Path Planning Advances in Multi-UAV Networks

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Path Planning Advances in Multi-UAV Systems

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

Path Planning Advances in Multi-UAV Networks

- **Motivation of this talk**
  - **UAV(drones)** - popular for **many applications and services** (civilian, military)
  - **Multiple UAVs** are **wirelessly interconnected** in ad hoc manner, UAV networks (**UAVNET**)
    - **FANET** acronym is also used for **Flying Ad hoc Networks -** able to forward packets, gather, and share information

  - **UAVNETs – different characteristics and requirements different from traditional mobile ad hoc networks (MANET) and vehicular ad hoc networks (VANET)**
    - **large variety of operational contexts**
    - **dynamic behavior, rapid mobility and topology changes (physical and logical)**
    - **cooperation needed: UAV-ground stations (GS), UAV-UAV, UAV- satellites, UAV swarms**
    - **3D Work-space/ environment** (including space communications)
      - **Obstacle-avoiding** paths
      - **Real-time** problems during flight
      - **Multi-UAV (e.g. swarms)-** specific problems (group formation, path planning, task assignment)
      - **Energy consumption** issues, ….
    - **specific methods and technologies** for **Data Plane and Management & Control Planes (M&C)** at different architectural layers
      - Physical layer, MAC layer, **routing**, **path planning, UAV** tracking, traffic engineering, cooperation, security, etc.
    - **Multi-UAV Path Planning–important topics in UAV area**

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1. Introduction
2. Multi-UAV and Swarms
3. Path Planning in Multi-UAV Networks
4. Challenges and Open Problems
5. Conclusions

1. Introduction

1.1 Unmanned Aerial Vehicles (UAV) (**drones**)

- **UAVs- popular solutions** for many applications (civilian domains, military domains)
  - **Missions**
    - surveillance, delivery, searching, transportation, agriculture, forestry, environmental protection
    - **mission critical operations -** rescue/emergency, military actions, security
- **UAVs are wirelessly interconnected** in ad hoc manner → **UAVNET**
- **UAV Communication in multi-layered networks** – complex process
- **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
    - **Satellite communication** - preferable solution - for security, defense, or more extensive outreach operations
    - **Civil and personal applications** - cellular communication technologies are preferred
    - **UAV swarms-** utilize mixed communication technologies
- **Limitations and challenges in UAV technology:** battery capacity, limited flight autonomy, manufacturing costs, environment issues, security concerns and others

1. Introduction

1.2 Unmanned Aerial Vehicles (UAV) - classification

- **Different criteria** depending on UAV missions and specific parameters
  - **Missions and applications -** civil and commercial UAVs: agriculture, aerial photography, logistics, data collection; mission critical, special domain - military missions
  - **Performance-related** characteristics: range, maximum altitude, aircraft weight, wingspan, payloads, speed, endurance, cost design and size
- **Engine type**: fuel engines or electric motors
- **Mechanical/physical characteristics**:
  - **weight** - *Micro*, *Light, Medium*, *Heavy*, and *Super Heavy* classes
    - range: ~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*)- need external support
      - longer flight ranges, can carry larger payloads,
    - **Hybrid**- combines the capability of both VTOL and HTOL types
  - **flight range:** close, short, medium, and large endurance categories, spanning distances from under 10 to 1500 kms

1. Introduction

1.3 UAV Networks

- **Single UAVs systems-** have been utilized for quite a long time in many apps.
  - UAVs wireless connections: to ***ground base station (GS)*** or to a satellite station
  - **star topology**
- **Multi UAVs** systems i.e., **UAV networks including swarms of UAVs**; no need to connect every UAV to GS
- **Other terminologies**
  - **UAV communication networks (UAVCN) ,** a.k.a. **flying ad hoc network (FANET)**

- **Relationships with MANET** (Mobile Ad hoc Network) and **VANET (**Vehicular Ad hoc Network): **FANET ⊆ VANET ⊆ MANET**

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

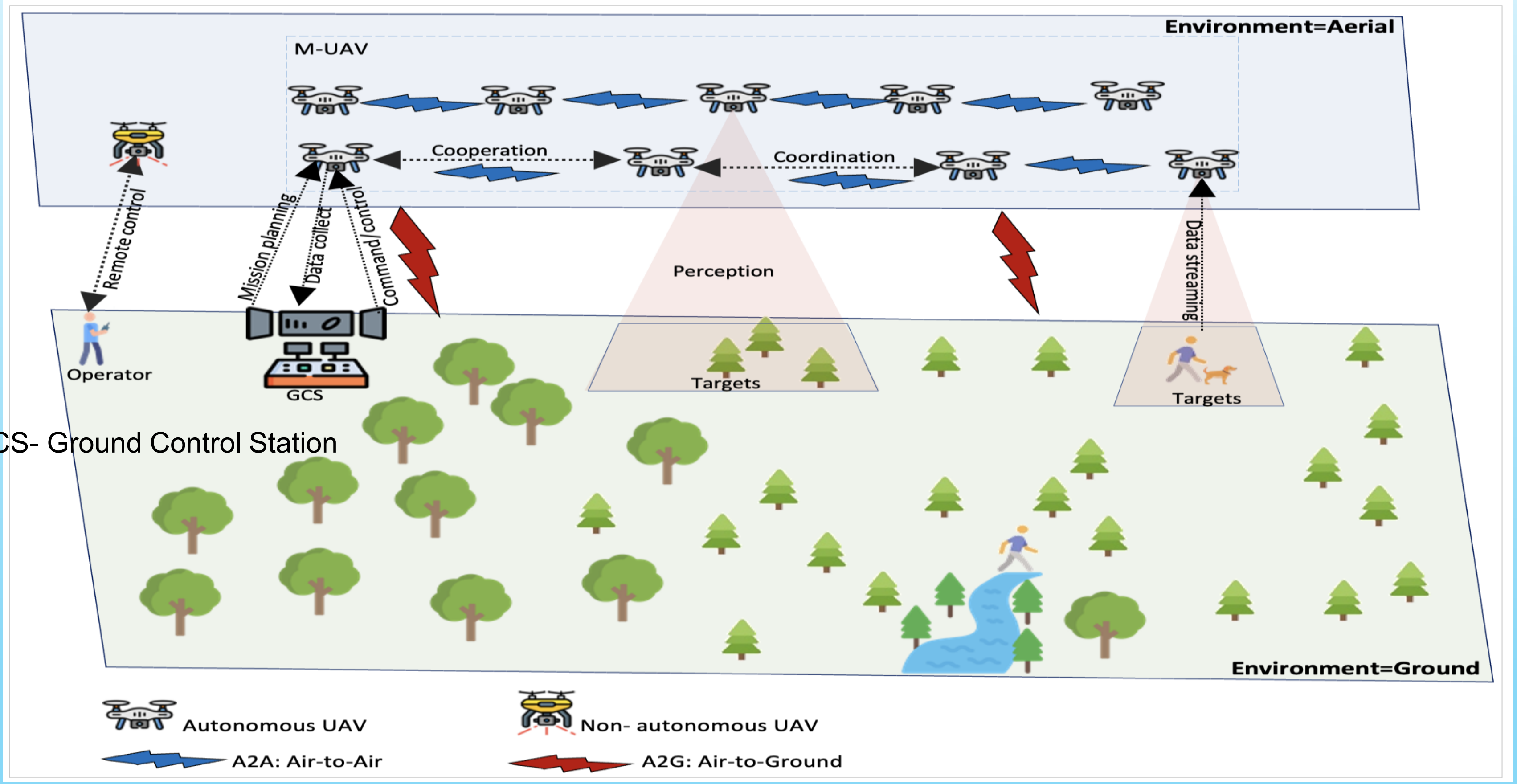
- **Different topics on Multi-UAV networks**: Cooperative/swarm Multi-UAVs; Opportunistic relaying networks; Delay-tolerant UAVs networks; Energy issues; Ground WSN; Internet of Things (IoT); Cooperation with Cloud Computing; Heterogeneity; Self-organization; Security; AI applied in UAV

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

1.3 UAV Networks

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



GCS- Ground Control Station

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

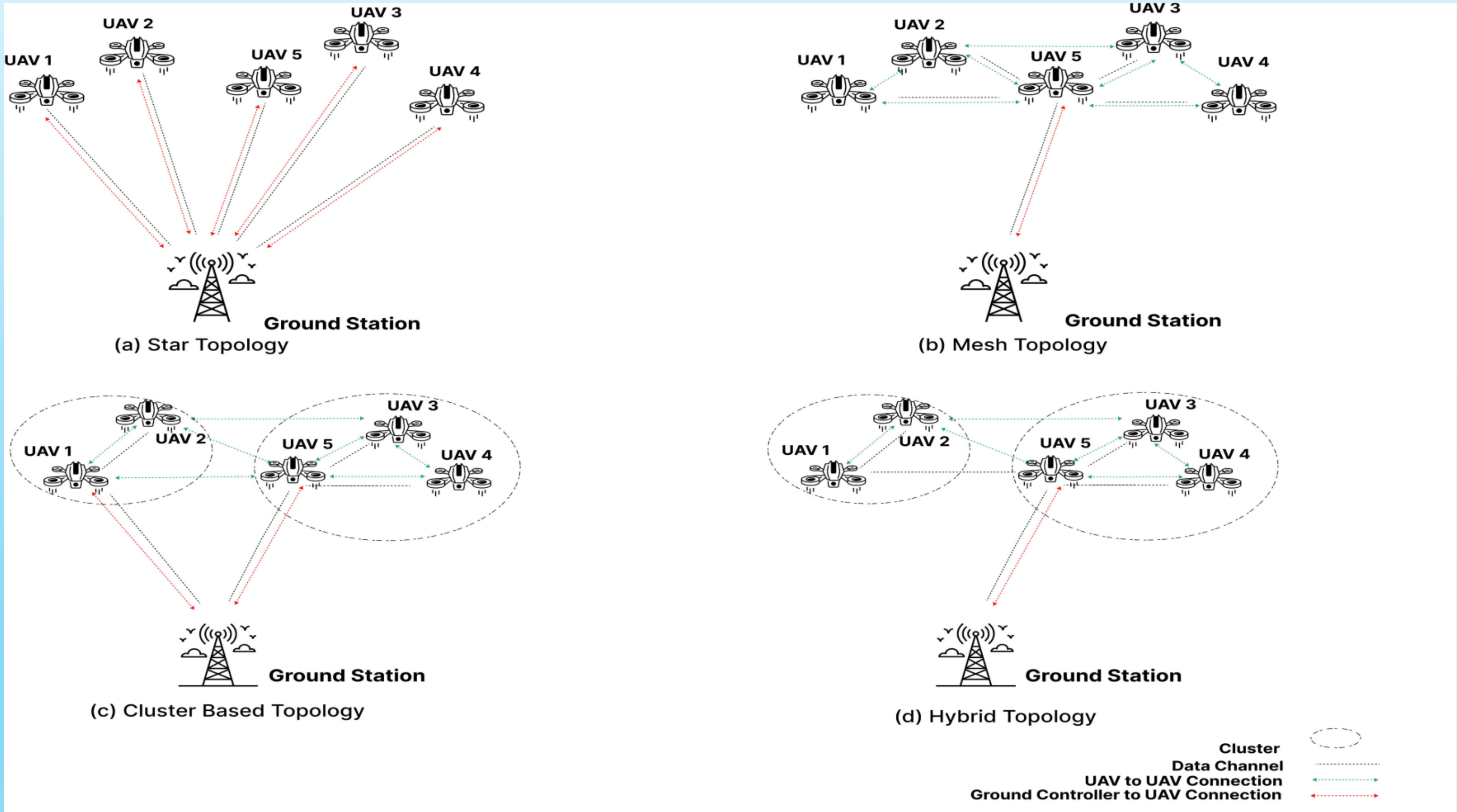
1.3 UAV Networks

- **Basic Multi-UAV topologies- examples**
  - **(a) Star topology:** each UAV (node) is directly connected with GS node
  - **(b) Mesh topology**: a.k.a. ***Single-Group Swarm Ad hoc Network***
    - The GS is only connected to a single node (this is the **cluster head** of the UAV group- playing a role of Gateway)
    - The **cluster head passes the data packets from the GS to the member nodes** and vice-versa
    - **Intra-group** communication topologies: **star, ring, mesh**
  - **(c) Cluster-based network topology;** a.k.a. ***Multi-group Swarm Ad hoc Network***
    - The **UAVs are grouped in several groups/clusters**; **each cluster** has a **head**
    - **The GS is connected to the head 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-** a.k.a ***Multi-layer Swarm Ad hoc Network***
    - **One cluster head UAV is connected to the GS**
    - The cluster head can pass the information
      - from the GS and vice-versa
      - to the UAVs of its group
      - to other nearby cluster heads
    - The GS can be connected also to some single UAVs or group cluster heads
  - **Inter-UAV communication topology types: star, ring, mesh**

1. Introduction

1.3 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. ➡ Multi-UAV and Swarms
3. Path Planning in Multi-UAV Networks
4. Challenges and Open Problems
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2. Multi-UAV and Swarms

2.1 Multi-UAV systems

- **Multi-UAV systems advantages vs. single UAV**
  - ***Time efficiency***: The missions operational times can be significantly reduced
    - (e.g., target search, exploration, etc.)
  - ***Cost:*** it could be cheaper (e.g., concerning power consumption)
  - ***Simultaneous-synchronized actions**:* a team of UAVs can accomplish tasks in different geo-locations at the same time (e.g., to collect information from the points that cannot be reached by a single UAV)
  - ***Complementarity***: each team member can have a specific set of sensors
    - All the sets would be complementary to each other
    - Applicable when all the payload could not be physically located on a single UAV
  - ***Fault tolerance**:* the loss of a UAV unit could be mitigated by the algorithm managing the flight by assigning additional tasks to other UAVs
  - ***Flexibility:*** a group of UAVs could be dynamically allocated to different tasks at the same time and rearranged if necessary.
- **Multi-UAV system issues**
  - Group piloting problems
  - Regulatory restrictions
  - Safety issues (e.g., collision avoidance)

Source: Skorobogatov, C. Barrado, E. Salamí, Multiple UAV Systems: A Survey, Unmanned Systems, Vol. 8, No. 2 (2020) 149–169, DOI: 10.1142/S2301385020500090

2. Multi-UAV and Swarms

2.1 Multi-UAV systems

- **Multi-UAV systems taxonomy – multi-criteria - *examples***
  - **Collective organization:** team (e.g. ≤10), squadron (≥1 teams), group (≥ 1 squadrons)
  - **System autonomy:** low/medium/high level
  - **Spatial UAV relations:** Physical (links)/virtual/no coupling
  - **Temporal UAV relations:**
    - simultaneous (all UAVs execute the same task simultaneously)
    - asynchronous:
      - sequential (≤ 1 in the air)
      - stand in (1 in the air + one back-up)
      - call-in (≥1 in the air + they can call help from others)
  - **UAV similarity:** identical, similar, heterogeneous
  - **Task separation:** functional, cross-functional
  - **Mission Control: centralized, decentralized, mixed**
  - **User interaction:** real-time, pre-planning, no interaction
  - **Automatic plan:** full, fixed, none

