Navigation and Trajectory Planning Techniques for Unmanned Aerial Vehicles Swarm

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Abstract Navigation and trajectory planning algorithms is one of the most important issues in unmanned aerial vehicle (UAV) and robotics. Recently, UAV swarm or flying ad-hoc network which have much interest and extensive attentions from aviation industry, academia and research community, as it becomes one of the great tools for smart cities, rescue/disaster managements and military applications. UAV swarm is a scenario makes the UAVs interacted with each other. The control and communication structure in UAVs swarm require a specific decision to improve the trajectory planning and navigation operations of UAVs swarm. In addition, it requires high processing time and power with resources scarcity to efficiently operates the flights plan. Artificial intelligence (AI) is a powerful tool for optimization and accurate solutions for decision and power management issues. However, it comes with high data communication and processing. Leveraging AI with navigation and path planning it gives much adding values and great results for the system robustness. UAV industry moves toward the AI approaches in developing UAVs swarm and promising more intelligence UAV swarm interaction, according to the importance of this topic, this chapter will provide a systematic review on AI approaches and most algorithms those enable to developing the navigation and trajectory planning strategies for UAV swarm.

Keywords UAV swarm · Drones · Small unmanned aircraft systems (UASs) · Flight robotics · Artificial intelligent · Control and communication

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1 Introduction

The Drones are known as an unmanned aerial vehicle (UAVs) which can operate remotely without onboard humans [1]. UAVs have been investigated as a disruptive technology that complement and support operations, which are performed traditionally by human. Due to their excellent mobility, flexibility, easy deployment, high-performance, low maintenance, adaptive altitude UAVs are widely used in many applications related to civil and military issues, for example, wildfire and monitoring, traffic control, emergency rescue, medical field and intelligent transportation. UAVs enable to provide wide coverage sensing for different environments [2].

For AUVs, various communication technologies and standards emerge. Such techniques like cloud computing and software defined network, in addition to big data analytics. The UAV design also passed through different communications evolutions, beginning from using 3G broadband signals, and to achieve high data rate, in addition to 5G end to end connectivity. The evolution of UAVs communications from 4 to 5G provides new technologies to support cellular communications for UAVs operations with high reliability, and high energy utilization [3]. The cellular network based 5G provide an enhanced UAVs broadband communication, and also enables the UAVs to act as a flying base station for swarm UAVs, and gateways to the ground cellular stations.

Navigation process and trajectory planning are the most important issues which are considered a crucial for UAVs. The process of planning the UAVs trajectories in complex environments that contains a number of obstacles is one of the major challenges facing its application [4]. In addition, the establishment of a network consisting of a number of UAVs that have the ability to avoid collision while taking into account the kinetic characteristics is the most important requirements in UAVs swarm applications.

In accordance with the challenges mentioned, and to achieve the operational efficiency of the swarm UAVs with their safety, it is important to intelligently estimate the journey plan especially in complex environments. Therefore, trajectory planning for UAVs has become a research hotspot. In this chapter we provide a comprehensive review about technical conceptual about UAVs swarm architectures, application, navigation and trajectory planning technologies. Our main contributions are summarized as follows.

- Provides a review about UAVs swarm Architecture, communications and control systems.
- Discussed the UAVs swarm navigations and trajectory planning classifications.
- Provides a review about most important intelligent technologies used for UAVs swarm trajectory planning.

The rest of this chapter is organized as follows, Sect. 2 provides UAVs technical background in addition to UAV swarm advantages and applications. Swarm communication and control system architectures are provided in Sect. 3. Section 4 provides navigation and path planning for UAV swarm. The classical techniques for UAV swarm navigation and path planning are reviewed in Sect. 5. In Sect. 6, the reactive approaches for UAV Swarm navigation and path planning are discussed. Finally, the conclusion is provided in Sect. 7.

2 UAV Technical Background

The beginning of the development of drone technology is when the federal law was announced from the United States in the year 2016 regarding regulating the public use of UAVs. Corresponds to the purpose, it has been used in a number of fields such as agricultural monitoring, power lines and photography, in addition to various search and rescue operations [5]. In recent years, the concept of a UAVs swarm has become an important research topic, which is the possibility of managing a swarm of drones and enabling interaction between them through intelligent algorithms that enable the swarm to conduct joint operations among themselves according to predefined paths that are controlled from the operations center. The operations of UVAs are depending on it capability of controlling, maneuvering and power utilization. The following section provides a brief concept about UVAs architecture and intelligence operations.

2.1 UAV Architecture

The architecture of UAV consists of three layers, as shown in Fig. 1. These layers relate to data collection, processing and operation [7]. The data collection layer consists of a number of devices such as sensors, light detectors and cameras. The other layers also contain processing devices, control systems, and other systems related to maps and decision-making [8].

In UAVs, the central control system shown in Fig. 2 controls the UAV trajectory in the real environment. The controller adjusts the speed, flight control, and radio and power source. More clearly, the components are described as follows [9].

- Speed controller: provides high frequency to operate the UAV motors and control their speed.
- Positioning system: It calculates the time and location information of the UAV and determines the coordinates and altitude of the aircraft.
- Flight controller: It manages flight operations by reading location system information while controlling communications.
- Battery: In UAVs, batteries are made of materials that give greater energy and a long range as a material, like Lithium polymer, in addition other batteries are added to help long-range flight
- Gimbal: It stabilizes the UAVs on its three-dimensional axis.

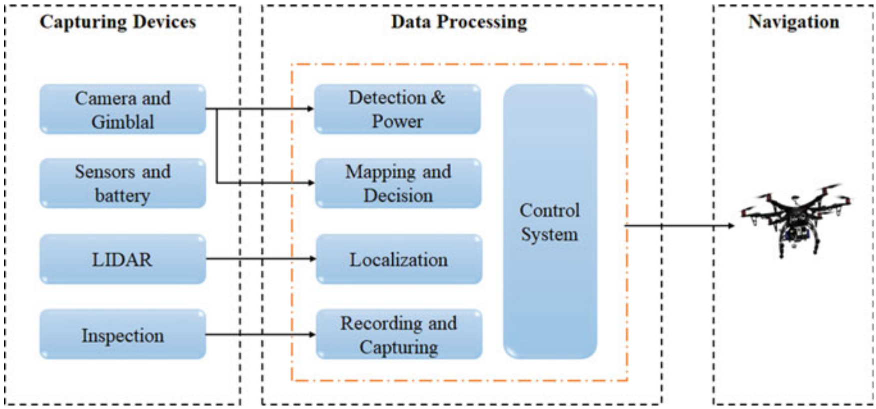
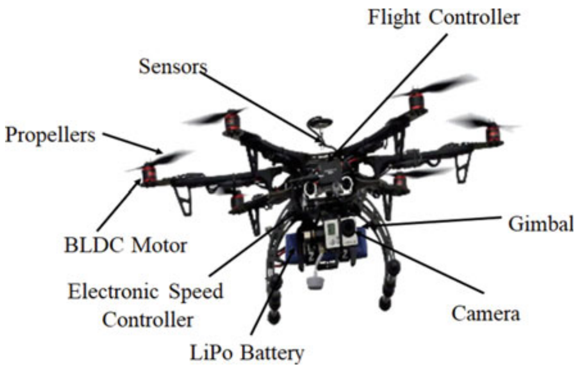


Fig. 1 UAVs architecture layers

Fig. 2 UAV systems and devices



- Sensors: There are a number of sensors in the UAVs that work to capture 3D images or detect and avoid collisions.

2.2 *UAV Swarm Current State*

UAVs can be act and make different operation scenarios in swarm as a set of UAV group. Recent studies tried to explore the benefits and features of swarm insect's behavior in nature [10]. As example, bee and eagle bird swarm provides an intelligent concept of flying which can help to provide a good solution for UAVs tasks. Also, the concept of swarm as a behavior of complex collective operations can take place through interactions between large numbers of UAVs in an intelligent manner [11]. The UAVs swarm can provide a tactical operation with high efficiency and performance, in addition to increase the operations quality and reliability when used in different applications [12].

