AI based Path Planning for Unmanned Aerial Vehicles

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AI based Path Planning for Unmanned Aerial Vehicles

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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 NUSTB 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, AI in UAV
  - **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 overview is limited to a *high-level view only*.**
    - **The list of topics discussed is also limited.**

AI based Path Planning for Unmanned Aerial Vehicles

- **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**)
  - **UAVNETs –characteristics and requirements different from traditional mobile ad hoc networks (MANET) and vehicular ad hoc networks (VANET)**
    - **large variety of operational contexts**
    - **dynamic behavior, mobility and fast 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, 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 and complex topic in UAV area**
    - ***Artificial Intelligence/ Machine Learning (AI/ML) - significant support for UAV Path Planning***
    - ***This overview: principal focus is on Machine Learning applied to UAV PP***

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1. Introduction

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

- **UAVs- popular solutions** for many applications (civilian, military - domains)
  - **Missions:** surveillance/monitoring, delivery, searching, transportation, environmental protection, different physical actions
    - **Special 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 application type
- **Limitations and challenges in UAV technology:** battery capacity, limited flight autonomy, costs, environment issues (maybe hostile), security concerns and others
- **Unmanned Aerial Vehicles (UAV) – classification criteria**
  - **Missions and applications - Civil UAVs:** agriculture, aerial photos, logistics, data collection; **Mission critical:** special domain, military missions
  - **Performance**: altitude, flight range (close, short, medium, large nx10**2 km), payload, speed, endurance, cost, and size
- **Engine type**: fuel engines or electric motors
- **Mechanical/physical characteristics**:
  - **weight** - *Micro*, *Light, Medium*, *Heavy*, and *Super Heavy* classes
  - **takeoff and landing : VTOL** (*Vertical)* **HTO**L (*Horizontal)*

1. Introduction

1.2 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. traditional 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

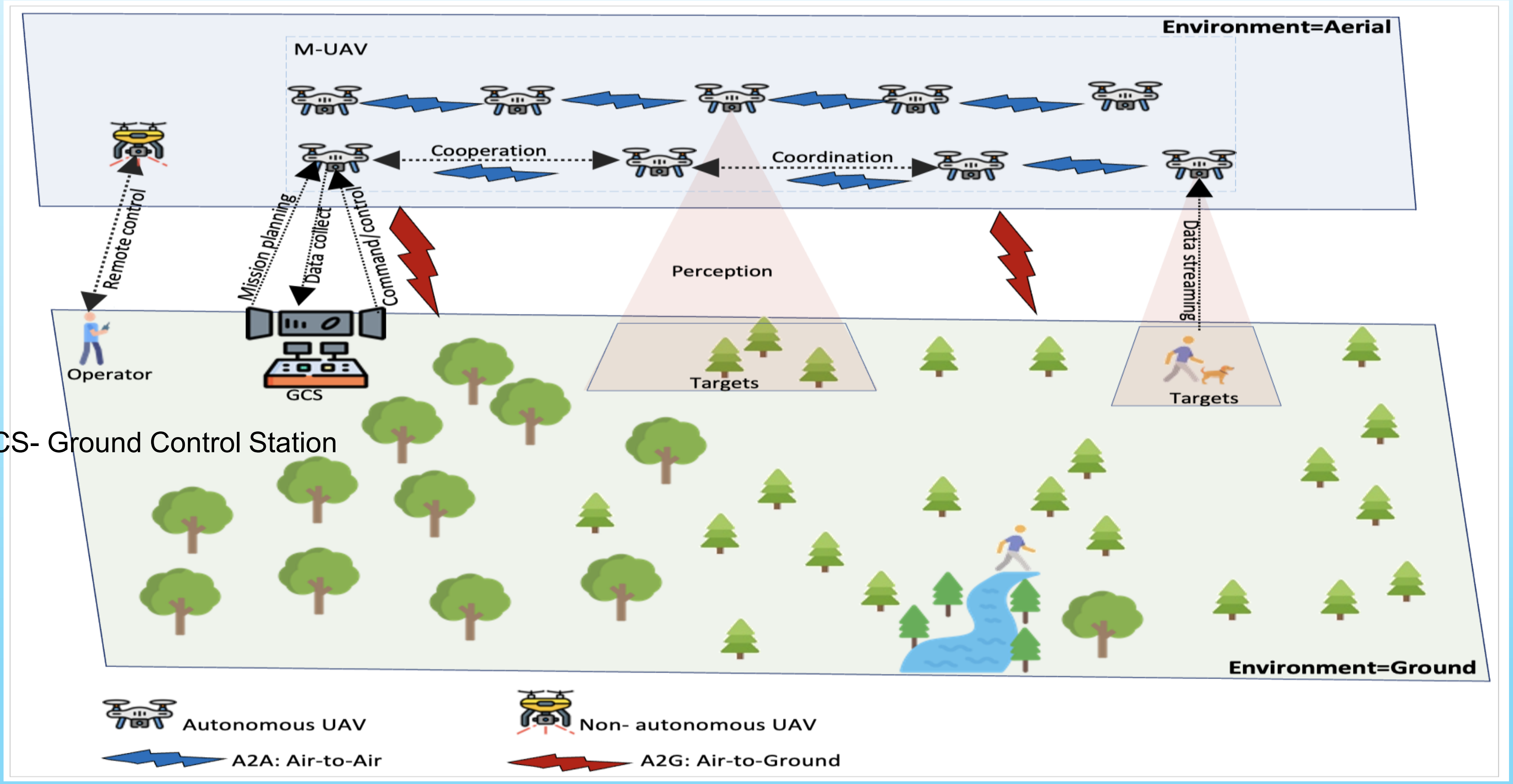
- **Different topics on Multi-UAV networks**: Cooperative/swarm Multi-UAVs; Opportunistic relaying networks; Delay-tolerant UAVs networks; Energy issues; Ground WSN; Internet of Things (IoT); Cooperation with Cloud Computing; Heterogeneity; Self-organization; Security; AI applied in UAV

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

1.2 UAV Networks

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



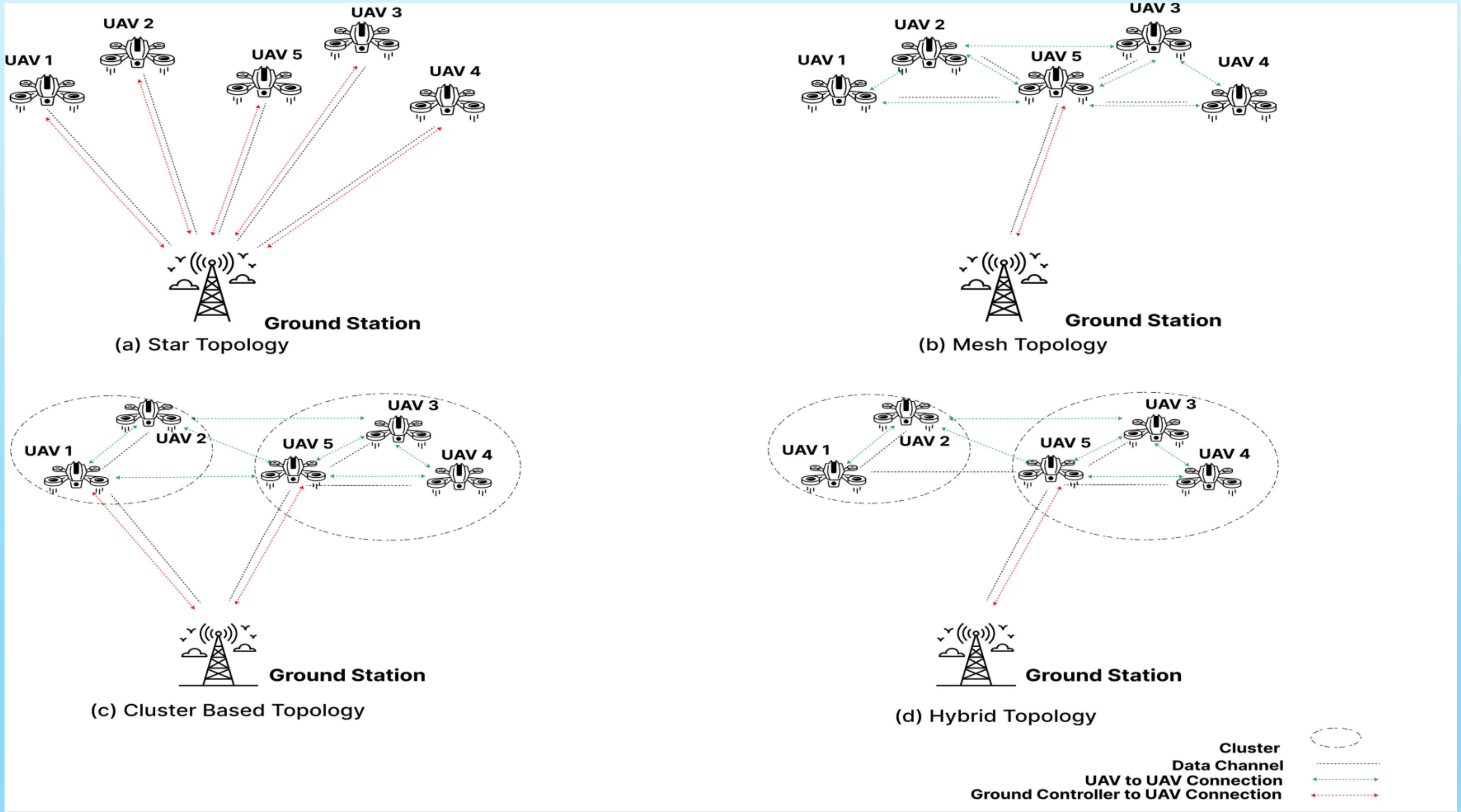
GCS- Ground Control Station

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 Multi-UAV Networks- topology examples

- (a) Star b) Mesh (c) Cluster-based (d) Hybrid mesh



(a) Star Topology

(b) Mesh Topology

(c) Cluster Based Topology

(d) Hybrid Topology

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

1. Introduction

1.4 Multi-UAV systems

- **Multi-UAV systems advantages vs. single UAV**
  - Time efficiency, Cost, Simultaneous-synchronized actions, Complementary /collective actions, Fault tolerance, Flexibility
- **Multi-UAV system issues:** Group piloting, Regulatory restrictions, Safety (collisions)
- **Typical applications :** Disaster rescue, Area coverage, Monitoring patrols, Military
- **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: p**hysical (links)/ virtual/ no coupling
  - **Temporal UAV relations:** simultaneous, asynchronous
  - **UAV similarity:** identical, similar, heterogeneous
  - **Task separation:** functional, cross-functional
  - **Mission Control:** centralized, decentralized, mixed
  - **User interaction:** real-time, pre-planning, no interaction