Source: Skorobogatov, C. Barrado, E. Salamí, Multiple UAV Systems: A Survey, Unmanned Systems, Vol. 8, No. 2 (2020) 149–169, DOI: 10.1142/S2301385020500090

2. Multi-UAV and Swarms

2.1 Multi-UAV systems

- **Typical applications based on of multi-UAV collaboration- examples**
  - ***Disaster rescue*** - UAVs collaborate (search, delivery, positioning
    - algorithms - adaptive GA and PSO for task assignment and PP
  - ***Area coverage*** -dynamically adjusting paths and optimizing mission execution, addressing battery shortages and reducing working time
  - ***Monitoring* patrols-** enable r.t. surveillance over large areas, employing algorithms for obstacle avoidance and maintaining safe paths

2.2 Special case: UAV swarms

UAV swarm : a set of aerial UAV/robots *working together for a specific goal*

- UAV swarm domain belongs to aerial robotics area, leveraging collaborative autonomy between them to enhance operational capabilities
- **Applications**
  - ***Civilian sectors*** (entertainment, infrastructure inspection, and delivery services etc.)
  - ***Military domain*:** surveillance, combat support/actions and logistics
- **Topics of interest** (research and implementation): applications, routing, **coordinated PP**, task assignment, formation control, communication, scalability, energy, resource limitations and allocation, security and privacy, AI/ML in UAV swarms

2. Multi-UAV and Swarms

2.2 UAV swarms

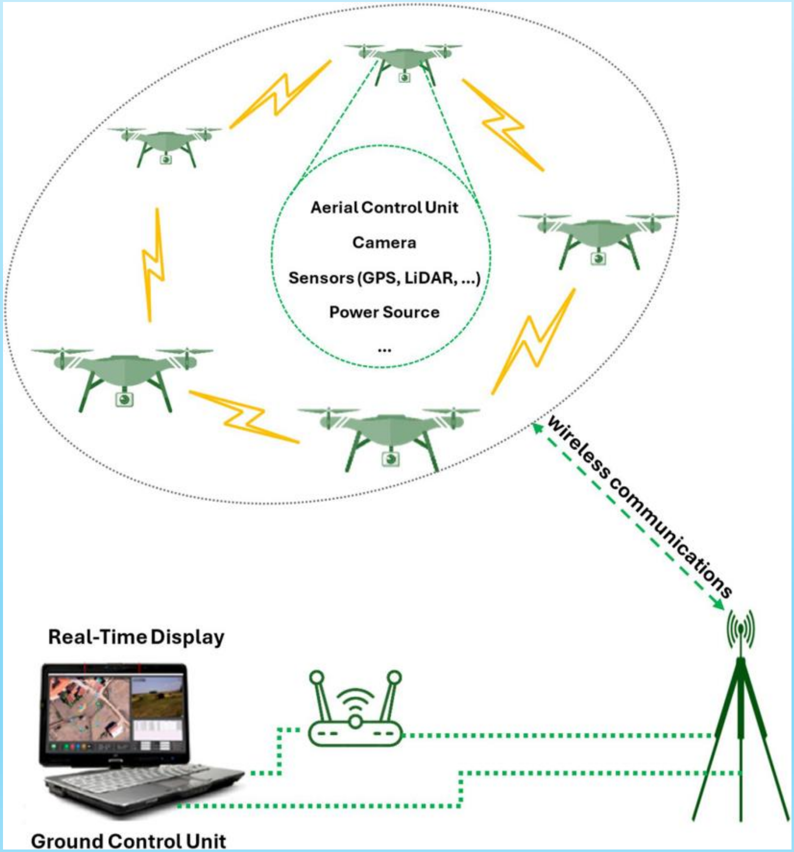
- **General Swarm Robotics (SR)** – includes (UAV) swarms
  - SR: groups of robots- they collaborate with each other and with their environment to execute complex tasks efficiently
- **Multi-Robot Systems (MRS)**
  - group of autonomous and relatively simple robots with similar capabilities
  - equipped with local sensing and communication abilities, interacting locally with each other and with environment
  - autonomous aerial agents cooperate for PP, task allocation, and formation control
  - decentralized and self-organized behavior enhance efficiency, reliability, and adaptability
- **Swarm Intelligence (SI)** algorithms
  - inspired by natural behavior, they facilitate collaborative decision-making and coordination in dynamic environments
- **UAV swarm infrastructure**
  - Each UAV is an individual unit within the swarm, equipped with sensors, processors, and communication HW
  - A **control unit** plays a central role in managing the swarm

2. Multi-UAV and Swarms

2.2 UAV swarms

- **Basic components of UAV swarms**
  - ***Drones/Quadrotors*** -individual units with sensors, processors and communication HW
  - ***Control Unit***
    - central entity for control, monitoring, and data reception, (e.g., **ground station (GS) or a cloud-based system**)
    - it manages the swarm, ensuring operation within desired parameters
  - ***Communication System*** - wireless network for r.t. info exchange, (Wi-Fi, Bluetooth, Zigbee)
  - ***Integrated sensors*** (e.g., cameras, LiDAR, "laser imaging, detection, and ranging"), GPS, accelerometers, gyroscopes) for environment data gathering and processing
  - ***SW Algorithms*** for: PP, collision avoidance, formation control, and decision making
  - ***Power Source*** - batteries or tethered power supplies critical for flight time and performance
  - ***Navigation System***: GPS, inertial navigation, visual odometry for autonomous navigation and collision avoidance.

Source: Y.Alqudsi and M. Makaraci UAV swarms: research, challenges, and future directions Journal of Engineering and Applied Science (2025) 72:12 https://doi.org/10.1186/s44147-025-00582-3



2. Multi-UAV and Swarms

2.2 UAV swarms

- **Features and characteristics of UAV swarms**
  - Cost-effectiveness, Scalability, Robustness, Survivability, Redundancy and Fault-tolerance, Adaptability & Flexibility Autonomy, Parallelism, Multi-tasking capability, Distributed coordination and tasks, High speed of mission, Radar cross-section
- **Key topics in UAV swarms**
  - Task Allocation, **Path Planning**, Resource Allocation, Formation Control, Sensor Placement, Network Optimization – are necessary for communication and data exchange between multiple UAVs, to minimize latency and maximize efficiency,

2.3 UAV swarm communication architectures and topologies (see also Section 1.3)

- ***UAV-UAV*** **or** ***UAVs - Control center***
  - **U-U:** direct link or multi-hop communication between UAVs, to exchange info from sensors or radar
  - **U-I (Infrastructure):** UAVs direct communication with the fixed central control center (e.g.,GS), to get r.t. mission or control information and return collected data
- **Approaches: centralized** and **decentralized** architectures
- **Centralized architecture**
  - 1-to-1 direct comm.: UAV - controller (e.g. GS); star topology *(case a.– slide 11)*
  - (+) simple routing, useful for small systems
  - (-) long delays might appear, (-) GS – single point of failure.

2. Multi-UAV and Swarms

2.3 UAV swarm communication architectures and topologies

- **Decentralized architectures**
- **Single-Group Swarm Ad hoc Network** *(see case b.– slide 11)*
  - A single point - **gateway UAV** (GW-UAV) communicates to infrastructure; upload and download of swarm information
  - U-U communications are also active between the swarm members
  - GW-UAV has two transceivers: for **GW-U** and for **GW-I** communication
  - (+) non-GW UAVs only need to carry low-cost/ lightweight short-reach transceivers
  - ***Example application****: UAV cloudlet layer in Disaster Resilient three-layered architecture for Public Safety Long-Term Evolution*
  - **Intra-swarm communication** possible topologies:
    - **Ring**- bidirectional loop
      - (+) any UAV could play the GW role; redundancy (two paths between two UAVs); (-) low scalability
    - **Star** (the GW is placed in the swarm middle)
      - (+) good r.t. response (low delay); (-) GW- single point of failure
    - **Mesh** (combination star + ring); frequently used topology
      - all UAV nodes the same capabilities; (+) any UAV node can be a GW

2. Multi-UAV and Swarms

2.3 UAV swarm communication architectures and topologies

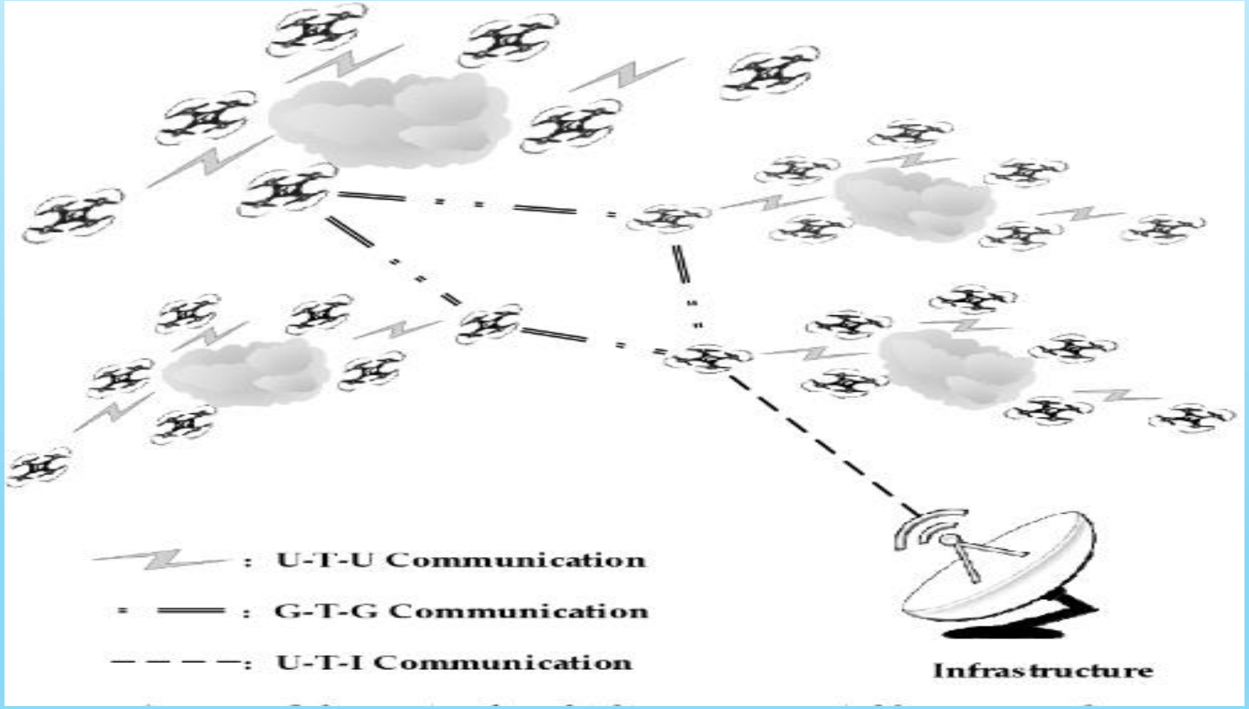
- **Multi-Group Swarm Ad hoc Network**
  - *(see case c) in Introduction – slide 11)*
  - This is a centralized architecture w.r.t. groups
  - Inter-group i.e., **Group-to-Group (G-G)** communications – via the infrastructure
  - GW-UAVs of each group is responsible for communicating with the infrastructure
  - (+) different types of groups/clusters **may perform different tasks** for different applications
  - (-) G-G communication might expose high latencies (the path is G-I-G)
  - ***Example app***. *Multi - theater joint operation* (military domain)

- **Multi-Layer Swarm Ad hoc Network**
- *(see case d) in Introduction – slide 11)*
  - **First layer:** a group of adjacent UAVs of the same type
    - Intra-group communications: ring, star, mesh
    - Communication between any two UAVs does not require infrastructure relay
  - **Second layer:** different types of UAV groups; rely on GW-UAVs to perform G-G communication
  - **Third layer:** the closest GW-UAV communicates with the infrastructure

2. Multi-UAV and Swarms

2.3 UAV swarm communication architectures and topologies

- **Multi-Layer Swarm Ad hoc Network** (cont'd)
  - This architecture is appropriate for scenarios with complex missions
  - high number of UAVs executing the mission is required
  - network topology frequently changes, and communication between the UAV nodes is frequent



Source: X. Chen, J.Tang and S. Lao, Review of Unmanned Aerial Vehicle Swarm Communication Architectures and Routing Protocols, Appl. Sci. 2020, 10, 3661; doi:10.3390/app10103661

2. Multi-UAV and Swarms

2.3 UAV swarm communication architectures and topologies

- **Conclusions on swarm communication architecture**
- **Centralized architecture** - suitable for UAV small swarms and simple tasks
- Each individual UAV requires a long-range communication link U-I.

- **Decentralized architecture** - communication coverage is through a multi-hop network
  - The GW-UAV performs U-I communication
    - **Single-group swarm Ad hoc network** - appropriate for a swarm having the same type UAVs
    - **Multi-group swarm Ad hoc network-** accept different UAV types; however, G-G communication can experience high delays
    - **Multi-layer swarm Ad hoc network -** relatively reliable because it overcomes Single Point of Failure (SPOF)
- UAV swarms have requirements of high coverage and maintaining connectivity
  - high coverage: to be able to gather intelligence and analyze situations
  - connectivity – assures r.t. communication of the swarm
- In unknown environments, threats /obstacles could appear randomly in time and space
- **UAV members should be able to withdraw or rejoin**; the connectivity may have disruptions
- To achieve an uninterrupted connectivity the distance in the UAV swarm should not
- exceed the sensitivity of the receiver

Source: X. Chen, J.Tang and S. Lao, Review of Unmanned Aerial Vehicle Swarm Communication Architectures and Routing Protocols, Appl. Sci. 2020, 10, 3661; doi:10.3390/app10103661

2. Multi-UAV and Swarms

2.3 UAV swarm communication architectures and topologies

- **Conclusions on swarm communication architecture** (cont'd)
- UAVs swarm should be able to react cognitively to changes of the environment to
- adapt their movement to positions with channel characteristics

Features	Centralized Communication Architecture	Decentralized Communication Architecture		
		Single-Group	Multi-Group	Multi-Layer
Multi-hop Communication	×	√	√	√
UAVs Relay Traffic	×	√	√	√
Different Types of UAVs	×	×	√	√
Self-configuration	×	√	×	√
Limited Coverage	√	√	√	×
Single Point of Failure	√	×	√	×
Robustness	√	×	×	√

Note: "√" = supported, "×" = not supported.