UAV swarm enable to provide high-level tasks compared to one UAV. Moreover, UAV swarms also allow for fault tolerance, if one UAV of the swarm teams are lost, others swarms or group member can accomplish the assigned tasks by reallocating the missions to the surviving team members [13]. A swarm of UAVs can be deployed to perform various delivery missions including searching, performing target tracking, high-accuracy search and surveillance [14]. All of these operations are carried out by a squadron or group of UAVs that are directed by navigation, guidance and control systems that work to manage the UAVs allocation, flying area coordination and communications. All these tasks operate within a complex system that includes various integrated and integrated technologies [15]. Additionally, the artificial intelligence (AI) technologies are also used in building UAVs systems for different purposes such for intelligent maneuvering, trajectory planning, and swarm interaction.

2.3 UAV Swarm Advantages

Many previous papers discussed individual UAV systems and their various applications however, few did offer the study of UAV swarms and their associated limitations versus advantages. Through a lot of literature, it is clear that UAV work in a number of applications and scenarios related to surveillance and have an advantage when used alone [15]. However, the operations of the UAV in a swarm gives more advantages appear in exchange for the operation of single UAV, especially in search tasks. By using swarm of UAVs searching task can be done in parallel and the range of operations can be increase largely. Even though that, UAV swarm can face issues in trajectory planning and interactions. In general, the swarm UAV advantages can be summaries in table 1, when compared with single UAV [16].

A. **Synchronized Actions**

A swarm of UAV can simultaneously collect information from different locations, and it can also take advantage of the collected information to build a model decision-making system for complex tasks [17].

Table 1 Comparisons between a single UAV and swarm UAVs systems

Features	Single UAV	Swarm UAV
Operations duration	Poor	High
Scalability	Limited	High
Mission speed	Slow	Fast
independence	Low	High
Cost	High	Low
Communication requirements	High	Low
Radar cross sections	Large	Small

B. **Time Efficiency**

The swarm of UAV enable to reduce the time of making task and missions of searching or monitoring. As an example, author in [7] provide a study of using UAV swarm for detecting the nuclear radiation to build a map for rescue operations.

C. **Complementarities a Team Member**

Having a swarm of heterogeneous UAVs, more advantages can be achieved due to the possibility of its integration in different operations and tasks at the same time [18].

D. **Reliability**

The UAV swarm system delivers solutions that provide greater fault tolerance and flexibility in case of single UAV mission fails.

E. **Technology Evaluation**

With the development of integrated systems and techniques of miniaturization, models of UAVs to operate in a swarm can be produced, characterized by lightness and small size. [18].

F. **Cost**

Single high-performance UAV to perform complex tasks are very costly when compared to using a number of low-cost UAVs to perform the same task. Where cost is related to power, size and weight [18].

2.4 UAV Swarm Applications

A big variety application as shown in Fig. 3 exists where UAVs swarm systems are used. Figure 4 shows the review publications in UAVs swarm and their applications between years 2018 to 2022. The following subsection provides an overview of most important UAVs applications.

A. **Photogrammetry**

Photogrammetry enables to extract the quantitative information's from scanned images, in addition to recover point surface position. Several works addressed UAVs swarm performing imagery collection. For example, [19] presented low altitude thermal image system enable to observe specific area respected to flight plan.

B. **Security and Surveillance**

Many applications use UAVs swarms in video surveillance by cameras to cover specific targets [20]. It also helps in monitoring, the traffic control operations, in addition to many military monitoring operations.

Fig. 3 UAVs swarm systems applications

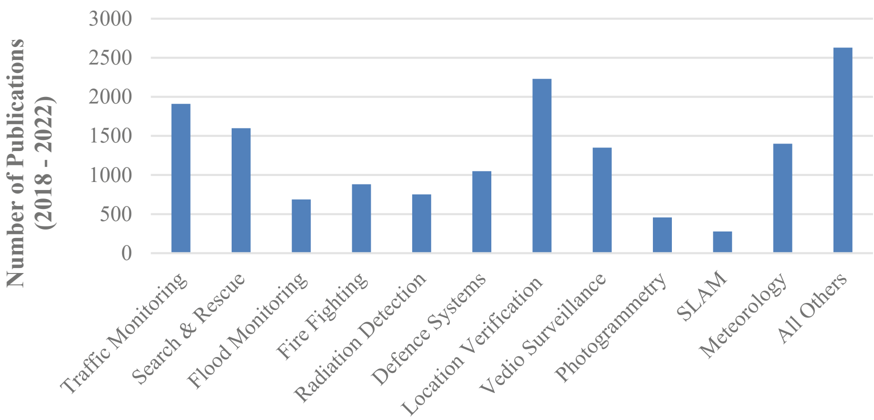


Fig. 4 Publications of UAVs Swarm systems applications (Google scholar)

C. **Battlefields**

Swarms of UAVs help cover battlefields to gather intelligence and transfer it to ground receiving stations for decision-making [21]. In many military applications, UAV swarms serve to locate enemy locations in urban or remote areas, in lands or seas.

D. **Earth Monitoring**

UAVs swarms are used to monitor geophysical processes and pollutant levels by means of sensors and processing units that make independent surveys along a predetermined path [21].

E. **Precision agriculture**

In the agricultural field, UAVs swarm help in spraying pesticides on plants to combat agricultural pests while ensuring high productivity and efficiency [22]. They can also monitor specific areas and analyze data to make spraying decisions.

F. **Disaster management and good delivery**

AUVs swarm assist in rescue operations during disasters, especially in the early hours, and help deliver emergency medical supplies [24]. It can also assess risks and damages in a timely manner by means of integrated atmospheric computing. Some companies, such as Amazon, are working on using UAVs swarms to deliver goods through computing systems and the Internet [25, 26].

G. **Healthcare Application**

In healthcare, UAVs help to collect data from different medical levels, from sensor information related to patients, to health centers [27]. One of the examples of these applications is the UAVs star network topology which uses radio alert technology to allocate resources, which consists of the following stages.

- Stage 1: data collection, enables the UAV to gathering patients' information.
- Stage 2: data reporting, enable to reporting the information's collected by the UAV to medical servers, or doctors end devices.
- Stage 3: data processing enables to take decisions about patient's healthcare to provide diagnosis and prescription.

3 Swarm Communication and Control System Architectures

To design an efficient and high stable UAV swarm communication architectures and protocols, it is necessary to take these challenges into account [28]. Figure 5 shows general reliable communication service scenario for UAVs. The UAVs swarm communications architectures and it provided services are deal with many requirements as follows.

- Increasing in spectrum demand accordingly to expected UAV applications.
- Higher bandwidth and data rates to support upstream data traffic for several UAVs surveillance applications. Accordingly, there is a need to develop new strategy to handle the big data traffic between the UAV members in swarm.

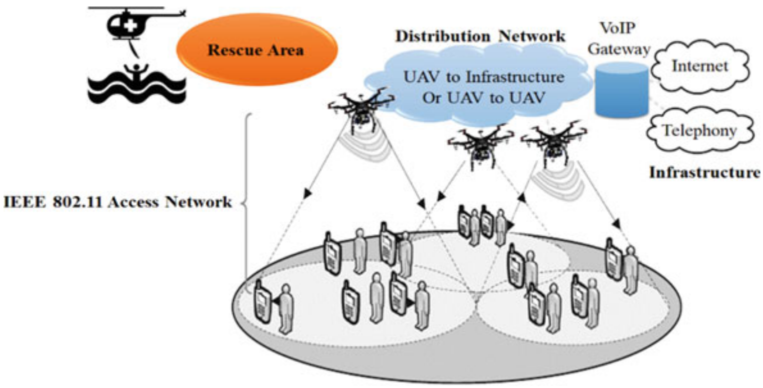


Fig. 5 UAVs network communication architecture

- A heterogeneous QoS is required in both uplink and downlink communications for integrate the operations of UAV in swarm through the cellular network [19].
- High mobility and dynamic topology for UAV swarms, in addition to the high-speed distinction where it needs high reliability and low latency communication networks.
- Ability to manage spectrum overcrowding, since the UAVs can be operated on different IEEE bands such as L and S bands, in addition to others related for medical and industrial bands [13]. The UAVs also able to communicate with other wireless technologies such as Bluetooth, WI-FI networks [29]. Accordingly, UAVs such consist many operating devices to have deal with all these communication bands.

