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A COMPREHENSIVE REVIEW OF ARTIFICIAL INTELLIGENCE-BASED UAV NAVIGATION METHODS

Abstract: *This article explores modern AI-based approaches for the autonomous navigation of Unmanned Aerial Vehicles (UAVs), delving into the evolution, methodologies, and emerging trends that define this dynamic field. It provides a comprehensive review of state-of-the-art techniques in UAV navigation by categorizing them into two primary paradigms: optimization-based methods and learning-based methods. The article begins with a historical overview that outlines key milestones and technological breakthroughs — from early deterministic, rule-based algorithms to advanced AI-driven systems — laying the foundation for understanding current approaches.*

The article describes optimization-based methods, considering both classical and advanced techniques, including algorithms such as Dijkstra, A, Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Differential Evolution (DE), Simulated Annealing (SA), Genetic Algorithms (GA), Grey Wolf Optimization (GWO), and Pigeon-Inspired Optimization (PIO). It details their fundamentals, operating principles, and the recent modifications that researchers have employed to meet specific navigational objectives. Similarly, the review categorizes learning-based methods by examining Reinforcement Learning (RL), Deep Reinforcement Learning (DRL), Asynchronous Advantage Actor-Critic (A3C), and Deep Learning (DL) techniques, emphasizing various proposed approaches, their benefits, and the goals they aim to achieve.*

As a result, this article offers a comprehensive analysis of existing navigation methods, describing their features, drawbacks, and inherent complexity. Although AI-driven navigation can be computationally expensive, the significant improvements in flexibility and overall performance enhance UAV robustness in complex dynamic environments. These findings provide insights for researchers and developers, helping to choose the most suitable approach for their work while highlighting the promise of hybrid strategies that combine the deterministic reliability of optimization techniques with the adaptability of learning-based methods.

Finally, the review identifies current research gaps — such as the need for improved big data processing, increased computing power, enhanced energy efficiency, and better fault handling — and outlines future research directions to accelerate advancements in autonomous UAV navigation. These insights provide clear guidance for future studies aimed at developing more robust, scalable, and efficient UAV navigation systems.

Keywords*: navigation, artificial intelligence, unmanned aerial vehicles, UAV, path planning, autonomous navigation, trajectory planning, obstacle avoidance.*

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ВСЕБІЧНИЙ ОГЛЯД МЕТОДІВ НАВІГАЦІЇ БПЛА НА БАЗІ ШТУЧНОГО ІНТЕЛЕКТУ

Анотація: *Ця стаття досліджує сучасні підходи на основі штучного інтелекту (ШІ) для автономної навігації безпілотних літальних апаратів (БПЛА), заглиблюючись в еволюцію, методології та нові тенденції, які визначають цю динамічну галузь. Вона пропонує всебічний огляд передових методів навігації БПЛА, класифікуючи їх на два основні напрями: методи, засновані на оптимізації, та методи, засновані на навчанні. Стаття починається з історичного огляду, що висвітлює ключові віхи та технологічні прориви — від ранніх детермінованих алгоритмів, що працюють за заданими правилами, до сучасних систем, керованих ШІ, — закладаючи основу для розуміння сучасних підходів.*

У статті розглядаються методи, засновані на оптимізації, включаючи як класичні, так і сучасні техніки, зокрема алгоритми Дейкстри, A, PSO, ACO, DE, SA, GA, GWO та PIO. Детально описано їхні основні принципи, механізми роботи та нещодавні модифікації, що застосовуються для вирішення конкретних навігаційних завдань. Також проведено класифікацію методів, заснованих на навчанні, з аналізом алгоритмів RL, DRL, A3C та DL із акцентом на запропоновані стратегії, їхні переваги та цілі.*

Як результат, ця стаття пропонує всебічний аналіз існуючих методів навігації, описуючи їхні особливості, недоліки та обчислювальну складність. Хоча навігація, керована штучним інтелектом, може вимагати значних обчислювальних ресурсів, суттєві покращення в гнучкості та загальній продуктивності підвищують стійкість БПЛА у складних, динамічних умовах. Ці висновки надають цінну інформацію для дослідників і розробників, допомагаючи їм обирати найбільш відповідний підхід для своєї роботи. Окрему увагу приділено перспективності гібридних стратегій, що поєднують детерміновану надійність оптимізаційних методів із адаптивністю методів, заснованих на навчанні.

