A survey of 3D Space Path-Planning Methods and Algorithms

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Due to their agility, cost-effectiveness, and high maneuverability, Unmanned Aerial Vehicles (UAVs) have attracted considerable attention from researchers and investors alike. Path planning is one of the practical subsets of motion planning for UAVs. It prevents collisions and ensures complete coverage of an area. This study provides a structured review of applicable algorithms and coverage path planning solutions in Three-Dimensional (3D) space, presenting state-of-the-art technologies related to heuristic decomposition approaches for UAVs and the forefront challenges. Additionally, it introduces a comprehensive and novel classification of practical methods and representational techniques for path-planning algorithms. This depends on environmental characteristics and optimal parameters in the real world. The first category presents a classification of semi-accurate decomposition approaches as the most practical decomposition method, along with the data structure of these practices, categorized by phases. The second category illustrates path-planning processes based on symbolic techniques in 3D space. Additionally, it provides a critical analysis of crucial influential approaches based on their importance in path quality and researchers' attention, highlighting their limitations and research gaps. Furthermore, it will provide the most pertinent recommendations for future work for researchers. The studies demonstrate an apparent inclination among experimenters toward using the semi-accurate cellular decomposition approach to improve 3D path planning.

CCS Concepts: • **Computer systems organization** → **Robotic autonomy**;

Additional Key Words and Phrases: Path-Planning, Collision Avoidance, Three-Dimensional Space

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1 Introduction

Introducing UAVs is credited to Daniel and Whitfield [1]. Their ease of deployment, low maintenance costs, high maneuverability, and hovering ability have led to numerous social applications [2]. The future promises extensive UAV capabilities in the industrial, security, commercial, educational, and service sectors. This mandates their adoption by police fire departments and other organizations [3]. UAV usage rapidly expands, including real-time monitoring, wireless coverage, remote sensing, search and rescue, delivery, security and surveillance, precision agriculture, and social infrastructure inspection [4]. The advent of intelligent drones, marking the second revolution in drone technology, presents new opportunities in various applications, especially civil infrastructure, by reducing risks and costs [5]. Furthermore, drones provide viable prospects for equipment manufacturers and commercial service providers, such as communication boosters [6]. According to a report by PwC [7], drones are worth over $127 billion and have risen to $45 billion in the civil infrastructure sector [8]. Monitoring and inspecting structures and infrastructure constitute about 45% of drone network applications. This is followed by agriculture (32%), cargo transportation (13%), military and security (10%), media and entertainment (8%), telecommunications (6%), and mining (4%) [7]. Consequently, drones are strongly desired for monitoring applications, such as significant construction projects [9], power lines, and gas, oil, and water transmission lines [10].

1.1 Challenges Influencing the Coverage Path Planning

The study is divided into five parts: In the first section, fundamental Challenges are introduced. The second section delves into routing definitions and related algorithms. The third section examines path-planning phases and techniques. The fourth section focuses on path-planning data structures. The final section presents the authors' recommendations and conclusions from the evaluation. C_i represents the challenges in this study, and S_i represents the solutions. Table 1 categorized characteristics of drone networks based on drone number and network topology.

***C1.* Topology:** One of the most critical challenges in drone networks is maintaining user sessions while seamlessly transferring information from passive to active drones. In mobile networks, nodes are frequently disconnected from the network and reconnected, and the number and position of nodes and links constantly change. The movement of drones at varying speeds within these networks can lead to intermittent changes in communication between network nodes. This creates a dynamic network topology and complicates path planning.

***C2.* Routing and Motion Planning:** The domain of UAV path planning presents a formidable challenge due to the environment's highly mobile and dynamic topology, heterogeneous distribution, and the requirement to navigate through diverse geographical locations and congested routes without collisions [11]. Conventional technologies like big data and cloud computing cannot address these issues since drones can autonomously find probability solutions [12]. UAVs must operate autonomously to determine the optimum path. The selection of optimal evaluation criteria varies according to the specific application. In this context, the optimal path evaluation criteria encompass cost, time, and path length.

C3.* Autonomy*: Autonomy or independence represents a mechanism by which drones can make informed decisions using information gathered from various sources, including sensors, cameras, or the **global positioning system** (**GPS**). This ability enhances drone efficiency. Incorporating autonomy and independence into UAVs has become a challenge however, it has found diverse applications in different fields, e.g., path planning, task planning, task allocation, and communication. [13].

***C 4.* Energy Consumption**: UAV networks face an energy storage challenge, whereas vehicular Ad-hoc networks have the benefit of relying on a vehicle battery, which is replenished during

Table 1. Characteristics of Drone Networks Categorized by Drone Number and Network Topology

Features of Drone Networks				
Examples of Applications	**Features**	**Multi-Drone**	**Single-Drone**	**Network Topology Features**
High-risk communications [14]	Impact of failure	Low, reconfigure	High, Mission Failure	Mesh: Many-to-Many Star: Point-to-Point
Remote healthcare, Remote sensing [15]	Scalability	High	Limited	Mesh: Infrastructures may have a central control center, and Ad-hoc has no central control. Star: There is a central control point.
Surveillance [16]	Survivability	Strong	Weak	Mesh: Infrastructure-based or Ad-hoc Star: Infrastructure-based
Forest fire detection, Precision agriculture [3]	Speed	Fast	Slow	Mesh: Self-configured Star: Not self-configured
Oil extraction, wildlife tracking, mining [17]	Bandwidth	Average	High	Mesh: Multi-hop communications Star: Single-hop from nodes to central point
Multi-Drone Collaboration, Providing wireless coverage [18]	Antenna coverage	Direct	Comprehensive	Mesh: In an Ad-hoc network, devices are autonomous and free to act. In an infrastructure network, movement is limited by central control. Star: Devices cannot move freely
Search and rescue, Real-Time monitoring [19]	Control complexity	High	Low	Mesh: Inter-node links are alternate Star: Communication is through a central controller
Infrastructure inspection [4]	Lack of coordination	Ready	Low	Mesh: Nodes relay traffic to other nodes Star: Communication is through a central control

car motion. Additionally, power sources for mobile phone networks generally can store energy for multiple hours. Nevertheless, small drones possess limited energy capacity, allowing thirty minutes of flight time. UAV networks require an innovative routing approach that uses energy-efficient routing protocols to extend network stability. Moreover, UAV networks are frequently established haphazardly, and thus, traditional solutions do not guarantee a reliable connection between nodes.

***C5.* Mobility**: The dimension of mobility is a noteworthy advantage of drones, enabling them to shift positions in two and 3D in a coordinated or randomized manner. Drones' mobility largely depends on their intended application. For instance, drones may assume a stationary hover position over the affected zone in disaster relief efforts while establishing a dynamic yet gradual network connection. Drones traverse wide expanses of terrain for agriculture and forest monitoring. This can lead to challenges such as intermittent breaks and inter-drone communication links re-establishment.

***C6.* Deterministic coverage:** This factor refers to sensor networks designed based on predetermined parameters, including network structure and sensor node placement.

***C7.* Being Online:** In the context of this research, online operation refers to collecting information from the environment at regular intervals from the present moment. The importance and reliability of information gathered about a target decrease over time. This information can be stored in memory. It is critical to note that the obstacles and objectives in this study are fixed, and the drone's movements are dynamic.

C8. The centralized solution involves a high-level sensor node that gathers general or sensory data, processes it, executes the algorithm, and transmits the solution to the sensor nodes. In contrast, the distributed solution involves each node collecting and covering information individually. A decentralized solution falls between these two extremes.

The challenge of devising an optimal path for UAVs, which entails navigating from an origin point to a destination while circumventing obstacles and other drones en route, has been posited as a potential solution for accomplishing objectives like collision avoidance and reducing the length and cost of travel [11]. Planning optimal paths for UAVs relies on various parameters, including algorithmic data structures, optimal parameters, and environmental characteristics. Each presents unique application challenges. The present study aims at exploring these challenges in the context of path-planning problems, prioritize the most significant issues, and propose suitable algorithmic solutions. The proposed algorithms were selected based on a comprehensive analysis and review of existing efficient algorithms in this field. This analysis reviews applicable algorithms for 3D path planning based on environmental characteristics, optimal parameters, and algorithmic data structures. Furthermore, it presents a comprehensive analysis of path-planning solutions based on their applicability in the real world. So, a comprehensive classification of representational techniques for path planning is provided. This classification details the state-of-the-art technologies related to UAV path planning approaches. In addition, influential parameters affecting path quality, as reflected in the extent of the investigation, are introduced. Furthermore, it highlights challenges and critical gaps in path-planning approaches and outlines open research questions and future directions. This breakdown includes:

— Introducing two new classifications for path planning approaches.
— Presenting relevant challenges and proposing methods to address them.
— Providing critical analysis of crucial influential systems and identifying research gaps.

