Gimbal	Integrated with Gimbal	Integrated with Gimbal	Integrated without Gimbal	Integrated with Gimbal
Video Resolution	4K	5.2K	4K	4K	5.2K	4K	4K	4K	4K	1080p	720p	2.7K
Megapixels	20 MP	20 MP	48 MP	12 MP	20 MP	48 MP	12 MP	12 MP	21 MP	12 MP	5 MP	12 MP
Media Format	microSDXC	microSDXC	Internal, microSDXC	microSDXC	microSDXC	Internal, microSDXC	microSDXC	microSDXC	microSD, microSDXC, microSDC	microSDXC	None	microSDXC
Remote	Dedicated with App	Dedicated with App	Dedicated with App	Dedicated with LCD	Dedicated with App	Dedicated with LCD	Dedicated with App	Dedicated with App	Dedicated with App	Smartphone/Tablet App, Dedicated with App	Smartphone/Tablet App	Dedicated with App
Live Video Feed	1080p	720p	1080p	720p	1080p	720p	1080p	1080p	Yes	Yes	Yes	Yes

Fig. 3.4 The best drones for 2020 (Jim Fisher from PCMag India)

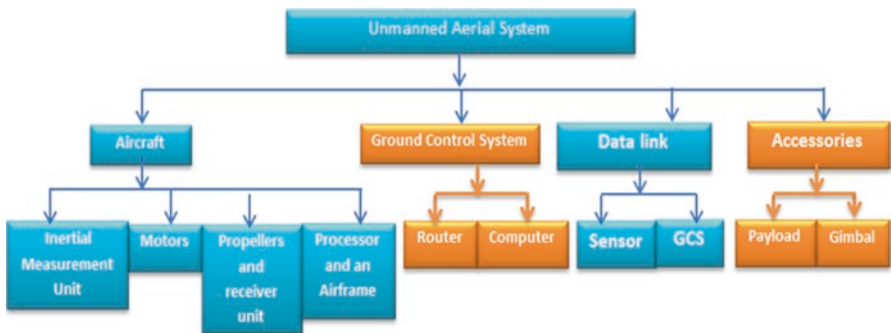


Fig. 3.5 Unmanned aerial system subsystems

common metals in manufacturing an aircraft. On the other hand, non-metallic substances such as transparent and recycled plastic are utilized. Electronic speed controller keeps itself useful by changing the force provided via motor. They can be in the air in a particular direction and also set their height by using signals based on the results of assessment of inertia. (2) Ground Control System: Computerized wireless router, by controlling ground system, could unlock a wide range of possibilities such as capturing, data processing, and data visualization. Ground control station is basically made into a standard to be able to act compatible with a variety of platform and also open system architecture [11]. (3) Data Link: Aircraft sensors and ground control station (GCS) have wide integration for running the computerized wireless router smoothly. The IEEE 802.11 wireless link is picked up to establish a link from the aircraft CPU and ground controller and vice versa. Routers should be planted with antennas which could scoop omnidirectional tracking for high gain which are utilized in lowering the path loss. Currently, modern antennas work on 2.4 GHz and a minimal gain of 12dBi. (4) Accessories: Multispectral, thermal, hyper-spectral, digital camera, and film imaging units are made compatible to UAV. The above are utilized to carry out photogrammetry, film shooting, and field mapping. Thermal and hyperspectral cameras seem to be appreciated more in remote sensing. Mining, oil, and gas industries use drones equipped with thermal sensors. Table 3.2 tabulates the achievements in wide variety of spectrum on sensors for UAV.

Table 3.2 Developments in multispectral sensors for UAV

Model	System summary	Image size	Optics	Weight (g)
MCAW	Embedded Linux computer system with sync'd capture interface to multiple snap shutter sensors	6 images of 1280 × 1024 pixels 8 or 10 bits/pixel	9.6 mm fixed lens	550
Micro-MCA + tau	6 Mpel configurable multi-spectral camera	7 images of 1280 × 1024 pixels 8 or 10 bits/pixel	9.6 mm fixed lens	900
ADC lite	3.2 Mpel multi-spectral R-G-NIR system	1280 × 1536 pixels 8 or 10 bits/pixel	8.0 mm user changeable lens	200
ADC micro	3.2 Mpel multi-spectral R-G-NIR system	1280 × 1536 pixels 8 or 10 bits/pixel	8.43 mm fixed lens	90
ADC snap	1.3 Mpel multi-spectral R-G-NIR snap shutter system	1280 × 1536 pixels 8 or 10 bits/pixel	8.43 mm fixed lens	90
Micro-MCA	5.2–15.6 Mpel configurable multi-spectral camera	4.6 or 12 images of 1280 × 1024 pixels 8 or 10 bits/pixel	9.6 mm fixed lens	uMCA-4500 uMCA-6530 uMCA-121000

3.4 Path Planning Overview and Issues

Having a path planning technique is imperative for computing safe path with minimal expenditure of time to reach the final desired destination. It consists of motion planning, trajectory planning, navigation, global path planning, and local navigation. It is prominent that in path planning in complex condition, the 2D (two-dimensional) strategies are not proficient to perceive the odds and other computerized wireless objected when compared with 3D (three-dimensional) path planning techniques, In such manner that it is sophisticated, a path planning for 3D (D^3) location with static *obsts* $O = \{O_1, O_2, \dots O_n\} \subset D^3$, from P_{start} to P_{target} , is as shown in Fig. 3.6. This situation includes a robot traveling through six dividers with minor fixes. The robot is bigger than the gaps and needs to twist to produce a crash free way the underlying setup to the last design [12].

