# NAVIGATION PROBLEMS OF UAV AND THEIR SOLUTIONS BASED ON ARTIFICIAL INTELLIGENCE

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**Abstract**

Unmanned aerial vehicles (UAVs) are becoming more and more common in applications because of their ability to integrate a variety of sensors with cheap operating costs, easy deployment, and improved mobility. However, using unmanned aerial vehicles (UAVs) in complex environments at a distance limits their capabilities and reduces the system's overall efficacy. Consequently, a lot of researchers are concentrating on autonomous UAV navigation, which enables UAVs to move and perform certain tasks in accordance with their surroundings. Recent technological advancements have led to an increase in the applications of artificial intelligence (AI). A comprehensive analysis and classification of several AI methods for autonomous UAV navigation has been carried out. Two distinct AI approaches are model-based learning and mathematical optimization. This study reviews the fundamentals, principles and key features of several optimization and learning-based strategies. Moreover, an assemblage of unmanned aerial vehicles (UAVs) fitted with cameras records or observes particular areas. The UAVs can create a distributed network to process and share the sensory data they have acquired before sending it to a data processing center. Between them, extensive data flow may cause excessive latency and energy consumption. Artificial intelligence (AI) techniques are used in this research to process the video data that is being broadcast among the UAVs. Therefore, all that is required of each scattered UAV is communication of the relevant information with the others. Each UAV processes data using AI, and only information that is significant to the others is transmitted. Features are automatically retrieved from images using convolution neural network (CNN) technology, allowing UAVs to broadcast only the moving objects and not the full picture. The network thus consumes far less energy and transmits significantly less redundant data to any given UAV or to the network as a whole. The UAVs are also capable of energy conservation so they can continue to move in the sensing field.

**Keywords:** Unmanned aerial vehicle (UAV), artificial intelligence (AI), Convolution Neural Network (CNN), deep neural network, optimization, navigation, information sharing.

## Introduction

Unmanned aerial vehicles (UAVs) are aircraft capable of taking to the air without the need for a human pilot [1]. UAVs are being utilized in both military and civilian applications more and more due to their great mobility, simplicity in deployment, and low maintenance. Furthermore, UAVs are able to carry a large variety of possible sensors for any important missions. Numerous uses for unmanned aerial vehicles (UAVs) exist, including medical support, search and rescue (SaR), emergency cellular deployment, crowd monitoring, target tracking, goods delivery, wildfire monitoring, and intelligent transportation. Unfortunately, due to their reliance on human control and the limitations of radio frequency (RF) communication, unmanned aerial vehicles (UAVs) are unable to operate at their best in a complex and dynamic environment [1]. For the best results, autonomous UAV navigation in large-scale dynamic environments is essential. Traditional methods to accomplish autonomous navigation frequently make use of sensing and avoidance techniques, mapping and localization techniques, and avoidance and sensing techniques.

CHARACTERISTICS OF UAVS AND MODELS OF NAVIGATION

Since the creation of airplanes, engineers and scientists have faced a great deal of difficulty in realizing unmanned aerial systems. Today, a wide variety of UAVs are available for both military and non-military use. As indicated in Table 2, UAVs are frequently categorized according to features including form, range, cost, maximum take-off weight, and pricing. A UAV's payload is one of its most important characteristics. The payload, or maximum weight a UAV can lift, is a measure of its lifting capability. A few grams to hundreds of kilograms can be carried by a UAV payload [2]. At the expense of the UAV's size, battery capacity, and flight duration, a larger payload allows for the carrying of more accessories and equipment. Cameras, sensors, cell phones, and base stations for cellular support are examples of conventional payloads.

**Table 2. Characteristics of different types of UAVs**

| Types | Characteristics | Advantages |
|---|---|---|
| Fixed-wing [33] | Weight: 0.5-2500 kg<br>Range: up to 1850 km<br>Speed: up to 500 km/h<br>Flight: up to 2000 min<br>Payload: up to 1500 kg<br>Power supply: LiPo/fuel | 1.Long Range<br>2.High payload<br>3.High Speed<br>4.Long Flight time |
| Helicopter [58] | Weight: 25-200 kg<br>Range: up to 400 km<br>Speed: up to 120 km/h<br>Flight: up to 250 min<br>Payload: up to 65 kg<br>Power supply: LiPo/fuel | 1.High maneuverability<br>2.Vertical payload lift<br>3.Easy deployment |
| Loon [59] | Weight: up to 75 kg<br>Range: up to 100 km<br>Speed: up to 30 km/h<br>Flight: up to 100 days | 1.Very long flight time<br>2. Vertical payload lift<br>3.Low maintenance<br>4. Ample power supply |

| | | |
|---|---|---|
| | Payload: up to 10 kg<br>Power supply: Solar battery | |
| Multi-coper [33] | Weight: up to 25 kg<br>Range: up to 10 km<br>Speed: up to 160 km/h<br>Flight: up to 60 min<br>Payload: up to 5 kg<br>Power supply: LiPo battery | 1.Inexpensive<br>2.Low weight<br>3.Very High maneuverability<br>4.Easy deployment |

Based on their flight methods, UAVs can be broadly divided into four categories, as seen in Fig. 1.

