

Path-planning for Unmanned Aerial Vehicles with Environment Complexity Considerations: A Survey

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Unmanned aerial vehicles (UAVs) have the potential to make a significant impact in a range of scenarios where it is too risky or too costly to rely on human labour. Fleets of autonomous UAVs, which complete tasks collaboratively while managing their basic flight and related tasks independently, present further opportunities along with research and regulatory challenges. Improvements in UAV construction and components, along with developments in embedded computing hardware, communication mechanisms and sensors which may be mounted on-board a UAV are nearing the point where commercial deployment of fleets of autonomous UAVs will be technically possible. To fulfil this potential, UAVs will need to operate safely and reliably in complex and potentially dynamically changing environments with path-planning, obstacle sensing and collision avoidance paramount. This survey presents an original environment complexity classification, and critically analyses the current state of the art in relation to UAV path-planning approaches. Moreover, it highlights the existing challenges in environment complexity modelling and representation, path-planning approaches, and outlines open research questions together with future directions.

Additional Key Words and Phrases: Unmanned Aerial Vehicles (UAVs), Path-planning, Environment Modelling Complexity

ACM Reference Format:

Michael R. Jones, Soufiene Djahel, and Kristopher Welsh. 2022. Path-planning for Unmanned Aerial Vehicles with Environment Complexity Considerations: A Survey. *ACM Comput. Surv.* 1, 1 (November 2022), 37 pages. <https://doi.org/10.1145/nnnnnnn>.

1 INTRODUCTION

Unmanned Aerial Vehicles (UAVs) are aerial vehicles capable of propelling themselves through the skies without the need for a human pilot on board. Although UAVs are unmanned by definition, true autonomous control of the aircraft is frequently restricted, either by the capabilities of the UAV or more commonly by strict airspace regulation. In most real-world scenarios, UAV operations are therefore remotely piloted, with a degree of automated control handed over to the UAV during flight, for specific tasks such as maintaining altitude and heading, and thus not strictly autonomous. The complex regulatory landscape with respect to UAV-specific aviation and operational control, is a significant challenge facing future UAV adoption and the potential opening up of the UAV marketplace, varying both regionally and by country [1]. Public safety, collision avoidance, data protection, and security issues are all important factors for consideration by regulators [2] in the progression

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0360-0300/2022/11-ART \$15.00

<https://doi.org/10.1145/nnnnnnn>

from Automated UAVs to Autonomous UAVs. Continued development and progression of a significant academic research evidence base, related to independent UAV decision-making and behaviour methodologies, will serve as a key mechanism for regulators to approve greater future UAV autonomy in a tightly-regulated environment.

Once a typical stalwart of military research and development, technological advancements and reductions in unit cost have widened the scope and interest of UAVs in civil markets. The study conducted in [3] predicts that civilian and civil infrastructure use of UAVs has the potential to significantly outstrip future military demand, primarily due to the combination of both flexibility and mobility that modern UAVs offer. A UAVs flexibility can be derived through the ability to mount a diverse range of sensing, transmitting and visual capture equipment upon a UAVs airframe, enabling the completion of a diverse range of real-world tasks. Such flexibility is packaged within an ultra-mobile airborne platform, with a significantly reduced cost compared to more traditional manned airborne solutions. Such an expansion in the potential scope of civilian UAVs usage, combined with the introduction of affordable and accessible commercial UAVs has driven significant interest from both the academic and commercial research fields. The potential market scope to implement UAV based solutions extends through a wide range of commercial and industrial sectors including but not limited to, delivery of goods [4], surveillance and security [5], agriculture [6], communication [7, 8], infrastructure inspection [9] along with search and rescue [10], with significant potential for cross diversification in the application of UAVs across multiple sectors.

A UAV path-planning algorithm seeks to discover a collision free path within an environment space that permits a UAV to travel from an initial starting point to a specific goal end point, discussed in more detail in Section 4. Researchers have investigated path-planning problems for decades, targeting optimal path finding solutions. However, such problems have typically been constructed around fixed transit infrastructure such as roads. Designing suitable path-planning solutions for UAVs is more challenging than for traditional path-planning problems [11] with the three dimensional environment, incomplete environmental knowledge and significant variations in UAV capability by weather reducing the applicability of existing approaches.

The complexity of implementing a UAV path-planning algorithm increases significantly from that of more traditional path-planning problems, most notably due to the introduction of a three-dimensional environment space. The diverse range of airborne movements a UAV may explore in a 3D space (subject to flight regulations), means an exponential growth in potential paths available. Where one object (UAV) is offered such a freedom of movement, consideration must also be given to the resulting relative unpredictability concerning the motion of other objects and obstacles within the environment space, presenting significant further complexity. This work seeks to define that environment complexity and discuss the current trends and approaches used to tackle it.

The main contributions of this survey paper are summarised as follows. (i) Proposing an original classification of UAV environmental modelling approaches, based on the characteristics of the environment they seek to model. (ii) Providing a critical analysis of the most important existing path-planning approaches for UAVs, and a discussion of their common limitations. Moreover, we present an insightful discussion of potential future directions to best overcome the highlighted challenges in this paper. In Table 1, we list a series of recent surveys which possess one or two related aspects with our survey paper, and outline their main objective, key topics investigated and their main limitations or weaknesses. This highlights the need for and importance of the above contributions made in our survey paper. Many of these surveys explore the wider applications and challenges of implementing future UAV systems [12–14], with UAV hardware and perceived benefits also classified in [3, 15, 16]. UAV path-planning and navigation approaches are discussed in [17] with [18] considering purely vision-based UAV navigation approaches, whilst both [19, 20] consider the application of planning algorithms within more generalised mobile robots path-planning scenarios suitable for cross application usage.

The remainder of this paper is organised as follows. Section 2 discusses strategies for building environmental models of UAV operating environments. Section 3 presents a novel classification of environmental modelling approaches which organises existing works by target scenario. Section 4 discusses the two linked but distinct path-planning processes required in large-scale UAV routing problems. Section 5 presents a taxonomy of environmental

Table 1. Comparison of the related surveys on UAV Path-planning

Survey	Main Objective Features	Research Object	Topic(s)	Weaknesses
[3]	Hybrid UAVs	UAV	UAV platform design, flight dynamics and modelling	Limited to construction and flight control surfaces
[15]	Routing in UAV networks	Multi-UAV/ Comm's	UAV classification, existing routing protocols	Limited to communication constraints
[12]	Design challenges for cyber-physical applications in multi-UAV systems	Multi-UAV	Area & target coverage, energy-efficient navigation, image analysis, networking	Limited exploration of environment constraints
[13]	UAV networks: A cyber-physical system perspective	UAV	Communication, computation, flight control	Limited exploration of environment constraints
[17]	3D UAV flight path-planning	UAV	Environment modelling, path-planning algorithms, path smoothing	Limited exploration of environment constraints
[20]	Robot path-planning using bio-inspired algorithms	General mobile robot	Bio-inspired algorithm comparison	Lack of UAV environment consideration and comparison
[19]	Path-planning for mobile robots	General mobile robot	Comparison of application area	Lack of UAV environment consideration and comparison
[14]	Key challenges of UAV civil applications	UAV	Classification, applications sensing, networks, security	Limited focus on path-planning
[18]	UAV vision-based navigation	UAV	Map-based, map-building & map-less vision systems	Limited to vision-based navigation
[16]	Civil UAV application and optimisations approaches	UAV	UAV classification, routing, area coverage & search, UAV self-organisation	Broad overview of a wide research area

modelling approaches applied to UAV path-finding problems in the literature, using our novel classification. Section 6 analyses the recent literature in light of our taxonomy, identifying key areas for discussion and future work in Section 7. Finally, Section 8 concludes the paper.

2 ENVIRONMENT REPRESENTATION STRATEGIES

Fundamentally, each environment space a UAV encounters may be represented mathematically through the application of graph theory [21]. Where a graph based representation of the environment is formed as a set of destination points (commonly referred to as vertices or nodes) interconnected by a set of transit paths (referred to as edges). Therefore, mathematically a graph G can be represented by the set of destination point vertices denoted

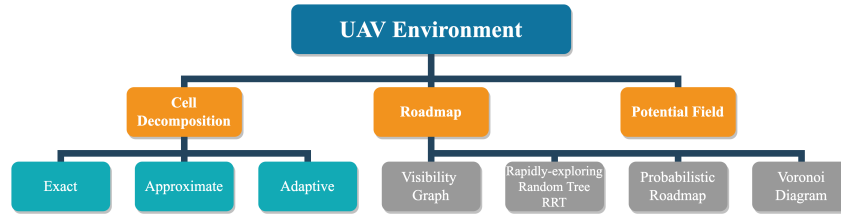


Fig. 1. Environment Representation Strategies

by V together with a set of traversable edge paths denoted by E so that $G = (V, E)$. A key question that exists with such an approach is the level of granularity to which an environment space is represented, purely target locations at one end of the spectrum through to every possible position a UAV may occupy within the environment. The successful execution of a UAV path-planning strategy can be generalised through the implementation of a two-stage planning process to enable a solution delivery. Stage one involves the pre-processing of raw physical environment data and generation of a problem space representation. This representation defines constraints for the planning algorithm applied in stage two of the planning process. The translation of a physical environment into a logically-navigable UAV problem space is tackled via one of three key strategies outlined in Figure 1.

2.1 Cell Decomposition Approaches

Cell decomposition approaches divide the environment space a UAV can operate within into a series of non-overlapping cells. Such representations offer a defined and navigable structure to the environment space, constructed around the availability of traversable relationships between cells [22].

2.1.1 Approximate Cell Decomposition. Approximate cell decomposition overlays a regular grid structure upon the environment problem space [23]. Decomposing the environment into a set of structured cells, each cell's location within the environment is typically represented by a Cartesian coordinate system. The boundaries of cells remain rigid, such that they may not precisely correlate with objects and obstacles within the environment. Therefore, a cell's total internal space must be classified as either free space or obstacle space, where even a cell only partially filled by an obstacle is classified as obstacle space. The approximate approach is implementable in either 2D or 3D environments. Figure 2 illustrates a two-dimensional environment representation providing either (a) orthogonal directions of motion, or (b) orthogonal and diagonal directions of motion. Within a three-dimensional environment the ability to access multiple layered grids increases the number of adjacent reachable grid cells illustrated in Figure 3, allowing either (a) six directions of available motion or (b) twenty-six.

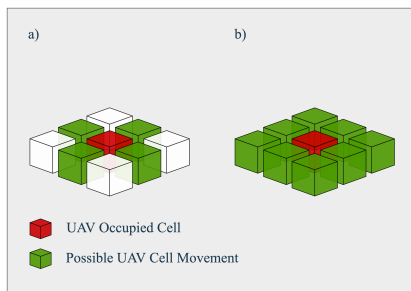


Fig. 2. 2D Cell Movement Possibilities

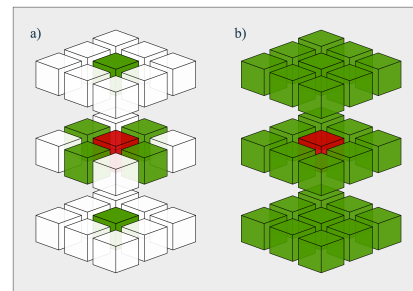


Fig. 3. 3D Cell Movement Possibilities

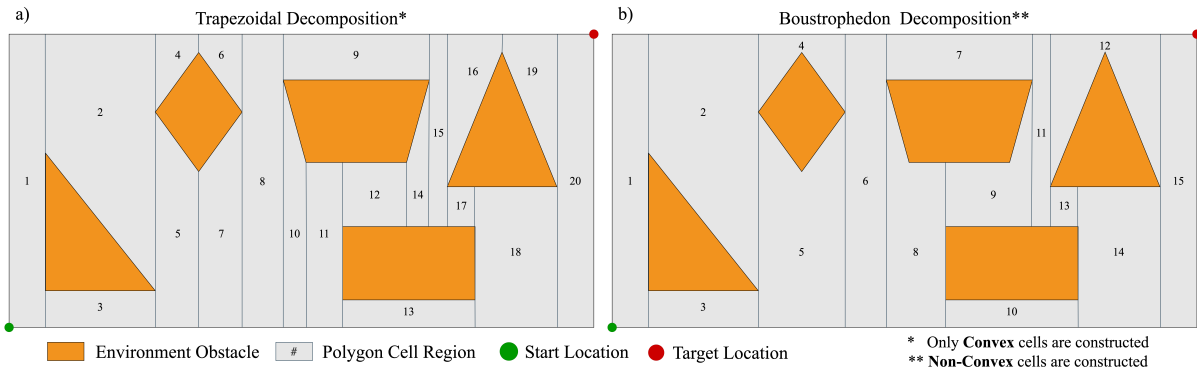


Fig. 4. Trapezoidal decomposition vs. boustrophedon decomposition

2.1.2 Exact Cell Decomposition. Exact cell decomposition deconstructs the complete environment space into a collection of non-overlapping polygon regions [24], with two key approaches to exact decomposition worth noting: Trapezoidal decomposition and Boustrophedon decomposition [22]. The construction of these region cells is directly influenced by objects and obstacles within the environment as illustrated in Figure 4.