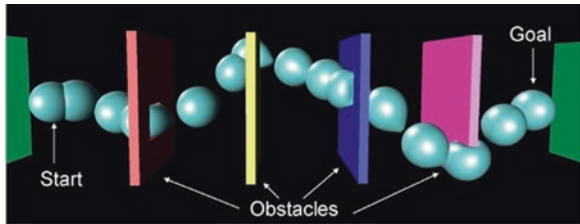
At that point, the problem on path planning for D^3 location is defined as $(P_{start}, P_{target}, W_{free})$ which comprises the following functions: $[0, T] \rightarrow D^3$ is clearly expressed in the bounded region where T is characterized as a time. At that point, the following holds $(0) = P_{start} \rightarrow$ at beginning time $(T) = P_{target} \rightarrow$ at target time $W_{free} \rightarrow$ workspace without obstacles there exists, $\emptyset = \delta(\beta) \in W_{free}$ for all, β in $[0, T]$. Then, \emptyset is entitled path planning of UAVs. A perfect path is clearly expressed as $\delta'(c, t, e) =$ optimum of $\delta(c, t, e)$, where δ is the function of set of all feasible path and δ' is an optimal path computation function. At that point, the following holds where $c \rightarrow$ cost (c), $t \rightarrow$ time (t), $e \rightarrow$ energy (e) should be minimized. The energy communication of UAVs base-station could be brought to a minimal amount on decreasing the power used in transmission. In the same way, there is a need for minimized mechanical support and resources. The energy-efficient consumption model in UAVs [13, 14] is shown in Eq. 3.1.

$$E = (P_{min} + \alpha h) + (P_{max}) (h/s) \tag{3.3}$$

whereas $t \rightarrow$ the operating time, $h \rightarrow$ the height, and $s \rightarrow$ the speed of the UAVs. $P_{min} \rightarrow$ minimum power needed to start the UAVs and $\alpha \rightarrow$ motor speed multiplier. P_{min} relies upon weight and engine characteristics. Hence, the total communication cost (T_{com}) to limit the time and cost in UAVs correspondence framework is shown in Eq. 3.2 (Shubhani Aggarwa, 2020) [14].

$$T_{com} = t_{startup} + (t_{overhead} + t_{hop})l \tag{3.4}$$

Fig. 3.6 Spherical robot through walls [12]



whereas t_{startup} \rightarrow UAVs start-up time, t_{overhead} \rightarrow overhead time, t_{hop} \rightarrow UAVs per-hop time and l \rightarrow source and target communication links. Aside from these constraints, robustness, completeness, and collision avoidance aspects need to be measured for finding the optimality in path planning of UAVs.

3.4.1 Steps in the Path Planning

Path planning of the UAVs is spoken to as ‘ U ’ comprises of two stages as follows. The main stage is the pre-preparing stage. In this stage, hubs and edges are drawn on the workspace ‘ W ’ with obstructions ‘ O ’. At that point, the idea of the configuration space (c-space) to portray U and O on W is applied [13]. For generating the graph maps, representation techniques are applied [15]. Identification of UAVs is done with help of the query phase. Graph-based search algorithms Dijkstra’s algorithm [16], regular chain of segments algorithm (RCS) [17], Floyd algorithm, and lazy counting-based splay tree algorithm [18] to name a few are used in query stage. Probabilistic models, Q-learning [19], mixed integer linear programming [20], and bio-inspired models like intelligent water drops [21] can also be utilized for path planning of UAVs. For representing the C-space on workspace W , there are an ample amount of path planning methods such as potential fields [22], cell decomposition [23], and roadmaps [24].

3.4.2 Challenges in Path Planning

Ample research recommendations are being talked about in the yester years to take care of path planning difficulties on UAVs [25]. For instance, Marina Torresa et al. [26] defined the regions by different sweep direction to discover an optimal path. Additionally, Torres et al. [26] investigated to lessen the distance between sub-areas by the back and forth pattern. Also, Balampanis et al. [27] projected the hybrid and approximate decomposition technique. Along these lines, Acevedo et al. [28] suggested spiral-like pattern in complex coverage areas. Path planning algorithms obtain an available drone path with hazard avoidance autonomously. Many parameters such as getting the path completed, optimizing the path, minimizing the length of the path, making it cost and energy efficient, and reducing the odds have been noted in path planning techniques.

3.4.2.1 Multi-Cloud Path Planning with Multi-criteria Decision Making

The multi-robot system is established on cloud technology with a high level of autonomy, which is set to play an increasing role in responding to the COVID-19 pandemic. The multi-cloud approach shifts agent computing load to the cloud and

provides influential processing skills to the multi-robot system. In order to improve the efficiency of trajectory path planning, the implementation of multi-criteria decision-making (MCDM) while using a full consistency method (FUCOM) is utilized [29]. Mustafa Hamurcu et al. [30] promises to determine the weight of factors influencing robot movement, with regard to mission specificity that involves managing multiple risks from diverse sources, thus optimizing the global cost map.

3.4.2.2 Internet of Drone-Based Data Analytics in Multi-Cloud

The latest technology behind Internet of Drone (IOD) safe exploitation on commercial and public use presents communication and computational challenges in aspects of the real world. Assigning individual tasks to multiple drones and using the data center values on the side, data are transferred to the cloud for technically balancing the data from an inaccessible area [31]. Methods for analyzing drone data with great efficiency in the areas of progress monitoring, inspections, and surveys to analyze the data to make key decisions are identified. The processing of drone data has just extended into the cloud with bandwidth management for data processing, and on the basis of image detection, an effective decision will be taken to protect human life and property [31].

3.4.3 Path Planning Techniques in UAVs

Ample number of time was invested in UAVs as it shows great promise. The versatile stages for path planning endeavor are (1) programming 3D environment and (2) graphing for the programmed 3D ecosystem. For starters, representation technique is based on configuration (Geraerts, 2010) [23], roadmaps (Ryan DuToit) [32] (Kwangjin Yang, 2008) [33], and potential field (Alex Nash) [34]. Furthermore, the next in line are integrating swarm intelligence algorithms (Hrabar, 2008) [35], simulated annealing method, to name a few (Shubhani Aggarwa, 2020) [14]. Optimization problems would be easily solved by path planning algorithms. The exact behavior of UAVs can be easily studied by the above algorithms.

3.4.3.1 Representation Techniques

Getting the UAVs projected into the 3D environment is a phase maker, and it is done using AI and sampling; the naming of those techniques is as shown in the Fig. 3.7.

