Advances in Unmanned Aerial Vehicles Path Planning

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- **Expertise:** telecommunications and computer networks architectures, technologies and services: network architectures and services, management/control/data plane, protocols, routing, 5G,6G, SDN, NFV, virtualization, QoS assurance, multimedia services over IP networks

- **Our UPB team:**
  - **Recent research interest :** Software Defined Networking (SDN), Network Function Virtualization (NFV), MEC/edge computing, 5G networking and slicing, vehicular communications, UAV, AI in 5G, 6G - management and control
  - **Partners in many research European** and bilateral projects in the above domains

- **Acknowledgement**

- This short **overview text** and analysis is compiled and structured, based on several public documents, conferences material, studies, research papers, standards, projects, surveys, tutorials, etc. (see specific references in the text and Reference list).

  - The selection and structuring of the material belong to the author.

  - **The domain is very large; therefore, this presentation is limited to a *high-level view only*. The list of topics discussed is also limited.**

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Advances in Unmanned Aerial Vehicles Path Planning

- **Motivation of this talk**
  - **UAV(drones)** - popular for **many applications and services** (civilian, military)
  - **Multiple UAVs** are **wirelessly interconnected** in ad hoc manner, composing UAV networks (**UAVNET**)
    - **FANET** acronym is also used for **Flying Ad hoc Networks -** able to forward packets, gather, and share information
  - **UAVNETs** - **characteristics and needs different from traditional mobile ad hoc networks (MANET) and vehicular ad hoc networks (VANET)**
    - **large variety of applications and operational contexts**
    - **dynamic behavior, rapid mobility and topology changes (both: physical and logical)**
    - **cooperation needed : UAV-ground stations (GS), UAV-UAV, UAV- satellites, UAV swarms**
    - **3D Work-space/ environment**, including space communications
      - **Obstacle-avoiding** trajectories
      - **Real-time** problems during flight
      - **Energy consumption** issues, ….
    - In some cases - **delay tolerant network (DTN)** – dedicated solutions to cope with high delays and intermittent connectivity
  - **Need of specific methods and technologies** for Data Plane and Management & Control Planes (M&C) at different architectural layers
    - Physical layer, MAC layer, **routing**, **path planning,** tracking, traffic engineering, cooperation, security, etc.
    - **UAV Path Planning– crucial topics in UAV area**

CONTENTS

1. Introduction

1.1 Unmanned Aerial Vehicles (UAV) (drones)

- **UAVs- popular solutions** for many applications (civilian, military domains)
  - objectives
    - surveillance, delivery, transportation, agriculture, forestry, environmental protection
    - **mission critical operations -** rescue/emergency, military actions, security

- **UAVs are wirelessly interconnected** in ad hoc manner → **UAVNET**

- The **communication technologies used in** UAVNETs depend on applications
  - **Examples:**
    - **Outdoor** - a simple line of sight 1-to-1 link with continuous signal transmission E.g.: surveillance–UAVs can communicate through satellite communication links
    - **Satellite communication** - preferable solution - for security, defense, or more extensive outreach operations
    - **Civil and personal applications** - cellular communication technologies are preferred
    - **Indoor communication** - e.g., in mesh network and Wireless Sensor Network (WSN) - Bluetooth or point-to-point (P2P) protocols

    - **UAV Communication in multi-layered networks** – complex process

1. **Introduction**

1.2 UAV Applications - examples

- **Individual, Business and Governments**
  - Express shipping and delivery, Unmanned cargo transport
  - Aerial photography for journalism and film
  - Disaster management: gathering information or supplying essentials
  - Storm tracking and forecasting hurricanes and tornadoes
  - Thermal sensor drones for search and rescue/emergency operations
  - Geographic mapping of inaccessible terrain and locations
  - Building safety inspections, Precision crop monitoring
  - Law enforcement and border control surveillance
  - **In progress: development of many other use cases**

YoY = Year-over-Year

Source: https://www.aonic.com/my/blogs-drone-technology/top-10-applications-of-drone-technology/

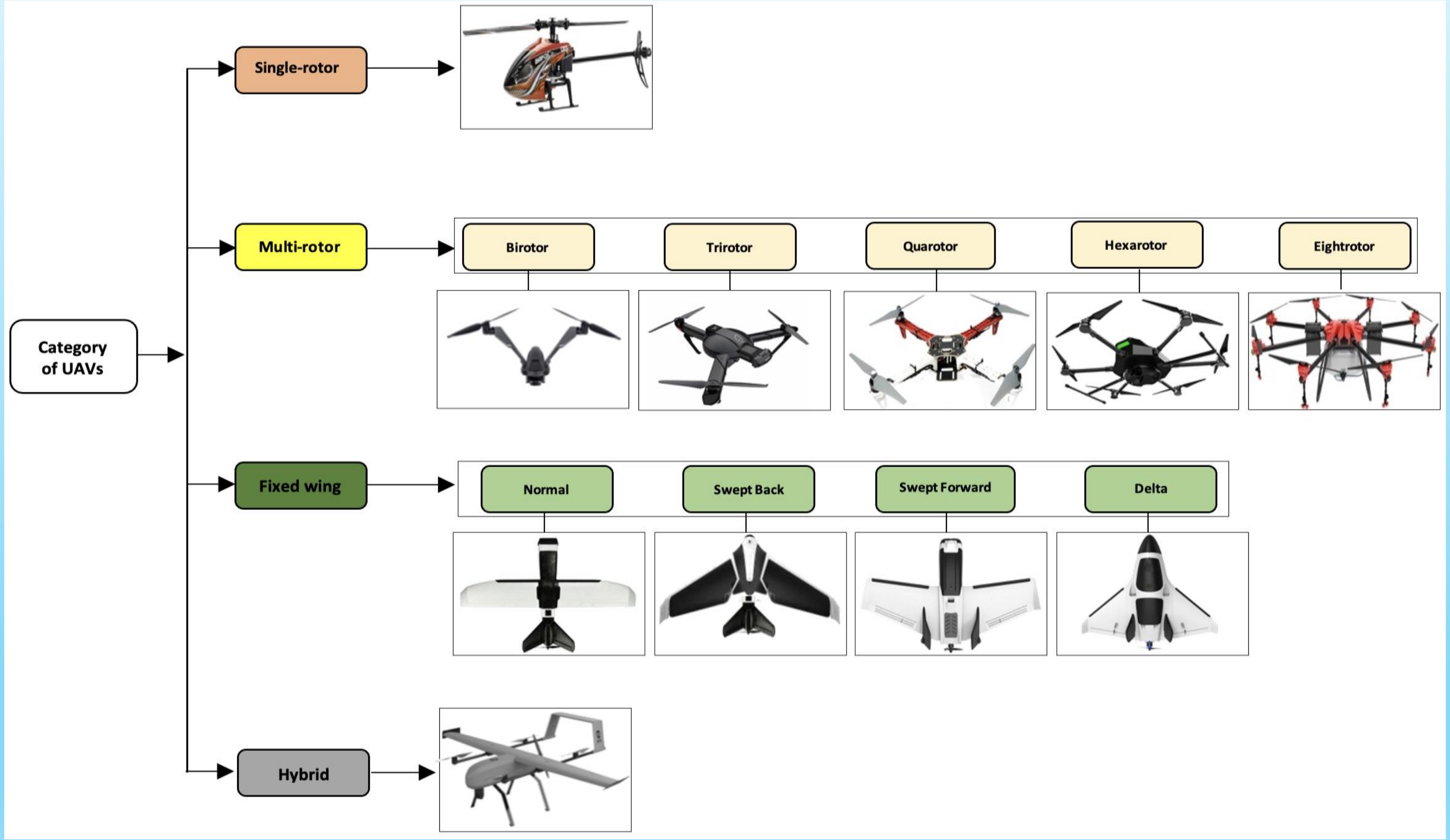
1. Introduction

1.3 Unmanned Aerial Vehicles (UAV) - classification

- **UAV Classification**- based on **different criteria** depending on UAV missions and specific parameters
  - **Missions and applications**: civil and commercial UAVs - in agriculture, aerial photography, logistics, data collection; special domain -military missions
  - **Performance-related** characteristics: range, maximum altitude, aircraft weight, wingspan, wing loading, speed, endurance, cost design and size
- **Engine type**: fuel engines and electric motors
- **Mechanical/physical characteristics**:
  - **weight** - *Micro*, *Light, Medium*, *Heavy*, and *Super Heavy* classes, spanning a range from under 5 kilograms to over 2 metric tons
  - **landing and takeoff capabilities**
    - **VTOL** (*Vertical Takeoff and Landing*) – no external support to takeoff and landing
    - **HTO**L (*Horizontal Takeoff and Landing*)- longer flight ranges, can carry larger payloads, but need external support
    - **Hybrid**- combines the capability of both VTOL and HTOL types
  - **flight range:** close, short, medium, and large endurance categories, spanning a range from under 10 to 1500 kms

1. Introduction

1.4 Unmanned Aerial Vehicles (UAV) -different equipment types



Source: W.Y.H. Adoni, S.Lorenz, J.S.Fareedh, R.Gloaguen and M.Bussmann, Investigation of Autonomous Multi-UAV Systems for Target Detection in Distributed Environment: Current Developments and Open Challenges, 2023, https://doi.org/10.3390/drones7040263

1. Introduction

1.5 UAV Networks

- **Single UAVs** frameworks have been utilized for quite a long time in many apps.
  - The UAVs are connected to either ***ground base station (GS)*** or connected with a satellite station for communication in a **star topology**
- **Multi UAVs** systems i.e., **UAV networks**; no need to connect every UAV to GS

- **Inter-UAV wireless communication** is necessary in **UAV communication networks (UAVCN) ,** a.k.a. **flying ad hoc network (FANET)**
  - **Notation: UAV network = FANET= UAVCN drone ad hoc network**

- **MANET** = Mobile Ad hoc Network; **VANET**= Vehicular Ad hoc Network
- **FANET ⊆ VANET ⊆ MANET**

- **UAV networks** – characteristics different w.r.t. MANETs and VANETs
  - **dynamic behavior -** rapid mobility and topology (physical, logical) changes
  - **new challenges** for communication at: PHY layer, MAC layer, management and control, **routing and path planning,** traffic management, cooperation, security

- **Different topics on Multi-UAV networks**: Cooperative Multi-UAVs; Opportunistic relaying networks; Delay-tolerant UAVs networks; UAV swarms; Ground WSN; Internet of Things (IoT); Cooperation with Cloud Computing; Heterogeneity; Self-organization

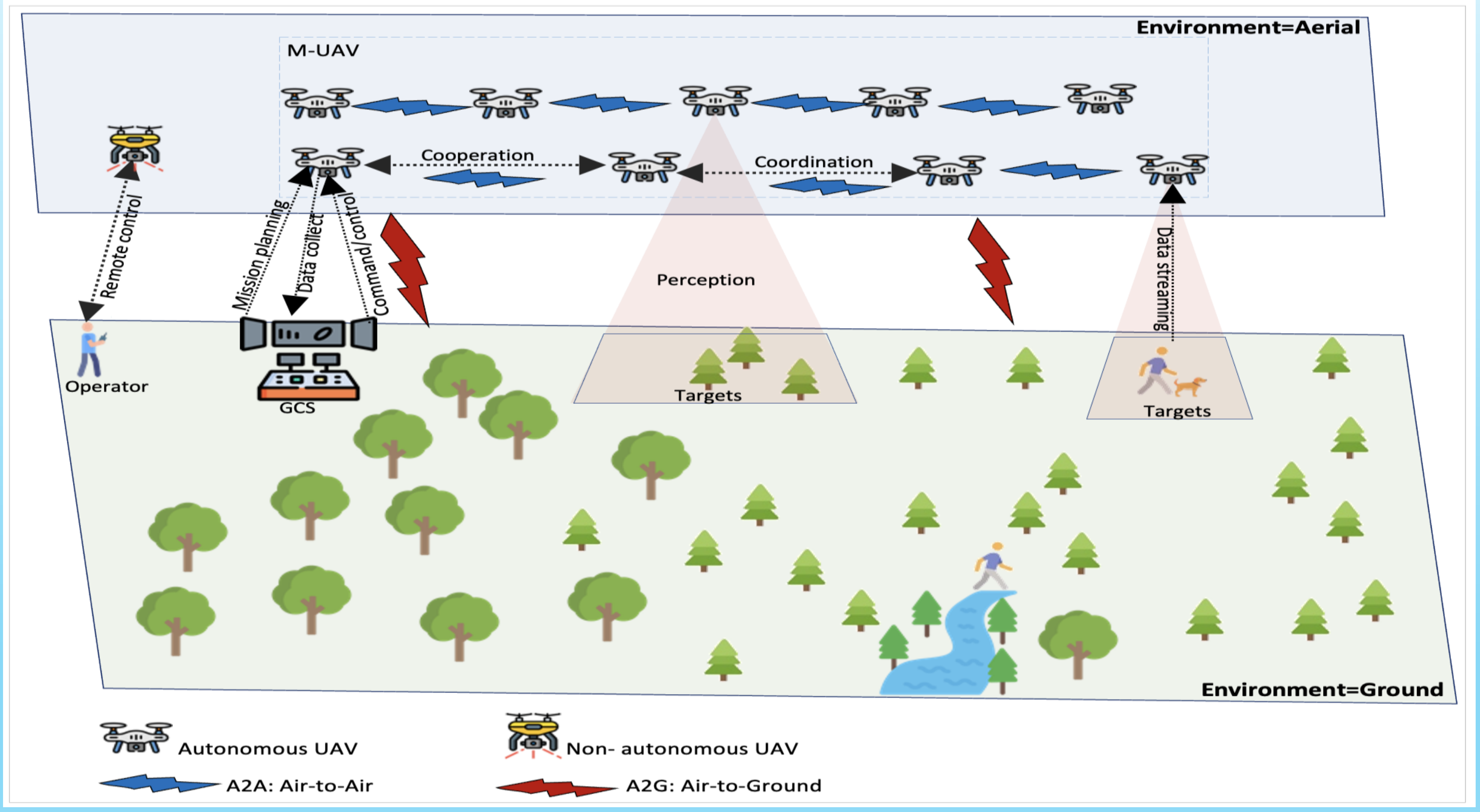
Source: A.I.Hentati, L.C. Fourati, Comprehensive survey of UAVs communication networks, Computer Standards & Interfaces 72 (2020) 103451, www.elsevier.com/locate/csi