The Trapezoidal decomposition approach divides the environment space into distinct convex cell regions. The method typically sweeps vertically left to right across the environment, appending vertical deconstruction lines, where an obstacle vertex is encountered. Thus, a series of polygon cell regions are created around the encountered obstacles within the environment space, as depicted in Figure 4a.

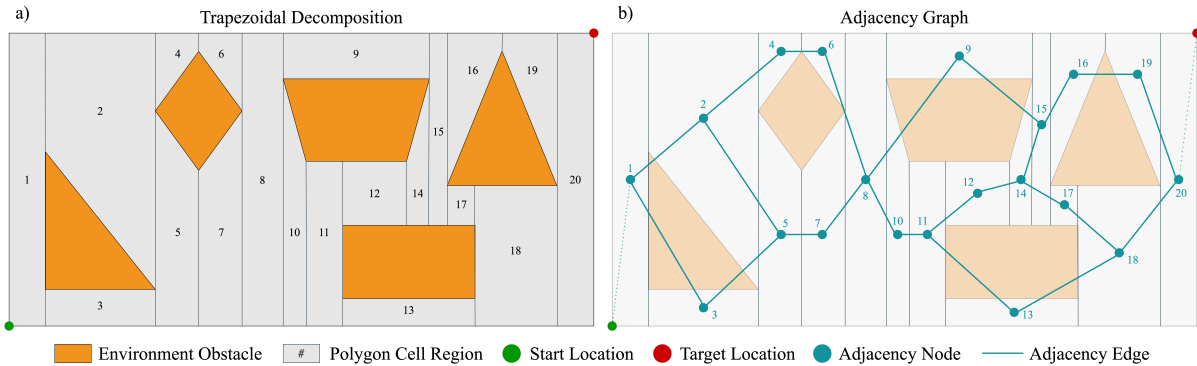


Fig. 5. Trapezoidal conversion to Adjacency Graph

The Boustrophedon decomposition approach illustrated in Figure 4b, results from analysis of the Boustrophedon method for coverage path planning [25], where complete coverage is achieved through adjacent straight-line paths across an environment, changing direction at boundary edges. The resulting analysis [25] identifies that boustrophedon decomposition minimises the coverage path length in comparison to the trapezoidal decomposition, through reducing the number of polygon cell regions created. To achieve this reduction a similar vertical sweep method to trapezoidal is applied, however, vertical deconstruction lines are only applied at critical locations. Critical locations are defined as points where the connectivity of the sweeping vertical line changes i.e., a single

sweeping line is broken as it encounters an obstacle. While fewer polygon cell regions are created, those regions are non-convex, which may need to be considered depending on the future path planning approach applied.

2.1.3 Adaptive Cell Decomposition. Critically, whilst the cell regions created using either trapezoidal or boustrophedon decomposition techniques do not possess uniform shape or structure, depicted in Figure 5a. The adjacency of resulting cell region relationships can be defined into a connectivity graph, with graph nodes extracted from the free space cell region locations. If cell regions are adjacent their relationship can be described through the application of non-directed graph edges between the adjacent node pairings [24], illustrated in Figure 5b. Thus, a continuous free space path can be planned across the environment space based upon cell region relationships.

Initially proposed as a data representation strategy [26], adaptive cell decomposition deconstructs the environment only where an obstacle's presence requires. When applied to a path-planning scenario the adaptive Quadtree schema is constructed by dividing the environment space into four equal sub-regions. Where an obstacle exists, regions are further recursively decomposed into four supplementary child regions until the desired stopping condition is met as illustrated in Figure 6. The adaptive strategy can also be applied to a 3D environment, decomposing the environment into eight adjoining cuboids, thus forming Octrees, with either method allowing for construction of a connectivity graph representative of those cells classified as free space.

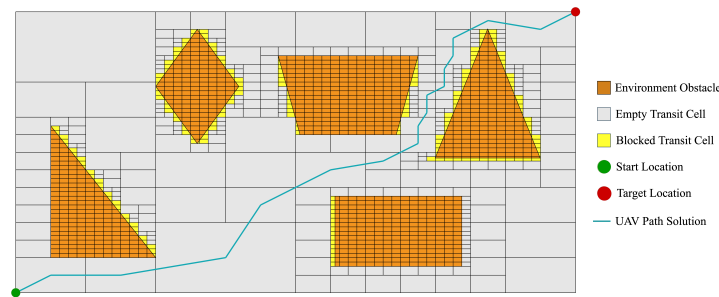


Fig. 6. Quadtree Adaptive Cell Decomposition

2.2 Roadmap Approaches

Whilst cell decomposition approaches clearly define both free and obstacle space within the overall problem space, the range of movement available to UAVs within free space is unbounded. This results in a large search space for any path-planning algorithm. A roadmap approach is typically a connectivity graph formed from a collection of nodes representing key free space locations within an environment [24]. The edges between nodes represent the ability to transit safely between the adjoined nodes, with edges often also possessing a weighting factor, such as time or distance serving to direct path-planning decisions. The reduction of an environment via a roadmap approach into a graph-based structure, closely resembles classical route planning optimisation problems, where optimal routes are identified by comparing the sum of edge weights in candidate paths, as discussed in Section 4. Whilst graph construction strategies discussed in the following subsections vary, they all conduct an initial environment processing stage to build an accessible arrangement of edges between nodes. The application of a planning algorithm to this arrangement seeks to discover an optimal path.

2.2.1 Visibility Graph. The notion of constructing a visibility graph through a problem space was first introduced in [27] with the concept being further extended in [28] where a more general collision avoidance problem is considered. The construction of a visibility graph allows a graph representation to be formed of all potential visible connections within the environment. Connectivity nodes are formed upon the vertices of polygon obstacles,

with connecting edges applied based upon the perceived visibility between these nodes as illustrated in Figure 7. The use of polygon objects allows for distinct connectivity nodes to be applied, where an object does not take a polygon form, an overlaid polygon representation can be applied e.g., a circle may be overlaid by a hexagon or octagon. Equally, as applied in [28] the bounds of an initial polygon obstacle can be expanded to account for the UAVs dimensions or to allow a safety margin.

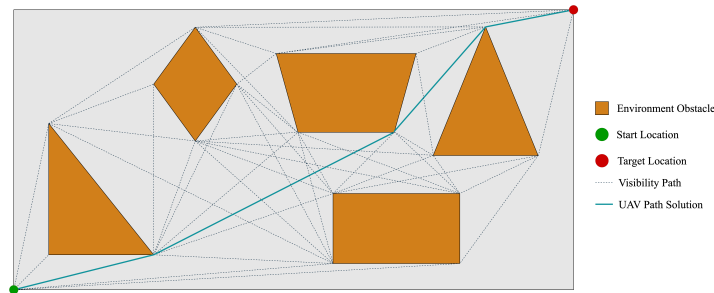


Fig. 7. Constructed Visibility Graph with a UAV Path Solution

2.2.2 Voronoi Diagram. A weakness of *visibility graphs* lies in the construction process, generated paths pass within close proximity to the obstacles they seek to avoid. Voronoi diagrams offer an alternate approach, enabling the decomposition of a 2D problem space into a set of polygon regions, with each region constructed around a single environment location. The result is a graph whose edges are constructed based upon the equidistant relationships of environment locations, as apposed to edges formed directly between them. The approach is illustrated in Figure 8, where the converging region edges allow for graph vertices to be defined [29, 30].

Environment representation using Voronoi diagrams offers a diverse range of use case scenarios. For instance [30] defines the key environment locations as radar threats, thus the edges generated during polygon region construction, maximise the available distance between UAV and threat. When considering IoT data collection scenarios such as that presented in [31], the generation of Voronoi polygon regions surrounding devices presents edge paths where a UAV may serve multiple devices within a transmissible range. While [32] constructs a Voronoi diagram of existing environment waypoints, the initial path is then manipulated based on the centroid locations of the Voronoi polygons to achieve a near optimal area coverage of the environment.



Fig. 8. Voronoi Diagram Path Solution

2.2.3 Probabilistic Roadmap. Path generation in both visibility and Voronoi diagrams is dictated solely by the placement of obstacles within the environment. A probabilistic approach deconstructs the available free problem space into a set of randomly placed connectivity nodes [33]. Connecting nodes with edges is based upon proximity to a nearest neighbour node, combined with the perceived visibility and ability to pass unhindered between nodes. As such, a significant level of environment knowledge is required in path construction. Whilst this random construction method lacks the capability to provide an optimal solution, it is able to guarantee completeness based upon the increasing number of nodes added, a concept discussed further in Section 4.2.

2.2.4 Rapidly-exploring Random Trees. In placing connectivity nodes across the whole problem space, the exploration of a probabilistic roadmap and its problem space is driven by the path-planning algorithm applied to it. LaValle’s Rapidly-exploring Random Trees (RRTs) method, defined in [34], focuses upon a randomised approach for exploration of the environment. Applying an explorative branching strategy, branching paths are constructed originating from a root node as illustrated in Figure 9. Again, a significant level of environment knowledge is required in tree construction to allow successful placement of future nodes, although the RRT approach offers a configurable strategy to manage tree growth and exploration of the problem space.

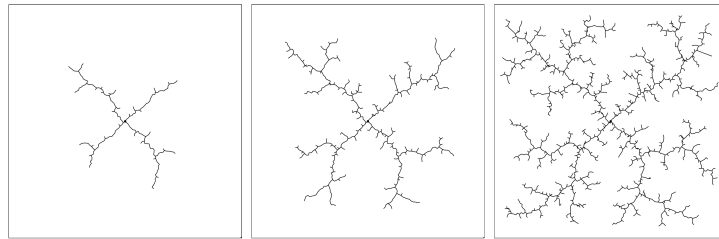


Fig. 9. RRT exploration expanding from central node [34]

2.3 Artificial Potential Field

Both cell decomposition and roadmap approaches focus upon building an environment representation from prior known environment knowledge. The application of an Artificial Potential Field (APF) approach seeks to calculate a directional force that can be applied to a UAV. This directional force is based upon the gravitational attractive forces applied by goal or target locations, as illustrated in Figure 10a, combined with the cumulative repulsive forces applied by obstacles within an environment depicted in Figure 10b. The initial concept of using potential fields as a prospective mobile robot navigation strategy was introduced in [35].

Within a real-world environment the gravitational force is proportional to the Euclidean distance from the UAV to target locations, while repulsive forces can be derived from mounted sensors capable of calculating obstacle distance. Allowing a UAV to move both quickly and accurately towards a target location, through successive evaluation of the resultant forces within an environment space. The abstract representation of APF field forces provided across a whole environment grants a UAV the potential for significant autonomy in determining a transit path across an environment. This approach enables a reactive path-planning, where dynamic obstacles influence APF forces in real-time allowing for adaptive navigation decisions.

However, achieving such autonomy is still challenging; local minima, local oscillation, and gravity imbalance problems [36], all serve as potential inhibitors to APF path solutions. Furthermore, the availability and completeness of APF environment data can also hinder path-planning. A UAV requires a significant depth of local environment data to be able to independently evaluate the APF in its vicinity [37]. If a centralised UAV position-to-APF model is used instead [38], then an accurate APF representation of the environment or simulated

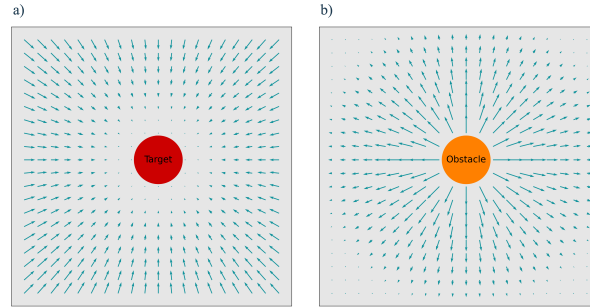


Fig. 10. Attractive and Repulsive forces illustration

APF data is required for the entire area of operation *a priori*. This relies heavily upon an additional appropriate communication mechanism for APF data exchange. A UAV will still, however, require access to wider APF data if it seeks to plan or transit between points dispersed across a greater area than its immediate sensing range.