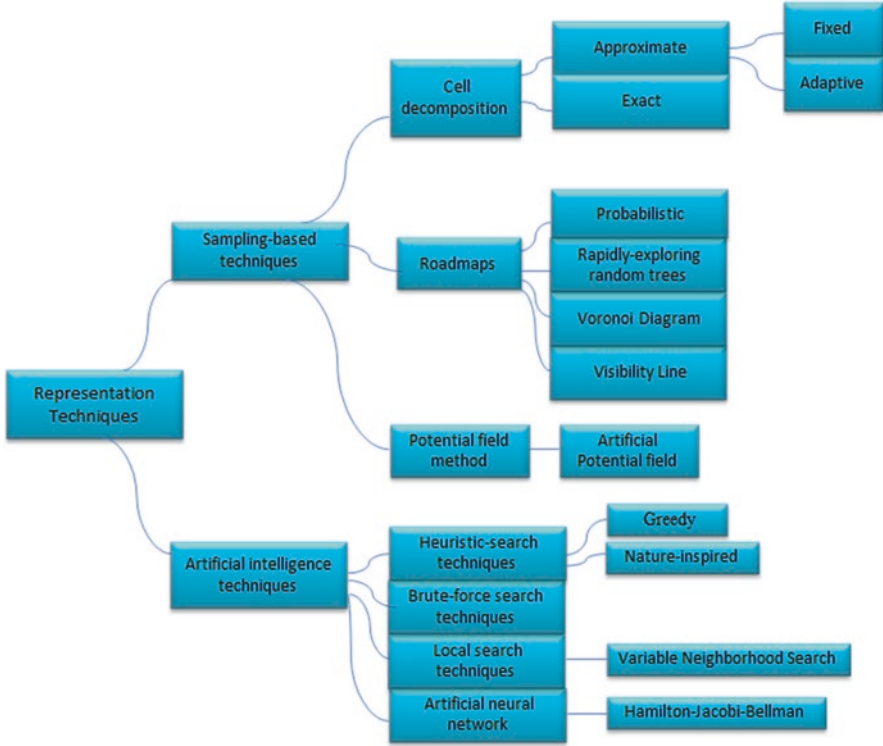


Fig. 3.7 The representation techniques

Sampling-Based Techniques

These techniques need the programming 3D environment that has already been pre-programmed. Division into nodes and making a map out of it are achieved via algorithm that undertakes direction and path of the UAVs. Rapid-exploring random trees (RRT) [32], RRTstar (RRT*), A-star (A*), probabilistic roadmaps (PRMs) with D* Lite (PRM) [36], particle swarm optimization (PSO), and improved intelligent water drop algorithm (IIWD) [21] are some of the versatile methods for sampling mechanisms.

Cell Decomposition

Creation of a safe path for intra- and inter-cell path is taken cared by cell decomposition. Types of cells, space, various strategies, and calculations are the key factors for basing the cellular organization in UAV path planning. The exact cellular decomposition works by dividing the area of interest and works into varied amount of

sub-areas. In this way, reduction of the coverage path problem (CPP) could be achieved to motion planning [37]. Decomposed cells could be swept to the site of need. Adjacency graph takes care of the decomposition, and a search can be performed to get to the connected path for picking up the nodes. Trapezoidal decomposition and boustrophedon decomposition help in the process. Formation of trapezoidal shaped cells is how the trapezoidal decomposition works. The other now creates non-convex cells. The boustrophedon decomposition decreases the number of trapezoidal cells for covering the distance of the path of travel and its path, which in turn is better than trapezoidal decomposition.

An approximate cellular decomposition is a fine-grid-based depiction of the free space [38]. Here, the cells are all the identical size and shape, but the combination of the cells only approximates the target area. This idea was pioneered by Elfes [39] and Moravac [40]. These regular cells normally take up many forms. Grid-based depiction does help in the formation of paths [41]. For example, Franklin Samaniego [37] worked on interpreting path planning by comparing the RRT, PRM, and ECD-PRM. The exact and approximate cell decomposition on a roadmap is interpreted by them as shown in Figs. 3.8 and 3.9 [42]. End result brings RRT, PRM, and ECD-PRM better than in MACD.

These algorithms aid in cell decomposition. Similarly, authors in [43] worked on the A*, RRT, and PSO algorithms and published RRT algorithm which in turn performs far better when compared to A* and PSO. The total cost is calculated by adding heuristics expenses to the expense of the travelled path by a UAV. The lowest expense is always preferred. Hence, there is no need to visit all nodes which are depicted in Fig. 3.10 and Table 3.3. The mapping used by A* in distance calculation is as follows:

$$f(n) = g(n) + h(n) \tag{3.5}$$

in the calculation 5, $f(n)$: a heuristic function that calculates, $g(n)$: the cost of access from the start node to the current node, and $h(n)$: the distance of the path to be travelled from the start node to the destination node is the estimated distance. The heuristic values are S ->5, A ->4, B ->5, and C ->0.

Fig. 3.8 Exact cell decomposition

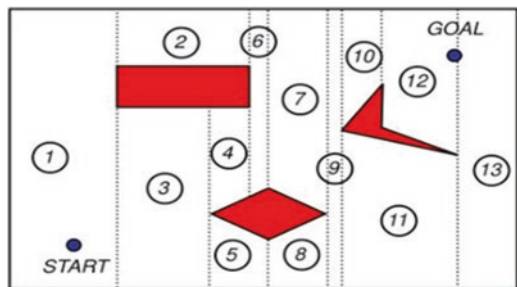


Fig. 3.9 Approximate cell decomposition (Nourbakhsh, 2004) [42]

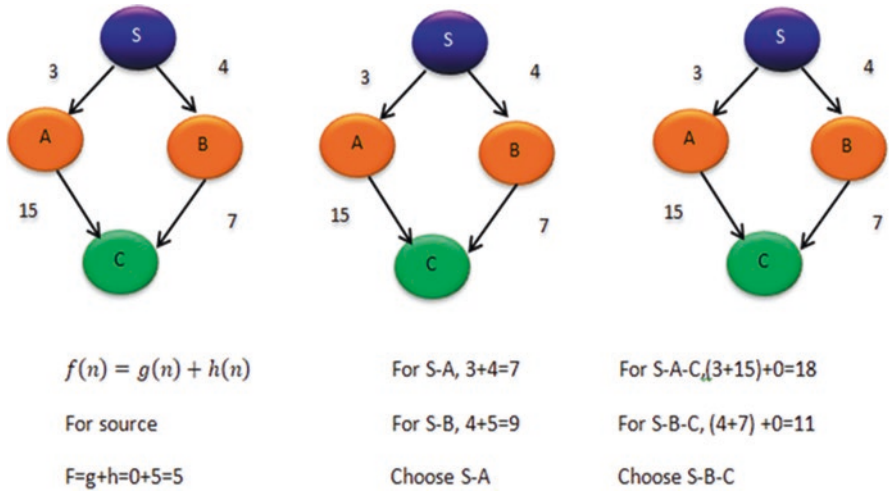
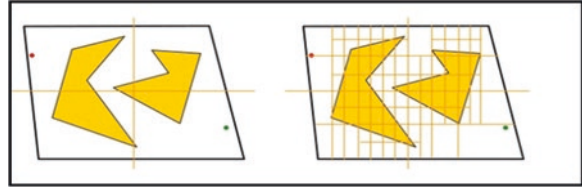