The second section discusses strategies for constructing path-planning approaches and algorithms related to each approach. A proposed classification of path planning approaches is presented, organizing existing studies based on the target scenario. In the fourth section, path planning data structures will be examined. The fifth section will introduce the advantages, disadvantages, and research gaps of path planning. The final section will present the conclusions drawn from the analysis and evaluation.

2 Path Planning Approaches

The coverage path planning problem, a subset of robot motion planning, aims at covering the entire area while avoiding collisions. Applications of the covering approach in robotics include floor cleaning robots, painting robots, demining robots, lawn mowing robots, minimization of moving parts in robot arms, window cleaning robots, and inspection of complex structures [20, 21]. The planning of coverage routes in inter-UAV networks can be categorized into two groups: static and dynamic, which is similar to the classification of wireless sensor networks [22, 13]. If a UAV remains stationary and suspended during the mission, it is considered a fixed node [23, 24]. In this case, UAV coverage is similar to wireless sensor networks. The solutions provided for the latter can be utilized [25, 26]. Conversely, if a UAV remains in flight throughout the mission, it is called a dynamic cover [27, 28]. Dynamic coverage methods require fewer drones than static methods in the same environment. However, static methods provide higher coverage accuracy and image resolution than dynamic methods [29]. Planning a dynamic coverage path in the UAV network involves pre-processing and modeling the environment and path search. The first phase models the environment and its obstacles as a geometric shape [30]. The second phase of coverage path planning involves the path search operation from the starting point to the target point. Since the environment is modeled as a graph in the pre-processing and modeling phase, various algorithms such as dual graph-based algorithms, graph search, and evolutionary algorithms can be employed to find the optimal route between the origin and destination, considering the presence of obstacles

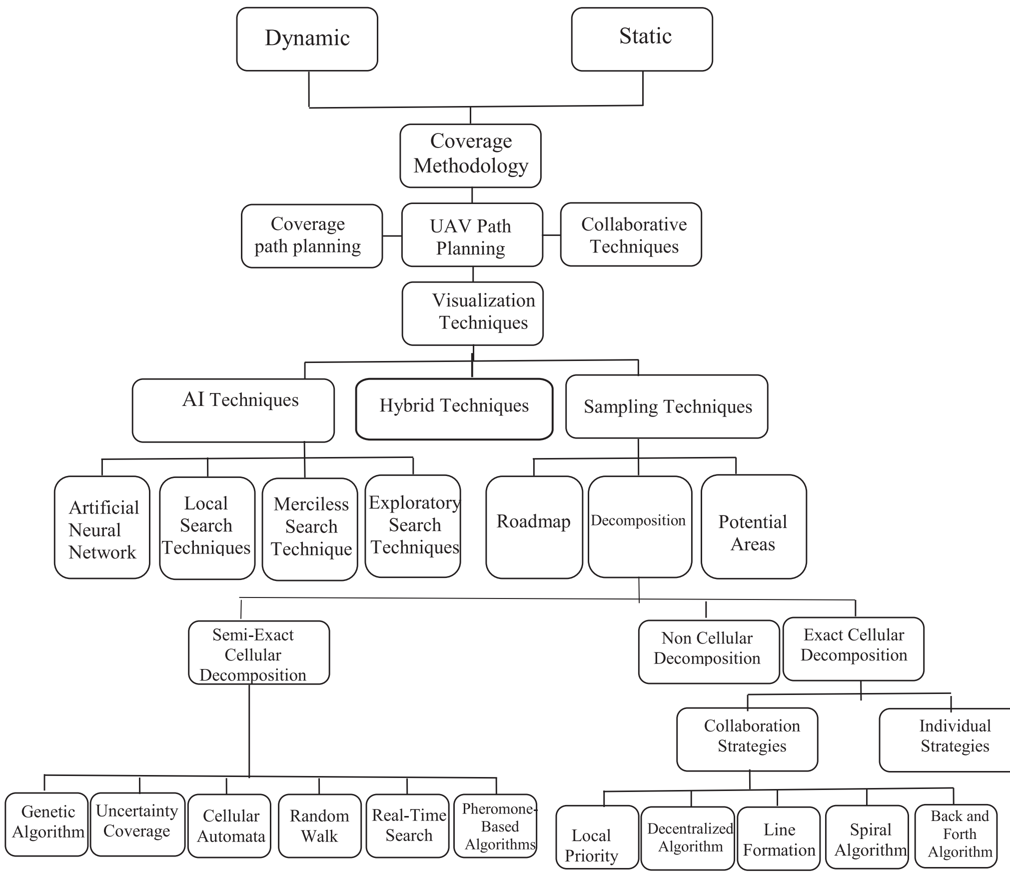

Fig. 1. Classification of path planning algorithms based on UAV path planning approaches.

[31]. In the subsequent sections, we introduce path-planning approaches and methods. Furthermore, the next section will present a comprehensive and novel classification of path-planning approaches. This classification is based on state-of-the-art technologies and covers sections related to sampling-based techniques, **Artificial Intelligence** (**AI**), and hybrid methods.

2.1 Classification of Path Planning Approaches Based on Representational Techniques

In this section, the algorithms for each approach will be examined depending on their capability to address the mentioned challenges. One of the objectives of this analysis is to first introduce practical algorithms in each approach in a challenge-oriented manner and then offer a critical analysis of the proposed path-planning solutions. Therefore, this article first lists algorithms used extensively in almost all reported works in each category. It then analyzes each algorithm. This enables the presented algorithms to be evaluated based on their merits and fundamental challenges. This provides researchers and academics with a comprehensive analysis of path-planning solutions. The foremost task in devising drone trajectory involves representing these vehicles in a 3D environment. This mechanism necessitates exploring three vital representational techniques: sampling-based, AI-based, and hybrid methods. Figure 1 classifies path planning methods.

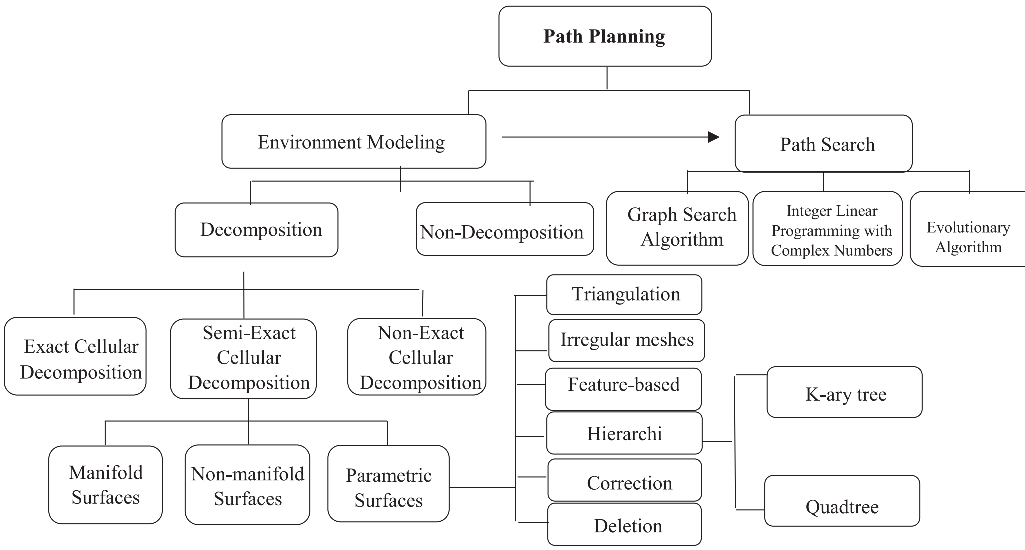

Fig. 2. Path planning approaches in environment modeling and path searching with data structures.

2.2 Classification of Path Planning Approaches

Path planning uses two approaches in the initial phase of modeling the environment: decomposition and non-decomposition. The decomposition approach involves dividing the desired environment into convex geometric shapes, whereas the non-decomposition approach explores the environment without dividing it into smaller parts. The decomposition approach is more widely applied because it uses convex cells. This results in a reduction in turning maneuver intensity and a decrease in UAV energy consumption. The decomposition approach comprises three categories: exact cellular decomposition, non-exact decomposition, and semi-exact decomposition [32]. If complete information is available, precise cellular decomposition is employed; otherwise, semi-exact cellular decomposition is employed. As exact environmental details are rarely available in the real world, semi-exact approaches are the most commonly used [32]. Therefore, one of the objectives of this article is to provide a new classification of existing algorithms in the semi-accurate decomposition approach in the real world. Semi-exact approaches to path planning rely on a network representation in which each network cell is assigned a value (either binary or probability) that reflects the likelihood of encountering an obstacle in that cell. This representation facilitates the identification and labeling of cells containing obstacles and targets. It can be displayed as an array, with each element having information about targets and obstacles. This feature avoids repeated visits to cells, making it a viable solution for challenges *C1* to *C5*. The grid map representation approach offers a simple and efficient implementation, but its exponential growth leads to high memory consumption [33]. Grid map representation uses two common approaches, showing network cells as squares or triangles. Triangular cells in grid map representation offer certain advantages, including flexibility, shorter path lengths, and higher image resolution, compared to square cells [34]. Figure 2 categorizes these approaches into different phases.