3 ENVIRONMENT MODELLING COMPLEXITY

This section explores the development of a high-level UAV environment classification strategy. The strategy differentiates between approaches by considering two key environmental challenges faced by UAV path-planning algorithms: (i) the level of global environmental knowledge available when planning a path solution; and (ii) the possibility of obstacles moving, entering or leaving the environment during operation.

Effective UAV path-planning requires consideration of the specific physical environment a UAV plans to operate within. As such, the operational environment must be modelled in a manner that allows translation and interpretation by a path-planning algorithm. This survey seeks to define a suitable taxonomy for such modelling a UAV's physical environment, focusing upon the two previously-mentioned factors (i.e., (i) and (ii)).

Firstly, the feasibility of planned paths depends heavily on the accuracy of the environmental model underpinning them. Paths planned based on incomplete or inaccurate knowledge of the environment are fundamentally more likely to require later revision than those based on a verified understanding. Thus, we classify approaches as modelling *known* or *unknown* environments. In techniques targeting known environments, knowledge of the environment and operations possible within it is available *a priori* to the path-planning algorithm. In unknown environments, this knowledge is unavailable.

Secondly, the viability of planned paths over time depends on the environment not changing in a way that affects them. Considering this variability, we classify environments as *static* or *dynamic* in nature. Static environments are fixed, which means the environmental model does not require modification after construction and paths will remain valid indefinitely. Dynamic environments vary over time, requiring the detection of these changes and the modification of the environmental model used in path-planning, as well as the adjustment of affected paths.

Combining these two modes of classification within a taxonomy table generates four distinct environmental complexity classification models, as shown in Table 2. This classification model can be applied to aid selection of both environment decomposition strategies together with the selection of a capable path-planning algorithm that fulfils a UAV needs.

3.1 Static-Known Modelling Approaches

A static-known environment provides a representation of the environment, whereby all obstacles and objects within the problem space environment are fixed; allowing for the concurrent overall knowledge of the problem

Table 2. Environment complexity classes

		Global Environment Knowledge	
		Known	Unknown
Obstacle Nature	Static	Static-Known	Static-Unknown
	Dynamic	Dynamic-Known	Dynamic-Unknown

space environment to exist, resulting in the ability for the environment's state to be defined at any point in time. Static-known environments represent the most commonly encountered complexity model, with significant research based upon traversal of such environment problem spaces, this can perhaps be attributed to the solid proving ground this model provides to demonstrating fledgling concepts, prior to further development whereby more challenging environment models are tackled.

3.2 Dynamic-Known Modelling Approaches

The dynamic-known environment begins to explore the concept of obstacles and objects within the problem space, possessing the ability to freely transition between environment locations. However, such movements within the environment problem space are known, resulting in path-planning approaches that are reliant upon centralised control with possession of global knowledge, or planned concurrently UAV-to-UAV through a suitable communication model. In this latter approach, each UAV becomes aware of all its peers' planned paths across its fleet, enabling cooperative path-planning. In both centralised and decentralised approaches, there may be multiple objects or obstacles moving within the environment at any point in time. Thus, current and future locations must be consistently known and communicated accordingly.

3.3 Static-Unknown Modelling Approaches

Encountering a static-unknown environment presents the first challenging scenario towards autonomous independence, with all obstacles and objects within the environment problem space being positioned statically. However, information regarding their location, together with the scale of the environment problem space remains unknown to the path-planning algorithm at the time it is applied. Thus, environmental characteristics at a local level must be measured by the UAV itself e.g. using a UAVs mounted sensing abilities. Whilst path-planning algorithms can be implemented at both a local or global environment level, the prevalence of an effective and reliable UAV-to-UAV Controller communication medium is a requirement of global planning where mission changes can be facilitated.

3.4 Dynamic-Unknown Modelling Approaches

The dynamic-unknown environment presents itself as the most challenging of the environment problem space models. In such a model, obstacles and objects within the environment problem space are potentially unknown to the planning algorithm, together with the potential for all obstacles and objects to move dynamically within the environment problem space over time. This dynamically unknown nature of the environment requires interpretation of the environment at a local level, with a reliance on a UAVs ability to sense its immediate environment. However, it is also perhaps the most critical environment model in relation to real world scenarios, with a UAVs ability to avoid collisions with both static and dynamic obstacles being an integral part of delivering future, safe, autonomous operation of UAVs within an unknown and changing environment.

4 UAV PATH-PLANNING

The overall UAV path-planning problem can be deconstructed into two distinct strands, a low-level, and high-level planning problem. In rudimentary form, low-level UAV path-planning focuses primarily upon movement and navigation between two distinct points, within a problem space that is potentially cluttered and/or dynamic in nature. In contrast, at a higher level of abstraction, there is the UAV Routing Problem (UAVRP), which considers the global planning picture, planning routes to serve multiple destinations and/or to be flown by multiple UAVs in an efficient manner. Similar to traditional Vehicle Routing Problems (VRPs), the nature by which this planning and routing problem can be approached will vary greatly depending on constraints and mission objectives.

4.1 UAV Control Theory

In driving towards UAV autonomy, the applied control theory relating to a UAV operation must also be considered. UAVs present themselves as dynamic systems requiring specific and controlled inputs to propel a UAV towards its desired state or location. Where the control problem can typically be solved through the generation of a regulator input that balances the properties and disturbances within a UAV control system [39]. When considering UAV path-planning within environments two key levels of UAV control exist to facilitate autonomous UAV operation, although this base interpretation may extend to further levels of control, depending on the complexity of interaction between the UAV and the environment.

Firstly, there exists the inner loop of control, named the *Flight Controller*, responsible for the stabilisation of the UAV (most notable in rotary UAVs). Ultimately, the inner loop allows the UAV to maintain balanced flight tasks such as hovering and directional or velocity changes, through direct interaction with the UAV motors or control surfaces. Inner loop flight controllers are typically constructed around the 32-bit ARM architecture supporting Inertial Measurement Units and a variety of interfaces [40], to maintain UAV airborne stability.

Secondly, there exists the outer loop of control, named the *Flight Computer*, which fulfils a role comparable to a human pilot and is the focus point at which an autonomous agent would seek to exist. The *Flight Computer* serves as the decision-making heart of the UAV, requesting vehicle state changes from the *Flight Controller*, based on the mission context and data acquired from a variety of available input sensors (GPS, barometric, LiDAR, etc.).

Consequently, the inertial management of the *Flight Controller* is focused upon rectifying a deviation between a UAVs current perceived position and its requested/intended goal position in a controlled manner. The *Flight Computer* provides the ability to deliver a path-planning algorithm to manipulate this deviation, based upon its (sensed) perspective of the environment. The granularity of this manipulation may vary by path-planning algorithm, from delivery of fine-grained control over a UAVs motion and trajectory, to a coarser waypoint approach where the deviation is large and directed solely by the inertial management of the *Flight Controller*.

Thus, when considering the UAV path-planning problem in its naivest form, a *Flight Computer* simply defines a set of Geo-spatial waypoints. A *Flight Controller* manipulates a UAVs actuators to achieve a target waypoint in the most efficient and therefore direct manner. The key caveat in this scenario however is that the *Flight Controller* cannot guarantee the ability to complete a transition (avoiding obstacle collision) to a target waypoint location. A *Flight Computer* must therefore provision for encountering environment obstacles within the set of Geo-spatial waypoints it provides and where an environment dynamically changes in flight, manipulate the supply of Geo-spatial waypoints to the *Flight Controller* accordingly to facilitate a safe flight path.

One critical consideration is the separation of these control systems, whilst it is possible to align both systems under a single hardware platform, process management is critical. The *Flight Computer* is a finite computing resource, both the diversity and potential complexity of path-planning tasks, may result in the potential inability for a *Flight Computer* to return a path solution within a specific computational time-frame. In contrast, the *Flight Controller* is required to be able to continuously process inertial flight data at high-speed to safely maintain

balanced flight. Therefore, separation between these two computational processes is essential to avoid the potential for CPU overload and deadlock states, interfering with a UAVs ability to maintain controlled flight.

4.2 Path-planning

The UAV path-planning problem seeks to discover a collision free path (i.e., collisions between UAVs or between UAVs and environment obstacles and objects) for travel from an initial starting point to a specific goal end point. Typically, within a path-planning problem there are two concepts that must be mastered for the effective discovery of a solution. Firstly, there is problem space construction, whereby the physical environment must be represented in such a manner that its current characteristics, which may change over time, may set constraints and bounds for the secondary process. The secondary process is focused upon a problem space search, a path-planning algorithm aims to search the perceived environment problem space for a planning solution or path based upon its given search parameters.

The effectiveness of a path-planning solution can be gauged on two key components, completeness and optimality. A path-planning solution is judged to be complete if it guarantees the discovery of a solution where one exists. A path-planning solution can also be gauged upon its optimality i.e., whether it is capable of finding the best solution, a typical example of optimality is selection of the shortest path, but alternative metrics such as the safest path may also be appropriate in some scenarios. This survey does not seek to define a comprehensive list of all path-planning algorithms, as such surveys have been previously undertaken and published in literature [11, 17, 19, 20, 41].

4.3 Multi-UAV Systems

Whilst UAV path-planning is focused primarily upon what can be considered as a localised transit problem between two points, the UAVRP considers the wider problem of planning multiple paths across a global environment. The UAVRP is derived from the traditional Vehicle Routing Problem (VRP) [42], a well-defined operational research and combinatorial optimisation problem, born itself from the preceding Travelling Salesman Problem (TSP) [43, 44]. While the TSP focuses upon single visits to a distinct number of locations in an optimised manner, considering path selection against a weighted metric (e.g. distance). The TSP concept is extended further through VRPs whereby routes are sought for a set of vehicles, such that a total cost metric (again e.g. distance) must be minimised across a corresponding set of required location visits.

VRPs in various forms have attracted significant research interest over a long period of time and are reviewed extensively in [45]. UAVRPs are a more recent extension of VRPs, posing significant challenges to researchers as a result of increased complexity. The unbounded capabilities of UAV flight, battery life restrictions, and limited computational power available aboard common UAVs mean that UAVRPs have significantly larger solution spaces than traditional VRPs with tighter constraints on resources available to find acceptable solutions. In addition, limitations in a UAV's ability to sense, interpret and react to environmental obstacles, combined with the unpredictability of external environmental variables such as wind conditions combine to form challenging combinatorial problems constructed around time [31], energy [46], and communication constraints [47].

4.4 UAV Positioning within an Environment

A critical consideration of UAV path-planning algorithms is their ability to identify the positions of a UAV and other objects within an environment and obstacle space. When considering real-world applications of UAVs this is typically achieved using one of the four Global Navigation Satellite Systems (GNSS): GPS (US), GLONASS (Russia), Galileo (EU), BeiDou (China). GNSS systems give a UAV access to current position and altitude data given a sufficient level and number of satellite signals received. The GNSS system provides a UAV with a geospatial

frame of reference across an environment space, facilitating a UAVs ability to hold fixed positions over time and navigate a series of defined waypoint locations [40].

In the literature two distinct approaches are being used to reduce the complexity of the environment space. First, the bounds of the environments problem space are defined, serving to constrain the environment to a fixed area, which may range from several meters [48–50], to several kilometres [51–53]. Second, the frame of reference system applied to the environment is simplified away from a geographic coordinate system (degrees of latitude/longitude) to an abstract coordinate system in which the origin, orientation and the scale of the reference frame can be defined by the user in problem simulations. However, whilst GNSS systems offer a suitable solution for a variety of UAV systems, GNSS is not infallible. Positioning accuracy is delivered through effective satellite signal strength, in the extreme case GNSS signals are susceptible to signal jamming. Within urban areas similar reception issues may be triggered due to the surrounding complexity of the built environment and non-existent in indoor scenarios.

Consideration must therefore be given to how a UAV can independently interpret the environment it operates within, where GNSS and/or communication abilities may be denied. To assist in environment detection there are four types of ranging sensors commonly in use, infrared, laser, ultrasonic and vision sensors [54]. Both laser and ultrasonic sensors are capable of evaluating the physical distance between a sensor module and an object falling within its sensing range. Whilst [37, 51] employ laser range finding to an advantageous effect, [54] identifies loss of signal and lack of stability concerns relating to accurate ultrasonic sensing.

In contrast to the direct evaluation of a physical distance, infrared and visual sensors typically generate an image as a representation of the environment. Such an image or series of images must then be extrapolated through techniques such as Visual Odometry (VO) [55] and Simultaneous Localisation and Mapping (SLAM) [56] to generate environment knowledge. While the SLAM approach aims to construct a globally consistent map of the environment and a UAV trajectory within it, VO is concerned with a localised frame of reference, incrementally estimating the path changes within an environment based on pose-by-pose transformations in an image [57].