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

1. Introduction

1.4 Multi-UAV systems

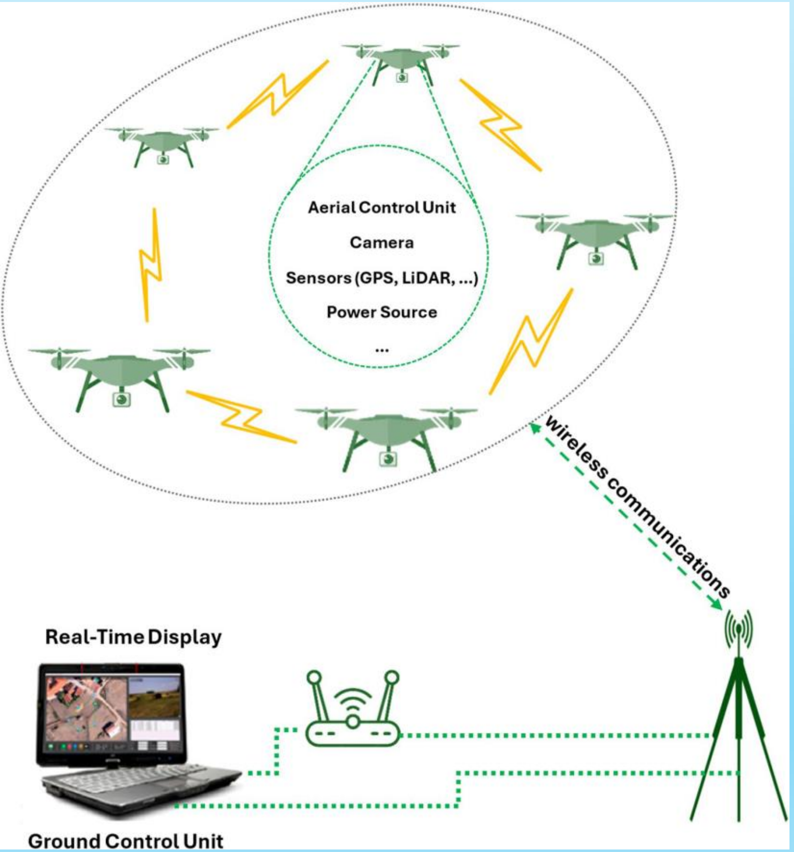
- **UAV swarm : a set of aerial UAV/ robots *working together for a specific goal***
  - UAV swarm domain – connected with robotics area, leveraging collaborative autonomy
  - **Applications**
  - ***Civilian sectors*** (entertainment, infrastructure inspection, delivery services, etc.)
  - ***Military domain*****:** surveillance, combat support/actions and logistics
  - **Topics of interest :**applications, routing, **PP,** task assignment, formation control, communication, scalability, energy, resource allocation, security and privacy, AI/ML
  - **Swarm Intelligence (SI)** algorithms: inspired from natural behavior
  - **UAV swarm infrastructure**
    - Each UAV is an individual unit having sensors, processors, and comm. HW
    - A **control unit** plays a central role in managing the swarm
  - **UAV swarm communication : *UAV-UAV* or *UAVs - Control center***
    - **U-U:** direct link or multi-hop comm. 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

1. Introduction

1.4 Multi-UAV Systems - 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



1. Introduction

1.4 Multi-UAV Systems - UAV swarms

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

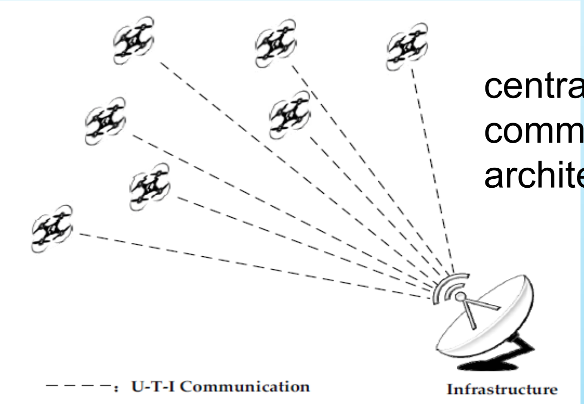
- **Decentralized architecture** - communication coverage is through a multi-hop network
  - The GW-UAV performs U-I communication
    - **Single-group swarm Ad hoc network** - appropriate for a swarm having the same type UAVs
    - **Multi-group swarm Ad hoc network-** accept different UAV types; however, 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

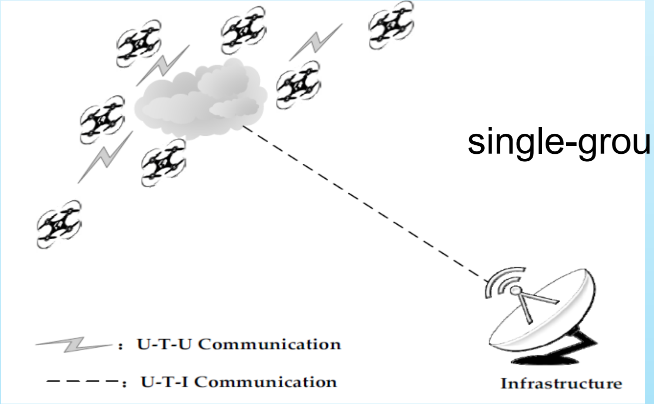
1. Introduction

1.4 Multi-UAV Systems - UAV swarms

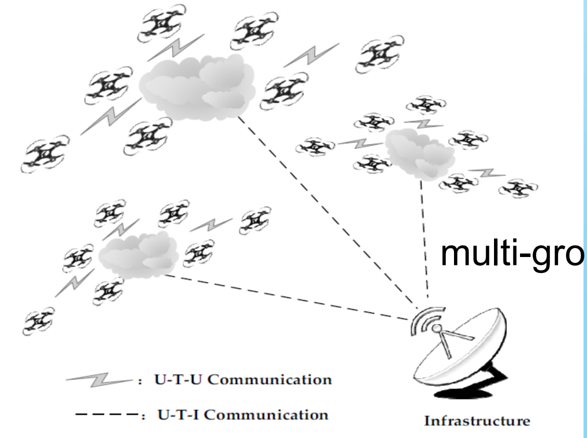
- **Swarm communication architecture** (cont'd)



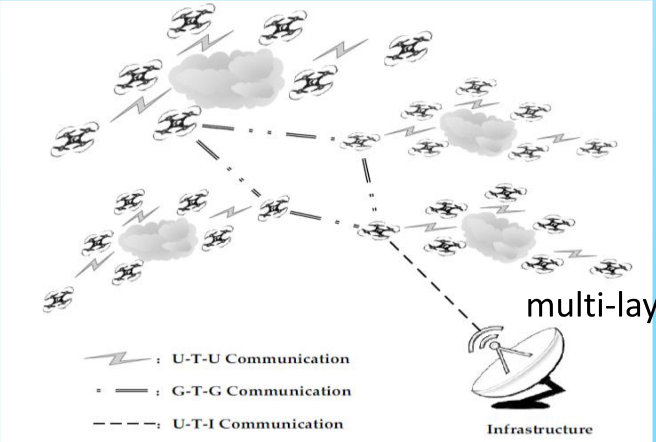
centralized communication architecture



single-group swarm



multi-group swarm



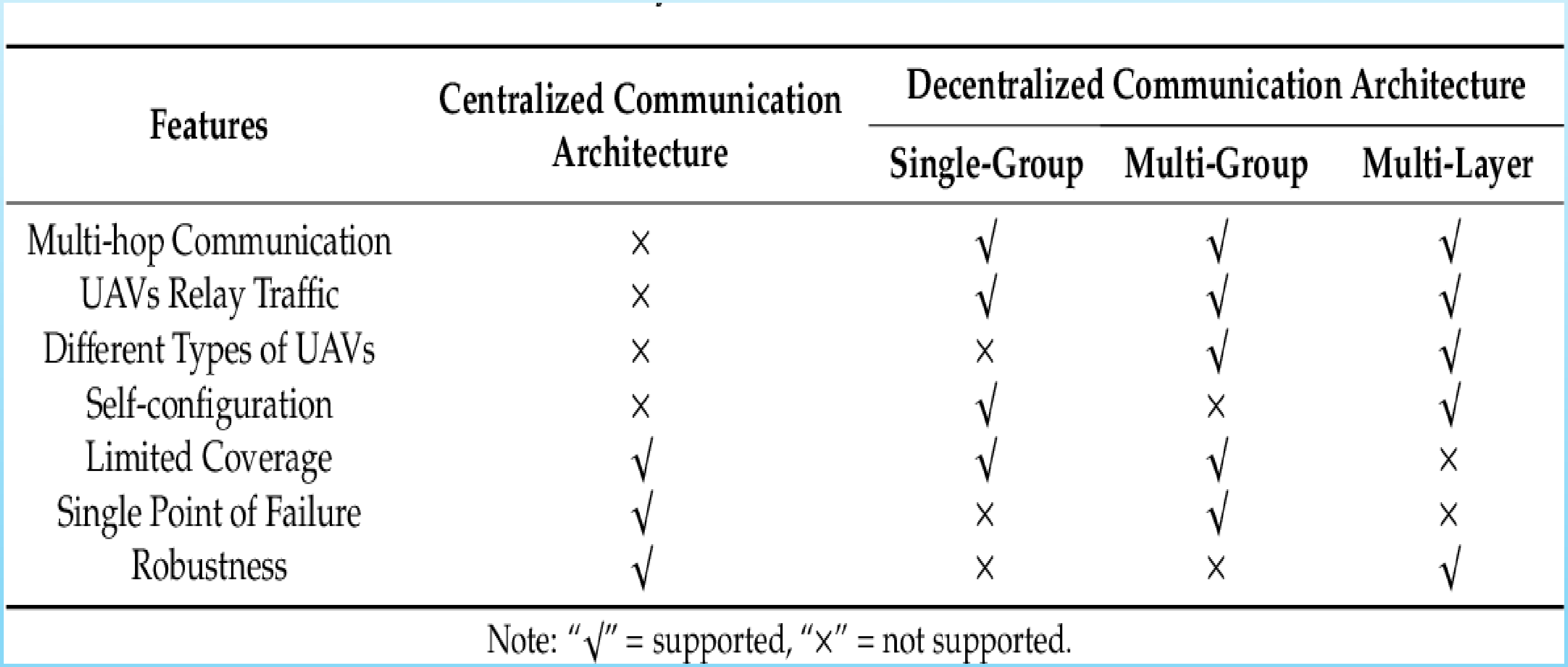
multi-layer swarm

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

1, Introduction

1.4 Multi-UAV Systems - UAV swarms

- **Swarm communication architecture** (cont'd)
- UAVs swarm should be able to react cognitively to environment changes
- 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

1. Introduction

1.4 Multi-UAV Systems - UAV swarms

- UAV Swarm Intelligence (SI)
  - **Collective decisions** and mission completion by using relatively simple instructions (**AI and edge computing** can assure intelligent support**)**
  - **Applications:** civilian domains, military purposes
    - 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

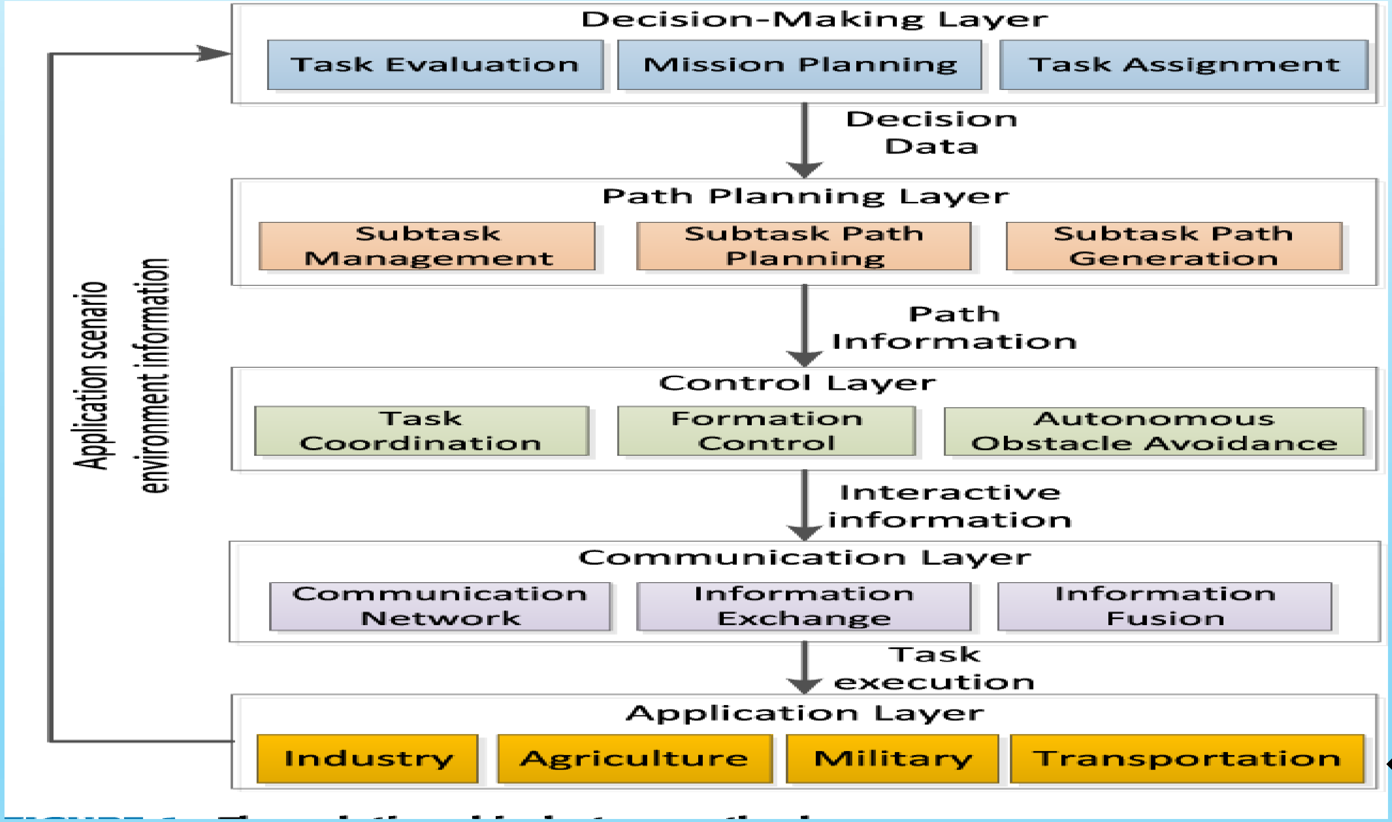
- ***SI basic principles:***
  - **Proximity:** the swarm individuals should respond to the environmental variance
  - **Quality:** a swarm should respond to quality factors like location safety only
  - **Diverse response:** enables to design of the distribution s.t. all the individuals are protected 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