Source: X. Chen, J.Tang and S. Lao, Review of Unmanned Aerial Vehicle Swarm Communication Architectures and Routing Protocols, Appl. Sci. 2020, 10, 3661; doi:10.3390/app10103661

2. Multi-UAV and Swarms

2.4 Tasks assignment in UAV swarms

- **Multi-UAV task planning and coordination** involves
  - Tasks allocation among UAVs and synchronizing their actions
  - **Activities**
    - creating action sequences for each UAV, resource allocation
    - mechanisms to prevent collisions
    - resolve conflicts during task execution
- **Algorithms proposed**
  - Combinatorial optimizations
    - have as objective a function representing the system's overarching goal
    - applied in task allocation, scheduling, and vehicle routing
    - it assigns usually 1-to-1 task vs. agent, while minimizing the total assignment cost
    - the number of agents vs. tasks count: -equal (N = M - balanced; N<> M - unbalanced allocation
  - Auction-based: UAVs bid on tasks, based on their capabilities and associated costs
  - Algorithm types: Market-based or swarm-based algorithms
  - *Linear Assignment Problem (LAP)* - the total assignment cost equals the summation of individual agent costs
- Task assignment and interchangeability focus on task allocation and adaptability
  - Task interchangeability - allocate tasks based on individual UAV capabilities
- **Application examples**
  - warehouse automation and search and rescue (SAR) missions
  - precision farming, monitoring multiple rows of crops for health, soil condition, and yield data

2. Multi-UAV and Swarms

2.5 Formation control in UAV swarms

- **Coordinating multiple UAVS to maintain specific formations**
  - common goal; cohesive motion and control of the team is necessary
- **Challenge:** to coordinate large groups of relatively simple UAVs to perform complex tasks

- **Robust and scalable control algorithms are needed** to handle real-world uncertainties and disturbances and to manage communication among swarm UAVs
- The formation control coordinates UAV swarms to meet specific state constraints
  - the **planning is collective** not individual
  - a **prescribed formation is maintained**
  - a single action drives the entire formation (reducing computational complexity)

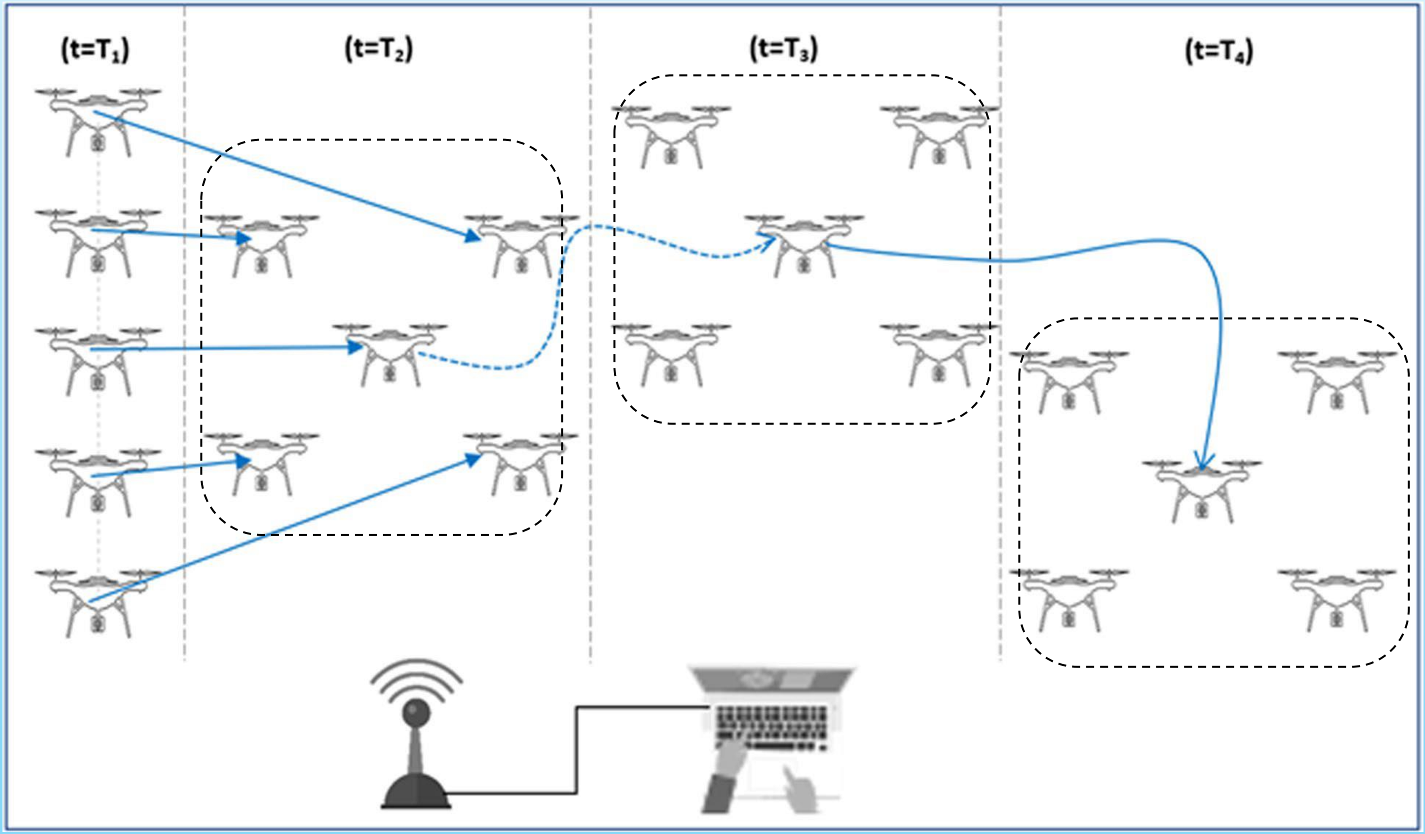
- **Formation control strategies**
  - ***Virtual-Structure-based* -** use a virtual structure to guide the formation of UAVs
    - Effective for maintaining rigid formations in applications like surveillance and mapping
  - ***Leader-Follower-based*** - One or more UAVs act as leaders, and the rest follow
    - Useful when specific paths need to be followed, such as SAR operations
  - ***Behavior-based*** - Each UAV follows simple behavior rules that result in the desired formation
    - Applicable in dynamic environments and tasks like reconnaissance and data gathering.

Source: Y.Alqudsi and M. Makaraci UAV swarms: research, challenges, and future directions
Journal of Engineering and Applied Science (2025) 72:12, https://doi.org/10.1186/s44147-025-00582-3

2. Multi-UAV and Swarms

2.5 Formation control in UAV swarms

- **Example**



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2. Multi-UAV and Swarms

2.6 UAV Swarm Intelligence (SI)

- **One can make decisions collectively** and complete the mission using relatively simple instructions (**AI and edge computing** can contribute**)**
- **Applications:** civilian, military purposes

- ***Swarm intelligence* (SI)**
  - SI is **an evolving area of bio-inspired AI; deep interconnection of the real system having feedback loops**
  - **SI** - **scheduling, clustering, optimizing, and routing a cluster of similar individuals**
    - Individuals follow rules and interact with each-other and with the environment

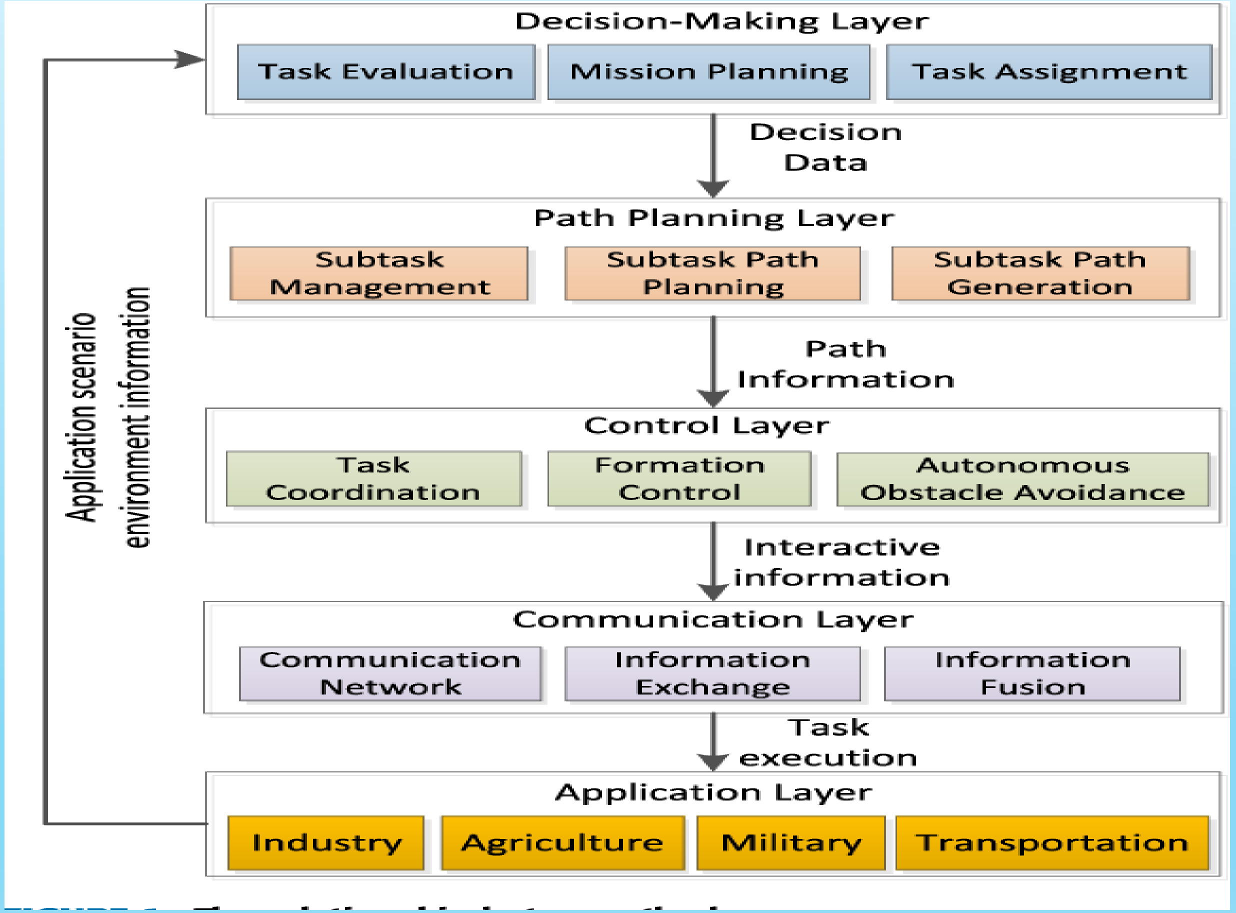
- ***SI basic principles:***
  - **Proximity:** the swarm individuals can respond to the environmental variance
  - **Quality:** a swarm can respond to quality factors like location safety only
  - **Diverse response:** enables to design of the distribution s.t. all the individuals are protected from environmental fluctuations to a maximum level
  - **Stability:** swarm stable behavior w.r.t. changes in the environment
  - **Adaptability**: to environment changes
  - **SI mechanisms should deal with*:*** environment, interactions, and activities of the individual UAVs

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

2. Multi-UAV and Swarms

2.6 UAV Swarm Intelligence

- **Example of SI architectural decomposition - five layers: *decision making, path planning, control, communication and application layer***



Source: Y. Zhou, B. Rao, W. Wang, UAV Swarm Intelligence: Recent Advances and Future Trends, IEEE Access, September 2020, DOI 10.1109/ACCESS.2020.3028865

2. Multi-UAV and Swarms

2.6 UAV Swarm Intelligence

- **SI architectural decomposition** – **short description of layers**
- **Decision-Making Layer**
  - Responsible for mission planning; task assignment and evaluation in UAV clusters
  - Key areas: swarm architecture, effectiveness assessment, scheduling and intelligent decision-making; Several architectures proposed
  - Effectiveness models utilize system dynamics to evaluate UAV performance based on survival rates and mission completion
  - Scheduling for complex task planning (e.g., using heuristic algorithms for efficient resource allocation)
- **Path Planning (PP) Layer**
  - It transforms decision data into actionable **flight paths** for UAVs
  - Determines feasible paths between start and endpoints (NP-hard problems!)
  - **Algorithms: classic (e.g., A*)** and **meta-heuristic (**e.g.**, *Particle Swarm Optimization* (PSO), *Gray Wolf Optimization* algorithm (GWO))**
  - **Important topics for PP: 3D-issues, dynamicity, optimality, area coverage PP**
  - PP in 3D environment is complex
    - methods like GWO and PRM are utilized for obstacle avoidance
    - dynamic PP: real-time obstacle avoidance and sudden threats (techniques like cubic spline and Kalman filters can be employed)

2. Multi-UAV and Swarms

2.6 UAV Swarm Intelligence

- **SI architectural decomposition** – **short description of layers** (cont'd)
- **Control Layer**
  - It coordinates tasks among UAVs based on path information and environmental data
  - Manages: formation control, task coordination and automatic obstacle avoidance **Design**: system control platforms, controller design, and collaborative search technologies
  - Enhance flight efficiency and ensures safety during operations
  - Running protocols for maintaining group cohesion and flexibility in dynamic environments
- **Communication Layer (for UAV Coordination)**
  - It supports information sharing UAV-UAV and UAVs - GS
  - Related topics: architecture, net technologies and secure communication methods
  - Aims to robust communication to support r.t. data sharing and coordination

- **Applications of UAV Swarm Intelligence- examples**
  - Intelligent transportation, Environmental monitoring, Agriculture , Emergency response, Military domain applications

Source: Y. Zhou, B. Rao, W.Wang, UAV Swarm Intelligence: Recent Advances and Future Trends, IEEE Access, September 2020, DOI 10.1109/ACCESS.2020.3028865

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1. Introduction
2. Multi-UAV and Swarms
3. Path Planning in Multi-UAV Networks
4. Challenges and Open Problems
5. Conclusions

3. Path Planning in Multi-UAV Networks

3.1 Path planning (PP) problem

- **PP is related to the UAV routing and dependent on geographical/environment information**
- **UAV PP (a.k.a. *motion planning*), is a branch of path-finding used in robotics**
  - UAV specific differences: 3D space, fixed-wing UAV (cannot hover), UAV swarms
- **UAV PP main objectives**
  - **Single PP:** to find the best (i.e., optimum) **collision-free path, *start -> destination*** Constraints: temporal, physical, and geometric
  - **Coverage PP (CPP) –** UAV applications for specific region exploration
- **PP Characteristics**
  - A **path is represented** as a continuous function with boundary conditions
  - A **cost function** includes path length, energy consumption, and collision risk
  - **Key objectives**: minimizing path length, energy consumption, collision-free navigation
  - **Constraints** arise from environment factors, physical limitations, task requirements, and energy reservations
  - **PP problems of interest:** environment modeling methods, path structures, optimality and completeness criteria, path finding methods, UAV simulators

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 Op. Research, https://doi.org/10.1051/ro/2024073 www.rairo-ro.org

3. Path Planning in Multi-UAV Networks

3.1 Path planning (PP) problem

- **Classes of UAV PP problems (from applications point of view)**
  - ***Informative PP (IPP)***: to maximize the amount and utility of data collection
  - ***Coverage PP (CPP)***: to find a path **that passes through all points of an area** or volume of interest, while avoiding obstacles
    - CPP algorithms can be divided (according to the employed cellular environment decomposition model), into main types: **no decomposition, exact cellular decomposition** and **approximate cellular decomposition**
  - ***Cooperative PP (specific to UAV swarms)*** to generate a coordinated mission through utilization of PP algorithms

