RAIRO-Oper. Res. 58 (2024) 2951–2989
https://doi.org/10.1051/ro/2024073

RAIRO Operations Research
www.rairo-ro.org

UAV PATH PLANNING TECHNIQUES: A SURVEY

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Abstract. Unmanned Aerial Vehicles (UAVs) are ideally suited for many real-world applications ranging from scientific to commercial, industrial, and military fields. Enhancing the efficiency of UAV-based missions through optimization techniques is of paramount significance. In this regard, the path planning problem that refers to finding the best collision-free path between the start point and the destination by addressing temporal, physical, and geometric constraints is a key issue. In this paper, a review of recent path planning methods from different perspectives with a clear and comprehensive categorization is presented. This study provides a general taxonomy categorizing the existing works into classical approaches, soft-computing techniques, and hybrid methods. Here, a detailed analysis of the recent techniques as well as their advantages and limitations is offered. Additionally, it provides an overview of environment modeling methods, path structures, optimality criteria, completeness criteria, and current UAV simulators.

Mathematics Subject Classification. 52B05, 05C38, 05C85.

Received April 27, 2022. Accepted March 24, 2024.

1. Introduction

UAVs, commonly known as drones, are referred to as aerial vehicles without a human pilot on board. They utilize aerodynamic forces to produce lift for the vehicle and possess the capability to operate either autonomously or under remote piloting control. UAVs can be expendable or recoverable and can carry a lethal or nonlethal payload [43]. UAVs, which were originally employed for military purposes, have now reached a greatly expanded role in many fields of aviation owing to their flexibility and cost-efficiency in comparison with conventional aircraft [209], as well as their potential in hazardous scenarios [218]. They predominantly work in uncertain environments where it is vital to keep their routes away from threats, barriers, and restricted areas. Hence, a noticeable trend in both the market and among UAV system designers is leaning towards increased autonomy [145]. Systems advancing in intelligence, diversity, and collaboration, operating independently of a human pilot and possessing the ability to self-plan missions, significantly contribute to their heightened effectiveness and value. In such scenarios, the main task of a UAV, as an autonomous vehicle, is to move from one location to another one while meeting defined criteria such as minimum path length, minimum flight time, minimum fuel consumption, and minimum danger exposure. Aditional aspects, such as lowering operational expenses and

Keywords. UAVs, path planning techniques, offline and online, classical methods, soft-computing approaches.

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mitigating the likelihood of detection can be integrated into the rudimentary objectives. Planning a suitable safe trajectory, known as the UAV path planning problem, is inevitable to make this mission possible.

Typically, the path planning problem is scrutinized from two points of view: robotics [100], and dynamics & control [308]. The computational cost is a primary focus in robotics, while the dynamics & control perspective emphasizes the dynamic behavior of trajectories in three-dimensional (3D) space. UAV Path Planning, however, is significantly different from most traditionally defined mobile and manipulator robots [113]. To give full play to the UAVs' maneuverability, the optimal trajectories should take non-trivial dynamics constraints into account while achieving self-control flight and computational efficiency. The problem has a non-linear nature where its complexity exponentially increases with its dimensionality [34].

Up to now, lots of studies carried out in-depth to deal with the UAV path planning problem. The current literature can be classified into classical or exact, soft-computing, and hybrid methods. This paper presents a general taxonomy of UAV path planning approaches. Each technique has its advantages over others in certain aspects. Early works, including classical methods such as graph search algorithms, are usually considered as time-efficient methods. In these approaches, a local path is generated based on the current information that spans the area of operation. Due to this assumption, the considered path is partially planned and cannot be considered a global optimum. Hence, soft-computing techniques are put forward as an alternative method. They have no assumption about the problem that is being optimized and adopt different learning strategies to perform an effective search toward the global path. One can use soft-computing techniques in conjunction with pre-processed and stored cost maps as a means to reduce computational time. Thus, the versatility of soft-computing approaches has rendered them an appealing option for tackling the intricacies of the UAV path planning problem [29, 235]. Indeed, there has been increasing attention placed on the application of soft-computing techniques in recent years [340]. In practical scenarios, they might not always be the most suitable option when computational resources are restricted. These challenges have inspired researchers to introduce hybrid (multi-fusion) strategies as a solution to address the problem.

There exist several helpful surveys covering UAV path planning methods [30,76,228,268,343] (see Tabs. 1 and 2 for a brief overview). For instance, in [113], a survey has been done by offering a valuable survey of current algorithms from the perspective of robotics, control fields, and autonomous UAV guidance approaches. This survey focused on classical algorithms and presented a general aspect of the particular problems arising with UAVs. In [69], authors provided a survey of motion planning techniques that deal with the presence of uncertainty by emphasizing their application to UAVs. In another study, Triharminto *et al.* [289] reviewed three kinds of algorithms, including grid-based, evolutionary-based, and curve-based algorithms for dynamic UAV path planning problems. In the same direction, Yang *et al.* [314] provided a review of the UAV path planning problem by classifying the existing methods into five categories: sampling-based, node-based, mathematical-based, bio-inspired based, and multi-fusion based algorithms. Another literature review of deep learning methods for UAVs, including shortest path, motion, navigation, or manipulation planning has been presented in [45]. In another research, Radmanesh *et al.* [233] provided a comparative study for several exact and heuristic algorithms. Very recently, Zhao *et al.* [340] put forward a summary of research on UAV path planning focusing on computational intelligence (CI) methods with three different points of view: characteristic of CI algorithms, types of time domain, and types of environment. Besides, Choi *et al.* [63] reviewed the state-of-the-art machine learning techniques that have been applied to UAVs for autonomous flight. In their work, a review of control strategies including parameter tuning, adaptive control for an uncertain environment, real-time path planning, and object recognition is considered. Very recently, Aggarwal and Kumar [4] considered the various UAV path planning techniques. They classified the existing methods into three broad categories including representative techniques, cooperative techniques, and non-cooperative techniques. In this regard, they discussed and analyzed the coverage and connectivity of the UAVs' network communication.

In the same direction, this study provides a more comprehensive picture of available approaches with an organized structure. A general taxonomy is introduced to categorize the existing works into classical or exact methods, soft-computing techniques, and hybrid (multi-fusion) approaches. The paper reviews available studies by considering the problem definition, the environment representation, the solution method, the type of path

Table 1. The list of existing surveys in the literature.

Subject	Year	Proposed taxonomy of techniques
Motion Planning Literature in the Presence of Uncertainty [69]	2012	– Uncertainty in Vehicle Dynamic – Uncertainty in Environment Knowledge – Uncertainty in pose – Reactive planning
Dynamic Path Planning for Intercepting of a Moving Target [289]	2013	– Grid-based Algorithm – Evolutionary Algorithm – The Curve Algorithm
On the performance comparison of multi-objective evolutionary UAV path planners [30]	2013	Evolutionary Heuristics – Genetic Algorithm – Particle Swarm Optimization – Differential Evolution Algorithm
3D Path Planning [314]	2014	– Sampling-based Algorithms – Node-based Algorithms – Bio-inspired Algorithms – Multi-fusion Algorithms
A Review of Deep Learning Methods and Applications for Unmanned Aerial Vehicles [45]	2017	– Deep Learning for Planning and Situational Awareness
Survey on computational-intelligence-based UAV path planning [340]	2018	Classification from the aspect of algorithms – Genetic Algorithm – Particle Swarm Optimization – Ant Colony Optimization – Artificial Neural Network – Fuzzy Logic – Learning-based methods Classification from the aspect of the time domain – Offline path planning – Online path planning Classification from the aspect of the space domain – Path planning in 2D environments – Path planning in 3D environments
Comparative Study of Path-Planning and Obstacle Avoidance Algorithms for UAVs [233]	2018	– Potential Field and Vector force field – Floydandndash; Warshal – Genetic Algorithm – Greedy algorithm and Multi-step Look Ahead Policy – Aandlowast algorithm – Dynamic Programming – Approximate Reinforcement Learning – Mixed Integer Linear Programming
Path and view planning for UAVs [343]	2019	– Planning for scene reconstruction – Environment exploration with obstacle avoidance – Aerial cinematography
3D Flight Path Planning for UAVs [268]	2019	Path Planning – Graph-based Algorithms – Heuristic Search Algorithms – Field-based Algorithms – Intelligent Optimization Algorithms
Energy Efficient Path Planning Algorithms for UAVs [76]	2019	– Combinatorial Path Planning – Sampling-based Path Planning – Biological-based Path Planning

TABLE 2. The list of existing surveys in the literature (continue...).

Subject	Year	Proposed taxonomy of techniques
UAVs using machine learning for autonomous flight [63]	2019	Machine Learning Applied to UAVs – Control Strategies (Parameter tuning/ Adaptive control based on neural networks/ Real-time path planning and navigation) – Object recognition (Collision avoidance/ Object recognition on task)
UAV motion planning [228]	2020	Path Finding – Sampling-based methods – Searching-based methods Trajectory Optimization – Hard-constrained methods – Soft-constrained planning
Path planning techniques for unmanned aerial vehicles: A review, solutions, and challenges [4]	2020	Representation techniques – Sampling-based techniques – Probabilistic roadmaps – Rapid-exploring random trees – Voronoi diagram – A^* algorithm – Artificial intelligence techniques Cooperative techniques – Mathematical models – Bio-inspired models – Machine learning models – Multi-objective optimization models Non-cooperative techniques Coverage and connectivity Security in UAVs path planning
Addressing disasters in smart cities through UAVs path planning and 5G communications: A systematic review [224]	2021	Classifying path planning methods into: – Conventional Methods – Learning-based Algorithms – Cell-based Algorithms – Model-based Techniques
A review of artificial intelligence applied to path planning in UAV swarms [223]	2022	AI algorithms in UAV swarms for Path Planning problems – Reinforcement Learning – Evolutive Computing – Swarm Intelligence – Graph Neural Networks
UAV Path Planning Using Optimization Approaches: A Survey [8]	2022	An overview of UAV path planning approaches – Classical methods – Heuristic – Metaheuristics – Machine Learning – Hybrid Methods
Path-Planning for Unmanned Aerial Vehicles with Environment Complexity Considerations: A Survey [141]	2023	Classification of UAV path planning approaches – Sampling-based Methods – Node-based methods – mathematical modeling – Bio-inspired techniques – reinforcement Learning-based methods – Multi-fusion Methods
Path planning optimization in unmanned aerial vehicles using meta-heuristic algorithms: a systematic review [310]	2023	Classifying metaheuristics into: – Evolutionary Algorithms – Physic-based Algorithms – Swarm-based Algorithms – Hybrid Metaheuristics

planning (offline/online), the dimensionality of the problem, and different criteria for evaluation. In addition, we had a thorough overview of the available simulators for the UAV path planning problem.