1. Introduction

1.5 UAV Networks

- **Overview of a multi-UAV ecosystem**

GCS- Ground Control Station



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1. Introduction

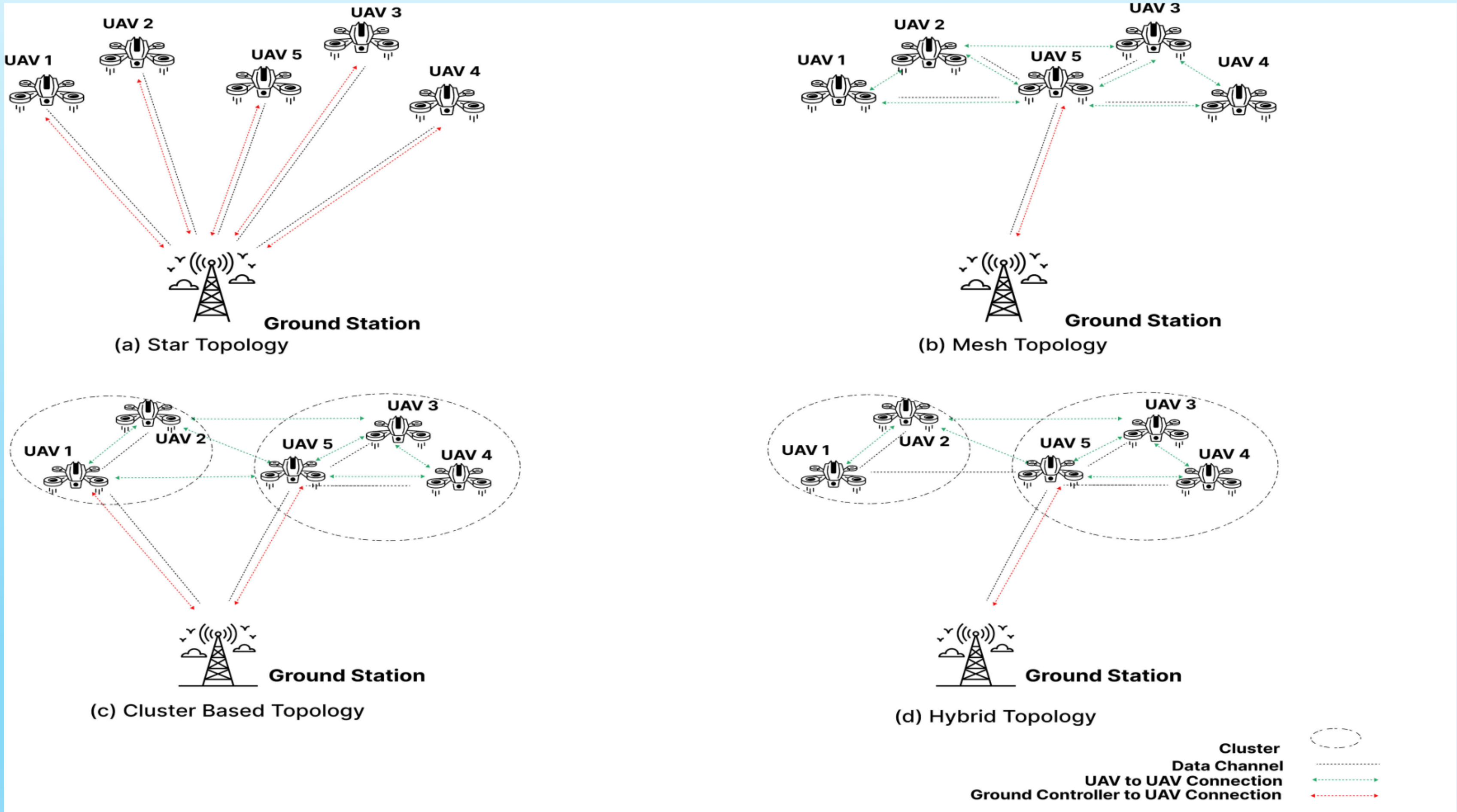
1.5 UAV Networks

- **Multi-UAV topologies- examples**
  - **(a) Star topology:** each UAV (node) is directly connected with GS node
  - **(b) Mesh topology**: the GS is only connected to a single node (**cluster head** of the UAV group- playing a role of Gateway)
    - The **cluster head passes the data packets from the GS to the other member nodes** and vice-versa
  - **(c) Cluster-based network topology**
    - The **UAVs are grouped in clusters**; **each cluster has a head**
    - **GS is connected to heads UAVs** of clusters
    - The heads collect data packets from the member UAVs and forward them to the GS and vice versa
  - **(d) Hybrid mesh network- one cluster head UAV is connected to the GS**
    - The cluster head can pass the information
      - to the UAVs of its group
      - to other nearby cluster heads
      - from the GS to other connected nodes and vice-versa
    - The GS can be connected also to single UAVs or group cluster heads
  - **Inter-UAV communication topology types: star, ring, mesh**

1. **Introduction**

1.5 UAV Networks

- **Multi-UAV topologies: (a) Star b) Mesh (c) Cluster-based (d) Hybrid mesh**



Source: N. MANSOOR et al., A Fresh Look at Routing Protocols in Unmanned Aerial Vehicular Networks: A Survey, IEEE Access June 2023

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2. Path Planning Problem in UAV Networks

2.1 Path planning (PP)

- **PP is related to the UAV routing**
  - **PP is dependent on geographical/environment information**

- **UAV PP main objectives**:
  - **Single path planning: to find for an UAV, the best (i.e., optimum) collision-free path between a start point and a destination point, while addressing temporal, physical, and geometric constraints**
  - **Coverage Path Planning (CPP) – movement in a region** - for specific exploring UAV applications
- **UAV PP (a.k.a. motion planning), is a branch of path-finding used in robotics**
  - However, UAV specific differences exist, e.g.:
    - 3D space/environment, 3D obstacles
    - Some UAVs (e.g., fixed-wing UAV), cannot hover; they must maintain a cruising speed; this leads to more constraints
      - In contrast, a robot can decelerate and have a complete stop as needed

- **PP specific problems of interest:** environment modeling methods, path structures, optimality criteria, completeness criteria, path finding methods, UAV simulators

2. Path Planning Problem in UAV Networks

2.1 Path planning (PP)

- **UAV Path Planning essential attributes**
  - **Security:** safety of UAVs, including when moving in hostile environments
    - Minimizing the probability of detection by hostile radars and other UAVs
  - **Physical Viability:** there are physical constraints and limitations (e.g., maximum path distance, minimum path length)
  - **Mission performance**: a path should satisfy the requirements of a specific mission
    - Designing a path to complete a mission involves meeting various requirements, e.g., maximal turning angles, maximum climbing/diving angles, and minimal flying heights
  - **Real-time implementation**: efficiency of the PP algorithm
    - The dynamic nature of UAV flight environments need computationally efficient PP algorithms to respond fast to changing conditions
- **UAV PP targets**: low computational cost, full UAVs' maneuverability, dynamic flight control, optimality of trajectories while respecting dynamics constraints

2. Path Planning Problem in UAV Networks

2.1 Path planning

- The PP problem has a **non-linear nature and frequently an exponential complexity**
- **Classes of UAV PP problems (from applications point of view)**
  - ***Informative path planning (IPP) problem***: UAV paths should maximize the utility of data collection
    - paths are planned such that the information gathered about an unknown environment is maximized, while satisfying the given budget constraint
  - ***Coverage path planning (CPP) problem*****:** to find a path **that passes through all points of an area** or volume of interest, while avoiding obstacles
  - ***Cooperative path planning***: to generate a coordinated mission through utilization of PP algorithms
    - **Example:**
      - a group of UAVs leave a base and should synchronously arrive at a designated rendezvous point
      - during their journey, the UAVs might execute different tasks (e.g., area searches and detecting objects along)

Source: S.Ghambari, M.Golabi, L.Jourdan, J.Lepagnot and L.Idoumghar, UAV Path Planning Techniques: A Survey, RAIRO-Oper. Res. 58 (2024) 2951–2989 RAIRO Operations Research, https://doi.org/10.1051/ro/2024073 www.rairo-ro.org

2. Path Planning Problem in UAV Networks

2.1 Path planning

- **Criteria to be considered** when searching a path

- minimum values for: path length, flight time, fuel consumption, and danger exposure

- Depending whether the environment is known or not, PP algorithms can be:
  - **Offline PP**
    - Assumption: all environmental information is known in advance
    - PP algorithms only depend on static environmental information
  - **Online PP**
    - The environment information is only partially known in advance
      - paths must be adjusted in real-time, based on sensor information
      - more complex problem

- According to the employed cellular environment decomposition model, the CPP algorithms can be divided into three main types:
  - **no decomposition, exact cellular decomposition** and **approximate cellular decomposition**

Source: Cabreira TM, Brisolara LB, Ferreira PR (2019) Survey on coverage path planning with unmanned aerial vehicles. Drones 3(1):4. https:// doi. org/10. 3390/ drone s3010 004

2. Path Planning Problem in UAV Networks

2.2 Path planning model

- Consider a **3D workspace**
- Let it be ***w;*** it may have obstacles; let $\boldsymbol{wo_i}$ be the $\boldsymbol{i_{th}}$ obstacle
- The initial point $\boldsymbol{x_{init}}$ and the goal region $\boldsymbol{x_{goal}}$ are elements in $\boldsymbol{w_{free}}$
- The **free workspace** (i.e., without obstacles) is the overall area represented by
  - $\boldsymbol{w_{free} = w \setminus \cup_i \; wo_i}$

- **The PP problem is defined by a triplet ($\boldsymbol{x_{init}, x_{goal}, w_{free}}$)**

- ***Definition 1-PP***: Given a function $\boldsymbol{\delta:[0,T] \to R^3}$ of bounded variation, where $\boldsymbol{\delta(0) = x_{init}}$ and $\boldsymbol{\delta(T) = x_{goal}}$,
  - if there exists a process $\boldsymbol{\Phi}$ which can guarantee $\boldsymbol{\delta(t) \in w_{free}}$, for all $\boldsymbol{t \in [0,T]}$, then $\boldsymbol{\Phi}$ is called **Path Planning**

- ***Definition 2-Optimal PP***
  - Let **Σ denote the set of all paths**
  - Given a PP problem (-, -, -) and a cost function $\boldsymbol{c : \Sigma \to R \geq 0}$, if a process fulfils the *Definition 1* and if exists a feasible path having the minimum of cost, then the associated process $\boldsymbol{\Phi'}$ is named ***Optimal PP***