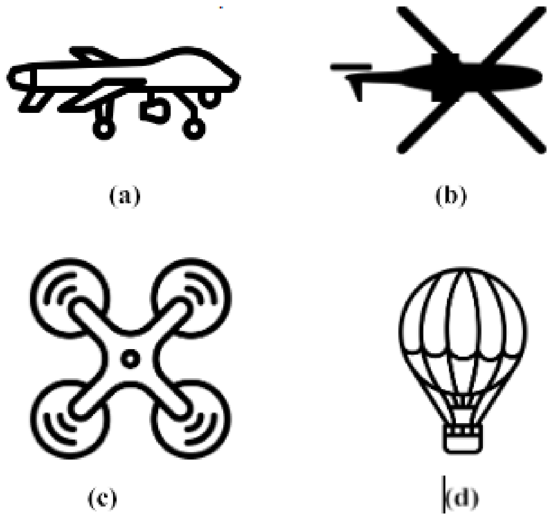


**FIGURE 1. Different types of UAVs: (a) fixed-wing, (b) helicopters, (c) multi-copters, and (d) loons.**

These categories include fixed-wing, helicopters, loons, and multi-copters. Because they can glide through the air, fixed-wing UAVs use less energy and can carry larger payloads. Furthermore, gliding can help fixed-wing UAVs move more quickly. They can't hover over a set spot, though, and they need more room to take off and land. Multi-copters and fixed-wing aircraft are combined to become helicopters. With their tail wings, they can fly through the air and land and take off vertically. Loons, on the other hand, lack motors for directed movement and are solely dependent on air pressure [3]. Finally, multi-copters are able to hover over a specific location while taking off and landing vertically. However, because they always fly against gravity, multi-copters have a limited flying time and consume a significant amount of energy.

Since flying is the primary function of UAVs, UAV navigation can be divided into four groups according to the applications they are used for: indoor navigation, outdoor navigation, SaR navigation, and wireless networking navigation (Fig. 2).

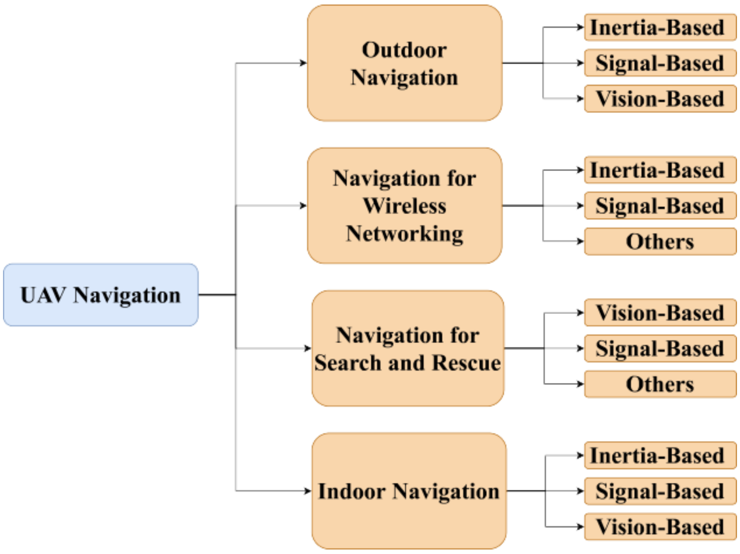


**FIGURE 2. Application-based categorization of UAV Navigation**.

In this case, indoor navigation comprises applications like inside mapping, factory automation, and indoor surveillance, and outdoor navigation includes applications like target tracking, good delivery, surveillance, and crowd monitoring. Furthermore, the navigation of UAVs can be divided into three categories: vision-based, signal-based, and inertia-based. Gyroscopes, accelerometers, and altimeters are the primary navigational aids used by UAVs for inertia-based navigation, guiding the onboard flight controller [4]. For signal-based navigation, UAVs utilize GPS modules and a remote radio head (RRH) when they have cellular connectivity; for vision-based navigation, they employ cameras.