In this survey paper, we conducted a systematic literature review following a well-defined process to identify the most relevant articles within the scope of this research, aligning with recent studies in the field. Initially, a selection of widely used search engines such as Google Scholar, Web of Science, Scopus, and IEEE Xplore was narrowed down to gather literature from reputable online resources. Semantic searches utilizing pertinent keywords and phrases were employed to retrieve articles closely related to the research questions outlined in this study. Subsequently, a meticulous screening process was undertaken to filter the retrieved articles, refining the number of publications and shortlisting those that exhibited the highest quality match with the present research. To further enhance the search results, a set of assessment criteria was introduced. The assessment involved a manual evaluation of each article's abstract to ascertain its relevance to the subject matter. Articles lacking relevant keywords in their abstracts or written content were excluded, while those deemed pertinent were thoroughly analyzed to assess their suitability for this study. Only papers that perfectly aligned with the review's scope were ultimately retained, culminating in a comprehensive evaluation of the latest trends and state-of-the-art approaches in UAV path planning studies. The gathered studies encompass a wide range of sources, including SpringerLink, ScienceDirect, IEEE digital library, ACM, Google Scholar, Taylor & Francis, Wiley, and arXiv. Additionally, the review examined previous literature, surveys, and cross-references to identify other works that demonstrated promising solutions to the path planning problem.

The remainder of this paper is organized as follows. Section 2 starts by briefly explaining the historical background of UAVs, classification, and different applications. In Section 3, a general review of the UAV path planning problem is presented by elaborating on the definition, different types of path planning, description of the problem space as well as the optimality and completeness criteria. Section 4 explains existing UAV path planning approaches with details by providing diagrams and pseudo-codes while mentioning the research example for each method. Section 5 discusses the time complexity of UAV path planning algorithms. In Section 6, the available resources including the datasets and developed simulators are introduced. In Section 7 the advantages and drawbacks of each path planning category are discussed. Section 8 outlines the unresolved issues in autonomous UAVs as potential avenues for future research. The conclusion of this study is presented in Section 9.

2. Background, classification, and application of UAVs

2.1. A short history of UAVs

In the early 1990s, the term UAV came into general use to describe robotic aircraft. From then until now, multiple terms are currently in service based on UAVs application. The U.S. Federal Aviation Administration defines any unmanned flying craft as a UAV regardless of size [202, 293]. The most common terms are "Unmanned Aerial Vehicle", "Unmanned Air Vehicle", "Unmanned Aircraft Vehicle", "Unmanned Aerospace Vehicle", "Uninhabited Aircraft Vehicle", "Unmanned Autonomous Vehicle", and "Upper Atmosphere Vehicle". The first unmanned flight was done in 1780 by the Montgolfier brothers in France. In 1840, the first military use of unmanned balloons equipped with bombs took place in Austria during an attack on Venice. The 90-second flight of steam-powered UAVs along the Potomac River near Washington, D.C. in 1896 was a milestone in the application of camera-equipped UAVs in surveillance. The Kettering Bug first flew in 1918 and the Queen Bee developed in the 1930s are among the first generations of radio-controlled unmanned aircraft applied in military operations. Advanced military reconnaissance and surveillance operations have led to the development of modern remote-controlled UAVs during 1980–2000. Since 2003, commercial UAVs gain popularity in search and rescue operations as well as delivery, film-making, construction, and real estate industries. The Amazon Prime Air project was a new milestone in commercial drones. Despite the launch of the Amazon Prime Air project in 2013, the formidable challenges, including the construction of secure delivery infrastructure and managing numerous drones operating simultaneously over vast urban areas, hindered the complete realization of this revolutionary initiative. Nevertheless, recent advancements in sense-and-avoid technologies, utilized to detect stationary and moving impediments, have encouraged Amazon to inaugurate its groundbreaking UAV-driven

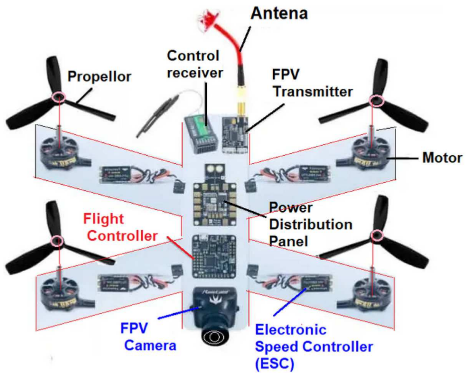

FIGURE 1. Major components of a UAV.

delivery network in Lockeford, California, starting from late 2022 [17]. The advent of novel technologies in UAVs has facilitated their utilization in a myriad of real-life civil operations, thereby expanding the horizon of possibilities in this domain. These include applications in agriculture, where UAVs equipped with multispectral cameras are used to survey and monitor crops [234, 296]. In search and rescue operations, UAVs can quickly and safely access difficult-to-reach areas, as applied in 2013, during the California Rim fire [66]. Additionally, UAVs can be used in disaster response [237] and even in the democratic process, as demonstrated in the case of Ghana's 2020 elections, where UAVs were used to distribute masks to polling stations [345]. Libya, Nagorno-Karabakh, Syria, and Ukraine wars indicate that the applications of UAVs are not limited to civil operations. The use of UAVs in military operations has drastically changed the way that modern warfare is conducted, attacking enemy targets or providing valuable intelligence and reconnaissance capabilities without putting human lives at risk. The evolution of UAVs can be traced through [79, 189, 202, 252].

2.2. Different types and key elements of UAVs

UAVs exhibit diverse shapes and configurations tailored to their specific purposes. Depending on the flight missions, the type and size of the installed equipment of the UAVs are different. In this study, we consider four types of UAVs. The first model is "*Multi-Rotor*" drones that have multiple propellers for flight. They are the most common UAV types generally utilized for video surveillance and photography applications. The multi-rotor drones are also categorized into six classes based on the number of propellers. These categories include "Bicopter" with two propellers, "Tricopter" with three propellers, "Quadcopter" with four propellers, "Pentacopter" with five propellers, "Hexacopter" with six propellers, and "Octocopter" with eight propellers. The second type is "*Fixed-Wing*" drones with wings instead of propellers, like airplanes. "*Single-Rotor*" drones are the third type of UAVs fitted with a singular rotor and a compact tail for directional adjustments. *Single-Rotor* drones exhibit a resemblance that aligns more closely with helicopters and in comparison with Fixed-Wing drones, they are very energy efficient. The last type is "*Fixed-Wing Hybrid VTOL*" drones. Here, VTOL represents Vertical Take-Off and Landing. These UAVs use propeller(s) to takeoff and wings for gliding [206, 293].

Here, we will explain the main components of the most popular structure of a "Quadcopter" model (see Fig. 1)[1]:

– Propellers: propellers, or wings depending on the availability, are the first element of a Quadcopter to provide direction and thrust. Propellers are classified into standard and pusher categories. Standard propellers are located on the front side of the Quadcopter to direct the drone, while pusher propellers are on the backside to offer thrust in both forward and backward directions.

[1] https://cfdflowengineering.com/working-principle-and-components-of-drone/.

– Flight Controller: the flight controller acts as the brain of Quadcopters. It possesses the capability to regulate the power supply to both the electronic speed controller and motors, while also detecting orientation changes.
– Electronic Speed Controller: the electronic speed controller regulates the speed of the motor. It can provide dynamic braking and reversing options.
– Motors: DC motors are utilized to maintain the Quadcopter airborne for the required duration. A quadcopter entails high torque motors that help to change the speed of the propellers.
– FPV Transmitter: the transmitter sends signals from the controller to generate commands of direction and thrust.
– Control Receiver: the control receiver captures signals from the transmitter and forwards them to the flight controller. Besides, the Quadcopter features a GPS module delivering navigation data such as longitude, latitude, and elevation to the controller. This module aids the controller in identifying previously traversed routes and ensures a safe return to the starting point in the event of a lost connection.
– Antenna: the antenna is a critical component of the UAV's communication system, allowing it to send and receive signals to and from ground stations or other aircraft. It is responsible for transmitting data such as telemetry, commands, and video. The performance of the antenna is essential for maintaining a reliable and stable connection between the UAV and the operator.
– Battery: the next component is a rechargeable battery that provides the power for the UAV.
– Power Distribution Panel (PDP): PDP is responsible for taking the input power from the battery and distributing it to various UAV components such as the flight controller, motors, and other electrical systems. It also provides protection against overcurrent and short circuits, ensuring the safe operation of the UAV.
– Camera: the Camera is generally used for monitoring the environment. It can be inbuilt or detachable.
– Landing Gear: the Landing Gear is used for big drones to avert any potential damage upon landing. The requirements of landing gear vary in terms of the drone's functionality. For instance, delivery drones carrying parcels need expansive landing gear to provide sufficient space for holding items.
– Chassis: the chassis serves as the primary structure of the Quadcopter, accommodating all other constituents.

When the UAV initiates the take-off command through the controller, it communicates with the receiver, which then transfers the command to the flight controller board. This board, in turn, activates the propellers, resulting in the generation of lift-off thrust that allows the UAV to become airborne. The propellers serve a dual function of providing both direction and speed to the UAV. To enhance reliability, UAVs employ a sophisticated multi-propeller system, enabling them to mitigate failures. The propellers operate collectively, so even if one propeller malfunctions, the drone can rely on the remaining propellers to ensure stability, navigate, and land safely. Furthermore, the GPS module plays a vital role by assisting the drone in identifying its flight path and obtaining real-time data such as location, speed, and altitude.

