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Recent Developments in Path Planning for Unmanned Aerial Vehicles

Abdul Majeed and Seong Oun Hwang

Abstract

Unmanned aerial vehicles (UAVs) have demonstrated their effectiveness in performing diverse missions at significantly lower costs compared to the human beings. UAVs have the capabilities to reach and execute mission in those areas that are very difficult for humans to even reach such as forest, deserts, and mines. Integration of the latest technologies including reactive controls, sense and avoid, and onboard computations have strengthened their dominance further in various practical missions. Besides the innovative applications, the use of UAVs imposes several challenges, and one of those challenges is computing a low-cost path for aerial mission by avoiding obstacles as well as satisfying certain performance objectives (a.k.a path planning (PP)). To this end, this chapter provides a concise overview of various aspects concerning to PP including basics introduction of the subject matter, categorization of the PP approaches and problems, taxonomy of the essential components of the PP, performance objectives of the PP approaches, recent algorithms that have been proposed for PP in known and unknown environments, and future prospects of research in this area considering the emerging technologies. With this chapter, we aim to provide sufficient knowledge about one of the essential components of robotics technology (i.e., navigation) for researchers.

Keywords: unmanned aerial vehicle, path planning, low-cost path, algorithms, aerial missions, urban environments, time complexity, coverage path planning

1. Introduction

In recent years, unmanned aerial vehicles (UAVs) have become a powerful tool for diverse missions including polymerase chain reaction (PCR) samples transportation between hospital and laboratories [1], UAV-based healthcare system to control COVID-19 pandemic [2], infectious diseases containment and mitigation [3], traffic condition analysis in co-operation with deep learning approaches [4], and human behavior understanding via multimedia data analytics in a real-time [5], to name a few. Currently, UAVs integration with the emerging technologies such as block chain, internet of things, cloud computing, and artificial intelligence can pave the way to serve mankind effectively compared to the recent past [6]. Further, the peculiarity of UAVs in terms of performing operations in 3D (dull, dirty, and dangerous) environments, they can play a vital role in realization of the smart cities.
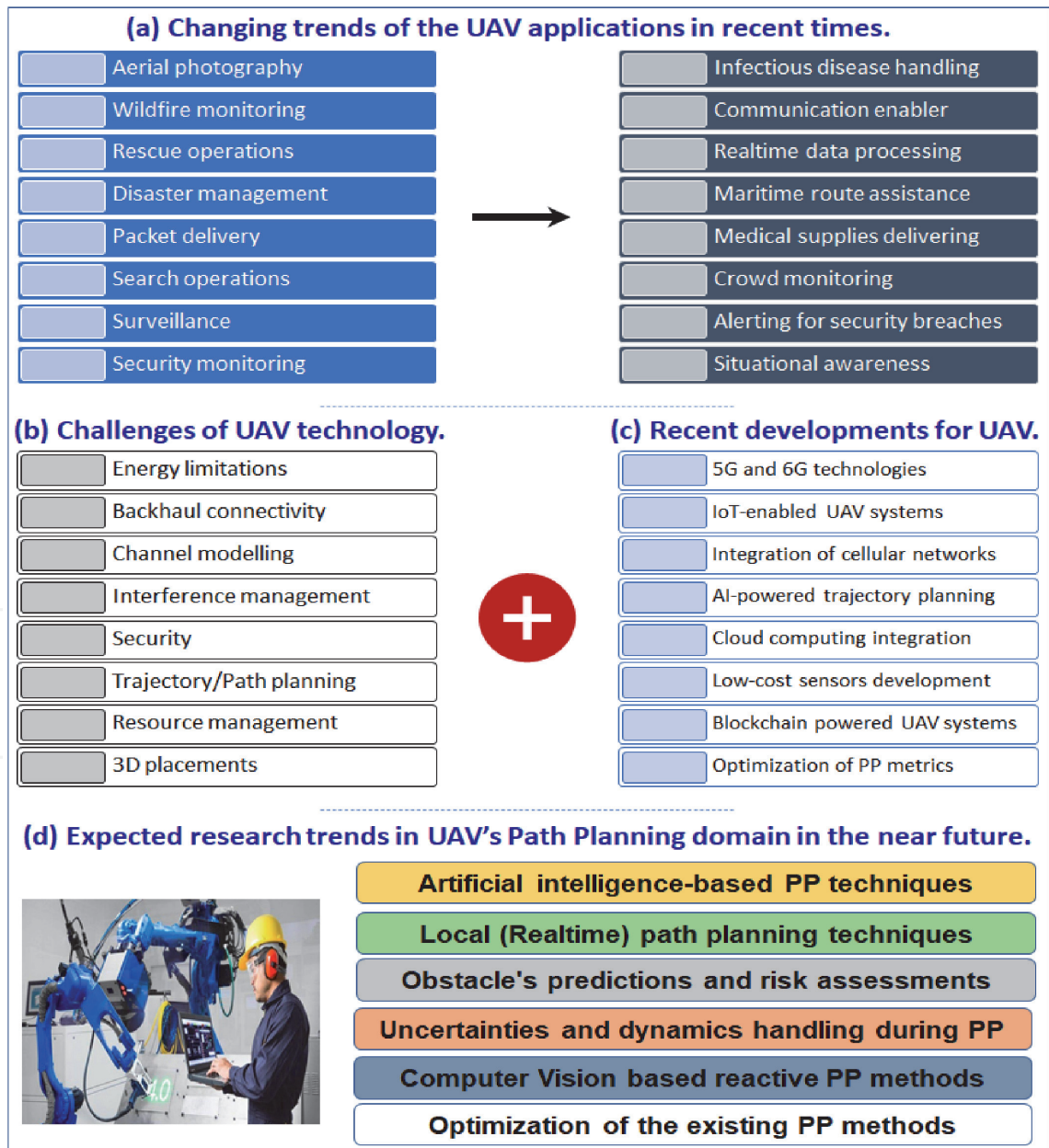
Furthermore, UAVs are inevitable tool during emergency planning and disaster management due to their abilities to perform missions aerially. Besides the UAVs applications and use cited above, they can be highly beneficial for military purposes including information collection and analysis, border surveillance, and transporting warfare items. The role of UAVs in agriculture from multiple perspectives have already been recognized across the globe. Recently, world's leading commerce company (i.e., Amazon) has started using UAVs for delivering their products to customers. Generally, the use of UAVs is expected to rise in many emerging sectors in the near future. We present actual and innovative use of the UAVs during the ongoing pandemic in **Figure 1**. Majority of the applications given in **Figure 1** employed multiple UAVs in order to accomplish the desired tasks.