A study by [35] presented a covering algorithm for robots that employed a representation based on triangular cells. This approach did not yield satisfactory results, which could be attributed to robots' inability to execute precise movements while following such paths. Moreover, grid map representation results in computational overhead due to increased memory consumption and processing time. Therefore, using network representations based on triangular cells is expected to reduce costs and memory consumption, making it an effective parameter in drone network applications. This approach is suitable for challenges *C2, C4*, and *C5*. The problem of network representation based on convex cells remains an open challenge in path planning. Triangular cells in decomposition enhance image clarity and flexibility. Considering structural data characteristics in the design is a novel approach to selecting and presenting suitable algorithms for drone path planning. However, certain critical aspects of air networks, such as dynamic changes in the height and volume of obstacles and targets, have yet to be considered [11]. An algorithm must be developed to plan the trajectory of UAVs operating while accounting for the environment's intricacies. Several algorithms have been proposed for this purpose, including probabilistic, nature-inspired, and evolutionary models [36, 37], potential fields [38], cellular decomposition, and roadmap-based methods [39]. These algorithms enable 3D optimization and visualization of the complex environment. Among these algorithms, meta-heuristic algorithms are recommended for their proficiency in addressing combinatorial problems [37].

3 Sampling Techniques

The environment modeling phase involves determining the desired environment, the start and end points of movement, obstacle locations, and other factors that impact path planning. Cellular decomposition is one of the practical approaches in sampling techniques. Numerous studies have been conducted on cellular decomposition approaches in the environment preprocessing and modeling phase, with various categories presented based on whether the environment is decomposed. The path planning problem consists of environment preprocessing and path search phases. This research investigates coverage approaches regarding scalability, image accuracy and resolution, memory consumption, and reducing turning maneuvers. This section reviews the covering path planning algorithms based on environment decomposition.

3.1 Cell Decomposition in Environment Modeling

Using decomposition techniques, the cellular decomposition approach decomposes the target environment into non-intersecting regions, known as cells. The size and resolution of cells may vary depending on the type of decomposition employed. This approach ensures that each cell is visited once and the entire environment is fully covered. For larger cells, multiple visits may be required to fully cover a single cell, while smaller cells may only require one visit. The size of the cells is typically based on the robot's size or the range of the sensor and camera used for aerial coverage. The coverage path planning problem encompasses several factors, including the target area, cellular decomposition techniques, performance criteria, and information availability. The cellular decomposition approach is classified into three categories: exact decomposition, semi-exact decomposition, and non-exact decomposition, each with its respective algorithms. These algorithms will be discussed in the following sections.

3.1.1 Exact Cellular Decomposition. The coverage path planning problem is simplified to a movement planning problem from one cell to another [32]. Movements are made between adjacent cells with a common border. The nodes of the neighborhood graph represent the cells, and the edges represent the connections between neighboring cells. Cells are created by moving a line from one side of the desired area to the other. Obstacles in the environment constrain cells. The resulting output is saved as a neighborhood graph in the cell decomposition process. Each node can be visited once through a path search. The final coverage path is composed of simple intra-cell and inter-cell movements. Two critical algorithms used in exact cellular decomposition are trapezoidal decomposition and boustrophedon cellular decomposition [40, 21]. Trapezoidal decomposition divides the target region into convex trapezoidal cells, while boustrophedon decomposition considers the vertices to obstruct larger non-convex cells. Compared to trapezoidal decomposition, Boustrophedon decomposition can reduce the number of trapezoidal cells and minimize the length of the coverage path. The exact cellular decomposition approach consists of individual and cooperative strategies.

(a) Individual Strategy: The individual strategy in exact cellular decomposition involves an exact cellular decomposition approach that considers concave polygonal regions. Researchers such as [41] and [42] have investigated this approach. The strategy begins by exploring the workspace in non-concave subsets using a greedy recursive method [42]. Back-and-forth movements are performed perpendicularly to the sweep direction to minimize rotation maneuvers, corresponding to the minimum distance between the edge and the apex [43] [*C2, C6, C8*].

(b) Cooperation Strategy: In cooperation strategies, multiple UAVs cover a target region that a single drone cannot cover due to its vast size. The coverage approach may divide the area into sub-areas and plan coverage routes separately for each UAV, depending on the complexity of the problem. The cooperation strategy encompasses a range of algorithms presented in sequence, including *C2* and *C4*. In the following, we introduce different categories of cooperation approaches. Next, we introduce different categories of cooperation approaches.

Round-Trip Algorithm: A ground control station decomposes the environment and assigns vehicle sub-regions to the round-trip algorithm. Each vehicle then calculates round-trip movements, minimizing the number of turning maneuvers required. This approach has been shown to improve coverage efficiency and reduce fuel consumption, making it a viable option for large-scale coverage tasks [44] [*C2, C6, C8*].

Spiral Algorithm: The spiral algorithm has been proposed for performing missions in coastal areas with multiple heterogeneous UAVs. Previous research on this topic recognized the working space as a triangle based on air vehicles' ability to measure it [45, 46]. These studies have shown that classical network decomposition methods produce regular square cells that may partially overlap with no-fly zones or extend beyond the workspace. The restricted **Constrained Delaunay Triangulation** (**CDT**) method has been proposed to address this issue, which generates triangular cells that closely match the target region's shape. To further improve uniformity, the authors applied Lloyd's optimization to adjust the cells' angles toward 60 degrees. Subsequently, the Spiral Algorithm, introduced in the previous section, is utilized with an improved smoothing parameter to generate coverage paths in sub-regions. This algorithm is suitable for cooperating UAVs and can be applied to minimize turning maneuvers [47, 48], as noted in citations C6 and C8.

Line Formation: The line formation technique is employed as a tactical measure to detect mobile smart targets in hazardous environments [49], wherein these targets deliberately endeavor to evade search vehicles within a delimited region. The underlying mission is grounded upon five primary criteria, namely, optimizing the likelihood of target detection, minimizing the duration of tracking and deployment of aerial vehicles, ensuring redundancy in case of failure of one or more drones, and restricting the amount of information exchange among the participating vehicles, denoted by C6 and C8, respectively.

Decentralized Algorithm: Acevedo et al. [50] proposed a decentralized algorithm for partitioning rectangular regions during surveillance missions. This algorithm involves homogeneous vehicles that employ one-to-one coordination techniques to distribute subsets and explore adjacent areas. The subsets are C6 and C8.

Local priority: Araujo et al [51] introduced a method for achieving local priority in convex polygonal regions' continuous covering and decomposition. This approach involves dividing the working space into partial areas using a displacement method, whereby each vehicle is allocated a portion of the region based on its relative capability, such as the amount of covered area per unit of time [C2, C6, and C8].

3.1.2 The Non-exact Cellular Decomposition Approach. The non-exact cellular decomposition approach divides the environment into identical cells, usually square but possibly triangular or hexagonal [32]. UAVs must collect information while navigating the environment to complete the internal map. “Offline environment” refers to acquiring information based on predefined maps. Network-based methods generate coverage routes in approximate areas [32]. This approach includes two modes: (1) Full information, where detailed knowledge of the environment is available, and (2) Incomplete information, which relies on non-exact network decomposition, where complete information about the environment is inaccessible. The latter mode is considered more practical since complete information about the environment is often unavailable at the outset in real-world scenarios. To address the challenges [*C1, C3, C7*], non-exact cellular decomposition methods are introduced as suitable solutions. Table 2 presents the covering path-planning approaches based on non-exact cellular decomposition.

Pheromone-based: The use of digital pheromones for controlling and coordinating swarms of unmanned vehicles is studied under various conditions to determine their effectiveness in multiple military scenarios [52]. The number of pheromones can fade over time and convey different types of information, where certain types may attract or repel vehicles. Vehicles’ field of view and measurement capabilities are typically limited to adjacent cells [45]. Pheromone-based methods have low computational costs.

Real-time search: The effectiveness of real-time multi-robot algorithms, including edge counting [53], Patrol PGRAPH* [54], node counting [55], and real-time A* [56], has been investigated.