2.3. Classification of UAVs

Generally, UAVs vary in their configurations based on the platform and the type of mission. Several UAV classifications are presented in the literature based on different distinguishing parameters. Hassanalian *et al.* [121] presented a general UAV classification in terms of the performance characteristics such as range, maximum altitude, aircraft weight, wingspan, wing loading, speed, endurance, cost design, and size. These are the main design parameters that distinguish different types of UAVs and provide beneficial classification systems. Based on the engine type, they classified UAVs into fuel engines and electric motors. UAVs are also categorized based on their weight, with classifications including Micro, Light, Medium, Heavy, and Super Heavy classes, spanning a range from under 5 kilograms to over 2 metric tons. Based on the flight range, UAVs can be classified into close, short, medium, and large endurance categories, spanning a range from under 10 to 1500 kilometers. According to Hassanalian *et al.* [121], UAVs are categorized into VTOL (Vertical Takeoff and Landing), HTOL (Horizontal Takeoff and Landing), and Hybrid classes based on their landing and takeoff capabilities. VTOL UAVs are able to take off and land vertically, without requiring a runway or other external support. HTOL UAVs, on the other hand, require a runway or other external support to take off and land. They typically have longer flight ranges and can carry larger payloads than VTOL UAVs, but are less maneuverable and more limited in their operational capabilities. Hybrid drones, including tilt-rotor, tilt-wing, tilt-body, and ducted fan UAVs combine the capability of both VTOL and HTOL types. Tilt-rotor UAVs undergo a transition from vertical to cruise flight by tilting the rotors forward for 90°. In tilt-wing UAVs, the entire wing is adjusted from a 0° angle to 90°, enabling a shift in flight modes from horizontal to vertical. Free-wing tilt-body UAVs possess a fuselage that serves as a lifting body and a wing that can pivot freely in the pitch axis. The central lifting body and the left/right wing pair are both free to rotate about the spanwise shaft, independently of the relative wind and of one another. Ducted fan UAVs refer to a type wherein the propulsive system, also known as the "fan", is enclosed within a duct. This design allows for efficient and effective airflow management, contributing to the UAV's overall performance. In some cases, UAVs are grouped according to their functionality such as target and decoy for providing ground and aerial gunnery targets; reconnaissance for providing battlefield intelligence; combat for providing attack capability in high-risk missions; research and development for improving UAVs technologies; and civil and commercial UAVs that are used in agriculture, aerial photography, logistics, and data collection [102, 249]. In the taxonomy of UAVs based on their practical applications, it is crucial to acknowledge that diverse UAV classes may be utilized to address a particular application. Such a nuanced understanding of UAV classification ensures that the most suitable and effective platform is selected for the desired operation. It is worth mentioning that an overview of different kinds of UAVs categorized based on size, endurance, range, configuration, wing loading, and engine type is provided with a detailed description in [19, 185, 267, 294].

2.4. Application of UAVs

UAVs were initially developed for military operations, and have been utilized in various conflicts, including Libya, Nagorno-Karabakh, Syria, and Ukraine [42]. However, the multifarious capabilities of these unmanned aerial platforms soon became evident, extending far beyond military applications. For instance, NASA's well-known X-37B drone was used in several space search missions [108]. As technology evolved, UAVs became increasingly accessible, and their potential in civil applications began to emerge. Advances in camera and sensor technology, improvements in battery life and flight control systems, and developments in artificial intelligence and machine learning algorithms opened up new possibilities for UAVs to be used in a variety of practical applications. One application of UAVs is in the delivery industry which is a prominent industry experiencing significant growth at present. The concept of delivery drones entered the mainstream with Amazon Prime Air [191]. In 2019, Google Wing, the drone company owned by Google's parent company Alphabet, achieved two milestones: launching the first public delivery by drone service in the suburbs of Canberra and becoming the first company to receive Federal Aviation Administration (FAA) approval for drone delivery to customers in Virginia, United States [243]. UAVs are also used in the agriculture sector to spray water and pesticides or to do mapping or video surveillance in expansive landscapes. To provide an illustration, back in October 2017, a team of Chinese researchers employed cutting-edge UAV RGB imagery technology to create a highly precise weed cover map of the rice fields located in the southern reaches of China [129]. The UAVS' maneuverability in hard-to-access locations makes them a useful means for search and rescue operations. This was exemplified on a dark and rainy night on November 2021 near Leicestershire, United Kingdom, when a thermal UAV located a missing woman within seconds of takeoff, swiftly leading to her safe rescue [153]. Several successful case studies of the application of UAVs in humanitarian operations including search and rescue, relief distribution, and damage assessment are collected in [96]. UAVs can also be used in construction, as Southwestern Florida Cougar Companies apply LiDAR surveying equipment to provide more detailed topographic surveys [195]. The other usage of UAVs is for internet service providers. Facebook Aquila and Google Loon were among the first projects working on the concept of some huge UAVs capable of sending signals to remote destinations, enabling direct access to the internet [4, 121]. Loon announced it is shutting down, citing the lack of a "long-term, sustainable business" [16]. The Aquila project was also halted due to technical challenges and changing priorities [22]. Although Aquila and Loon projects have come to an end, Airbus continues to develop its solar-powered aircraft, Zephyr, which aims to provide internet connectivity to remote areas for extended periods of time [7]. Generally, UAVs are equipped with various sensors and cameras for surveillance and reconnaissance missions in both outdoor and indoor environments. In this regard, the applications of UAVs can be categorized based on the type of missions (military/civil) and the type of flight zones (outdoor/indoor) in airspace environments.

3. UAV path planning problem

Optimizing UAV-based operations from different perspectives is thoroughly studied in the literature. The optimization problems in this area could be classified as vehicle routing problems to determine the flying routes, path planning problems to determine the optimal path to reach the destination, and location problems for finding launching and/or refueling stations.

3.1. Problem definition and different types of path planning

Nowadays, with the proliferation of applications of UAVs, autonomous navigation is more significant, of which the key component is path planning. UAV path planning, referred to as motion planning, is a branch of classical path-finding that has been extensively researched in the field of robotics [299]. However, two domain-specific challenges are covered by UAV path planners that may not be encountered in the robotics domain. First, UAVs work in a 3D space as they can change their altitude level during the flight. In contrast, motion planning for robots is usually considered in a two-dimensional (2D) space [113, 116, 137, 247]. This heightened degree of freedom greatly expands the range of possible missions. Secondly, a UAV (*e.g.*, fixed-wing UAV) lacks the capability to hover and must maintain a consistently high cruising speed. This imposes more intricate constraints on the path planning problem. In contrast, motion planning for robots remains unaffected by this demand, as robots can decelerate and come to a complete stop as needed. In an abstract term, the UAV path planning problem can be considered as an optimization problem aimed at generating a safe space path between an initial location and the desired destination under specific constraint conditions to carry out a specific task [116]. Along its trajectory, the UAV can navigate through certain regions while actively avoiding areas that might contain obstacles, radars, prohibited zones, and so on.

As an application aspect of the UAV path planning problem, one can refer to the following groups of path planning problems. The first group is *informative* path planning (IPP) problem which plans paths for the robots to maximize the utility of data collection [193, 219]. In fact, paths need to be planned such that the information gathered about an unknown environment while satisfying the given budget constraint is maximized. As the second group, *Coverage* path planning (CPP) problem is to determine a path that passes through all points of an area or volume of interest while avoiding obstacles [140, 197, 295]. *Cooperative* path planning constitutes the third category, involving the utilization of path planning algorithms to generate a coordinated mission [11, 301]. An example of such a mission involves a cluster of UAVs departing from a base and synchronously arriving at a designated rendezvous point. These UAVs have the capability to execute tasks during their journey, such as conducting area searches and detecting objects along their route. In the literature, it is also addressed the *reactive* path planning. In fact, path planning methods need to be reactive and adaptive regarding life situations, traffic, and obstacle crossing. It is similar to saying we have an online path planning [124, 181].

Generally, UAVs can fly in known, unknown, or partially known environments. Hence, the literature has delved into a range of perspectives on issues in UAV path planning problems, categorizing them into offline/global, online/local, and cooperative path planning challenges [262, 290, 319, 340]. In offline path planning, the path will be scheduled prior to the commencement of the flight, relying on either a pre-existing environmental map or the current and historical perceptual data within the search space. This approach is frequently inadequate for prompt responses, particularly in urban settings where the primary challenge lies in dealing with unidentified moving obstacles – an issue prevalent in real-world applications. In online path planning, elements in the environment (*e.g.*, obstacles or adversaries) are moving, and there is generally a significant level of uncertainty about the environment. Hence, online path planning strategies explore unknown regions using laser range finders, onboard cameras, or sensors to reach a high-resolution intermediate route limited to a segment of the overall path. Based on the reviewed literature, it can be deducted that although online path planners prove effective in unseen environments, they still exhibit inefficiency when dealing with distant targets or highly clustered spaces. As a solution, a combined approach is proposed, wherein offline path planners are utilized to establish a global path towards a specific destination, whilst online path planners guarantee the tracking of the global path by accounting for moving obstacles [204, 290]. If a mission is too complex to be accomplished by a single UAV, a team of UAVs is employed, and thereby cooperative path planning is studied [315].

For path planning, the dimension of the environment is another perspective that could raise a new classification as follows: (a) two-dimensional (longitude and latitude), (b) three-dimensional (longitude, latitude, and altitude), (c) four-dimensional (three spatial dimensions and the planning time) [65], and (d) five-dimensional (three spatial dimensions, the path planning time, and time horizon) [199].

3.2. Description of problem space

Modeling the environment and obstacles are the key elements of the UAV path planning problem. There are several terminologies to describe the problem space [75, 131, 170, 211] that could be briefly mentioned as follows. The UAV, as an aerial robot, flies in a 3D world space. The world space can be represented based on (i) "Voronoi diagram" and "Visibility graph" as the earliest and well-known variants of the roadmap method in which the free space is retracted, reduced to, or mapped onto a network of one-dimensional lines [169, 187] (see Figs. 2a and 4); (ii) cell decomposition that decomposes the free space into smaller convex polygons or regions called cells, which are then connected by a graph to depicts the adjacency associations between cells [20, 158] (Fig. 5); (iii) potential field which is based on the idea of assigning a potential function to the free space to simulate the UAV as a particle reacting to attractive and repulsive forces [154] (Fig. 2d)[2]; (iv) the occupancy grid map which is composed of equal-size cells, where each cell is represented by a unique index and can be free or occupied [74, 88] (Fig. 2e); (v) and finally 3D map representation techniques (*e.g.*, point clouds [101], voxel grids [292], surface maps [342]). These representation methods should be selected properly to handle complex and cluttered spaces, such as bridges, buildings (convex, and/or concave), etc. [316]. The world space often contains obstacles space comprising static or dynamic obstacles. The way used to model obstacles will affect the search algorithms and the determined route. Hence, the reasonable modeling approach can streamline the intricacies of the problem, especially for urban environments where the spaces are not always flat and include buildings, mountains, other vehicles, radar areas, and so on. Therefore, the obstacles can be supposed to be any geometrical figures in the form of cubes, floating balls, and other simple models [320]. In order to model a real environment, the parameterization of the obstacle set defined by the geometric centers of the physical obstacles will be a key factor. In fact, in the real environment, obtaining the accurate coordinates of the geometric centers of obstacles is typically challenging to estimate. In UAV path planning, obstacle modeling necessitates the inclusion of additional buffer space to mitigate the impact of measuring errors during the planning process.