Although UAVs are highly beneficial for mankind through their innovative applications, but there exist plenty of challenges that can hinder their use at a wider scale. For example, payload constraints and power issues can limit their carrier abilities. Similarly, decision making during flight to ensure UAVs safety by avoiding

(a) Surveillance by UAVs at Public Places

(b) UAVs delivering Essential messages

(c) UAVs spraying at multi-use facilities

(d) UAVs delivering medical equipment

(e) UAVs monitoring drivers

(f) UAVs delivering supplies

(g) UAVs getting Temp. data

Figure 1.
Innovative applications of the UAVs during the ongoing pandemic (adopted from [7]).

obstacles with sufficient accuracy is a non-trial task mainly due to no human-onboard control. Furthermore, communication from long distances, and co-ordination among multiple UAVs to perform complex tasks jointly are main barriers in the true realization of the UAVs technology. Besides the challenges and issues given above, many issues concerning software and hardware also exist that need rigorous developments and testing. Many solutions have been proposed to address these issues via cross disciplinary approaches. Meanwhile, extensive testing and analysis of these solutions is yet to be explored, especially in urban environments. In this chapter, we mainly focus on the 'navigation' that is one of the core challenges in the UAVs technology. The navigation quandary is classified into three cases: (i) where am I now?, (ii) where do I go?, and (iii) How do I get there?. The first two cases belong to the localization and mapping, and the third case is about path planning (PP) [8]. In this work, we cover third case comprehensively, and provide concepts and developments in this regard. We present a comprehensive overview about changing dynamics of the UAV applications in recent times,

Figure 2.
Overview of changing dynamics of the UAV applications, challenges, recent developments, and future research trends in the PP area.

challenges of the UAV technology, recent developments in the UAV technology, and future research trends in the PP area in **Figure 2**. With this concise overview, we aim to aid researchers in extracting the contents enclosed in this chapter conveniently.

The rest of this chapter is structured as follows. Section 2 discusses the basic concept of the path planning, and categorizes the path planning approaches based on the information available about underlying environment, and UAV used for the aerial mission. Section 3 describes the three essential components of the PP. Section 4 critically analyzes various approaches that were proposed to lower the computing time of the PP for UAVs. The future prospects of the research in the PP area are discussed in Section 5. Finally, this chapter is concluded in Section 6.
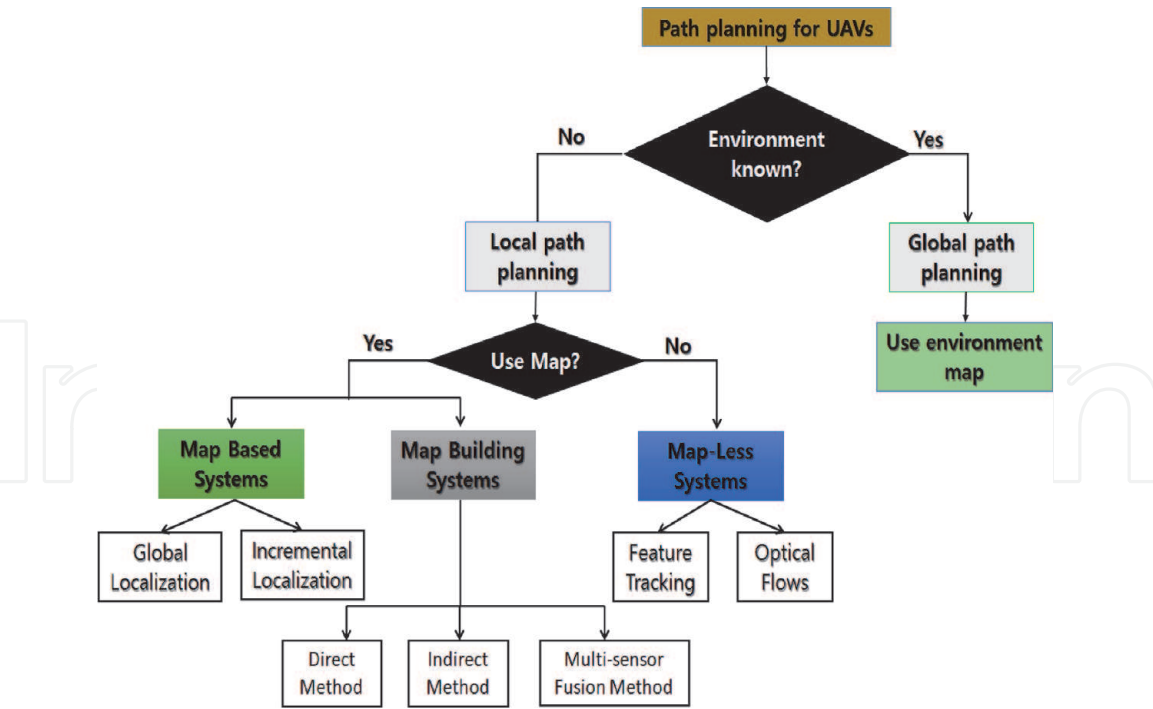
2. Path planning and categorization of the path planning approaches

PP is to find a safe (i.e., collision-free) path between two pre-determined locations (e.g., source and destination, denoted with s and t, respectively) by optimizing certain performance objectives. The performance objectives can be energy consumption, computing time, distance, path smoothness, and turns etc. depending upon the mission type, operating environment, and UAVs' type. The most important part of the PP is to identify the environment where the pathfinding is carried out for UAVs. In this work, we categorize the PP approaches based on the type of environment's information, and UAVs strength, respectively.