1. Introduction

1.4 Multi-UAV Systems - UAV swarms

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



← **Generical term**

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 have been 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: classical (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
  - Note : the semantic of this layer is larger than that of the TCP/IP classical stack

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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2. Path Planning in Multi-UAV Networks

2.1 UAV Path planning (PP) problem

- **UAV PP (a.k.a. *motion planning*), is a branch of path-finding used in robotics**
  - UAV specifics: 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*** Constraint factors: temporal, physical, environment, autonomy, energy
  - **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 - related to:** path length, energy consumption, or collision risk
  - **Key objectives**: minimizing the costs
  - **Constraints** - environment, physical limitations, task requirements, energy issues
  - **PP problems of interest:** environment modelling, path selection and optimization, completeness criteria,
  - **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)*****:** the path **should pass through a set of points in an area**
    - ***Cooperative PP (specific to UAV swarms)*** coordinated mission

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

2. Path Planning in Multi-UAV Networks

2.1 UAV Path planning (PP) problem

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

2.2 Path planning model

- Let it be 3D workspace w**;** it may have obstacles; let wo_i be the i_{th} obstacle
- The **free workspace** (no obstacles) is the overall area represented by $w_{free} = w \setminus \bigcup_i wo_i$
- The initial point x_{init} and the goal region x_{goal} are elements in w_{free}
- **The PP problem is defined by a triplet** $(x_{init}, x_{goal}, w_{free})$
- ***Definition 1-PP***: Given a function $\delta:[0,T] \to R^3$ of bounded variation, where $\delta(0) = x_{init}$ and $\delta(T) = x_{goal}$ if there exists a process Φ s.t. $\delta(t) \in w_{free}$, for all $t \in [0,T]$, then Φ is called **Path Planning**
- ***Definition 2-Optimal PP***
  - Let **Σ denote the set of all paths**
  - Given a PP problem (-, -, -) and a cost function $c : \Sigma \to R \geq 0$, if a process fulfils the *Definition 1* and if exists a feasible path having a minimum cost, then the associated process Φ' is named ***Optimal PP***

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

2. Path Planning in Multi-UAV Networks

2.2 Path planning model

- The PP problem has a **non-linear nature and frequently an exponential complexity**

- ***PP*** and ***Trajectory Planning***: two distinct problems in robotics, but related
  - ***Trajectory***: the path is parameterized by time **t**
  - ***Trajectory planning*** : It determines ***how*** the UAV moves along the path in $\boldsymbol{w_{free}}$
    - The ***path*** is a continuous curve which could be a set of discrete line segments that connects the start node $\boldsymbol{x_{init}}$ to the end node $\boldsymbol{x_{goal}}$
- **PP is influenced by UAV control-types**

- **Remotely guided UAVs)-** controlled either directly by a human operator (Remotely Piloted Aircraft - RPA) or through different levels of automation
  - ***Unmanned Aircraft System (UAS)*** : drone, GC, communication links
  - **Control Methods:** radio frequency, Bluetooth, Wi-Fi , 5G/6G, satellite links
  - **Operational Types:**
    - **Manual:** r.t . control of movement and camera functions - by a pilot
    - **Semi-Automatic:** The UAV handles basic flight tasks (takeoff, landing, hovering); an operator intervenes for mission-specific decisions
  - **Main Components: UAV** (multi-rotor, VTOL, HTOL, hybrid); **Sensors** (RGB cameras, LIDAR, multispectral/hyperspectral sensors, etc.); **GCS** (handheld controller or a browser-based system ; operators can remotely monitor and manage flights
  - **Advanced Features:** Onboard AI, Camera-Guided Navigation

2. Path Planning in Multi-UAV Networks

2.2 Path planning model

- **PP is influenced by UAV control-types** (cont'd)
  - **Semi-autonomous UAVs – hybrid solution**
    - automated flight capabilities (takeoff, navigation, collision avoidance, landing)
    - human supervision, allowing for operator intervention
  - **Fully autonomous UAVs** - perform entire missions—takeoff, navigation, waypoint tracking, and landing—without human intervention
    - Driven by AI and advanced sensors; operate in complex environments, often using LiDAR and computer vision for obstacle avoidance

- **Main components of UAV Path Planning**
  - **Environment Modeling:** Representing 3D spaces using sensor data (LiDAR, cameras) or satellite imagery to identify obstacles
  - **Path Generation:** Creating feasible, often optimal, paths while considering constraints like kinematics and power consumption
  - **Obstacle Detection & Avoidance**: Real-time adjustments to avoid static or moving obstacles
  - **Optimization Criteria:** Minimizing travel time, distance, or energy consumption.

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

2. Path Planning in Multi-UAV Networks

2.3 Environment Representation Problem (summary)

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

- **Obstacles: static or dynamic; any geometry**: cubes, pyramids, floating balls, etc.
  - The obstacles model will have impact on 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** (bridges, buildings (convex, and/or concave), complex and cluttered spaces, etc. **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 positions are unknown
  - ***Dynamic-unknown (DU)***: All obstacles /objects are both mobile and unknown

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

2. Path Planning in Multi-UAV Networks

2.3 Environment Representation Problem (summary)

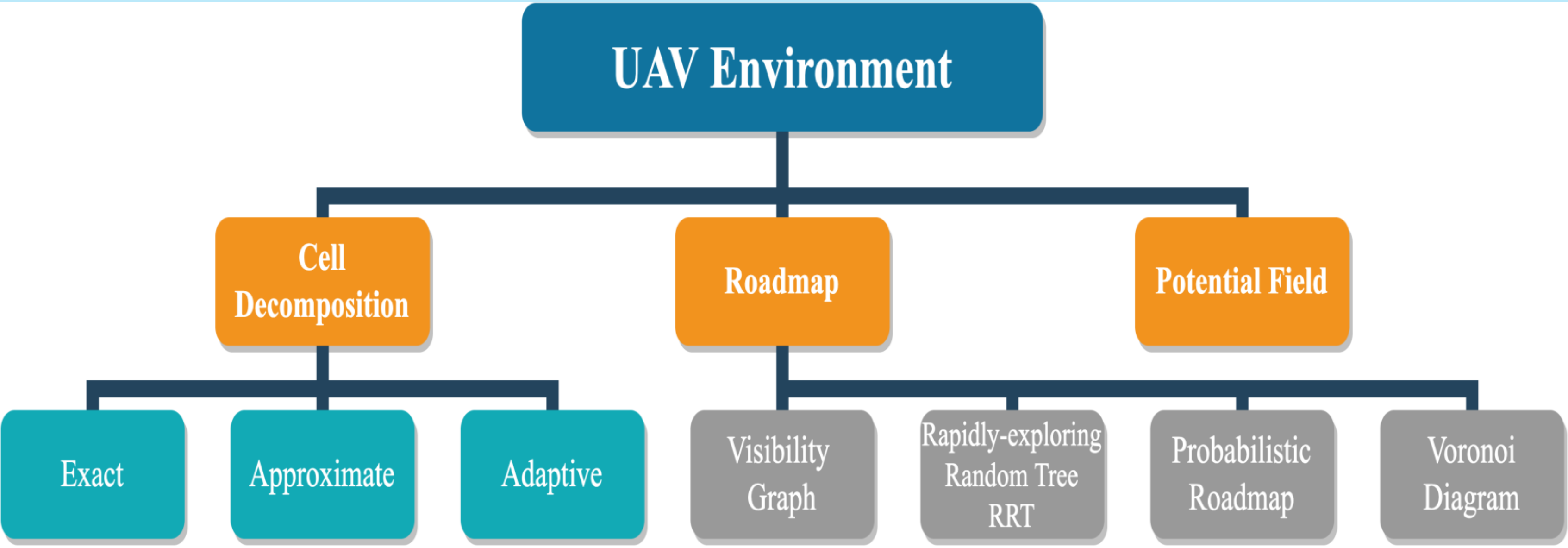
- **Evaluation Metrics for PP Algorithms**
    - **Path length -** the total distance travelled, influenced by obstacle distribution and environmental complexity
    - **Computation time (it** is critical for r.t. tasks)
    - **Energy consumption** relates to battery usage; crucial for long-duration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

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

2. Path Planning in Multi-UAV Networks

2.3 Environment Representation Problem

- 3D Environment representation- classes
  - ***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



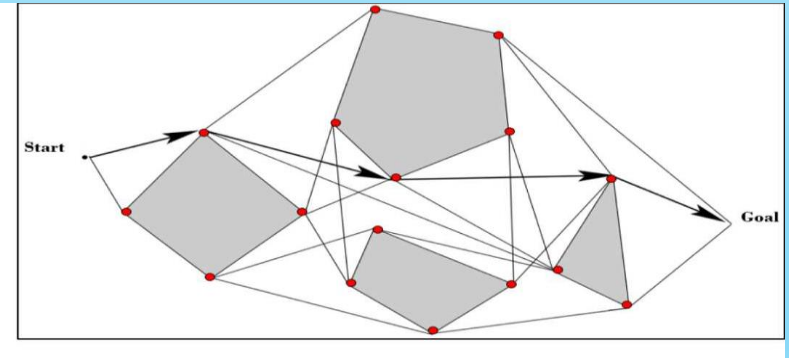
Source: M,R. Jones, S. Djhael, K. Welsh, Path-planning for Unmanned Aerial Vehicles with Environment Complexity Considerations: A Survey, ACM Comput. Survey, Vol. 1, No. 1, November 2022.