When considering the abilities of an autonomous UAVs path-planning process. There should exist the ability to accurately verify a UAVs location within the global environment space, whilst also provisioning for the ability to directly sense the potential for a dynamic and changeable events within the local environment space to facilitate safe path-planning and navigation.

5 TAXONOMY

The proposed taxonomy in this section aims to help readers identify the key differences within the various environment decomposition strategies that facilitate the path-planning approaches proposed in the literature, with the aim of guiding future research directions. In addition to the four environment classification characteristics proposed in Section 3, a further eleven attributes common amongst the literature are identified, representing commonalities between environments, UAVs, and proposed path-planning solutions. These attributes can be further categorised into four distinct classes focusing upon the environment complexity, strategies for the approach taken toward environment representation, considerations regarding the type and application of the UAV itself and finally the time considerations of the applied path-planning solution. These classes, and the attributes that characterise them, are depicted in Figure 11. Seventy such papers have been considered within this survey and these are listed with their attributes catalogued in Table 4.

Our proposed taxonomy classes and attributes, depicted in Figure 11, are explained below.

- **Environment Complexity related attributes:**

- (1) *Static-Known (SK)* – All obstacles and objects within the problem space are both static and known to the path-planning algorithm.

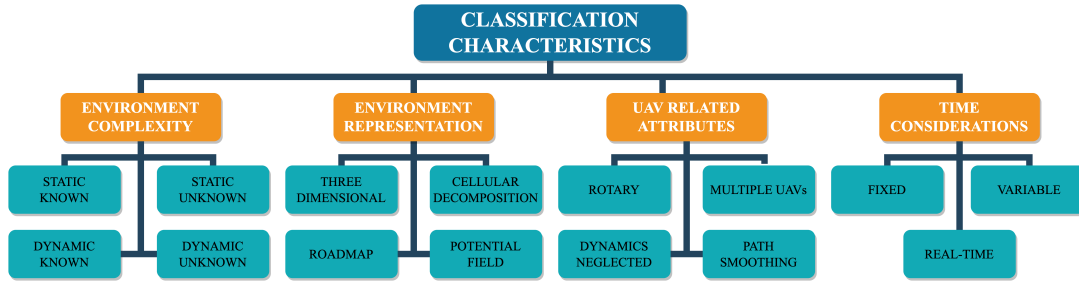


Fig. 11. Identified Classes and Attributes of Reported UAV Path-planning Approaches

- (2) *Dynamic-Known (DK)* – Although obstacles and objects within the problem space are mobile, their movement is known to the path-planning algorithm.
 - (3) *Static-Unknown (SU)* – Obstacles and objects within the problem space remain static, however their relative positions are unknown to the path-planning algorithm.
 - (4) *Dynamic-Unknown (DU)* – All obstacles and objects within the planning space are both mobile and unknown to the path-planning algorithm.
- **Environment Representation related attributes:**
 - (1) *3D* – Able to plan a UAVs path through a 3D environment (as opposed to a 2D environment).
 - (2) *Cellular Decomposition (CD)* – Applies a cellular decomposition strategy to generate a problem space.
 - (3) *Roadmap (RM)* – Constructs the problem space as a roadmap representation of the environment.
 - (4) *Potential Field (PF)* – Represents the problem space environment as a continuous artificial potential field.
 - **UAV related attributes:**
 - (1) *Rotary Wing (RW)* – Paths are planned in respect of rotary-wing UAVs (as opposed to fixed-wing).
 - (2) *Multiple (Mu)* – Planning considers a fleet of UAVs (as opposed to a single UAV).
 - (3) *Dynamics Neglected (DN)* – The specific flight dynamics and abilities of the UAV are neglected.
 - (4) *Path Smoothing (PS)* – Path-planning applies a smoothing mechanism to generated paths.
 - **Time considerations related attributes:**
 - (1) *Fixed (Fx)* – Path-planning uses fixed UAV velocities or time-steps in the planning process.
 - (2) *Variable (Vr)* – A UAVs velocity and flight time are optimisable by the planning process.
 - (3) *Real-Time (RT)* – The planning problem solution is solvable and implementable in real-time.

To enable an effective evaluation of current environment modelling trends within UAV path-planning research areas, the selected papers in this survey are limited to the preceding 5-year period, unless a paper is providing substance to the wider field of study. Such a selection criterion allows for the successful collation of a series of high-quality research papers, reflecting recent trends and research directions within this evolving research field.

In addition to the taxonomy defined above, the specific UAV application for each paper's contribution is also represented, by defining the prospective *role* of the UAV and the *target application* usage of the proposed path-planning algorithm. UAV roles include the following: *General* which refers to a non-descriptive UAV transit application; *Delivery* which provides a UAV service based on goods delivery; *Surveillance* which aims to ensure the monitoring of a specific entity/environment; and *Communication* which aims to maintain reliable communication links. The target applications of the surveyed path-planning algorithms can be split into 4 classes. *Exploration-based algorithms* where UAV paths are planned based upon environment influence/discovery; *Avoidance-based algorithms* aim to generate an obstacle free path within an environment; *Coverage-based algorithms* in which a UAV path is planned to deliver a specific level of environment coverage, through UAVs placement strategy; and *Recharge-aware algorithms* in which UAVs path is planned to facilitate in flight or operational recharging.

Table 3. Summary of the taxonomic classification of 68 selected papers (1-4: taxonomy attribute number)

		UAV Role				Algorithm Application												
		General	Communication	Surveillance	Delivery	Exploration		Avoidance		Coverage		Recharge						
Paper	Year	Target Application	Environment Complexity				Environment Representation				UAV				Time Consideration			
			SK	DK	SU	DU	3D	CD	RM	PF	RW	Mu	DN	PS	Fx	Vr	RT	
[58]	2021	Coverage			•								•					•
[58]	2021	Coverage			•								•					•
[59]	2021	Coverage	•										•					•
[60]	2021	Exploration					•		•				•					•
[61]	2021	Avoidance	•										-					•
[62]	2021	Coverage	•										•					•
[63]	2021	Coverage	•										-					•
[47]	2021	Coverage	•										•					•
[64]	2021	Exploration					•		•				•					•
[53]	2021	Avoidance					•		•				•					•
[65]	2021	Coverage					•						•					•
[66]	2020	Exploration					•						•					•
[5]	2020	Coverage			•								•					•
[67]	2020	Exploration	•						•				-					•
[68]	2020	Avoidance	•						•				-					•
[31]	2020	Coverage	•						•				•					•
[69]	2020	Coverage		•					•				•					•
[46]	2020	Coverage	•						•				•					•
[52]	2020	Coverage					•		•				-					•
[32]	2020	Coverage	•										•					•
[70]	2020	Avoidance			•				•				•					•
[71]	2020	Coverage			•				•				•					•
[72]	2020	Coverage					•		•				•					•
[73]	2020	Coverage					•		•				•					•
[74]	2020	Coverage	•						•									•
[49]	2019	Avoidance	•						•									•
[75]	2019	Coverage	•						•				•					•
[50]	2019	Exploration	•						•				•					•
[76]	2019	Coverage			•				•				•					•
[77]	2019	Avoidance	•						•				-					•
[4]	2019	Coverage	•						•				•					•
[78]	2019	Exploration			•				•				•					•
[37]	2019	Avoidance					•		•				•					•
[79]	2019	Avoidance	•						•				•					•

Paper	Year	Target Application	Environment Complexity				Environment Representation				UAV			Time Consideration		
			SK	DK	SU	DU	3D	CD	RM	PF	RW	Mu	DN	PS	Fx	Vr
[80]	2019	Avoidance				•	•		•					•		•
[51]	2019	Avoidance			•			•						•		•
[81]	2019	Coverage	•						•					•		
[82]	2019	Coverage		•				•						•		•
[83]	2019	Avoidance				•		•		-		•		•		•
[84]	2019	Exploration			•			•				•			•	•
[85]	2019	Avoidance	•						•			•		•		•
[86]	2019	Avoidance	•				•		•				•	•		•
[48]	2019	Avoidance	•				•		•					•		•
[87]	2019	Coverage	•				•	•		•	•			•		•
[88]	2019	Avoidance	•					•		•			•	•		•
[89]	2019	Avoidance		•			•	•			•			•		•
[90]	2019	Recharge		•					•		•				•	•
[91]	2019	Recharge	•				•		•		•			•		•
[92]	2019	Avoidance	•					•						•		•
[9]	2019	Recharge	•						•		•			•		•
[54]	2019	Avoidance			•			•		•			•			•
[93]	2019	Avoidance	•					•					•		•	•
[94]	2019	Avoidance			•		•		•				•	•		•
[29]	2018	Avoidance	•						•		•		•	•		•
[95]	2018	Avoidance			•				•			•		•		•
[96]	2018	Avoidance			•			•		•	•				•	•
[97]	2018	Avoidance				•		•		•	•				•	•
[98]	2018	Coverage	•					•		•		•		•		•
[99]	2018	Avoidance	•					•								•
[100]	2018	Coverage			•			•		•	•			•		•
[101]	2018	Coverage			•			•		•		•		•		•
[102]	2018	Coverage			•			•		•	•				•	•
[103]	2017	Avoidance				•		•		•		•		•		•
[104]	2017	Coverage	•					•		•	•	•				•
[105]	2017	Avoidance	•				•	•		•			•	•		•
[106]	2017	Avoidance			•				•	-		•	•	•		•
[107]	2017	Avoidance			•		•	•		-		•		•		•
[33]	2017	Avoidance			•				•	•				•		•
[38]	2017	Avoidance				•				•	-			•	•	•
[108]	2017	Avoidance	•					•		-		•		•		•
[109]	2017	Coverage			•			•		•		•		•		•

6 CRITICAL REVIEW OF THE RECENT LITERATURE

This section discusses and analyses the most important recent works and directions concerning UAV path-planning solutions published in the literature, based on the proposed taxonomy outlined in Section 5. We will also present a comparative study and summary of main characteristics of these works based on the attributes defined above.

The reviewed papers in this survey have been categorised in Table 4 based on the defined taxonomy attributes. Where such a numbered attribute is addressed by a particular work the respective column is marked with an ‘•’ in the table. An empty column cell indicates that the paper does not address a particular attribute; except for the ‘Rotary’ attribute where ‘-’ is used to define a paper that does not clearly identify its use of fixed or rotary wing UAVs.

6.1 Environmental Complexity

Across the range of papers considered in this survey, Table 5 summarises the complexity of the environment the contributions of these papers deal with. Unsurprisingly, nearly half of all papers reviewed seek to plan paths within a static-known environment, where the planning agent is fully informed of the environment’s state at all times. Whilst this class of environment poses the most tractable problems for researchers to approach, an over-reliance on static-known environments presents problems with regards to the scalability of reported solutions to other, more complex, classes of environment. Indeed, the authors of numerous papers expressed their desire to further extend their research, through the expansion of their static-known environment based solution toward dynamic and unknown environments [68, 105]. Whilst the literature demonstrates positive progress toward future dynamic-unknown environment planning (19.1%), the main body of reviewed work (75.0%) still only considers environments where the objects and obstacles within them are static in nature.

Consideration of an environment’s overall complexity can be viewed as a key scoping boundary when investigating a path-planning problem. Whilst the ultimate long-term goal of many authors may be the successful navigation and completion of a series of tasks by a UAV in a dynamic unknown environment, most work is targeted and evaluated only in terms of static known environments, the least complex class. It is, however, worth considering how advantageous the presence of static known freely available environment data may be. As an example, [98] conducts a path-planning task over a pre-known set of locations derived from a wider area search by a traditional airborne survey method. An optimised and efficient solution is sought for sampling the radiation levels in areas missed/unrecorded from the larger area survey. This allows a planning solution to be developed for distinct number of locations within an environment of limited size, using the cost efficiency of a small-scale deployable UAV or fleet.

Approaching a static known environment from the alternative direction of UAV exclusion was the focus of [85]. This work uses geofenced locations combined with a visibility graph representation of the environment to exclude UAV activity from a specific no-fly area and restrict flight to defined paths across the environment in much the same way as human pilots avoid restricted airspace and utilise air corridors. This method is both simplistic to implement and has the potential to significantly reduce the danger presented by UAVs in the vicinity of, for example airports. The technique is, of course, highly dependent upon the accuracy and availability of a GPS signal, along with knowledge of the location, size and shape of no-fly areas *a priori*.

Frequency of the planning task must also be of consideration, whilst UAV target locations are both static and known in [62], the action of path-planning introduces an unknown quantity, namely that not all locations must be visited by the UAV in a path-planning round. Therefore, as the data collection requirements by location change, a new path-planning process must be conducted at the start of each collection round.