The UAV in the world space can be defined by a vector of twelve variables including three position coordinates (3D), three velocity coordinates, three orientation angles (roll, yaw, and pitch), and three orientation rate angles [52, 113]. This vector is called the UAV configuration space. In the majority of studies, a vector of three position coordinates and three orientation coordinates is used to represent the UAVs' configuration space. The estimation of these attitudes as well as the representation of orientation is required to have a safe autonomous flight. The minimum set of points or variables needed to represent a configuration is called the Degrees of Freedom that is equivalent to the dimension of the UAV's configuration [52, 113]. Here, an example of the coordinate system and the free body diagram of a quadcopter are illustrated in Figure 2f. It is obvious that developing an algorithm that provides an exact analytic solution to such a problem is very difficult, if not say impossible. The path can be either obtained as discrete line segments or a continuous curve (*e.g.*, Splines or Bézier curve [127, 133]) using a sequence of waypoints connecting the start position to the destination in the free world space. If the path is parameterized by time, then we will have trajectory planning instead of path planning that only gives the positional information [233].

[2]Robert Platt, Classical Path Planning (http://www.ccs.neu.edu/home/rplatt/cs5335_spring2019/slides/path_planning_classical.pdf).

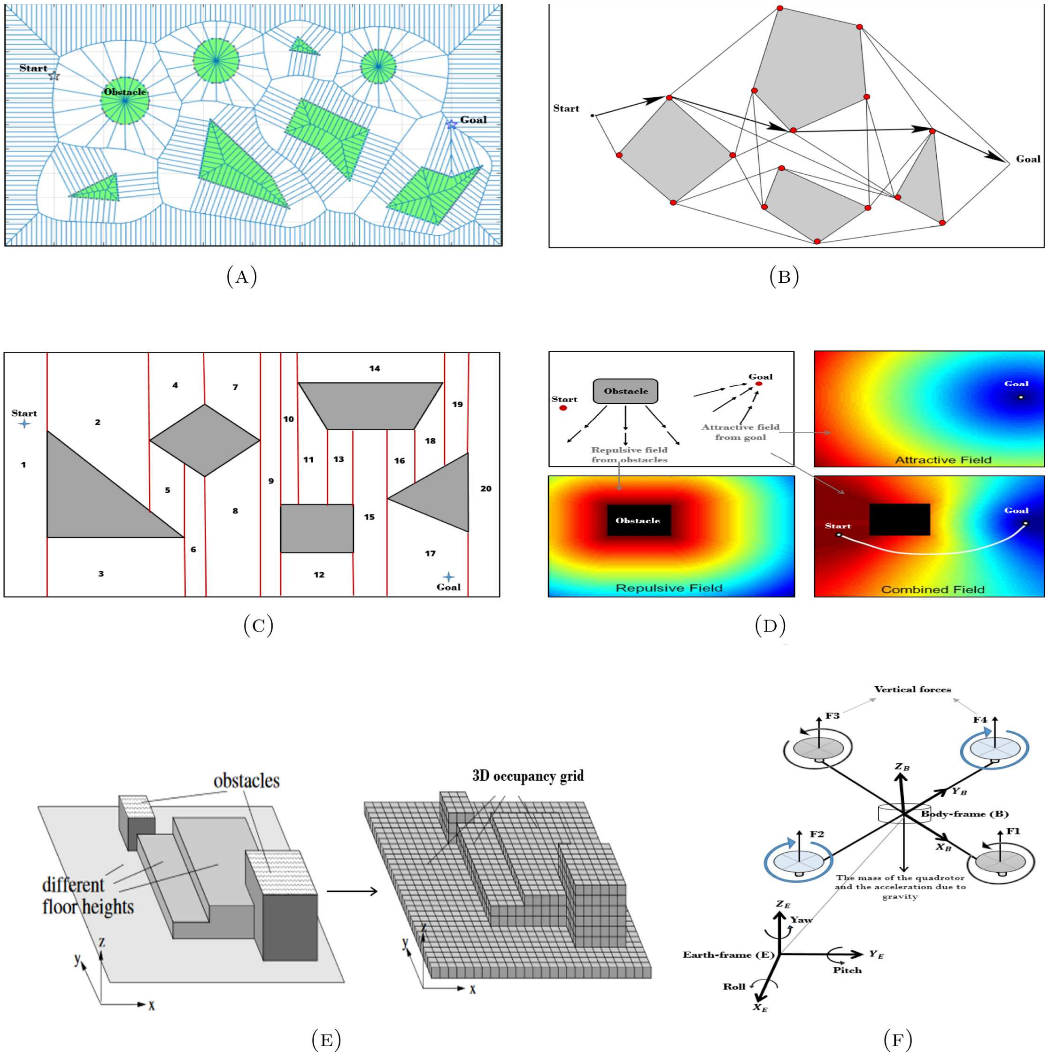

FIGURE 2. Modeling the environment. (a) An example of Voronoi diagram-based partitioning of an obstacle map [184]. (b) An example of visibility graph for path planning [39]. (c) An example of cell decomposition. (d) An example of potential field. (e) An example of occupancy grid map [119]. (f) An example of the coordinate systems and the quadrotor frame.

3.3. The completeness criterion

Completeness, an essential criterion for evaluating the performance of path planning algorithms [167], holds significant importance in UAV path planning techniques. It ensures the discovery of a path, if one exists, by providing a framework for UAVs and delivering a solution when the path planning technique can search for an optimal path [4]. The completeness criterion guarantees that the algorithm will always find a solution, regardless of the specific configuration of the environment [141]. There are two forms of completeness: probabilistic completeness and resolution completeness [328]. Probabilistic completeness implies that as time and computation resources approach infinity, the algorithm will find a solution with a probability of one [177]. In other words, given infinite time and resources, the algorithm will always find a feasible path if one exists. Probabilistic completeness is exhibited by sample-based methods such as RRT and evolutionary algorithms [328]. Resolution completeness, on the other hand, guarantees to find an existing solution within a finite time, provided that the resolution of the underlying discretization is fine enough [59]. Most resolution complete planners are graph search methods like Dijkstra, A*, and Field D* [328]. These completeness criteria play a crucial role in evaluating the effectiveness and reliability of UAV path planning algorithms.

3.4. The optimality criteria

UAV path planning problem is typically characterized by differential constraints such as limited speed and maximum acceleration, uncertainty in the world space, atmospheric violence, etc. Generally, the path length [106], the path smoothness [305], the optimality in time and cost as well as energy consumption [81, 118, 287], robustness to tolerate the position sensing device errors and the rotation driving errors, as well as linear driving errors [58], along with the collision avoidance with obstacles [245], are the principal factors in UAV path planning problems. These factors can be considered either in the form of objective functions that require to be minimized and/or maximized or in the form of constraints that a route must comply with. The UAV path planning problem is studied both in single objective [15, 56, 245, 320] and multi-objective [122, 325] contexts. As an example, Shao *et al.* [257] considered a combination of minimal flying path length, the safe flying cost around the mountain, the radar detection cost, and the collision cost among flying UAVs in a single objective model. In another study, the UAV path planning problem is modeled as the weighted sum of three optimization criteria comprising the minimization of path length, threat probability, and the flight safety altitude [338]. In a handful of multi-objective studies, Mittal and Deb [196] employed NSGA-II in conjunction with K-means clustering to simultaneously minimize the total path length and maximize the safety margin from ground obstacles. Ren *et al.* [238] introduced a crowding-distance-based NSGA-II to address a multi-objective UAV path planning challenge in urban settings, incorporating distance and safety objectives, and utilizing the octrees data structure. Golabi *et al.* [114] presented a novel multi-objective integer programming model for a collision-free discrete drone path planning problem. These constraints and objectives entail finding a path planning algorithm that has less computational time and cost. In another research, Yu *et al.* [325] considered the UAV path planning as a constrained multi-objective optimization problem considering the path length and path risk as the objectives, and the flight altitude and the turning angle as the constraints. Computational aspects including time complexity and memory requirements are among the criteria for judging whether a UAV path planning algorithm is efficient.

4. A review of existing UAV path planning methods

So far, various methods have been raised to deal with the UAV path planning problem regarding the different tasks, requirements, and environments [113, 314]. This study classifies the existing approaches into classical or exact methods, soft-computing techniques, and hybrid (multi-fusion) approaches. Each category contains a variety of methods that conform to certain characteristics. The following subsections scrutinize each category based on the related studies in the literature.

4.1. Classical methods

The most commonly used classical methods for solving the UAV path planning problem include various techniques for representing the environment space, such as roadmap and cell decomposition, as well as different search algorithms, including A* and Dijkstra, potential field methods, mathematical programming, and sampling-based approaches [208]. It is worth noting that the choice of environment representation method and search algorithm can significantly affect the efficiency and effectiveness of the path planning process. For example, roadmap and cell decomposition are two popular strategies for environment representation that require a search algorithm for path generation or planning [141]. A notable advantage of classical methods lies in their simplicity, leading to shorter computational times. They exhibit a deterministic characteristic in identifying the optimal collision-free path if it exists (*e.g.*, graph search algorithms). Nonetheless, their effectiveness is contingent upon the size of the search space, as they store all explored nodes in memory, making them susceptible to failure in the presence of uncertainty when the vehicle operates [20]. They also still have difficulties with system dynamics, sensors, and so on. In the following subsections, a detailed elaboration of the aforementioned methods in the context of UAV path planning is provided.

4.1.1. Classical methods for environment representation

The following methods primarily focus on environment representation, requiring a search algorithm to find the optimal or feasible path within the constructed representation.