Fig. 3.10 Sample nodes for A* algorithm

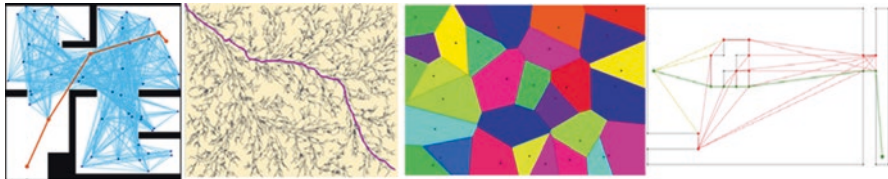
Roadmaps

(1) Construction and (2) query are components in roadmaps. 3D environment is used in construction stage and then comes the query stage. The concatenation of curves aids in path planning. The third stage makes the path planning even more sufficient. The computation does not take time as it worked up during processing. As-Rapidly-Exploring Random Tree (RRT), RRT*, Zammit, and E. Van Kampen [44] introduced ways to estimate the concert of the A* and RRT in making the path planning even more sophisticated. It is inferred that A* is better than the RRT in many aspects. But either can be used for path planning.

1. Probabilistic roadmap method (PRM) aids in trajectories that are very efficient and reasonable in UAV path planning. Similarly, Zhuang et al. [45] considered this probabilistic roadmap ideology for path planning in many innovative places like nuclear facilities as they have a radioactive surrounding. The issue of defining a path from the start configuration to the end configuration is wonderfully taken cared by probabilistic roadmap planner. The thick line in Fig. 3.11a picturizes the pathway. For instance, Mansard et al. [46] proposed on Kino dynamic probabilistic roadmap.

Table 3.3 A * algorithm

<p>Create an open_list of only the start node.</p> <p>Create a closed list blank.</p> <p>while (the goal node has not been made):</p> <p style="padding-left: 2em;">Consider the node with the lowest fscore in the open list.</p> <p style="padding-left: 2em;">if (this node is our target node): we are done.</p> <p style="padding-left: 2em;">if not:</p> <p style="padding-left: 4em;">Place the current node in the closed list and watch all its neighbors.</p> <p style="padding-left: 2em;">for (each adjacent to the running node):</p> <p style="padding-left: 4em;">if (the neighbour has a value g smaller than the current value and is in the closed list):</p> <p style="padding-left: 6em;">change the neighbor to the new lower g-value.</p> <p style="padding-left: 6em;">The current node is right away the neighbor's parent</p> <p style="padding-left: 4em;">else if (the current g-value is lower and this neighbour is in the open list):</p> <p style="padding-left: 6em;">change the neighbour to the new lower g-value.</p> <p style="padding-left: 6em;">change the neighbor's parent to our current node</p> <p style="padding-left: 4em;">else if this neighbor is not on either lists:</p> <p style="padding-left: 6em;">add it to the current list and adjust its g.</p>
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**Fig. 3.11** (a) Probabilistic RM (b) RRT (c) Voronoi diagram (d) Visibility line

2. Rapid-exploring random trees: Rapid-exploring random trees (RRT) are expressly intended to deal with no holonomic constraints (including dynamics) and high degrees of autonomy. It is iteratively reached output on control feedbacks that drive the framework somewhat toward arbitrarily selected focuses, as inverse to expecting point-to-point convergence [47] as shown in Fig. 3.11b. An advancement of RRT, i.e., RRT-Connect [48], developed a much more versatile method that is now used for getting an accident free path. For instance, Zhang et al. [49] proposed RRT-Connect and combined it with an area that has a promising potential artificially which contributes an optimal path for UAVs. It has the haphazardness and efficient planning methods, which alters the planned way of coverage nearer to the efficient travel path than the path of the single procedure.

For instance, in order to make the UAVs more sophisticated, Yang et al. [50] introduced environmental potential field-based RRT (EPF-RRT), as natural potential field is incorporated, target points produce virtual gravitational power and hindrances are repulsive, and the subsequent energy drives the RRT to dismiss into from the deterrent and close by to the goal. In this way, the productive arrangement of the path is done using the RRT. Zu et al. [48] were in urge to program a wide number of directions and path for the drones progressively, from beginning areas to objective areas in the occurrence of unknown pop-up interruptions. They also suggested that when given a path with obstacle, the UAVs would easily find another odd free path with the help of this algorithm. Qinpeng Sun et al. [49] introduced another improvement, for example, bidirectional-RRT; an improved variant of RRT contributes an extraordinary achievement phase and effectiveness in UAV path planning shown in Table 3.4.

O. Adiyatov et al. [50] utilized sparse-based RRT* algorithm for ques. about the odds as a binary variable (RRT*K) or with a quadrant-based representation (RRT*Q) to the database of the node to make it optimize the path. The above helps in getting a faster result and converges to the optimal result with fewer numbers of places of nodes.

According to Iram Noreen et al. [51], RRT*-adjustable bound (RRT*-AB) is a sampling-based planner which improved time and space requirements having quick convergence rate than RRT*. These points of interest of memory-efficient A* (MEA*) mark it reasonable for off-line requests utilizing trivial robots with well-ordered power and memory resources. But, RRT*-AB will overtake MEA* in high-dimensional problems for having developed with ensembling capability.