3. Path Planning Problem in UAV Networks

3.2 Path planning model

- ***Path Planning*** and ***Trajectory Planning***: two distinct problems in robotics, but related
  - ***Trajectory***: a path is parameterized by time **t**
  - ***Trajectory planning***
    - Usually, one considers the solution from a robot PP algorithm and determines ***how*** to move along the path in w_{free}
    - the ***path*** is either a continuous curve or discrete line segments that connects the start node x_{init} to the end node x_{goal}
    - one needs to find smooth and continuous trajectory segments to move along the path
      - it can be described mathematically as a twice-differentiable polynomial
      - i.e., the velocities and accelerations can be computed by taking the first and second derivatives with respect to time

Source: *Liang Yang, Juntong Qi Jizhong Xiao Xia Yong, A Literature Review of UAV 3D Path Planning, 2015, https://www.researchgate.net/publication/282744674*

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3. Environment Representation

3.1 Environment Representation Problem

- **Knowledge needed to a path planner**
  - about the environment
  - about dynamics of the objects encountered in UAV operation space

- **Issues on 3D obstacles representation**
- Obstacles:
    - **static or dynamic**
    - **any geometry**: cubes, pyramids, floating balls, etc.
  - The obstacles model will affect the path search algorithms
  - The **model should include the medium specifics** (urban, rural, forests, special zones, radar areas)

  - **Challenges:**
    - Obtaining enough accurate geometric coordinates of the obstacles

  - The **environment type** (containing bridges, buildings (convex, and/or concave), complex and cluttered spaces **will determine the selection of representation methods**

3. Environment Representation

3.1 Environment Representation Problem

- **Classes and attributes of reported UAV path-planning approaches**

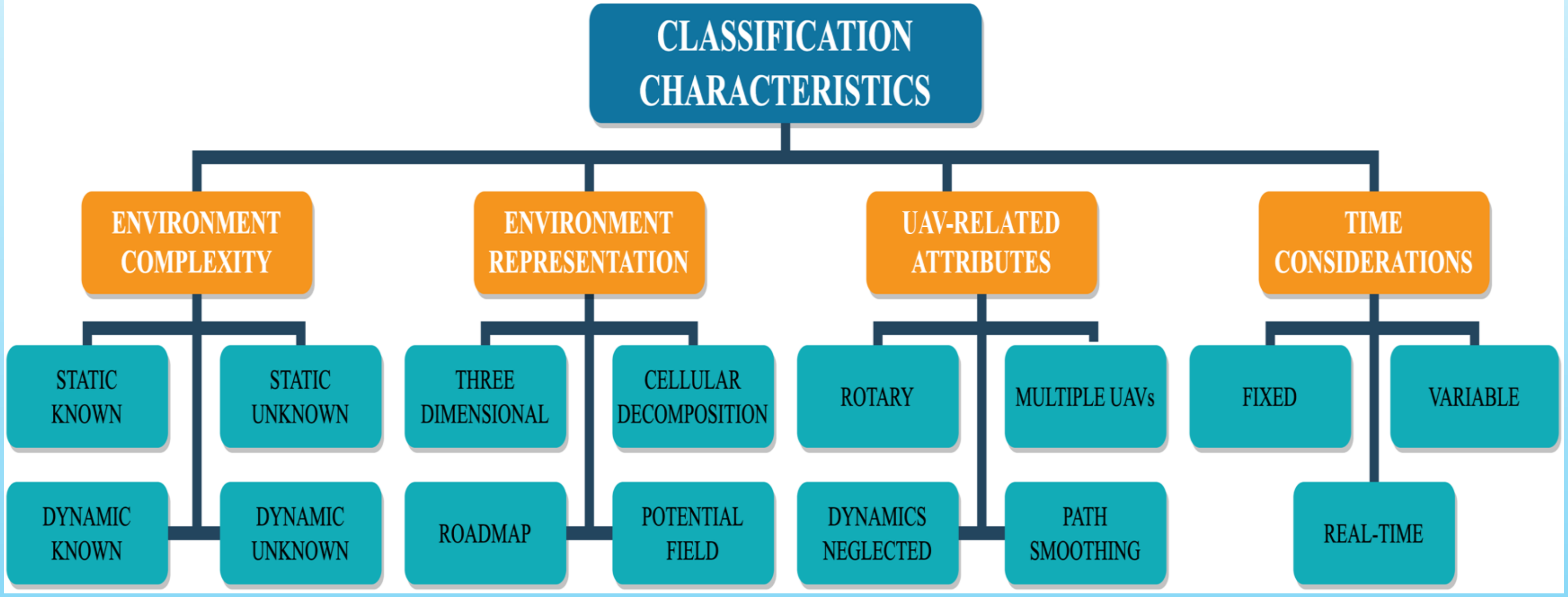


Figure Source: M,R. Jones, S. Djhael, K. Welsh, Path-planning for Unmanned Aerial Vehicles with Environment Complexity Considerations: A Survey, ACM Comput. Survey, Vol. 1, No. 1, November 2022.

3. Environment Representation

3.1 Environment Representation Problem

- **Environment complexity related attributes (related to the problem space and knowledge on them by the PP algorithm)**
  - ***Static-known (SK)*:** All obstacles /objects are both static and known
  - ***Dynamic-known (DK)*:** Although obstacles /objects are mobile, their movement is known
  - ***Static-unknown (SU)*:** Obstacles /objects are static, but their relative positions are unknown
  - ***Dynamic-unknown (DU)*:** All obstacles /objects are both mobile and unknown

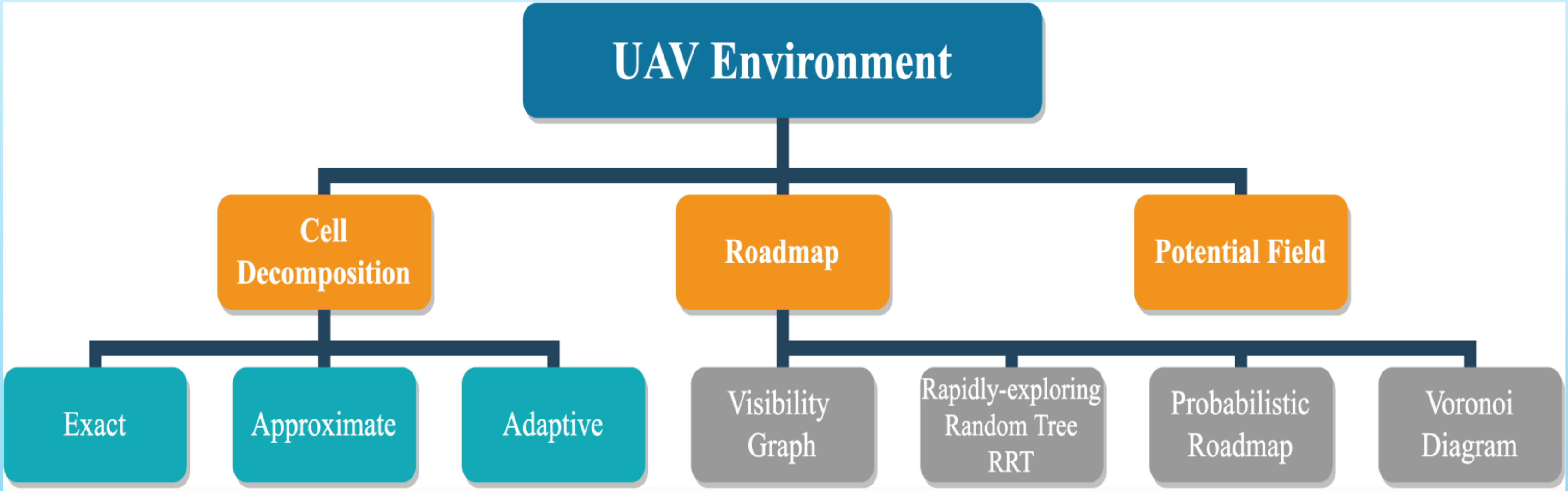
- **Environment representation related attributes:**
  - *3D*: Able to plan a UAV's path through a 3D environment (as opposed to a 2D environment).
  - *Cellular decomposition (CD)*: cellular decomposition strategy to generate a problem space.
  - *Roadmap (RM)*: Constructs the problem space as a roadmap representation of the environment.
  - *Potential field (PF)*: Represents the problem space environment as a continuous APF.

Source: M,R. Jones, S. Djhael, K. Welsh, Path-planning for Unmanned Aerial Vehicles with Environment Complexity Considerations: A Survey, ACM Comput. Survey, Vol. 1, No. 1, November 2022.

3. Environment Representation

3.2 Environment Representation Methods

- The 3D world space/environment can be represented in several approaches
  - **Cell decomposition; Roadmap; Potential field**



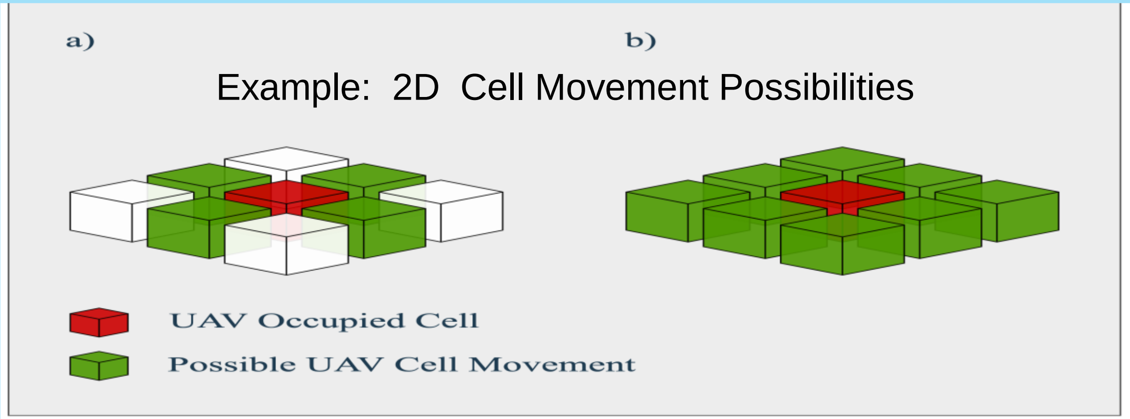
- **Cell decomposition**
  - The **environment space is divided** into a series of **nonoverlapping cells**
  - Result: a defined and navigable structure within the environment space, constructed around the availability of traversable relationships between cells

Figure Source: M,R. Jones, S. Djhael, K. Welsh, Path-planning for Unmanned Aerial Vehicles with Environment Complexity Considerations: A Survey, ACM Comput. Survey, Vol. 1, No. 1, November 2022.