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

2. Path Planning in Multi-UAV Networks

2.3 Environment Representation Methods

- **Cell decomposition**
  - The **environment space is divided** into a series of **nonoverlapping cells**
  - **Decomposition types: *Approximate ; Exact; Adaptive decomposition***
- **Roadmap Representation:** **Connectivity graphs -** the **nodes represent key free space locations**
  - ***Visibility graphs (VG); Voronoi diagrams* and *path solutions***
  - ***Probabilistic Roadmap (PRM); Rapidly-exploring Random Trees (RRTs)***
- **Artificial Potential Field (APF)**
  - **computes in real-time a directional** force to be applied to a UAV
  - **Examples:** (left) ***Voronoi diagrams* and *path solutions;*** *(right)* ***Visibility graph***



Source: Tong, Wu et al., 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.2012.01.642 [*www.sciencedirect.com*](http://www.sciencedirect.com)

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

2. Path Planning in Multi-UAV Networks

2.4 Path Planning Methods

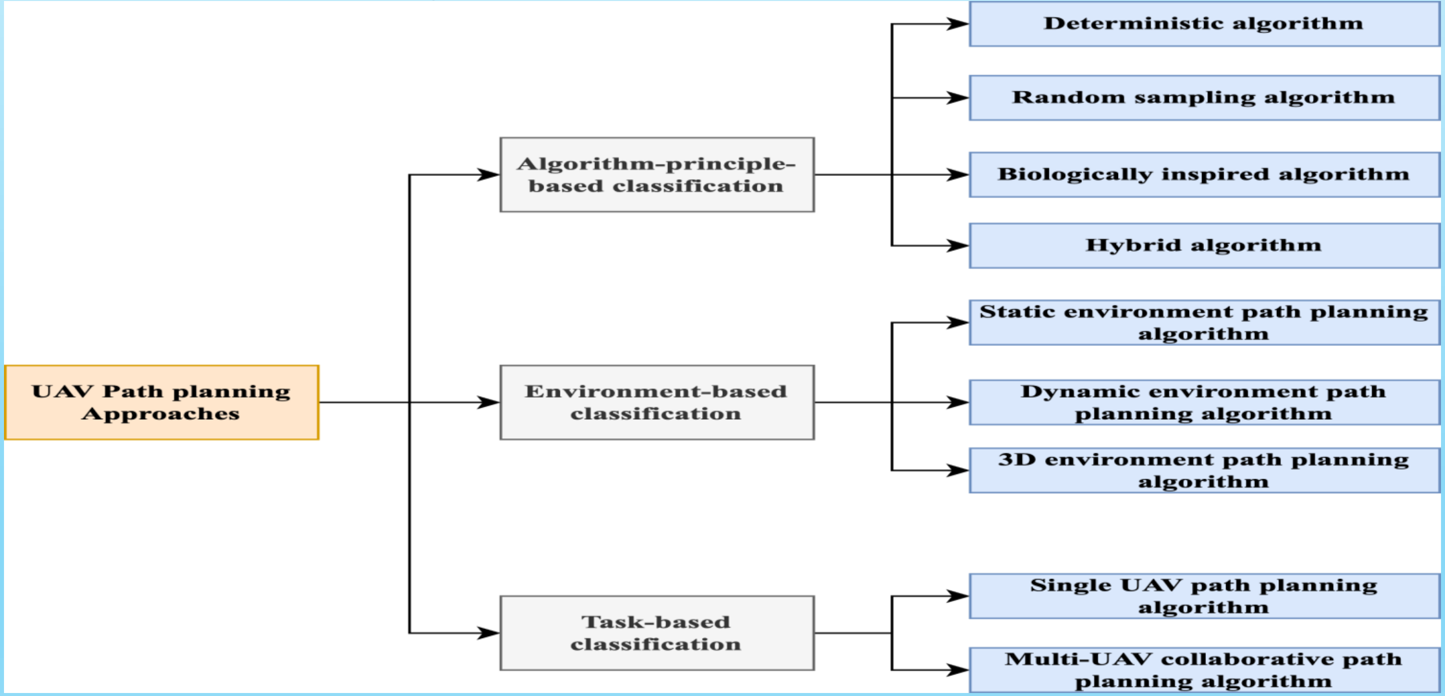
- **Path Planning process actions** (aiming to safe, efficient, and effective navigation)
  - *Note : some of these actions are executed in parallel*
  - **1. *Environment Modeling*:** mapping physical features and identifying obstacles, using imagery (e.g., from satellites) or real-time sensory data
  - **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)
  - **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 need
  - **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

2. Path Planning in Multi-UAV Networks

2.4 Path Planning Methods

- Classification of UAV PP methods (1)
  - **Criteria:** algorithms, environmental conditions, task requirements
  - **Algorithms -** examples: deterministic algorithms (e.g., Dijkstra, A*); random sampling (e.g., RRT, PRM); biologically inspired ; hybrid algorithms
  - **Environmental - conditions :** static PP; dynamic PP; 3D path planning
  - **Task requirements:** single-UAV; collaborative multi-UAV



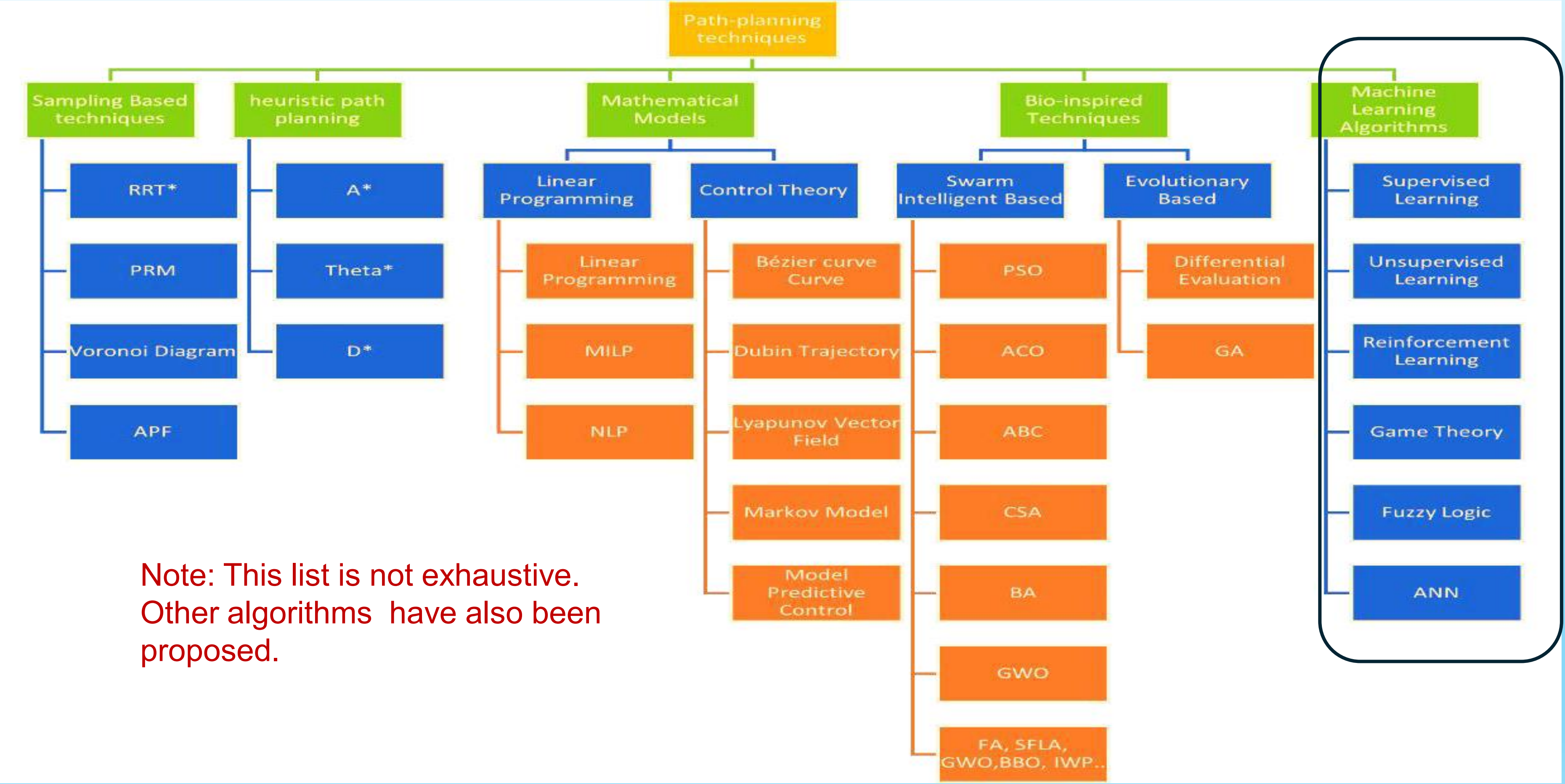
Source: W. Meng, X.Zhang, L.Zhou, H. Guo and X.Hu , Advances in UAV Path Planning: A Comprehensive Review of Methods, Challenges, and Future Directions, MDPI, 2025, https://doi.org/10.3390/drones9050376

2. Path Planning in Multi-UAV Networks

2.4 Path Planning Methods

Classification of UAV PP methods (2) – criteria: algorithm types

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



- Path-planning techniques
  - Sampling Based techniques
    - RRT*
    - PRM
    - Voronoi Diagram
    - APF
  - heuristic path planning
    - A*
    - Theta*
    - D*
  - Mathematical Models
    - Linear Programming
      - Linear Programming
      - MILP
      - NLP
    - Control Theory
      - Bézier curve Curve
      - Dubin Trajectory
      - Lyapunov Vector Field
      - Markov Model
      - Model Predictive Control
  - Bio-inspired Techniques
    - Swarm Intelligent Based
      - PSO
      - ACO
      - ABC
      - CSA
      - BA
      - GWO
      - FA, SFLA, GWO,BBO, IWP..
    - Evolutionary Based
      - Differential Evaluation
      - GA
  - Machine Learning Algorithms
    - Supervised Learning
    - Unsupervised Learning
    - Reinforcement Learning
    - Game Theory
    - Fuzzy Logic
    - ANN

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

2. Path Planning in Multi-UAV Networks

2.4 Path Planning Methods Classification of UAV PP methods (2)

Notations (partial list- swarms)

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

2. Path Planning in Multi-UAV Networks

2.4 Path Planning Methods

Classification of UAV PP methods (2)–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 Examples*: **Rapidly-exploring Random Trees (RRT), RRT*, Probabilistic Roadmap (PRM), Voronoi Diagram(VD), Artificial Potential Field (APF)***
    - RRT and PRM are effective in high-dimensional spaces by randomly sampling the environment to build a search tree/graph

- **Heuristic Path Planning**
  - They **guide searches through complex spaces**
  - Examples: ***Dijkstra, Greedy Best First Search, Hill Climbing, A* and Variants, Theta*, D****
    - Classical algorithms such as A* and Dijkstra guarantee, to varying degrees, finding an optimal path by exploring a discretized grid
    - A* is favored for efficiency, however can be computationally intensive

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

2. Path Planning in Multi-UAV Networks

2.4 Path Planning Methods

Classification of UAV PP methods (2)–criteria: algorithm types

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

- **Mathematical Models**
    - ***Linear Programming (LP):*** optimization problems in which linear equations or inequalities represent the objective and constraints
        - ***Basic LP: Binary LP (BLP), mixed integer LP (MILP), non-linear(NLP)***
            - ***Mixed Integer LP (MLP):*** dynamic and robust, for large, complicated problems with both continuous and discrete variables
            - ***Non-Linear Programming (NLP):*** optimizes an objective function (relationships between variables are non-linear)
            - optimizing the UAV trajectory, energy, data collecting interval for each ground sensor nodes

    - ***Control Theory- based methods***
        - They design and analyze control systems, including feedback control, optimal control and adaptive control
        - **Examples:** ***Model Predictive Control (MPC), Bézier curves, Dubin algorithm, Lyapunov function, Markov decision model*** and others

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

2. Path Planning in Multi-UAV Networks

2.4 Path Planning Methods

Classification of UAV PP methods (2) –criteria: algorithm types

- **Bio-inspired Swarm intelligence –based algorithms**
  - They typically **deconstruct an environment into a searchable problem space** using exclusively **approximate cell decomposition approaches**
  - **Genetic Algorithms (GA) can** solve complex, non-convex optimization problems for path planning
  - **Examples**:
    - **Ant Colony Optimization (ACO)** =inspired by the **collective behavior of ants**
      - **SI–based algorithm** The **walking path of ants** express the feasible solution
    - **Particle Swarm Optimization (PSO)**
      - **PSO simulates** the social **behavior of a swarm of birds** or fishes
      - Simple agents, called particles, move in the search space
      - The **position of a particle shows a candidate solution**/path
      - Optimization – use the shared info of the global and local solutions in the swarm
      - Several PSO extensions have been developed

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.