3. Voronoi diagram: Voronoi diagram (VD) is a diagram which divides the plane into smaller paths having close to each of a given set of objects as shown in Fig. 3.11c. The sophistication of the paths is achieved by Waypoint Path Planner (WPP) HanTong [52] by taking the initial path which was created by VD. For

Table 3.4 RRT algorithm

<ol style="list-style-type: none"> 1. $T = (V, E) \leftarrow \text{RRT}(z_{\text{init}})$ // initial state of the tree 2. $T \leftarrow \text{TreeInitialize}()$; 3. $T \leftarrow \text{NodeInsert}(\emptyset, z_{\text{init}}, T)$; // adds a node z_{new} to get z_{min} 4. for $i=0$ to $i=N$ do 5. $z_{\text{rand}} \leftarrow \text{ConfigurationSample}(i)$; // random state from configuration space Z 6. $z_{\text{Nodenearest}} \leftarrow \text{NodeNearest}(T, z_{\text{rand}})$; // nearest node from T to z_{rand} 7. $(z_{\text{new}}, U_{\text{new}}) \leftarrow \text{Steer}(z_{\text{Nodenearest}}, z_{\text{rand}})$; //control input U 8. if $\text{FreeObstacle}(z_{\text{new}})$ then 9. $T \leftarrow \text{NodeInsert}(z_{\text{min}}, z_{\text{new}}, T)$; 10. return T
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example (Mengxiao Song et al. [53]), based on VD and watershed segmentation procedure, global seam-line network generation technique for mosaicking UAV orthoimages is developed. Xin Feng et al. [54] utilized heterogeneous Voronoi graph for a path planning which involves emergency drone delivery. Shen et al. [55] suggested an enhanced kind of VD to divide the sharing space which is from a very low attitude on many different areas. Taking help from Automatic Dependent Surveillance-Broadcast (ADS-B), track method is set up to regulate and screen drones and reduce the chance of collision and ensure security between manned and remote-controlled aircraft systems.

4. **Visibility Line:** Visibility line is utilized to discover a result of autonomous mobile robot path planning in an unknown obstacle location [56]. The VL was built steadily which is shown in Fig. 3.11d. A learning component was consolidated so as to build the VL. Moreover, a sensor with constrained range was utilized to acquire data around the odds in the specified location. Notwithstanding, the produced path was not enough by reason of the inaccessibility of whole data about the specified environment. Rao [57] recommended a broad-spectrum framework of robot navigation that could be functional to any new location including mobile robots where an appropriate steering could be commenced using the Restricted Visibility Graph (RVG). Wooden and Egerstedt [58] derived oriented visibility graph (OVG) strategy which fundamentally decreased road-map for unstructured polygonal situations suitable for real-time path planning application of outdoors robots. Thus, as to heighten the performance over runs, the intermediate graphs were kept between runs, and dynamic update instructions were specified. Huang Sunan et al. [59] recommended a novel technique founded on visibility graphs by utilizing the path with no odds and minimal distance of coverage in all 2D path planning and then collecting the paths that get a minimal distance to cover to reach the destination in the complete 3D environment.

Potential field method (PFM) denotes the location to particulate an odd. Its path of travel is hugely influenced by areas of potential around the c-space. The path of the drones is well determined basing on the areas of reluctant from the initial point to the destination point. Notwithstanding, the regular PFM experiences the local minima making the UAVs stuck before it arrives at the objective. For example, Budiyanto et al. [60] recommended the hierarchical PFM by incorporating some rotational force between the UAVs to resolve the problem of inaccessible destinations and collision challenges among the UAVs.

So as to upgrade the PFM for multi-UAVs, Bai et al. [22] presented a longitudinal random factor, and B-spline interpolation is utilized to resolve the problem of dropping into local minimum and to smooth the planned route respectively. Authors in [22, 60, 61] indicated that there are numerous techniques to overpower the restrictions of PFM and utilize for collision avoidance in path planning of UAVs. For example, Abeywickrama et al. [62] proposed an improved variety of PFM, which is utilized to plan the path and to draw the UAVs for the preferred goal configurations. It helps the drones to steer clear from the odds thus avoiding accidents.

Artificial Intelligence Techniques

It is a disposition to program a wireless device with could function as a robot that can be unsurprisingly composed by the software plug-ins and meditates cleverly similarly an astute human thinks. It is a part of computer science, pointing on building machines and programming with knowledge like people so they can perform comparative reasoning, thinking, dynamic, critical thinking, and natural language processing like human. It is an approach to utilize and arrange the information proficiently and viably with the goal that it tends to be utilized much of the time. It is an innovation dependent on the advancement of technologies like engineering, mathematics, and biology.

Heuristic-Search Techniques

These techniques are utilized in UAVs for finding sophisticated path by minimizing the expanse using cost estimation programming methods. Revenues from AI market worldwide from the beginning point to the end point are collected and optimized in the cost estimation method. For example, Park et al. [63] recommended the DroneNetX framework for network by accompanying aerial wireless links into the quarantined ground network by means of UAVs. It does searching of connection between the computers from scratch and discovers critical locations where the path is sophisticated.

Essentially, Carpin et al. [64] proposed a procedure which, dependent on greedy technique, is the most uncovered first (MUFT) that conquers the problem of “cooperative multirobots observation of multiple moving targets” (CMOMMT) by utilizing many UAVs. Arantes et al. [65] proposed genetic with greedy technologies to evaluate the hardware glitches and path re-planning of UAVs. Decision-making algorithms are soulfully done using in-fly awareness (INF) security system. For instance, Li et al. [66] presented a genetic algorithm for searching and rescue. They have applied this algorithm to optimize the priority field to help the smart energy cycling and improve the performance of UAVs. The smart energy cycling has been appreciated more by using energy-efficient trajectories. In Zhou et al. [67], point was made energy efficient. Specifically, UAV-aided mobile crowd sensing MCS system has anytime and anywhere accessibility, yet it lacks the good battery; thus, Gale–Shapely algorithm and an energy-efficient perspective approach are used to improve the battery.

Xixia et al. [21] suggested using multiple swarms (multiswarm) IWD (LMIWD) algorithm for optimization of path planning. LMIWD algorithm is depended upon for cooperation and competition among UAVs. It is inferred that this method outperforms random search, greedy search, and particle swarm optimization (PSO) algorithm.

Brute-Force Search Techniques

Brute-force techniques do require a lot of theory as they work on small states, yet they do expect valid operators and initial states to work with for building the description. Breadth first search and depth-first search are two of the most vital components in brute force techniques. Sharma et al. [68] worked on depth first search programming. Farid et al. [69] worked on waypoints-based trajectory generation to improve the quality of UAVs.

Local Search Techniques

Hard problems are solved using local search techniques. Optimization of values is done using these techniques which uses hill climbing and TSP as the main components. For example, Huang et al. [70] helped in finding a short path planning ideas for the UAVs. Cluster algorithm and PSO algorithms used for doing so small coverage of the area by UAVs are addressed using local search techniques. Similarly, Wang et al. [71] further helped his method by giving a 2-tie search algorithm for lost UAVs. According to Perazzo et al. [72], location finding and identification in UAV path is sorted using TSP algorithm and LocalizerBee. It is observed that the heuristic-based genetic algorithm is basically used in getting a path for UAVs. Bit-Monnot et al. [73] proposed variable neighborhood search (VNS) swiftly to produce planning with multiple UAVs that are fine grained even though they span over large spaces and long periods.