3. Environment Representation

3.2 Environment Representation Methods

- **Cell decomposition** (cont'd)
  - ***Approximate Cell Decomposition***
    - It overlays a regular grid structure upon the environment space
    - Decomposition into a set of structured cells: each cell's location within the environment is 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
    - A cell's total internal space is composed of free space and obstacle space
    - A cell only partially filled by an obstacle is classified as obstacle space
    - Implementation variants: 2D or 3D



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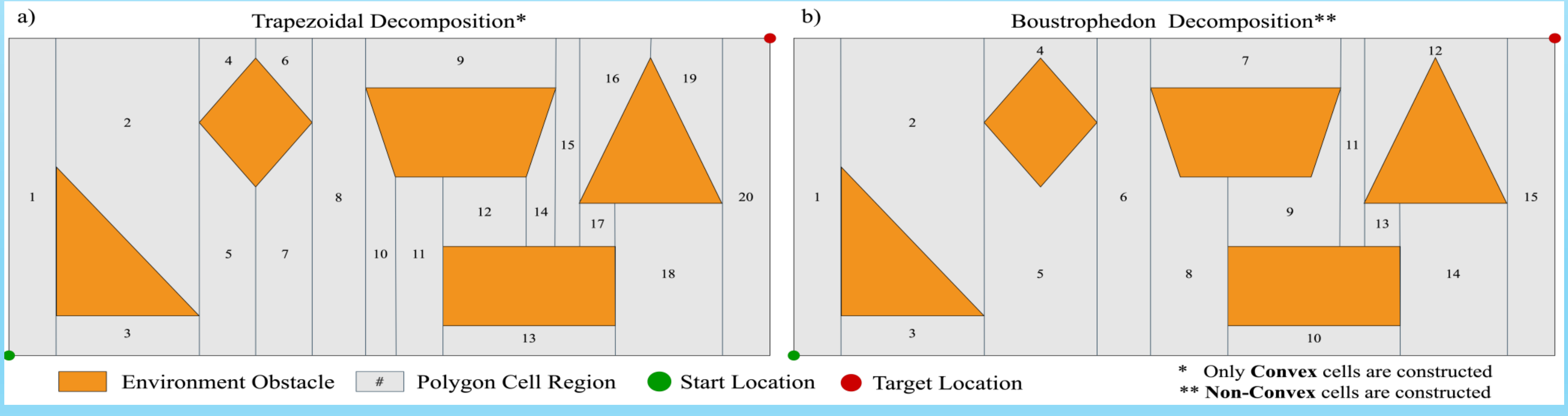
3. Environment Representation

3.2 Environment Representation Methods

- **Cell decomposition** (cont'd)
  - ***Exact Cell Decomposition***
    - The space is divided into several **non-overlapping polygon regions**
    - Approaches:
      - ***Trapezoidal***: the space is split in **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
      - ***Boustrophedon:*** It minimizes the coverage path length in comparison to the trapezoidal, through reducing the number of polygon cell regions created



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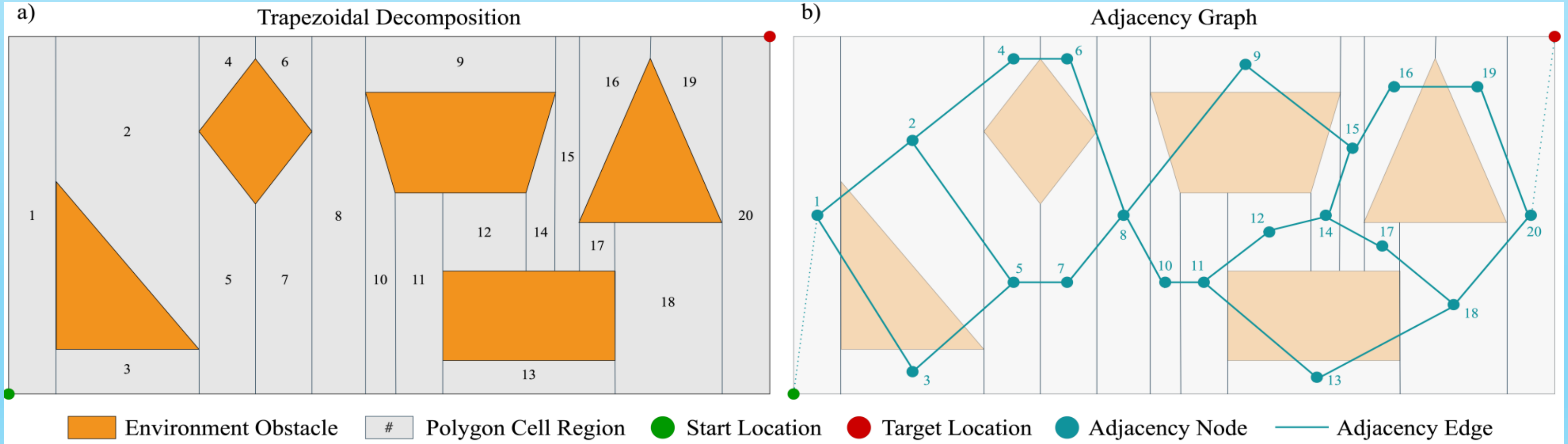
3. Environment Representation

3.2 Environment Representation Methods

- **Cell decomposition** (cont'd)
  - ***Exact Cell Decomposition*** (cont'd)
  - *Note: Boustrophedon is a style of writing in which alternate lines of writing are reversed, with letters also written in reverse, mirror-style*
  - Between **cell regions**, an **adjacency relationships** can be defined, leading to a **connectivity graph**
    - The **graph nodes are placed in the free space** cell region locations
    - **Result: a continuous free space path can be planned** across the environment space based upon cell region relationships

Trapezoidal conversion to Adjacency Graph



Source: M,R. Jones, S.Djhael, K. Welsh Path-planning for Unmanned Aerial Vehicles with Environment Complexity Considerations: A Survey, ACM Comput. Surv., Vol. 1, No. 1, November 2022.

3. Environment Representation

3.2 Environment Representation Methods

- **Cell decomposition** (cont'd)
  - ***Adaptive Cell Decomposition*** (applicable to 2D and 3D space)
  - It deconstructs the environment only where an obstacle's presence requires
  - For a PP scenario an **adaptive schema called (*Quadtree*) is constructed** by dividing the space into four equal sub-regions
    - **Where an obstacle exists**, then **regions are further recursively decomposed** into four supplementary child regions until the desired stopping condition is met
  - **Cell decomposition define both free and obstacle space**, so the range of movement available to UAVs within free space is unbounded
  - **Results: large search space for any PP algorithm**
- **Roadmap Representation**
  - **Connectivity graph** is constructed; the **nodes represent key free space locations**
    - The graph construction strategies can be different
  - The **edges may have weights** (e.g., related to time or distance); they represent the ability to transit safely between the adjoined nodes
  - This **reduction** of an environment **into a graph-based structure, is similar to a classical route planning optimization problem**
    - where **optimal routes are identified by comparing the sum of edge weights** in candidate paths (additive metric)
  - A **PP algorithm is applied to this arrangement to discover an optimal path**

3. Environment Representation

3.2 Environment Representation Methods

Roadmap Representation (cont'd)

- ***Visibility graphs (VG)***
  - Let it be a **set *O* of pairwise disjoint objects** in the plane (considered as obstacles in UAV motion planning)
  - The **visibility graph is a representation model**

- For polygonal obstacles the vertices of these polygons are the nodes of the visibility graph
- Two **nodes are connected by an arc** if the corresponding **vertices can see each other**
- **Algorithms for computing the visibility graph of a polygonal scene have been developed**
- Computing the visibility graph: different complexity orders exist, for a polygonal scene with a total of **n** vertices: e.g., $O(n^2 \log n)$, $O(k + n \log n)$ (k is the number of arcs of the visibility graph)
- **Weakness:** in the construction process, generated paths pass within close proximity to the obstacles they seek to avoid

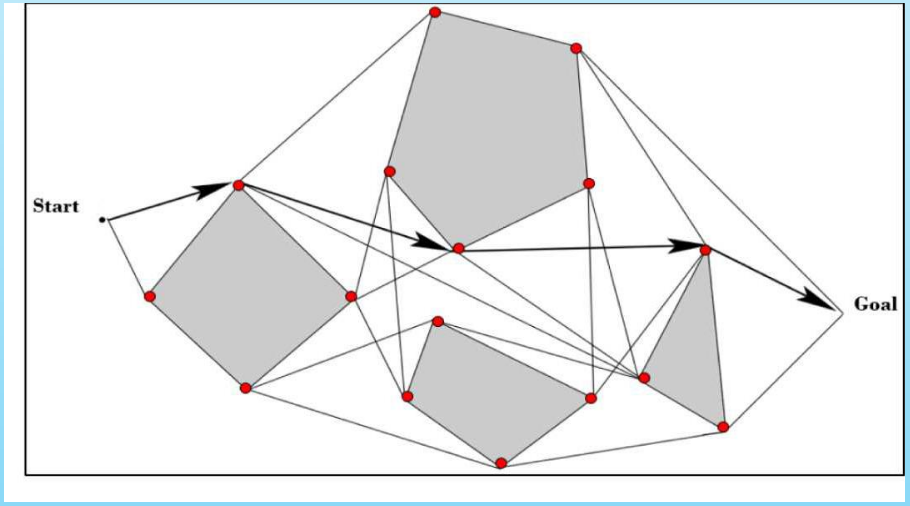
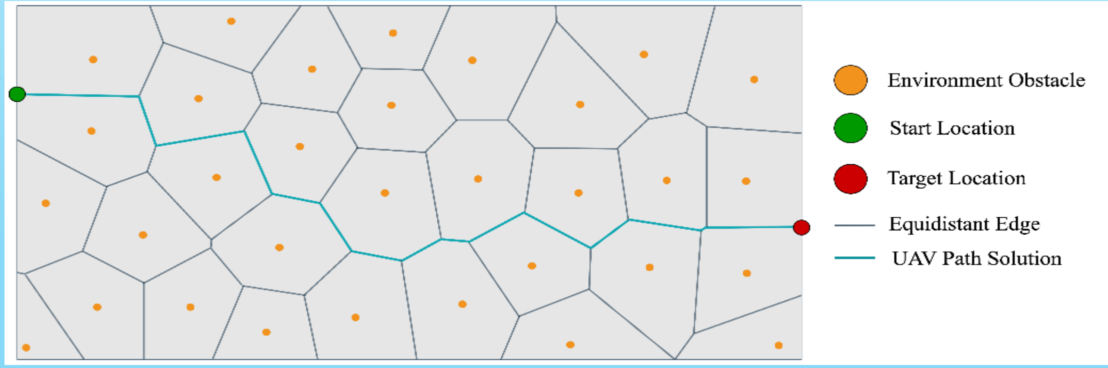


Figure- Source: M. N.Bygi, 3D Visibility Graph, https://sharif.edu/~ghodsi/papers/mojtaba-nouri-csicc2007.pdf

3.2 Environment Representation Methods

- **Roadmap Representation** (cont'd)
  - ***Voronoi diagrams* and *path solutions***
    - Let **$P = \{p_1, p_2, \ldots p_n\}$** be a set of points (called *sites*) in a 2D Euclidean plane
    - The **space is decomposed into regions around each site**, s.t. all points in the region around p_i are closer than to any other point in *P*
    - For UAV movement, one can consider the **points in P as representing obstacles/threats**
    - The **cells edges can be available paths** (of an UAV) to the nearest node to the target positions
    - A **PP algorithm searches the shortest path** to go to the nearest node to the target positions



Source: Tong, Wu Wen chao, H. Chang qiang, X. Yong bo, Path Planning of UAV Based on Voronoi Diagram and DPSO H., Elsevier, Procedia Engineering 00 (2011) 000–000 4198 – 42031877-7058, doi:10.1016/j.proeng.2012.01.643, www.sciencedirect.com

3. Environment Representation

3.2 Environment Representation Methods

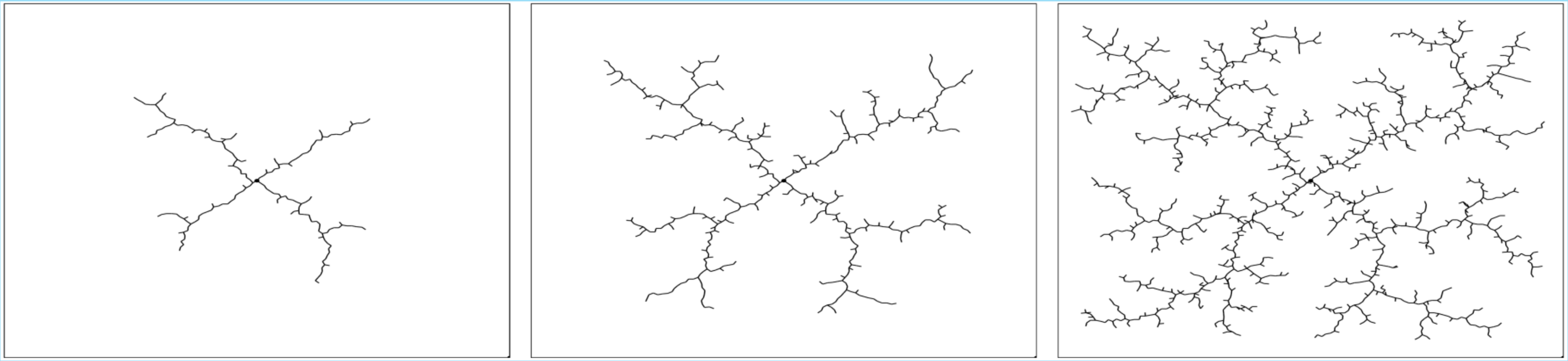
- **Roadmap Representation** (cont'd)
  - **Probabilistic Roadmap**
    - Visibility graph and Voronoi: **the path generation is dictated solely by the placement of obstacles** within the environment
    - A **probabilistic approach deconstructs the available free problem space into a set of randomly placed connectivity nodes**
    - **Connecting nodes with edges is based upon proximity to a nearest neighbor node,** combined with the perceived visibility and ability to pass unhindered between nodes
    - In path construction a **significant level of environment knowledge is required**
    - This construction method **does not provide an optimal solution**, but is able to guarantee completeness based upon the increasing number of nodes added
      - **A motion planner is said to be *complete*** if the planner, in finite time, **either produces a solution or correctly reports that there is none**

Source: M. Farooq et al., Quadrotor UAVs flying formation reconfiguration with collision avoidance using probabilistic roadmap algorithm. In 2017 International Conference on Computer Systems, Electronics and Control (ICCSEC), pages 866–870. IEEE, 2017.