Random walk: Random walk technique maps the environment. It involves a discovery strategy that utilizes multiple drones employing enhanced random walks to detect obstacles. The objective function of each drone yields a distinct profit based on the movement and angular difference between the current cell and the scanning direction, with each drone independently exploring one of the half-fields. Information exchange between cells is facilitated to avoid redundant examination of examined cells [57].

Cellular automata: The cellular automata algorithm has been used to coordinate robots in coverage techniques [58], control two quadcopters’ exploration and surveillance tasks [16].

Uncertainty of Coverage: This approach utilizes a hexagonal network to represent the environment and incorporates **Information Points** (**IPs**) with assigned confidence levels. IPs with reliable information prevent further exploration of the surrounding areas. The algorithm employs cost functions to direct the vehicles and determine subsequent points to explore.

Genetic Algorithm: This algorithm combines digital pheromones and evolutionary strategies for cooperative applications and energy consumption [59]. The working space is decomposed into rectangular sub-regions, and each vehicle is assigned a specific sub-region. The rectangle’s vertices’ coordinates are known beforehand. The drone positions move through the algorithm’s natural evolution stages of production, reproduction, and mutation to generate new samples. A function is evaluated based on digital pheromones containing region information.

The size of the cells is proportional to the drone’s camera view and discrete because drones fly at a specific altitude and use cameras as sensors to complete their tasks, in the non-exact decomposition of the network. Coverage is considered complete when the drone visits the center of each cell. Based on the available information before execution, the ability to cover the environment, collision avoidance, and algorithmic simplicity, various methods such as spanning trees, neural networks, genetic algorithms, and general innovative searches can be used for UAV path-planning [80]. This method decomposes the workplace into a geometric shape like a rectangle. A central point is placed in each rectangle to represent the area covered by the drone upon reaching that point [81]. The size of the cells is calculated based on the camera’s **Field of view** (**FOV**) and the amount of overlap required during the process [80]. The present approach utilizes several algorithms, namely:

Table 2. Path Planning Approaches for Non-exact Cellular Decomposition-based Coverage

Algorithm	Offline/ Online	Environment Decomposition Method	Performance Metrics	Single/ Multiple	Reference
Slope-based approach	Offline	Irregular/regular network	Coverage time	Single	[60]
Wavefront algorithm and cubic interpolation	Offline	Irregular/regular network	Path length, number of turning maneuvers	Single	[61]
Multi-RTT* with fixed node and genetic algorithm	Offline	Regular network	Path length	Multiple	[62]
Wavefront algorithm	Offline	Irregular/regular network	Position and altitude errors, wind disturbances, flight time and configuration, path length	Multiple	[63]
Harmony search	Offline	Irregular/regular network	Number of turning maneuvers	Single	[64]
BFS, DFS, and A* heuristic search strategies	Online	Square	Total coverage distance	Single	[65]
Hilbert space-filling curves	Online	Square	Total coverage distance	Multiple	[66]
BOA Algorithm	Online	Regular network	Path length, Obstacle Avoidance, UAV's operational power minimization	Single	[67]
Longest straight-line algorithm	Offline	Irregular/Sensor network	Total distance, number of turns, and cellular transitions	Multiple	[5]
Edge counting and graph traversal algorithm	Online	Graph network	Path length, the average distance between robots	Multiple	[19]
Reinforced random walk	Online	Rectangular-shaped	Coverage time, global detection efficiency	Multiple	[68]
Cellular automata	Online	Regular network	Exploration time with/without obstacles	Multiple	[69]
Waypoint to Planning under Uncertainty	Online	Rectangular-shaped	Confidence in informational points	Multiple	[70]
Information fusion for cooperative search	Online	Rectangular-shaped	Target localization	Multiple	[71]
Fixed-horizon with CMA-ES	Online	Rectangular-shaped	Entropy, classification rate	Multiple	[72]
Learning-based Preferential Surveillance Algorithm (LPSA)	Online	Regular network	Target distribution and localization, threat avoidance	Single	[73]
Back-and-Forth algorithm	Online	Regular network	Total distance, coverage rate, growth rate	Multiple	[74]
Genetic algorithm (GA)	Offline/ Online	Polygonal/Regular network	Path length	Single	[75]
Genetic flood fill algorithm	Offline/ Online	Polygonal/Regular network	Path length	Multiple	[76]
Multi-objective path planning with GA	Offline/ Online	Rectangular-shaped	Mission completion time	Multiple	[77]
Chaotic Ant Colony Optimization (ACO) to Coverage	Offline/ Online	Regular network	Coverage rate, recent coverage ratio, fairness (Coverage distribution), connectivity (drone distribution)	Multiple	[78]
ACO with Gaussian distribution functions	Online	Regular 3D network	Path length and rotation angle, overlap rate	Multiple	[79]

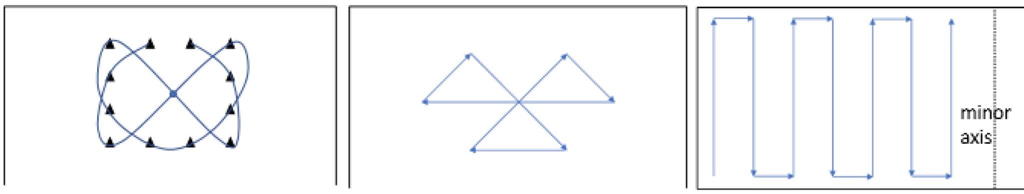

Fig. 3. Path planning approaches based on non-decomposition methods.

(1) the wavefront algorithm with a steep ascent, which seeks to determine an optimal coverage path for the UAV to return before power depletion while minimizing the number of turns and path length [82, 83]; (2) the pedestrian pocket algorithm, which focuses on efficient navigation through narrow and congested areas; (3) the backward tracking method, aimed at identifying the nearest optimal path; and (4) the quadtree algorithm, which serves to expedite computation time through the reduction of computational complexity.

3.2 Coverage Path Planning Approaches

In regular and straightforward environments, non-decomposition is commonly used for UAV missions. The environment does not require extensive decomposition, and simple geometric patterns such as **Back and Forth** (**BF**) and **Spiral** (**SP**) suffice for exploration. Mission Planner, the widely used flight control software, adopts these patterns for area coverage as a standard. The movements are carried out in straight lines that revolve with a closed angle at the end of each round. The outer vertex of the region is traversed in the last mode, with a reduction in radius toward the center point. Figure 3 depicts non-decomposition method-based coverage path planning approaches that address challenges such as [*C4, C6, C8*].

Andersen [84] proposed that specific methods can examine rectangular regions. Comparing distinct flight patterns, the sweeping pattern is categorized into two techniques: parallel lines and spirals. The former approach is more suitable when the search area is vast and no prior knowledge exists about the potential target point. The square flight pattern comprises straight lines and 90-degree turns to the right. This method originates from the central point and progresses toward the peripheries, following an oval-shaped pattern with uniform coverage. Researchers' strategies focus on decreasing path length, cost, and energy consumption, and avoiding concentrated collisions. Minimizing path length is essential due to drone energy storage, and lowering costs, including saving time and computational expenses, is necessary. Energy optimization is directly related to drone endurance and operational range. By reducing energy consumption, drones can prolong flight duration and cover a significant portion of the environment. These objectives align with drone requirements to achieve optimal performance, save energy, and optimize direct communication coverage. Minimizing drone altitude reduces energy consumption and increases flight stability. In addition, shortening the distance enables shorter communication links and facilitates faster data transmission. Table 3 provides an overview of coverage critical parameters.

3.3 AI Techniques

The path search phase in drone path planning involves two categories of techniques. The first category pertains to sampling-based approaches [105], which encompass three cellular decomposition methods [84], the road map approach utilizing probabilistic methods [106–108, 109], rapid-exploring random tree [110–119], Voronoi diagram [120, 121], A* algorithm [122–130], and the potential field approach [30, 131–136]. These algorithms are commonly used [127] in the pre-processing phase for environment modeling and pre-processing tasks. To overcome

Table 3. Computational Geometry-based Methods for Coverage Problems

Drone distribution		Type of drone		Drone mobility		Dimension		Problem-solving approach			Fault tolerance	Energy consumption	Reduced maneuvering	**Reference**
Random	Deterministic	Homogeneous	Heterogeneous	Static	Dynamic	2D	3D	Decentralized	Centralized	Distributed	K- coverage			
√		√		√		√	√		√		√		√	[12]
√		√		√		√				√				[13]
√		√	√	√		√				√	√	√	√	[85]
√		√		√		√				√				[27]
√		√		√	√	√				√				[86]
√		√		√		√			√					[87]
√		√		√		√				√				[88]
√		√			√	√				√				[29]
√	√	–	√	√	√	√	√	√	–	–	–	√		[67]
√	√	√		√		√	√							[89]
√		√		√		√				√				[90]
√		√	√		√	√				√				[91]
√					√	√				√	√			[92]
√		√		√	√	√			√					[93]
√		√		√		√	√			√	√			[94]
√		√			√	√			√					[95]
√		√			√	√				√				[96]
√		√		√	√	√				√				[97]
√		√		√	√	√				√		√		[98]
√		√		√		√					√	√		[99]
√		√		√	√					√	√			[100]
√		√			√	√				√		√		[101]
√			√		√	√				√				[102]
√		√		√		√			√					[103]
√	√	√		√		√			√					[104]

sampling-based challenges, AI methods have been developed. Exploratory methods do not guarantee the optimal solution, but they may be faster and more efficient than classical methods [137].