Pitch and yaw controls are initially guided by the altitude and horizontal controllers, which get data from these sensors based on the intended path planning. Based on the feedback from these sensors, the elevators and ailerons are then guided by the pitch and yaw controls to steer the UAV, as seen in Fig. 3 [5]. When using different AI algorithms, UAVs can navigate autonomously and yet obtain the necessary path planning, as demonstrated in Fig. 3. Thus, the focus of this work is on various AI techniques used for UAV navigation by various researchers.

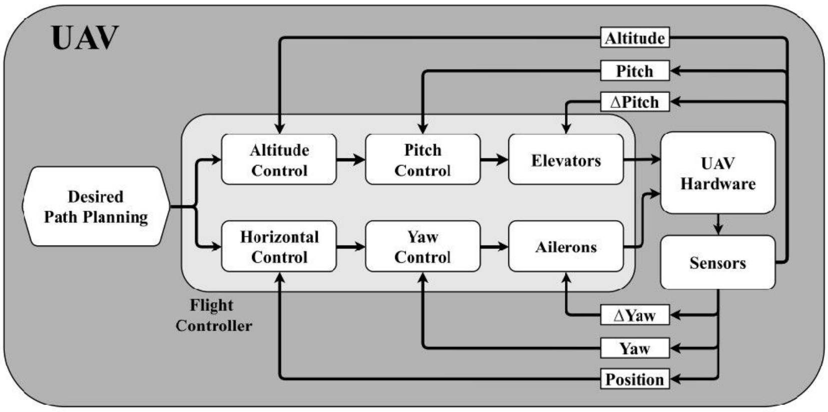


**FIGURE 3. UAV navigation system model [5].**

## OPTIMIZATION-BASED APPROACHES

The conventional mathematically based AI problem-solving methods are covered by optimization-based techniques. These algorithms are able to solve any given non-deterministic polynomial-time hard (NP-hard) issue almost optimally. These algorithms are, nevertheless, very intricate in terms of both space and time. The most popular optimization-based AI techniques for autonomous UAV navigation are covered in brief in this section. The algorithm, PSO, ACO, GA, and other random algorithms. Additionally, Table 3 presents a comparative analysis of these optimization-based AI systems, emphasizing their key characteristics, temporal complexities with multiple m procedures, and hyper-parameter counts.

**Table 3 Comparative study of different optimization based AI approaches**

| Algorithm | Type | Feature | Complexity | Hyper-parameter Cout |
|---|---|---|---|---|
| PSO | MPSO | Covert the infeasible paths generated by PSO into feasible paths using an error factor | $O(mn^2)$ | 6 |
| | DPSO | Takes discrete steps to propagate and multiple augmentations are done for better convergence | $O(mn+mn^2)$ | 5 |
| | GBPSO | Compares the current global path with the other global path candidates to select the optimal one | $O(2mn^3+mn^2)$ | 7 |
| ACO | Multi-Aco | Solves the TSP problem and both intra-colony and inter- colony pheromone values are considered | $O(mn^2)$ | 8 |
| | Double-ACO | Utilizes GA to generate the initial population | $O(mn^2)$ | 9 |
| | PFACO | Utilizes MMAS and APF for better global searching, fast convergence | $O(mn^2)$ | 4 |
| GA | GA | Chromosomes are made up of the acceleration, climbing angle rate, and heading angle rate of the UAVS | $O(mn^2)$ | N/A |
| | Improved-GA | Consists of an encoding vector based on the UAV yaw angle sequence | $O(mn^2)$ | 5 |
| | HR-MANGA | Uses a hierarchical recursive process to determine a refined path | $O(mn^2)$ | 7 |
| | OCGA | Utilizes TLBO and OC searching for fast convergence | $O(mn^2)$ | 4 |

## PARTICLE SWARM OPTIMIZATION (PSO)

PSO was first presented in 1995 by Eberhart and Kennedy. PSO is a population-based search method designed to mimic many animal species, including bees and birds. Every animal in PSO can be modeled as a vector particle in a three-dimensional space. A particle's movement is determined by PSO based on its velocity and present position. As illustrated in Fig. 5, the particle's velocity keeps updating in accordance with the swarm's (Gbest) and its own optimal position vector (Pbest). When PSO meets its objective or the lowest possible error, it is at its optimal position.