3.1 Centralized Communication Architecture

The UAV swarm communications architecture illustrates the mechanism for exchanging information between UAVs among themselves or with the ground infrastructure, as it plays an essential role in network performance, intelligent control and cooperation of UAV swarms. [30]. Figure 6 shown the general UAV swarm communication architecture in centralized based approach. The center station is known as Ground Control Station (GCS), which enable commutations to all UAV swarm members [31]. The centralized architecture approach enables to let UAV swarm network extended from single UAV to manage many UAVs. The GCS motoring the UAV swarm to have decision making related to UAVs to manage their speeds and positions [32]. The GCS also provides message control to let UAVs communicate together [14].

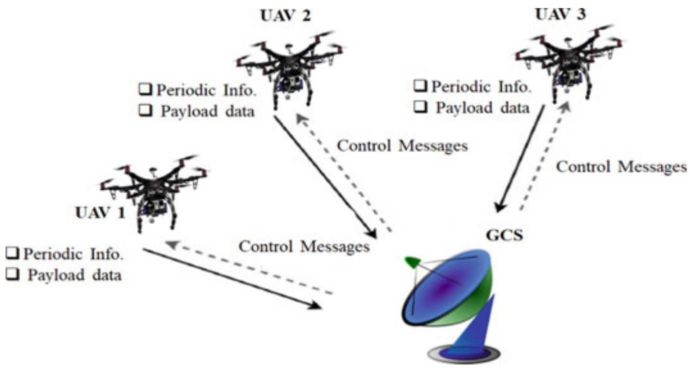


Fig. 6 Centralized UAVs swarm architecture

3.2 Decentralized Communication Architecture

With the increase in the number of UAVs in the swarm, the centralized communication approach can be used, which provides an organizational structure that reduces the number of swarm and UAVs numbers connected to the central network and gives the independency for some UAVs [33]. Also, the long distances that UAV can travel can lose their connection to the central network, so other decentralized networks are allocated to the aircraft to carry out interactive communications in real time [15].

3.2.1 Single Group Swarm Ad Hoc Architecture

In single-group swarm Ad hoc network as shown in Fig. 7, the swarm's internal communication is not dependent on infrastructure. The communication between the swarm and the infrastructure is a single point link based on a specific UAV acting as a gateway [34]. In single group swarm ad-hoc networks, some UAVs act as a relay node to forward data between UAV members is swarm. The UAVs can share situation information in real time to improve collaborative control and efficiency. Likewise, the interconnection between the UAV gateway and the infrastructure also enables exchange the swarm information [35].

The UAV gate works as a tool for communicating with UAVs in short distances and also with infrastructure in the long range. The gates reduce the burden on other UAVs by reducing their devices and reducing their cost, which helps to expand the range of communication and speed up the maneuvering performance of the UAVs [16, 35]. However, in order to ensure consistent swarm communication, the flight patterns of all UAVs in the swarm must be similar and operate under a single scenario proportional to their size and speed [17, 36].

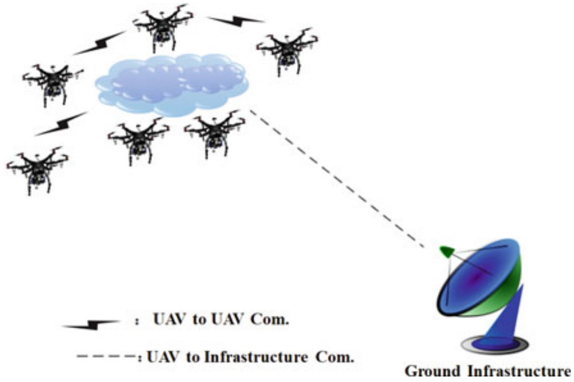


Fig. 7 Single group swarm Ad hoc network architecture

3.2.2 Multi Group Swarm Ad Hoc Architecture

A dedicated single group swarm network can be combined with other networks as shown in Fig. 8, so that each network has a central architecture and a special architecture with different applications depending on the task. The architecture is organized in a centralized manner but the difference is at the level of the UAVs within each private network group [37]. The architecture of communication within UAVs swarm groups is similar to the architecture of communication within a swarm, with a mechanism for communication between groups defined by the infrastructure. The responsibility for connecting to the infrastructure lies with the gateway's UAVs and for coordinating communications between the missions of the various UAV groups. This architecture helps to conduct specific multitasking applications for groups to conduct joint multi-theater military operations so that the central control center can communicate with different UAV swarms [18, 37].

3.2.3 Multi-Layer Swarm Ad Hoc Architecture

An ad hoc multi-layer swarm network architecture is an important type of architecture that is suitable for a wide range of UAVs, as shown in Fig. 9. In which a group of neighboring drones of the same type form a dedicated network as the first layer of the communications infrastructure [38]. In this architecture there are different types of drone kits on the drone gateway and it contains a second layer to enable connection to the nearest drone gateway to the infrastructure. At the third layer it does not require communication between any two drones in an ad hoc multi-layer swarm network architecture but the interconnection of the drones in the same group is done on the first level. Multi-layer custom network architecture compensates for the increase or decrease of UAV nodes and quickly implement network reconstruction [39]. The multi-layer ad-hoc network architecture works with scenarios where swarm UAVs

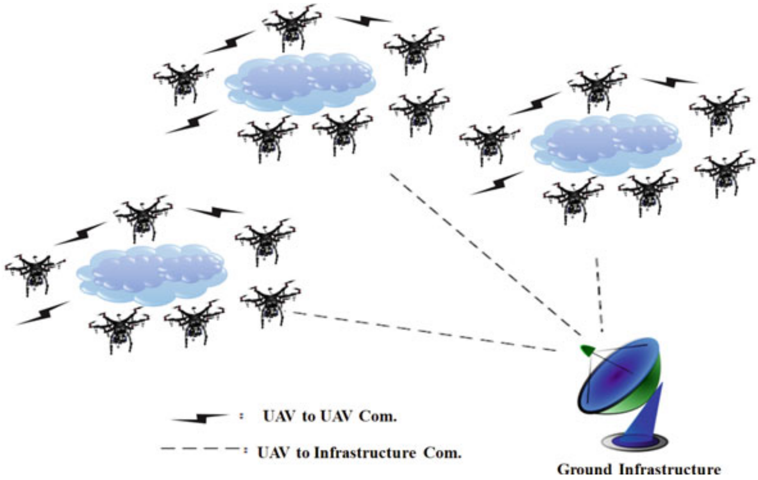


Fig. 8 Multi-group swarm Ad hoc network architecture

missions are complex and there are a large number of UAVs performing the missions allowing for a change in the network topology, and communication between the UAVs [19, 39].

According to what has been reviewed, UAV communications engineering has evolved significantly to serve a number of different and important scenarios. According to this, there are different communication structures to choose from among these structures. Table 2 summarizes the advantages and disadvantages of the discussed architectures. It turns out that the central communications architecture

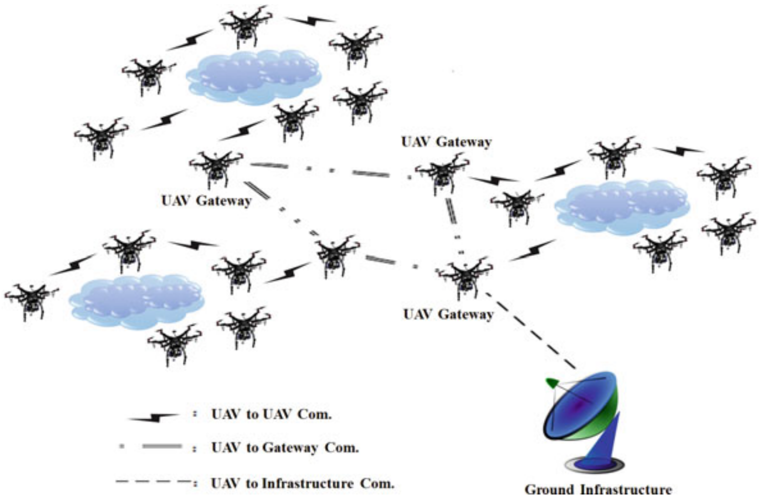


Fig. 9 Multi-layer swarm Ad hoc network architecture

Table 2 UAVs Swarm communication architectures summary

Features	Centralized architecture	Decentralized architecture		
		Single-group	Multi-group	Multi-layer
Multi-hop communication	✕	✓	✓	✓
UAVs relay	✕	✓	✓	✓
Heterogeneous UAVs	✕	✕	✓	✓
Auto configuration	✕	✓	✕	✓
Limited coverage	✓	✓	✓	✕
Single point of failure	✓	✕	✓	✕
Robustness	✓	✕	✕	✓

Note "✓" = supported "✕" = not supported

is suitable for scenarios with a small number of UAVs swarms with relatively simple tasks. The more complex the tasks and the larger the swarms, the other architectures are used according to the required scenario [40]. In case of expanded coverage through, multi-hop network scenario, the decentralized communication architecture is suitable for this purpose [41].