The second category of techniques involves AI [138, 30] and is implemented during the path search phase. AI has three novel search approaches [139–141] for 3D path planning. These approaches incorporate diverse algorithms, such as genetic algorithms [142–145], **Particle Swarm Optimization** (**PSO**) [146], evolutionary models, **simulated annealing** (**SA**), ACO [147, 148], brute-force search approach [149], local search approach [150–153], and artificial neural network approach. 3D path planning necessitates adherence to the dynamic environment and is classified as an NP-hard problem with high dimensions. Furthermore, the problem entails multiple constraints that limit the optimization of the flight path, resulting in many control points. Traditional methods fail to solve this problem. Consequently, devising a plan for the coverage route poses a formidable challenge. Numerous investigations have been conducted into developing exploratory and heuristic algorithms that exhibit favorable performance metrics, focusing on enhancing coverage criteria and path cost. However, these algorithms have suboptimal performance regarding environment coverage or path cost (e.g., coverage time or energy consumption). Table 4 presents a comparative analysis of the proposed algorithms' sampling-based techniques employed in the initial phase.

The table indicates that the strength criterion has received comparatively less attention, while time and cost consumption criteria (AI algorithms) have been utilized most frequently in algorithms. The optimal solution selection depends on available environmental information. In a dynamic environment, the UAV is tasked with acquiring the requisite information from its sensors to facilitate the implementation and planning of the coverage route. This coverage category is called sensor-based coverage since it utilizes sensor information to guide the coverage performance. Table 5 comprehensively reviews the relevant criteria for path planning based on AI techniques.

As indicated by Table 5, most AI users prioritize time and cost consumption, whereas collision prevention receives less emphasis than other parameters. Additionally, completeness has been accounted for in some references. However, the path length is not mentioned in most references.

3.4 Hybrid Approaches

To overcome this limitation, reinforcement learning techniques can enhance efficiency [168]. Given that environmental modeling is predicated on pre-established data, reinforcement learning techniques offer a potential solution to improving algorithmic performance [106]. These techniques are classified under the AI algorithm subgroup. Sampling-based techniques and exploration-based approaches have strengths and weaknesses and are deeply interconnected in many fundamental concepts. Therefore, these algorithms have been combined in many applications and have provided a solution that is the primary methodology for developing path-planning proposals. This method helps to effectively and efficiently plan motion [170]. Combination systems constitute the third category of path-planning approaches. In recent years, sampling-based motion planning algorithms have been widely used to solve motion planning problems for robots in high-dimensional configuration spaces. They have also been integrated into combination methods to leverage other techniques' advantages. About [171], a hybrid graph-based approach to path planning is presented. This algorithm combines a flexible normalized fuzzy controller with Lazy Theta* algorithms. By dynamically adjusting the drone's altitude online, it finds the most efficient path to overcome obstacles. This simple, fast, and adaptable approach can find optimal paths on randomly generated maps. Leo et al. [172] introduced a combined visual-geometric learning approach followed by a deep neural network model for analyzing and guiding UAVs and creating 2.5D height maps.

Table 4. Relative Comparison of Existing Proposals in Sampling-based Techniques

Path length	Optimization	Centralized solution	Cost consumption	Time consumption	Energy consumption	Autonomy	Collision avoidance	Reference
–	Optimal	–	√	√	x	x	√	[105]
–	Optimal	–	x	x	x	√	x	[146]
–	Optimal	–	√	√	x	x	x	[106]
–	Optimal	–	x	√	√	√	√	[107]
–	Optimal	–	√	√	x	x	x	[108]
–	Optimal	–	x	√	x	x	√	[109]
–	–	PC	x	√	x	x	√	[110]
–	Optimal	PC	√	√	x	x	x	[111]
–	Non-optimal	PC	√	x	x	√	√	[112]
–	–	PC	x	x	x	√	√	[113]
√	Optimal	–	√	√	√	x	√	[114]
–	Non-optimal	–	x	√	x	x	x	[115]
–	Optimal	–	√	√	x	x	√	[116]
–	Optimal	–	√	√	x	√	x	[117]
–	Optimal	PC	√	√	x	x	x	[118]
–	–	–	√	√	x	x	√	[119]
–	Optimal	–	√	x	x	x	√	[121]
√	PO	–	√	x	x	x	√	[154]
√	Optimal	–	√	√	√	x		[155]
–	Optimal	–	x	√	x	x	√	[120]
–	Optimal	–	√	√	√	√	√	[121]
–	Optimal	–	√	x	x	x	x	[122]
√	NO	√	√	√	x	x	√	[156]
√	Optimal	–	√	√	x	x	x	[124]
–	Optimal	–	√	x	x	x	x	[157]
√	Optimal	–	√	√	x	x	x	[158]
√	Optimal	√	x	√	x	x	x	[159]
–	Optimal	–	x	x	x	x	x	[160]
–	Optimal	–	√	√	x	x	x	[125]
–	Optimal	–	√	√	x	x	x	[161]
–	Optimal	–	√	√	√	√	x	[126]
√	Optimal	–	√	x	x	x	x	[127]
√	–	–	√	√	x	√	√	[128]
√	NO	–	√	√	x	x	√	[129]
–	Optimal	PC	√	√	√	√	√	[130]
–	Non-optimal	–	x	x	x	x	x	[162]
–	Optimal	–	√	x	x	√	x	[163]
√	Optimal	–	x	x	x	x	√	[164]
√	Optimal	–	x	x	x	x	√	[131]
√	NO	–	x	x	x	x	x	[132]
–	–	–	x	√	x	√		[133]
–	–	–	√	x	x	x	√	[134]
–	Optimal	–	√	x	x	x	√	[135]

(Continued)

Table 4. Continued

Path length	Optimization	Centralized solution	Cost consumption	Time consumption	Energy consumption	Autonomy	Collision avoidance	Reference
√	Optimal	–	√	x	x	x	√	[165]
–	Optimal	–	x	x	x	x	√	[136]
√	NO	√	√	x	√	x	√	[67]

x: Not considered, √: Considered, -: Not mentioned, PC: Probabilistic Complete, PO: Probabilistic Optimal, NO: Near-optimal

Table 5. Relative Comparison of Existing Proposals in AI Techniques

Path length	Optimization	Centralized solution	Cost consumption	Time consumption	Energy consumption	Autonomy	Collision avoidance	Reference
–	Optimal	–	√	√	x	x	√	[139]
–	Optimal	–	x	x	x	x	x	[140]
–	–	–	x	√	x	x	x	[141]
			√	√	√	x	x	[166]
–	Optimal	–	x	x	x	x	x	[167]
–	–	–	√	x	x	√	x	[142]
–	Optimal	–	x	√	x	x	x	[143]
–	Optimal	–	√	√	√	x	x	[144]
–	Optimal	√	√	√	x	x	x	[145]
–	AO	–	√	√	√	x	x	[149]
–	Optimal	–	x	√	x	√	x	[150]
√	–	–	x	√	x	√	x	[151]
–	AO	–	x	√	√	x	x	[152]
–	AO	–	x	√	√	x	x	[153]
–	Optimal	–	x	x	x	x	√	[168]
–	–	–	x	√	x	x	x	[169]

x: Not considered, √: Considered, -: Not mentioned, AO: Approximate Optimal

In reference [173], a combined approach comprising classical and exploratory algorithms is used for drone path planning. The **Probabilistic Roadmap Method** (**PRM**) [174] and **Artificial Bee Colony** (**ABC**) [175] algorithms are combined to traverse the most acceptable flight path in a complex zone without colliding with environmental elements. The results show that the proposed combined path planning algorithm performs better regarding flight time, energy consumption, accuracy, and safety than conventional algorithms. In [176], the **Rapidly-exploring Random Tree** (**RRT**) and RRT* algorithms have been integrated with a computational framework inspired by a computational model called **Membrane Computing** (**MC**), whose computational models are executed non-deterministically and in parallel. MC a branch of natural computing, was introduced by Păun in 1998 [177]. Thomson Scientific's **Institute for Scientific Information** (**ISI**) introduced this field as an emerging research frontier in computer science in 2003, transforming MC into a branch of natural computing [178, 179, 180]. MC has evolved into a robust scientific discipline. MC is a computational paradigm inspired by living cells, known as membrane systems or P systems. Cellular systems like P provide a hierarchical structure of membranes, rules types (e.g., transformations and communications), and inherent parallelism [181, 182]. These features make them highly effective computationally and attractive for modeling complex problems. The **Membrane-Inspired Evolutionary Algorithm** (**MIEA**) is a successful example of combining