Artificial Neural Networks

Artificial neural network (ANN) is utilized to locate an optimal path planning for UAVs. For instance, Kurdi et al. [74] tackled the route and position issues of UAVs by utilizing neural network. In this scheme, ANN takes response from the Global Positioning System (GPS), Robot Vision System (RVS), and quad-copter vision system (QVS) and gives out the optimized path localization to the UAVs. And then also, Zhang et al. [75] used a self-adjustable integral line-of-sight (LOS) guidance to make the UAVs to act decisively in unfavorable conditions. They have additionally introduced control method for path planning to locate an optimized path for UAVs. Hamid Shiri et al. [76] proposed Hamilton-Jacobi-Bellman equation (HJB) in real time, yielding the control decisions even when the connection is lost.

3.4.3.2 Cooperative Techniques

Cooperative techniques are substantial to identify ample number learning approaches that can be investigated to relate from many classifications like problem-solving and graphic organizers. They consist of machine learning, multi-objective optimization, and mathematical and bio-inspired models that are utilized in getting a direction for the drone to reach the target. The taxonomy of the cooperative techniques is presented in Fig. 3.12.

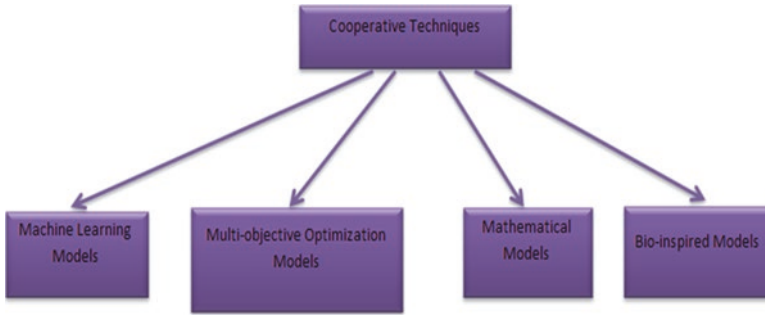


Fig. 3.12 Taxonomy of cooperative techniques in UAV path planning

Machine Learning Models

A variety of computer systems responds to the situations automatically without a need for getting explicitly programmed. They are divided into supervised, unsupervised, and reinforcement learning categories which are utilized in getting a sophisticated direction for the path of travel to reach the destination for the drones. First, identify and collect the relevant data from several resources, then select the suitable machine learning algorithm, and finally different data sets are utilized to train the model; based on that, the optimized path is envisioned.

In supervised learning, an algorithm for path planning procedure is trained yet unable to figure out the exact role. It constructs the model where dependencies occur between the input factors and expected the target value like Gaussian filter (GF) and Kalman filter (KF). Non-linear least-square method was suggested by Jiang and Liang [77] to estimate UAV path planning in a threat atmosphere.

Likewise, Kang et al. [78] suggested the Kalman filter (KF) algorithm to resolve noise and deliver the protected flight path to UAVs in a challenging atmosphere. Also, Wu et al. [79] commended KF algorithm to resolve many challenges like noise in the air, collision probability, cluster state approximation, and track planning of UAVs. They have validated that the collision probability among the UAVs is just 0.2% by using KF, but rate of error does not reach an acceptable level. Thus, to tackle the error, Yoo et al. [80] suggested another filter algorithm Gaussian in UAVs. To compute the posterior density in UAV path planning, the KF update equations are applied directly [81].

In unsupervised learning, descriptive modeling and pattern recognition methods are used. Clustering algorithms like k-mean clustering are utilized in UAV path planning [82]. For instance, Farmani et al. [83] used clustering algorithm for tracking the multiple targets and KF to identify the precise position of the target in UAV path planning which shows the reduced time complexity. Similarly, Tartaglione and Ariola [84] presented quality threshold clustering based on an obstacle avoidance strategy for searching landmarks.

Reinforcement learning is a constant process and always studies from the environments in an iterative way. The reinforcement learning [85], deep reinforcement learning [86], and deep Q-network [87] are utilized for the optimized path planning of UAVs. For instance, S. Luan et al. [88] proposed the G-Learning procedure; simultaneous computation and recognition is achieved by cost matrix which also aids in location-based information for accident free path traveling in concurrently and reorganized based on the distance of geometric and information. Zhang et al. [89] proposed the Q-learning algorithm for extracting an optimal or suboptimal path for UAVs. Similarly, Yijing et al. [90] put forth this algorithm for creative smooth usage without any prior knowledge and disturbing the environment by taking adaptive and random exploration into account. Bouhamed et al. [91] created a Deep Deterministic Policy Gradient (DDPG) for navigation of UAVs to travel without any abstinence.

Multi-objective Optimization Models

This model takes into account the convex optimization [92] and two-echelon optimization [93]. C. Yin et al. [94] utilized safety index amps for optimization for taking a picture of obstacles in the path ahead. Luo et al. [95] suggested two-echelon optimization to do so. In Angley [96], proposal of large number of targets is better understood using optimization of the research and other vital strategies. To conclude, they also found that it increases the results by 10 percent. Koothifar et al. [97] proposed the steepest descent posterior Cramer–Rao lower bound for getting in hand with ratio frequencies. Ti and Li [98] showed some work on as-joint task, resource allocation, and computation offloading. They improved convex optimization method. Similarly, Zeng et al. [99] reduced the time of travel to 50% by working on the algorithm. Y. Zeng et al. [100] used a rotary wing to connect with multiple ground nodes (GNs) to be environmental protective. Jeong et al. [101] connected mobile and UAVs for optimization. Lee and Yu [102] tried to optimize using the concept of gravitation and energy.

Mathematical Models

It takes in arithmetical stuff like Lyapunov function [103], Bezier curve [104], and Ergodic Exploration [105] which are used for working on optimizing the path. They do involve many algorithm and models to optimize the path. For example, Mathew et al. [106] worked on traveling salesman problem and recharging the programs. Likewise, De Waen et al. [107] made trajectory planning more worthwhile and forceful and also worked on scaling. Control theory includes non-linear predictive models like model predictive control method, Lyapunov function, and Dubin algorithm for UAV path planning. Keyu Wu et al. [79] observed that RRT programming goes well with PSO for getting the drone a clear and smooth path. Similarly, Luo's

[108] proposal is based on the work on algebraic equation to have a clear agricultural reliability.