There are many communication technologies enable to provide UAVs communications. Figure 10, shows the classifications different UAVs communication technologies categorized four types based on, cellular, satellite, Wi-Fi based, and cognitive radio UAVs communications.

4 Navigation and Path Planning for UAV Swarm

Navigation of UAV could be described as a procedure for robot makes a strategy on how to quickly and safely reach the goal position, which typically depend on current location and environment. In order to effectively for the scheduled assignment to be completed, a UAVs should be aware fully of its statuses, comprising, heading direction, navigation speeds, location, as well as target location and starting point [41]. Today, several navigation techniques have been introduced and could be basically alienated into three groups: satellite, vision-based and inertial navigations. However, all these techniques are not perfect thus, it is critical to propose a suitable one for navigation of UAV conferring to the explicit mission [42]. The navigation base vision demonstrates to be a promising and primary autonomous research of navigation direction with the fast computer vision development. First, the visual sensor could offer rich surroundings operational information second, sensors also, are extremely suitable for active environment perception due to their extraordinary anti-interference capability. Third, utmost visual sensors are passive, which correspondingly avoid to be detected by attackers [43].

Table 3 Summarization of Trajectory planning methods

Algorithms	Approach	Extend to 3D	Advantages	Disadvantages
CD	Workspace modeling	Yes	Could be expanded to 3D, Mobile robots' applications	Needs searching A* algorithm
VD	Workspace modeling, and Roadmap	Yes	The obstacles will be far from the planned routes	Difficult to apply in a 3D environment
VG	Workspace modeling, and Roadmap	Yes	In polygon-based and regular environments have better performance	The obstacles will be closed to planned route Hard in cluttered environments
APF	Potential field	Yes	No need algorithm of modeling environment, complexity time is low, generated easy path, avoidance of obstacle in real-time	Easy to fall in a local minimum
A*	Searching	Yes	A low-cost and short path, could be associated with algorithm of modeling environment i.e., GD	Possible high time complexity
Dijkstra	Searching	Yes	the shortest path is Guaranteed	High time complexity
RM	Workspace modeling, and Roadmap	Yes	Path finding is Guaranteed (needs sampling nodes to be increased with no boundaries)	No optimal path is guaranteed Hard generate path in a slight gap, Complexity of computation

Planning of the path is defined as the method of finding shortest and an optimal path between destination and source. One of the utmost important difficulties to be discovered in the UAVs arena. The core goal of UAV's path planning is to discover an effective flight cost through a path that fulfil the requirements of UAV performance with small collision probability during the flight [20]. Planning of UAVs route, normally comprises three main terms [21, 44]: Planning of motion, navigation, and planning of trajectory. Planning of motion contents restraints alike flight route, turning the motion crank of the route planning. On the other side, Planning of trajectory includes the route planning having velocity, time, and UAVs mobility kinematics of whereas navigation is concerned with localization, and avoidance of collision.

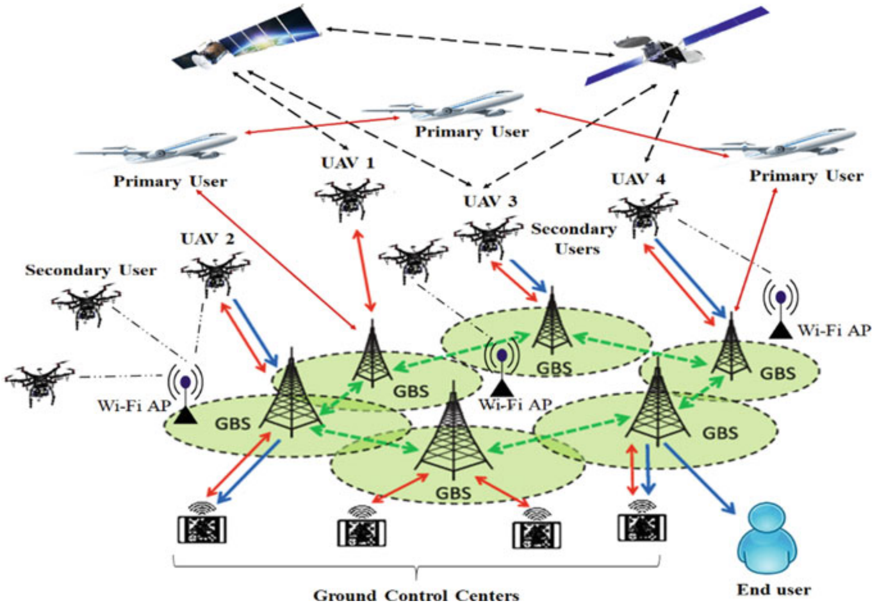


Fig. 10 UAV swarm communication technologies

For UAV route planning, a three-dimension for environment is essential, as in a multifaceted environment two-dimension (2D) route planning technique would not be capable to discover the objects and obstacles. There are several UAVs route planning techniques for obstacle navigation. The three-dimension (3D) techniques are formulated route-planning as a problem of optimization [45].

4.1 UAVs Network Communication and Path Planning Architecture

UAV needs to accomplish route planning during motion from a source to a destination. UAVs recognize the neighboring environment by utilizing sensors to navigate, control and plan flight mobility. The UAV route planning stages that required to be tracked during the operations execution are (i) climate and weather sensing, (ii) navigations, (iii) UAVs movement control. The mentioned above stages are to be applied throughout the trip [46]. The climate and weather sensing for the environments gives the UAVs awareness. The route planning and navigation methods are to be applied continuously seeking for an optimal route. The UAVs movement and velocity are monitored by central controller for avoidance of collision. Furthermore, the UAVs need to communicate with neighbor UAVs for the network management during their goal of mission [47].

There are requirements for 3D route planning in multifaceted environment. The 2D route planning techniques are not suitable for such environments which would be confused about discovering objects and obstacles compared to the sophisticated 3D environments. Then, 3D route planning methods are on severe demand for UAV navigation and surveillance applications a complex and cluttered environments [47]. The UAVs energy of communication of base-stations could be decreased by optimizing the power of transmission. Likewise, reducing the UAVs machine energy, it required a model for consumption in UAVs systems where the efficient UAVs energy could be modeled as:

$$\mathrm{E} = (\mathrm{P}_{\min} + \mathrm{h})\,(\mathrm{t}) + (\mathrm{Pmax})(\mathrm{h/s}) \tag{1}$$

where, t presents the time of operating, h is the height, and s is the UAVs velocity. $\mathrm{P}_{\min}$ and Pmax depend on motor specification and weight. One can write, $\mathrm{P}_{\min}$ is the lowest power that required for UAV to start with α as the motor velocity. Hence, forth, the entire communication cost ($\mathrm{T}_{\mathrm{com}}$) that reduced the UAVs cost and time can be modeled as:

$$\mathrm{T}_{\mathrm{com}} = \mathrm{t}_{\mathrm{s}} + (\mathrm{t}_{\mathrm{o}} + \mathrm{t}_{\mathrm{h}})l \tag{2}$$

whereas, ts denoted as UAVs start time, to denoted as time overhead, t_{h} denoted as UAVs hop time, and l denoted as the accumulated links between the start point and target. Having such parameters, collision avoidance, robustness and completeness aspects, which were used and considered for optimal path finding for UAVs algorithms.

4.1.1 Trajectory Planning in 2D Environments

In conventional route planning techniques, information of environment has generally been defined by a 2D level. In UAV case, it is supposed to maintain manual adjustment or height for its flight. Optimization in a 2D route planning issues are non-deterministic polynomial-time hardness (NP-hard) issue hence, no certain solution is occurred [48]. Luckily, Collective Influence (CI) algorithm reduces the gradients computing requirements of constraint and cost functions. This empowers the NP-hard technique to be optimized and resolved. Usually, 2D route planning algorithms can be categorized to three forms rendering to the UAV constraints. The first algorithms deal with the UAVs as particles. In this situation, designers could concentrate on the optimal path computation. Though, this type computation is quite sophisticated and hard to implement, as NP-hard problems could be consistently converted to optimal route constraint with spatial-search [49]. Though NP-hard problem has no regular solution, multiple CI algorithms [23, 24] could work for route planning optimization by simplifying the cost and constraint functions gradients computation.