3. Environment Representation

3.2 Environment Representation Methods

- **Roadmap Representation** (cont'd)
  - **Rapidly-exploring Random Trees (RRTs)**
    - RRT focuses upon a **randomized approach for exploration of the environment**
    - The algorithm searches nonconvex, high-dimensional spaces by **randomly building a space-filling tree**
    - **An explorative branching strategy** is applied; branching paths are constructed originating from **a root node**
    - The **tree is constructed incrementally** from **samples drawn randomly from the search space** and is inherently biased **to grow towards large unsearched areas** of the problem
    - A high level of **environment knowledge is required** in tree construction to allow successful placement of future nodes
    - RRT offers a configurable strategy to manage tree growth and exploration of the problem space



Source: S.M. LaValle et al. Rapidly-exploring random trees: A new tool for path planning. 1998 Technical *Report (TR 98–11). Computer Science Department, Iowa State University..*

3. Environment Representation

3.2 Environment Representation Methods

- **Roadmap Representation** (cont'd)
  - **Rapidly-exploring Random Trees (RRTs)** (cont'd)
    - **RRT**
      - can **handle problems with obstacles and differential constraints** (nonholonomic and kinodynamic) and can be used in autonomous robotic/UAV motion planning
      - **generates open-loop trajectories** for nonlinear systems with state constraints
      - can also be considered as a **Monte-Carlo method** to bias search into the largest Voronoi regions of a graph in a configuration space

    - *Note 1*: **A *nonholonomic*** system: - definition
      - a mechanical system with velocity constraints not originating from position constraints (e.g.: rolling without slipping)
      - its state depends on the path taken in order to achieve it
      - the system is described by a set of parameters subject to differential constraints and non-linear constraints
    - *Note 2:* ***Kinodynamic planning*** (In motion planning), is a class of problems for which velocity, acceleration, and force/torque bounds must be satisfied, together with constraints such as avoiding obstacles

3. Environment Representation

3.2 Environment Representation Methods

- **Artificial Potential Field (APF)**
  - The cell decomposition and roadmap approaches **build an environment representation from prior known environment knowledge**
  - **(APF) computes in real-time a directional** force to be applied to a UAV, based on
    - the gravitational **attractive forces** applied by **goal or target** locations
    - the cumulative **repulsive forces** applied by obstacles
  - **In a real-world environment**
    - the gravitational force is proportional to the **Euclidean distance from the UAV to target locations**
    - the **repulsive forces can be derived** from **mounted sensors** capable of calculating obstacle distance
  - The **UAV makes successive evaluation** of **the resultant forces**
  - The **abstract representation of APF field forces** provided across a whole environment **grants a UAV the potential for significant autonomy** (to find a transit path across an environment)
  - **APF enables a reactive path-planning**; dynamic obstacles influence APF forces in real-time allowing for adaptive navigation decisions

N. He et al., Dynamic path planning of mobile robot based on artificial potential field, 2020 Int'l Conf. on Intelligent Computing and Human-Computer Interaction (ICHCI), IEEE, 2020.

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4. Path Planning Algorithms and Methods

Path Planning Algorithms Taxonomy

- The PP algorithms can be associated with methods of environment representation

1. **Node-based Optimal**
2. **Sampling-based**
3. **Mathematical Model-based**
4. **Bio-inspired**
5. **Multi-fusion based**
6. **Machine learning – based**

Ref: L.Yang et al. Survey of robot 3D path planning algorithms. Journal of Control Science and Engineering, 2016

4. Path Planning Algorithms and Methods

4.1 Node-based Optimal Algorithms

- **Classical: Dijkstra** (*shortest path* – SP) and **A*;** it finds **optimal routes within a graph**
- **Enhancements** of the classical solutions are proposed
  - E.g.: **add to Dijkstra's SP algorithm additional parameters**, (e.g., waiting and charging times within the environment's fast charging machines), augmenting the traditional E2E SP calculation
- ***Dijkstra enhancement examples - in UAV domain***
  - **Combine an existing algorithm with novel PP methods** thus generating feasible paths for multiple UAVs using a heuristic prioritized planning approach
  - Enhanced multi-UAV planning through a **new cooperative planning capability**
    - to **support UAV swarm scenarios** at a low computational cost
    - whilst applying a traditional sparse A* algorithm to plan each individual UAVs path
  - **Improved Voronoi diagram graph generation** strategy to deconstruct the environment, once implemented the traditional Dijkstra algorithm
- ***Issue**: the **predefined nature of the graph** itself, **limits** the applicability of such algorithms to **dynamic-unknown scenarios***
- Future work is needed to adapt Voronoi techniques to dynamic or unknown scenarios

Ref: E.W. Dijkstra et al. A note on two problems in connexion with graphs. Numerische mathematik, 1(1):269–271, 1959.
P.E. Hart et al. A formal basis for the heuristic determination of minimum cost paths. IEEE transactions on Systems Science and Cybernetics, 4(2):100–107, 1968.

4. Path Planning Algorithms and Methods

4.2 Sampling –based algorithms

- A required **prerequisite of problem space knowledge exists**, s.t. **obstacle or free space environment information can be sampled** and interpreted by a PP algorithm
- **Such approaches** are considered as a **black box returning a feasible collision-free path** (they have advantages of high-speed implementation)
- **Information from a collision detector is used**, while searching the configuration space to sample the environment as a set of nodes or other forms; then map the workspace or just search randomly to an optimal path
- **Examples**: ***Probabilistic Roadmap (PRM); Rapidly exploring Random Tree (RRT)***
  - These are efficient for navigating in high-dimensional spaces, to generate feasible solutions
  - **Issue: it is not sure** an optimal solution will be achieved the
  - **PRM** works well in high-dimensional search spaces
    - **Idea: take random instances from the configuration space**
    - Then it **checks whether or not they are in the free space**, and **utilize a local planner** to connect these configurations to other nearby configurations
    - **Issue:** PRM is **inefficient** when **obstacle geometry is not known** beforehand
  - **RRT** is a solution regardless of the geometry of the obstacles
    - It **explores a random tree** to produce the first feasible solution to the goal through a cluttered environment with non-convex obstacles

Source: S.Ghambari, M.Golabi, L.Jourdan, J.Lepagnot and L.Idoumghar, UAV Path Planning Techniques: A Survey, RAIRO-Oper. Res. 58 (2024) 2951–2989 RAIRO Operations Research, https://doi.org/10.1051/ro/2024073 www.rairo-ro.org

4. Path Planning Algorithms and Methods

4.3 Mathematical model-based algorithms

- Emerging field, applying **Linear Programming (LP)** and **Mixed-integer Linear Programming** (MILP). These math optimization methods can provide valuable insights into the problem's structure

- **A set of inequalities model the obstacles and environment.** The methods:
  - seek to **reduce the problem's complexity** through bounding the diverse number of possibilities presented by a variable, to integer values
  - employ **probability and mathematical models to predict future events** and to determine the most efficient curve between the start and goal by minimizing a certain scalar quantity

- **Dynamic programming** is another approach, to obtaining an **optimal path when full information and unlimited computation resources are available**

- **Problems**: often failure appears to achieve global optimality within a reasonable time frame and are occasionally ineffective in generating feasible solutions
  - **MILP cannot obtain optimal solutions for large instances** (i.e., sets of routing destinations) without the application of such a metaheuristic approach.

Source: S.Ghambari, M.Golabi, L.Jourdan, J.Lepagnot and L.Idoumghar, UAV Path Planning Techniques: A Survey, RAIRO-Oper. Res. 58 (2024) 2951–2989 RAIRO Operations Research, https://doi.org/10.1051/ro/2024073 www.rairo-ro.org

4. Path Planning Algorithms and Methods

4.4 Bio-inspired algorithms

- They typically **deconstruct an environment into a searchable problem space** using exclusively **approximate cell decomposition approaches**
- **Examples**: **Ant Colony Optimisation (ACO); Particle Swarm Optimisation (PSO)**
- **Ant Colony Optimisation (ACO)**
  - **Swarm intelligence-based algorithm** inspired by the **collective behavior of ants**
  - The standard algorithm is inherently parallel and straightforward to execute
  - It has **resilience and the capacity to explore improved solutions**
  - The **walking path of ants** is used to express the feasible solution
  - In UAV PP each ant is intended to **search for the shortest path** in the free space
  - Over time, there is a **continuous increase in the concentration of pheromones** along shorter paths, accompanied by a corresponding **rise in the preference of ants** for those paths
  - This **reinforcement mechanism eventually converges**, guiding the entire ant colony toward the identification of the optimal path
  - **ACO improvement examples**:
    - novel Max-Min adaptive ACO for multiple UAV PP in dynamic and uncertain environments
    - ACO PP in indoor environments

Source: S.Ghambari, M.Golabi, L.Jourdan, J.Lepagnot and L.Idoumghar, UAV Path Planning Techniques: A Survey, RAIRO-Oper. Res. 58 (2024) 2951–2989 RAIRO Operations Research, https://doi.org/10.1051/ro/2024073 www.rairo-ro.org

4. Path Planning Algorithms and Methods

4.4 Bio-inspired algorithms (cont'd)

- **Particle Swarm Optimisation (PSO)**
  - **PSO simulates** the social **behavior of a swarm of birds** or a school of fishes
  - Optimization is achieved by utilizing the shared information of the global and local solutions in the swarm
  - **PSO Actions summary**
    - **Simple agents, called particles, move in the search space**
    - The **position of a particle shows a candidate solution**/path
    - Each **particle velocity : subject of systematic adjustments** in adherence to defined rules, aimed at refining their positions within the search space
    - Concurrently, **the collective intelligence of the best solution is captured** and **communicated to fellow particles** in subsequent iterations
    - When the stopping conditions are reached the algorithm stops and the **best solution is recorded as a safe and feasible path**
  - **PSO algorithms improvement proposals:**
    - maximum density convergence **DPSO (MDC-DPSO)**
    - fast cross-over DPSO algorithm **(FCO-DPSO)**
    - accurate coverage exploration DPSO algorithm **(ACE-DPSO)**

Source: M,R. Jones, S.Djhael, K. Welsh Path-planning for Unmanned Aerial Vehicles with Environment Complexity Considerations: A Survey, ACM Comput. Surv., Vol. 1, No. 1, November 2022.

Source: S.Ghambari, M.Golabi, L.Jourdan, J.Lepagnot and L.Idoumghar, UAV Path Planning Techniques: A Survey, RAIRO-Oper. Res. 58 (2024) 2951–2989 RAIRO Operations Research, https://doi.org/10.1051/ro/2024073 www.rairo-ro.org

4. Path Planning Algorithms and Methods

4.5 Multi - fusion based algorithms

- This approach seeks an **improvement** in planning ability/ efficiency through **integration of two established algorithms**
  - **Examples**
    - **Introducing guiding factors** (from the A* algorithm), for a more efficient exploration using a guiding force, directing the UAV towards the target destination
    - Introducing a **taboo node matrix**, to support the prevention of a deadlock state occurrence
    - **Combinatorial path improvement strategies** implement an initial path Dijkstra-selection policy, plus a PSO being applied to produce smoothed transitions between path edges

References

- *C.Yin et al. Offline and online search: UAV multiobjective path planning under dynamic urban environment. IEEE Internet of Things Journal, 5(2):546–558, 2017.*
- *Y. Feng et al. Path planning of uninhabited aerial vehicle added the guiding factor. In 2019 IEEE International Conference on Unmanned Systems (ICUS), pages 866–870. IEEE, 2019.*
- *Z. Chen et al. Obstacle Avoidance Strategy for Quadrotor UAV based on Improved Particle Swarm optimization Algorithm. In 2019 Chinese Control Conference (CCC), pages 8115–8120. IEEE, 2019.*

4. Path Planning Algorithms and Methods

4.6 Machine Learning – based algorithms

- **Machine learning (ML) algorithms** are recently proposed in UAV PP area
- ML algorithm types *: **Supervised Learning, Unsupervised learning, Reinforcement Learning (RL), Deep Learning (DL), Deep Reinforcement Learning (DL),*** etc., learn from existing data to build and refine models to solve different tasks.
- **ML applied in UAV PP area**: **clustering methods (QT and K-means), DL, RL, DRL, cooperative and geometric learning, etc**. – can be employed for UAV PP and collision avoidance.
- **ML-based applications in UAV -examples:**
  - to deal with different perspectives of autonomous UAV flights including tuning the parameters for the controller
  - adaptive control algorithms for autonomous flight
  - recognizing objects in farming; real-time path planning
  - real-time collision avoidance considering obstacles or other aerial vehicles
  - decisions within environment problem space, seeking to optimize a given cumulative reward (RL)

Refs: J.L. Junell, E.J. Van Kampen, C.C. de Visser and Q.P. Chu, Reinforcement learning applied to a quadrotor guidance law in autonomous flight, in AIAA Guidance, Navigation, and Control Conference. American Institute of Aeronautics and Astronautics, Inc. (2015) 1990.
G. Kahn, A. Villaflor, V. Pong, P. Abbeel and S. Levine, Uncertainty-aware reinforcement learning for collision avoidance. Preprint arXiv:1702.01182 (2017).
R. Jones, S.Djhael, K. Welsh Path-planning for Unmanned Aerial Vehicles with Environment Complexity Considerations: A Survey, ACM Comput. Surv., Vol. 1, No. 1, November 2022.