На завершення, огляд визначає актуальні проблеми досліджень — такі як необхідність удосконалення обробки великих даних, збільшення обчислювальної потужності, підвищення енергоефективності та покращення обробки збоїв — та окреслює напрямки майбутніх досліджень, спрямованих на прискорення розвитку автономної навігації БПЛА. Ці висновки надають чіткі орієнтири для подальших досліджень, спрямованих на розробку більш стійких, масштабованих та ефективних систем навігації БПЛА.

Ключові слова: *навігація, штучний інтелект, безпілотні літальні апарати, БПЛА, планування шляху, автономна навігація, планування траєкторії, уникнення перешкод.*

1. Introduction

Unmanned Aerial Vehicles (UAVs) have evolved from niche experimental platforms into crucial components of numerous modern applications, including surveillance, environmental monitoring, search and rescue, and beyond. The main component of the success of UAV systems is the ability to navigate complex and dynamic environments reliably. For instance, UAVs have rapidly become a transformative force in modern logistics, offering efficient and innovative solutions to the challenges of last-mile delivery. With the potential to reduce operational costs, optimize times, and minimize environmental impacts, autonomous UAV-based cargo delivery is increasingly attracting attention from both industry and academia. Moreover, UAVs can meet global e-commerce demands, deliver medical supplies during emergencies, and support industrial automation processes. Additionally, integrating UAVs into such systems enables the retraining of corresponding workers for roles in other sectors where automation is not feasible, contributing to economic recovery and growth.

However, achieving reliable and adaptable navigation in dynamic real-world environments remains a significant challenge. Traditional navigation systems — relying on preprogrammed routes or simple rule-based approaches — often fall short in real-world settings with unpredictable obstacles, variable weather, and uncertain terrain.

In recent years, Artificial Intelligence (AI) has emerged as a powerful enabler, providing advanced methodologies for real-time path planning and decision-making. By leveraging advanced optimization and learning techniques, AI-based navigation systems enable UAVs to process sensory data, learn from their environment, and make intelligent real-time decisions. The use of AI allows UAVs to dynamically adjust flight paths, optimize efficiency, respond to unpredictable factors, and enhance operational safety. However, the development and deployment of effective AI-based navigation algorithms come with challenges, including ensuring computational efficiency, scalability, and robustness in complex dynamic environments.

2. Purpose of the study

This article provides a comprehensive review of the state-of-the-art AI methodologies applied to UAV navigation. It examines two broad categories: optimization-based approaches that use mathematical models and heuristics to plan paths, and learning-based approaches that employ machine learning and deep learning techniques for adaptive decision-making.

3. History

The evolution of UAV navigation has advanced from simple, deterministic methods to advanced AI-driven techniques, enabling fully autonomous flight in complex environments. Early systems relied on simple algorithms for path planning in controlled, static settings. With the advent of advanced sensors, UAV navigation began integrating real-time data and adaptive control. Today, AI technologies have further revolutionized UAV guidance, offering enhanced adaptability, efficiency, and robustness. This section traces the historical development of UAV navigation technologies, providing essential context for understanding and appreciating today's innovative solutions in detail.

3.1 Early Navigation Techniques (1950s–1970s)

In the early days of UAV development, navigation was predominantly based on deterministic, rule-based algorithms. Pioneering methods such as Dijkstra's algorithm and the A* search algorithm were applied to UAVs operating in controlled environments. These algorithms were designed to calculate the shortest or least-cost paths between predefined waypoints on static maps. While effective in simple scenarios, these early approaches lacked the flexibility required to handle dynamic and uncertain environments.

As early as the 1960s, researchers began formulating UAV path planning as a shortest-path problem subject to terrain and threat constraints [1]. During these formative years, UAVs were mainly deployed in benign settings—such as open fields or controlled test ranges—where the navigation challenges were limited. The predictable performance of these early algorithms provided a strong foundation, but their inherent rigidity became apparent as the applications for UAVs began to expand. By the 1970s, deterministic planners like A* had been adopted in experimental unmanned aircraft guidance systems, enabling UAVs to compute feasible routes around obstacles and no-fly zones. Several refinements (e.g. D* and D-Lite* for dynamic replanning) were later developed specifically for UAV navigation in changing environments, laying the groundwork for reliable autonomous flight path computation.