The second algorithm model the problem based on the shape of the UAV. For UAV shape-based algorithm, the problem can be converted [25, 49] to be considered as 2D shape with shape parameters i.e., gravity center and wing span. Then, it could be resolved by the method used UAV as a particle.

The third technique is UAV to be modeled as dynamic and kinematic constraints, such as, its max and min radii turning. Related to the previous techniques, the third technique is more complicated however more applied in applications. For the dynamic and kinematic constraints, CI method [26, 50] could be used with the advantages in computation and fast convergence.

4.1.2 Trajectory Planning in 3D Environments

As growing fields range, for example, navigation, detection, operations and transportation, are all needed for UAVs application. Because of the environment's complexity, which have many factors with uncertainty and unstructured, 3D route planning robust methods are crucially required [51]. Though route planning of UAV for 3D spaces presents excessive opportunities, contrasting to route planning for 2D. The challenges are dramatically increased for kinematic constraint. One of the traditional problems can be modeled for the 3D space while considering the kinematic constraint for collision-free route planning. Bear in mind, kinematic constraints such as temporal, geometric, and physical difficult to be resolved by conventional CI methods which may encounter numerous of difficulties i.e., convergence rate is low and exploration range is wide [52].

This article focuses and discusses 3D environments with emphasis on the challenges mentioned in the above sections. 3D techniques have various advantages and characteristics when joint with suitable CI algorithms. To avoid the challenges of 3D unmature and slow convergences in UAV route planning with low-height, numerous of Genetic Algorithm (GA) can be used for route planning [27, 28]. The enhanced particles swarm optimizations (PSO) techniques [29, 30] can be utilized to solve blind exploration of wide range problems and execute comprehensive 3d route optimization.

An improved ant colony optimization (ACO) techniques [31] for planning for 3D route have been discussed extensively, where it could also enhance the selection speed and reduce the finding optimal local points probability. Unlike swarm methods, Federated learning (FL) algorithm has generally been utilized for navigation vision in UAV to enable images decisions and detection [32]. To discuss UAV route planning attack problem, fusion neural-network (NN) based technique has been proposed [33]. This method could simply be enhanced by parallelization methods. Recently, with the computing chip development, need more computing time and high performance

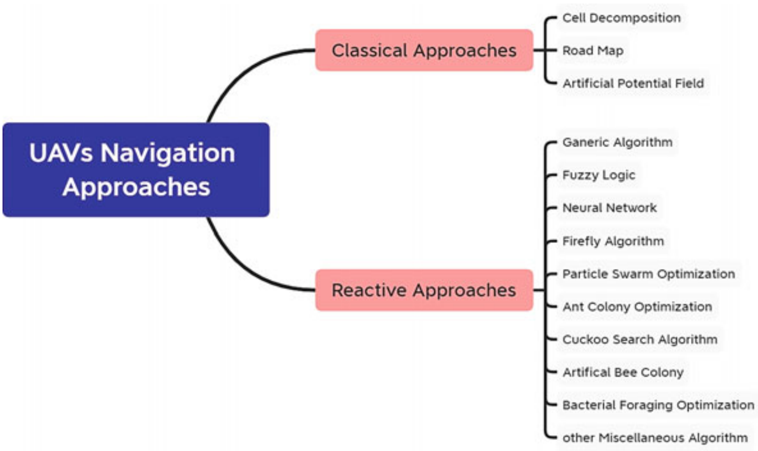


Fig. 11 Classification of trajectory planning algorithms

for deep learning (DL) and machine learning (ML) techniques [34, 35] have been guaranteed. These techniques (i.e., ML and DL methods) were greatly been used in UAV 3D route planning to resolve the NP-hard problems more accurately in a wide search region [53].

4.2 *Trajectory Planning for UAVs Navigation Classifications*

The route planning for UAV could be categorized in three methods namely combinative sampling-based and biologically-inspired methods as presented in Fig. 11.

4.3 *Route Planning Challenges*

- ***Route length:*** The route length is identified as the total path that UAVs can move from start points to the end points.
- ***Optimization:*** which defined as the route calculation and parameters should be efficient in time, energy and cost. It could be identified to three classes, i.e., non-optimal, sub-optimal and optimal.
- ***Extensiveness:*** which is identified as the characteristics that utilized in route planning for discovery the route. It offers the UAVs a platform and an optimal route solution.

- ***Cost-efficiency:*** it relies on the UAVs network cost computation. It comprises of several influences such as peer-to-peer cost, cost of fuel, cost of charging the battery, cost of memory spaces, cost of hardware and software.
- ***Time-efficiency:*** it defines the minimum time that UAVs can move from start point to the target point assuming there are obstacles on the path. This could be likely if UAVs utilize shortest and optimal path.
- ***Energy-efficiency:*** it is meaning the minimum UAVs consumption of energy in terms of energy, fuel, battery used for pass from starting to destination points.
- ***Robustness:*** which is identified as tolerance of the UAVs and resilience against errors i.e., hardware, software, protocols and communication during route planning.
- ***Collisions avoidance:*** is identified as the capability of UAVs to for collision detection and avoidance to avoid any crashes or physical mutilation to UAV.

5 Classical Techniques for UAV Swarm Navigation and Path Planning

5.1 Roadmap Approach (RA)

The Roadmap Approaches (RA) is also identified as highway approaches. It is a two-dimensional network of straight lines connecting the start and the destination points without intersecting the obstacles defined in the map [54]. The basic idea of this algorithm is to generate sampling nodes in the C-space randomly and connect them. The RA consists of generating a fixed number of random points, which could be called milestones in the search space. Milestones within an obstacle are discarded. All remaining milestones are sequentially interconnected by straight lines, starting from the robot starting point. Straight line segments within obstacles are discarded [55]. The remaining line segments become the edges through which the robot can travel collision-free. For a given start point (Ps) and target or finish point (Pf), all possible connecting paths or routes are generated by collision to avoid obstacles. A typical factor such as A* search technique is used to finding the shortest route between initial point and destination. The resulting route consists of a series of way points connecting the start and target locations.

In overall, the algorithm works as shown in Fig. 12. The map is identified by a range named the total range, Crange. Then, separated to free obstacle range Cfree and the obstacle range Cobst. Then, a connectivity graph network Qfree is created by choosing a group of points that could be linked by straight line such that the consequential discretization generates a group of polygons that surrounded obstacles in Crange. The achieved graph connectivity is utilized to create a proposal for all probable collision-free paths. Then, A* search algorithm is utilized to discover one or more paths based on parameters that used from start to end points or positions in between [56].

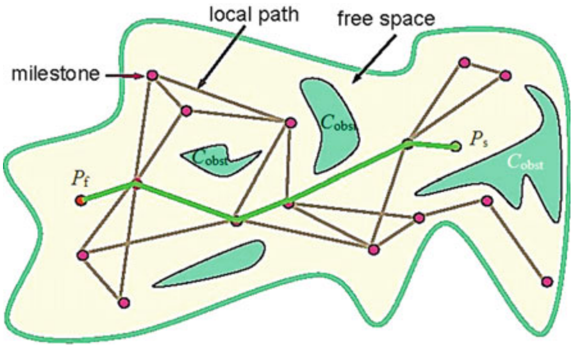


Fig. 12 The road map method

This technique is also utilized for obstacles in polygonal environments in which the polygon ribs are illustrated by edges and nodes. Two of these techniques were used to represents paths by graph connectivity. An example of such techniques is the graph visibility and Voronoi's diagram [36, 56].

A. **Visibility Graphs**

The visibility graphs (VGs) are widely utilized for route planning algorithms based on the Cspace modeling roadmap algorithm. This is an earliest method used for path planning. As the name proposes, the VG produce a lines-of-sight (LoS) routes throughout an environment. In the visibility graphs, the obstacles vertices represented by finite number of nodes between start and end point. Each node VG is representing a location of point, while the route between points is represented by a connected lines [57]. If the connected lines do not cross any obstacles, means the path is feasible and considered as visible path and draws in the visible graph as solid line, as shown in Fig. 13. Otherwise, it considered as un feasible route which requires to be deleted from the visible graph. The similar procedure is recurring for the other nodes remaining until the finish point/node. VG builds the roadmap which identifies the free spaces around obstacles, thus translating the connected Cspace into a structure with graph skeleton. Lastly, A path is then produced utilizing searching graph algorithm such as Dijkstra protocol to discover the shortest route that links route from start to end point [58].