2.1 Categorization of the path planning approaches based on information about environment

Generally, there are three possibilities about the availability of information regarding environment where UAVs tend to operate. The operating environment can be fully known in advance (e.g., obstacles' geometry information is known.), it can be completely unknown, and/or it can be partially known (e.g., few portions are known, and some portions are explored and modeled during the flight.). Based on the degree of information about environment, PP approaches are mostly classified into two categories, local PP (LPP) and global PP (GPP). In LPP, the environment is not known, and UAVs use sensors or other devices in order to acquire information about the underlying environment. In GPP, PP is performed in a fully known environment, meaning all information about environment is known in advance. Based on the availability of the information regarding underlying environment, GPP approaches have lower complexity compared to the LPP approaches. Recently, some PP approaches have jointly employed LPP and GPP concepts in order to find a path for UAVs [9]. In literature, GPP and LPP approaches are also classified as offline and online PP approaches, respectively. Based on the extensive review of the literature, we present a categorization of the PP approaches based on information about environment in **Figure 3**. We refer interested readers to gain more insights about the LPP approaches in the previous studies [10, 11].

Apart from the categorization provided above, environment can be classified into rural and urban environments. The tendency of UAVs applications were high in the non-urban environments in the past. Moreover, due to the significant development in control domain, UAVs are increasingly employed in the urban environment these days. For instance, in urban environments, they can be used to monitor people compliance with the social guidelines given by the respective governments in order to control the COVID-19's spread.

Figure 3.
Categorization of the PP approaches based on the availability of information about operating environment.
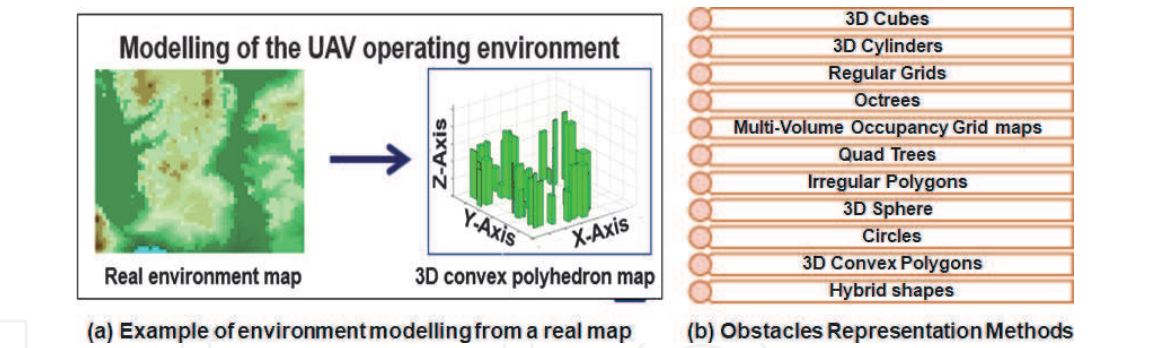
2.2 Categorization of the path planning problems

Based on the mission's type, either one or multiple UAVs can be employed. The scenarios in which only one UAV is deployed are referred as single agent PP problem. In contrast, those scenarios in which multiple UAVs are used are called multiple agent PP problems. PP for multiple agents is relatively complex since UAVs need to avoid collision with the companion UAVs, and obstacles present in an underlying operating environment. In addition, allocating target areas for coverage and optimizing throughput also remain challenging, especially while operating at lower altitudes in urban environments.

3. Essential components of the path planning for UAVs

Generally, there are three essential components of the PP: (i) modeling of the environment with geometrical shapes by utilizing the obstacles/free spaces knowledge provided by a real-environment map, (ii) task modeling with the help of graphs/trees keeping source and target locations in contact, and (iii) applying search algorithm inclusive of the heuristic function to determine a viable path.

3.1 Modeling of the environment with geometrical shapes

In the first step, a raw environment map is converted into a modeled one, in which obstacles are represented with the help of geometrical shapes. For example, poles information provided by a real environment map can be modeled with the help of cylinders in the modeled map. Similarly, buildings can be modeled with the help of rectangles or polyhedron. In some cases, UAVs do not model the whole environment map, and utilize sense and avoid (SAA) abilities to operate safely in
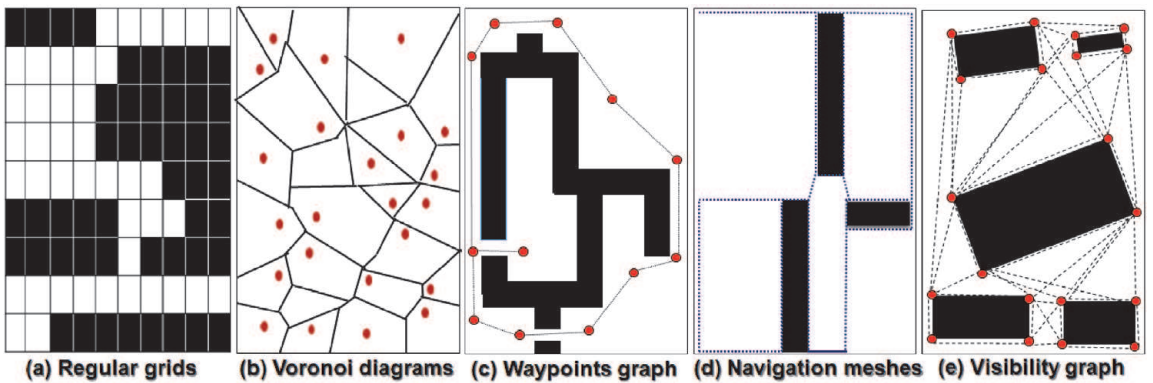
Figure 4.
Overview of environment modeling and obstacles' representation techniques.

the airspace. We present an example of environment modeling, and well-known obstacles' representation techniques used for the PP in **Figure 4**. Each obstacles representation technique has different complexity and accuracy in terms of real environment obstacles representations. In addition, each representation can be adopted considering the UAV operating environment. For example, polygons can be used to model an urban environment populated by various buildings.