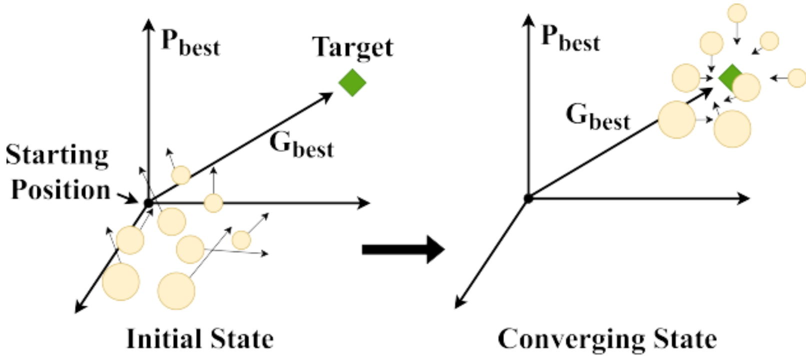


**Figure 5. Particle swarm optimization (PSO)**

PSO manages the movement of UAVs in a three-dimensional space by treating them like particles during UAV navigation. Autor Jalal altered the traditional PSO in [5] to enable offline UAV navigation around obstructions. Similar to a traditional PSO, the modified PSO (MPSO) models an extra error element to guarantee convergence. The error factor's primary job is to change the unfeasible paths produced by PSO into workable ones. For verified optimality, MPSO moves and re-initializes particles that are inside an obstacle boundary. The authors simulated scenarios with both single and multiple obstacles to guarantee the effectiveness of the MPSO. Similar to this, Phung et al. changed the traditional continuous PSO into discrete PSO (DPSO) in order to address the issue of UAV path planning in [6]. The authors took discrete 3D space and obstacles into consideration when modeling the UAV path planning problem as a traveling salesman problem (TSP). In addition, the DPSO's convergence was accelerated by using random mutation, edge exchange, deterministic initialization, and parallel GPU implementation techniques. A competition strategy-based PSO (GBPSO) was presented by Huang et al. in 2018 [7] to choose the global optimal path for UAVs. To determine the best path for particles, the suggested competition technique contrasts the existing global path with other global path possibilities.

## ANT COLONY OPTIMIZATION (ACO)

As the name implies, ACO was inspired by the way ants forage for food. Ants communicate and work together while searching for food by using a highly volatile chemical called pheromone. When ants first find a food supply, they begin to look for routes there and release pheromones along the way. Other ants follow the pheromone traces left by the first ant and find alternative routes to the food source. As a result, as Figure 6 illustrates, the ant colony that finds the shortest path will have a higher concentration of pheromones. Furthermore, over time, the pheromone concentration on the deserted routes decreases.

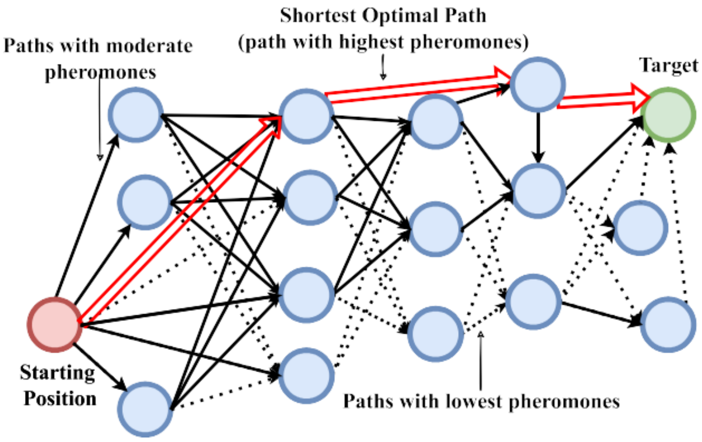


**Figure 6. Ant colony optimization (ACO)**

Cekmez et al. developed a multi-colony ACO-based method in [8] for autonomous UAV navigation while avoiding obstacles in a 3D space. The authors claim that the premature convergence issue brought on by single-colony ACO is resolved by multi-colony ACO. The UAV navigation problem was first stated by the authors as a TSP problem, after which several UAV groups looked for the best routes to the target. The UAVs are in charge of both intra- and inter-colony pheromone value exchange in multi-colony ACO. Similar to this, Guan et al. presented a double-colony ACO in [9] where pheromones are produced by taking use of the GA.

To solve the premature convergence issue, it is suggested combining an artificial potential field (APF) with an ACO called potential field ACO (PFACO). The APF algorithm is designed to avoid obstacles and maintain the UAV's optimal speed and safety in environments where there are repulsive and gravitational forces. Moreover, to enhance global searching, the APF modifies a UAV's transition probability from one ACO node to another. Additionally, the authors updated the global pheromone value for faster convergence while identifying the best and worst paths using the min-max ant system (MMAS) and weakening the worst path.