The VG concept could be expanded to a 3D graph environment, which utilizing the 3D plane rather than lines. Many papers in literature discuss the usage of VG in 3D spaces. For example, authors in [38] presented a technique for transferring 3D into 2D problems, then discover the route by using the legacy 2D VG algorithms. Finally, it adds additional view which is the path altitude [59].

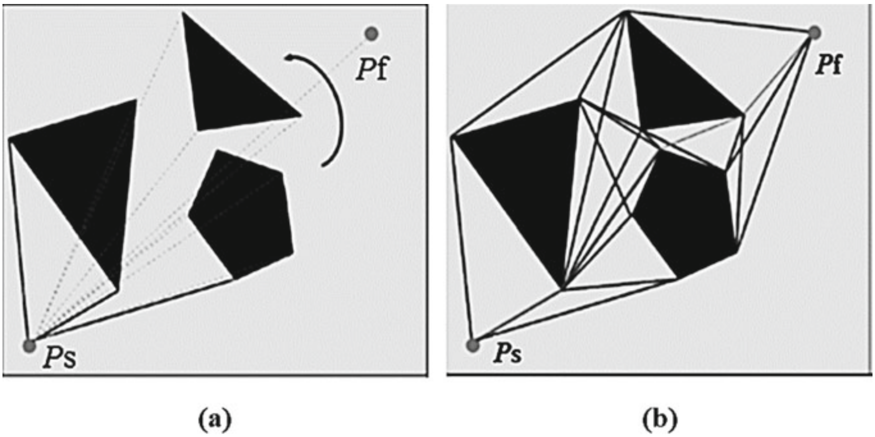


Fig. 13 Visibility graph

B. **A* algorithm**

A* algorithms are a traversal graph and route searching algorithms which is commonly utilized for discovering the optimum route due to its optimality and completeness [60]. It discovers the optimum route with less processing time and it has to store and remember all nodes that have been visited earlier. It uses those memories to identify the best path that can be taken from its current state. To find the following node, one can use the below expression.

$$f(n) = g(n) + h(n) \tag{3}$$

where n denotes as following node on the route, g(n) is the route cost from node S to n, and h(n) is a heuristic process that calculates the lowest path cost from G to n.

The minimum path cost is approximated and estimated to reach the next optimum node point. The repeated optimum node points are estimated based on these expenses of the optimum route by obstacles avoiding [61]. Figure 12 illustrates the phases that elaborate in searching the optimum route in the A* searching algorithms. It is basically based on efficient heuristic cost, the high expanded search areas, and appropriate only in a static circumstance. Since A* algorithm solve the optimum routes that made by neighbor nodes to build the roadmap, it results with route jagged and long solution.

Algorithm 1: The A* Algorithm

Input: start, *goal(n), h(n), expand(n)*
Output: path
if *goal(start)* = *true* **then**
return *makePath(start)*
end
open←*start*
closed ← ∅
while *open* ≠ ∅ **do**
sort(open)
n ←*open.pop()*
kids   *expand(n)*
forall *kid* ∈ *kids* **do**
kid.f   *(n.g + 1) + h(kid)*
if *goal(kid)* = *true* **then return** *makePath(kid)*
if *kid* ∩*closed* = ∅ **then** *open*←*kid*
end
closed   *n*
end
return path

5.2 Cell Decomposition (CD)

Cell decomposition (CD) is a path-planning algorithm based on a 2D C-space modeling approach. In the cell decomposition method, the environment is divided into non overlapping grids (cells) and uses connectivity graphs for traversing from one cell to another to achieve the goal. Possible routes from the start to finish points are then created that pass-through neighbor free cells (no obstacles in these cells) [62]. The obstacles are isolated by connectivity finding among the free cells. Thus, a discrete version of the environments is created. Search algorithms are utilized to connect neighbor free cells. Figure 16 presents the process schematic. The shaded cells are removed due to obstacles occupation in grey. A connectivity between the start and destination points is computed by linking the free cells by a straight lines' series [63]. The Fig. 14 represents a simple environment division, which is known as the cell decomposition exact method. If no path is found, then the cells are then decomposed into smaller cells and a new search is completed The CD method is characterized as exact, adaptive, and approximate.

In the exact CD cells does not have a precise size and shape, but could be determined by the environment map, location and obstacle shape [63]. This approach utilizes the regular grid in several ways. Firstly, the available environment free space is disintegrated into small parameters (triangular and trapezoidal) followed by a number for each parameter. Each parameter in the environment represents a node in the graph connectivity. The neighbour nodes are then permitted to joint in the space

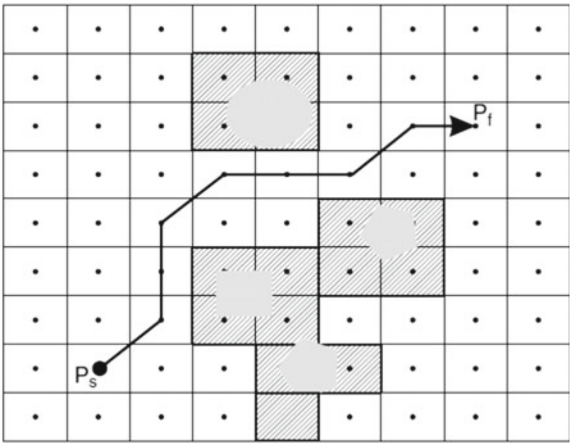


Fig. 14 Cell decomposition (CD)

arrangement and a route in this chart equivalences to a digression in free space. This is drawn by the striped cells succession [64]. A route in this graph associated to a free space network, which is drawn by the striped cells succession. These channels are then changed into a free route by linking the underlying arrangement to the objectives design through a midpoint of the crossing points of the contiguous cells in the channel.

In approximate CD, planning spaces have been utilized to identify a regular grid has an explicit size and shape, henceforth it is easy to configure. Adaptive CD recognizes the presented information in the free space and follows the avoidance basic concept of the free space in regular CD [44, 64].

The benefits of this method are that it is practical to implement above two-dimensions and relatively quick to compute. However, because it is an iterative process, it is not necessarily practical to compute online as there is no guarantee when, or if, a solution is found. Additionally while there are both exact and approximate cell decomposition methods, the approximate method (shown in the figure above) can provide very suboptimal solutions.

5.3 *Artificial Potential Field (APF)*

Motion planning field using APF initially used for online avoidance of collision for where UAVs do not have previous knowledge about obstacles however it avoids it in real-time manner. The comparatively simple concepts treat the vehicles as a node under the effect of an APF where the differences in the spaces characterize the environment structure [65]. The attractive potentials reflect the vehicle pull to the goal and the repulsive potentials reflect the UAV push from the obstacle [44, 66]. Consequently, the environment is disintegrated into values set where high value is linked to obstacles and low value is linked to the goal. Several steps are used to

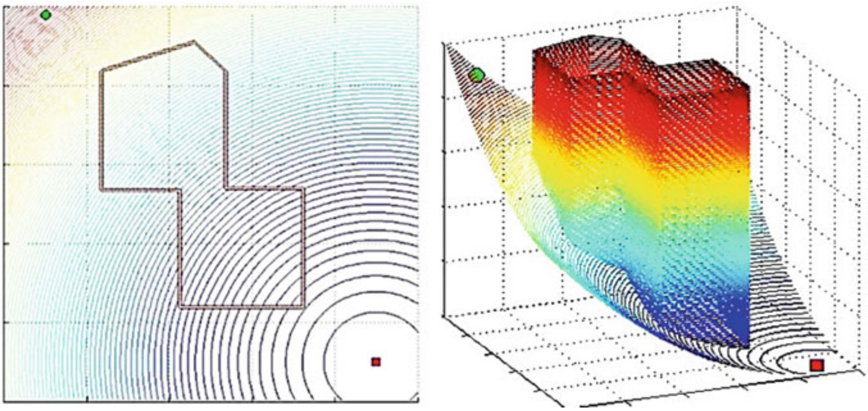


Fig. 15 Example of the potential field method

construct the map using potential fields. First, the target point is assigned a large negative value and Cfree is assigned increasing values as the distance from the goal increases. Again typically, the inverse of the distance from the goal is used as a value [10, 65]. Second, Cobstacle is assigned as the highest values and Cfree is assigned decreasing values as the distance from the obstacles increases. Typically, the inverse of the distance from the obstacle is used as a value. Finally, the two potentials in Cfree are added and a steepest descent approach is used to find an appropriate path from start point to the end point (see Fig. 15 on the right) [45] (Table 3).