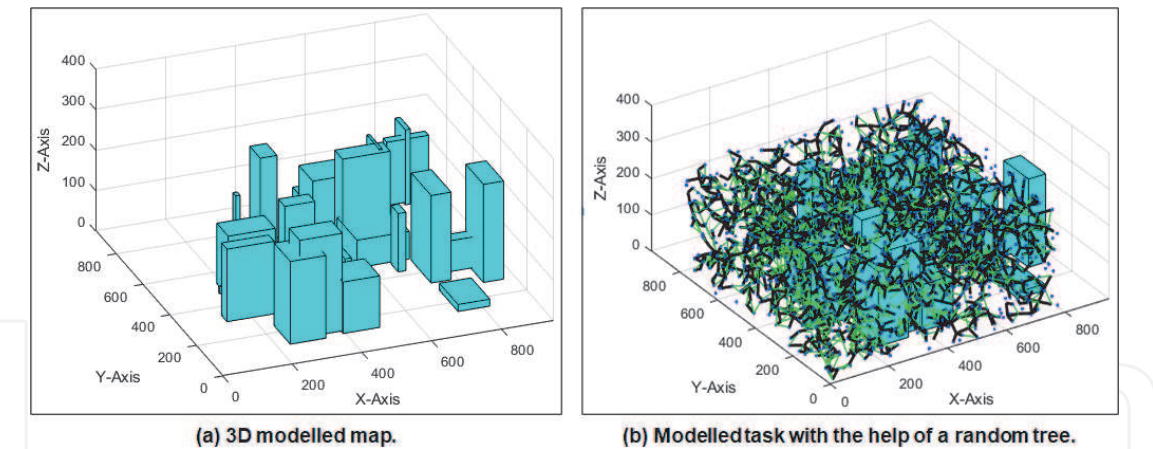### 3.2 Task modeling with the graphs/trees

After modeling environment with the help of geometrical shapes, the next step is task modeling (e.g., generating network of paths with a graph/tree or selecting a desired portion to be modeled). For example, road-map approach is a well-known task modeling approach for the PP, in which a graph is constructed from the starting location to destination location by capturing the connectivity of free spaces and obstacles' corners. Apart from it, cell-decomposition and potential field are promising solutions for the task modeling. We present most widely used task modeling methods in **Figure 5**.

Recently, trees-based task modeling methods have been widely used for the task modeling due to their quick convergence in the final solution. We present an overview of the task modeling with the help of tree in **Figure 6**. Furthermore, in some cases, more than one methods are jointly used to model the tasks on a provided map. In addition, some approaches use task modeling and path searching simultaneously [12].

Figure 5.
Overview of the famous task modeling methods used in the PP adopted from [26].
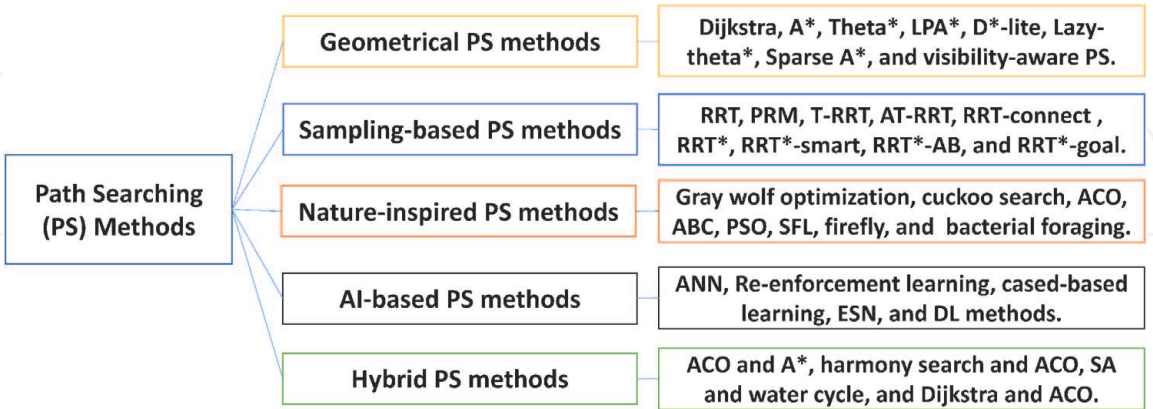
Figure 6.
Overview of task modeling with a random tree.

3.3 Applying path search algorithm to determine a viable path

In the last step, a search algorithm is employed on the graph/tree to find a viable path. During the path search, a heuristic function usually accompany the path search. For example, in the A* algorithm, the low-cost nodes are determined leveraging distance as a heuristic function. Similarly, the heuristic function can be energy consumption or smoothness depending upon the scenario. In literature, many techniques have been suggested to find reliable paths. The path search algorithms, such as differential evolution [13], firefly algorithm [14], ant colony optimization [15], genetic algorithms [16], artificial bee colony [17], particle swarm optimization [18], fuzzy logic [19], central force optimization [20], gravitational search algorithm [21], simulated annealing [22] and their advanced variants are used in the PP. Every algorithm has numerous distinguishing factors over others regarding conceptual simplicity, computational complexity, robustness, and convergence rates etc. We categorize the existing path search methods into five categories, and present representative methods of each category in **Figure** 7.

Figure 7.
Categorization of path searching methods/algorithms.

3.4 Performance objectives of the path planning approaches

Every PP approach tends to optimize one or more performance objectives (PO) while finding a viable path for UAVs. The PO can be related to hardware and software. These PO are considered in the previous three components (i.e., environment modeling, task modeling, and path searching) related to the PP. For instance,

in order to lower the PS computing time, only some portion of a map can be modeled and a sparse tree/graph can be constructed/used while finding a path. Similarly, memory can be preserved by exploring some portions of a graph/tree rather than loading and exploring whole graph/tree at a same time. The selection of PO solely depend on the nature and urgency of the mission. For example, in search and rescue missions, the PO can be path computing time in order to reach the affected regions quickly. In contrast, in normal circumstances, the PO can be the path length in order to reach the target location in a most economical way by preserving UAV's resources. We describe various most commonly used PO in **Table 1**.