Where dynamic known environments are considered, the ability to maintain a complete knowledge of all dynamic obstacles within the problem space at any juncture is critical. As such, a suitable communication strategy

is identified as a fundamental for the dissemination of knowledge across the problem space, facilitating the ability to plan effectively within a changing environment.

The work presented in [90] adopts a centralised approach to a communication model by proposing a cloud-based drone navigation framework to facilitate the coordination of multiple UAVs across an environment based on the UAVs' current charging state and current charger availability, attempting to reduce flight and waiting time across the network. To achieve this, it is important to concurrently communicate UAV states across the network to enable a centralised cloud-based path-planning decision making process, with the subsequent planned paths communicated back to UAVs.

Conversely, [89] follows a decentralised communication approach by applying a coupling-degree-based heuristic of prioritized planning order, established through UAV-to-UAV communication method. Planning for each UAV path is sequential, based upon a priority order. Each UAV, in turn, constructs its own path based on its knowledge of environment obstacles, together with knowledge of the planned paths of the preceding UAVs in the priority order.

While intercommunication is critical for multi-UAV path-planning within a known environment, in unknown environments - either static or dynamic in nature - the ability of a UAV to build local environmental knowledge independently is vital. By contrasting four common sensing approaches (i.e., infrared, laser, ultrasonic or visual) [54] identified laser range sensing as being a resilient, lightweight, low power and cost-effective solution for environment sensing, a conclusion also supported by [37]. However, according to the reviewed articles in this survey it is not uncommon to encounter reference to the use of virtual sensor data [96, 103], or planning based upon speculative range detection information [51, 66] where the data collection sensor used, cannot be evaluated to a specific sensor type or specification. While UAV path-planning algorithms in the literature may be agnostic towards the specific technology by which distances and obstacle geometry are obtained power, weight, or cost constraints on hardware may mean that some degree of inaccuracy must be tolerated by path planners in real-world scenarios.

A UAVs ability to independently harvest local knowledge of its surroundings and influence its path-planning decisions can be seen as critical when encountering an unknown environment. However, UAVs may also be used to construct knowledge of an environment for a wider purpose. For example [58] abstracts its approach into two tasks, an initial environment evaluation task followed by a planning task. A preliminary UAV flight follows a pre-defined flight path to identify broadcasting sensor locations, facilitating the extraction of an overall environment knowledge from an initially unknown state. A reinforcement learning approach is subsequently applied to plan future optimised visiting strategies.

Even in environments that are dynamic in nature or where knowledge is incomplete, there will likely be some elements that are always constant. This idea is embraced in [95] where an alternative two stage planning process is proposed. The first stage defines an offline planning strategy that pre-plans a route based upon the known static obstacles within a problem space. This path can then be further augmented in the second stage, which occurs in-flight. In this second stage, an online planning approach based upon the environment's dynamic obstacles and their interactions with on-board sensors is used to adapt the earlier path.

6.2 Environmental Representation Strategies

While the previous subsection devotes significant attention to the overall environment complexity, this subsection investigates the ability to represent a physical environment as an interpretable problem space. When considering the modelled environment, 39.7% of the studied papers acknowledge the complexities of path-planning within a 3D environment and are focused upon developing a 3D path-planning solution as shown in Table 6. However, a number of the surveyed papers discuss strategies to reduce the dimensional complexity of UAV path-planning

Table 5. Distribution of Reviewed Work by Environmental Complexity

Environment Complexity	Papers
Static-Known	48.5%
Dynamic-Known	5.9%
Static-Unknown	26.5%
Dynamic-Unknown	19.1%

Table 6. Distribution of Reviewed Work by Environmental Representation Strategy

Environment Representation Strategy	Papers
3-D Environment	39.7%
Cell Decomposition	66.2%
Roadmap	32.4%
Potential Field	1.5%

problems. Specifically, these conversion methods seek to flatten the problem space, reducing computationally expensive 3D path-planning to a more manageable 2D planning problem.

The most simplistic of these flattening approaches are altitude fixing strategies such as [93], which constrain a UAVs operations to a single altitude to avoid three dimensional considerations. This altitude fixing approach is extended further in [71] by constraining multiple UAVs to fixed but unique flight altitude levels, thus negating the possibility of collisions due to the resulting layered approach. In some scenarios this altitude separation may prove impossible to maintain due to topography, weather, sensor limitations or mission objectives.

In [77], the authors proposed to initially generate a computationally less expensive 2D path, then applying a conversion heuristic to translate the generated 2D path onto the 3D environment space using an approach that both balances a UAVs ability to vary its altitude, and the complex topographical changes the environment presents.

Approaching the 3D path-planning problem from an alternate viewpoint, [109] maintains an altitude fixing policy similar to those discussed previously, however, the UAVs' placement is performed using a complex 3D urban environment where the existence of a direct line of sight between the UAV and end user is a fixed requirement. Offering a unique approach in forming an environment representation [94] introduces 3D obstacle avoidance map generation, directly translating a 3D map from a 2D colour image of the environment. This approach has the potential to enable efficient translation of large-scale areas into a navigable environment, and certainly holds merit for further exploration. Even where 3D environments have been studied, limited considerations only were given towards the earth's curvature and the resulting 3D distance problems, all of which are essential factors when considering high altitude and long distance UAV path-planning as highlighted in [52, 79].

Based on the surveyed papers, three key approaches are applied for the deconstruction of a physical environment into a suitable problem space representation that provisions the extraction of environment state information for use by planning algorithms. There exists a clear preference amongst these papers (66.2%) for the adoption of a cell decomposition approach. Whilst popular, the centralised management of a large problem space can be viewed as computationally expensive, with the complexity of the overall planning problem increasing heavily as the granularity of the decomposition increases i.e. as cell size decreases. This complexity is further increased where the dimension state of a problem space is expanded from two dimensions, as shown in Figure 2, into a three-dimensional problem space, as shown in Figure 3. Thus the application of dimensional reduction strategies discussed above are a commonly encountered approach for reducing an environment's computational complexity.

Nevertheless, the use of approximate cell decomposition strategies is both well suited and prominent within the reviewed works. Bio-inspired explorative planning approaches, such as Ant Colony Optimisation (ACO) [108], whereby individual ant agents randomly traverse the environment cells until discovering a goal location, which they disclose to other ants using a so-called pheromone communication method that enables reinforcement of an optimal path over time. Along with Particle Swarm Optimisation (PSO) [93], in which a population of particles represent candidate solutions and changes are guided by both the individual and global best solutions,

require consistent access to wider environmental knowledge. As a result, these techniques are well suited to environments deconstructed using an approximate cell decomposition approach, with key path-planning information maintained centrally for each cell location. A significant challenge, however, is the ability to manage the scale of such environment knowledge, over a large problem space. The scale of this challenge highlights the management of the computational search resource as a critical factor in planning approaches that embrace approximate cell decomposition.

Whilst cell decomposition strategies are revealed as the most prevalent environment deconstruction technique (66.2%), roadmap approaches are also prominently represented (33.4%). The use of roadmap graph generation presents an established approach in terms of reducing the depth of an algorithm's search, enabling a commensurate reduction of the overall search space explored by a planning algorithm. This offers a guaranteed set of edges within a problem space that serve as available transit paths between graph nodes. The generation of such a roadmap requires an implicit knowledge of the environment itself, to enable suitable placement of uninhibited nodes within a roadmap. This knowledge allows the visibility between current and future nodes to be assessed effectively, verifying whether node placement would be successful. Where a problem focuses upon multiple UAVs or an environment that is dynamic in nature, reliance is again placed on centralised information, control, and sharing. As a result, finding innovative ways to facilitate the transition from a centralised model towards a UAV-centric, dynamic planning approach is a key research challenge to further developing roadmap approaches for fully autonomous operation.

The use of an artificial potential field (APF) method to model the whole environment problem space is limited to a single paper and thus cannot be seen as influential. While a theoretical APF allows a UAV to independently plot its path across an infinite environment, the practical application relies heavily upon a UAV's capacity to effectively extract the wider environment data. Although the use of APF as a sole path-planning approach is limited, an alternative APF approach proposed in [66] recommends applying the principles of APF in a more localised manner. This UAV centric approach uses mounted proximity sensor data, allowing a UAV to define and interpret its own relationship with the surrounding environment in real-time. Such approaches offer scope for the exploration of a variety of combinatorial path-planning approaches, whereby real-time obstacle avoidance control is supplied through a local APF supplementing a wider environment path-planning framework. However, [60] highlights that limitations in the current state-of-the-art with respect to on-board sensors indicate an inherent inability to guarantee UAV safety in regard to the successful detection of dynamic obstacles. This means that future work towards fully autonomous UAV operation may require a centralised detection system for the successful tracking of dynamic obstacles, in the absence of significant advances in sensor technology.

6.3 UAV Related Attributes

As shown in table 7, after exploring the literature with particular focus upon the operational characteristics of the UAVs themselves, we have found that there is a notable preference towards the application of rotary-wing UAV technology (67.6%) to path-planning scenarios. Thus, researchers clearly favour the perceived benefits offered by rotary-wing UAVs, notably the ability for vertical take-off and landing, which reduces the physical footprint required for ground-based interactions such as recharging and control. Similarly, the commercial availability of rotary-wing UAV solutions is plentiful, and multi-rotor designs offer an increased degree of redundancy against rotor/motor failure, with most models at least able to land in a controlled manner in the event of a single rotor/motor failure. Perhaps most appealing of all is the stationary aerial positioning ability provided by rotary-wing UAVs, which enables the exploration of a wider variety of use cases.

Such stationary or low speed placement is especially beneficial when considering the placement of mobile aerial base stations [104] and similar communication link enabling applications [46, 71, 109]. In particular, the use of rotary-wing UAVs is prevalent within a broad range of surveillance tasks [75, 98, 100, 110], together

with industrial inspection activities [111]. Both classes of scenario are benefited by the precision operational positioning of a rotary-wing UAV. However, the surveillance model scenario is also tackled effectively in [74] by exploiting the benefits of high altitude, long endurance flight given by fixed-wing UAVs.

Unusually, [64] openly defines a military use case, describing multiple fixed-wing UAVs performing search & attack missions within a battlefield environment. Although there are many potential military applications for controlled or autonomous UAVs, most authors do not explicitly discuss or address the challenges inherent in such scenarios in the literature. Other counterexamples include [74, 93, 99], which all focus on fixed-wing path-planning while notably referencing use cases with clear military applications such as radar avoidance.

The use of multiple UAVs within an environment is also an emerging research field, seeking to expand the scope and scale of problems for which UAVs can offer a solution. 45.6% of the papers reviewed declare an interest in multi-UAV planning problems, most notably when considering path-planning in relation to the effective placement of multiple UAVs within a single physical environment based upon a given communication scenario [87, 104]. Similarly, once the availability of multiple UAVs is envisioned, both [69, 82] seek to minimise the number of UAVs required to serve the number of users encountered and optimise trajectories to effectively facilitate data delivery in vehicular networks where vehicle presence varies.

The wider characteristics of the UAV may also contribute to the overall mission time as highlighted in [59] which discusses the ingrained relationship between UAV and operator. Whilst UAV autonomy and optimisation are sought, overall mission time remains influenced by the external UAV operator's requirement to setup and initialise all UAVs. Thus, in a multi-UAV system the time spent by the operator to launch and retrieve UAVs may detrimentally impact on overall mission time.

Intriguingly, whilst there is significant interest in multi-UAV path-planning, there is a reluctance with the proposed planning solutions to consider UAV dynamics or path smoothing approaches. Approximately 85% of multi-UAV papers fail to recognise either UAV dynamics or smoothing approaches, highlighting an area of future research that requires greater attention to understand the potential complexity of a combined approach.

Among all the reviewed papers, 50% neglected the flight dynamic considerations of the UAV itself. As highlighted in Section 4.3, the combinatorial complexity of intrinsic UAV dynamics makes UAV path-planning significantly challenging. Indeed, either under or over-constraining a UAV's dynamic ability within a path-planning algorithm may prevent the desired translation from the planned path into the real-world physical ability of UAV technology to follow the planned path accurately. This point is demonstrated in [98] where an effective path-planning solution for radiation dose monitoring following the Fukushima nuclear disaster is sought. Given a set of grid locations to visit, [98] applies both a flood-fill and 2-opt algorithm together as a simplistic combinatorial solution. First, this solution clusters the target locations using a flood-fill algorithm to extract a series of sub-route paths, then connecting paths between sub-routes are formed using a 2-opt algorithm. Computationally the combinatorial approach applied by [98] fails to deliver an optimal path result, when compared to a baseline path implemented using the existing 2-opt approach on its own. However, during operational testing using a physical UAV, the shorter 2-opt planned route was completed four minutes slower than the proposed combinatorial route. This paper provides a clear illustration of the potential inability of a physical UAV to follow a pre-planned route that was calculated without regard to its flight characteristics, attributing this problem to the large number of high energy turns ($\geq 90^\circ$) undertaken in flight. It is envisaged within this paper that a greater distance is flown due to the increased number of path corrections required, although the results are highly dependent on the distribution of locations within the environment.