Ergodic explorations of distributed information (EEDI) are used for creating low-cost path derivations [105]. Lyapunov creates a stability and control on versatile environment [109]. Darbari et al. [110] proposed Markov decision process (MDP) to develop an optimal direction for the drones to reach the destination with the decision process. Similarly, Yu et al. [111] proposed to use Bayesian filter and observable Markov decision process (POMDP) to develop an optimal path for UAVs. Eaton et al. [112] suggested the use of POMDP to make the UAVs less fragile in handling tough situation where it can handle reaching the target even in a cumbersome path which in turn is a much needed development as UAVs often fail to reach the targets. Q. Yang [113] look a step further and suggested adding Kalman filter (UKF) with POMDP to make the UAVs reach the cumbersome target. Alessandretti and Aguiar [114] traveled totally in a different path to make the UAVs reach the target via its path by using model predictive control (MPC) and angular B. Sun et al. [115] observed that the use of MPC made sense taking it a bit higher level to design the path. The cost function considering load swing angle and the distance between obstacle and UAV are designed and generate an optimal trajectory. Yel et al. [116] proposed a self-triggered framework for adding feathers to the path.

Non-linear model is based on at least one independent variable. It is a framework where change of output is not relative to the difference in input. Hausman et al. [117] proposed on updating for self-calibration applications by non-linear applications. Li et al. [118] proposed optimizing the path using parallel search options. Moustris [119] proposed a feedback linearization method for pointing out the location by coordinates which in turn aids to the complete state space and also in demonstration of the fact that there is an information change with the end goal that the dynamical conditions stay invariant.

Tian et al. [120] idealized the improved artificial bee colony (IABC) for helping the drones in escaping the cumbersome situations. Cheng and Li [121] called in for a genetic algorithm as it decreases the cost and gives out a pretty optimal path. Xixia et al. [21] proposed IWD to work on water population. However, it is significant that this technique could not totally avoid cumbersome paths. Likewise, Popovic et al. [122] model finds the presence of weeds on farmland to give an optimal path by getting data. Mostafa et al. [123] worked on getting chi-square interference.

Similarly, Ji et al. [124] suggested the 2-opt algorithm to enhance the operations like search and rescue of UAVs. The simulation outcomes illustrate that the 2-OptACO technique ensures a quicker phase of convergence than the GA and ACO. Similarly, Yang et al. [125] proposed Gaussian process (GP) regression method to finish the consignment drop mission with an optimal flight-time and reduced errors of landing in UAVs. In Marija Popović [81], in area monitoring of UAVs, the multi-resolution mapping is used.

Bio-Inspired Models

These models help in solving the complications due to ecological factors like neurodynamics and physiological biology. Sun B et al. [126], P. Fazio et al. [127] designed networks flying ad hoc NETWORK (FANET) to aid in developed and theologized agricultural areas. Evolutionary techniques modified shuffled frog leaping algorithm for fighting of UAV path planning [128, 129]. It is a living mass determined meta-heuristic algorithm with variety of mathematical functions. In Jia Song [130], tackling of UAVs in 3D spaces is done using biogeography-based optimization (BBO). G. Tian et al. [120] used adaptive multi-objective evolution programming in the field of UAVs. Aditya A. Paranjape et al. [131] proposed using waypoint algorithm compared to birds and UAVs.

Z. Sun [132] took geosynchronous synthetic aperture radar (SAR) into consideration for transmitting signals to sophisticate the bio-inspired models. Similarly, Liu et al. [133] suggested the binocular vision-based technique for getting the path in all the environments.

S. Ren [134] aids in avoiding collision and reaching the destination faster. Yang et al. [113] used multiobjective programming for getting the right time to fly, mapping, safety, and much more. Kamel [135] used hierarchical fuzzy logic controller (HFLC) for getting UAVs some insane features. Shikai Shaoa [136] used comprehensively improved particle swarm optimization (PSO) for mapping and helps in optimality. Similarly, J. Chen [137] solved traveling salesman problems by using improved genetic algorithm in UAVs. They also proved that it helps in convergence and optimization of UAVs.

3.4.3.3 Non-cooperative Techniques

This acts autonomously, and one must be mindful of one another's standard and guidelines to determine the direction of travel for the drones. Search-based algorithms like circular digraph, Floyd method, and flood-fill graph techniques are utilized for path planning of UAVs as shown in Fig. 3.13.

Chen et al. [138] proposed ACO for path planning and greedy algorithm for task allocation in multi-UAV path planning and task allocations. It is necessary to decompose the task into sub-tasks and to decide which UAV should execute which

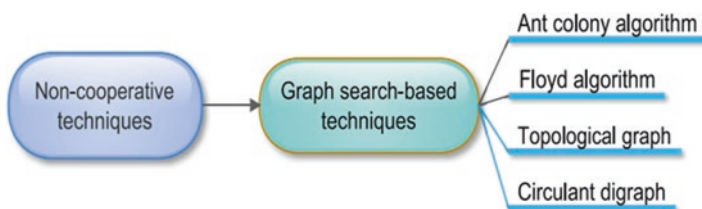


Fig. 3.13 Taxonomy of non-cooperative techniques (Shubhani Aggarwa, 2020) [14]

sub-task in the optimal time. Razzaq et al. [139] recommended the algorithm based on graph for providing deconfliction of UAVs. Morita et al. [140] proposed flood-fill and greedy 2-opt algorithms in annulled zones to extract the sub-routes for radiation dose mapping. Based on the results, the model outperforms if there should arise an occurrence of many hindrances. Yang et al. [141] explore the Floyd algorithm to judge the initial location of start, and Push Forward Insertion Heuristic algorithm (PFIH) is utilized for getting then optimized path. Du and Cowlagi [142] worked on an idea that although the UAVs can fly distance, 3D analysis and coordination could help the UAVs more. It is also observed that the repair cost decreases by 38.8%. Bogdanowicz [143] suggested the 360° mapping for army security, monitoring, and checking for distinctive arrangement of zones. The above strategy delivers a save and troubled path and maximizes the coverage area throughout search operations.