4.1.1.1. Roadmap. The roadmap method is among the earliest motion planning techniques [169]. To construct the roadmap, the free space is retracted, reduced to, or mapped onto a network of one-dimensional line segments. Then, a search mechanism based on an artificial intelligence approach is used to find a solution that is limited to the network. The roadmap method has been proven to be effective in simple polygonal environments [187] where the obstacles are static. The earliest and well-known variants of roadmap methods are "Voronoi diagram" [23,190,304] and "Visibility graph" that have been used for both single [6,250] and multiple UAVs path planning [190]. However, the authors of Beard *et al.* [23] and Wang *et al.* [298] introduced solution methods that employ the Voronoi diagram and visibility graph, respectively, particularly in scenarios involving dynamic threats.

4.1.1.2. Cell decomposition. The cell decomposition technique decomposes the obstacle-free space into non-overlapping convex polygons, known as cells [20, 111, 176]. After decomposition, a connectivity graph is constructed according to the adjacency relationships between the cells (*i.e.*, nodes), and their connecting links. From this connectivity graph, a continuous path can be determined by simply following adjacent free cells from the start to the target point. Cell decomposition methods can be classified as exact [168] (that a graph associated with the approximate cell decomposition is a tree that can be a quadtree for 2D spaces and an octree for 3D spaces [103]), regular grid [36], and adaptive [54]. If a feasible path exists in the free space, then the cell decomposition method will find the path easily by sequentially organizing the cells. Nevertheless, the cell decomposition method depends on the format of the cells and if the formed cell is too large or rough then it will not attain the smallest path distance or length in a reasonable time [158]. The cell decomposition method could not provide acceptable performance in dynamic and real-time circumstances [77]. As an example of applying this technique for UAVs, Li *et al.* [176] suggested an exact cellular decomposition method for the coverage path planning with UAVs. Authors of [135] presented a combination of cell decomposition and fuzzy logic for quadrotor path planning to avoid collisions with dynamic obstacles.

4.1.2. Classical search-based methods

This section focuses on classical UAV path planning methods searching the solution space to identify the shortest or near-optimal paths. These algorithms systematically explore different paths and evaluate their suitability based on defined criteria.

4.1.2.1. Mathematical programming. The mathematical programming method employs probability and mathematical models to predict future events and to determine the most efficient curve between the start and goal configurations by minimizing a certain scalar quantity. In this approach, a set of inequalities is used to model the obstacles and environment, and the path planning problem is solved as a mathematical optimization problem. An earlier and comprehensive review of mathematical programming methods can be found in [2,32]. Some popular mathematical programming methods used in UAV path planning problems are linear programming [55] and mixed-integer linear programming [80, 157, 164, 251] models. Dynamic programming is another mathematical programming approach that is adopted for obtaining an optimal path when full information and unlimited computation resources are available [92, 109, 139, 233]. These methods often fail to achieve global optimality within a reasonable time frame and are occasionally ineffective in generating feasible solutions. However, these methods can provide valuable insights into the problem's structure [98].

4.1.2.2. Graph search methods. A graph can be briefly introduced as a non-linear data structure consisting of nodes and edges. The nodes are vertices and edges are arcs or lines that attach any two other nodes in the graph. These algorithms carve paths through the graph, but there is no expectation that those paths are computationally optimal [200]. The Dijkstra's algorithm and the A* algorithm are the most commonly used graph search algorithms in the community to successfully apply in finding the shortest path for UAVs [27,62,165,192,260]. The well-known Breadth-first and Depth-first search algorithms also fall within this category [76]. You can find a brief summary of the mentioned algorithms in the subsequent content, where their key aspects and functionalities are explained.

Dijkstra's algorithm. Dijkstra's algorithm was first introduced by Edsger W. Dijkstra in 1956 [82, 94]. As a classical method derived from dynamic programming, Dijkstra embodies an iterative approximation approach to solve dynamic programming equations within the context of the shortest path problem. Based on the distance from the origin, the algorithm uses a single heuristic to create labels associated with vertices. The labels represent the cost from the source vertex to that particular vertex [142]. This algorithm determines the costs between a given vertex and all other vertices in a graph to determine alternatives in decision-making [266]. Dijkstra's algorithm is known to be computationally intensive based on nodal density [207].

A* algorithm. The A* algorithm is an informed search algorithm introduced by Hart *et al.* [120] as a generalization of Dijkstra's algorithm. This algorithm is widely applied in graph traversal and robot path planning problems. It is a best-first search heuristic that can potentially search a wide area of a grid map to determine the least-cost path from a given initial node to the final one [57]. Best-first search is categorized as a heuristic search algorithm that utilizes the distance between the current node and the target point to discover a path within a graph [76]. The greedy best-first search results in a feasible path instead of the optimal one [198]. The best-first search algorithm employs a greedy approach to expand nodes in close proximity to the target node, resulting in improved efficiency. However, in scenarios with increased obstacles, the quality of the planned path may not match that of the Dijkstra algorithm. Consequently, the A* algorithm can be considered an amalgamation of the advantageous aspects of both the Dijkstra and best-first search algorithms [335].

During the years, several modified versions of A* algorithm such as D* [271], D*-Lite [159], field D* [91], fringe saving A* (FSA*) [276], and generalized adaptive A* (GAA*) [278] are developed for UAV path planning problem.

According to the above explanations, the Dijkstra's and A* algorithms keep a set of nodes in a memory to determine the potential shortest path. The main difference between these two algorithms is the order in which these nodes are explored. A* focuses on reaching the target node from the current node, while Dijkstra tries to visit every node to catch the goal. Therefore, in practice, the A* algorithm is often more suitable because of using less memory when the search space is large, and a decent lower bound on the remaining distance exists.

Depth-First Search (DFS). Depth-first search algorithms traverse a tree by exploring one node and its descendants[3] at a time. The algorithm initiates from a selected node and progressively expands its search to the deepest nodes, backtracking only when there are no more child elements to explore [212]. If the deepest node does not contain the desired solution, the algorithm backtracks to the start of the tree and continues the search by exploring adjacent nodes on the right, following a similar "deep" format [241, 285]. This process continues until the solution is found. DFS may miss large portions of the workspace since it tries to search several paths at a time before completing one path [110, 170]. DFS may not always yield the most optimal solution as it prioritizes the first successful path found, disregarding the time or steps taken to reach it, with the risk of falling into a loop of exploring an infinite depth [212].

Breadth-First Search (BFS). In the breadth-first search algorithm, all the current level nodes are visited prior to their descendants [212], following a systematic approach where shallow nodes are expanded first by exploring all the subsequent level nodes along the path [76]. Unlike the depth-first search algorithm that focuses on exploring a single path to its deepest depths, BFS expands its search by including all nodes within each layer, adhering to the first-in-first-out (FIFO) principle implemented through a queue structure [38]. Although BFS may be slower than DFS in finding a path, it is often considered more favorable due to its systematic

[3] A descendant refers to a node that can be reached from a particular node by traversing one step down the path.

exploration of all nodes within each layer and its ability to keep track of visited nodes before moving on to the next layer [212]. In contrast, DFS can be time-consuming as it may delve into uncharted depths of a single node without necessarily leading to a viable solution [38, 241]. Despite the potential efficiency, BFS requires more memory compared to DFS due to the need to store all visited nodes in the order they were encountered [38]. This storage step is crucial in BFS tree traversal as it influences the sequence in which the algorithm explores nodes in the subsequent layer [76].

4.1.2.3. Potential field. Inspired by the concept of electrical charges, the potential field was first introduced by Khatib [154]. This method involves assigning repulsive forces to obstacles and attractive forces to the target. This allows the vehicle to navigate towards the target while simultaneously avoiding obstacles (see Algorithm 1). Sfeir *et al.* [253] presents an enhanced repulsion mechanism aimed at minimizing oscillations and preventing conflicts in scenarios where obstacles are situated near a target. This approach is extended successfully to navigate single and multiple robots to perform complex tasks. Because of its flexible and simple structure, concise mathematical description, and convenience for real-time control, it is efficiently applied to both single and multiple UAVs for both offline and online path planning problems [53, 64, 70, 125, 179, 182, 259, 281]. Despite the quick response speed of artificial potential field in real-time path planning, the potential field can be swiftly stuck in local minima in the case of extensive search spaces [90, 174, 188].

Algorithm 1: The artificial potential field algorithm [233].

Input: An open list of nodes of graph
Output: The shortest path
Start with tessellating the area
The Goal Weight ← 0
while *next position is not goal* **do**
  for *all the obstacles* **do**
    Evaluate the repelling function
  Evaluate the attracting function for the goal
  Apply the resultant forcing function to obtain next location of UAVs
  if *UAV encountered local minima* **then**
    Assume a virtual obstacle there
  Go to next position
return *The shortest path*

4.1.2.4. Sampling-based methods. Sampling-based approaches are considered as a black box returning a feasible collision-free path [87] with significant advantages of high-speed implementation [162]. These methods use only information from a collision detector while searching the configuration space to sample the environment as a set of nodes or other forms, then map the workspace or just search randomly to find an optimal path [178]. Arguably in the literature, the most popular variants of sampling-based planners are probabilistic roadmap (PRM) and rapidly exploring random tree (RRT) [217]. These two approaches have demonstrated efficacy as frameworks for navigating high-dimensional spaces to generate feasible solutions. However, it is important to note that they do not ensure the attainment of an optimal solution.

The PRM method, simultaneously developed at Stanford and Utrecht, has been proven to work well in high-dimensional search spaces [148, 149]. The basic idea behind PRM is to take random instances from the configuration space. Thereafter, it checks whether or not they are in the free space, and utilize a local planner to connect these configurations to other nearby configurations (see Algorithm 2). There are various proposals in the literature regarding the UAV path planning problem. Authors of [216, 277, 309, 311] suggested improved approaches using PRM for solving both offline and online UAV path planning problems. However, PRM tends to be inefficient when obstacle geometry is not known beforehand [147]. As an alternative, RRT algorithms that present a solution regardless of the geometry of the obstacles have been extensively explored [231].

Algorithm 2: PRM algorithm.