MC and evolutionary algorithms, demonstrating the integration of membrane computations and evolutionary algorithms. In recent years, considerable research has been conducted on MIEAs. These algorithms are a class of combined optimization algorithms aiming at investigating the interactions between MC and evolutionary computations. MIEAs utilize concepts and principles from metaheuristic search methodologies and hierarchical structures to optimize various problems efficiently. In [183], Xiao et al. applied nature-inspired algorithms based on MC to engineering design problems. MC abstracts parallel and distributed computational models from living cells' structured and interactive nature. Huang and Cheng [184–186] combined genetic algorithms and differential evolution with membrane systems to solve single and multi-objective optimization problems. An evolutionary algorithm inspired by quantum-based P systems has been proposed to solve classical theory [187, 188] and practical issues [189]. Some updated MIEAs based on PSO and an artificial fish swarm algorithm have also been suggested. All of these research efforts support the claim by Pˇaun and P'erez-Jim'enez that MIEA represents a novel investigation direction with a specific scope [190]. In path planning, MIEA can evolve by relying on biochemical processes to find the most appropriate parameters for creating a feasible and safe path. Given the emerging nature of this field, further details of research conducted in the area of combined path-planning algorithms inspired by membrane-based evolutionary algorithms will be examined.

In reference [191], a computational algorithm based on the membrane-inspired ACO algorithm and the robot algorithm is proposed for optimizing the coal mine path and compared with the traditional ant colony algorithm. Considering the complex environment of the coal mine, empirical results demonstrate that the membrane-driven ant colony algorithm can overcome the inadequacy of the traditional ant colony algorithm in local optimization and achieve an optimal solution in a short time. In [192], the proposed algorithm, **Membrane Pseudo-Bacterial Potential Field** (**MemPBPF**), combines membrane-inspired computations (a P-cell-like system), a pseudo-bacterial genetic algorithm, and an artificial potential field method to perform path planning for **Autonomous Mobile Robot** (**AMR**). It integrates these methods to generate a practical, safe, and smooth path while considering minimal evolution lengths. This improves convergence speed and robustness. The results indicate that the proposed MemPBPF algorithm effectively achieves three essential requirements for solving path planning problems: safety, length, and smoothness. This makes the MemPBPF algorithm suitable for competitive results in AMR navigation in complex environments. [193] proposes a hybrid algorithm that synergistically combines MC with a **Genetic Algorithm** (**GA**) and the **Artificial Potential Field** (**APF**) method to solve path-planning problems. The hybrid approach is based on a suitable combination of three methods: MC [194, 195], evolutionary computation (specifically a genetic algorithm) [196], and the APF method [197], which addresses path-planning problems. The evaluation results of this algorithm in offline mode in completely static environments and online mode in dynamic environments demonstrate that memEAPF combines a GA with APF through a membrane structure. It utilizes active membranes with membrane fusion and division operations to enhance information communication among agents and provides feasible and efficient paths. In [198], an algorithm inspired by modified **Membrane-based PSO** (**mMPSO**) is proposed, which integrates membrane systems with PSO. In mMPSO, a dynamic two-level membrane structure is introduced for particle arrangement with different dimensions and communications between particles on different membranes. In [199], an algorithm for path planning based on incremental sampling with a computational framework inspired by MC has been proposed. This process utilizes the computational model of P systems in a non-deterministic and parallel manner. This algorithm combines MC with sampling-based approaches. In [200], using a **Q-learning Artificial Potential Field** (**QAPF**) learning algorithm, feasible paths for mobile robots are computed in both known and

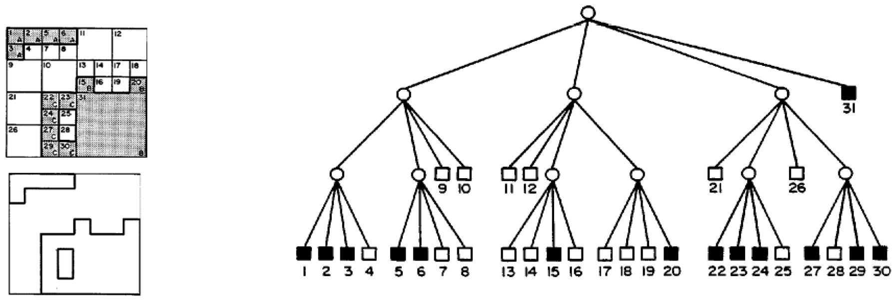

Fig. 4. The maximum blocks of an image and its corresponding quadtree.

unknown environments. The QAPF learning algorithm is designed based on criteria such as learning time, path length, smoothness, and collision avoidance. In [201], the **Modified ACO algorithm** (**MACO**) and a variant of A*, namely the **Memory Efficient A*** algorithm (**MEA***), are combined to develop an optimal path planning algorithm without collision with obstacles. In this algorithm, by using an enhanced version of the pheromone strategy in MACO, local pheromone evaporation and early convergence are minimized. An optimal path is found through a reward and penalty mechanism.

A flexible and simple data structure is one of the most influential parameters for improving path quality. The algorithm data structure should be designed to store algorithm data with minimal memory consumption. For simplification, the site should be capable of transforming from a two-dimensional environment to a 3D one and vice versa. In the next section, we will examine researchers' data structures.

4 Data Structures

The objective of this section is to introduce a suitable data structure to store the triangulation approaches to the environment with imaging at various heights, creating multiple resolutions that conform to the characteristics of the ground surface and the position of obstacles and targets while minimizing the complexity of the environment without compromising image resolution. The triangulation data structure should enable variable accuracy information extraction. This should allow for storing images with various resolutions at different heights. The initial step toward simulating the environment involves hierarchical partitioning. Hierarchical partitioning methods provide a fast and straightforward means to construct multi-resolution models. Such methods include quadtree and k-tree, which utilize a divide-and-conquer strategy to recursively partition a surface into regions and create a tree hierarchy. Previous research suggests that the quadtree structure with an error measure is the most efficient representation of triangulation [202, 203]. This representation only stores the elevation and error values for each network point and does not require information on multiple-resolution hierarchies. Triangulating the terrain is often accomplished by creating an irregular triangular network based on two-dimensional Delaunay triangles. A multi-resolution extension of Delaunay-based **Triangulated Irregular Networks** (**TINs**) is the Delaunay pyramid, in which sets of fewer triangles replace groups of hierarchically connected triangles. A study by [204] utilized a hierarchical quadtree method with a 2D wavelet transform to simplify the terrain. This method removes height points from the network based on wavelet coefficients. The remaining quadtree points are locally triangulated using lookup tables. The set of remaining quadtree points is also used for image compression. Figure 4 shown hierarchical structure based on a quadtree.

4.1 Hierarchical Restricted Quadtree

In reference [202], an adaptive triangulation technique based on a hierarchical, restricted quadtree with two levels was introduced for sampling and adaptive triangulation. The quadtree is divided recursively until sampling is performed for each region. This method offers various triangulation approaches.

Restricted Quadtree: Restricted quadtree triangulation is a method that prevents gaps in quadtree polygonal representation. In this approach, each region of the quadtree is triangulated based on the size of its neighboring areas without leaving any gaps or mismatching. To begin, initial sampling is performed on a uniform network. Each location is evaluated based on specific acceptance criteria, such as approximation error. This process is repeated until comparative sampling meets the acceptance criteria across the entire level. Finally, triangulation and rendering of all regions in the quadtree are performed.

Planar Quadtree Maps: Digital network environments commonly use 2.5D-level data to represent elevation models. In [205], the restricted quadtree technique is applied to this data type. Additionally, [202] presents two efficient construction algorithms for generating and triangulating a restricted quadtree from a set of points on a regular network. These algorithms utilize a bottom-up and top-down method to create a hierarchy of four limited trees. The restricted quadtree technique is used in this context to ensure that no gaps appear in the triangulation of each region without leaving or matching.