These PO are usually considered during PP irrespective of the environment whether it is known or unknown. Furthermore, plenty of techniques have been

PO	Concise description
Computing time	It denotes overall time required to find a path using a graph/tree.
Path length	It denotes the Euclidean distance between two locations.
Energy	It denotes amount of energy required/consumed while reaching to target from source.
Turns	It denotes number of turns (infeasible curvature) a path has in total.
Smoothness	It denotes a turns in a path with a feasible curvatures.
Memory	It denotes amount of memory used while computing a path.
Path nodes	It denotes set of nodes that a UAV follows during flight.
No. of obstacles	It denotes set of obstacles to be processed during path search.
Accuracy	It denotes accuracy of obstacles modeling or path clearance from obstacles.
Problem size	It denotes size of problem on which path is determined.
Graph size	It denotes size of graph (no. of nodes, edges) employed to find a path.
Convergence rate	It denotes how quickly a feasible solution can be obtained.
Constraints handling	It denotes the effective resolution of constrains UAV faces during mission.
Completeness	It denotes availability/non-availability of solution in a finite time.
Flexibility	It denotes efforts/time required to make a solution usable for different missions.
Path re-configuration	It denotes efforts/time required to gain the control of a lost path.
Path following	It denotes the ability to keep following a path despite disturbances.
Path safety	It denotes the ability to avoid collisions with static/dynamic obstacles.
Hyper parameter	It denotes the number and variety of parameters to find a path.
Obstacle avoidance	It denotes the ability to avoid static/dynamic obstacles with low-cost.
Generalization	It denotes the ability of a method to be applicable for different types of UAVs.
Application-speciality	It denotes the ability of a method to yield superior performance in some context.
Endurance	It denotes the ability of a UAV to fly for a long period of time with low-cost planning.

Some PO are positively co-related. For example, finding path with less turns can save energy.
Improving two negatively co-related PO (speed and time) require optimization of another PO (problem size).

Table 1.
Overview of the PO improved by the PP approaches.

proposed to improve these PO with innovative techniques or employing cross-disciplinary concepts. In addition, many PP approaches have targeted optimizing multiple objectives rather than one/two for practical UAVs application. These PO can be expressed as a functional model while finding a path P between two locations s and t. Some algorithms tend to optimize more than one POs. The overview of two PO to be optimized by a PP approach is mathematically expressed as follows.

$$\begin{cases} P = [s = p_1, p_2, p_3, \ldots, p_n, p_{n+1} = t] \\ Minimize\, f_1(P) = Path\ \ Length(P) \\ Minimize\, f_2(P) = Computation\ \ Time(P) \end{cases} \tag{1}$$

4. Path planning algorithms that were proposed in the past five years

In this section, we discuss various PP algorithms that were proposed to lower the time complexity of the PP process. We selected various algorithms that were proposed in last five years (i.e., 2016–2021), and have somewhat identical concepts in terms of space restrictions and problem size reduction etc. We provide brief overview, and technically evaluation of all algorithms and highlight their deficiencies. Consequently, this analysis can pave the ways to improve PP algorithms for future UAVs' applications.

4.1 Global path planning algorithms

4.1.1 Brief overview of the selected path planning algorithms

We present brief overview of the selected algorithms in **Table 2**. These algorithms have become state-of-the-art for many practical applications of the UAVs in the urban/non-urban environments. They are famous due to their novel working mechanisms, and conceptual simplicity. In addition, they have mainly focused on the UAV applications in urban environments that is focus of research across the globe. Also, the UAVs' applications in the urban environments are likely to increase in the coming years.

Ref.	Publication year	Environment used	PO improved
Maini et al. [23]	2016	3D	Computing time and collision-free paths.
Frontera et al. [24]	2017	3D	Computing speed and solution quality.
Ahmad et al. [25]	2017	3D	Computing speed and energy-optimized paths.
Majeed et al. [26]	2018	3D	Computing speed and path quality.
Han et al. [27]	2019	3D	Feasible paths with reduced time.
Ghambari et al. [28]	2020	3D	Computing time and memory consumption.
Majeed et al. [29]	2021	3D	Computing speed and path quality.

All these approaches have used concepts related to search space reduction in order to find time-efficient paths.

Table 2.
Overview of the latest GPP approaches that were proposed to reduce the computing time of PP process.

4.1.2 Technical evaluation of the selected path planning algorithms

In this subsection, we provide concise description of the selected algorithms, and highlight their technical problems. We mainly describe the key steps of the proposed algorithms.

- Maini et al. [23] algorithm computes a low-cost path using two-steps approach. In the first step, modified version of the Dijkstra algorithm is used to find an initial path. In the second step, initial path is optimized more by considering the initial path nodes, and reverse path search.

- Frontera et al. [24] algorithm computes a low-cost path using three-steps approach. First, the proposed method reduce the search space by considering the obstacles that are on the straight axis between s and t. Later, a visibility graph is generated solely from the corners of the selected obstacles. In the last step, A* algorithm is employed to compute a shortest path incrementally.

- Ahmad et al. [25] algorithm computes a low-cost path using four-steps approach. Firstly, search space is bounded using obstacles of the straight line only. Later, the bounded space is extended to next level by using the obstacles that hit the boundary of the first bounded space. In the third step, a relatively dense visibility graph is generated from the bounded spaces. In the final step, A* algorithm is employed to find an energy-optimized path.

- Majeed et al. [26] algorithm computes a low-cost path using five-steps approach. First, the space is reduced into a half-cylinder form with path guarantees between s and t. In the second step, multi-criteria based method is employed to check the suitability of the reduced space for low-cost pathfinding. Later space is extended if needed, and sparse visibility graph is generated that ensure connectivity between s and t, and path is computed. Moreover, in some cases, path is improved by adding more nodes around the initial path's nodes.