- **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

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

3. Path Planning in Multi-UAV Networks

3.2 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 **free workspace** (i.e., without obstacles) is the overall area represented by
  - $\boldsymbol{w_{free} = w \setminus \bigcup_i wo_i}$
- The initial point $\boldsymbol{x_{init}}$ and the goal region $\boldsymbol{x_{goal}}$ are elements in $\boldsymbol{w_{free}}$

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

- ***Definition 1-PP***: Given a function $\boldsymbol{\delta:[0,T] \rightarrow R^3}$ 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 $\boldsymbol{c : \Sigma \rightarrow R \geq 0}$, 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 in Multi-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 $\boldsymbol{w_{free}}$
    - the ***path*** is either a continuous curve or discrete line segments that connects the start node $\boldsymbol{x_{init}}$ to the end node $\boldsymbol{x_{goal}}$
    - 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
  - The PP problem has a **non-linear nature and frequently an exponential complexity**

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

3. Path Planning in Multi-UAV Networks

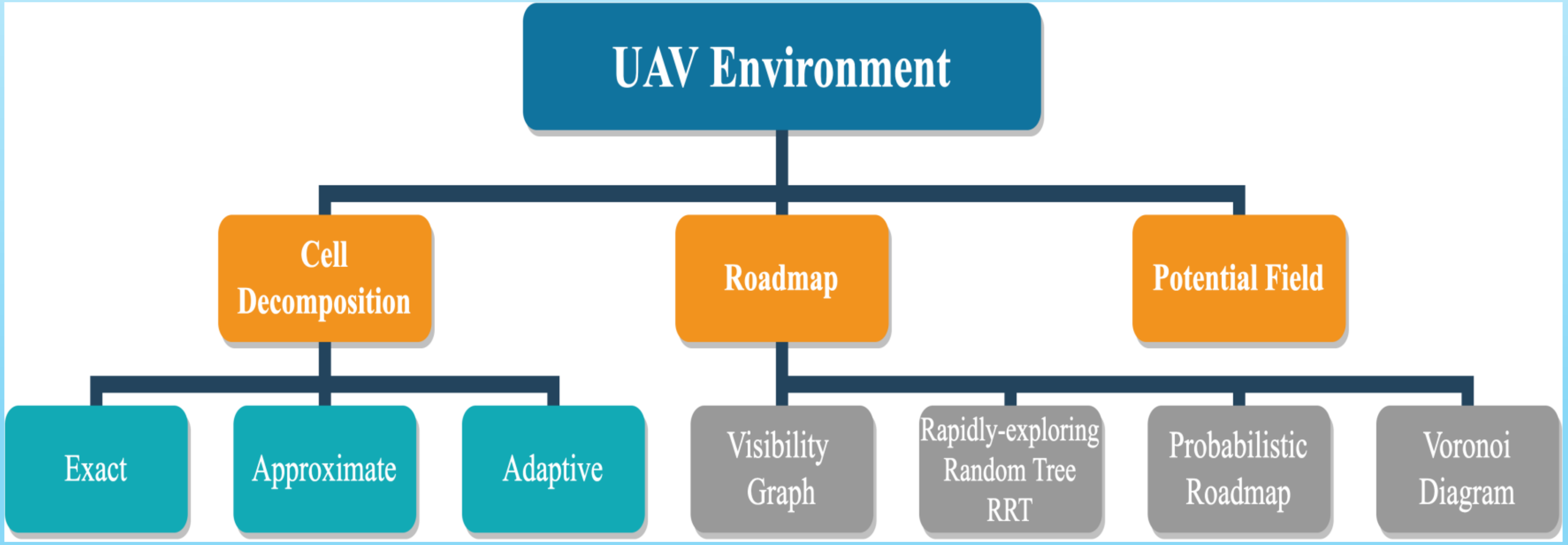
3.3 Environment Representation Problem (summary)

- **Knowledge needed to a path planner**
  - about the environment and 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:** how to get 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**
- **Environment complexity-related attributes**
  - ***Static-known (SK)*****:** All obstacles /objects are both static and known
  - ***Dynamic-known (DK)*****:** Mobile obstacles /objects, their movement is known
  - ***Static-unknown (SU)*****:** Static obstacles /objects; their relative positions are unknown
  - ***Dynamic-unknown (DU)*****:** All obstacles /objects are both mobile and unknown

3. Path Planning in Multi-UAV Networks

3.3 Environment Representation Problem

- **3D Environment representation- classes**
  - ***Cell decomposition; Roadmap; Potential field***
    - ***Cellular decomposition*** *(CD)*
    - ***Roadmap*** *(RM)*: the problem space is 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. Path Planning in Multi-UAV Networks

3.3 Environment Representation Problem

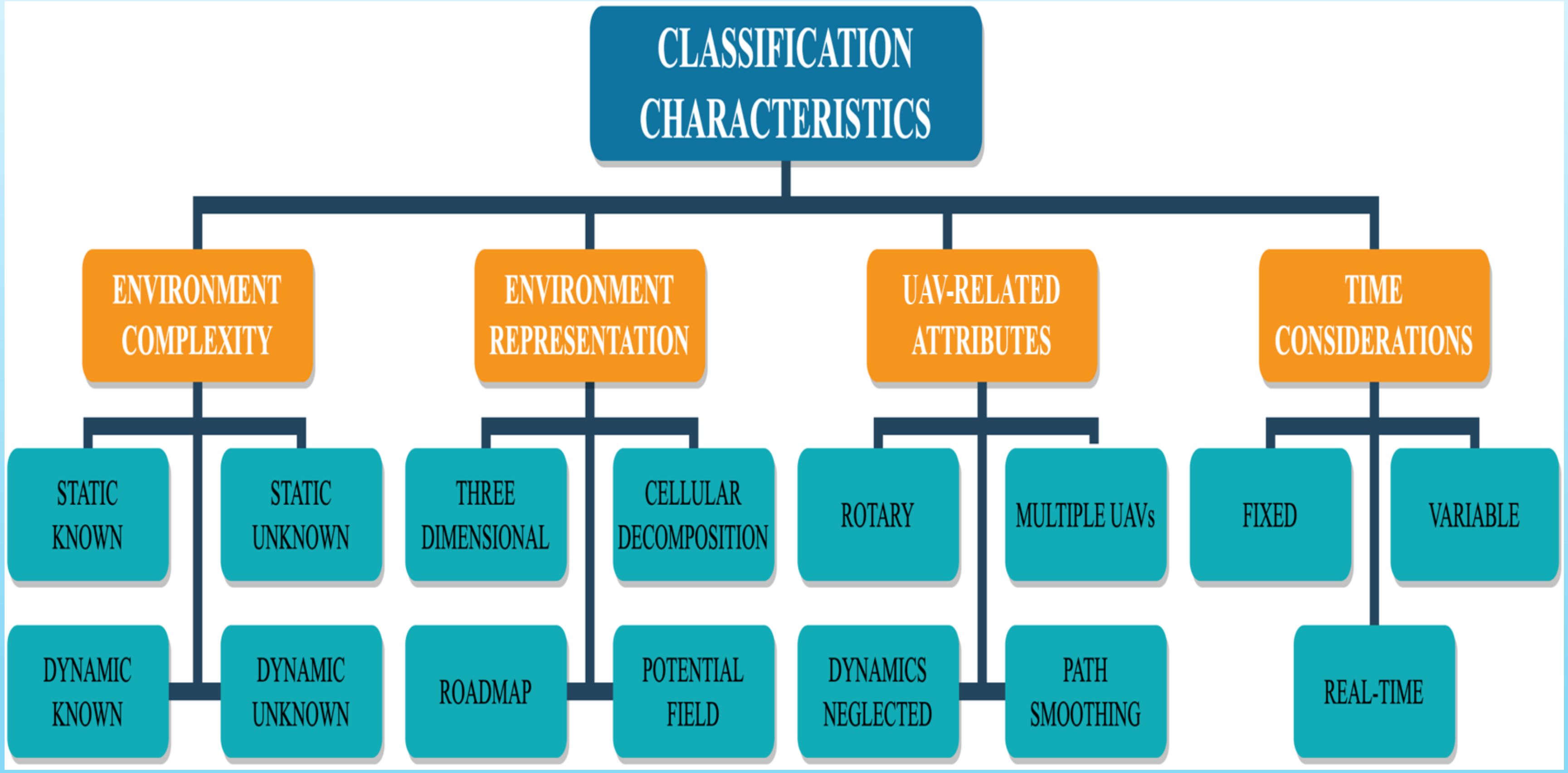


Figure Source: M,R. Jones, S. Djhael, K. Welsh, Path-planning for Unmanned Aerial Vehicles with Environment Complexity Considerations: A Survey, ACM Comput. Survey, Vol. 1, No. 1, November 2022.

3. Path Planning in Multi-UAV Networks

3.3 Environment Representation Methods *(See details in Backup slides)*

- **Cell decomposition**
  - The **environment space is divided** into a series of **nonoverlapping cells**
  - ***Approximate Cell Decomposition***
    - It overlays a regular grid structure upon the environment space
    - Decomposition into a set of structured cells
  - ***Exact Cell Decomposition***
    - The space is divided into several **non-overlapping polygon regions**
      - ***Trapezoidal***: the space is split in **distinct convex cell regions**
      - ***Boustrophedon:*** It minimizes the coverage path length in comparison to the trapezoidal, through reducing the number of polygon cell regions created
  - ***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
- **Roadmap Representation**
  - **Connectivity graph -** the **nodes represent key free space locations**
    - The graph construction strategies can be different
    - The **edges weights** are related to time or distance
    - The graph is similar to that one in classical route planning

3. Path Planning in Multi-UAV Networks

3.3 Environment Representation Methods

- **Roadmap Representation - examples**(cont'd)
  - ***Visibility graphs (VG)***
  - ***Voronoi diagrams*** **and** ***path solutions***
  - ***Probabilistic Roadmap (PM)***
  - ***Rapidly-exploring Random Trees (RRTs)***
- **Artificial Potential Field (APF)**
  - The cell decomposition and roadmap approaches **build an environment representation from prior knowledge on environment**
  - **(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

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

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

Source: M. Farooq et al., Quadrotor UAVs flying formation reconfiguration with collision avoidance using probabilistic roadmap algorithm. In 2017 Int'l Conf. (ICCSEC), pages 866–870. IEEE, 2017

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..

Source: 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.

3. Path Planning in Multi-UAV Networks

3.4 Path Planning Methods

- **Evaluation Metrics for PP Algorithms**
  - **Path length** measures the total distance traveled, influenced by obstacle distribution and environmental complexity
  - **Computation time** is critical for r.t. tasks
  - **Energy consumption** relates to battery usage; important for long-duration missions
  - **Path safety** assesses collision avoidance capabilities, while path smoothness ensures efficient UAV motion
  - **Robustness** evaluates adaptability to environmental changes and uncertainties

- **Path Planning process actions** (aiming to safe, efficient, and effective navigation)
  - Note : some of these actions are executed in parallel
  - **1. *Environment Modeling**:* mapping physical features and identifying obstacles, using imagery (e.g., from satellites) or real-time sensory data
  - **2. *Setting Objectives and Constraints*:** define objectives – e.g., minimizing travel time or distance; identify constraints, e.g., maximum altitude and no-fly zones
  - **3. *Defining Start and End Points***: - including any intermediate waypoints or targets
  - **4. *Path Generation*:** use algorithms - A*, Dijkstra, RRT, PSO, ACO, ML-based etc. , to generate possible paths (based on objectives and constraints)

3. Path Planning in Multi-UAV Networks

3.4 Path Planning Methods

- **Path Planning process actions** (cont'd)
  - **5. *Obstacle Detection and Avoidance***: employ sensors for r.t. obstacle detection and dynamically adjust the flight path to avoid obstacles
  - **6. *Path Optimization***: Select the optimal path from generated options, balancing factors like safety, efficiency, and compliance
  - **7. *Collision Risk Assessment***: assess the path for potential collision risks (here, communication with air traffic control could be needed)
  - **8. *Final Path Selection and Execution***: select and execute the path, adjusting the UAV's position, altitude, and speed as necessary
  - **9. *Monitoring and Re-planning*:** continuously monitor the path and re-plan if unexpected changes occur in the environment or UAV performance
  - **10. *Arrival and Post-Flight Analysis*:** Upon arrival, complete the mission and perform a post-flight analysis to assess and learn from the PP efficiency and any deviations

Source: P.Kumar, K. Pal, M.Govi, Comprehensive Review of Path Planning Techniques for UAVs, ACM Computing Surveys, ACM 0360-0300/2025/05-ART, http://dx.doi.org/10.1145/3737280

3. Path Planning in Multi-UAV Networks

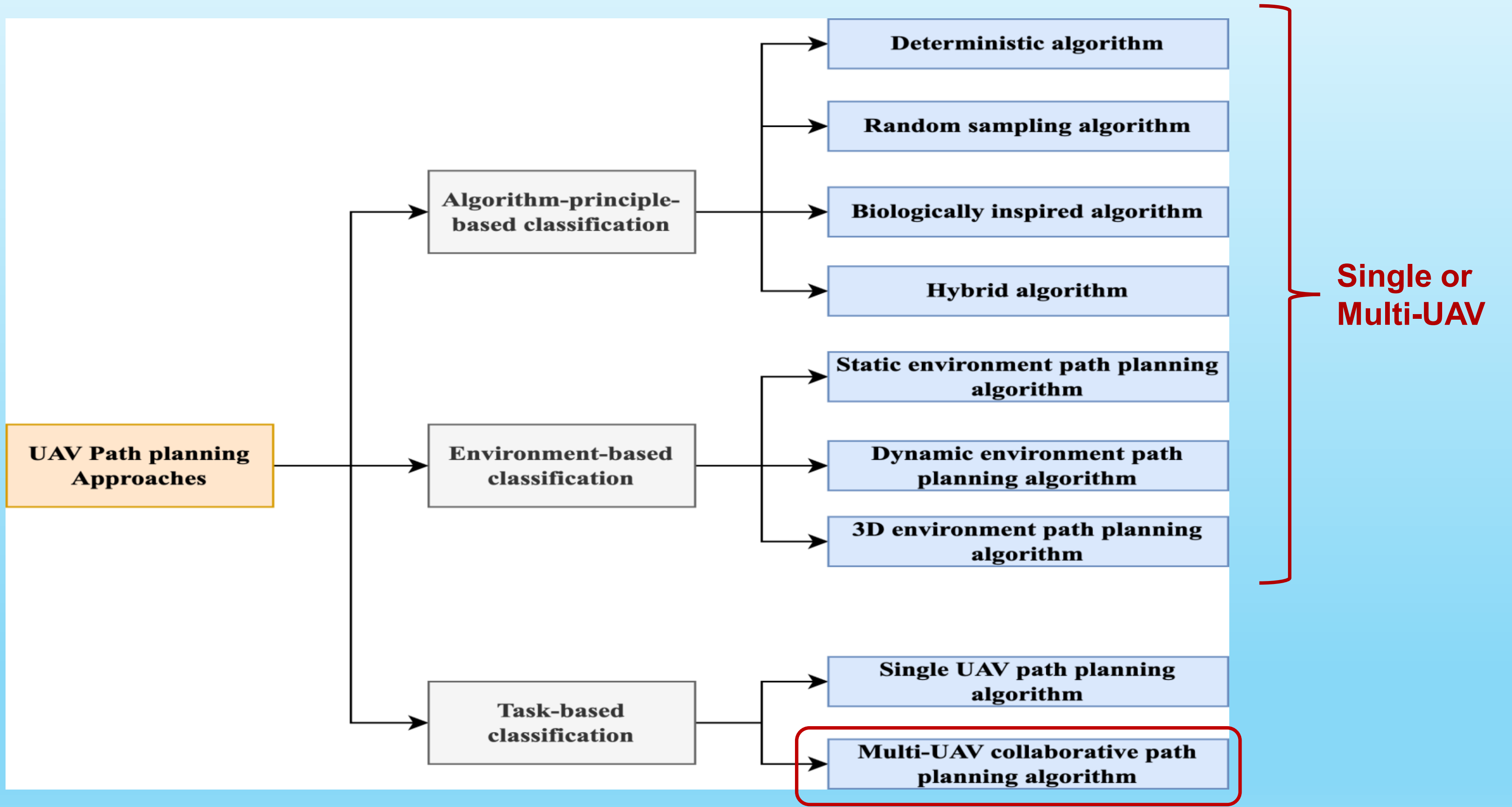
3.4 Path Planning Methods

- **Classification of UAV PP methods**
  - **Criteria: algorithmic principles, environmental conditions, task requirements**
  - **Algorithmic principles:** examples
    - deterministic algorithms (e.g., Dijkstra, A*)
    - random sampling algorithms (e.g., RRT, PRM)
    - biologically inspired algorithms
    - hybrid algorithms
  - **Environmental - related conditions**
    - static PP
    - dynamic PP
    - 3D path planning
  - **Task requirements**
    - single-UAV
    - multi-UAV collaborative PP (focus on coordination and task allocation)