6 Reactive Approaches for UAV Swarm Navigation and Path Planning

6.1 Genetic Algorithm (GA)

The Genetic Algorithms (GA) is an dynamic stochastic searching algorithms based on the natural genetics and selection utilized to resolve the optimization issues [46, 66]. In the terms of route-planning, Genes are points that are waypoints on the route, and GA uses genetic operations to for initial route optimization. There are five genetic operations' stages in GA route planning [47, 66]:

- The cross operation: randomly select two points from two routes exchange the remained route after the selected points.
- The mutation operation: randomly select one point from a route and swap it with a point that does not select by any route.
- The mobile operation: random select a point in the route and change it to a neighboring location.

- The delete operation: randomly select a point in the route, then connect any two neighbor nodes together. If eliminate the selected node results in a short without collision route, then eliminate this point from the route.
- The enhance operation: can be only utilized in the collision-free routes. Choose a point from the route and enclose two new points in two sides of the chosen point. Then, link the two new points with a route. If the new route is viable, eliminate the chosen point.

The mentioned genetic operations are used for parent routes to create an optimized child route. In GAs, the parent route is identified as the preliminary route achieved from the preceding route planning operation, which could be achieved using Roadmap. The parent routes should be line sections that link the start and the end via numerous midway points. GAs are robust search algorithms which needs very minor information on the environment for efficient search [67]. Most of the studies have studied static environment navigation only by utilizing GAs however, navigation in dynamic environment with existing of mobile obstacles is not been discussed extensively in the literature. To have excellent achievements in UAB route planning, several studied have been studied GAs applications along with other intelligent algorithms jointly which sometimes called hybrid approaches [50].

6.2 Neural Network (NN)

The ANN structure concept is stimulated by the neural biological network operation. It is built on a group that connected with computation function known as artificial neuron (AN). Each link between ANs has ability to transmit a signal from one point to another [68]. The ANs process the signal received and then signal the ANs associated to it. In ANN configuration of UAV route planning, the link between the neurons is called signal and it is usually real number. The neuron output is computed by a nonlinear function. They are typically optimization through mathematical stochastic approaches based on huge amounts of data fitting [69]. Then, we can attain a suitable solution which can be converted by mathematical function.

The ANN algorithms reduce the mathematical complexity by eliminating the collocating requirement for the computational environments and providing fast computer equipment [62]. Since an ANN is created by using parallel computation the convergence is generally very fast, and the created route is safe and optimal [63]. There are, two key forms of ANN approaches have been used in UAV route planning: firstly, a UAV built its route on a sample trajectory and utilizes a direct association approach to optimize and compute the trajectory [64]. Secondly, it uses NNs to estimate the system dynamic, objective function, and gradient, which eliminate the collocation requirement, thus reducing the nonlinear programming problems size [65]. Presently, second type approaches are more popular. Then, it has been expanded to determine its best for resolving multiple-UAVs problem [66]. Additionally, ANN has generally been combined with other approaches and algorithms [67, 68] such as the PFM, PSO, and GA, to maximize their advantages. Deep neural networks (DNNs) are a multi-layer NNs and have been extensively used in the AI field recently, such as speech recognitions and images processing. Due to its capability to characterize and extract features precisely, it can be applied for UAV future facilitation for route planning in complex environments.

6.3 Firefly Algorithm (FA)

Firefly algorithms (FAs) are stimulated by the fireflies' behavior and flashing activities, although it is also known as the meta heuristics' algorithms. Its concepts include general identifications and random states as trial/error of firefly which is present in nature statistically [70]. The firefly is a flying beetle of the Lampyridae family and usually is called lightning bugs due to its capability to create light. It creates light by a process of Luciferin oxidation in the enzymes Luciferase presence, which arises very rapidly. The light creation process is known as bio luminescence and fireflies utilize this light to glow without spending heat energies. Firefly uses the light for mate selection, message communication and occasionally also for terrifying off other insects who try to attack it.

Recently the FAs have been utilized as an optimized tool and its applications are spreading in nearly all engineering areas such as robot mobile navigations. In [70], the authors presented Firefly algorithms-based robot mobile navigations approach in the of static obstacles presence. The paper attained the three primary navigation objectives such as route safety, route length, and route smoothness. In [71], authors showed the FAs for the shortest path with free collision for single robot mobile navigation in simulations environment. In [72] established the FAs for underwater robot mobile navigation. Authors established strategy for swarm robots scheduling for jamming and interference avoidance in 3D marine space environment. Reference [73] discussed a similar environment, where a real-life underwater robot navigation in partially pre-known environment is presented by utilizing the levy light-fireflies based method.

The FAs based cooperation for dead robot detection strategy in a multi-mobile robot environment is discussed by [74]. The FA 3D application for world exploration with aerial navigations is implemented and developed by [75]. An enhanced version of FAs is applied for unmanned combat aerial vehicle (UCAV) route planning in a crowded complex environment and to avoid hazard areas and minimizing the fuel cost. The concentric sphere based modified FA algorithm has [76] been presented to avoid random moving of the fireflies in less computational efforts. The experimental and situational results show a great commitment in achieving the goals of navigation in a complex environment. Reference [77] Addressed the problem of navigation specifically in dynamic conditions.

6.4 Ant Colony Optimization (ACO)

The ACO algorithms initiated from the ant community behaviour and its capability to search for the best shortest route from the source (nest) to a destination while they are seeking for food [78]. In route planning method, all the routes of ant swarm establish the optimized solution space for the problem. The pheromone concentration is increasingly accumulated on shorter routes, and the number of ants selecting the route is also growing. Ultimately, the entire ants concentrate on the shortest route under confident feedback, and the consistent solution is the optimum to the route planning of optimized problem [80]. ACO algorithm for UAV route planning is typically developed by dividing the area of flying into a grid and enhancing a route between a grid point and the destination points [85] to conduct the optimal route efficient and rapid search [81]. An improved algorithm was discussed in [81] with the assistance of a climbing weight and a 3D grid. Today, the ACO is utilized for efficient route planning, and to handle the robot mobile navigation problems for obstacles avoidance.

The ACO compared with other Collective Influence (CI) algorithms, the ACO has solid robustness and capability to search for a best solution. Furthermore, the ACO is an evolution population-based algorithms that are fundamentally easy and parallel to run in parallel. To enhance the performance of ACO algorithm in route planning problematic issues, the ACO algorithms can be simply combined with a various heuristic algorithm.

6.5 Cuckoo Search (CS)

The CS algorithms are based on the cuckoo's lazy behavior for putting their eggs in the of other birds' nests. The algorithms follow three basic guidelines for an optimized solution problem as discussed in [79]. At a time, each cuckoo put one egg in a randomly selected nest. The best nest with high eggs quality will be passed to the next generation. The number of nests available is usually fixed, and the cuckoo egg laid has a probability of $P \in (0, 1)$ to be discovered by the host bird. In such case, the host bird can either abandon the current nests and build another one or get rid of the egg. The CS algorithms are an enhanced approach due to the grows of the efficiency and rate of convergence, henceforth it is extensively recognized in various optimization engineering problems. Robot mobile navigations are one the area where computational time and performance are need to be optimized [80].

The CS algorithms utilized for wheeled robot navigation in a static environment the environment is partially known, and have shown real-life experiments and simulations over the complex environments. The simulation and experimental results present good arrangement as there was a much slighter deviation errors [81].