- Han et al. [27] algorithm computes a low-cost path using three-steps approach. First, critical obstacles are identified through straight-axis between s and t. In the second step, a node set is generated around the corners of the critical obstacles only. In the last step, a feasible path is obtained by exploring nodes set. This approach is beneficial by resolving constraints related to obstacles shapes.

- Ghambari et al. [28] computes a global and local path with the help of four-steps. In the first step, search space is reduced around the straight axis. In the second step, differential evolution algorithm is applied to construct a graph. Later, A* algorithm is used to find a path from a graph constructed in the first step. In the third step, subspace is divided into small portions with alternate routes in each subspace. In the last step, a mechanism is suggested to avoid collision with the dynamic obstacles that may appear unexpectedly during the flight.

- Majeed et al. [29] recently proposed a PP method for low-cost pathfinding for UAVs based on the constrained polygonal space and a waypoint graph that is extremely sparse. In proposed approach, search space is restricted into a polygonal form, and its analysis is performed from optimality point of view

with the help of six complexity parameters. Later, space can be extended to next level if needed, else a very sparse graph is generated by exploiting the visibility, far-reachability, and direction guidance concepts. The suggested approach computes time-efficient paths without degrading path quality while finding paths from urban environments.

Besides the computing time, these algorithms can indirectly optimize certain PO listed in **Table 1**. For example, Ahmad et al. [25] PP approach reduces the number of turns also in order to lower the energy consumption. Han et al. [27] PP approach can be applied to the environments with arbitrary shaped obstacles (e.g., there exist no constraint related to the obstacles' geometries). Hence, it can be applied in different settings (e.g., areas with sparse obstacles or areas with dense obstacles) of the urban environment. Similarly, Majeed et al. [29] PP approach can significantly reduce the problem size, thereby memory requirements can be magnificently lower. Ghambari et al. [28] approach can be used to re-configure paths during the flight when a UAV finds an unexpected obstacle. Hence, this approach can be used in both (i.e., local, and global) environments. Despite the utility of these approaches in many real-world applications, they often yield poor performance due to the local/global constraints. Based on the in-depth review of all studies, we identified potential problems of all approaches that may hinder their use in actual deployment. We describe technical challenges of the existing approaches in **Table 3**.

Ref.	Technical problems in the proposed approach
Maini et al. [23]	The performance cannot be ensured in each scenario due to heavy reliance on specific maps. Overheads can increase exponential with the problem size. It models the whole map thereby path exploration cost is very high.
Frontera et al. [24]	Path can collide with the nearby obstacles. In some cases, proposed approach fails to find a path even though it exists. Visibility graph can contain many needless and redundant nodes. Memory consumption is higher due to loading of whole visibility map in the memory.
Ahmad et al. [25]	Two bounded spaces are used that can increase the computing time of the PP. Visibility graph is constructed using layered approach with many redundant nodes and edges. Visibility check function is expensive since visibility in all directions and nodes is checked.
Majeed et al. [26]	Path can contain turns due to the strict boundary of the search space. Path optimization cost may increase if initial path has many nodes.
Han et al. [27]	Path quality cannot be ensured in all scenarios if obstacles' sizes are large. Path cost can increase exponentially with the point set. Both time and optimality can be impacted if diverse shape obstacles exist in a map. Since this is grid-based approach thereby memory consumption is higher.
Ghambari et al. [28]	Path computing time can rise with the distance between s and t. Recognition and avoiding obstacles in realtime can be costly. Fidelity of the proposed approach were analyzed with limited testing. Since path searching is carried out twice, thereby computing time can rise.
Majeed et al. [29]	Accurate modeling of the tiny obstacles is not possible. Excessive calculations are performed in space analysis thereby complexity can rise.

All these problems have been highlighted by existing studies or reported by the authors.

Table 3.
Overview of the technical problems in the proposed GPP approaches.

These challenges lay foundation for the future research in the UAVs area. Furthermore, they can assist researchers to devise better and practical PP approaches in order to address these technical problems. Apart from the challenges provided in **Table 3**, it is paramount to take into account the local constraints while devising PP methods that have been mostly assumed in the existing approaches.

4.2 Local path planning algorithms

Majority of the approaches discussed above are the GPP approaches, and LPP approaches have not been discussed. To cover this gap, we discuss various representative LPP approaches in **Table 4** along with the methodological specifics.

These approaches perform PP in environments that are mostly unknown, and are complex compared to the GPP approaches. These approaches enable UAVs to perform tasks in complex environments in real time leveraging low-cost sensors, and robust artificial intelligence (AI) techniques. In addition, these techniques have abilities to co-work with the emerging technologies including cloud, edge, and fog computing etc. for variety of applications. The role of UAVs was dominant during the ongoing pandemic in different countries across the globe. To this end, LPP approaches contributed significantly, and enhanced UAVs role in curbing the pandemic spread via online missions. Barnawi et al. [47] proposed an IoT-based platform for COVID-19 scanning in which UAVs were used as a main source of temperature data collection in the outdoor environments. Apart from the COVID-19 scanning, UAVs were extensively used for spraying and disinfecting multi-use facilities and contaminated places. In some countries, they were used for alerting

Ref.	UAV used	Technical aspects of the approach
Stecz et al. [30]	Multiple	Indicated sensors based LPP approach.
Wojciech et al. [31]	Single	EO/IR systems and SARs based navigation.
Siemiatkowska et al. [32]	Multiple	MILP based LPP using EO/IR camera and SARs.
Hong et al. [33]	Multiple	MILP-based multi-layered hierarchical architecture.
Hua et al. [34]	Multiple	Multi-target intelligent assignment model based LPP.
Cui et al. [35]	Single	Reinforcement learning (RL)-based LPP approach.
Maw et al. [36]	Single	Graph and learning based LPP approach.
Wei et al. [37]	Single	Improved ACO for LPP.
Zhang et al. [38]	Single	Markov decision process (MDP) based LPP approach.
Zammit et al. [39]	Multiple	LPP in the presence of uncertainties.
Wu et al. [40]	Single	Interfered fluid dynamic system (IFDS) based LPP.
Bayerlein et al. [41]	Multiple	Multi-agent reinforcement learning (MARL) approach for LPP.
Jamshidi et al. [42]	Single	LPP based on improved version of Gray Wolf Optimization.
Yan et al. [43]	Single	Sampling based LPP approach in urban environments.
Sangeetha et al. [44]	Single	Gain-based dynamic green ACO (GDGACO) LPP approach.
Sangeetha et al. [45]	Single	Fuzzy gain-based dynamic ACO (FGDACO) LPP approach.
Choi et al. [46]	Single	Improved CNN based LPP approach for UAV.