Continuous Level of Detail (LoD) rendering: [203] describes an alternative method for creating and triangulating restricted quadtrees based on triangle fusion. This method starts with the triangulation of the entire digital network environment dataset. It simplifies it by merging triangles from the bottom to the top. Triangle merging is done in two phases. In the first phase, pairs of isosceles triangles with a typical short edge are joined in an atomic node. The midpoint of the square boundary edge is removed. In the second phase, the central vertex of a quadrilateral region is removed by merging pairs of isosceles triangles along the diagonal.

Real-time optimal mesh matching: This method is based on a binary triangular hierarchy. This recursively modifies triangles by splitting the longest edge at the base vertex to achieve optimal mesh matching [206].

Irregular right triangular networks: This framework presents a multi-resolution triangulation method for a restricted quadtree based on a triangular tree hierarchy [207]. This approach focuses on the efficient hierarchical representation of binary triangles and fast mesh traversal for neighbor finding. From a triangulated square, triangles are recursively divided at the base vertex or the midpoint of their longest edge. In the worst case, the division terminates in O (log n) time, where n is the size of the triangular tree hierarchy (number of leaf nodes).

Restricted quadtree triangulation: The main purpose of the restricted quadtree triangulation technique, proposed in [208], is visualization of large-scale terrains. The triangulation method is based on the quaternary tree hierarchy similar to [205] and employs the dependency relationship introduced in [203] to produce quaternary tree triangles with minimal matching. Two pseudocodes for top-down and bottom-up triangulation algorithms are presented for an elevation field where each vertex is associated with an approximation error.

Compression with multiple resolutions: In [206], the authors investigate the compression of restricted quadtree or irregular right triangular networks for efficient data storage, processing, search and access, and data compression. They suggest that data should always be managed compactly, even when interactive processing is performed. The authors use the triangular hierarchy approach within multi-resolution triangulation.

5 Research Gaps and Future Directions

This section aims at analyzing the most prominent drone path planning strategies. We will discuss their gaps and weaknesses, which will pave the way for future research. It is imperative to note that this article focuses only on widely used methods and offers only a brief overview of other conventional methods. Section 3 provides a comprehensive review of path-planning approaches, comparing various algorithms based on sampling-based and AI methods. This section analyzes path-planning approaches successfully implemented in two-dimensional and 3D areas without focusing on any specific algorithm. It addresses the challenges of 3D environments and suggests efficient and optimal solutions for implementing the mentioned algorithms. Furthermore, the impact of data structure on drone path planning and environment modeling will be discussed. Finally, the proposed algorithms in each category of path-planning approaches will be introduced as solutions to meet the challenges outlined in the earlier sections of the article.

5.1 Advantages and Disadvantages of Different Path Planning Approaches

This article categorizes 3D coverage path planning algorithms into sampling-based, AI, and hybrid methods. It compares them for design simplicity, scalability, online planning, global optimal planning, and so on. Advantages and disadvantages will be discussed. Sampling-based strategies divide the environment into cells, making execution straightforward. Therefore, they are suitable for both static and online planning scenarios. The precise decomposition method requires relatively complete pre-defined information, so path planning has fewer challenges. Therefore, it is evident that many articles seek path planning using the precise decomposition method, which follows this approach. This category of system is suitable for static and offline environments. However, excessive reliance on pre-defined locations poses challenges regarding the scalability of existing solutions for more complex zones. On the other hand, in the real world and at the moment of path planning initiation, complete information about the surroundings is not available. For this reason, many authors want to expand their research by extending environment-based solutions to dynamic and unknown domains [68, 104]. This article focuses on examining approximate decomposition methods. In places where incomplete information about the site exists and by exploring the area, the search agent's knowledge will increase. Semi-accurate decomposition algorithms divide the domain into different cell sets, allowing distance between cell centers. Then, during the search phase, the cells are distributed across the workspace using optimal path-planning algorithms. Therefore, like precise decomposition algorithms, they can have simple designs. Additionally, these methods can be combined with other techniques to achieve global optimality and used for online tasks. Non-decomposition-based algorithms also accomplish missions with a single agent in regular and simple locations where environment decomposition is unnecessary and simple geometric patterns are sufficient for exploration. Therefore, this method is also suitable for static and offline environments, as discussed earlier regarding their challenges. AI methods are exploratory and can effectively cope with limitations such as complexity, lack of structure, and other NP-hard problems. These algorithms optimize the path through optimal mutations, but mutations require long iteration times. Therefore, these types of algorithms can only operate offline. As one of the three critical algorithmic path planning approaches examined, hybrid methods integrate the advantages of several techniques, such as AI procedures. This is to achieve global optimization and minimum cost. Most of them consider time and information savings simultaneously. Combined with several relatively simple methods, such as sampling-based methods, they can form a relatively efficient online implementation method. However, a meager percentage of reviewed articles use combined approaches.

For this research, 350 articles were retrieved from databases such as Scopus, depending on their titles, abstracts, and conclusions. These registries index significant digital libraries such as

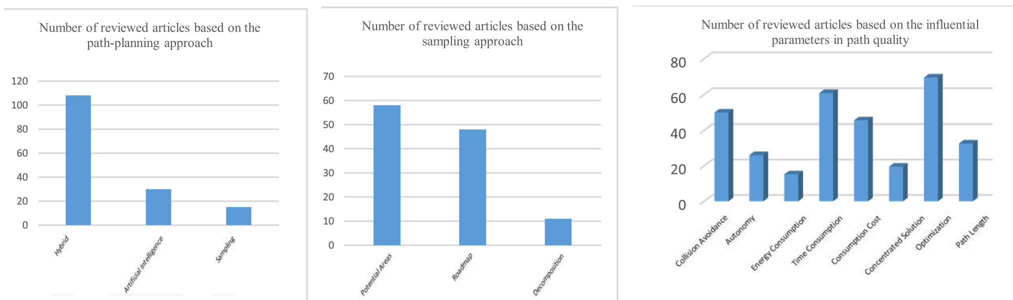

Fig. 5. Distribution chart of articles based on the utilization level of methods, techniques, and parameters in path planning.

Institute of Electrical and Electronics Engineers (**IEEE**) Xplore, Springer Link, Science Direct, or the **Association for Computing Machinery** (**ACM**). This comprehensive database contains a wealth of information from the literature in a domain [24]. Articles that did not pursue research objectives were excluded, resulting in 210 articles being evaluated. Among these, 153 articles were selected to examine path-planning approaches and influential parameters in path quality. Three key strategies are applied to transform a physical environment into a problem space representation based on the reviewed articles. These methodologies extract information about site state for planning algorithms. Among the reviewed studies, there is a clear tendency toward sampling-based techniques (70.58% sampling-based, 19.6% AI, and 9.8% hybrid). Among sampling-oriented methods, 74.13% of the articles are focused on non-exact cell decomposition approaches, 24.13% on exact cell decomposition procedures, and 1.17% on non-decomposition practices. On the other hand, a significant portion of hybrid approaches are based on a cell decomposition strategy, indicating a greater tendency toward sampling-centered approaches. Figure 5 illustrates the distribution of articles based on methods, techniques, and path-planning parameters. Table 6 also introduces path-planning challenges and corresponding approaches.

5.2 Dominant Strategies in 3D Path Planning Based on Data Structure

The design and implementation of path planning algorithms for UAVs face several limitations, including dealing with dynamically moving and suspended UAVs in 3D space and considering physical characteristics, endurance, maneuvering limitations, load-carrying limitations, and external environmental conditions. Furthermore, the extensive development of UAVs in various fields may render existing algorithms ineffective or undesirable. 3D path planning techniques are needed to facilitate UAV exploration in complex environments with complex objects. Therefore, appropriate algorithms need to be introduced based on the applications and characteristics of the UAVs. As a result, another challenging issue is modeling the surroundings in 3D. Since drone flight is 3D and most existing literature only focuses on path planning in two-dimensional environments, this research systematically examines proposed solutions in 3D space.