3.2 Transition to Sensor-Based and GPS-Assisted Navigation (1980s–2000s)

By the 1980s and 1990s, UAV navigation had expanded beyond pure computation into sensor-based guidance. Early drones were often remote-controlled or flew pre-set routes, but advances in onboard sensors and microprocessors enabled real-time perception and autonomy. UAV autopilot systems began integrating inertial measurement units (IMUs), altimeters, and compasses to estimate the vehicle's state, and Global Positioning System (GPS) soon became a game-changer for navigation accuracy. After the GPS became fully operational in the 1990s, UAVs could utilize GPS for waypoint navigation, allowing them to follow predefined routes with high precision. By the early 2000s, lightweight autopilots (e.g. Piccolo, Paparazzi, Pixhawk) combined IMU and GPS data to perform autonomous flight maneuvers such as grid searches and route tracking. Although these early sensor fusion systems improved situational awareness, the processing power required to analyze and interpret large volumes of data remained a challenge, limiting the real-time applicability of traditional navigation algorithms. UAVs were equipped with range sensors (LIDAR, radar) and cameras to support obstacle detection and avoidance. This shift from abstract graph-based path planning to real-time environmental awareness marked a significant advancement in navigation. By the 2000s, the combination of GPS for global positioning and local sensors for collision avoidance had become a standard architecture for UAV navigation, forming the foundation for both military drones and the first consumer drones with autonomous flight capabilities.

3.3 The Emergence of Artificial Intelligence (2010s–Present)

The past decade has witnessed an explosion in AI research and its application to UAV navigation. Advances in machine learning, deep learning, and computational hardware have paved the way for UAVs to operate autonomously in highly complex and dynamic environments. AI enables these vehicles not only to process vast amounts of sensor data in real time but also to learn from past experiences and continuously refine their navigation strategies. The result of these efforts is a new level of autonomy: modern UAVs can learn navigation strategies for scenarios that are too complex to hand-code, such as dense forests, urban canyons, or dynamic environments with moving obstacles. AI-driven techniques have also improved path planning under uncertainty, where the UAV must contend with sensor noise or unknown terrain.

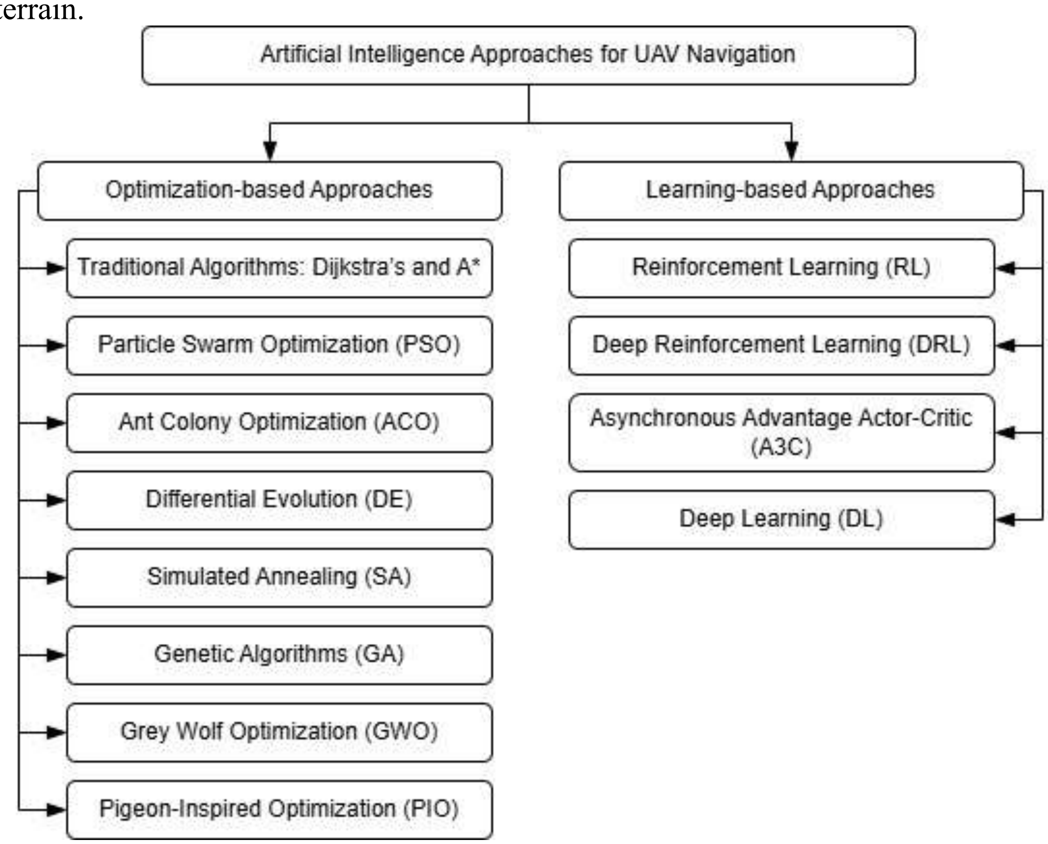

Fig. 1 – Artificial intelligence approaches for UAV navigation.