4. Path Planning Algorithms and Methods

4.7 Examples of Traditional Path Planning Algorithms

- **They are related to specific representations of the environment**
- **Dijkstra Algorithm**
  - **Classical solution to solve the shortest path problem**
  - It make a **breadth first state space search** looking for the **shortest distance** of any point in the whole free space, layer by layer, through the initial point until it reaches the target point
  - **Issue:** In **UAV PP,** due to the use of free search, the **amount of data of Dijkstra algorithm is greatly increased,** which affects the speed of solution
  - **Different researchers have improved and optimized Dijkstra algorithm**

- **A* (A-Star)**
  - Used in **path finding problems on graphs and meshes**
  - It is using **a heuristic function to perform an informed search, to estimate the cost of the remaining path to the goal**
  - It has **fast calculation** speed and can efficiently obtain UAV path information.
  - It is efficient in environments with precise and known information
  - Issue: **its performance degrades in complex and unknown 3D environments** (lack of enough information about space structure)

Source: C. G. Arnaldo , M.Z. Suárez , F.P.Moreno and R.Delgado-Aguilera Jurado, Path Planning for Unmanned Aerial Vehicles in Complex Environments Drones 2024, 8, 288. https://doi.org/10.3390/drones8070288

4. Path Planning Algorithms and Methods

4.7 Examples of Traditional Path Planning Algorithms

D* (D-Star)

- **D* - real-time search algorithm** that **recalculates the route when changes occur** in the environment; It is suitable for dynamic environments
- **Issue: its computational complexity can be high** (e.g., in 3D, with many moving objects and obstacles

- **Theta* (Theta-Star)**
  - It is an **improvement of A*** that performs a **search in the discretized search space** using linear interpolation to smooth the path
  - **Theta* can produce more direct and efficient trajectories than A***
  - **Issue: lower performance in environments with multiple obstacles** and complex structures
- **PRM (Probabilistic Roadmap)**
  - It **creates valid paths through the *random sampling*** of the search space
  - **Issues**:
    - it can **generate valid trajectories**, but its **efficiency is lowering by the density of the search space**
    - it **may require a high number of sampling points** to represent accurate trajectories in a 3D environment with complex obstacles

4. Path Planning Algorithms and Methods

4.7 Examples of Traditional Path Planning Algorithms

- **RRT (Rapidly Exploring Random Tree)**
  - RRT uses ***random sampling* to *build a search tree*** that represents the **possible trajectories of the UAV**
  - It is **widely used in PP for complex and unknown 3D environments**with obstacles and unknown structures
  - It has a **probabilistic nature** and able to efficiently explore the search space
- ***Note: Many other RRT variants have been developed in different studies***
- ***Examples***
- **RRT* (Rapidly Exploring Random Tree Star)**
  - It is an **enhanced RRT**; it optimizes the trajectories generated by the original algorithm
  - **RRT* reduces the path length and optimizes the tree structure**
  - It can provide optimal routes, but **its computational complexity is higher in complex 3D environments**
- **RRT*-Smart**
  - It **accelerates the convergence rate of RRT*** by using **path optimization** (in a similar fashion to Theta*) and **intelligent sampling** (by biasing sampling towards path vertices, which – after path optimization are likely to be close to obstacles)

4. Path Planning Algorithms and Methods

4.7 Examples of Traditional Path Planning Algorithms

- **A*-RRT and A*-RRT***
  - A ***two-phase*** **PP** method that uses a **graph search algorithm**
    - 1. **search for an initial feasible path** in a low-dimensional space (not considering the complete state space) avoiding hazardous areas and preferring low-risk routes
    - 2. **which is then used to focus the RRT* search** in the continuous high-dimensional space
- **Real-Time RRT* (RT-RRT*)**
  - A **variant of RRT* and informed RRT*** that uses an online **tree rewiring strategy** that allows the tree root to move with the agent without discarding previously sampled paths, in order to obtain real-time path-planning in a dynamic environment
- **Theta*-RRT**
  - A **two-phase PP** method **similar to A*-RRT*** that uses a **hierarchical combination of any-angle search with RRT motion planning** for fast trajectory generation in environments with complex nonholonomic constraints
- **…. other of RRT variants**
- **Artificial Potential Fields**
  - It uses **attractive and repulsive forces** to guide the UAV movement towards the goal and away from obstacles
  - **Transform the impact of targets and obstacles on the movement** of the drone **into an artificial potential field;** It can generate smooth trajectories
  - **Issue:** it may suffer from **local minima and oscillations in environments with complex obstacles**

4. Path Planning Algorithms and Methods

4.7 Examples of Traditional Path Planning Algorithms

- **Depth-First Search (DFS)**
  - It **traverses a tree by exploring one node and its descendants at a time**; a node is selected initially
  - The **search is progressively expanded to the deepest nodes** (backtracking only when there are no more child elements to explore)
  - **If the deepest node does not contain the desired solution, the algorithm backtracks to the start of the tree** and continues the search by exploring adjacent nodes on the right, following a similar deep format
  - This process continues until the solution is found
  - **Problems**:
    - **DFS may miss large portions of the workspace since** it tries to search several paths at a time before completing one path
    - **DFS may not always yield the optimal solution** as it prioritizes the first successful path found, disregarding the time or steps taken to reach it, with the risk of falling into a loop of exploring an infinite depth
    - **DFS can be time-consuming** because it may delve into uncharted depths of a single node without necessarily leading to a viable solution

Source: L. Paulino, C. Hannum, A.S. Varde and C.J. Conti, Search methods in motion planning for mobile robots, in Intelligent Systems and Applications, edited by K. Arai. Springer International Publishing (2022) 802–822.

4. Path Planning Algorithms and Methods

4.7 Examples of Traditional Path Planning Algorithms

- **Breadth-First Search (BFS)**

  - In BFS **all the current level nodes are visited prior to their descendants**, following a **systematic approach** where shallow nodes are expanded first by **exploring all the subsequent level nodes along the path.**

  - **DFS versus BFS**
    - **DFS is exploring a single path to its deepest depths**
    - **BFS expands its search by including all nodes within each layer**, adhering to the FIFO principle implemented through a queue structure.
    - **BFS could be slower than DFS in finding a path**, however, it can be preferred due to its systematic exploration of all nodes within each layer; it is able to keep track of visited nodes before moving on to the next layer.
    - **BFS requires more memory compared to DFS** due to the need to store all visited nodes in the order they were encountered
      - This storage step is important in BFS tree traversal as it influences the sequence in which the algorithm explores nodes in the subsequent layer

Source: L. Paulino, C. Hannum, A.S. Varde and C.J. Conti, Search methods in motion planning for mobile robots, in Intelligent Systems and Applications, edited by K. Arai. Springer International Publishing (2022) 802–822.

4. Path Planning Algorithms and Methods

4.8 The time complexity of UAV path planning algorithms

Voronoi Diagram $O(n\log(n))$; n is the number of the vertices

Visibility Graph $O(n^2)$; n is the number of the vertices

PRM $O(n\log(n))$; n is the number of iterations

RRT $O(n\log(n))$; n is the number of iterations

Dijkstra $O(|E| + |V|\log|V|)$; V is the set of vertices, E the set of edges

BFS & DFS $O(|E| + |V|)$

A* $O(n^2)$; n is the number of vertices

Exact Cell Decomposition; $O(n\log(n))$; n is the number of obstacle vertices

CONTENTS

5. UAV Swarm related topics

5.1 UAV Swarm Path Planning

- **An UAV swarm can make decisions collectively** and complete its aerial mission using relatively simple instructions **due to the AI technology and edge computing**
- UAV swarm is its application for both civilian and military purposes using **swarm intelligence**
- ***Swarm intelligence*** **(SI)**
  - SI is **an evolving area of bio-inspired artificial intelligence**
    - This is obtained due to the **deep interconnection of the real system having feedback loops**
    - SI concept allows **scheduling, clustering, optimizing, and routing a cluster of similar individuals**
    - All the individuals follow clear rules and interact with each other and also with the environment
- ***SI basic principles:***
  - **Proximity:** the swarm individuals can easily respond to the environmental variance that is caused by interactions among them
  - **Quality:** a swarm can respond to quality factors like location safety only

Source: M.M. Iqbal, Z.Anwar Ali, R. Khan and M.Shafiq, Motion Planning of UAV Swarm: Recent Challenges and Approaches, IntechOpe, 2022, DOI: http://dx.doi.org/10.5772/intechopen.106270

5. UAV Swarm related topics

5.1 UAV Swarm Path Planning

- ***SI basic principles (cont'd)***
    - **Diverse response:** enables to design of the distribution s.t. all the individuals are protected from environmental fluctuations to a maximum level
    - **Stability:** restricts the swarm to show a stable behavior with the changes in the environment
    - **Adaptability** : the swarm sensitivity as the behavior of the swarm changes with the change in environment
- ***SI mechanisms:*** concern the environment, interactions, and activities of the individuals
    - There is **no direct communication among the individuals in a swarm**; they interact with each other through environmental alterations
    - Thus, **environmental alterations serve as external memory**
    - This simulation of work is done by applying the ***stigmergy*** behavior of all the swarm members
        - **stigmergy**- a **mechanism of indirect coordination** through the environment, between agents or actions
    - The individuals choose their actions with an equilibrium between a **perception-reaction model and any other random model**

Source: M.M. Iqbal, Z.Anwar Ali, R. Khan and M.Shafiq, Motion Planning of UAV Swarm: Recent Challenges and Approaches, IntechOpe, 2022, DOI: http://dx.doi.org/10.5772/intechopen.106270