Source: W. Meng, X.Zhang, L.Zhou, H. Guo and X.Hu , Advances in UAV Path Planning: A Comprehensive Review of Methods, Challenges, and Future Directions, MDPI, 2025, https://doi.org/10.3390/drones9050376

3.4 Path Planning Methods

- **Classification of UAV PP methods-** criteria: algorithms, environment, tasks



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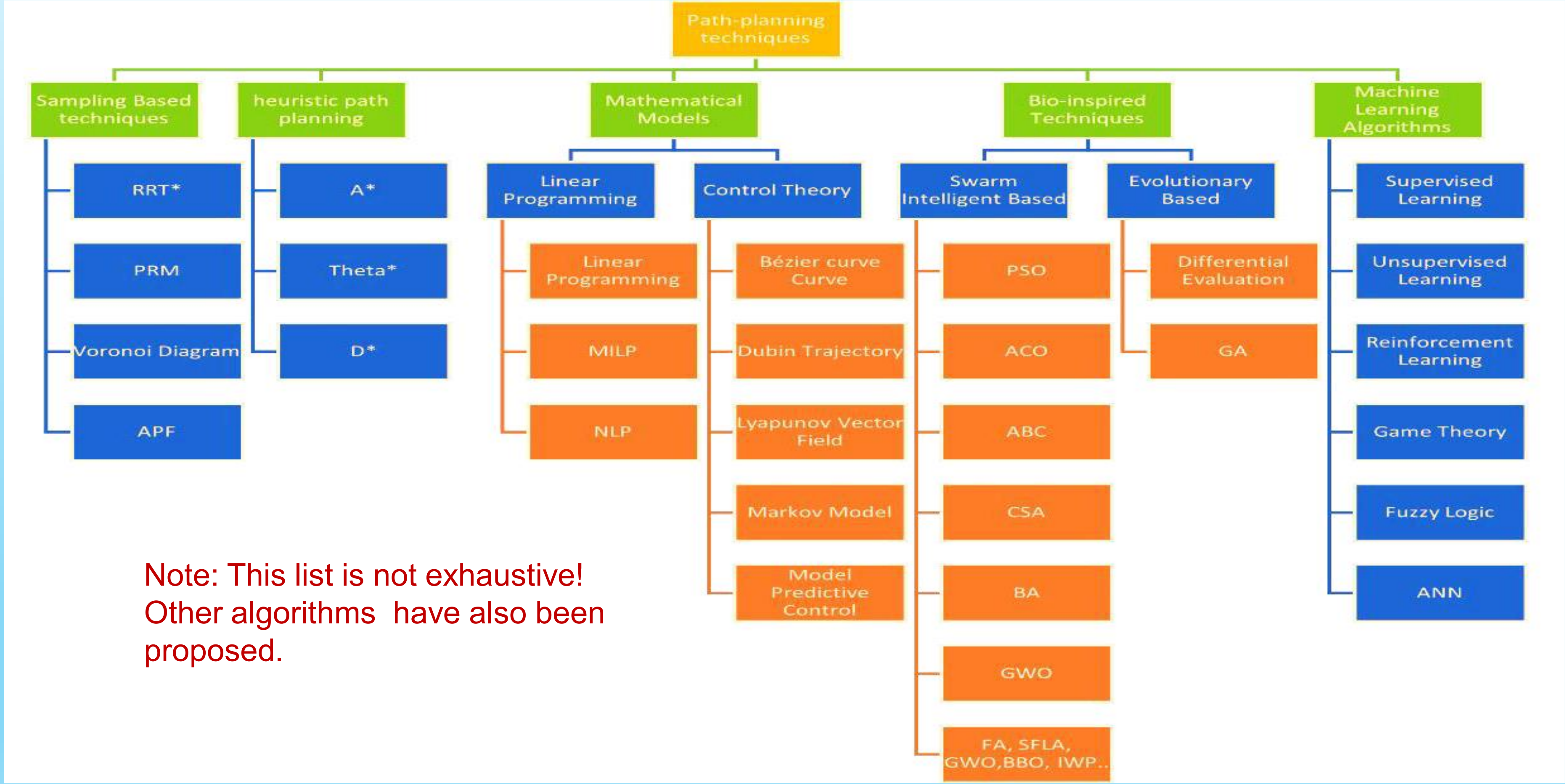
3.4 Path Planning Methods

Classification of UAV PP methods – criteria: algorithm types

- sampling-based, heuristic, math models, bio-inspired, machine learning-based



Note: This list is not exhaustive!
Other algorithms have also been proposed.

Source: P.Kumar, K. Pal, M.Govi, Comprehensive Review of Path Planning Techniques for UAVs, ACM Computing Surveys, ACM 0360-0300/2025/05-ART, http://dx.doi.org/10.1145/3737280

3.4 Swarm Path Planning Methods

Notations (partial list)

Classic algorithms

- RMA Road map algorithm
- A* and APF Artificial Potential Field

Swarm intelligence (SI)- based PP techniques- examples

- In SI systems, a group of UAVs interact with each other and its environment to solve problems collectively or accomplish tasks
- ABC Artificial Bee Colony
- ACO Ant Colony Optimization
- BA Bat Algorithm
- CSA Cuckoo Search Algorithm
- FA Firefly Algorithm
- GWO Grey Wolf Optimization
- PSA-ACO Parallel Self-Adaptive ACO
- PSO Particle Swarm Optimization

The UAV swarm PP is a NP-hard problem
Categories: classic and meta-heuristic algorithms
Classic algorithms require environmental information: e.g., A*, RMA, APF
Meta-heuristic algorithms require information on the r.t. position and measured environmental elements: e.g., PSO, PIO, FOA, GWO

Other SI-based algorithms

- FOA Firefly Algorithm
- TS Tabu Search
- EHO Elephant Herding Optimization
- FPA Flower Pollination Algorithm
- IPA Immune Plasma Algorithm
- GEO Golden Eagle Optimizer
- AEO Artificial Ecosystem Optimizer
- RLGWO Reinforcement learning based GWO
- AGWO Adaptive GWO algorithm

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

3. Path Planning in Multi-UAV Networks

3.4 Path Planning Methods

Classification of UAV PP methods –criteria: algorithm types

- **sampling-based, heuristic, math models, bio-inspired, machine learning-based**

- **Sampling-Based Techniques (SBTs)**
  - SBTs use random sampling to solve optimization problems or to estimate specific quantities. They can search the best path in complex and dynamic environments
  - Most Sampling techniques used inspection and 3D reconstruction applications
  - Examples*:* ***Rapidly-exploring Random Trees (RRT), RRT*, Probabilistic Roadmap (PRM), Voronoi Diagram(VD), Artificial Potential Field (APF)***
  - (+) SBTs PP is useful when it is difficult or impractical to use deterministic algorithms
  - (+) RRT, PRM, VD, and PF are widely used; they excel in dynamic, uncertain envs.
  - (-) less efficient and inaccurate than deterministic methods for specific problems
  - (-) sensitive to initial conditions, risk local minima, and are resource-intensive

- **Heuristic Path Planning**
  - They leverage heuristics to effectively guide searches through complex spaces
  - Widely used in various fields: robotics, gaming, transportation and logistics
  - Examples: ***Dijkstra, Greedy Best First Search, Hill Climbing, A* and Variants, Theta*, D****
  - (-) possible problems with high-dimensional spaces and dynamic obstacles, requiring enhancements for adaptability and computational efficiency in large, complex domains

Source: P.Kumar, K. Pal, M.Govi, Comprehensive Review of Path Planning Techniques for UAVs, ACM Computing Surveys, ACM 0360-0300/2025/05-ART, http://dx.doi.org/10.1145/3737280

3.4 Path Planning Methods

Classification of UAV PP methods –criteria: algorithm types

- **sampling-based, heuristic, math models, bio-inspired, machine learning-based**

- **Mathematical Models**
  - They employ **math. functions** (e.g., Dubin, Bézier curves, Lyapunov function), utilized to solve the geometry and UAV motion model- based trajectory-generating process
  - The models may be based on optimization, control/graph theory, or other maths.
    - they can represent the constraints, objectives and UAV dynamics; account for other aspects (cost, time, and energy)
    - (-) can be computationally intensive and often require prior environmental knowledge
    - (-) problems in integrating dynamic obstacles, complex terrains, and constraints like energy consumption
  - ***Linear Programming (LP)***
    - solves optimization problems in which linear equations or inequalities represent the objective and constraints; LP minimizes or maximizes a linear function when applied to certain conditions
    - ***Basic LP***
      - generate the best solution to a wide range of problems, including issues in path planning ***Binary linear programming (BLP), mixed integer linear programming (MILP)*** and ***non-linear programming (NLP)***
      - LP PP can identify optimal paths, while minimizing distance, time, or energy consumption

3.4 Path Planning Methods
Classification of UAV PP methods –criteria: algorithm types

- **Mathematical Models** (cont'd)
  - ***Linear Programming*** *(cont'd)*
    - ***Mixed Integer Linear Programming (MLP)***
      - MILP - dynamic and robust tool for large, complicated problems with both continuous and discrete variables
      - **Examples**
        - discrete rescue PP model in a dynamic environment
        - path optimization for multi-UAVs with collision avoidance and maximization of the fleet utilization in 3D environment
        - scalable and robust trajectory generation scheme for multi-target PP
  - ***Non-Linear Programming (NLP)***
    - NLP optimizes an objective function (relationships between variables are non-linear)
    - NLP can handle complex problems; suitable for real-world scenarios with dynamic environments and non-linear constraints
    - **Examples**
      - optimization trajectory framework by decoupling state variables from temporal factors, dividing a complex NLP problem into two simpler NLP subproblems
      - control system for tracking highly mobile targets

3. Path Planning in Multi-UAV Networks

3.4 Path Planning Methods

Classification of UAV PP methods –criteria: algorithm types

- **Mathematical Models** (cont'd)
  - ***Non-Linear Programming (NLP)*** *(cont'd)*
    - **Examples**
      - optimizing the UAV trajectory, energy efficiency, and data collecting interval for each ground sensor nodes
      - double-loop iterative algorithm utilizing the UAV mobility pattern and developing an energy-efficient trajectory generation scheme in a dynamic environment

  - ***Control Theory- based methods***
    - They design and analyze control systems, including feedback control, optimal control and adaptive control
    - In PP they design control laws that manipulate the inputs to the UAV (thrust, attitude, etc.), to achieve a desired objective (stability, accuracy, efficiency, or performance)
    - **Examples: *Model Predictive Control (MPC), Bézier curves, Dubin algorithm, Lyapunov function, Markov decision model*** and others
    - (+)LP/variants, Bézier curves, and Dubin trajectories, offer precision and efficiency
    - (+)Lyapunov-based methods ensure path stability
    - (+) Markov models and MPC address environmental uncertainties robustly
    - Bézier curves, Dubin trajectories and MPCs are suitable for military apps and r.t.