The CS-based algorithms perform well when combined with other navigation methods. One such method is a combined of adaptive neuro fuzzy inference systems

(ANFIS) and CS were proposed to obtain better navigation results in uncertain environments. Another hybrid route planning method for an uncertain 3D environment by hybridizing the CS with differential evolution (DE) algorithms for the global convergence speed acceleration. The enhanced convergence speed aids the aerial robot to discover the 3D environment. The CS 3D applications particularly for a battleground has been discussed in [82]. In the manuscript, hybrid method (combing CS and DE) has been proposed for aerial 3D route planning optimization problem. The DE is added for the cuckoo's selection process optimization which enhanced CS algorithm noticeably, where the cuckoos were act as searching agent for optimum route.

6.6 Particle Swarm Optimization (PSO)

PSO is an algorithm that describe birds flocking based optimization approach. There are two parameters in this approach: position and speed. Position defines the movement direction, while speed is the movement variable. Each element in the search space individually searches for the optimum solution, and saves it as the present individual value, and shares this value with other elements in the whole swarm, and finds the optimum individual value for the entire swarm [82]. The present global swarm optimum solution is that all elements belong to the swarm adapt their position and speed according to the present individual value they found and the present global optimum that distributed to the whole entire particle swarm [83].

Extensive studies have been done based on the UAVs route planning by applying PSOs approaches and its alternatives. In PSOs, individual or particle is initialized randomly. Each one of these particles represent a probable solution to path planning problem and search around within certain space to look for optimum position. PSOs have advantage compared with other computing approaches as it can faster finds solution [81, 83].

Each particle in the swarm has its own individual speed, Vi and individual location, Xi and search towards the local optimal position, Pi and global optimal position, Pg. Local optimal location is the location at which the elements in swarm meet its optimum suitability during fitness evaluation phase. For global optimal position, X' is obtained by particle for the whole swarm obtained. It achieves the optimum solution by iterations. In each iteration, each element would apprise their position and speed until extreme iteration is reached.

6.7 Bacterial Foraging Optimization (BFO)

BFO inspired by the behavior of an M. Xanthus and E. coli bacteria optimization process. The bacteria searches for nutrients by applying the best usage of energy attained per time. The BFOs algorithms are characterized by chemotaxis that observes chemical inclines by which bacteria send special signals between each other. This process has four key concepts such as reproduction/swarming, chemotaxis, dispersal, and elimination. The bacteria behavior [84] for nutrient searching is shown as below.

- Bacteria continually move in search for more regions of nutrient on the space. Bacteria with enough food life longer and can be split into two equivalent parts while bacteria with the lesser nutrient regions will die and disperse.
- Bacteria exist in the more nutrient regions are involved with others by chemical phenomenon and bacteria exist lesser nutrient regions give a caution signal to other bacteria utilizing a special signal.
- Bacteria grow a highly nutrient regions on the space.
- Bacteria are disseminated in the space for new nutrients regions.

The BFO algorithm applications for robot mobile navigations in static environments is discussed initially by [84] with variable speed based on Cauchy, uniform, and Gauss distributions. The same strategy in the existing of obstacles is discussed, for navigation in static environments. Real-time navigations in building floor, corridor and, lobby environments for a single robot mobile system are discussed in [85]. For Performance improvement for wheeled robots in route planning, an improved BFO algorithm is proposed [86]. The proposed method models the environment by utilizing an APF algorithm between two contrasting forces i.e., repulsive forces for the obstacle and attractive forces for the goals. The method examines the negative feedbacks from the algorithm to choose appropriate direction vectors that lead the search processes to the auspicious area with a optimum local search. The navigation in the exist of several robots is itself a problematic issue BFOs algorithms are proposed to deal with such a condition [87]. The authors combined the search harmony algorithm with BFOs. Away from the application of wheeled robots, the BFOs algorithms have been validated effectively for an industrial manipulator as reviewed authors in [88] who discovered that the enhanced BFOs give best results compared to the conventional BFOs. The UAV navigations problem by utilizing BFOs have proposed by [88]. In the manuscript, the BFOs have been combined with a proportional integral derivatives (PIDs) controller to obtain optimum search coefficients in 3D spaces and to avoid complex models while adjust the controller for UAVs.

6.8 Artificial Bee Colony (ABC)

The ABCs algorithms are an intelligent-based swarm techniques adapted from the honey bees' activities in food search and it is initially introduced [83]. The ABC algorithms are populations-based protocol comprising of inherent solutions population (i.e., food sources for bee). It is comparatively simple, light processing and it is populations-based stochastic search method in the swarm algorithm field. ABC food search cycles comprises of the following three stages. Send the working bee to food sources and assessing the juice quality. Onlookers' bees selecting the food source after attaining information from working bees and computing the quality of nectar. Having the scout bee and send it onto probable food source [87].

The ABCs algorithms application to the robot mobile navigations in static environments is proposed by [89]. The proposed method applies ABCs for local search and evolutionary algorithms to identify the optimum route. Real-time experiment in indoor environments is discussed for result verification.

Similar techniques in static environments are also discussed by [89] however the results were limited to simulations environment. For the navigation goal meeting in a real-life with dynamic environments, the ABCs' based technique is proposed by [90]. Authors proposed hybrid method which combined the ABC with a rolling time window protocol. Several robot mobile navigations in environments are a challenge issue, the development of ABC is successfully finalized in static environments. Similar to the wheeled robot mobile navigations, the ABC is examined for navigation aerial underwater and autonomous vehicles routine problem [83].

UCAV route planning purposes to attain an optimum 3D flight path by consider the constraints and threats in the battle field. The researchers discussed the UCAV navigation problems utilizing an enhanced ABC. The ABC is amended by balance-evolution strategies (BESs) which completely uses the information convergence throughout the iterations to employ the investigation accuracy and conduct balance pursue between global explorations and the local exploitations capability [89]. ABC algorithms applications in the military sectors have been discussed by [90], where an unmanned helicopter has been examined for a stimulating mission such as accurate measurements, information gathering, and etc.

6.9 Adaptive Artificial Fish Swarm Algorithm (AFSA)

AFSA is a part of Intelligence swarms, which proposed by [91]. Mostly, fishes move to a location for best consistency food by execution social search behaviors. AFSAs have roughly four behaviors' prey, follow, swarm, and leap behaviors [90]. Lately, with its robust volume of global search, good robustness, and fast convergence rates, AFSA is extensively utilized for dealing with robot route planning issues. Hence, several researches proposed methods to enhance the standard AFS performance by fictitious entities of real fish. In a noble AFSA algorithm, identified as NAFSA, has been presented to enhance the weak issues of the standard AFSA and fastening the speed of convergence for the algorithm. A mended form of AFSA called MAFSA by dynamic parameters control has been proposed to choose the optimum features subset to enhance the categorization accuracy to enhance vector machines experimental result show that the proposed method is outperform the standard AFSA [91].

A new optimization AFS is presented to enhance the counterfeiting of AFSA behavior, which was near to reality that to enhance the ambient sense for the fishes' foraging behavior. By testing the environment, artificial fish could monitor the surrounded information to attain an optimum state for better movement direction. The hybrid adaptive systems niche artificial fishes swarm algorithms (AHSNAFSAs) is proposed to resolve the vehicles' routing problems, and the ecological niche concept is discussed and presented to enhance the deficiency of conventional AFSA to achieve an optimum solution [92].

7 Conclusions

A review of on UAVs navigation and route planning approaches for autonomous robots mobile, the advantages, and disadvantages of these algorithms were discussed and presented extensively in this chapter. An inclusive argument for each method in the research field under study for UAVs route planning and navigation algorithms were presented. This survey is despite the major enhancement in last studies over some years ago, a very few works of these studies has been reported in this chapter. This survey categories the various techniques into conventional and reactive techniques. The main themes of this review are shown below.

- Reactive techniques achieve much better than conventional techniques due to higher ability to handle uncertainty presence in the environments. A few researches studies were presented based on dynamic environments compared with static environments.
- Reactive approaches use is common for real-time navigation issues.
- In dynamic environments, there are less researches on UVAs navigation for mobile goals issue compared with mobile obstacles problem.
- Most researches establish a simulation environment researches on the real-time environments are much fewer.
- Researches on the navigation of UASs are few compared with the single UAS.
- There are countless scopes in using newly algorithms developed such as CS, SFLA, BA, FA, DE, HS, ABC, BFO and IWO for navigations in an uncertain complex environment in the existence of high uncertainty and these could be utilized to propose new types of hybrid mechanisms.
- The classical approaches efficiency can be optimized by mongrelizing with reactive mechanisms

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