5. UAV Swarm related topics

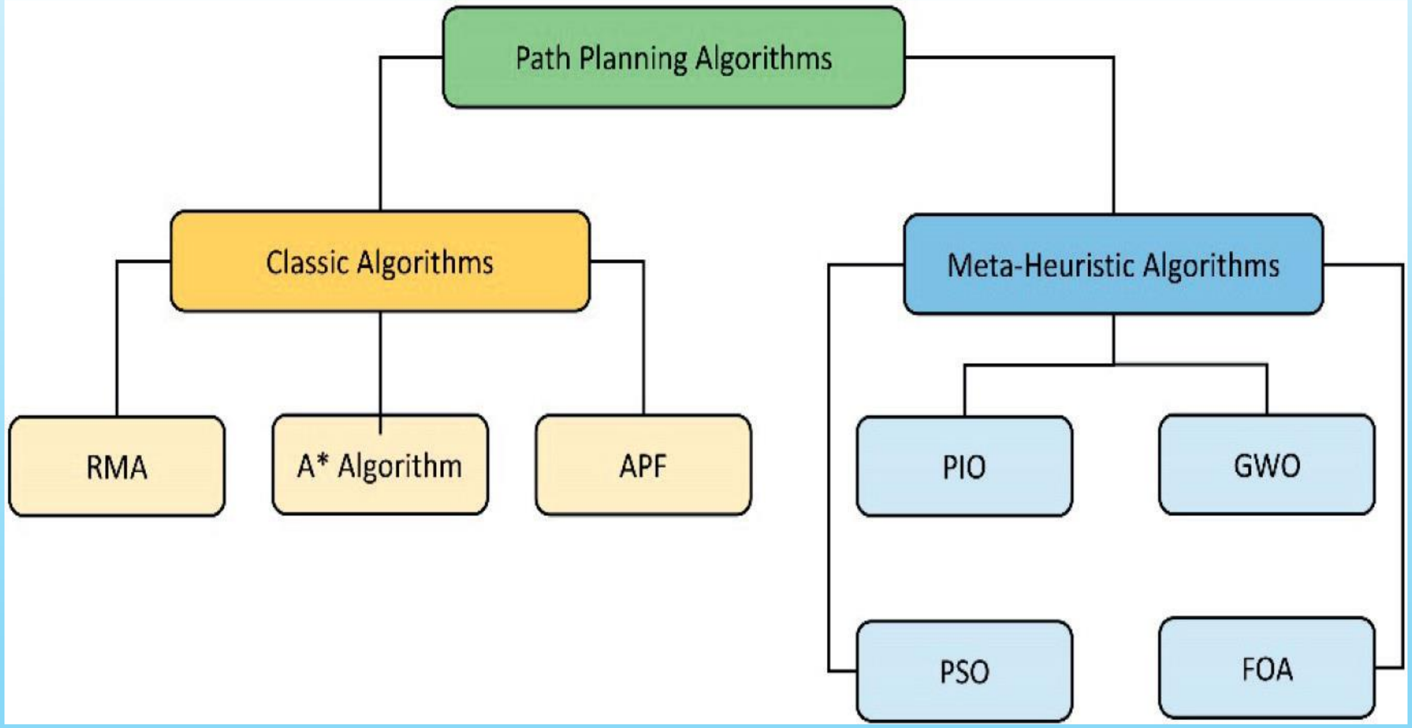
5.1 UAV Swarm Path Planning

- Examples **of programming languages for SI**: Proto-swarm, swarm, Star-Logo, and growing point
  - The **UAV PP of a swarm is challenging (NP-hard problem)**
  - The PP algorithms proposed for swarm are generally classic and meta-heuristic algorithms
  - Classic algorithms require environmental information
    - **Examples:**
      - ***Road map algorithm (RMA)***
      - ***A**** **and** ***Artificial Potential Field (APF)*** **algorithms**
  - Meta-heuristic algorithms require information on the real-time position and measured environmental elements.
    - **Examples:**
      - ***Particle swarm optimization (PSO)***
      - ***Pigeon-inspired optimization (PIO)***
      - ***Fruit Fly Optimization algorithm (FOA)***
      - ***Gray Wolf Optimization algorithm (GWO)***

5. UAV Swarm related topics

5.2 UAV Swarm Path Planning - taxonomy

- **PP algorithms solutions for UAV swarm**



Source: M.M. Iqbal, Z.Anwar Ali, R. Khan and M.Shafiq, Motion Planning of UAV Swarm: Recent Challenges and Approaches, IntechOpe, 2022, DOI: http://dx.doi.org/10.5772/intechopen.106270

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6. Challenges and Trends

- **Path Planning in 3D environments and time domain**
  - Further **studies and optimization methods are needed for real time in 3D space**
  - Difficulties are higher and the problem is much more complex than 2D PP
    - **Need to consider kinematic, geometric, physical and temporal constraints, flight risk levels, airspace restrictions**, etc.
  - 3D UAV PP are needed, especially in complex environments such as urban areas caves, and forests
- **Mathematical models for the PP**
  - **Multi-objective optimization is not enough addressed** in the current models.
  - **Multi-objective functions, Pareto optimal solutions can be obtained taking all factors into consideration** will make the math UAV PP models more realistic
  - Multiple types of **static and dynamic constraints** are necessary to be considered in PP models
- **Experimental work**
  - **Many works** perform some computational **simulation**
  - However, for the UAV use in many different **applications it is necessary to work with real experiments.** Problem in experiments : number of UAVs considered
  - **The complexity of considering many UAVs is very high**, but this is a necessary future work so that the use of UAVs especially in urban centers becomes a reality

6. Challenges and Trends

- **Optimization techniques**
  - Many **optimization** algorithms and methods have been **already studied**:
    - **Sampling-based, Node -based, Mathematic Model- based, Bioinspired. Multifusion-based, AI,** etc.
  - Future research combining different methods, such as **AI-based (e.g., Neural networks, Deep Learning (DL), Reinforcement Learning, DRL, etc.), evolutionary** algorithms with heuristic, fuzzy inference methods, and variants of more widely used methods
  - This need is due to the **complexity of the problem of the UAV PP in real environments**, and the different constraints

- **Integration of different segments**
  - The **integration and communication of UAVs with terrestrial and space environments** is a primary factor and involves also the architecture of the Internet of Drones (IoD).
  - Work is needed in order to **integrate different spaces connected to each other via communication protocols**
  - **Different factors** need to be considered: **data rate, coverage. scalability, reliability, security**

Source J.V.Shirbayashi and L. B. Ruiz , Toward UAV Path Planning Problem Optimization Considering the Internet of Drones, IEEE Access, 2023

6. Challenges and Trends

- **Security and privacy**
  - **Many types of possible attacks exist**, to which UAVs have to resist
  - Threat areas need to be diverted by the UAVs during the aerial path to be traveled
  - **Security and privacy should be considered at each architectural layer**: application, transport, network and physical layer
  - **Privacy needs to be addressed more in future work**, given the UAV's connectivity to ground and air space, large amounts of data need to be stored securely

- **UAVs in smart cities**
  - In smart cities **things are connected and can collaborate intelligently and automatically** to improve quality of life, save lives, and sustain resources.
  - UAV technology can play a vital role in improving **many real-time applications of smart cities**
  - More research involving UAVs and smart cities is necessary
  - **Policies** to encourage the use of UAVs are developed, promoting the economy of the sector, together with the development of **new technologies** such as
    - **DAA (Detect and Avoid)**
    - **UTM (UAS Traffic Management), etc.**

6. Challenges and Trends

- **Current achievements in PP have included**
  - 3D UAV PP considering the **energy consumption and safety** of drones.
  - **Multi-objective mathematical modeling of UAV PP**
  - **Route planning in smart cities** considering the IoD.
  - Development of **tools that contribute to the advancement of real applications** in IoD.

- **Additional challenges** in this context are:
  - **Airspace regulations** to govern the development of real UAV applications in different environments
  - **UAV PP in real time considering energy-efficient and safety**
  - **Integration between UAVs and other means of transport** (trucks, buses, etc.) for practical and safe applications in the context of smart cities
  - **Development of tools and methodologies for real experiments** that consider several UAVs

Source J.V.Shirbayashi and L. B. Ruiz , Toward UAV Path Planning Problem Optimization Considering the Internet of Drones, IEEE Access, 2023

6. Challenges and Trends

- **3D Environment complexity issues**
  - **UAV PP is a complex and multifaceted problem**
  - The **environment modelling techniques reported are applied only to the less complex classes** of environment
  - The **binary choice between a known/ unknown environment is a notable limitation** capturing only the extreme cases
    - However, some problems may exist in which partial environmental knowledge is available
  - **Research started**, to **define bounds for how much complete and accurate pre-existing environmental knowledge must be**, such that the planned paths could be sufficiently flyable, or at least flyable with minor modification

- **Availability of static-known environment knowledge, is acceptable in a simulated environment** ; **more work is necessary** to allow usage in **the real-world**
  - **Potential solutions**
    - Exploration of the **hybridised environment planning**
      - **pre-planning a path** with a static representation of the environment
      - **dynamic unknown obstacles are evaluated in flight**, with minor changes supplied to a global path
    - **Individual ability of a UAV to map or sense surroundings throughout an unknown environment**
      - It is needed an initial environment survey, before requiring centralised processing to produce optimal transit paths

Source: M,R. Jones, S.Djhael, K. Welsh Path-planning for Unmanned Aerial Vehicles with Environment Complexity Considerations: A Survey, ACM Comput. Surv., Vol. 1, No. 1, November 2022.

6. Challenges and Trends

- **3D Environment complexity issues** (cont'd)
  - **3D dimensionality creates inherent complexity** problems in determining the UAV paths
  - **Solutions**
    - **Split the problem into more manageable chunks**, e.g. fixing of a UAV 3D altitude; PP becomes a 2D problem
      - **Advantage**: easier to address both time and computational constraints that might be otherwise not possible to meet in 3D computations
      - **Drawback-** the path could be non- optimum
    - Find some means for **offloading some computational task from UAVs**

- Many (preferred) methods **reduce the route planner's search space to enable real-time planning** and re-planning (e.g., approximate cellular decomposition); other methods use the roadmap approach
- **Further research is necessary to decide which method is best suited towards a static vs dynamic environment or a known vs unknown environment**
- Bio-inspired, RL and multi-fusion based algorithms are mainly constructed around a cell decomposition approach

- The **majority of the node-based and sampling-based algorithms focus upon a roadmap approach**
- The APF is not so much used due to the limited ability to maintain field knowledge over large areas

Source: M,R. Jones, S.Djhael, K. Welsh Path-planning for Unmanned Aerial Vehicles with Environment Complexity Considerations: A Survey, ACM Comput. Surv., Vol. 1, No. 1, November 2022.

6. Challenges and Trends

- **Communication models – should be refined and improved**
  - **Usually, the simulations assume a static-known knowledge of the environment** being easily accessible to the UAV and planning agent
  - However, **such simulation models are constructed around a centralised control of the PP** (**scalability issues exist in non-centralised topologies** – e.g. UAV swarm)
    - In such cases each UAV should wait for its peer to complete planning, thus **large UAV systems face a potential computational planning bottleneck,** affecting the communication model
  - 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
  - **Introducing an unknown environment presents an increased likelihood of conflict between either a UAV and obstacle or multiple UAVs**
    - So more rich set of requirement is needed for a communication model that interacts with the wider UAV and planning agent
  - For **large scale UAV networks- increased communication volume difficulties** are identified and such issues should be solved

6. Challenges and Trends

- **Time considerations**
  - To achieve a **reduction in computational complexity** one **may fix UAV's velocity** constraining an active planning variable
  - To explore both a UAV's dynamic constraints precisely and limited application of path smoothing approaches may complicate the UAV path generation process
  - **A computed optimal route could become worthless when the physical abilities of a UAV cannot replicate the route in real time**
  - **Open research issue: to adapt the environment model to a given problem, or vice-versa**

CONTENTS

7. Conclusions

- **UAV Path Planning**
  - **Path Planning-** very **important aspect** in UAV-based systems
  - Many **traditional algorithms have been used/adapted/developed** for UAV environment
  - **Novel techniques based on AI/ML are proposed**
  - Many **open research issues exist**, given the multitude of requirements, constraints and factors
    - 3D space, static/dynamic environment, requirements related to energy consumption, specific types of UAVs and journey ranges, real-time requirements, partial knowledge on environment (including static/dynamic obstacles), cooperative tasks for swarms, etc.)
  - **PP algorithms:**
    - **No algorithm can guarantee the discovery of an optimal path in all scenarios**
    - The **algorithm optimality depends on different factors** (problem domain, environmental complexity, problem representation, algorithm's native characteristics)
    - **Certain algorithms are better in finding optimal paths within specific contexts** (trade-offs between different algorithms exist)
    - **Practical issues** such as computational time and optimality **requirements will determine the selection of an appropriate PP method**
  - **Novel techniques, refining existing algorithms, and addressing emerging challenges will lead for advancements in UAV path planning**

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- Thank you !
- Questions?