Input: A graph with initial and goal points
Output: Find the shortest path between the start and goal
The vertices $V \leftarrow \emptyset$
The edges $E \leftarrow \emptyset$
while *next vertex is not goal* **do**
    $c \leftarrow$ a random configuration in the free space
    $V \leftarrow V \cup c$
    $N_c \leftarrow$ a set of neighbor vertices chosen from V
    for *all* $c' \in N_c$ **do**
        if *the line* (c, c') *is collision free* **then**
            add the edge (c, c') to E
Find the shortest path from the start point to the goal on the constructed graph using a shortest path finding algorithm
return *The shortest path*

The RRT method, which was first introduced by LaValle *et al.* [171] is another computationally efficient algorithm that explores a random tree to produce the first feasible solution to the goal through a cluttered environment with non-convex obstacles (see Algorithm 3). Many works have studied the RRT algorithm and its variants in the application of UAV path planning problems and collision avoidance [5, 172, 221, 339]. For instance, Saunders *et al.* [248] presented a two-part solution technique that uses a modified RRT algorithm on a prior terrain map to create a waypoint path around known obstacles. Yang *et al.* [312] introduced a 3D path planning algorithm based on a modified RRT method by combining biased sampling and the greedy extension of nodes. In their method, the unnecessary waypoints are removed by a simple path pruning RRT method to deal with a piece-wise linear path. Aguilar *et al.* [5] presented a path planning system for autonomous navigation of UAVs in a 3D space based on two improved versions of the RRT method called RRT*Goal and RRT*Limit.

Algorithm 3: RRT algorithm.

Input: Initial configuration q_{init}, number of vertices in RRT K, incremental distance (Δq)
Output: RRT graph G
G.init (q_{init})
for $k = 1$ *to* K **do**
    $q_{\text{rand}} \leftarrow$ Random State()
    $q_{\text{near}} \leftarrow$ Nearest Vertex(q_{rand}, G)
    $q_{\text{new}} \leftarrow$ New State$(q_{\text{near}}, q_{\text{rand}}, \Delta q)$
    G.add Vertex (q_{new})
    G.add Edge $(q_{\text{near}}, q_{\text{new}})$
return *The graph G*

4.2. Soft-computing methods

Soft-computing or intelligent techniques have emerged as new optimization tools mimicking the capability of the human brain in reasoning, modeling, adapting, and responding to address real-world problems [132]. In this section, the state-of-the-art machine learning, fuzzy approaches, and metaheuristics or evolutionary algorithms that have been applied successfully for the autonomous flight of UAVs will be discussed.

4.2.1. Machine learning

Machine learning consists of supervised learning, unsupervised learning, reinforcement learning, and deep learning algorithms that learn from existing data to build and refine models to make predictions for different tasks instead of following traditional pre-programmed instructions [45, 63, 258]. In recent years, such algorithms are extensively applied to deal with different perspectives of autonomous UAV flights including tuning the parameters for the controller [138], applying adaptive control algorithms for autonomous flight [163], recognizing objects in farming [214], real-time path planning [143, 146, 180, 332], and real-time collision avoidance considering obstacles or other aerial vehicles [144, 173]. Among the machine learning techniques, the clustering methods such as QT and K-means [286, 327], reinforcement learning[4] (see Algorithm 4) and deep reinforcement learning [156, 284], cooperative and geometric learning [333], and neural network [210, 321] are widely employed for UAVs path planning problem and collision avoidance.

Algorithm 4: Reinforcement learning algorithm for UAV path planning.

Input: A state space $\mathcal{S}$, an action space $\mathcal{A}$, a reward function $R(s, a)$, a discount factor γ, an exploration rate ϵ, and a maximum number of episodes N
Output: A policy $\pi(s)$ that maps states to actions

Initialize a Q-function $Q(s, a)$ arbitrarily Initialize an empty replay buffer D
for *episode* $= 1$ *to* N **do**
  Initialize the state s_0 to the start position
  while s_t *is not the goal position* **do**
    With probability ϵ choose a random action a_t from $\mathcal{A}$, otherwise choose $a_t = \operatorname{argmax}_a Q(s_t, a)$
    Execute action a_t and observe reward r_t and next state s_{t+1}
    Store transition (s_t, a_t, r_t, s_{t+1}) in D
    Sample a mini-batch of transitions (s_i, a_i, r_i, s_{i+1}) from D
    Update the Q-function using the Bellman equation:
    $Q(s_i, a_i) \leftarrow Q(s_i, a_i) + \alpha\,(r_i + \gamma \max_a Q(s_{i+1}, a) - Q(s_i, a_i))$
    Set $s_t = s_{t+1}$
return *The learned policy* $\pi(s) = \operatorname{argmax}_a Q(s, a)$

4.2.2. Fuzzy inference system

The fuzzy approaches deal with uncertainty representing the input and output relation in the *if-then* manner and constructing a knowledge base [194]. The ability to handle unknown conditions makes the fuzzy logic system an ideal tool to address the obstacle avoidance problem for performing navigation tasks [246, 344]. However, they have rarely been applied in the UAV path planning domain owing to challenges associated with adjusting membership functions. For a better understanding of the method, an example of the structure of a fuzzy inference system for path planning is shown in Figure 3. In recent years, employing the fuzzy logic methods integrated with other UAV-based techniques has shown promising results [150, 152, 302, 334].

[4]For further information on reinforcement learning, interested readers may refer to [282]. The agent–environment interaction is illustrated in Figure 3.1 of this book.

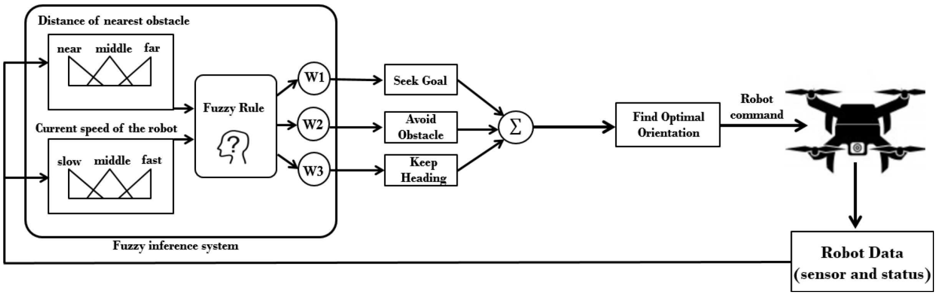

FIGURE 3. An example of Fuzzy Inference System for path planning [50].

4.2.3. Metaheuristics

Metaheuristics are widely used approaches for solving optimization problems that cannot be efficiently solved by exact methods. They are commonly nature-inspired algorithms that adopt some principles from nature (*e.g.*, physics or biology *via* evolutionary concepts). Metaheuristics utilize stochastic components and random variables and do not apply the gradient or Hessian matrix of the objective function. Besides, they have several important parameters that should be fitted to the problem at hand [35].

In the application of the UAV path planning problem, metaheuristics consider 2D or 3D map information (*e.g.*, the bounded of the environment, the position of the obstacles, the initial position of the vehicle, and the destination coordinate) as the input values. Then, an initial population of candidate solutions, which are paths, is generated randomly. Next, according to the defined objective function that is limited to some constraints, the algorithm tries to find collision-free solutions or paths that connect the initial position to the destination while satisfying the constraints. This procedure continues until meeting the termination conditions. Finally, the best path is recorded as the output of the algorithm [105]. In the following, we present the most widely used metaheuristics in the application of UAV path planning problems. Then, a list of some other metaheuristics that are also applied successfully in this special application is provided.

Simulated Annealing (SA). Simulated Annealing is a metaheuristic algorithm that can be used in UAV path planning applications to find a near-optimal solution in a large search space [61, 130, 261]. It is inspired by the annealing process in metallurgy, where a metal is heated and slowly cooled to increase its strength and stability. In simulated annealing, the algorithm starts with an initial solution and randomly perturbs it to find a new solution. The algorithm then evaluates the new solution and decides whether to accept it based on a probability function. This probability function is designed to allow the algorithm to escape from local minima and explore the search space more thoroughly. In the context of UAV path planning, simulated annealing can be used to optimize a path for a set of objectives, such as minimizing energy consumption or maximizing coverage while avoiding obstacles and maintaining a safe altitude. The literature on UAV path planning extensively showcases the widespread adoption of SA as a prominent solution method. Examples include its application in finding flight paths for UAVs to inspect multiple points of interest across a designated region [25], obtaining nearly optimal paths in 2D radar-constrained environments [291], determining the shortest feasible path between sensors for data gathering of IoT nodes in a three-dimensional setting [71], and identifying optimal energy-efficient paths for UAV transmission tower inspection [307].

Genetic Algorithm (GA). GA is a stochastic search procedure that imitates the natural selection and survival of the fittest mechanism in nature [115]. A population of solutions/paths is generated and evolved towards better solutions. Each solution is encoded as a chromosome with a set of properties. GA iteratively enhances the population by adjusting to the fitness landscape. The fitness of each solution is assessed using an objective function and the fittest solutions are selected from the current population. The new generation of solutions is evolved based on crossover and mutation operators and the proceeding procedure continues until the termination criteria are met. In literature, GA is adopted for both single and multiple UAVs with satisfactory results [73,239,263–265]. For example, Nikolos *et al.* [204] introduced a combination of modified breeder GAs by incorporating characteristics of the conventional method to design an offline/online path planner for autonomous UAV navigation. Macharet *et al.* [183] presented a feasible path planning approach for UAVs using GA and Bézier curve. Snomez *et al.* [269] proposed a GA based on a combination of traveling salesman problem approach for determining the optimal flyable trajectory for UAVs in a 3D environment. Cekmez *et al.* [48] put forward a parallel GA on Graphics Processing Unit (GPU) architecture for multiple UAVs. Similarly, Roberge *et al.* [240] presented a parallel implementation of GA on GPU cores to generate routes as a series of line segments connected by circular arcs.

Ant Colony Optimization (ACO). ACO is a swarm intelligence-based algorithm inspired by the collective behavior of ants in nature [84]. The standard algorithm is inherently parallel and straightforward to execute. It possesses considerable resilience and the capacity to explore improved solutions. In this algorithm, the walking path of ants is used to express the feasible solution for the problem. In the application of UAV path planning problems, each ant is intended to search for the shortest path in the free space. Over time, there is a continuous augmentation in the concentration of pheromones along shorter paths, accompanied by a corresponding rise in the preference of ants for those paths. This positive reinforcement mechanism eventually converges, guiding the entire ant colony toward the identification of the optimal path. As a result, the solution derived represents the optimal resolution for the given path planning problem. Here, we mention several works that applied ACO to tackle the UAV path planning problem addressing both singular and multiple UAV instances in certain and uncertain workspace [60,117,161]. Duan *et al.* [85] introduced a novel Max–Min adaptive ACO for multiple UAV path planning in dynamic and uncertain environments. Authors of [123] presented an ACO search strategy to find the optimal trajectory for a UAV path planning problem in an indoor environment. Cekmes *et al.* [47] solved the UAV path planning problem using a highly parallelized ACO algorithm based on Compute Unified Device Architecture (CUDA). In another research, Cui *et al.* [68] suggested a bidirectional searching mechanism incorporated in the ACO algorithm to deal with offline UAV path planning problems. Authors of [48] presented a UAV path planning algorithm to construct a feasible path by using a multi-colony ACO algorithm to reach an optimal or near-optimal solution.