This evolution has led to the development of two primary paradigms for AI-based navigation: optimization-based approaches that rely on well-established mathematical models and heuristic search techniques, and learning-based approaches that utilize data-driven models to adapt to new and unforeseen challenges [2]. The integration of these approaches has opened new avenues for research and has significantly enhanced the performance and reliability of UAV navigation systems. This paper presents the core concepts and operating mechanisms of various AI techniques for autonomous UAV navigation, developed by different researchers. These methods are categorized into optimization-based and learning-based approaches, as illustrated in Fig. 1.

4. Optimization-Based Approaches

Optimization-based approaches serve as a cornerstone for addressing traditional mathematical problem-solving algorithms in artificial intelligence, offering near-optimal solutions for non-deterministic polynomial-time hard (NP-hard) problems. However, their practical application often comes with significant computational demands, both in terms of time and memory usage. Optimization-based approaches have long served as the backbone of navigational systems for UAVs. These methods aim to compute the most efficient path by minimizing a predefined cost function that may incorporate factors such as distance, energy consumption, risk, and time. This section presents a detailed review of optimization-based methods for UAV navigation, with a focus on addressing complex path planning challenges.

4.1 Traditional Algorithms: Dijkstra's and A*

Developed in the 1950s, **Dijkstra's** algorithm is renowned for its ability to find the shortest path in a weighted graph. In UAV navigation, the environment is often represented as a graph with nodes corresponding to waypoints and edges representing the possible paths [3]. Dijkstra's algorithm guarantees an optimal solution given a static environment, making it a valuable tool in scenarios where the environment is predictable. However, its computational intensity and lack of adaptability to real-time changes limit its applicability in dynamic settings.

In turn, built on Dijkstra's approach, the **A*** search algorithm introduces heuristic functions to guide the search process toward the target more efficiently. By estimating the remaining cost to the goal, A* often reaches a solution faster than Dijkstra's algorithm while still ensuring optimality under appropriate conditions. Despite its improvements, A* is still fundamentally based on static maps and struggles with environments that change rapidly, necessitating frequent re-planning.

Classic path planning algorithms such as A* and Dijkstra's have been widely used due to their simplicity and proven reliability. These algorithms work well in static environments where the map does not change frequently. However, their deterministic nature and reliance on pre-defined waypoints render them less effective in dynamic scenarios. Their inability to adjust to real-time changes necessitates frequent re-planning, which increases computational overhead and reduces overall efficiency.

To overcome the limitations of purely static algorithms, researchers have developed hybrid models that integrate classical path planning with dynamic feedback mechanisms. For example, Zhang et al. [4] extend this concept by introducing a hybrid real-time A* algorithm enhanced with Model Predictive Control (MPC). This hybrid model employs a rolling optimization framework through MPC, enabling the UAV to continuously update its flight path based on real-time sensor feedback. This integration marries the robustness of classical algorithms with the flexibility of dynamic adaptation, though it introduces increased computational and integration complexity that can challenge the scalability of smaller UAV systems with limited processing power.

4.2 Particle Swarm Optimization (PSO)

Population-based algorithms draw inspiration from natural processes to search for optimal solutions in complex, high-dimensional spaces. These methods have found applications in UAV navigation due to their ability to explore multiple candidate paths concurrently.

Particle Swarm Optimization (PSO), originally introduced by Eberhart and Kennedy in 1995, simulates the collective behavior of swarming animals, such as birds and bees, to solve optimization problems. In this technique, a swarm of particles (candidate solutions) moves through the search space, with each particle adjusting its position based on its own experience and that of its neighbors. PSO has been successfully applied to UAV navigation for finding collision-free paths while optimizing energy usage. For example, Jalal [5] modified the conventional PSO (MPSO) for offline UAV navigation, demonstrating its effectiveness in avoiding obstacles and generating efficient paths. Despite its advantages, these methods are sensitive to initial conditions and requires careful parameter tuning to achieve reliable performance in dynamic environments.