## GENETIC ALGORITHM (GA)

The initial population of the GA, a stochastic optimization technique, is a population of randomly generated chromosomes. Every chromosomal gene is represented by a string of digits. In this work, every chromosome or individual represents a UAV trajectory constrained by the UAV dynamics. Every generation, the population will change regularly due to genetic processes such crossover, mutation, selection, insertion, and deletion; the modified chromosomes will be chosen based on a fitness function. Through the identification of the chromosome with the near-minimum fitness value, this approach seeks to minimize the fitness function as much as feasible. The chromosomes thus arrive to a close to ideal solution. In [10], the GA approach is discussed in detail.

We can use GA to address the NP-hard UAV navigation problem. Initially, as illustrated in Fig. 7, the author encodes the three-dimensional position of the UAV into chromosomes comprising the acceleration, climbing angle rate, and heading angle rate at discrete time steps of a UAV. This chromosome is decoded at the current time-step so that the UAV can obtain 3D coordinates at the following time-step. Next, a fitness function that takes into account the costs of path length, barriers, height, and distance between two points is used to evaluate the 3D coordinate. Then come the genetic operations: insertion and deletion take care of managing path information, crossover deals with sharing path information, mutation deals with information loss, and selection deals with choosing paths.

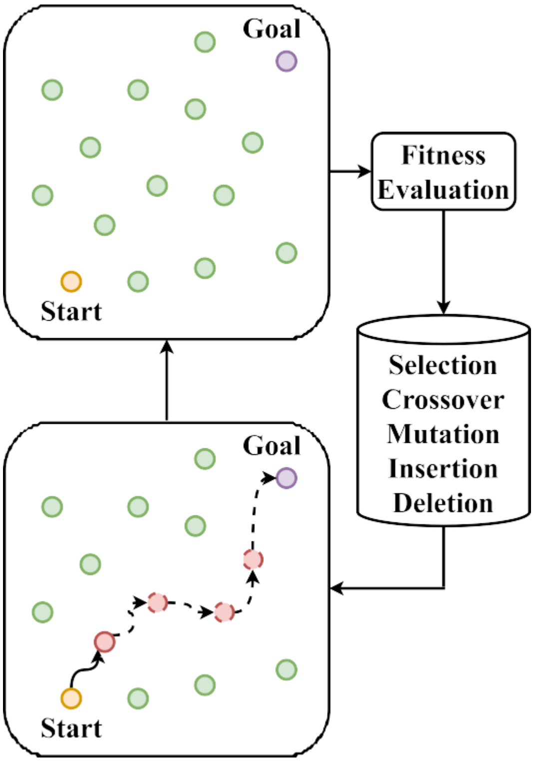


**Figure 7. Genetic algorithm (GA) for UAV navigation.**

By creating a temporary path based on the encoding vector and including the status variables in addition to the guide point position information in each guidance, Tao et al. enhanced the GA [11]. It therefore records whether the guiding point is viable if it satisfies the constraint requirement and whether the path with the lowest performance cost between the connecting point and the subsequent guide points is feasible. If every one of the guiding points is accurate, then the temporary path is feasible. The shift in the UAV yaw angle sequence serves as the basis for the encoding technique.

Agents can sense their surroundings, interact with nearby neighbors, and reduce their loss by using the appropriate operators, who quickly find a workable solution, as HR-MAGA evolves. Furthermore, HR-MAGA can use the hierarchical recursive process to optimize the local path in order to generate a more refined path.

To generate an initial population of good quality, an opposing and chaotic search strategy is employed. A certain range of solutions can be covered via chaos searching. Conversely, opposite searching can yield more appropriate reverse sequences based on chaotic searching. Thus, the authors suggested a novel crossover strategy based on the teaching-learning-based optimization learning mechanism (TLBO) in order to speed up convergence.

## CONCLUSION

In complicated and dynamic environments, autonomous UAV navigation has improved performance and brought about significant flexibility. To introduce the reader to UAV architecture, this survey focuses on the key traits and varieties of UAVs. In addition, an overview of the application-based classification and UAV navigation system was provided to facilitate researchers' understanding of the ideas presented in this survey. The foundations, guiding principles, and essential elements of several AI algorithms used by various researchers for autonomous UAV navigation were explained in terms of optimization-based and learning-based techniques. Various optimization-based techniques, including the PSO, ACO, and GA algorithms, were examined and emphasized. To accomplish their goals as best they could, numerous researchers have adjusted these techniques.

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