2. Path Planning in Multi-UAV Networks

2.4 Path Planning Methods

Classification of UAV PP methods (2) –criteria: algorithm types

- **Bio-inspired Swarm intelligence –based algorithms**

- **Gray Wolf Optimization (GWO)**
  - **Metaheuristic** that mimics the hunting behavior of grey wolves It defines ranks of wolves: (α), (β), (δ), (ω) and their hunting process to guide the population of candidate solutions towards the best solution.
  - **Concepts:** Social Hierarchy: (α) strongest- the best current solution; then - (β), (δ), (ω)
    - Hunting Mechanism steps: Searching, Encircling, Attacking
    - Mathematical Model: equations to update the wolves' positions
    - Improved GWO variants examples **:*Ensemble GWO (EGWO***);***Representative-based grey wolf optimizer (R-GWO); RL - based GWO (RLGWO)***
- ***Evolutionary-based Algorithms***
  - ***Differential Evaluation (DE)***
    - DE evolves a population of potential paths using obj. functions (distance, time)
    - Operations: inheritance, crossover, mutation, to refines paths towards optimum
  - ***Genetic Algorithm (GA):*** natural selection and genetics to iteratively evolve optimal UAV navigation routes through selection, crossover, and mutation
- **AI/ML- based Path Planning methods (see Chapter 3)**

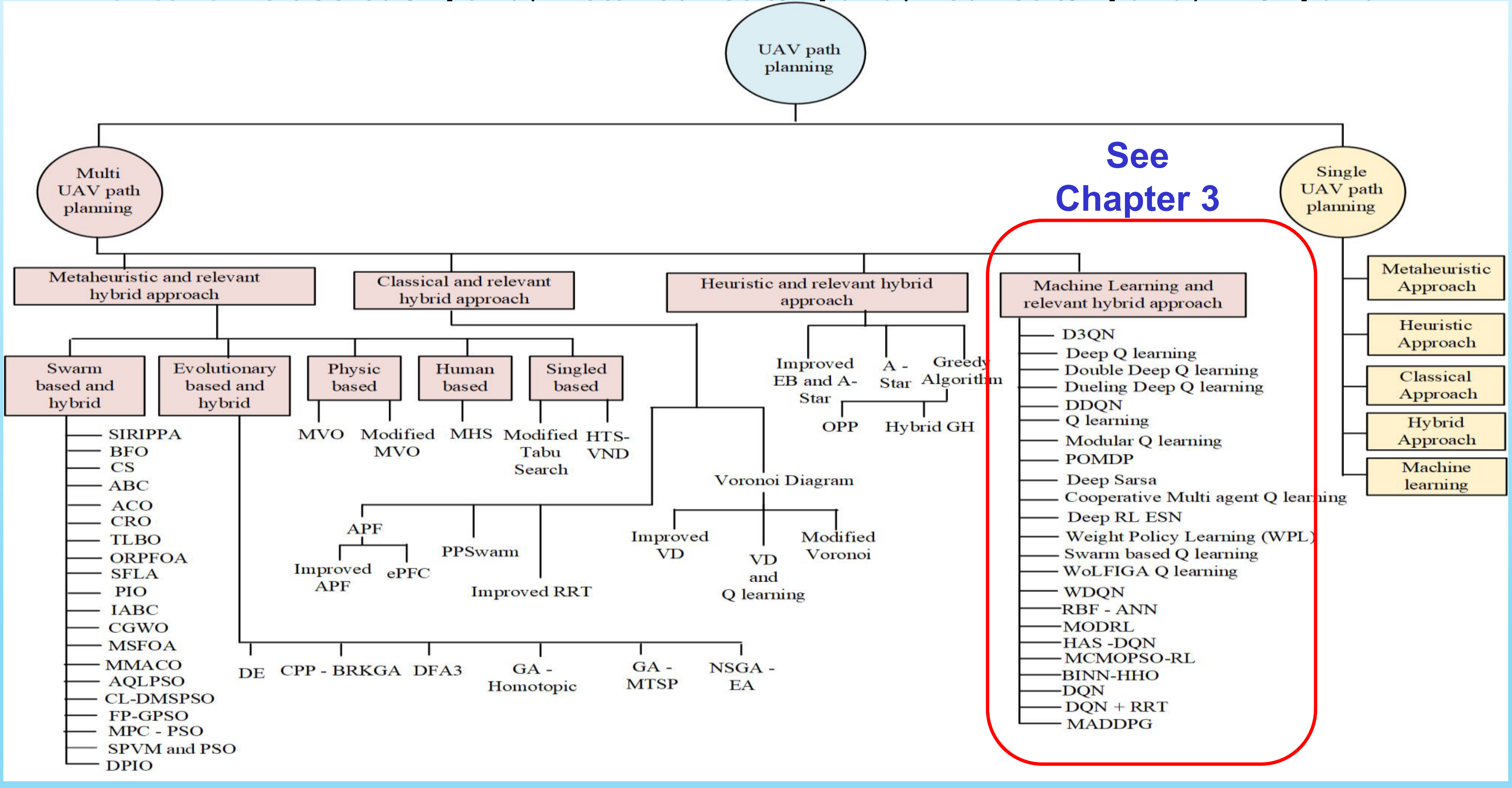
Swource: P.Kumar, K. Pal, M.Govi, Comprehensive Review of Path Planning Techniques for UAVs, ACM Computing Surveys, ACM 0360-0300/2025/05-ART, http://dx.doi.org/10.1145/3737280

2. Path Planning in Multi-UAV Networks

2.4 Path Planning Methods

Classification of multi-UAV PP methods (3)

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



See Chapter 3

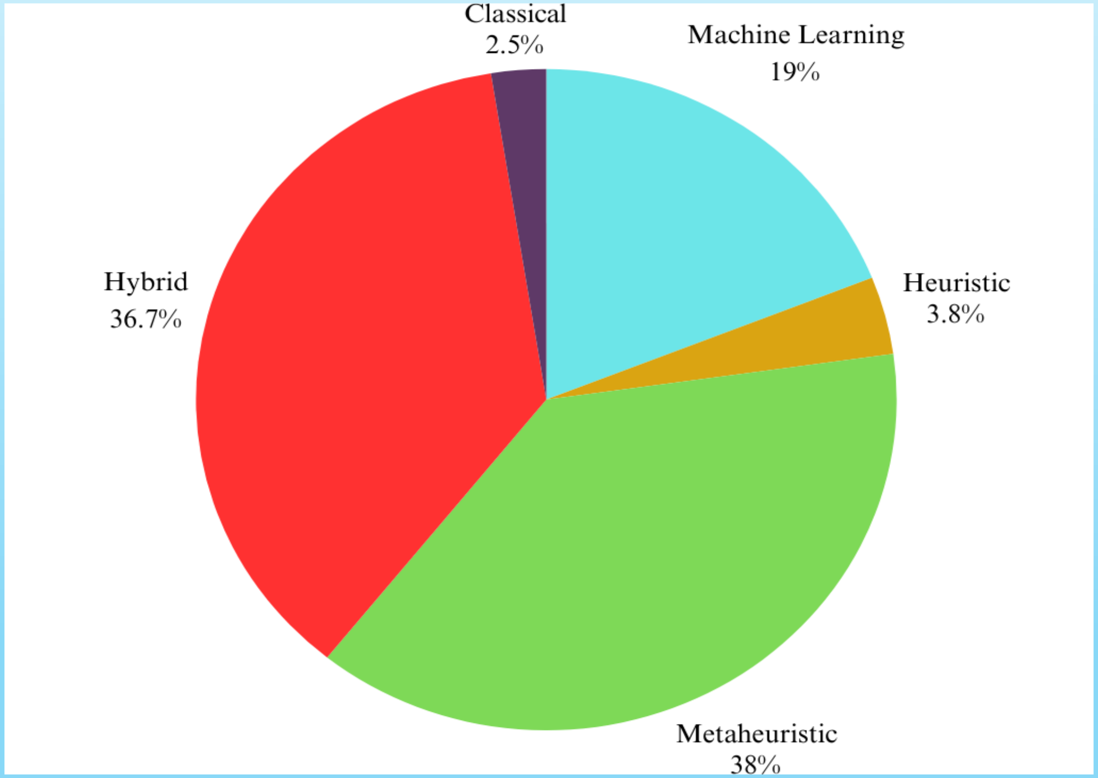
Source: M.Rahman, N.Sarkar and R.Lutui, A Survey on Multi-UAV Path Planning: Classification,Algorithms, Open Research Problems, and Future Directions, MDPI,Drones 2025,9,263 https://doi.org/10.3390/drones9040263

2. Path Planning in Multi-UAV Networks

2.4 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. Path Planning in Multi-UAV Networks
3. ➡ AI/ML Algorithms and Methods in UAV Path Planning
4. Challenges and Open Problems
5. Conclusions

3. AI/ML Algorithms and Methods in Path Planning

- **AI/ML- based Path Planning methods**
  - **AI/ML methods** – novel powerful approach in UAV PP, enabling efficient navigation in complex and dynamic environments ; AI/ML- significant progress for UAV PP
  - **Innovative algorithms** - optimize trajectories, obstacle avoidance, real-time computation, navigation in complex and dynamic environments
  - **Machine learning (ML) algorithms -** recently proposed in UAV PP
    - ***Supervised Learning (SL), Unsupervised learning (UL), Reinforcement Learning (RL), Deep Learning (DL), Deep Reinforcement Learning (DL),*** etc.

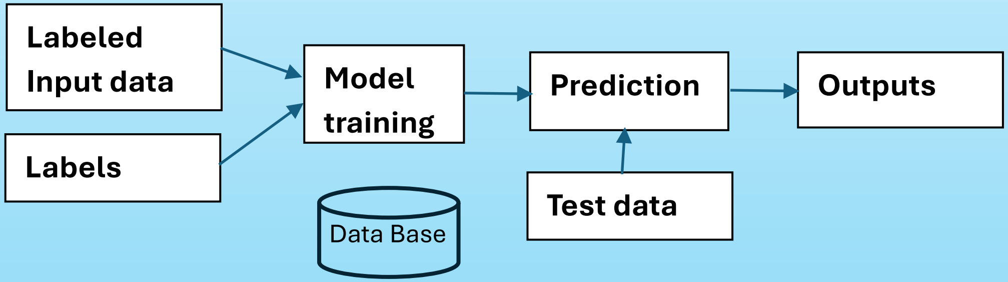
- **ML- based applications in UAV -examples:**
  - to deal with different types of autonomous UAV flights, tuning the parameters
  - adaptive control algorithms
  - recognizing objects in journey; real-time and dynamic PP
  - real-time collision avoidance considering obstacles or other UAVs
  - decisions in environment space, seeking to optimize a given cumulative reward (RL)
  - ……

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. AI/ML Algorithms and Methods in Path Planning

3.1 Machine Learning Taxonomy- Summary

- **Supervised Learning**
- The model is **trained on labeled data (both input and desired output are provided)**
  - **Classification:** Predicts a categorical label (e.g., "spam" or "not spam," in image recognition). Examples: *Support Vector Machines (SVM), Naïve Bayes, Decision Trees, Neural Networks*
  - **Regression:** Predicts continuous, numerical values (e.g., physical parameters) Examples: *Linear Regression* and *Polynomial Regression*