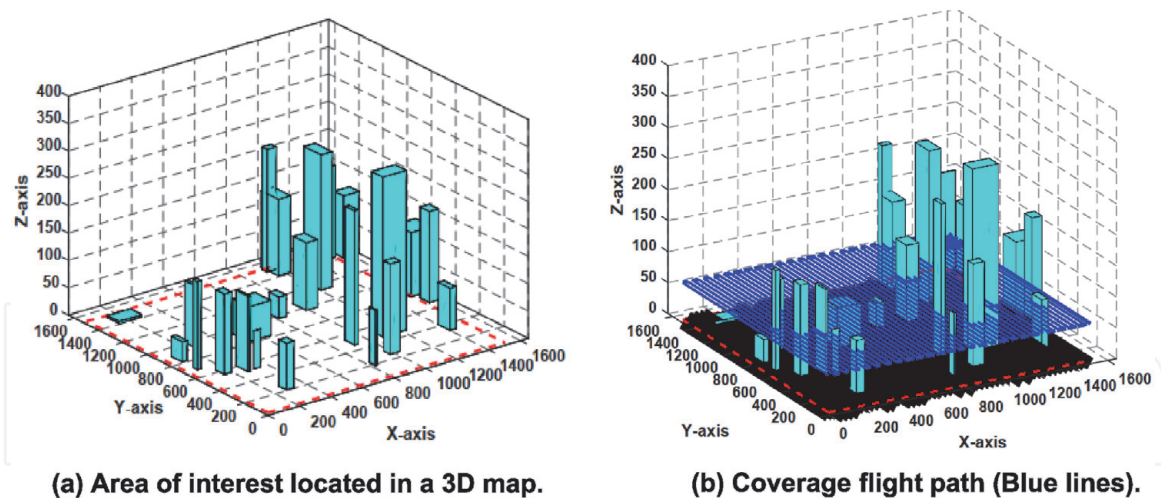*All these approaches have used the unknown environment during the PP.*

Table 4.
Overview of the latest LPP approaches used for UAVs.

people to wear masks properly, and stay indoors. The true realization of these innovative application is possible through LPP approaches.

4.3 Coverage path planning: a subtopic of the path planning

Besides the LPP and GPP, another important subtopic of the PP is coverage path planning (CPP) [48]. In the CPP, a path is determined that enables UAV to cover a target area fully with the help of a device/tool mounted on it. The attached tool/ device can be a sensor, camera, speaker, and/or a spray tank depending upon the mission. We present overview of the CPP in **Figure 8**. In **Figure 8(a)**, a target area in the form of a rectangle is given that need to be covered with a UAV. In In **Figure 8(b)**, a coverage path is shown that a UAV follows in order to cover the target area.

In the CPP, most of the POs are identical with that of the PP, but path overlapping, and coverage guarantees are two additional POs. Moreover, ensuring consistent path quality with respect to shape of the target area is very challenging. Therefore, shape of the target area is considered while finding a coverage path. CPP can be performed in five steps, modeling of the operating environment, locating target area on the modeled map, decomposition of the target area into disjoint sub parts, task modeling (mainly traversal order of the sub parts) with the help of a graph, and covering each sub-part using motion pattern (e.g., back and forth, spiral, and circular etc.). In recent years, UAVs' coverage applications in the urban environments have significantly increased, and a substantial number of CPP approaches have been proposed [49].

(a) Area of interest located in a 3D map.   **(b) Coverage flight path (Blue lines).**

Figure 8.
Overview of coverage path planning for UAVs in a 3D urban environments.
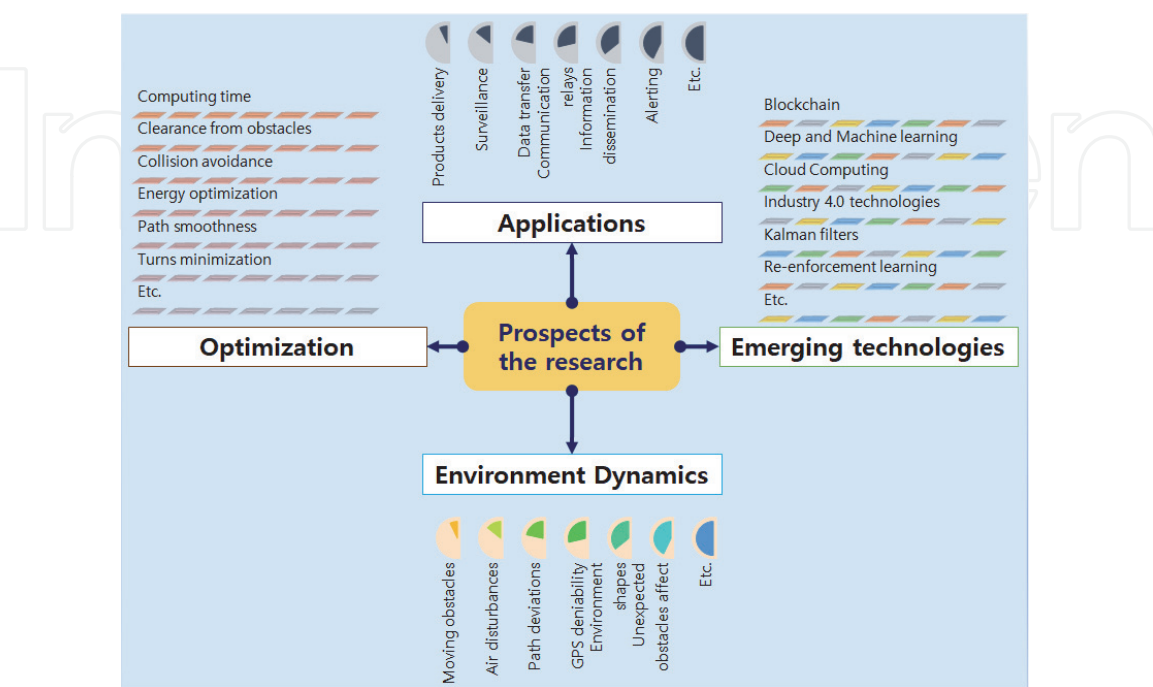
5. Prospects of the research in the near future in the PP area