Particle Swarm Optimization (PSO). PSO simulates the social behavior of a swarm of birds or a school of fishes [151]. In the application of UAV path planning, the problem is optimized by utilizing the shared information of the global and local solutions in the swarm. In PSO, simple agents, called particles, move in the search space and the position of a particle shows a candidate solution/path. The velocity of each particle undergoes systematic adjustments in adherence to defined rules, aimed at refining their positions within the search space. Concurrently, the collective intelligence of the best solution is captured and communicated to fellow particles in subsequent iterations. Whenever the stopping conditions are reached, the algorithm terminates and the best solution is recorded as a safe and feasible path. PSO attracted the increasing attention of scholars in the field of UAV path planning in recent years [136,257,300]. Foo *et al.* [93] proposed a 3D multi-objective path planning problem formulation and solution approach for UAVs by employing PSO algorithm to minimize the risk of enemy threats, fuel consumption, and path length. In another study, Sujit *et al.* [275] addressed the path planning problem of multiple UAVs in a cluttered environment by developing the anytime algorithm based on the PSO method. Bao *et al.* [21] proposed a modified PSO for reconnaissance UAV path planning problems. Fu *et al.* [97] introduced a new variant of the PSO algorithm based on phase angle-encoded and quantum-behaved for 3D UAV route planning in different known and static threat environments. Authors of [9] introduced a system to plan collision-free 4D trajectories of multiple UAVs based on an anytime approach and PSO. Huang *et al.* [128] proposed an improved PSO for 3D path planning of fixed-wing UAVs.

Differential Evolution (DE). DE [272] is an evolutionary algorithm commonly employed for solving path planning problems involving single UAVs as well as multiple UAVs, in both known and unknown environments. DE has good convergence properties with easy implementation. It constitutes an iterative process involving a population of individuals or paths generated through the integration of a parent and fellow individuals within the population. Similar to GA, each individual in DE possesses a set of variables representing waypoints. These variables undergo mutation and crossover search operators to generate a novel solution. During the optimization process, it only accepts candidate solutions that are superior to their parents and incorporates them into the next generation of the algorithm. DE is a fast and efficient algorithm for finding a high-quality solution to the UAV path planning problem while completing the mission robustly. For example, authors of [203] applied DE to design an offline path planner for UAVs to have coordinated navigation in known static marine environments. Zhang *et al.* [330] proposed an improved DE algorithm for online UAV path planning problems. Zhou *et al.* [341] developed a novel DE based on a chaotic approach for UAV trajectory planning problems in 3D environments. Sun *et al.* [280] presented a constrained adaptive multi-objective format of the DE algorithm to produce multiple feasible paths for a UAV path planning problem. Authors of [324] suggested an adaptive selection mutation-constrained DE algorithm for a UAV path planning problem in disaster scenarios. In another research, Yu *et al.* [325] considered a multi-objective UAV path planning problem and applied a knee point-based DE algorithm as the solution algorithm.

In the literature, there exist other metaheuristics used to solve UAV path planning problems from different aspects. Here, we listed the most popular and recent techniques. Li *et al.* [175] proposed an improved gravitational search algorithm (GSA) to generate the feasible flight route for UAVs. Zhang *et al.* [331] introduced a memetic algorithm for path planning of curvature-constrained UAVs for surveillance of multiple ground targets. Authors of [106, 323] applied teaching-learning-based optimization (TLBO) to find the shortest flight route. In another study, Chen *et al.* [56] introduced a modified central force optimization (CFO) method using the idea of the PSO's search operator and the mutation operator of the GA to address the UAV path planning problem. Radmanesh *et al.* [232] employed grey wolf optimization (GWO) to solve the UAV path planning in the presence of fixed and moving obstacles in an uncertain environment. Similarly, Yao *et al.* [318] integrated the model predictive control and an improved version of GWO for solving the cooperative target tracking by multi-UAVs in an urban environment. Alihodzic *et al.* [12] introduced a fireworks algorithm for optimization of UAV path planning problem in a 2D space. In another research, Alihodzic *et al.* [13] used the elephant herding optimization (EHO). Yongbo *et al.* [320] proposed a modified version of the wolf pack search algorithm (WPS) to compute the quasi-optimal trajectories for the UAV path planning in complex 3D spaces. Yao *et al.* [317] presented a new algorithm based on ant lion optimizer (ALO) to plan feasible UAV routes in 2D spaces. Goel *et al.* [112] utilized glow-worm swarm optimization (GSO) for online UAV path planning in a 3D environment. Zhang *et al.* [338] applied an improved version of the fruit fly optimization (FFO) algorithm to solve the problem in a 3D static environment. Authors of [226] suggested a multi-objective pigeon-inspired optimization algorithm to coordinate UAVs to fly in a stable formation and guarantee the safety of the flight in a complex workspace. Dasdemir *et al.* [72] proposed a preference-based multi-objective evolutionary algorithm (MOEA) to solve UAV route planning. For those seeking further information, we recommend referring to a recent survey conducted by Yahia and Mohammed [310]. This comprehensive survey offers an extensive overview of metaheuristic approaches applied to the UAV path planning problem.

4.3. Hybrid or multi-fusion methods

In recent years, there has been a growing trend toward hybridizing different methods in UAV path planning problems. A hybrid or multi-fusion approach refers to the combination of different techniques to obtain better results, where a single algorithm is not able to achieve the optimal solution individually [314]. A hybrid approach can combine the advantages of different methods and overcome their limitations. Choosing an adequate combination of complementary algorithmic concepts can be the key to achieving top performance in solving many hard optimization problems [33].

In the domain of UAV path planning problems, the hybridization may involve the combination of different soft-computing approaches [86, 104, 239, 313, 322]. Combining the grey wolf optimizer with modified symbiotic organisms search [227], using the knee solution to guide the search direction of the differential evolution algorithm [325], and hybridizing reinforcement learning with the grey wolf optimizer algorithm [227] are some studies hybridizing soft-computing approaches in solving UAV path planning problems. The combination of classical

TABLE 3. The time complexity of UAV path planning techniques.

Algorithm	Complexity	Explanation
Voronoi Diagram	$O(n\log(n))$ [205]	n is the number of the vertices
Visibility Graph	$O(n^2)$ [205]	
Exact Cell Decomposition	$O(n\log(n))$ [113]	n represents the number of obstacle vertices
PRM	$O(n\log(n))$ [220]	n is the number of iterations
RRT	$O(n\log(n))$ [303]	
Dijkstra	$O(\|E\|+\|V\|\log\|V\|)$ [228]	V is the set of vertices, E the set of edges
BFS & DFS	$O(\|E\|+\|V\|)$ [228]	
A^*	$O(n^2)$ [40]	n is the number of vertices

methods with each other has also been considered in several studies [83, 326]. Combining artificial potential field method and RRT-Connect algorithm [336], hybridizing D^* with probabilistic roadmaps [126], and integrating artificial potential field method with the idea of bidirectional biased sampling [306] are some sample studies of this type of hybridization. Furthermore, combining classic methods with soft-computing techniques has also been considered in the literature [3, 288]. For instance, combining RRT with the grey wolf optimizer [155], hybridizing the fuzzy logic with the cell decomposition approach [135], or combining multi-population genetic algorithm with visibility graphs [18] have been scrutinized in the literature.

5. COMPLEXITIES AND COMPUTATIONAL TIME OF PATH PLANNING ALGORITHMS

The computational time of a path planning algorithm refers to the amount of time it takes for the algorithm to generate a feasible path from a starting point to a goal location [141, 242]. The computational time of a path planning algorithm can vary depending on several factors such as the size of the search space, the complexity of the environment, and the number of obstacles to be avoided [337]. Some path planning algorithms, such as Breadth-First Search (BFS), have a high computational cost because they systematically explore all possible paths in the search space [212]. On the other hand, Depth-First Search (DFS) has a lower computational cost, but it may not always find the shortest path [212]. Other algorithms, such as A^* and Dijkstra's Algorithm, are optimized to find the shortest path but may still require significant computational resources for large search spaces [49, 244]. In addition to the algorithm itself, the computational time of a path planning algorithm can also be affected by the processing power and memory of the computer or device running the algorithm [256].

The general time complexities for certain UAV path planning problems are documented in Table 3. In this table, the time complexity of the unmentioned methods varies due to numerous factors, making it difficult to provide a general expression. Hence, it necessitates a case-by-case assessment, taking into account specific problem characteristics and constraints. Nevertheless, it is important to acknowledge that the comparison of UAV path planning methods in terms of the required computational time presents a significant challenge, primarily due to the impact of diverse factors, including the size and complexity of the environment, as well as the desired level of path accuracy. When considering factors such as computation time and path length performance, determining the most suitable algorithm for a particular task relies on the specific requirements and constraints inherent to the problem at hand. While some algorithms may be faster but may not always find the optimal path, others may take longer to compute but can generate more optimal solutions. It is worth noting that researchers and developers commonly employ techniques such as search space pruning, precomputation, data caching, and parallel processing to optimize the computational time of path planning algorithms [37].

6. Available resources

This section provides a brief overview of the existing databases and simulators that are employed for UAV path planning problems and other types of applications relevant to UAVs.

6.1. Dataset

The dataset used for the UAV path planning problem depends on the type of mission (indoor/outdoor) and application (package delivery, surveillance, agriculture, etc.). According to the literature and based on the necessities, researchers utilized 3D elevation map [104, 225, 283], TOP benchmark instances [51, 255], TSP libraries [41, 48], spatial data using Open Street Map [107] and Google Earth data [297], Sinusoidal terrain model [213], and New York City (NYC) open data [6].