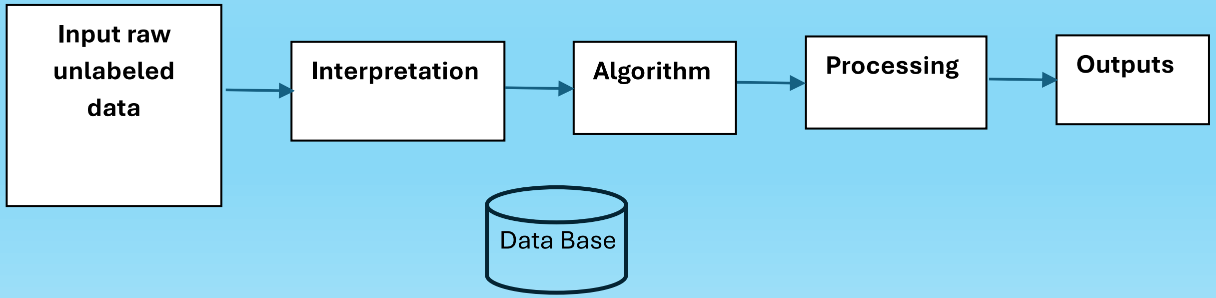


- **Semi-Supervised Learning (SSL)**
  - Training: - uses a combination of a **small amount of labeled data** and a **large amount of unlabeled data** for bridging SL and UL
  - Usage: when labeling data is too costly or time-consuming
  - Applications: *Generative Adversarial Networks (GANs)* and text document classifiers
- **Self-Supervised Learning**
  - The data provides set its own labels (e.g., predicting the next word in a sentence), transforming unsupervised problems into supervised ones

3. AI/ML Algorithms and Methods in Path Planning

3.1 Machine Learning Taxonomy- Summary

- **Unsupervised Learning**
  - The model is **trained on unlabeled data** and **must find (on its own) hidden patterns or structures**
  - The **training is stopped** when the **model reaches convergence;** the internal parameters (e.g., cluster centroids) stabilize; further iterations do not significantly improve the results
  - **Applications**
    - **Clustering:** Groups similar data points together (e.g., classes of network traffic). Common algorithms: *K-Means, Hierarchical Clustering, and Gaussian Mixture Models*
    - **Dimensionality Reduction**: Reduces the number of variables to consider, simplifying data without losing critical information. Common algorithms include *Principal Component Analysis (PCA) and t-SNE.*
    - **Association Rule Learning:** Identifies rules that describe large portions of data (e.g., finding items frequently bought together).



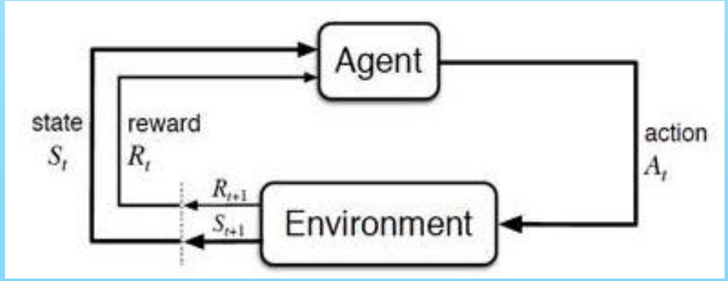
3. AI/ML Algorithms and Methods in Path Planning

3.1 Machine Learning Taxonomy- Summary

- **Reinforcement Learning (RL)**
  - **RL- general-purpose framework for decision-making**
  - **Components: Environment, Agent**
  - **Agent :** an entity that acts upon and perceives the environment
  - **Environment** changes due to the agent’s actions and possibly other factors outside the agent’s influence
  - The agent **perceives** the *state (s)* of the environment (a potentially incomplete observation), and **must decide** which *action (a)* to take based on that information, such that the accumulation of *rewards (r)* it receives from the environment is maximized
  - RL is also is called *approximate dynamic programming*, or *neuro-dynamic programming*

RL algorithm main phases:

- **Training phase**: is to tell the agent which action should be taken under a given environment from a series of trials
- **Inference phase**: the agent takes appropriate actions according to the experience learned during the training
- **RL Concepts: states, actions, reward**



Source: M. NAEEM, S. T.H. RIZVI ,A.CORONATO, A Gentle Introduction to RL and its Application in Different Fields, IEEE TRANSACTIONS and JOURNALS, IEEE Access 2016

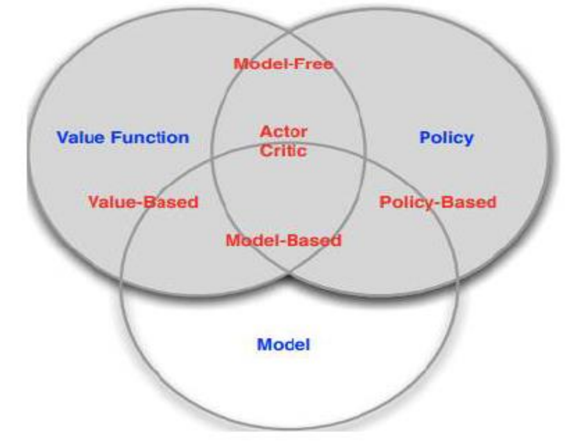
A1. Machine Learning Algorithms – Summary

- **3.1 Machine Learning Taxonomy- Summary**
- **Reinforcement Learning (RL)**
- **Model-based:**
    - the **agent tries to learn the model of how the environment works** from its observations and then plan a solution using that model
    - does not rely on trials instead **it exploits already learned** model
    - can **make predictions** about states and corresponding rewards after learning
  - After the agent gains an accurate model, it can use a planning algorithm with its learned model to find a policy
- **Model-free**
  - The **agent**
    - **uses trial /error method** to update its experience and knowledge about the Env
    - does not have knowledge of the transition model and reward function
    - has to learn the system dynamics by interacting with the Env over a large number of times; it does not directly learn how to model the Env (e.g., Q-learning) but estimates the Q-function values of each (s, a) pair
    - derives an **optimal policy** by choosing the action yielding the *largest Q-value in the current state ;* Q-learning cannot predict the next state and value before taking the action
  - Examples **: Q-learning**, **Monte Carlo (MC),Temporal Difference (TD)**

A1. Machine Learning Algorithms – Summary

- **3.1 Machine Learning Taxonomy- Summary**
- **Reinforcement Learning (RL)**
  - **Policy: guides an agent which action to choose in a given state**
    - It is a **mapping from a set of states to a corresponding set of actions**
    - An **optimal policy** gives long term optimized reward which an agent could get in a lifetime
  - **RL : On-policy versus Off-policy** - depending on coupling of the function update and the update policy executed
    - Before updating the value function, the agent also needs to sample and learn the environment by performing some non-optimal policy
    - **Off policy update**: If the update policy is irrelevant to the sampling policy
    - **On-policy update**: $Q(s,a) \leftarrow Q(s,a) + \alpha(R(s, a) + \gamma(Q(s',a') - Q(s,a))$
      - where a′ and a need to be chosen according to the same policy

Types of of Reinforcement Learning algorithms http : //www0.cs.ucl.ac.uk/staff/d.silver /web/Teachingf iles/introRL.pdf



Exploitation vs Exploration
Exploitation mode: an agent takes the best action out of already known knowledge

Exploration mode: an agent may attempt stochastic action to increase its information in order to get more reward

3. AI/ML Algorithms and Methods in Path Planning

3.1 Machine Learning Taxonomy- Summary

- **(Artificial) Neural Networks ((A)NN)** - computational model inspired by the biological NNs in the human brain
  - The basic unit of computation: **neuron** (node); its **node** applies an **activation (non-linear) function *f*** to the **weighted sum of its inputs** (including a bias)
  - The **bias** provides every node with a trainable constant value (in addition to the normal inputs)
  - **NN can be both Supervised or Unsupervised Learning** depending on the training data and task
    - SL networks use labeled data for prediction (e.g., classifying images)
    - UL networks find patterns in unlabeled data (e.g., clustering customers)
  - **They can also learn through RL with rewards and penalties**
  - **Supervised Learning NNs: e.g.,** Image classification, spam detection etc.
    - *Data:* Requires labeled data (input-output pairs)
    - *Process:* The NN learns to map inputs to correct outputs by adjusting weights based on errors, guided by a "teacher"
  - **Unsupervised Learning NNs**
    - *Data:* Uses unlabeled data, finding inherent structures
    - *Process:* Identifies patterns, groupings (clustering), or underlying relationships without predefined answers
    - *Examples:* Customer segmentation, anomaly detection, dimensionality reduction

3. AI/ML Algorithms and Methods in Path Planning

3.1 Machine Learning Taxonomy- Summary

- Deep Learning
  - It uses **multilayered NNs** (with **several hidden layers**) to learn complex patterns from data, enabling advanced AI tasks and exceeding traditional models by automatically discovering features
  - **Key architectures examples**
    - Convolutional NNs for images, Recursive NNs for sequences, Transformers for language

  - **Examples of Deep NNs**
    - ***Convolutional Neural Networks (CNNs):*** Excellent for visual data (images, video).
    - ***Recurrent Neural Networks (RNNs):*** Good for sequential data like text and time series, remembering past info
    - ***Transformers:*** Revolutionized NLP (like ChatGPT) using self-attention to weigh word importance
    - ***Generative Adversarial Networks (GANs):*** Used for creating new data, like realistic images
  - **Applications**
    - Image/Speech Recognition, Natural Language Processing NLP (translation, chatbots)
    - Self-driving Cars, UAV/Robots, Spam Detection

3. AI/ML Algorithms and Methods in Path Planning

3.1 Machine Learning Taxonomy- Summary

- **Recurrent Neural Networks (RNN)- special class of ANN**
  - designed to **process sequential data** or time-series data by using **hidden states** as internal memory
  - RNNs feedback loops allow information to persist; RNN - ideal for natural language processing (NLP), speech recognition, etc.

  - **Important concepts**
    - **Architecture:** RNN can handle various input/output scenarios: one-to-one, one-to-many, many-to-one, and many-to-many

    - **Sequential memory:** in order to make predictions a RNN processes input sequences step-by-step, combining the current input with information from previous steps (hidden state)

    - **Hidden state (h_t):** plays the role of network memory, capturing information about previous time steps computations

    - **Weight sharing:** the same weight parameters are used across all time steps, reducing the total number of parameters to learn