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References

1. https://www.aonic.com/my/blogs-drone-technology/top-10-applications-of-drone-technology/
2. W.Y.H. Adoni, S.Lorenz, J.S.Fareedh, R.Gloaguen and M.Bussmann, Investigation of Autonomous Multi-UAV Systems for Target Detection in Distributed Environment: Current Developments and Open Challenges, 2023, https://doi.org/10.3390/drones7040263/
3. C.Yan, L.Fu, J.Zhang, , and J.Wang , A Comprehensive Survey on UAV Communication Channel Modeling, IEEE Access, 2019, https://ieeexplore.ieee.org/document/8787874
4. A.I.Hentati, L.C. Fourati, Comprehensive survey of UAVs communication networks, Computer Standards & Interfaces 72 (2020) 103451, www.elsevier.com/locate/csi
5. M.Yeasir Arafat and S.Moh, Routing Protocols for Unmanned Aerial Vehicle Networks: A Survey, DOI 10.1109/ACCESS.2019.2930813, IEEE Access
6. N. Mansoor et al., A Fresh Look at Routing Protocols in Unmanned Aerial Vehicular Networks: A Survey, IEEE Access June 2023
7. S.Ghambari, M.Golabi, L.Jourdan, J.Lepagnot and L.Idoumghar, UAV Path Planning Techniques: A Survey, RAIRO-Oper. Res. 58 (2024) 2951–2989 RAIRO Operations Research, https://doi.org/10.1051/ro/2024073 www.rairo-ro.org
8. D.S.Lakew, U.Sa’ad, N.Dao, W.Na and S.Cho, Routing in Flying Ad Hoc Networks: A Comprehensive Survey, IEEE Communications Surveys&Tutorials, Vol.22, No.2, 2020
9. Cabreira TM, Brisolara LB, Ferreira PR (2019) Survey on coverage path planning with unmanned aerial vehicles. Drones 3(1):4. https:// doi. org/10. 3390/ drone s3010 004
10. L.Yang, J. Qi, J.Xiao, X.Yong, A Literature Review of UAV 3D Path Planning, 2015, https://www.researchgate.net/publication/282744674
11. M,R. Jones, S.Djhael, K. Welsh Path-planning for Unmanned Aerial Vehicles with Environment Complexity Considerations: A Survey, ACM Comput. Surv., Vol. 1, No. 1, November 2022.

Advances in Unmanned Aerial Vehicles Path Planning

References

12. M. N.Bygi, 3D Visibility Graph, https://sharif.edu/~ghodsi/papers/mojtaba-nouri-csicc2007.pdf
13. Tong, Wu Wen chao, H. Chang qiang, X. Yong bo, Path Planning of UAV Based on Voronoi Diagram and DPSO H., Elsevier, Procedia Engineering 00 (2011) 000–000 4198 – 42031877-7058, doi:10.1016/j.proeng.2012.01.643, www.sciencedirect.com
14. M. Farooq et al. Quadrotor UAVs flying formation reconfiguration with collision avoidance using probabilistic roadmap algorithm. In 2017 International Conference on Computer Systems, Electronics and Control (ICCSEC), pages 866–870. IEEE, 2017.
15. S.M. LaValle et al. Rapidly-exploring random trees: A new tool for path planning. 1998 Technical Report (TR 98–11). Computer Science Department, Iowa State University.
16. N. He et al., Dynamic path planning of mobile robot based on artificial potential field, 2020 Int'l Conf. on Intelligent Computing and Human-Computer Interaction (ICHCI), IEEE, 2020.
17. L.Yang et al. Survey of robot 3D path planning algorithms. Journal of Control Science and Engineering, 2016
18. E.W. Dijkstra et al. A note on two problems in connexion with graphs. Numerische mathematik, 1(1):269–271, 1959.
19. P.E. Hart et al. A formal basis for the heuristic determination of minimum cost paths. IEEE transactions on Systems Science and Cybernetics, 4(2):100–107, 1968.
20. C.Yin et al. Offline and online search: UAV multiobjective path planning under dynamic urban environment. IEEE Internet of Things Journal, 5(2):546–558, 2017.
21. Y. Feng et al. Path planning of uninhabited aerial vehicle added the guiding factor. In 2019 IEEE International Conference on Unmanned Systems (ICUS), pages 866–870. IEEE, 2019.
22. Z. Chen et al. Obstacle Avoidance Strategy for Quadrotor UAV based on Improved Particle Swarm optimization Algorithm. In 2019 Chinese Control Conference (CCC), pages 8115–8120. IEEE, 2019.
23. : L. Paulino, C. Hannum, A.S. Varde and C.J. Conti, Search methods in motion planning for mobile robots, in Intelligent Systems and Applications, edited by K. Arai. Springer International Publishing (2022) 802–822.
24. J.V.Shirbayashi and L. B. Ruiz , Toward UAV Path Planning Problem Optimization Considering the Internet of Drones, IEEE Access, 2023

Advances in Unmanned Aerial Vehicles Path Planning

References

25. C. G. Arnaldo , M.Z. Suárez , F.P.Moreno and R.Delgado-Aguilera Jurado, Path Planning for Unmanned Aerial Vehicles in Complex Environments Drones 2024, 8, 288. https://doi.org/10.3390/drones8070288
26. J.L. Junell, E.J. Van Kampen, C.C. de Visser and Q.P. Chu, Reinforcement learning applied to a quadrotor guidance law in autonomous flight, in AIAA Guidance, Navigation, and Control Conference. American Institute of Aeronautics and Astronautics, Inc. (2015) 1990.
27. G. Kahn, A. Villaflor, V. Pong, P. Abbeel and S. Levine, Uncertainty-aware reinforcement learning for collision avoidance. Preprint arXiv:1702.01182 (2017).
28. J.L. Junell, E.J. Van Kampen, C.C. de Visser and Q.P. Chu, Reinforcement learning applied to a quadrotor guidance law in autonomous flight, in AIAA Guidance, Navigation, and Control Conference. American Institute of Aeronautics and Astronautics, Inc. (2015) 1990.
29. G. Kahn, A. Villaflor, V. Pong, P. Abbeel and S. Levine, Uncertainty-aware reinforcement learning for collision avoidance. Preprint arXiv:1702.01182 (2017).
30. M.M. Iqbal, Z.Anwar Ali, R. Khan and M.Shafiq, Motion Planning of UAV Swarm: Recent Challenges and Approaches, IntechOpe, 2022, DOI: http://dx.doi.org/10.5772/intechopen.106270

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- **List of general Acronyms**

5G CN	Core Network
5G-AN	5G Access Network
ACO	Ant Colony Optimisation
AI	Artificial Intelligence
AODV	Ad Hoc On Demand Distance Vector
APF	Artificial Potential Field
BFS	Breadth-First Search
CC	Cloud Computing
CP	Control Plane
CPP	Coverage Path Planning
CR	Cognitive Radio
D2D	Device to Device communication
DFS	Depth-First Search
DL	Deep Learning
DN	Data Network
DRL	Deep Reinforcement Learning
DoS	Denial of Services
DP	Data Plane (User Plane UP)
DTN	Delay Tolerant Network
E2E	End to End
FANET	Flying Ad hoc Network
FRZ	Flight Restriction Zone
GF	Greedy forwarding
GS	Ground Station
HRP	Hybrid Routing Protocol
HTOL	Horizontal Takeoff and Landing
IPP	Informative Path Planning

Advances in Unmanned Aerial Vehicles Path Planning

- **List of general Acronyms**

IoT	Internet of Things
MANET	Mobile Ad hoc Network
MAC	Medium Access Control
MCC	Mobile Cloud Computing
MEC	Multi-access (Mobile) Edge Computing
MILP	Mixed-integer Linear Programming
ML	Machine Learning
NF	Network Function
NFV	Network Function Virtualisation
ONF	Open Networking Foundation
PP	Path Planning
PRM	Probabilistic Roadmap
PRP	Proactive Routing Protocol
PSO	Particle Swarm Optimisation
QoE	Quality of Experience
RAN	Radio Access Network
RL	Reinforcement Learning
RRP	Reactive Routing Protocol
RRT	Rapidly-exploring Random Trees
SCF	Store-carry-and-forward
SDN	Software Defined Networking
UAV	Unmanned Aerial Vehicle

Advances in Unmanned Aerial Vehicles Path Planning

- **List of general Acronyms**

UAVNET	Unmanned Aerial Vehicle Network
UAV-BS	UAV- Base Station
UAV-RS	UAV Relay Station
UL	Uplink
V2X	Vehicle-to-everything
VANET	Vehicular Ad hoc Network
VG	Visibility Graph
VM	Virtual Machine
VTOL	Vertical Takeoff and Landing

- ANNEXES
  - Backup slides

8. Path Planning Algorithms Examples

- **Algorithm 1 Standard Rapidly-exploring Random Trees (RRT) Algorithm**

PP objective : to find a path from a starting position (*xstart*) to a goal position (*xgoal*) through a configuration space.

1: Choose an initial node x_{init} and add to the tree *t*

2: Pick a random state x_{rand} in the configuration space *C*

3: Using a metric *r*, determine the node x_{near} in the tree that is nearest to x_{rand}

4: Apply a feasible control input u to move the branch towards x_{rand} at a pre-chosen incremental distance

5: If there is no collision along this branch, add this new node x_{extend} to the tree t

6: Repeat steps 2 to 5 until *xgoal* is included in the tree *t*

7: Find the complete path from x_{init} to x_{goal}

Source: S. M. LaValle, "Rapidly-exploring Random Trees: A New Tool for Path Planning," 1998, TR 98-11, Computer Science Dept., Iowa State University.

Source: Mangal Kotharia Ian Postlethwaiteb, Da-Wei Gua, A Suboptimal Path Planning Algorithm Using Rapidly-exploring Random Trees, Int'l Journal of Aerospace Innovations, Volume 2 · Number 1&2 · 2010

8. Path Planning Algorithms Examples

Algoritm 2: Modified RRT Algorithm

- The tracking of the generated waypoints depends on the feedback control policy
- The resultant path accuracy depends on the validity of the state space model being used. In reality, there exist also sensor inaccuracies, wind effects and other unmodeled factors.
- Because of incremental growth, the path generated usually includes several extraneous waypoints, which is undesirable (travel cost)
- RRT can be extended to generate paths in the output space

1: Choose an initial node w_{init} and add to the tree t

2: Pick a random waypoint w_{rand} in the space C, with small probability, set w_{rand} = w_{goal} to pull the graph towards the goal

3: Using a metric *r,* determine the node w_{near} in the tree that is nearest w_{rand}

4: Extend the branch toward w_{rand} by an incremental distance while taking care of the turn angle constraint

5: If there is no collision along this branch, add this new node w_{extend} to the tree

6: Repeat steps 2 to 5 until w_{goal} is included in the tree t

7: Find the complete path from w_{init} to w_{goal}

Source: S. M. LaValle, "Rapidly-exploring Random Trees: A New Tool for Path Planning," 1998, TR 98-11, Computer Science Dept., Iowa State University.

8. Path Planning Algorithms Examples

Algorithm 3: PRM algorithm

Input: A graph with initial and goal points

Output: Find the shortest path between the start and goal

1 The vertices $V \leftarrow \emptyset$

2 The edges $E \leftarrow \emptyset$

3 while next vertex is not goal do

4 $c \leftarrow$ a random configuration in the free space

5 $V \leftarrow V \cup c$

6 $Nc \leftarrow$ a set of neighbor vertices chosen from V

7 for all $c' \in Nc$ do

8 if the line (c, c') is collision free then

9 add the edge (c, c') to E

10 Find the shortest path from the start point to the goal on the constructed graph using a shortest PP algorithm

11 return The shortest path

Source: S.Ghambari, M.Golabi, L.Jourdan, J.Lepagnot and L.Idoumghar, UAV Path Planning Techniques: A Survey, RAIRO-Oper. Res. 58 (2024) 2951–2989 RAIRO Operations Research, https://doi.org/10.1051/ro/2024073 www.rairo-ro.org

8. Path Planning Algorithms Examples

Algorithm 4: Reinforcement learning algorithm for UAV path planning.

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

Output: A policy $\pi(s)$ that maps states to actions

1 **Initialize** a Q-function $Q(s, a)$ arbitrarily Initialize an empty replay buffer D
2 for $episode$ = 1 to N do
3 Initialize the state s_0 to the start position
4 **while** s_t is not the goal position do
5 With probability ϵ choose a random action at from $\mathcal{A}$, otherwise choose $a_t = \text{argmax}_a\ Q(s_t, a)$
6 Execute action a_t and observe reward r_t and next state s_{t+1}
7 Store transition (s_t, a_t, r_t, s_{t+1}) in D
8 Sample a mini-batch of transitions $(s_i, a_i, r_i, s\ i_{+1})$ from D
9 Update the Q-function using the Bellman equation:

$$Q(s_i, a_i) \leftarrow Q(s_i, a_i) + \alpha\ (r_i + \gamma\ \text{max}_a\ Q(s_{\ i+1}, a) - Q(s_i, a_i))$$

10 Set $s_t = s_{t+1}$
End while
End do
11 return The learned policy $\pi(s) = \text{argmax}_a\ Q(s, a)$

Source: S.Ghambari, M.Golabi, L.Jourdan, J.Lepagnot and L.Idoumghar, UAV Path Planning Techniques: A Survey, RAIRO-Oper. Res. 58 (2024) 2951–2989 RAIRO Operations Research, https://doi.org/10.1051/ro/2024073 www.rairo-ro.org