The problem of UAV path smoothing is commonly approached in two different ways. A path can be smoothed at creation, by considering UAV flight dynamics as part of the path-planning algorithm. Alternatively, a path can be smoothed retrospectively by applying a transformation to a path generated by a path-planning algorithm that makes no such consideration. It is likely that smoothing during path creation will be more computationally expensive, but there may be some generated paths for which it is impossible to smooth into a flyable route *post*

hoc. The importance of path smoothing consideration is acknowledged in 25% of the surveyed papers, with both classes of path smoothing approach emerging as areas worthy of further research.

Planning a path across a 3D environment using an RRT solution, such as [48] which highlights the explorative nature of RRT, must also consider the flight capabilities of a UAV when generating new nodes within the tree. As such, the generation process considers UAV flight height, step distance and pitch within the planning criteria, when provisioning for a new node placement. Whilst [48] actively considers UAV dynamics, it is conceded that even where a guiding metric is applied, the placement of new path nodes remains random. Therefore, the approach remains unlikely to yield an optimally smoothed path solution. To compensate for this, a midpoint joining strategy is proposed to refactor adjacent edges within a path whose adjoining angle is less than 90° .

Alternatively, where UAV dynamics are not directly considered, as in the Voronoi diagram roadmap creation approach presented in [29], a path is selected based on mission criteria. Subsequently, the directional changes between path edges are considered through the application of a path smoothing capability using B-spline curve fitting, although such a curve fitting approach is based solely on the perceived benefit of a curved transition between graph edges and not the UAV's ability. Both [29, 48] present successful post planning smoothing strategies, nonetheless both demonstrate their dependence upon the available environment information to facilitate the safe and available alteration in an existing pre-planned path.

Table 7. Distribution of Reviewed Work by UAV Related Attributes

UAV Related Attribute	Papers
Rotary-Wing UAVs	67.6%
Multiple UAVs	45.6%
UAV Dynamics Neglected	50%
Path Smoothing Applied	25%

Table 8. Distribution of Reviewed Work by Path-planning Time Considerations

Time Consideration	Papers
Planning time variables are fixed	77.9%
Time variables are optimisable	17.6%
Real-time application	66.2%

6.4 Time Considerations

The UAV path-planning problem has been shown as an NP-hard problem if the velocity of a UAV is unbounded [112], therefore it is unsurprising that 77.9% of the reviewed papers selected to fix the UAV's velocity, as shown in Table 8. The act of fixing a UAV's velocity allows a UAV's flight time between destinations to be pre-calculated prior to the commencement of a planning action, thus aiding in the reduction of the overall complexity of the optimisation problem. Conversely where a UAV's velocity is variable, both its time and distance coverage attributes themselves become optimisation variables within the planning problem. Whilst this approach was only identified within 17.6% of the papers surveyed, those papers that did were consistent in focusing upon bio-inspired algorithms [68, 84, 97] along with the application of an artificial potential field [113] to the environment. Such strategies facilitate the UAV's velocity to be influenced based upon its environmental surroundings, ultimately presenting a more realistic approach to how a UAV would operate, and a more concurrent representation of a UAV's overall flight dynamics problem.

One key attribute considered when searching for a path-planning solution is the ability to effectively demonstrate its real-time application potential. Whilst it was possible to identify that 66.2% of the reviewed papers express such an ability to plan a path solution both quickly and efficiently, it remains a challenge to enumerate such responses into a comparable efficiency metric. Those contributions that clearly define real-time application potential are those that aim to extract environment knowledge independently from the problem space to allow informed path-planning decision making. Such works demonstrate a consistent ability to be applied in

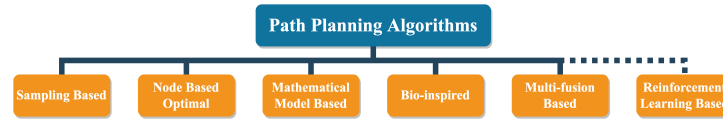


Fig. 12. Path-planning algorithms classification expanded from [114]

a real-time manner, through their use of laser range finding sensors [37, 51] or via independent assessment of live communication data [72, 73]. Therefore, there exists a clear direction to deliver real-time planning solutions based upon the interpretation of real-time environmental changes or challenges.

6.5 UAV Path-planning Approaches

Articles reviewed in this survey are representative of the diverse range of approaches exercised when tackling the UAV path-planning problem. Because of this broad range, the application of a categorisation model reflecting the planning approaches taken allows trends and research directions to be more readily identified. The path-planning algorithms within this survey have been categorised into six distinct strands, which are shown in Figure 12. This classification structure expands upon an existing five strand model for algorithm classification introduced in [114] through the addition of a new category.

In Figure 12, in addition to the five categories of path-planning algorithm identified in [114], a new algorithm category is introduced for reinforcement learning based algorithms to account for path-planning decision making approaches within the literature that adopted a reinforcement learning approach. Each category is discussed further in the forthcoming sections. Application of this classification model to the surveyed articles within this paper is shown in Figure 13, which numerically proportions the papers into their respective algorithm category.

6.5.1 Sampling-based Algorithms. Sampling based algorithms are constructed around a required prerequisite of problem space knowledge, such that obstacle or free space environment information can be sampled and interpreted by a planning algorithm. Encountered within this survey are two distinct approaches to sampling-based planning by which the approach can be either passive or active in nature. Active planning approaches, such as RRT [34] and APF [38], can independently achieve a feasible path solution through their own path processing abilities. Contrasting with passive planning approaches, the generation of a Voronoi diagram [29] or probabilistic roadmap [33] provides only a framework of feasible paths, from which a supplementary search algorithm is required to define a suitable path.

By applying a sampling-based approach in its most simplistically passive form [33] independently generates a probabilistic roadmap upon encountering a static obstacle within the environment. This process involves generating many randomly placed nodes across the environment's free space, again successful placement is based

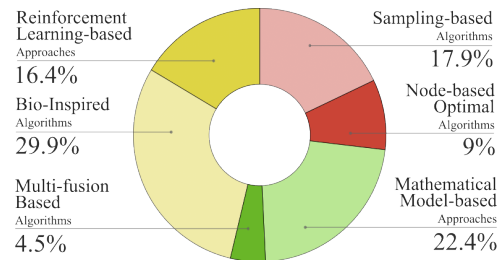


Fig. 13. Distribution of path-planning approach adoption over the reviewed papers

upon a prior requirement of free space knowledge. While several such nodes can be easily connected for path generation, such an approach still requires a graph search algorithm to be implemented for finding an effective path across a problem space.

Within the articles surveyed the most encountered sampling-based method is RRT (64%) or a directly derived descendant of it, as an active planning approach RRTs independently plan their own path across a problem space. Whilst all RRTs follow broad principles regarding their exploration of an environment, the individual management of an RRTs exploration parameters offers a diverse range of freedom and flexibility on how the explorative tree nodes can be placed within the environment, paving the way for continued research advancement and improvement.

The existing RRT algorithm [34] was further developed in [80] to explore a 3D problem space by adding an artificial potential field method into the algorithm design to improve the convergence rate upon a target destination, thus reducing unnecessary computational exploration of the environment. To handle interactions with dynamic obstacles in flight, [80] marks transit nodes in its environmental model as impassable. When such transit nodes become impassable, the existing path is modified through the addition of an interim node. Interim nodes are placed at a safe passable location between the current position and the target destination, with a suitable path being planned that travels through the interim node and on to the target destination. An effective path smoothing method is also introduced in this work to reduce the twists and turns formed in the planned paths, which is a common issue identified in all RRTs by virtue of the random placement of new tree nodes.

Whilst parameters can be modified to dictate the placement of tree nodes and ultimately used to define the explorative nature of RRT algorithms, paths are consistently formed from origin until a destination is reached. Applied from the opposite direction (i.e., destination to origin) [49] presents a Modified-RRT (M-RRT) path-planning solution, employing a reverse path search conducted across an existing RRT three dimensional tree structure. Applied as a greedy strategy, M-RRT has achieved good real-time performance and proven its ability to solve real-time 3D route problems.

Employing a novel approach to the modelling of a UAVs path through an environment, [32] presents a concept by which a UAVs path is modelled upon a chained mass-spring-damper system. In this system, path waypoints are represented by masses, with spring forces between adjacent waypoints used to maintain a waypoint spacing arrangement. Through a series of iterative steps [32] continually deconstructs both the path and environment into a series of Voronoi diagrams, applying an additional spring force to each of the original path waypoints, with the spring force pulling toward the centroid of each respective Voronoi polygon region until a convergence occurs upon a final waypoint location. The results obtained are characterised as striking a good balance between optimality and runtime, with the ability to generate near optimal results, whilst running quickly enough for field-based implementation.

6.5.2 Node-based Optimal Algorithms. Established node-based algorithms such as Dijkstra [115] and A* [116] are well-recognised for finding optimal routes within a graph structure. In this survey, the use of node-based optimal algorithms is somewhat limited in the articles reviewed, with only 9% of papers applying this class of approach. In these papers, we distinguish the adoption of two key approaches, either an approach aiming to enhance an established well-defined algorithm, or conversely where an existing algorithm is implemented as a component part within a wider path-planning heuristic.

The authors of [90] enhanced Dijkstra's shortest-path algorithm by considering additional parameters, namely the waiting and charging times, within the environment's fast charging machines, augmenting the more traditional end-to-end shortest path calculation. By combining both an existing node-based optimal algorithm together with a novel planning methodology, [89] generates feasible paths for multiple UAVs using a heuristic prioritised planning approach. This later enhances multi-UAV planning through a new implementation of cooperative planning capability, supporting a UAV swarm scenario at a reduced computational cost, whilst applying a

traditional sparse A* algorithm to plan each individual UAVs path. In [29], a similar approach is adopted to implement an improved Voronoi diagram graph generation strategy to deconstruct the environment, once implemented the traditional Dijkstra algorithm is used for shortest path generation across the problem space.

One challenge observed in node-based algorithms relates to the predefined nature of the graph itself, limiting the applicability of such algorithms to dynamic-unknown scenarios. By applying a Voronoi diagram to deconstruct the environment, [29] highlighted the impractical computational cost required for graph re-construction and thus within a dynamically changing environment, continued Voronoi diagram reconstruction becomes infeasible. To the best of our knowledge, no work has been completed on adapting Voronoi techniques to dynamic or unknown scenarios.

6.5.3 Mathematical Model-based Algorithms. Mathematical model-based approaches represent 22.4% of the articles reviewed and apply mathematical formulation capable of tackling the complexity of UAV path-planning. This is certainly an emerging field, with significant interest in Mixed-integer Linear Programming (MILP) approaches that seek to reduce a problem's complexity through bounding the diverse number of possibilities presented by a variable, to integer values favouring a reduction in the overall problem complexity.

In [81], the authors addressed a mixed vehicle routing problem, combining both UAVs and road vehicles, by formulating it as a MILP problem. To resolve the proposed MILP, they applied a standard solver, although they recognised the limited performance abilities of such solvers, and noted the requirement for an additional metaheuristic approach. One weakness identified by this work is the inability of MILP approaches to obtain optimal solutions for large instances (i.e., sets of routing destinations) without the application of such a metaheuristic approach. These concerns relating to the time complexity of NP-Hard techniques are also shared by the authors of [91]. Proposing an iterative algorithm for solving a non-convex mixed integer optimisation problem through the application of a block coordinate descent and successive convex optimisation technique, [102] partitions the optimisation variables into three blocks that are alternately optimised during each iteration.

Both [31] and [4] implement metaheuristic solutions conceptualised around the branch-and-bound approaches for solving discrete programming problems. [31] implements a branch, reduce and bound approach supplemented with a low complexity successive convex approximation method to define a UAV trajectory for serving the maximum number of IoT devices. Branch and bound approaches relax the initial discrete problem, branching alone would amount to a brute force approach for solving a problem which is infeasible, thus a bounding strategy is applied by dividing the solution space into subsets. A subset's relative upper and lower bounds are obtained, the resulting candidate solutions can be pruned, eliminating those bounds that will not contain an optimal solution. [4] further expands the basic principles of a branch-and-bound algorithm, presenting a branch-and-price concept, to fulfil a mixed UAV and Truck routing problem. Introducing a pricing sub-problem, designed to distinguish between the differing paths of UAV and Truck to deliver a customised pruning and extending strategy. The evaluation results presented in [4] highlight that the proposed branch-and-price concept outperforms Gurobi MIP solver in terms of finding the optimal path solutions where the average time for generating such optimal solutions is 2 hours. Where MILPs presented as a non-convex problem they become infeasible to solve, with computation time rising exponentially as the number of assigned integer values increases. Therefore a heuristic approach is required to 'convexify' [31] the problem and provide a low complexity solution.