Simulation of a large-scale flight environment presents significant challenges in computational efficiency, making it a critical area of focus. To enhance algorithmic performance, environment modeling complexity should be reduced while maintaining high image resolution. This can be achieved by controlling geometric simplification via an approximate error threshold. Furthermore, varying levels of detail can be applied to different segments of the environment. This allows the image to be rendered and displayed efficiently after modeling and simplification. Most existing preprocessing and modeling methods adopt a flat and simplistic approach to environment modeling [209]. While this approach suffices for specific applications such as landmine detection, floor

Table 6. Introduction of Challenges and their Corresponding Approaches

	Challenge	Proposed Approaches	Proposed Algorithms
c_1	Topology	Semi-exact approach	Genetic, Cellular Automata, Random Walks, Real-Time Search, Pheromone-Based
c_2	Path planning and motion planning	Exact approach, non-decomposition	Local Priority, Line Formation, Spiral, Round-Trip
c_3	Autonomy	Semi-exact approach	Genetic, Cellular Automata, Random Walk, Real-Time Search, Pheromone-Based
c_4	Energy consumption	Exact approach, non-decomposition	Local Priority, Line Formation, Spiral, Round-Trip
c_5	Mobility	Semi-exact approach	Genetic, Cellular Automata, Random Walk, Real-Time Search, Pheromone-Based
c_6	Deterministic coverage	Exact approach, non-decomposition	Local priority, Line formation, Spiral, Round-Trip
c_7	Being-online	Semi-to non-exact approach	Genetic, Cellular Automata, Random Walk, Real-time search, Pheromone-based
c_8	Centralized solution	Exact approach, non-decomposition	Local priority, Line formation, Spiral, Round-Trip

cleaning, and lawn mowing, it falls short of critical surveillance applications such as infrastructure inspection, where the UAV operates in a 3D space during the path-planning phase. Consequently, traditional two-dimensional path planning methods are inadequate for identifying obstacles and analyzing the 3D environment. Specific algorithms for 3D space are required to account for the inherent uncertainties of the real world, necessitating the discretization of the continuous space of the environment [148]. When displaying digital input data on a network display, such as data derived from various heights of the earth in the form of a multi-resolution model and space discretization, hierarchical data structures are highly recommended. Specifically, the most efficient structures for this purpose include multi-resolution triangulation and four trees [36]. Triangulation must align with the specific characteristics of the ground surface and the placement of obstacles and targets. This will simplify modeling an environment without compromising image resolution. As a result, triangulation methods for smooth and obstacle-free surfaces may differ from those used for non-flat surfaces. Furthermore, the triangulation data structure must enable the extraction of information with varying precision levels to support several levels of detail during runtime. The most effective way to represent triangulation is via an implicit quadtree structure with an error measurement system. This representation eliminates the need to store information describing multiple-resolution hierarchies and requires only elevation and error values for each network point. After extensive research, it has become clear that the path-planning process during the environment modeling phase is fraught with challenges, including coverage, scalability, and failure tolerance. Similarly, the path search phase poses difficulties such as path length, collision prevention, and energy consumption. Despite their significant impact on path planning, collision prevention, and path length criteria have received less attention. Additionally, a data structure tailored to UAV applications has yet to be developed. Therefore, it is recommended that triangular clustering algorithms, which are highly effective in terms of coverage and scalability, be utilized alongside a hierarchical data structure during the modeling phase. Height-based AI algorithms should also optimize target estimation during path searches.

5.3 Research Gaps and Future Directions

As mentioned, path-planning approaches have been examined based on their intrinsic capabilities and evaluated according to the problem space. Therefore, non-exact path-planning approaches have been introduced as the most common. However, factors such as environmental dimensions, obstacles, whether obstacles are static or dynamic, and overall ecological dynamics still significantly impact path quality. Many articles analyzed by the semi-accurate decomposition method ignored dynamic obstacles or only considered static ones. However, as stated, this research continues in this category of articles. This indicates positive progress toward dynamic ecological planning in the future. It is pertinent to note that insufficient knowledge of the zone can lead to other problems, such as collisions and an increased frequency of revisiting paths. This adds a computational burden due to processing incomplete information and does little to improve path quality. Therefore, an appropriate path planning algorithm that can be used in the real world and overcome implementation challenges should ideally reduce its dependency on the known domain and static obstacles as much as possible to be able to make correct decisions in operational and dynamic environments.

Furthermore, it should be able to generalize and extend into 3D space. Increasing the ability to understand the problem and design dynamic and 3D areas for safe and reliable operations, considering acceptable computational overhead for UAVs, is highly relevant. Future research should focus on developing path-planning algorithms to identify locations and avoid real-time obstacles dynamically. Furthermore, leveraging UAV network potential can increase scalability while maintaining simplicity. Therefore, in these circumstances, selecting the main parameters to determine path quality is a challenge. Decision-making regarding the significance of environmental parameters should depend on the UAV's application domain and the level of awareness of the site's conditions. Scenario 1: In non-critical applications and situations where specific but not necessarily complete information about the domain is available, offline path planning and online feedback-based path correction from the environment can be a viable solution. Pre-defined information enables path-planning methods to enhance global coverage and accuracy, leading to higher-quality outcomes and smoother paths. However, as mentioned, most existing path-planning approaches are offline and need to update computed paths based on online feedback. Therefore, given the computational power of processing units, locally updating and correcting global path designs based on real-time feedback can be a very intriguing idea for future research. In addition to designing suitable data structures to reduce the volume of exchanged data in memory and facilitate information processing, leveraging state-of-the-art technologies such as 5G for high-speed data transmission, cloud-based processing and more efficient service selection in a dynamic environment based on QoS can significantly contribute to realizing this idea [210]. Nowadays, accelerating data transmission and processing is feasible thanks to rapid data transfer technologies and cloud-based processing capabilities. This idea can also bridge the gap between modeling and path planning, which currently require double visits to a cell. This approach represents a desirable developmental extension of the approximate decomposition technique based on the sampling approach. Scenario 2: Where precise information about the surroundings and obstacles is lacking, one optimal solution is sampling a small portion of the zone. This is done by developing a scalable algorithm with low error rates for simulating the entire area. Path planning in a complex location and on a large scale is inherently challenging. Even with the assumption of designing a path for such an environment, implementing and repeated testing in the final stage would be costly. Therefore, designing scalable algorithms can be one of the exciting ideas for researchers and developers in this field. Scalable algorithms based on computational sampling methods can intelligently select a small subset of the domain as a sample. They choose it based on pre-defined criteria. Simulations are run on these samples to generate customized mappings with reduced computational overhead. This is done while preserving the baseline mapping output features. In this approach, selecting appropriate criteria for choosing an optimal set is challenging and requires precise computations and experiments on the samples. A novel proposal to address this challenge is a hierarchical approach to sampling the environment. According to this approach, the size, quality, and number of samples can be adjusted in a hierarchical structure to achieve maximum coverage.

Displaying the problem space in large and complex dimensions incurs significant costs. In such cases, simplifying the environment is necessary. One technique for simplification involves reducing cell size in two-dimensional space and extending it to 3D space. Therefore, this technique suits sites with an approximate cellular decomposition approach. Another simplification technique that has garnered more attention and was mentioned in the reviewed studies is the implementation of path-planning algorithms in 2.5-dimensional space. Here, the choice of an appropriate data structure proves crucial. The proposed algorithm will succeed despite its advantages if the data structure generalizes from two-dimensional to 2.5-dimensional space.

Collaborative strategies among UAVs or distributed networks for disseminating required information throughout the environment are emphasized in critical applications. The need for more attention to multiple UAV use is one of the weaknesses in most reviewed research. The majority of studies under consideration have examined scenarios involving single UAVs, while UAV networks have substantial potential to enhance scalability. In this case, the communication topology among UAVs facilitates collision avoidance, error tolerance, and flexibility to provide a reliable and seamless UAV network. Optimizing operational power to maximize data speed and network efficiency and determining the type and size of information UAVs disseminate, especially in challenging and dynamic environments, can significantly impact problem-solving quality. Therefore, multi-UAV scenarios require further analysis and investigation to address communication challenges and leverage the benefits of these scenarios to increase efficiency and improve path-planning algorithms. Developing future planning algorithms and a deeper understanding of how existing methods can be optimized can allow UAVs to achieve individual goals more effectively. This will address issues arising from multi-UAV data structure management and task allocation.

6 Conclusion

Previous studies have proposed various classifications for path planning, providing an overview of the algorithms available in this field. However, most of the introduced algorithms are suitable for static and well-known environments, and they may need to be more practical or require significant development and modification of the primary structure for use in the real world. Furthermore, in other studies, less attention has been paid to the implementation phase and the associated challenges. This investigation proposes two novel classifications of non-exact decomposition practices for path planning based on symbolic techniques and data structures. Additionally, state-of-the-art technologies related to UAV path-planning approaches have been analyzed. This article only focuses on presented methods with extensive applications and briefly mentions other conventional methods. To conduct a comprehensive review of 3D UAV path planning, this article critically analyzes the essential existing path planning approaches for UAVs. It offers efficient and optimal solutions for implementing these algorithms in 3D space by addressing the challenges and research gaps in the 3D area. Based on these foundations, suggestions such as the impact of appropriate data structure design and environment modeling on 3D path planning and addressing challenges have been stated, providing an outlook on the authors' future ideas. Moreover, it offers the most pertinent suggestions for future work to researchers.

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