3. AI/ML Algorithms and Methods in Path Planning

3.1 Machine Learning Taxonomy- Summary

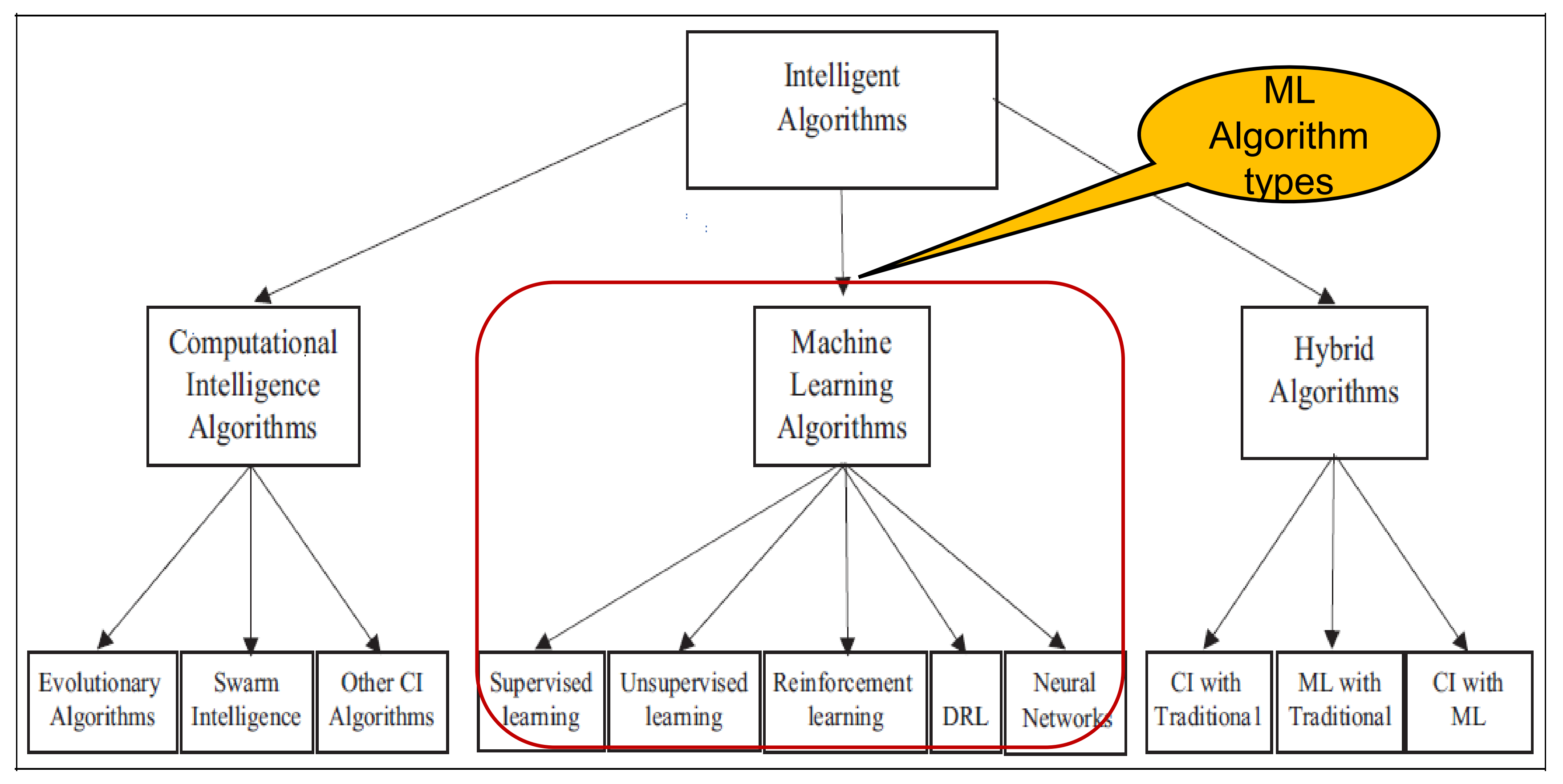
- **Deep Reinforcement Learning (DRL)**
  - **It** combines **RL with DL/NN (DNN)** to enable agents to make decisions from high-dimensional, unstructured data
  - Key techniques include *DQN (value-based) and PPO/Actor-Critic (policy-based),* commonly used in robotics, gaming, and autonomous systems.
  - **Main Concepts**
    - **Agent & Environment: an agent** interacts with an environment, taking **actions** and **receiving feedback** in the form of **rewards or penalties**.
    - DNN: These function as function approximators, essential for handling large state spaces (e.g., pixel inputs).

    - **Key Algorithms:**
      - **Value-based (DQN): l**earns a *Quality Function (Q)* to select the best action for a state.
      - **Policy-based (REINFORCE): d**irectly optimizes the policy (behavior) network
      - **Combined (Actor-Critic/PPO): u**ses a policy network (Actor) and a value network (Critic) to reduce variance in learning
    - **Techniques for Stability: e**xperience replay (storing past experiences) and target networks are used to improve convergence.

3. AI/ML Algorithms and Methods in Path Planning

3.2 AI/ML Algorithms in Path Planning -Classifications

- **General Classification Criteria: algorithm types**



Source D. Alaa1, K. Abdelmadjid1 and L.Fadhila, Intelligent path planning algorithms for UAVs: Classification, complexity analysis, hybrid ablation insights, and future directions, Advances in Mechanical Engineering 2025, Vol. 17(7) 1–26, DOI: 10.1177/16878132251355020

3. AI/ML Algorithms and Methods in Path Planning

3.3 ML in UAV Path Planning- high level view

- **Supervised Learning (SL) in UAV PP**: it can **utilize historical flight records** (*routes, velocities, weather* data) to **develop *regression* or *classification*** models that assist with flight path prediction
- **Unsupervised Learning (UL) in UAV PP** helps **create efficient, adaptive routes** in unknown environments by finding patterns in unlabeled data, overcoming SL limitations
  - UL clustering (e.g., *K-means, Self Organizing Maps- SOM, Fuzzy C-means, Gaussian mixture models*) group tasks or map areas
    - **dimensionality reduction** simplifies complex data, enabling UAVs to **autonomously *discover optimal paths***, *explore areas*, and *avoid obstacles* without prior training (important for tasks like surveillance or mapping)
- **Reinforcement Learning (RL) in UAV PP** enables UAV
  - **to generate and update the selection strategies** actions according to the env. rewards which are based on the UAV's last state and last action
  - to **operate within unpredictable and changing environments**, addressing issues e.g., r.t. obstacle avoidance, optimizing routes for energy saving
- **Artificial Neural Networks (ANN) in UAV PP**
  - ANN **can minimize the uncertainty of the evolutionary computation** induced by the probability model; it **can prevent slipping into a local point**
  - ANN-based PP can be effective **for dense and complex environments**, as they can learn to adapt to changing conditions

3. AI/ML Algorithms and Methods in Path Planning

3.4 ML Algorithms in Path Planning - Examples

- ***Supervised Learning (SL)*** **Example 1**
- **UAVs learn optimal paths from labeled data; It enables precise and efficient navigation in various environments**
  - ***Support Vector Machine (SVM)*** **PP** (classification, regression, and exception detection)
  - It finds an optimal hyperplane in an n-dimensional space that maximizes the margin (distance) between different data classes; high accuracy and minimal overfitting
  - **PP- SVM makes classification; it generates safe, smooth, and optimal collision-free paths in known or partially known environments**
  - SVM separates space with a maximum margin hyper-surface
  - **Key Aspects**
    - **Problem model:** The 3D flight environment is often converted into a 2D "safe-map" using a *Surface of Minimum Risk (SOMR).* The **SVM then acts as a binary classifier**, separating the space into **"flyable" and "no-fly" zones**
    - **Path Generation:** The boundary (made by the SVM) between the classes (flyable/non-flyable) serves as the initial safe flight path
    - **Kernel Trick:** SVMs often use kernel functions (e.g., Gaussian/RBF kernels) to handle non-linear, complex environments, mapping the input data to higher-dimensional spaces to find the optimal path
    - **Optimization: The goal is to generate a smooth path that keeps the UAV far away from obstacles**

Yanhong Chen, Wei Zu, Guoliang Fan, and Hongxing Chang. 2014. Unmanned aircraft vehicle path planning based on SVM algorithm. Advances in Intelligent Systems and Computing 215 (2014), 705–714. DOI: https://doi.org/10.1007/978- 3- 642- 37835- 5 _ 61

3. AI/ML Algorithms and Methods in Path Planning

3.4 ML Algorithms in Path Planning - Examples

- ***Supervised Learning (SL)*** **Example 2**
- **Automatic PP task scheduling between an edge and cloud environment**
  - An automatic **PP offloading mechanism in edge-enabled environments** (as for UAVs)
  - ML predicts computational complexity and analyzes network metrics to **reduce latency and save energy**
  - **Decision: whether the classical PP algorithm A* is run locally on UAV or offloaded to edge/cloud servers**
  - **Main components**
    - **System Architecture: three layers**—sensing, communication, and decision-making
    - It allow UAVs to manage local resources while utilizing edge/cloud infrastructure.
    - **Offloading Decision Mechanism:** uses classification ML to analyze the PP complexity and network status (e.g., bandwidth, signal strength) to decide offloading **Performance Optimization:** it **minimizes overall latency and energy consumption** by **offloading computationally intensive tasks** (e.g., complex A* navigation) from resource-constrained devices to more powerful edge nodes
    - **Network Evaluation:** utilizes **Mean Opinion Score (MOS)** to gauge network quality and ensure that data transfer time for offloading does not exceed the time saved in computation

Source: D.Herich, et al., Automatic path planning offloading mechanism in edge-enabled environments. Mathematics 9, 23 (2021), 3117. DOI: https://doi.org/10.3390/MATH9233117

3. AI/ML Algorithms and Methods in Path Planning

3.4 ML Algorithms in Path Planning - Examples

- ***Unsupervised Learning (UL)***
- UL discovers hidden patterns and structures in **unlabeled data**; clustering is a typical result ;
- UAVs can optimize routes in complex and unknown environments autonomously
- **Example 1 Scalable multitarget tracking (MTT) system for cooperative UAVs**
  - decentralized arch. and **clustering algorithms** to **manage many mobile targets** with limited sensing resources; team of UAVs is considered
  - **clustering technique for tracking multiple targets** as an efficient PP and sensor manager
  - it distributes tasks across a fleet; it overcomes the field-of-view and fault-tolerance limitations of single-UAV setups
  - **Core Components**
    - **A scalable MTT framework** integrates several autonomous processes across each UAV
    - **Target State Estimation**: Each UAV uses a set of **Extended Kalman Filters (EKFs)** to estimate and predict the target's actual state (location, linear /angular velocity, altitude)
    - **Scalable Clustering**: Systems can employ the **Density-Based Spatial Clustering Applications with Noise (DBSCAN)** algorithm. So, the swarm can group targets dynamically, making the tracking workload manageable even with growing number of targets
    - **Optimal Sensor Management**: An onboard manager determines the best gimbal poses for cameras to maximize the number of targets tracked within limited fields of view
    - **Cooperative Path Planning**: UAVs collectively coordinate their movements to maintain optimal tracking geometry while avoiding collisions and minimizing energy consumption

Source: Negar Farmani, Liang Sun, and Daniel J. Pack. 2017. A scalable multitarget tracking system for cooperative UAVs. IEEE Trans Aerosp Electron Syst 53, 4 (2017), 1947–1961. DOI: https://doi.org/10.1109/TAES.2017.2677746