Alternatively, by adopting a non MILP approach [74] presents Quintic polynomials for use in UAV trajectory generation due to their ability to provide complete solutions to complex problems whilst requiring few inputs. A more simplistic mathematical approach is also applied by [37] using a nonlinear evaluation of sensed Lidar environment data to enable appropriate UAV attitude control movement.

Similarly, Optimal Transport theory offers a mathematical framework for the simultaneous mapping of multiple entities within an environment space, from one set of arbitrary locations to another that minimises the total transportation cost of doing so [117]. Distance is a common metric for optimisation, although other problem-based

metrics may be sought as well. [118] models a semi-discrete optimal transport problem whereby the total system data service is sought to be maximised in which a continuous distribution of user UAVs is mapped to a discrete distribution of base station UAVs. Tackling a similar wireless communication problem from the perspective of an energy related time constraint, [119] proposes a gradient-based algorithm wherein the communication user distribution as well as UAV flight time and locations are considered to optimally partition the environment space, leading to a significantly higher service fairness among users. Whilst optimal paths and placements are defined, consideration must be given to both the achievability and calculability within a dynamic environment space.

6.5.4 Bio-inspired Algorithms. Bio-inspired approaches are popular for solving UAV path-planning problems accounting for 29.9% of the reviewed articles. Our review of the literature reveals that bio-inspired algorithms typically deconstruct an environment into a searchable problem space using exclusively approximate cell decomposition approaches. With both the application of Ant Colony Optimisation (ACO) [50, 77, 92] and Particle Swarm Optimisation (PSO) [88, 93] algorithms adopting such an approach. ACO and PSO both present established path-planning approaches, as with node-based algorithms represented in Section 6.5.2, particular focus has been paid regarding the adaptation of the core ACO and PSO algorithms. As a result, the refinement and adaptation of core algorithm parameters is commonly required to tune path-planning performance in such approaches.

Seeking to improve the existing core ACO concept [77] reduces the explorative search ability of the ant colony, constraining and guiding Ants' towards the target destination, whilst also allowing an Ant's step size to be varied, based upon environment obstacles within its surroundings. This concept of modification and improvement upon a core algorithm is also demonstrated in [78], three refined PSO algorithms are created, a maximum density convergence DPSO algorithm (MDC-DPSO), a fast cross-over DPSO algorithm (FCO-DPSO), and an accurate coverage exploration DPSO algorithm (ACE-DPSO), each proposing to fill a corresponding defined need within the reconnaissance problem the authors seek to solve. The extensibility of the PSO algorithm is also demonstrated in [61] extending previous work on time-varying inertia weight and adaptive inertia weight approaches implementing a multi-fusion, adaptive inertia weight approach. Whilst the fundamental core ACO and PSO principles remain in these implementations, highlighted is the significant potential that exists for refinement and explorative evaluation of differing control parameters within the core algorithm concepts itself, together with the exploitation of combinatorial solution approaches that can be taken.

Solving real world UAV problems using bio-inspired algorithms is rather problematic, due to issues with solution convergence speed that may be encountered [120], especially where a problem space's size is significant. One way of balancing convergence speed concerns into a real-time solution can be the early acceptance of an initial solution (though suboptimal) whilst continuing to generate potential solutions with any remaining processing time available, updating the initial solution if and when superior paths are discovered. However, [120] argues that the future of bio-inspired algorithms potentially lies in hybridised and multi-fusion based approaches capable of generating real-time path solutions.

6.5.5 Multi-fusion Based Algorithms. The classification model defined in Figure 12 identifies multi-fusion based methods as one of six key path-planning algorithm approaches, through which the benefits of two or more existing algorithms are combined to better exploit a suitable path-planning solution. However, when the classification model is applied to the surveyed literature only 4.5% of the papers reviewed apply a multi-fusion based approach. This figure represents the lower bound of research interest in such hybrid approaches, as we consider only a paper's primary approach taken towards a path-planning solution when categorising the work.

While there are examples where two existing planning algorithms are very clearly defined and combined (2-opt & Flood Fill) to generate a new algorithmic approach [98], if a wider view of the overall planning approach is considered, it can be observed that approximately 75% of papers seek to improve their planning performance via some form of multi-fusion approach.

Multi-fusion approaches seek an improvement in planning ability and/or efficiency through the complimentary integration of two established algorithms, resulting in an improved planning outcome. Both [92, 95] introduce guiding factors inspired by the A* algorithm, allowing for a more efficient exploration of the problem space using a guiding force, directing the UAV towards the target destination. While [50] introduces a taboo node matrix, to support the prevention of a deadlock state occurrence, together with any future unnecessary problem space exploration associated with unrewarding paths, through their application of Self Heuristic Ants. Combinatorial path improvement strategies also implement a multi-fusion based approach, [54] implements an initial path selection policy using the Dijkstra algorithm, with the additional use of PSO being applied to produce smoothed transitions between path edges. Similarly, other post planning and path smoothing approaches such as Bezier curves [75, 110] and B-spline curves [29, 67] are encountered for post planning path refinement purposes.

6.5.6 Reinforcement Learning-based Algorithms. Reinforcement Learning (RL) is the area of machine learning that deals with sequential decision-making [121]. Its diverse range of approaches are represented in 16.4% of papers surveyed. Providing an overview of such approaches for a cellular internet of UAVs, [70] summarises, multi-armed bandit learning, Q-learning, actor-critic learning and deep reinforcement learning in respect of potential UAV applications. The RL agent itself must make decisions within an environment problem space, seeking to optimize a given cumulative reward [121], learning good behaviour through a trial and error approach over a number of learning episodes. This approach incrementally constructs a learning policy based on the agent's experience and decision making to optimise future rewards. A learned policy may therefore be applied separately to a similar problem to independently generate a solution. A notable advantage with RL approaches over Supervised Learning is the requirement for large sets of pre-labelled learning data.

Typically, RL approaches represent the environment space via a Markov Decision Process whose conditions are modelled as a Markov chain of state/reward. Applying such an approach, [69] implements a Q-Learning RL strategy to minimise the number of UAVs providing vehicles' coverage over a defined section of a highway. The Q-Learning approach is an off-policy RL algorithm, meaning that during the learning process (random) actions outside its current policy are taken to influence the policy learning process, that maximises future reward. Thus, learned policies can be applied to future environments, allowing appropriate actions to be calculated with the impetus of achieving a goal state.

A Q-Learning strategy is also applied by the authors of [58] to facilitate UAV trajectory planning whilst assisting in localising ground objects signal strength. Whilst the RL is well suited to the exploration of unknown environments, environments may be dynamic and routinely change over time. Seeking to develop an independent knowledge of the environment space at the point of learning, [58] employs a two-stage process. First, a static path is flown across the unknown area, gathering initial signal strength and approximate location data. A second phase implements a RL strategy, formulating a trajectory that minimises the average signal localisation error of UAV placement, under various UAV energy consumption, flight time and waypoints constraints. When compared against existing methods in the literature [58] is shown to be advantageous through numerical evaluation. Considering wider environment planning constraints [65] outlines a value-decomposition based reinforcement learning algorithm to design the trajectory paths of a group of cooperative UAV communication nodes, specifically focused on path generation/placement that considers connectivity constraints.

The application of Deep Reinforcement Learning (DRL) has attracted significant interest from a number of authors such as [46, 51, 53, 96, 103]. The key advantage of combining RL and Deep Learning consists in enabling complex high-dimensional input data to be handled, moving away from the ridged state and action spaces defined in traditional RL environments. In [53], a DRL approach is applied for three-dimensional path-planning by implementing a recurrent neural network with a temporal memory component. The temporal memory approach allows extraction of crucial information from historical state-action sequences to aid path-planning. However, one key consideration identified is the prospective learning cost to achieve an effective collision avoidance policy.

Tackling a similar large scale complex environment [96] develops a DRL algorithm that combines RL and flocking control to learn a shared policy in a centralized manner. The learning process is constructed using three UAV agents for policy generation, where the resulting learned policy is executed within the UAV environment in a fully decentralized manner. A key concept demonstrated in [96] is that the learned policy is also efficient when enabling larger groups of UAVs to operate within the environment space.

To deal with the increased stochastic complexity when generating a solution for a Partially Observable Markov Decision Process (POMDP), the combined works of [51, 103] implements a DRL based on two strictly proved policy gradient theorems within the actor-critic framework. The resulting technique directly maps the UAV's raw sensor measurement data into navigation control signals, albeit with some concerns regarding how to fine-tune the current reward function to avoid unsatisfactory performance.

The DRL approach may also be applied to ensure optimal placement of UAVs to guarantee the desired communication coverage level and quality. Inspired by other DRL successes, [46] proposes a UAV control policy based on Deep Deterministic Policy Gradient (DDPG) which is a deep actor-critic algorithm. DDPG is used to address challenges in relation to the 3-D mobility of multiple UAVs and their energy replenishment scheduling, and aims to provide a persistent service over a large region, that is both efficient and fair (from the users perspective).

Whilst RL approaches can be applied to a varied range of learning problems, when considering the perspective of UAV path-planning within an environment, there are two potential strands of future work required to progress future reinforcement learning approaches. First, focusing on specific sensor hardware development which is itself suitable for use onboard UAVs (i.e., lightweight and low power hardware module), supporting environment translation and recognition purposes. Second, improving the attenuation mechanisms to process sensor data from multiple channels to support reasoned decision making using DRL approaches. RL approaches offer a diverse and complex range of features that cannot be reflected effectively within this survey, however, we refer interested readers to Sutton & Barto [122] which provides the seminal text on reinforcement learning with significant focus on the various approaches and the supporting learning algorithms. Moreover, François-Lavet et al. [121] provides a concise introduction to deep reinforcement learning.

[72] proposes an alternative Machine Learning approach to adaptive environment learning by implementing a dual layer neuron network approach to act as a self-organising map. By defining the upper neuron layer as an array of UAVs' locations and the lower layer as a provider of end user (EU) input neurons/locations, proximal relations between surrounding upper layer (UAV) neurons facilitates movement towards those more heavily selected neurons, via a numerical vector method. Consequently, a self-organising map can generate a low-dimensional intelligible topology from high-dimensional input data [72].

A critical consideration against using deep neural networks for path-planning is the fact that they require experience data first. Therefore, [62] implements a partially supervised reinforcement learning process that focuses on generating path-planning experiences. By using a Genetic Algorithm, a set of states and paths data from various scenarios is generated and used to train a Convolutional Neural Network (CNN) so that when faced with similar scenarios an optimized path can be quickly generated.

Federated Learning Concepts: Since the emergence of Google's Federated Learning (FL) concept in 2016 [123], there has been significant interest in its applications. Its core concept was to prevent data-leakage and address privacy concerns within the application of machine-learning models to large scale distributed user data. In relation to UAV path-planning the same data privacy and sharing concerns may or may not exist depending on the ownership of the UAV. However, the concepts of policy aggregation that FL frameworks apply to Machine Learning models offers significant potential to supplement Reinforcement Learning path-planning approaches. Applying a FL approach to a UAV swarm [124], where each UAV uses local collected data to train a local FL model, with a single parent (i.e., cluster head or the root node within the swarm) UAV integrating received local model

Table 9. Algorithms distribution per environment complexity type

Classification	Static Known	Dynamic Known	Static Unknown	Dynamic Unknown
Sampling Based Algorithms	15.2%	-	17.6%	31%
Node-Based Optimal Algorithms	9.1%	50%	5.9%	-
Mathematical Model-Based Algorithms	21.2%	25%	29.4%	15%
Bio-Inspired Algorithms	39.4%	-	17.6%	31%
Multi-Fusion Based Algorithms	6.1%	-	5.9%	-
Reinforcement Learning-Based Algorithms	9.1%	25%	23.5%	23%

parameters into a global FL model and redistributing it to child UAVs. Therefore, Federated Learning concepts hold significant potential to supplement existing and future path-planning approaches.

6.5.7 Environment Complexity & Algorithms Distribution. To summarise the relationship between different path-planning approaches and their application to different environment complexities, Table 9 provides a summary of how such approaches have been applied across the surveyed papers.