Coverage and Connectivity

Unmanned aerial vehicles are becoming increasingly important in a variety of applications, such as defense and security, emergency response and recovery, humanitarian and disaster relief aid, conservation of energy, disease control in humanitarian emergencies, healthcare and biomedical devices, agriculture and inspection of agricultural fields, weather forecasting and climate change, maritime and logistics management, waste management and sustainable development, energy and environment, mining and metallurgy, urban planning and transportation, telecommunications, game consoles and controllers, and space and universe. The connection between the drones and ground control stations (GCSs) happens to be vital for saving the information and sending information for their efficient functioning. For instance, Lee and Batsoyol [144] introduced wireless ad hoc network (WANET) to cover the area fully with minimum number of UAVs by utilizing Dijkstra's algorithm shown in Table 3.5 and Fig. 3.14, which delivers an optimal and collision-free path for UAVs in an urban location.

In Zouaoui H et al. [19], quality of experience (QoE) is improved by utilizing Q-learning reinforcement learning algorithm in the process of UAV path planning and prevention of service interruption avoidance between drones that is more than one drone serving the same field. In Challita et al. [145], reinforcement learning echo state network (ESN)-based procedure has been suggested to decide on path and resource allocation optimally.

Various authors like Bouzid et al. [146] suggested the Rapidly Exploring Random Tree Fixed Nodes (RRT*FN), Xiaojing et al. [147] proposed Biased Sampling Potentially Guided Intelligent Bidirectional RRT* (BPIB-RRT*), and Cabreira et al. [148] introduced the energy-aware spiral coverage and back and forth (E-spiral and E-BF) algorithms for UAV's path planning.

Table 3.5 Dijkstra’s algorithm

<ol style="list-style-type: none"> 1. $Dista[source] \leftarrow 0$ //distance to source vertex is zero 2. for all $vert \in V - \{source\}$ //set all other vertex distance to infinity 3. do $Dista[vert] \leftarrow \infty$ 4. $S \leftarrow \emptyset$ // S, the set of visited vertices is initially empty 5. $Q \leftarrow V$ //(Q, the queue initially contain all vertices) 6. while $Q \neq \emptyset$ do //while the queue is not empty 7. $u \leftarrow \min Dista(Q, Dista)$ // select the element of Q with the min.distance 8. $S \leftarrow S \cup \{u\}$ // add u to list of visited vertices 9. for all $vert \in neighbours[u]$ // if new shortest path found) 10. if $Dista[vert] > Dista[u] + weight(u, vert)$ then 11. do $Dista[vert] \leftarrow Dista[u] + weight(u, vert)$ // set new value of shortest path 12. return Dista
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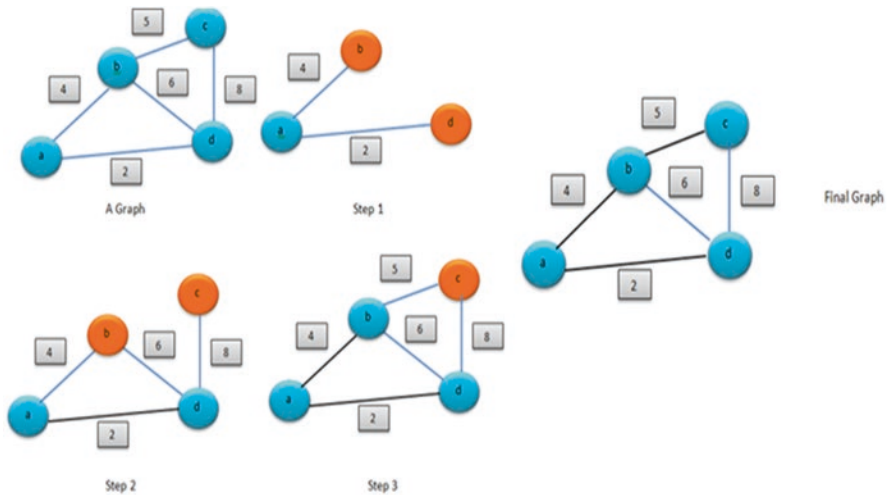


Fig. 3.14 Sample nodes for Dijkstra algorithm

3.4.3.4 Multi-Cloud Security in UAV Path Planning

Z. Zheng et al. [149] explored the planning of 3D trajectories for UAV in 3D cloud environments. A 3D-oriented trajectory algorithm uses point clouds directly to derive optimized trajectories for a drone in path planning. This approach investigates unobstructed, low-cost, smooth, and dynamically achievable pathways by analyzing a point cloud of the target environment, using a modified RRT with the k-d tree. In perusing direction for the destination in a drone, security and privacy is a significant concern, and most of the authors are truck on the security odds in the drones. They primarily concentrated on how the communication of drones can be

forbidden from the odds due to lack of safety. Talking for instance, Lin et al. [150] deliberated the requirements of security and privacy in UAV network architecture. Likewise, Javaid et al. [151] analyzed the security vulnerabilities and origins of loss of control and delivered the mitigation and deterrent solutions of UAVs.

Fu et al. [152] proposed an improved artificial potential field to empower multi-UAV collision resistant. For instance, Challita et al. [153] proposed ANN-based solution structures to address the wireless and security challenges that emerge with regard to UAVs such as distribution frameworks, transportation frameworks, and casting of digital data. These methodologies empower a gateway for the UAVs to function at par with wired devices even though its wireless. Kharchenko and Torianyk [154] used Internet of Drones for digital data securities and analysis of cyber security. Similarly, Bin Li et al. [155] suggested addition of 5G to give an optimized energy transmission. It gives null postponements, improved safety, and sophisticated usage of UAVs. Liang et al. [156] shared an idea of using blockchain to share data. Furthermore, this has shown incredible amount of promise as it enables transaction safety and user privacy.

3.5 Conclusion

This paper is written on an aim to see the sophistication of UAVs with the help of survey. It is a must to know that the path panning in UAVs is of three main divisions. They are representative, coordination, and non-coordination methods. Working ahead on the above methods, it has been found that UVAs could be more sophisticated when incorporated with the above methods by increasing the distance under range, networking in UAVs. Learning of safekeeping mechanisms of UAVs has been fascinating. UAVs on top of having more research papers based on them, they still got more bugs and glitches. Higher distance to cover, good networking, overtaking a cumbersome path, optimization of paths, user friendliness, developments, and cost-effectiveness are still a nightmare in UAVs, but thanks to IoT systems and multi-cloud security algorithms for making it progress toward the development of UAVs. To hit on the specifics, vivid and vide number of papers are further needed to address the network treats in UAVs.

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