3. AI/ML Algorithms and Methods in Path Planning

3.4 ML Algorithms in Path Planning - Examples

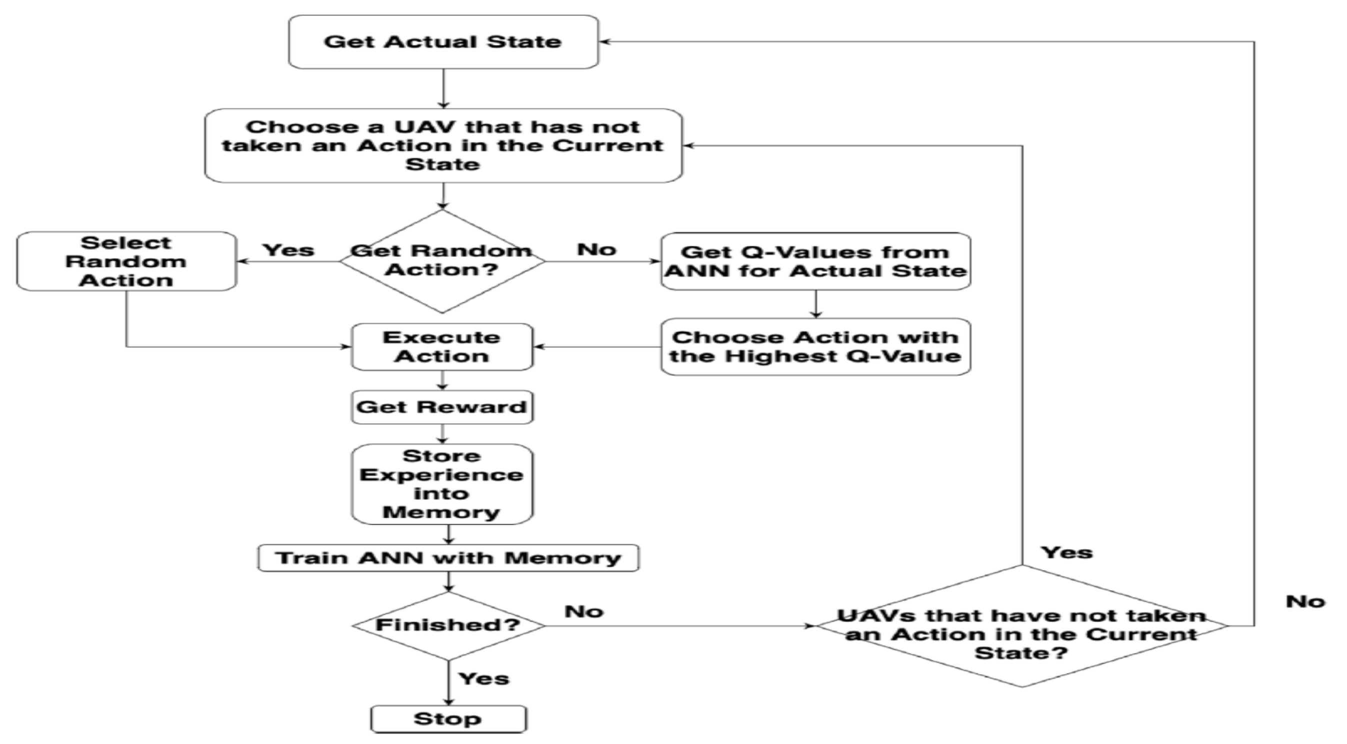
- *Deep Reinforcement Learning (DRL)*
- *Example 1: Q-Learning based system for PP with UAV swarms in obstacle environments*
  - **Autonomous control of multiple UAVs** is frequently used in special scenarios
    - Advantages: personnel expenses can be reduced
    - However, many obstacles might exist like power lines, trees, buildings and so on
    - The flight paths must be also optimized, energy consumption reduced
  - **Deep Q-Learning or Deep Q-Network (DQN)** are important DRL techniques that provide a solution for such a problem
  - **Example: Q-Learning and ANNs with two dense layers to control UAV swarms in maps with obstacles**
  - **Goal: complete area coverage with fixed obstacles** for tasks like f*ield prospecting*
  - The system includes an ANN model, used to self-adjust by learning from its mistakes and successes
  - **Q-Learning algorithm** implementation: **two-layer ANN;** Setting goals or having any prior information apart from the provided map is not required
  - The results indicate that the system achieves solutions with fewer movements as the number of UAVs increases.

Alejandro Puente-Castro, et. al., Q-Learning based system for Path Planning with Unmanned Aerial Vehicles swarms in obstacle environments, Expert Systems With Applications 235 (2024) 121240, www.elsevier.com/locate/eswa

3. AI/ML Algorithms and Methods in Path Planning

3.4 ML Algorithms in Path Planning - Examples

- ***Deep Reinforcement Learning (DRL)***
- ***Example 1 :Q-Learning based system for PP with UAV swarms in obstacle environments***
- Figure: steps followed within each episode. It shows how the ANN interacts with Q-Learning
- The ANN learns from the experience gained from performing actions on one or more UAVs



Alejandro Puente-Castro, et. al., Q-Learning based system for Path Planning with Unmanned Aerial Vehicles swarms in obstacle environments, Expert Systems With Applications 235 (2024) 121240, www.elsevier.com/locate/eswa

3. AI/ML Algorithms and Methods in Path Planning

3.4 ML Algorithms in Path Planning - Examples

- ***Hybrid Solutions***
- ***Example 1 : A Hybrid DL Model for UAV Path Planning in Dynamic Environments***
  - Unpredictable conditions, require robust PP to adapt to real-time changes
  - **Issues**
    - The popular ***Rapidly-exploring Random Tree (RRT)*** algorithm often generates suboptimal paths requiring extensive post-processing to improve
    - RRT variants can converge to the optimal solution, but need more memory and computation
    - **Purely learning-based methods could result in planning failures** or excessively long paths generated for obstacle avoidance
  - An **UAV PP hybrid model** can integrate diverse sensor data through a NN featuring ***Convolutional Neural Network (CNN,) Long Short-Term Memory (LSTM),*** and an attention mechanism
    - **LSTM** is a type of ***Recurrent Neural Network (RNN)*** designed to learn long-term dependencies in sequential data, overcoming the vanishing gradient problem of standard RNNs)
    - Then, the **DL-enhanced RRT combines the neural module with the informed sampling methods** for adaptive path finding in dynamic environments.
  - This solution is proved to be better than *Informed RRT*, Batch Informed Trees (BIT*) algorithms, and the state-of-the-art Layered RQN*.

J.ZHANG , Y.XIAN, X.ZHU , and H.DENG, A Hybrid Deep Learning Model for UAV Path Planning in Dynamic Environments, IEEE Access, 2025. DOI: 10.1109/ACCESS.2025.3557394

3. AI/ML Algorithms and Methods in Path Planning

3.4 ML Algorithms in Path Planning - Examples

- *AI-powered drone interception*
- **AI-powered counter-drone systems** - used for military/ critical infrastructure protection: detecting, tracking and neutralizing fast-moving, swarm-based, and evasive aerial targets
- **Key AI technologies examples:**
- **Detection and classification algorithms**
  - **Computer vision and Deep Learning: Convolutional Neural Networks (CNNs)** and r.t. frameworks (e.g., ***YOLO (You Only Look Once)*** can identify and classify drones from cameras and infrared sensors, distinguishing them from other objects

  - **Sensor Fusion: AI algorithms can merge data from multiple sources**—3D pulse doppler radar, sensors thermal/acoustic, RF scanners, sensors—to enhance detection accuracy, particularly for small, low-flying drones

  - **Anomaly Detection:** ML algorithms, such as Isolation Forest, **identify unusual drone behavior patterns** that deviate from normal traffic, identifying potential threats

Source: https://www.nqdefense.com/the-future-of-ai-and-automation-in-anti-drone-detection/

3. AI/ML Algorithms and Methods in Path Planning

3.4 ML Algorithms in Path Planning - Examples

- *AI-powered drone interception*
- **Key AI technologies examples:**
- **Predictive tracking and interception algorithms**
  - **Trajectory prediction: AI-based regression** models, such as LSTMs analyze velocity history and aerial maneuvers to predict future positions
  - **RL:** agents are trained to learn optimal interception paths and strategies. **Multi-agents RL** coordinate multiple interceptor drones to intercept a single, highly maneuverable target, optimizing for both interception success and energy usage
  - **Predictive energy firing:** AI adjusts in r.t. laser beams in directed energy weapons (DEWs), to maintain focus on fast-moving, maneuvering UAVs
- **Adaptive counter-drone strategies**
  - **Rogue drone Identification & Defense Systems (RDDS):** use AI to classify threats and decide the appropriate neutralization method (e.g., net, jammer, or kinetic) based on threat levels
  - **Autonomous Interception drones:** AI-powered interceptors can operate in GPS-denied environments, using onboard AI to navigate and engage targets even when comm. links are jammed
  - **Anti-jamming & Electronic warfare:** AI enables systems to dynamically adjust jamming frequencies and power levels to target specific rogue drones while minimizing collateral interference with surrounding communications

Source: https://www.nqdefense.com/the-future-of-ai-and-automation-in-anti-drone-detection/

3. AI/ML Algorithms and Methods in Path Planning

3.4 ML Algorithms in Path Planning - Examples

- *AI-powered drone interception*
- **Recent developments and trends (2025-2026)**
  - **Ukraine's AI Interceptor Systems:** autonomous anti-aircraft turrets powered by AI to engage drones and missiles. New, autonomous interceptors like SEEDIS operates at speeds up to 320 km/h, utilizing AI to track and engage targets

  - **Example: NATO deployment:** NATO Merops system - a modular counter-drone system using AI and 3D radar to launch interceptor drones
  - **Swarm Defense:** AI is used to manage "drone walls" to counter massive, synchronized drone swarm attacks, with AI providing the necessary speed to handle numerous threats simultaneously

- **Challenges**
  - **False Positives: differentiating malicious /benign drones**, particularly in high-density urban areas
  - **Adversarial AI attacks:** evasion attacks or data poisoning to confuse detection algorithms
  - **Computational Limits:** edge AI on drones requires significant processing power to process data in ms, often limiting the complexity of the models

Source: https://www.nqdefense.com/the-future-of-ai-and-automation-in-anti-drone-detection/

CONTENTS

4. Challenges and Open Problems

- **General**
- **Need for more advanced AI-based PP algorithms and methods considering:**
- **3D PP issues**
  - **PP for large search space,** (still, computationally expensive to find an optimal solution)
  - **UAVs placement** and maintaining efficient distance for the targets, in the case of multi-UAV task allocation, such as assigning UAVs some targets and load balancing
  - **Collision-free and dynamically feasible paths** while also considering factors such as wind and atmospheric conditions, energy consumption, and UAV dynamic constraints
- **Multi-UAV cooperation and scalability**
  - robust algorithms for **uncertain/unknown 3D environment**
  - robust, **decentralized algorithms for swarms** to handle task allocation, communication constraints, and collision avoidance among many UAVs simultaneously
- **Real time and dynamic environments**
  - **plan paths on-the-fly** to handle moving obstacles, unpredictable weather, or changing mission goals
  - **low-latency** computation
  - dynamic **obstacle avoidance**

4. Challenges and Open Problems

- General
- Need for more advanced AI-based PP algorithms and methods considering
- **Robustness in unstructured/ unknown 3D Environments**: moving beyond simulation
  - to real-world operations for better 3D modeling and adaptation to environments where maps are not provided upfront

- **Computational complexity and energy optimization**: balancing complex AI model
  - with limited on-board power and computing resources
  - efficient, lightweight AI algorithms that minimize energy consumption

- **Advanced Hybrid AI Techniques:** Combining traditional methods (e.g., A* or RRT) with ML to utilize both efficiency and adaptability

- **6G-Enabled Path Planning:** Leveraging high-speed communication for better, faster data exchange in large-scale operations

- Need of **leveraging multi-objective** path planning

4. Challenges and Open Problems

Specific algorithms topics

- **Supervised Learning**
  - Developing more efficient algorithms for **handling large-scale datasets**
  - Addressing the issue of **overfitting in SL models**
    - overfitting modeling error in ML: the model learns training data *too* well, capturing noise and specific fluctuations rather than general patterns; have high accuracy on training data, but performs poorly on new, unseen data

- **Unsupervised Learning**
  - Developing more efficient algorithms for **handling high-dimensional data**
  - Enhanced **interpretability of UL models**

- **Reinforcement Learning**
  - Efficient algorithms for **handling continuous and high-dimensional action spaces**
  - **Improving the sample efficiency**; **generalize new scenarios** (rather than just trained environments) while meeting safety constraints

- **Artificial neural Networks**
  - Further exploration about **use of ANN for multi-agent path planning** and coordination

CONTENTS

5. Conclusions

- AI/ML – **important set of algorithms and tools** to support **advanced path planning processes**
- The **autonomous data-driven** nature of ML makes it a powerful solution for PP problem

- AI/ML- develop **innovative algorithms** allowing to: optimize trajectories, obstacle avoidance, real-time computation, navigation in complex and dynamic environments

- Still **many directions exist to develop more** and enhance the architectures, algorithms, methods and systems
  - Need to **reduce the computation complexity** and hardware resources requirements
  - **Enhanced 3D models** for large dynamic, unknown environment spaces
  - **Multi-UAV operation** (including swarms), **multi-criterial optimization objectives-** open research issues
  - **Hybrid solutions** - cooperation between classical algorithms with those AI/ML-supported - fruitful way to benefit from previous developments
  - **Enhanced models for external conditions**, weather, wind, obstacles, etc.
  - **Integration of AI/ML subsystems** into existing computing and communication architectures and technologies

- Thank you !
- Questions?

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AI based Path Planning for Unmanned Aerial Vehicles

- **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

AI based Path Planning for Unmanned Aerial Vehicles

- ## 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