7 DISCUSSION AND FUTURE DIRECTIONS

The effective modelling of complex environments encountered by UAVs is a critical component for the successful and efficient planning of UAV paths. This survey presents a classification model using two key dimensions of environmental complexity, delivering a useful metric for classifying the encountered problems highlighted in Section 3. These two dimensions are: (i) the knowledge available to a path planner regarding the environment a UAV is required to operate in, and (ii) whether objects encountered within such an environment are dynamic in nature. UAV path-planning remains a complex and multifaceted problem, and there is a clear trend among reported environmental modelling techniques being applied only to the less complex classes of environment. The concept of a binary choice between a known or unknown environment presented in this survey represents a notable limitation because there may well be problems where the level of environmental knowledge available to a UAV path planner falls between these two extremes. There may be problems in which partial environmental knowledge is available, and these problems may differ in terms of the completeness or the accuracy of this information. We make no claim as to the potential bounds of this knowledge level, or as to any threshold of completeness or accuracy at which approaches that envisage complete information will become unsuitable.

We do envisage, however, that over time researchers will begin to define bounds for how complete and accurate pre-existing environmental knowledge must be for planned paths to be sufficiently flyable, or at least flyable with minor modification. In some cases, this problem-level operating envelope will be demarcated by some physical distance constraint or the availability of communication infrastructure. The limitations imposed by such constraints are not dissimilar to the way that a wind limit, minimum runway length and/or fuel range defines the operating envelope of conventional aircraft, constraining the destinations they may serve. In the following subsections we will present our vision, based on the lessons learnt from this survey, on how to develop effective and practical path-planning approaches to overcome the challenges encountered by current state of the art path-planning approaches.

7.1 Environment Complexity

Over 48% of articles surveyed construct their path-planning solution based upon the availability of static-known environment knowledge, clearly such approaches are acceptable in a simulated environment or when applied to

toy problems. However, solutions that have been applied only to this class of environment will require significantly more work for use in the real-world. To facilitate the use and improve the practicality of such approaches three potential future directions are identified. First, there is a clear possibility of exploring hybridised environment planning [95]; pre-planning a path with a static representation of the environment, whilst dynamic unknown obstacles are evaluated in flight, with minor changes supplied to a global path. The level of static knowledge required can also be limited to the effective range of the UAV itself, as it would not have the ability to explore past its own powered range which is advantageous.

Second is the individual ability of a UAV to map [54] or sense [70] surroundings throughout an unknown environment. However, such approaches can be delivered in a disjointed manner, with [54] requiring an initial environment survey, before requiring centralised processing to produce optimal transit paths.

The third direction is built around the refinement and improvement of existing communication models. Simulation approaches studied in this survey are built around the assumption of a static-known knowledge of the environment being easily accessible to the UAV and planning agent. The ability to provision such a communication model over a physical wide area network is certainly of interest, however such simulation models are constructed around a centralised control of the path-planning methodology. Such centralised models bring concerns over the scalability of a planning approach, even where a centralised topology is not applied, as with the synchronous communication model defined in [89]. This results in each UAV waiting for its peer to complete planning, thus large UAV systems face a potential computational planning bottleneck.

When considering the environmental complexity classification of a planning problem, conclusions can be drawn based on the complexity model encountered. Where an environment's complexity is known to the planning agent, it is implied that a communication model exists, supporting consistent knowledge sharing across the whole environment. However, this does not denote a requirement for an uninterrupted communication model, a minimum requirement exists for UAVs to be allocated segments of airspace at specific time periods, allowing a planning agent to dispatch a UAV with no further communication until its return. Similarly, UAV-UAV communication is not a requirement as paths are planned with prior knowledge, avoiding UAV-UAV interaction.

Introducing an unknown environment presents an increased likelihood of conflict between either a UAV and Obstacle or multiple UAVs. Consequently, we see greater requirement for a communication model that interacts with the wider UAV and planning agent in these scenarios. However, for large scale UAV networks increased communication volume difficulties are identified in [66]. Making planning decisions centrally could hinder the ability for decision making in real-time, therefore focus should be placed on distributed decision-making schemes. Overcoming such communication overload may be achieved through the segmenting of a planning agent's resources, a Beacon, Sense, Transmit model is implemented in [70] synchronising multiple UAVs communication.

Where a single telecommunication layer is described, handling communication across all UAVs, [72] describes a hierarchical UAV control structure, using control UAVs to manage a subsection of the UAV network. Consideration of a UAV's specific communication constraints is critical: [78] exchanges swarm knowledge over short-range communication links, highlighting swarm velocity control and sharing of completed task data. However, a decentralised approach inevitably means situations will exist where decision making is required without complete situational information [70]. Decentralised path-planning conducted by each individual UAV is achieved in [89] based on a prioritised UAV order. However, this planning is conducted prior to UAV mission commencement, with further work being required to handle any dynamic changes to the context of the environment whilst UAVs are in flight.

7.2 Environmental Representation Strategies

The unconfined explorative ability of UAVs represents a significant factor in their attractiveness for future applications, however this range of freedom offered in a three-dimensional space can also be considered their

greatest challenge when planning suitable paths. This complexity has been addressed by a number of solutions, for a variety of optimisation problems. Emerging amongst the literature is a common theme of splitting the optimisation problem into more manageable chunks, the most common of which being the fixing of a UAV altitude in a 3D space to simplify the problem of path-planning for each individual UAV into a 2D space. Whilst such strategies will invariably remove the ability for the selection of a truly optimum solution, within such approaches there is a potential to address both time and computational constraints that may otherwise be limited by the computational power of a UAV. It is the potential computational limitations of UAVs' onboard computing power, that fuel the requirement for further research and development of computation offloading strategies, along with handling associated issues that arise with hardware failure and recovery calculations.

This survey covered the application of a wide variety of environment representation strategies when deconstructing an encountered environment into a relatable problem space. Most methods attempt to significantly reduce the route planner's search space for performance reasons, to enable real-time planning and re-planning. Two thirds of the approaches reviewed employed an approximate cellular decomposition approach, generating a representation of the environment with a traditional cartesian structure, with the majority of the remaining third of papers opting for a roadmap approach. Whilst a cellular decomposition approach is clearly favoured, overall, there seems to be no definitive consensus upon which approach is best suited towards a *static vs dynamic* environment or a *known vs unknown* environment. Instead, focusing on the path-planning algorithm employed is more reflective, both Bio-inspired and multi-fusion based algorithms were entirely constructed around a cell decomposition approach. When we include reinforcement learning methods as well, the three categories of methods represent 82% of the algorithms using a cell decomposition approach. Similarly, in respect of node-based and sampling-based algorithms, over 82% of articles focus upon a roadmap approach, with the mathematical model-based approaches being representative of the overall quantities. The use of APF was extremely limited, primarily due to the ability to maintain field knowledge over large areas, although APF principles have been applied on a localised basis [80] using mounted UAVs sensors to gauge an environment representation.

Ultimately, what can be shown is that there is a relationship between a proposed path-planning algorithm and its requirement for the ability to form an accurate perception of an often extremely complex environment. This emerges as the key influencing factor in selection of an environment representation strategy.

7.3 UAV Related Attributes

Most of the planning approaches encountered focus on the use of rotary-wing UAVs (67.6%) as opposed to their fixed wing counterparts. The papers profiled that discussed this decision identify key advantages of rotary technology e.g. sustained hover placement combined with a fine-grained dexterity of motion. Such control however is energy intensive, with those papers favouring fixed-wing UAV focused upon long range endurance-based problems where an airframe body capable of generating aerodynamic lift is critical. What is clear is the decision to implement a rotary or fixed wing solution to a planning problem is based primarily upon the used case scenario of the problem itself. Hybrid UAVs are an emerging technology [3] and may offer a one size fits all solutions to UAV role selection, however their current implementation in literature is limited.

Of the articles reviewed, 50% neglected to consider the individual dynamic capabilities of a UAV, with generated paths presumed flyable, regardless of path geometry. When known environments are removed, this rate rises to 55%, given the unavailability of environment knowledge, this indicates a desire amongst authors for the UAV to autonomously handle flight and attitude management, as well as collision avoidance. While such approaches are valid, failure to consider UAV capabilities, opens the possibility generated planned paths may be infeasible, even with some limited on-board capability for adjusting or smoothing a path or avoid a collision. In dealing with dynamic environments, the risk exists that planned paths may become unachievable, with a change in

prevailing environment conditions. It is therefore surprising to see the lack of exploration of wind as an external or controlling factor within the path-planning process, with only [52, 125] exploring the impact upon path-planning.

There too exists significant disagreement within the literature regarding the application of smoothing approaches towards UAV paths. Highlighted within this survey is a clear issue between generation of computationally optimised UAV flight path, and a UAVs physical ability to accurately replicate the path. This study highlights the existence of three main approaches to perform path smoothing, exact smoothing applies UAV specific flight characteristics within the path-planning process, a post-planning approach applies a path smoothing framework to an existing planned path which offers a broad representation of a UAV's abilities. Alternately, in the third approach a UAV independently generates and flies its own path based upon a sensed interpretation of an environment. Ultimately, there exists a balance to be struck, between algorithms that offer a highly focused smoothing approach for a specific UAV type or a broader approach that is representative of several UAV types.

Whilst UAV path-planning remains an open problem, further consideration of the approaches taken to direct planning towards successful real-world planning and application is definitely a required component for expanding this research field.

7.4 Time Considerations

The approach of fixing a UAV's velocity features heavily within the surveyed articles (77.9%), constraining an active planning variable to achieve a reduction in computational complexity. Combining this factor together with a reluctance to explore both a UAV's dynamic constraints precisely and limited application of path smoothing approaches may hinder a UAV path generation process. Such approaches may offer a computationally attractive approach to path-planning, however it has been shown in [98] that there are inherent risks in these methods. In extremis, a computed optimal route could become worthless when the physical abilities of a UAV cannot replicate the route in real time. Naturally, this raises the question of whether a problem is formulated to the environment or the environment is formulated to the problem? This issue certainly warrants consideration in future work.

7.5 UAV Path-planning Approaches

Once a discussed environment's complexity had been established, the approaches studied in this survey were further classified into six methodologies used to formulate a solution to the planning problem, as shown in Figure 12. It is clear that static-known environments enable the successful application of varying path-planning algorithms due to the total environment knowledge provided to a planning algorithm. However, a significant question exists around how such a knowledge can be scaled over much larger environments. The ability to move away from a single environment control entity, towards multiple entities of control, across multiple environment footprints, that can cooperatively and effectively share environment information remains open.

Whilst the utilisation of Feynman diagrams seeks to apply the principles of subatomic particle behaviour, to provide the RRT with smoothed path step trajectory generation [94], is an interesting new direction. The added requirement for applying path smoothing between adjoining trajectory steps, leads to the question of whether a more simplistic path smoothing approach can be applied to the generated 3D RRT paths from the outset.

The application of reinforcement learning holds as an interesting concept especially in placement related trajectory generation through repetitive single environment path-planning. If computationally balanced to the given UAV problem, reinforcement learning is demonstrated as having a significant potential to generate near optimal solutions in the field. The benefits of implementing a training phase, especially when presented with a complex 3-D space for exploration are noted, removing wasted investigation and evaluation time. However, whilst the application of Q-learning is potentially less computational demanding than other reinforcement learning frameworks, its ability to both scale and continue to learn in a decentralised manner over large environments requires further investigation.

The range of scenarios discussed in the literature highlights that UAVs have significant scope for use in civil sector applications. Regulatory control of airspace and safety considerations present significant hurdles to be overcome before fully autonomous operation becomes the norm. Supported by [78], [126] speculates that “there exists no single algorithmic path-planning solution that fits all”. Thus, focusing on the development or enhancement of a single algorithmic solution, which is capable of reflecting multiple real-time UAV coordination tasks is unrealistic. Instead, there exists scope for a wide range of specialised research questions based upon specific UAV use cases with the potential to enhance a complex field. The creation of future planning algorithms, together with the development of a greater understanding of how existing approaches can be effectively combined, has the potential to allow autonomous UAVs to more effectively achieve individualised goals and to allow problems that feature wider multi-UAV task management objectives to be addressed.

8 CONCLUSION

This paper has presented a comprehensive survey of applied UAV path-planning approaches with environment complexity considerations. First, we have presented an overview of environment representation strategies and current approaches used to deconstruct environments into a machine interpretable problem space. We introduced an original high-level UAV environment classification strategy to differentiate the key environmental challenges encountered during UAV path-planning, in conjunction with a synopsis of the UAV path-planning problem. Thereafter, we presented a detailed critical analysis and comparison of the recent literature investigating the complexity of a UAV’s environment and its representation strategies. Moreover, we studied also the encountered UAV characteristics and time related considerations, including a comparative breakdown of the current algorithmic trends applied in UAV path-planning. Finally, we discussed the issues and challenges currently encountered together with future research directions in UAVs path-planning.

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