3. Path Planning in Multi-UAV Networks

3.4 Path Planning Methods
Classification of UAV PP methods –criteria: algorithm types

- **Mathematical Models** (cont'd)
  - ***Control Theory- based methods*** *(cont'd)*
    - ***Bézier Curve***
      - *BC approximates a real-world shape that otherwise has no mathematical representation or whose representation is unknown or too complicated*
      - In PP the B curves are used to define the shape and curvature of the path, taking into account the constraints and objectives of the problem
      - **Examples:** ***Multi-step process*** for creating smooth, practical paths for UAVs in the 3D environment, **Combined GA** and **Bézier curve**; GA generates the path, and the Bézier curve makes the obtained path smoother for multi-UAV systems
    - ***Dubin Trajectory***
      - *[Note: In geometry the Dubin path is the shortest curve that connects two points in the 2D Euclidean plane with a constraint on the path curvature and with prescribed initial and terminal tangents to the path, and an assumption that the vehicle moves unidirectionally]*
      - The Dubin trajectory in UAV PP supports navigating between points in a plane with a minimal turning radius, offering precise and smooth flight paths
      - **Examples:**
        - ***R.t. trajectory planning scheme*** for flight line tracking utilizing Dubin's path generation to account for the dynamic restrictions of UAV
        - ***Dubin path combined with path-oriented RRT*,*** to meet UAV dynamic constraints

3.4 Path Planning Methods

Classification of UAV PP methods –criteria: algorithm types

- **Mathematical Models** (cont'd)
  - ***Control Theory- based methods*** *(cont'd)*
    - ***Model Predictive Control (MPC)***
    - It offers r.t adaptability and precision by *forecasting and optimizing future trajectories* based on current and anticipated environmental conditions and constraints
    - **Examples**
      - Used where the system's dynamics are highly nonlinear or uncertain or where there are significant time delays or constraints on the control inputs
      - (+) Low computational cost for high-dimensional systems with nonlinear dynamics
      - Cooperative minimum time PP scheme for multi-UAVs using nonlinear dynamics
        - It considers the synchronicity formation of the network
        - It could be used for systems with many UAVs
        - (-) it doesn't consider obstacles
      - ***Combined MPC and Improved Grey Wolf Optimizer (IGWO)*** to generate optimal trajectories in a highly dense environment
      - ***Learning Based MPC (LBMPC)*** for trajectory planning for multi-UAV cooperating to execute a required mission
        - (-) group formation control of multi-UAVs - is computationally expensive

3.4 Path Planning Methods

Classification of UAV PP methods – criteria: algorithm types

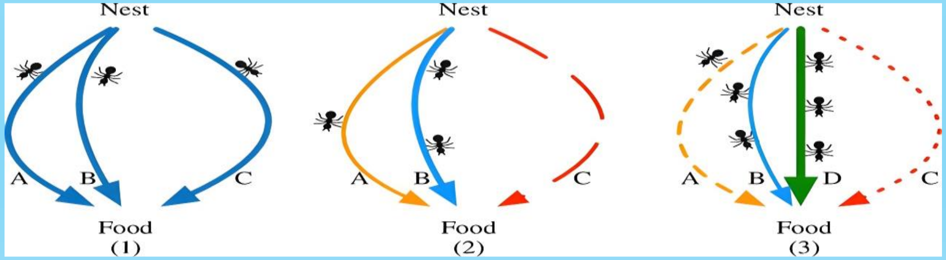
- **Mathematical Models** (cont'd)
  - ***Control Theory- based methods*** *(cont'd)*
    - **Markov Decision Process (MDP)** represents the system behavior over time
      - widely used for PP using ***Deep Reinforcement Learning (DRL)***
      - (-) complexity for PP in dense and uncertain environments
      - **Examples**
        - ***Partially observable MDP*** scheme for UAV PP in a dynamic environment.
        - ***Fast MDP(FMDP) -*** can solve a specific subclass of MDPs quickly and illustrates how to keep a safe distance in real-time and avoid collisions
    - ***Lyapunov Vector Field Guidance (LVFG)-*** framework for assessing system stability and convergence
      - UAV PP involves defining objectives and constraints and modeling the UAV and environment, which measures path stability and convergence
      - **Examples**
        - LVFG used for 3D UAV PP
        - bifurcation theory-based PP for UAVs targeting dynamic ground objectives
        - feedback control to get the UAVs closer together, a variable airspeed controller to keep the UAVs at different angles
        - graph theory to follow moving targets

3. Path Planning in Multi-UAV Networks

3.4 Path Planning Methods

Classification of UAV PP methods – criteria: algorithm types

- **Bio-inspired algorithms**
  - They typically **deconstruct an environment into a searchable problem space** using exclusively **approximate cell decomposition approaches**
  - **Examples**: Ant Colony Optimization (ACO); Particle Swarm Optimization (PSO) etc.
  - ***Ant Colony Optimization (ACO)***
    - **SI–based algorithm** inspired by the **collective behavior of ants**
    - The standard algorithm is inherently parallel and straightforward to execute
    - The **walking path of ants** is used to express the feasible solution
    - Each ant is intended to **search for the shortest path** in the free space
    - Over time: **continuous increase in the concentration of pheromones** along shorter paths → 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



Source: W. Meng, X.Zhang, L.Zhou, H. Guo and X.Hu , Advances in UAV Path Planning: A Comprehensive Review of Methods, Challenges, and Future Directions, MDPI, 2025, https://doi.org/10.3390/drones9050376

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

3. Path Planning in Multi-UAV Networks

3.4 Path Planning Methods

Classification of UAV PP methods – criteria: algorithm types

- **Bio-inspired algorithms** (cont'd)
  - **Ant Colony optimization (ACO)** (cont'd)
    - **ACO Problems:**
      - (-) local optima and slow convergence in complex scenarios; it is sensitive to objective function choices and parameters; it can be computationally demanding in complex problems
  - **Examples**
    - low-altitude PP and adjusting pheromones adaptively
    - multi-UAV PP, incorporating threat modelling and coordination functions
    - optimal for border surveillance, considering sensing, energy, and risk factors
  - **ACO Extensions**
    - optimal solutions for large domains; multi-UAV operations and multi-depot PP
    - dynamic green ACO algorithm for energy efficient PP
    - joint PP approach for UAV-assisted IoT systems
    - optimal PP across multiple heterogeneous UAVs
    - parallel Self-Adaptive ACO for coverage PP, improving speed and performance
    - enhanced dynamic obstacle avoidance with an elite-ACO scheme, focusing on path selection and pheromone updating

Swource: P.Kumar, K. Pal, M.Govi, Comprehensive Review of Path Planning Techniques for UAVs, ACM Computing Surveys, ACM 0360-0300/2025/05-ART, http://dx.doi.org/10.1145/3737280

3. Path Planning in Multi-UAV Networks

3.4 Path Planning Methods

Classification of UAV PP methods – criteria: algorithm types

- **Bio-inspired algorithms** (cont'd)
- **Particle Swarm optimization (PSO)**
  - **PSO simulates** the social **behavior of a swarm of birds** or a school of fishes
  - Optimization - by utilizing the shared information of the global and local solutions in the swarm
  - PSO- widely used for finding optimal solutions in UAV PP
  - PSO excels in PP due to its effective search process
  - **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**

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

3. Path Planning in Multi-UAV Networks

3.4 Path Planning Methods

Classification of UAV PP methods – criteria: algorithm types

- **Bio-inspired algorithms** (cont'd
- **Particle Swarm optimization (PSO)** (cont'd)
  - **PSO Problems**
    - (-) speed and global convergence limitations
    - (-)traditional PSO variants often face early convergence and limited search scope
  - **PSO Algorithms Extensions**
    - maximum density convergence **DPSO (MDC-DPSO)**
    - fast cross-over DPSO algorithm **(FCO-DPSO)**
    - accurate coverage exploration DPSO algorithm **(ACE-DPSO)**
    - PSO-based scheme to improve convergence and avoid local optima.
    - hierarchical, multi-objective PSO algorithm focused on Pareto dominance
    - coordinated PP for UAVs, addressing flight time and obstacle avoidance, using a Spatial Refined Voting scheme for better convergence
    - motion-encoded PSO for dynamic targets, encoding UAV motion in particle generation
    - enhanced PSO by maintaining population diversity and introducing probabilistic mutation for better optimization.
    - spherical vector-based PSO for complex environments, correlating particle positions with movement vectors for optimal path finding

3. Path Planning in Multi-UAV Networks

3.4 Path Planning Methods

Classification of UAV PP methods – criteria: algorithm types

- **Bio-inspired algorithms** (cont'd)

- **Gray Wolf Optimization (GWO)**
  - **Metaheuristic** algorithm that mimics the hunting behavior of grey wolves to find optimal solutions for various problems. It uses hierarchical ranks of wolves: (α), (β), (δ), (ω) and their hunting process to guide the population of candidate solutions towards the best solution.
  - **Core Concepts**
    - **Social Hierarchy**: (α) strongest- the best solution found so far; then - (β), (δ), (ω)
    - **Hunting Mechanism steps**: Searching, Encircling, Attacking.
    - **Mathematical Model**: Math. equations used to update the positions of the wolves, simulating these hunting and hierarchy behaviors

- **Working steps**
  - **Initialization:** a random population of candidate solutions is created
  - **Fitness Evaluation:** the fitness of each wolf is calculated
  - **Best Wolves Identification:** The wolves with the best fitness (α), (β), (δ) are identified
  - **Position Update:** The other wolves (ω) update their positions based on the positions of the (α) (β), (δ) wolves, simulating the encircling and attacking phases
  - **New Generation:** This process continues to create new generations of wolves until the optimal solution is found, or a stopping criterion is met

3. Path Planning in Multi-UAV Networks

3.4 Path Planning Methods

Classification of UAV PP methods – criteria: algorithm types

- **Bio-inspired algorithms** (cont'd)
  - **Gray Wolf Optimization (GWO)** (cont'd)
    - (+) Simplicity and Flexibility
    - (+) Competitive performance w.r.t other metaheuristics
    - (-) Slow convergence and Poor exploration
    - **Improved GWO variants examples**
      - ***Ensemble GWO (EGWO***)
      - ***Representative-based grey wolf optimizer (R-GWO)***
      - ***Reinforcement learning - based GWO (RLGWO)***

  - ***Evolutionary Based Algorithms***
    - ***Differential Evaluation (DE)***
      - DE evolves a population of potential paths using objective functions, such as travel distance or time
      - Through inheritance, crossover, and mutation, it iteratively refines paths until an optimal solution is found, or a predetermined limit is reached, proving versatile in various UAV PP cases

Swource: P.Kumar, K. Pal, M.Govi, Comprehensive Review of Path Planning Techniques for UAVs, ACM Computing Surveys, ACM 0360-0300/2025/05-ART, http://dx.doi.org/10.1145/3737280

3. Path Planning in Multi-UAV Networks

3.4 Path Planning Methods

Classification of UAV PP methods – criteria: algorithm types

- **Bio-inspired algorithms** (cont'd)
  - ***Evolutionary Based***
    - ***Genetic Algorithm (GA)***
      - GA PP leverages principles of natural selection and genetics to iteratively evolve optimal UAV navigation routes through selection, crossover, and mutation
      - (-) Convergence speed performance is imprecise, resulting in an inefficient optimization process, especially for real-time scenarios
      - Improvements: modified target function, population initialization, selection, and mutation phases
        - Combined the advantages of DL and GA in DL-GA algorithm

- **AI/ML- based Path Planning methods (short summary)**
  - **Artificial intelligence methods – significant progress for UAV PP**
    - efficient navigation in complex and dynamic environments
    - ML, RL, DL algorithms have been developed to optimize trajectories, enhance obstacle avoidance, and meet r.t. computational demands

W. Meng, X.Zhang, L.Zhou, H. Guo and X.Hu , Advances in UAV Path Planning: A Comprehensive Review of Methods, Challenges, and Future Directions, MDPI, 2025, https://doi.org/10.3390/drones9050376

3. Path Planning in Multi-UAV Networks

3.4 Path Planning Methods

Classification of UAV PP methods – criteria: algorithm types

- **AI/ML- based Path Planning methods** (cont'd)
  - **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**. –used 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)

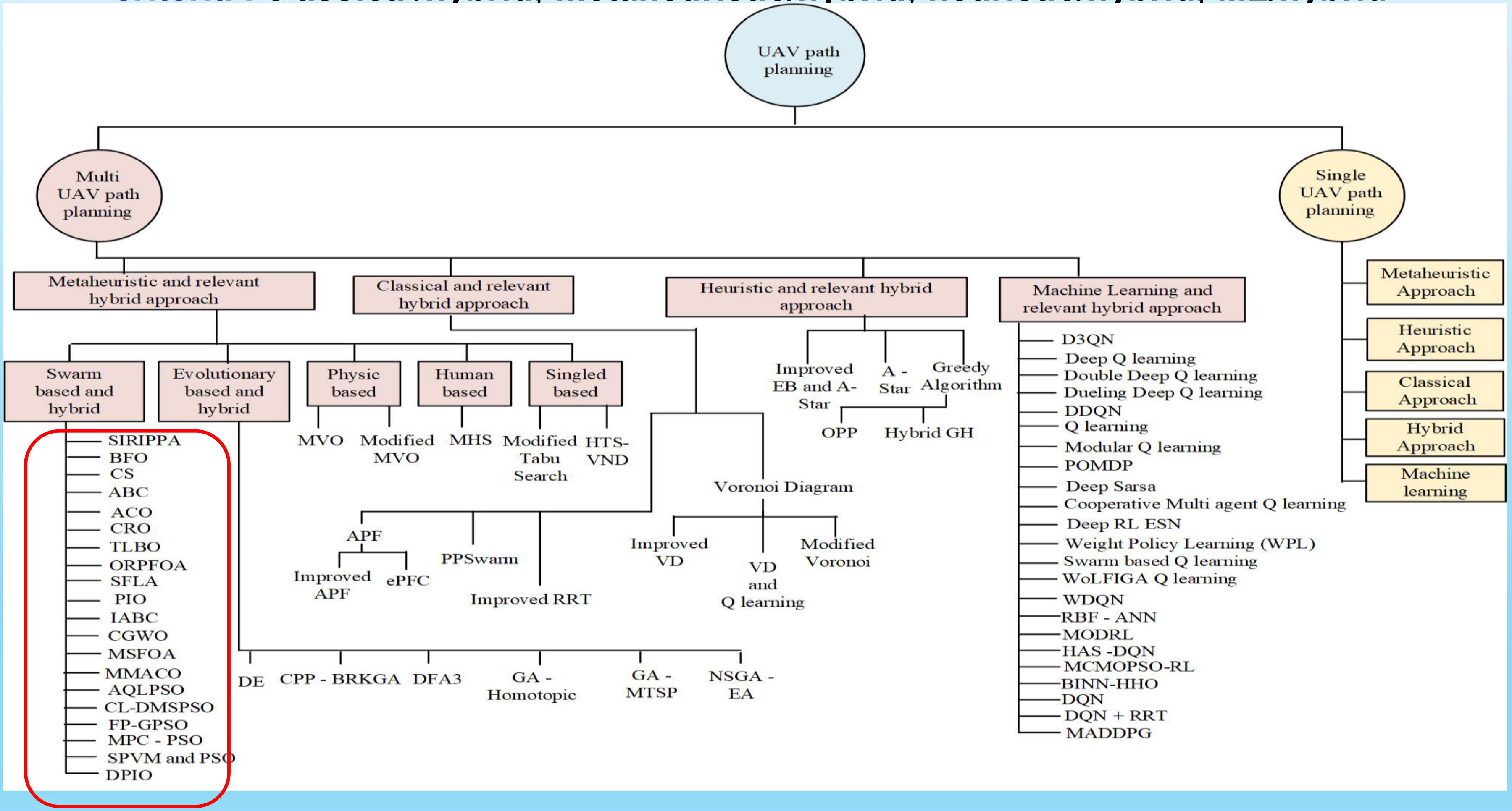
Refs: J.L. Junell, E.J. Van Kampen, C.C. de Visser and Q.P. Chu, Reinforcement learning applied to a quadrotor guidance law in autonomous flight, in AIAA Guidance, Navigation, and Control Conference. American Institute of Aeronautics and Astronautics, Inc. (2015) 1990.
G. Kahn, A. Villaflor, V. Pong, 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.