In the near future, UAVs will be regarded as an inevitable tool for various practical missions, especially in the urban environments. A substantial number of developments are underway to fully realize smart cities, smart infrastructure, and smart buildings, to name a few. Thence, the use and applications of the UAVs are expected to grow significantly in the near future. Recently, many innovative technologies such as block-chain, IoT, 5G/6G technologies, and deep/machine learning approaches have been integrated with the UAVs technology to serve mankind in

effective ways [50]. For example, BloCoV6 scheme [51] is one of the wonderful applications of the UAVs in the new normal (e.g., COVID-19 era). Similarly, many such innovative applications are likely to emerge in the near future as a replacement of human beings for complex tasks. Therefore, refinements in the existing PP approaches in relation with peculiarities of the applications/tasks, and development of robust approaches leveraging cross-disciplinary (e.g., biological inspired, AI-powered, and technology-driven) concepts have become necessary. Considering the emerging applications of the UAVs, we list prospects of the research in the near future in PP area in **Figure 9**. We categorize the avenues of future research in the PP area on four grounds (e.g., UAV application specific PP approaches, optimization of the existing approaches' PO, integration of the emerging technologies and their issues handling, and developing PP approaches that can cope up with the dynamics of the UAV operating environment.).

The most important research avenues from the optimization point of view are, devising new environment restriction methods to reduce the problem sizes, devising low-cost methods for reducing the task modeling overheads (i.e., graph/tree sizes), and accelerating the PS methods that enable UAV to reach the target location safely with a significantly reduced cost. Furthermore, improving overall cost of the PP process is an important research direction to increase UAVs' applications in the urban environments. Optimization of multiple objectives rather than single/two is handy in order to preserve UAV's resources during aerial missions. From applications point of view, low-cost methods that can improve certain POs and can satisfy the applications features at the same time are needed. To this end, identifying each application's features/requirements and embedding them into the PP process can enhance the UAVs use in the coming year significantly. Therefore, applications-oriented PP methods will be embraced more in the near future considering the UAVs potential in executing tasks at low costs. From environment dynamics point of view, PP methods that can effectively respond to the uncertainties/dynamics emerging from the environment are paramount. For example, in LPP, decision making to avoid obstacles with as least cost as possible can enhance UAV's endurance in the aerial missions. In this regard, LPP methods that can cope up with the

Figure 9.
Categorization of the avenues of future research in the PP/UAVs area.

underlying operating environment variations and can ensure UAV's safety consistently in the practical applications are paramount.

Recently, many emerging technologies have been integrated with the UAV technology. For example, blockchain, transfer learning, computer vision, federated learning, 5G and 6G technologies, and cloud computing etc. have revolutionized the UAVs' applications. In this regard, incorporating more emerging technologies in the UAV domain, and extending the current emerging technologies use to more application areas is an important research direction for the future. Furthermore, improving the hardware capabilities of the UAV by integrating latest technologies are important need from technical perspectives. Despite the technical aspects mentioned above, tailoring computer vision applications in the UAV area is a most promising avenue of the research considering UAV abilities to capture images with good resolution [52]. In addition, identifying niche areas (i.e., water quality analysis, target tracking, covering spatially distributed regions, and detection of wildfire smoke, to name a few) where UAVs can perform well compared to humans, and performing cost–benefit analysis of the UAVs versus human is important research direction in the UAVs' technology. Finally, exploring the possibilities towards joint use of multiple latest technologies in order to serve mankind in an effective way using UAVs is a vibrant area of research. Apart from the PP, devising low-cost CPP methods for UAVs is also an attractive area of research in the near future. Development from hardware perspectives (e.g., battery power, wing-span, payload capabilities, robust decision making abilities, and control aspects) are also a potential avenues for development/research.

6. Conclusions

In this chapter, we have presented concepts, methods, and future research prospects in the area of path planning (PP) for unmanned aerial vehicles (UAVs). Specifically, we have presented the high-level categorization of the PP approaches based on the availability of information regarding UAV operating environment, and UAV strengths. We have discussed three essential components of the PP approaches that are widely adopted by most of the PP approaches. We have discussed substantial number of performance objectives that are improved/optimized by the PP approaches via new concepts/propositions. Furthermore, we have discussed latest approaches that have been proposed to lower the time complexity of pathfinding and their technical challenges. We have described various PP approaches that are used for the PP in unknown environments (aka local PP). We have briefly described the concepts of coverage path planning (CPP) that is subtopic of the PP. The prospects of future research in the UAVs PP area keeping emerging technologies in the loop have also been discussed. With this concise overview, we aim to provide deep understanding about the PP concepts related to the UAVs, and need of the further developments/research in order to enhance UAVs endurance in the airspace specifically in the urban environments. The contents presented in this chapter can help early researchers to quickly grasp the status of existing developments and potential avenues of the research in this area.

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Conflict of interest

The authors declare no conflict of interest.

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