The DARPA FLAIRS dataset contains airborne sensor data and ground truth annotations for multiple flights over various terrains [78]. It is used to test and evaluate path planning algorithms. The MAV Urban Localization dataset includes aerial images and LiDAR scans of urban areas, and it is used for UAV navigation, mapping, and localization [186]. The RotorS simulator dataset consists of simulated sensor data and ground truth information generated using the RotorS UAV simulator [10]. It is used to evaluate path planning algorithms in simulated environments. The AirSim dataset provides realistic simulated environments for UAVs to test and evaluate various algorithms, including path planning [254].

6.2. UAVs simulators

As discussed in Sections 3.2 and 3.3, UAVs differ in the type of application, size, shape, and aerodynamic models. Any defects in design, modeling, and UAV aerodynamic behavior endanger the success of a UAV mission whilst being so costly and challenging. Hence, to deal with such challenges, developers provided the simulators and emulators adapted to the viability standards of UAVs before finalizing them for airborne missions. Based on functionality there exist three types of simulators that are meant for the low-cost training purpose (*e.g.*, droneSim Pro [31], Zephyr Sim [222, 329]), research and development purpose (*e.g.*, HEXAGON [44], Simbeeotic [26], SUAAVE [273], JSBSim [28], AirSim [254], RotorS [99], D-MUNS [166], DIMAV [160]), and entertainment aspect (*e.g.*, FlightGear [134, 215], Heli-X [67, 89], Real Drone Simulator [236]). Some of these simulators are publicly available, while the other open-source platforms (*e.g.*, Robotic Operating System (ROS) [229, 230], Open Motion Planning Library (OMPL) [46, 274], and Virtual Robot Experimentation Platform (V-REP) [95, 201]) are accessible with limited features. Among the mentioned drone simulators, RotorS[5] [99] is used for the application of navigation in the military, farming, film-making, and fire department domains or organizations.

It is worth mentioning that autonomous UAV navigation systems have the basic elements including mapping, localization, SLAM (Simultaneous Localization and Mapping), path planning, path following, trajectory tracking, and obstacle avoidance. Accordingly, the results of three main tasks called mapping, localization, and path planning are simultaneously needed to have an autonomous navigation [270]. Before planning a path to catch the goal, knowing the environment, as well as the information about the current pose of the UAV would be required at the same time (see Fig. 4). This figure illustrates the relationship between these three tasks to perform the mission and the simulator makes this possible easily. A detailed description of accessible UAV simulators along with their models, creators, and network-support is provided in [185, 279].

7. Summary and discussions

After scrutinizing the literature, it can be said that the number of studies concerning UAV path planning from different perspectives grew dramatically in recent years. In this study, a list of the most commonly used path planning techniques for autonomous UAV navigation is provided. Since there exist various techniques in this research domain, the final decision to choose an appropriate method based on the necessities could be a

[5] http://wiki.ros.org/rotors_simulator.

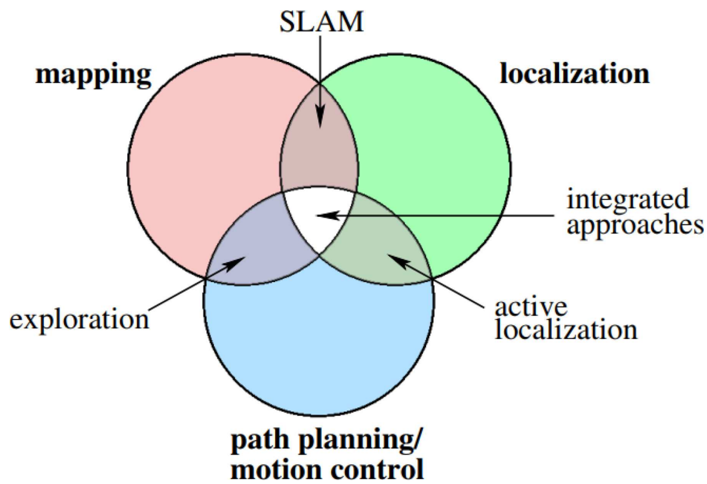

FIGURE 4. Tasks that need to be solved by an autonomous robot at the same time [270].

challenging issue. It entails an accurate and complete insight into the application of the problem, the available hypotheses, and environment modeling. Hence, researchers can deal better with the existing challenges such as the efficiency in path length, flying time, energy consumption, robustness, etc.

Due to the simplicity of the classical approaches, they were among the first techniques for dealing with UAV path planning problems. These techniques are easy to implement and are sometimes suggested for real-time path planning. However, these methods are criticized for being trapped in local minima, as well as the inefficiency in controlling uncertain situations, computational intensiveness, and the lack of accurate sensing mechanisms for real-time navigation. In addition, there is always a doubt in the adoption of the classical approach whether a feasible solution will be grabbed, or it would be supposed that such a solution does not exist. Although many studies have developed and merged new strategies with the classical approaches to improve their performance, they are not always the best choice especially in real-time conditions or in large search spaces. Generally, the classical approaches have a better navigation performance in known environments and quite often for the application of ground robotics instead of aerial robotics.

On the other hand, we had soft-computing approaches which are applied for path planning both in known and unknown environments. The ability to tackle the high level of uncertainty in the search space resulted in the wide use of these approaches, making their usage flexible in a real-time situation [1, 14, 24]. Among the recently developed techniques, machine learning approaches and metaheuristics are relatively novel and have much scope in navigation tasks. They encounter all main concerns and can find the best feasible path in a relative span of the time frame in large environments that provide better efficacy. Authors of [1] presented a comparison between classical and metaheuristics approaches applied for robot motion planning. To have a final analysis concerning the different path planning approaches that were mentioned in this paper, Figure 5 briefly summarizes some of the features of these methods.

8. FUTURE RESEARCH DIRECTIONS

The researchers studying UAV path planning problems still face different challenges (*e.g.*, highly nonlinear dynamics, unknown and moving obstacles) regarding real-time path planning that needs further investigation. Hence, many perspectives can arise from these issues. Undoubtedly, it is of great importance to consider multiple criteria as the objective functions for the UAV path planning problem; however, there are still some concerns in this domain. The question raised here is whether these criteria should be considered in a single objective

UAV Path Planning Methods				
Category	Method	Advantages	Disadvantages	Environment
Classic Methods for environment representation				
Roadmap	Visibility Graph	Time efficiency Flexibility	Just for 2D Unsafe path	Static
	Voronoi Diagram	Safe path generation Good in real-time	Path length Convergence	Static
Cell decomposition	Regular Grid	Easy implementation Path completeness	Computational complexity Limited adaptability	Static & dynmic
	Adaptive Cell Decomposition	Computational efficiency	Sensitivity to parameters	Static & dynamic
	Exact Cell Decomposition	Accuracy Flexibility	Sensitivity to obstacle representation Computational complexity	Static & dynamic
Classic shortest path searching methods				
Potential Field	Potential Field	Low time complexity Fast convergence Easy implementation	Poor performance in case of multiple obstacles	Static
Sampling based methods	RRT	Path completeness Easy implementation	Not optimal path	Simple & static
	PRM	Short path generation Path re-planning	Long processing	Complex & static
Graph search	Dijkstra	Short path generation Easy implementation	Time complexity	Complex & static
	A*	Near-optimal solutions Low time complexity Fast convergence	Memory usage	Complex & static
	BFS	Wide exploration Path completeness	Memory consumption	Static
	DFS	Early solution discovery Memory efficiency	Lack of optimality Infinite loops Weak exploration	Static & dynamic
Soft computing methods				
Machine learning	RL	UAV measurability Multi-UAV	High processing time Memory usage	Static & dynamic
	ANN	Fast convergence Multi-objective	High processing time	Static & dynamic
Fuzzy systems		Dealing with uncertainty	Computational complexity Lack of optimality Sensitivity to input data	Static & dynamic
Metaheuristics	Evolutionary	Fast convergence Near-optimal solutions Multi-objective	High time complexity High learning cost	Static
	Swarm-based	Fast convergence	Low time efficiency Local optima stagnation	Static & dynamic
	Single-solution-based	Time efficiency	Local optima stagnation	Static & dynamic

Figure 5. Analysis of path planning methods.

framework using the weighted sum approach, or objectives should be formulated and treated in the format of a multi-objective optimization problem. Besides, the impact of parameter tuning (*e.g.*, attitude control) for the controller in autonomous UAVs is another important factor. We strongly believe that using automatic configurators for attitude control may bring valuable insight to have a reliable autonomous flight in the future. Also, there is still a lack of a standard dataset for UAV path planning problems and it is required to be investigated. Furthermore, in most cases, the available computation resources are not compatible with real-time procedures and re-planning is essential. Hence, there is a need to develop and design advanced embedded hardware technologies in UAVs as well as encourage researchers to propose more efficient strategies.

9. Conclusion

In conclusion, this survey paper has provided a comprehensive review of UAV path planning techniques found in the literature. By categorizing the methods into classical approaches, soft-computing techniques, and hybrid approaches, the paper has effectively presented the technical ideas behind each method, showcased successful applications, and provided pseudo-code or diagrams to aid understanding. Additionally, the paper has offered a thorough overview of different representation strategies for modeling the environment, further enriching the knowledge base. Throughout the discussion, the advantages, disadvantages, optimality, and complexity of each path planning technique have been carefully analyzed. It is important to note that no path planning algorithm can guarantee the discovery of an optimal path in all scenarios. The optimality of an algorithm is influenced by factors such as the problem domain, environmental complexity, problem representation, and the algorithm's inherent characteristics. However, certain algorithms exhibit a higher likelihood of finding optimal paths within specific contexts. Considering practical considerations such as computational time and optimality requirements, the selection of a path planning method becomes a crucial decision. Researchers and practitioners must weigh these factors against the specifications of their problem domain. By understanding the trade-offs between different algorithms, they can make informed choices that align with their goals and constraints. Lastly, this paper has highlighted potential future research directions and provided suggestions for researchers interested in further advancing UAV path planning problems. As this field continues to evolve, exploring novel techniques, refining existing algorithms, and addressing emerging challenges will pave the way for advancements in UAV path planning. In summary, this survey paper serves as a valuable resource for understanding the landscape of UAV path planning methods. It encapsulates a wealth of knowledge, aids in decision-making processes, and provides a solid foundation for future research endeavors in this exciting and dynamic field.

Funding

This work was supported by the French *Agence Nationale de la Recherche* under the grant number ANR-16-SEBM-0004.

Conflict of Interest

The authors declared that they have no conflicts of interest to this work.

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