3. Path Planning in Multi-UAV Networks

3.4 Path Planning Methods

Classification of multi-UAV PP methods – another view:

- **criteria : classical/hybrid, metaheuristic/hybrid, heuristic/hybrid, ML/hybrid**



Source: M.Rahman, N.Sarkar and R.Lutui, A Survey on Multi-UAV Path Planning: Classification,Algorithms, Open Research Problems, and Future Directions, MDPI,Drones 2025,9,263 https://doi.org/10.3390/drones9040263

3. Path Planning in Multi-UAV Networks

3.4 Path Planning Methods

Classification of multi-UAV PP methods :

- **criteria : classical/hybrid, metaheuristic/hybrid, heuristic/hybrid, ML/hybrid**

Recall - Notes:

- ***Heuristic technique*** *(problem solving, mental shortcut, rule of thumb) - any pragmatic approach to problem solving that, not fully optimized, perfected, or rationalized, but "good enough" as an approximation or attribute substitution.*

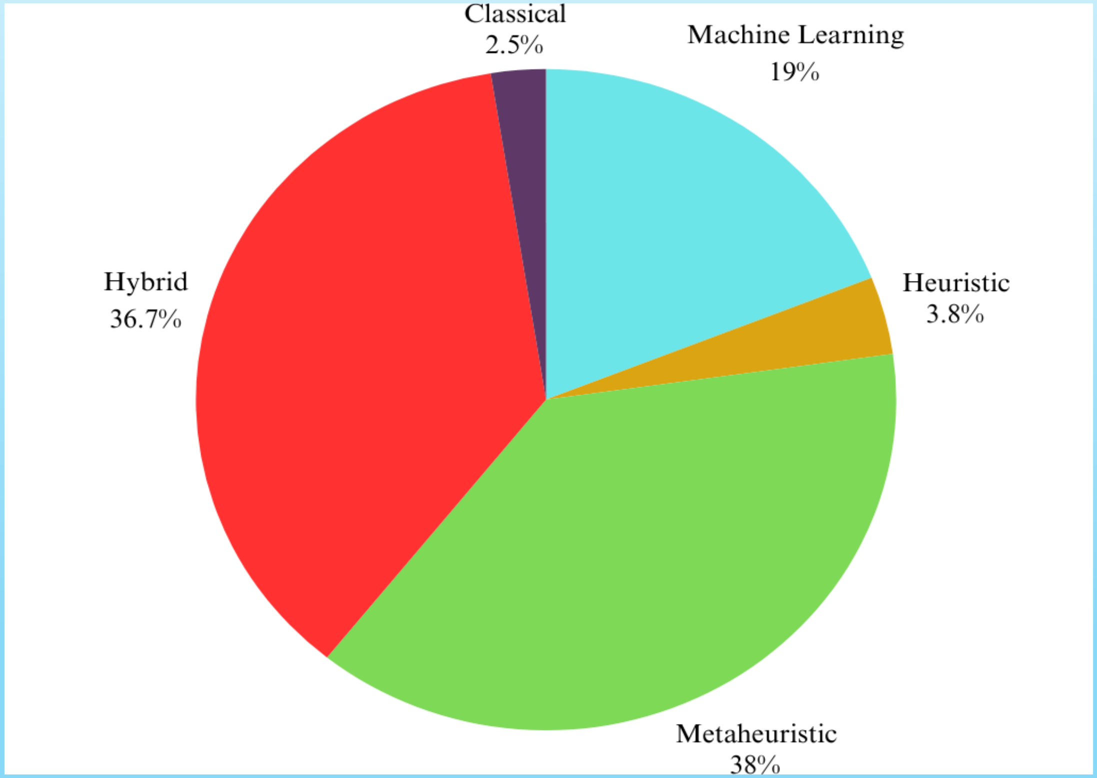
- ***Metaheuristic -*** *high-level, problem-independent algorithmic framework providing guidelines for developing heuristic optimization algorithms in complex problems, (e.g. when exact solutions are computationally infeasible). It can find, generate, tune, or select a heuristic (partial search algorithm) that may provide enough good solution to an optimization problem. Metaheuristics act as strategies for finding optimal solutions by intelligently exploring vast solution spaces.*
- ***Main Characteristics***
  - *High-level: general strategies, not specific algorithms for a single problem*
  - *Problem- independent: the framework can be adapted to a wide range of optimization problems*
  - *Heuristic nature: no guarantee on finding the absolute optimal solution but aim for sufficiently good ones*
  - *Exploration of large solution spaces: effective at searching large sets of possible solutions*

3. Path Planning in Multi-UAV Networks

3.4 Path Planning Methods

Classification of multi-UAV PP methods

- **criteria: classical/hybrid, metaheuristic/hybrid, heuristic/hybrid, ML/hybrid**
- **Statistics on Multi-UAV Path Planning** – methods published 2021-2025



Source: M.Rahman, N.Sarkar and R.Lutui, A Survey on Multi-UAV Path Planning: Classification,Algorithms, Open Research Problems, and Future Directions, MDPI,Drones 2025,9,263 https://doi.org/10.3390/drones9040263

CONTENTS

1. Introduction
2. Multi-UAV and Swarms
3. Path Planning in Multi-UAV Networks
4. Challenges and Open Problems
5. Conclusions

4. Challenges and Open Problems

- **Summary of challenges in Multi-UAV Path Planning**

  - **Key challenges: communication and collaboration, obstacle avoidance, safety and reliability, security, energy efficiency**

  - **Consider dynamic 3D environments** – to adapt adapting PP algorithms to changing conditions

  - **Reduce system complexity and computational costs** - with environmental complexity and the number of UAVs

  - **R.t. path adjustments** and efficient communication among UAVs to prevent collisions

  - **Integrate AI/ML** algorithms and methods in Multi-UAV Path Planning

  - **Special scenarios** path planning

4. Challenges and Open Problems

- **Summary of Open Research Problems**
  - **PP Algorithms**
    - To adapt classical algorithms for larger, dynamic environments in order to enhance their applicability
    - R.t. algorithms need to be further developed for PP in complex 3D environments
    - Metaheuristic approaches should focus on decentralization and r.t. optimization
    - Hybrid algorithms need to be tested in real-world scenarios to ensure effectiveness
  - **Obstacle and collision avoidance**
    - Enhance heuristic approaches to improve scalability and collision avoidance
  - **Communication and Collaboration**
    - Improving the communication protocols for seamless coordination among UAVs
  - **Energy efficiency**
    - Extending operational range and duration by improving energy efficiency
  - **Complexity and cost**
    - Reduce system complexity and computational costs while maintaining high-quality solutions.
  - **AI/ML approach**
    - AI/ML integration while considering computational resource demands and adaptability

4. Challenges and Open Problems

- **Specific Topics**
- **Path Planning in 3D environments and time domain**
  - **Enhanced optimization methods** are needed for **real time in 3D space**
    - **Consider kinematic, geometric, physical** and **temporal constraints, flight risk levels, airspace restrictions**, etc.
  - 3D UAV PP in complex environments (urban areas, caves, forests etc.)
- **Mathematical models for the PP**
  - **Multi-objective functions, (Pareto…)** to 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**
  - **More work is necessary with real experiments.** Issue: number of UAVs considered
  - **Real time** aspects to be considered
- **Optimization techniques**
  - Many **optimization** algorithms and methods have been **already studied**:
    - **Sampling-based, Node -based, Mathematic Model- based, Bioinspired Multifusion-based, AI,** etc.
  - Combining different methods, such as **AI-based (NN, DEL RL, DRL..) evolutionary** algorithms with heuristic, fuzzy inference methods

4. Challenges and Open Problems

- **Specific Topics**
- **Integration of different segments**
  - The **integration and communication of UAVs with terrestrial and space**
    - **integrate different spaces connected to each other via communication protocols**
    - **Different factors** need to be considered: **data rate, coverage. scalability, reliability, security**
- **Security and privacy**
  - **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**
  - **Integration between UAVs and other means of transport** (trucks, buses, etc.)
  - **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.**
  - **Airspace regulations** to govern the development and operation of real UAV applications in different environments

4. Challenges and Open Problems

- **Specific Topics**
- **3D Environment complexity issues**
  - **Solutions**
    - **Split the problem into more manageable chunks**, e.g. fixing of a UAV 3D altitude; PP becomes a 2D problem
    - Find some means for **offloading some computational task from UAVs**
  - The **binary choice between a known/ unknown environment is a notable limitation**
  - To **define bounds** for how much complete and accurate pre-existing environmental knowledge must be
  - **Further research - to select the best method in static/dynamic or a known/unknown vs environment**
  - **Potential solutions**
    - Exploration of the **hybrid environment planning**
      - **pre-planning a path** with a static representation of the environment
      - **dynamic unknown obstacles to be evaluated during the flight**, with minor changes supplied to a global path
    - **Individual ability of a UAV to map or sense** surroundings throughout an unknown environment

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.

4. Challenges and Open Problems

- **Specific Topics**
- **Communication and collaboration**
  - **New algorithms** need to be developed to optimize **coverage time**.
  - The system **must monitor the connectivity** between UAVs and the ground control station
  - **Multi-hop connectivity** of many UAVs is necessary to guarantee redundancy

  - **Effective resource utilization** is essential in order to avoid communication losses
  - Algorithms should be able to manage **seamless communication** for numerous UAVs in a **complex environment**.

  - Facilitating the **sharing of drone data, position, and status** is required
  - One UAV needs to act as controller to maintain the formation during swarm operations
    - If **controller failure**, another UAV should take the controller role.
  - Decentralization of the control system should be possible with an advanced algorithm
  - The **communication protocols** should be able to reduce communication time and packet loss

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5. Conclusions

Path Planning- essential aspect in Multi-UAV systems

Many **traditional algorithms have been re-used/adapted/developed** for UAV environment

Many **open research issues exist**, (many requirements, constraints and factors)

3D space, static/dynamic environment, energy consumption requirements, specific types of UAVs and journey ranges, real-time problems, security and privacy, partial knowledge on environment (including static/dynamic obstacles), cooperative tasks for swarms, etc.)

PP algorithms:

Enhancements are needed to allow more significant number of UAVs, real-time efficient PP, better adapted to changes in ever-changing environments (obstacles, weather etc.).

System efficiency needs to be increased

Enhance coordination and communication among UAVs to optimize group behavior and task allocation.

Optimize and balance multiple objectives (minimizing risk, conserving energy, reducing travel time, etc.)

Reduce system complexity and costs

Integrate novel techniques based on AI/ML

Path Planning Advances in Multi-UAV Networks

- Thank you !
- Questions?

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Path Planning Advances in Multi-UAV Networks

- **List of general Acronyms**

5G-AN	5G Access Network
ABC	Artificial Bee Colony
ACO	Ant Colony optimization
AEO	Artificial Ecosystem Optimizer
AI	Artificial Intelligence
ANN	ANN Artificial Neural Networks
AGWO	Adaptive GWO
AODV	Ad Hoc On Demand Distance Vector
APF	Artificial Potential Field
ARA*	Anytime Repairing A*
BA	Bat Algorithm
BFS	Breadth-First Search
BLP	Binary Linear Programming
CC	Cloud Computing
CP	Control Plane
CPP	Coverage Path Planning
CR	Cognitive Radio
CSA	Cuckoo Search Algorithm
D2D	Device to Device communication
DFS	Depth-First Search
DL	Deep Learning
DN	Data Network
DNN	Deep Neural Network
DRL	Deep Reinforcement Learning
DoS	Denial of Services
DP	Data Plane (User Plane UP)
DPMC	Distributed Model Predictive Control
DTN	Delay Tolerant Network
E2E	End to End
EHO	Elephant Herding Optimization
FA	Firefly Algorithm

FRZ	Flight Restriction Zone
GBFS	Greedy Best-First Search
GDGACO	Gain-Based Dynamic Green ACO
GEO	Golden Eagle Optimizer
GF	Greedy forwarding
GNSS	Global Navigation Satellite System
GS	Ground Station
GWO	Grey Wolf Optimizer
HRP	Hybrid Routing Protocol
HTOL	Horizontal Takeoff and Landing
ILP	Integer Linear Programming
IMOPIO	Improved Multi-Objective PIO
IPP	Informative Path Planning
IPA	Immune Plasma Algorithm
IoT	Internet of Things
KF	Kalman Filter
LF	Lyapunov Function
LQR	Linear-Quadratic Regulator
LP	Linear Programming
MANET	Mobile Ad hoc Network
MAC	Medium Access Control
MCC	Mobile Cloud Computing
MDP	Markov Decision Process
MEC	Multi-access (Mobile) Edge Computing
MILP	Mixed-integer Linear Programming
ML	Machine Learning
MOP	Multi-Objective Optimization Problem
MPC	Model Predictive Control

Path Planning Advances in Multi-UAV Networks

- **List of general Acronyms**

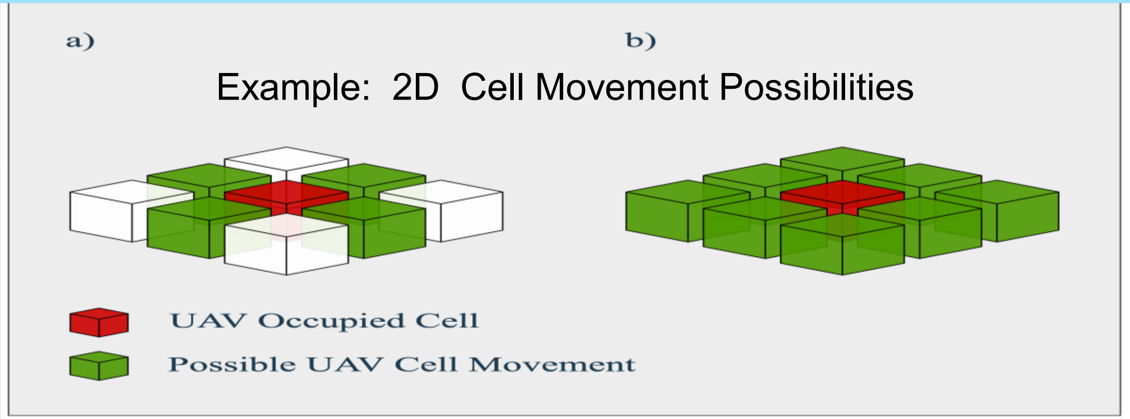
NF	Network Function
NLP OPP	Non-Linear Programming Optimal Path Planning
PIO	Pigeon Inspired Optimization
PP	Path Planning
PRM	Probabilistic Roadmap
PRP PSA-ACO	Proactive Routing Protocol Parallel Self-Adaptive ACO
PSO	Particle Swarm optimization
QoE	Quality of Experience
RAN	Radio Access Network
RL RLGWO	Reinforcement Learning Reinforcement learning based GWO
RRP	Reactive Routing Protocol
RRT	Rapidly-exploring Random Trees
SCF	Store-carry-and-forward
SDN TS	Software Defined Networking Tabu Search
UAV	Unmanned Aerial Vehicle
UAVNET	Unmanned Aerial Vehicle Network
UAV-BS	UAV- Base Station
UAV-RS	UAV Relay Station
UL	Uplink
V2X VD	Vehicle-to-everything Voronoi Diagram
VANET	Vehicular Ad hoc Network
VG	Visibility Graph
VM	Virtual Machine
VTOL WDQN	Vertical Takeoff and Landing Whale inspired deep Q-network

Path Planning Advances in Multi-UAV Networks

- ANNEXES
  - Backup slides

3.3 Environment Representation Methods (Cont'd - Details)

- **Cell decomposition**
- ***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



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. Path Planning in Multi-UAV Networks

3.3 Environment Representation Methods {DETAILS)

- **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

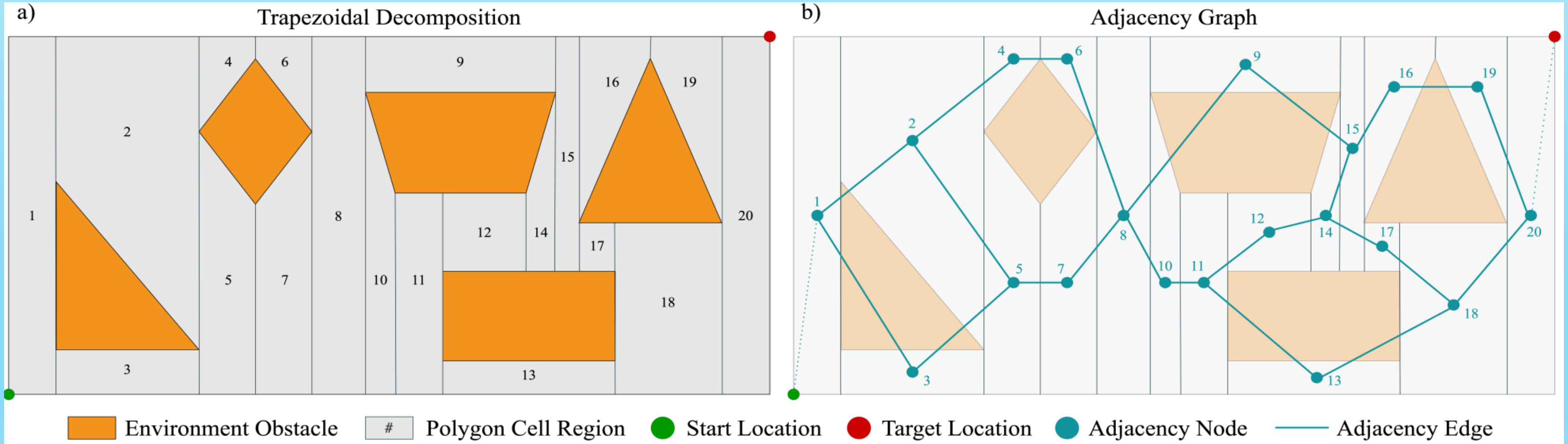
Source: M,R. Jones, S.Djhael, K. Welsh Path-planning for Unmanned Aerial Vehicles with Environment Complexity Considerations: A Survey, ACM Comput. Surv., Vol. 1, No. 1, November 2022.

3. Path Planning in Multi-UAV Networks

3.3 Environment Representation Methods (Details)

- **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. Path Planning in Multi-UAV Networks

3.3 Environment Representation Methods (Details)

- **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**

3.3 Environment Representation Methods (Details)

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

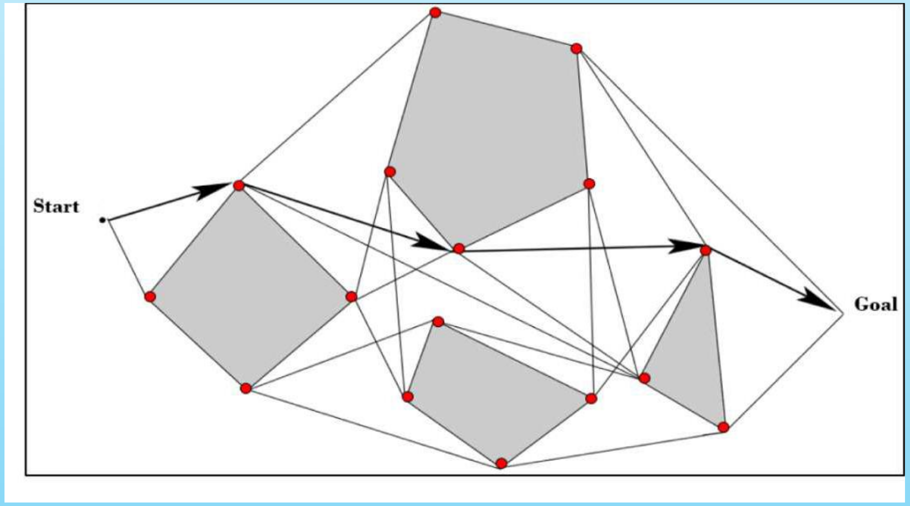
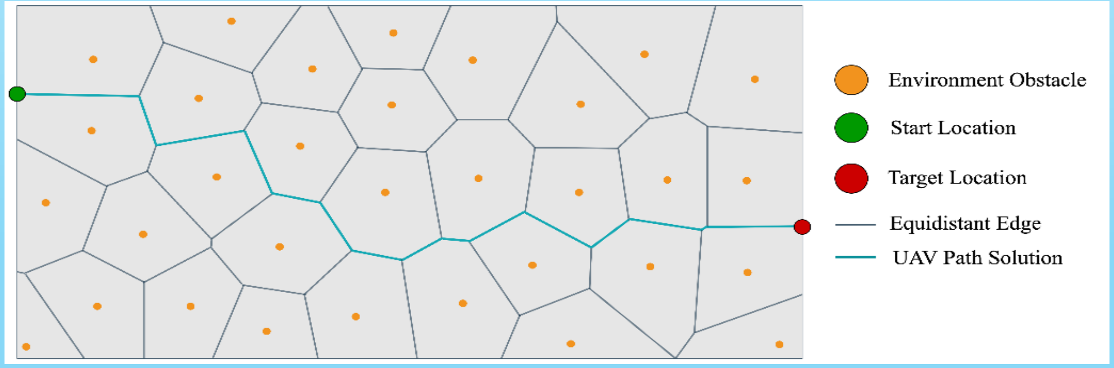


Figure- Source: M. N.Bygi, 3D Visibility Graph, https://sharif.edu/~ghodsi/papers/mojtaba-nouri-csicc2007.pdf

3. Path Planning in Multi-UAV Networks

3.3 Environment Representation Methods (Details)

- **Roadmap Representation** (cont'd)
  - ***Voronoi diagrams* and *path solutions***
    - Let **P = {p_1, p_2, …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

3.3 Environment Representation Methods (Details)

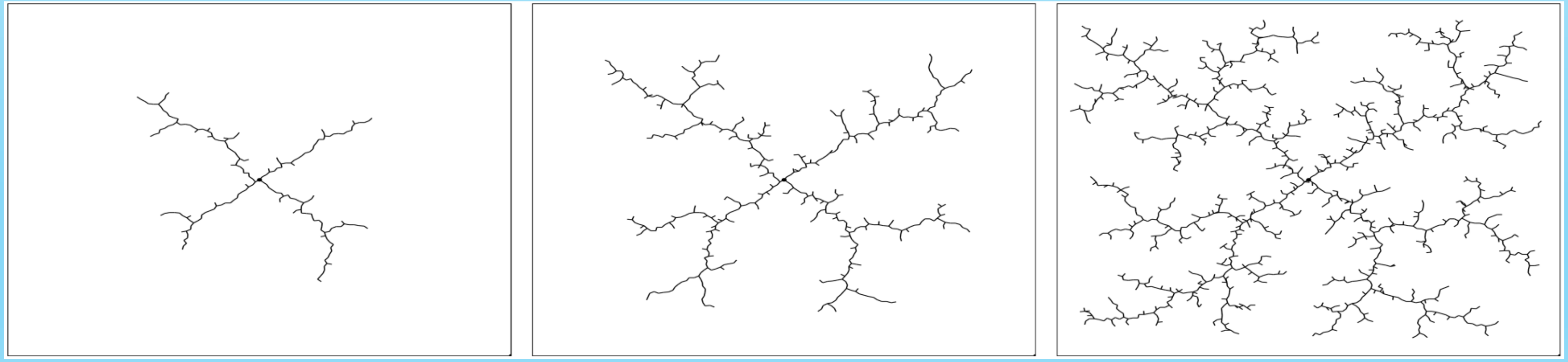
- **Roadmap Representation** (cont'd)
  - **Probabilistic Roadmap**
    - Visibility graph and Voronoi: **the path generation is dictated solely by the placement of obstacles** within the environment
    - A **probabilistic approach deconstructs the available free problem space into a set of randomly 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. Path Planning in Multi-UAV Networks

3.3 Environment Representation Methods (Details)

- **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..

3.3 Environment Representation Methods (Details)

- **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. Path Planning in Multi-UAV Networks

3.3 Environment Representation Methods (Details)

- **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.

3. Path Planning in Multi-UAV Networks

3.5 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.

3. Path Planning in Multi-UAV Networks

3.5 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.

3. Path Planning in Multi-UAV Networks

3.5 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

3. Path Planning in Multi-UAV Networks

3.5 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

3. Path Planning in Multi-UAV Networks

3.5 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)

3. Path Planning in Multi-UAV Networks

3.5 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**

3. Path Planning in Multi-UAV Networks

3.5 Traditional Path Planning Algorithms

Time complexity of the 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

3.6 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

3.6 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.

3. Path Planning in Multi-UAV Networks

3.6 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

3. Path Planning in Multi-UAV Networks

3.6 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 = 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:

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

10 Set $s_t = s_{t+1}$

End while

End do

11 return The learned policy $\pi(s)$ = 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

3. Path Planning in Multi-UAV Networks

- **3.7 Swarm Path Planning Algorithms – Examples**
- **3D Path Planning**
- ***Improved GWO*** - for 3D PP determines a feasible flight trajectory while avoiding obstacles
  - *R. K. Dewangan, A. Shukla, andW.W. Godfrey, 3D path planning using grey wolf optimizer for UAVs, Int. J. Speech Technol., vol. 49, no. 6, pp. 2201_2217, Jun. 2019.*
- ***Probabilistic road map (PRM)*** - it finds a multi-trajectory PP for the UAV cluster
  - The UAV swarm can reach different places (marked and unmarked) in different situations and support emergency conditions in the city environment
  - *Á. Madridano, A. Al-Kaff, D. Martín, and A. A. D. L. de la Escalera, 3D trajectory planning method for UAVs swarm in building emergencies, Sensors, vol. 20, no. 3, p. 642, Jan. 2020.*
- ***Multi-swarm fruit fly optimization algorithm (MSFOA)*** – solves a non-linear optimization problem with multiple static and dynamic constraints, through a multi-UAV collaborative PP path on 3D rugged terrain
  - *K. Shi, X. Zhang, and S. Xia, Multiple swarm fruit fly optimization algorithm-based path planning method for multi-UAVs," Appl. Sci., vol. 10, no. 8, p. 2822, 2020.*
- ***Pigeon Inspired optimization (PIO)*** - the UAV is used for 3D oil field detection
  - PIO optimizes the initial path, and then *Fruit Fly Optimization Algorithm (FOA*) performs local optimization to avoid obstacles while finding the best path.
  - *F. Ge, K. Li, Y. Han, and W. Xu, PP of UAV for oil field inspections in a 3D dynamic environment with moving obstacles based on an improved pigeon-inspired optimization algorithm, Appl. Intelligence, 2020*

Source: Y. Zhou, B. Rao, W. Wang, UAV Swarm Intelligence: Recent Advances and Future Trends, IEEE Access, September 2020, DOI 10.1109/ACCESS.2020.3028865

3.7 UAV Swarm Path Planning- Examples

Dynamic Path Planning

- The PP has special requirements In dynamic environment contexts
- ***Multiple path and selection***
  - Several candidate paths are generated using the cubic spline second-order continuity principle
  - A total cost function is defined to select the optimal obstacle avoidance path
  - This method has short time consumption and strong r.t. performance
  - *X. Chen, M. Zhao, and L. Yin, Dynamic path planning of the UAV avoiding static and moving obstacles, J. Intell. Robotic Syst., vol. 99, nos. 3_4, pp. 909_931, Sep. 2020.*

- ***Adaptive route planning*** –in changing unknown condition, with complementary sensors
  - *Memory-based Wall Following-Artificial Potential Field (MWF-APF)*
  - The algorithm switches between *Wall-Following Method (WFM)* and *Artificial Potential Field method (APF)* with improved situation awareness capability.
  - It solves some problems of the *WFM* and *APF*
  - *H. Wang, M. Cao, H. Jiang, and L. Xie, Feasible computationally effficient path planning for UAV collision avoidance, Proc. IEEE 14th Int. Conf. Control Autom. (ICCA), Jun. 2018, pp. 576_581.*

3.7 UAV Swarm Path Planning Examples

Dynamic Path Planning (cont'd)

- **UAVs in complex outdoor environments** (e.g., isolated disaster scenes)
  - Track detection and automatic scene understanding based on abstract vision
  - Method: Combine a *support vector machine*-based tracking detection and tracker combination framework
  - Achieve tracking direction estimation and stalking with lower computation and input
  - *Y. Liu, Q. Wang, Y. Zhuang, and H. Hu, A novel trail detection and scene understanding framework for a quadrotor UAV with monocular vision, IEEE Sensors J., vol. 17, no. 20, pp. 6778_6787, Oct. 2017*
- ***Path planning of UAVs based on collision probability***
  - A method for calculating the collision probabilities of UAVs under the constraints of mission space and the number of UAVs
  - In cluster flight mode, automatic tracking and prediction of UAV cluster tracks should be implemented to avoid path conflicts
  - To address the inconsistency problem because of noise caused by the state information of multi-UAV communication, a state estimation method is proposed based on the Kalman algorithm
  - *[**Kalman filtering** (a.k.a **linear quadratic estimation**) uses a series of measurements observed over time (including statistical noise and other inaccuracies), to produce estimates of unknown variables, more accurate than those based on a single measurement, by estimating a joint probability distribution over the variables for each time-step]*
  - *Z. Wu, J. Li, J. Zuo, and S. Li, Path planning of UAVs based on collision probability and Kalman filter, IEEE Access, vol. 6, pp. 34237_34245, 2018.*

3. Path Planning in Multi-UAV Networks

3.7 UAV Swarm Path Planning

Optimal PP- Examples

- **Fixed-wing UAV-assisted *mobile crowd perception* (MCS)**
  - The joint *PP* and *task allocation* problems are considered aiming to energy efficiency
  - The NP-hard joint optimization problem is transformed in bilateral two-stage matching problem
  - Good results in energy consumption, overall profit and matching performance
  - *Z. Zhou, J. Feng, B. Gu, B. Ai, S. Mumtaz, J. Rodriguez, and M. Guizani, When mobile crowd sensing meets UAV: Energy-ef_cient task assignment and route planning, IEEE Trans. Commun., vol. 66, no. 11, pp. 5526_5538, Nov. 2018.*

- **Group of heterogeneous fixed-wing UAVs with traversing multiple targets and performing continuous tasks**
  - Optimal flight trajectory is found; a coupled distributed planning method combining task assignment and trajectory generation is used
  - The cooperative task planning problem is reconstructed
  - The method improves the system operating rate; it can be applied to practical tasks
  - *W.Wu, X.Wang, and N. Cui, `Fast and coupled solution for cooperative mission planning of multiple heterogeneous unmanned aerial vehicles,' Aerosp. Sci. Technol., vol. 79, pp. 131-144, Aug. 2018.*