4.3 Ant Colony Optimization (ACO)

Ant Colony Optimization (ACO), another population-based approach inspired by the foraging behavior of ants, which use pheromone trails to communicate and find optimal routes, has been applied to UAV navigation. In UAV navigation, ACO algorithms are adapted to handle the three-dimensional movement of aerial vehicles and complex obstacle configurations. The dual-ant ACO (DACO) algorithm proposed by Guan et al. [6] enhances traditional ACO by integrating a genetic algorithm to generate pheromones in its early stages. This modification accelerates the algorithm's convergence and improves its pathfinding efficiency. Despite these innovations, ACO-based methods still face limitations in addressing dynamic obstacles and considering UAVs' kinematic and dynamic constraints, particularly in highly dynamic scenarios, which restrict its application in complex real-world environments.

4.4 Differential Evolution (DE)

Differential Evolution (DE), yet another population-based evolutionary algorithm introduced in 1997, evolves a population of candidate solutions through mutation, crossover, and selection. In each iteration, a potential solution is mutated by combining it with scaled differences of randomly chosen solutions and then recombined to form a trial solution. If the trial solution is better, it replaces the original candidate. This process, which requires only a few control parameters and no gradient information, makes DE well-suited for complex, non-linear optimization problems. Its robustness in handling non-differentiable cost functions and multiple constraints, along with its fast convergence and ease of implementation, has led to its successful use, especially in environments with moving obstacles. For example, Ghambari et al. [7] combined DE with the A* algorithm for offline UAV navigation, demonstrating improved obstacle avoidance and efficient route generation in dense urban environments.

4.5 Simulated Annealing (SA)

Simulated Annealing (SA) is a probabilistic optimization technique inspired by the annealing process in metallurgy. It starts at a high “temperature” and gradually cools down, which corresponds to slowly decreasing the probability of accepting worse (higher cost) solutions as the search progresses. This mechanism of occasionally accepting worse solutions enables SA to escape local minima and explore the solution space more broadly in pursuit of a global optimum. In UAV navigation, SA can optimize flight routes by treating the path (or waypoints) as variables in a search space and then iteratively refining them. Unlike many population-based algorithms, SA operates on a single candidate solution and has fewer parameters to tune (mainly the cooling schedule), yet its stochastic search can explore complex cost surfaces effectively.

Behnck et al. [8] adapted SA for multi-UAV path planning by framing the problem as a multiple Traveler Salesman Problem. Their method encodes routes for multiple UAVs, swaps or reassigns points of interest, and uses a cost function that combines travel distance with task assignment penalties. The provided experiments showed efficient execution on a low-resource device (Raspberry Pi), and claimed compliance with commercial UAV communication standards simplifies integration into real-world applications.

4.6 Genetic Algorithms (GA)

Genetic Algorithms (GAs) is a stochastic optimization method inspired by the process of natural evolution. In this approach, each potential solution is represented as an individual, where its genotype — typically a string of binary or real values — for our domain will be explored as an encoded possible UAV trajectory according to the constraints of UAV dynamics. The algorithm starts with a randomly generated population of such individuals and evolves them over successive generations using genetic operations like selection, crossover, mutation, insertion, and deletion. Parent selection is performed based on a fitness criterion that ensures both controlled population growth and diversity, while the crossover and mutation rates govern the combination and variability of genetic information. These operations gradually refine the population by favoring individuals with lower fitness values, thus steering the search toward near-optimal solutions to minimize function.

The GA method, as explained by Bagherian and Alos [9], has proven effective in addressing NP-hard UAV navigation problems by converging to robust trajectories that balance multiple navigational objectives. That was performed by encoding 3D positions and evaluating them based on distance, path length, altitude, and obstacle avoidance. As result, proposed GA algorithm was compared with the PSO algorithm showing that the GA finds the better solution but requires more calculations in a general case.

As additional instance, a hierarchical recursive multi-agent genetic algorithm (HR-MAGA) introduced by Yang et al. [10]. In HR-MAGA, agents continuously sense their environment and interact with neighboring agents, using specialized operators to reduce their losses and quickly converge on effective solutions. Additionally, by employing a hierarchical recursive process, the algorithm optimizes local paths, yielding increasingly refined trajectories. Comparing to the traditional GA, HR-MAGA exhibits notable advantages in search efficiency while maintaining competitive solution quality.

4.7 Grey Wolf Optimization (GWO)

Grey Wolf Optimization (GWO) is a meta-heuristic swarm intelligence algorithm inspired by the social hierarchy and cooperative hunting behavior of grey wolves, first proposed in 2014 [11]. In GWO, candidate solutions are classified into four groups: alpha, beta, delta, and omega wolves based on fitness rank. The alpha wolf, representing the best solution found so far, leads the search, while the beta and delta wolves assist by guiding the swarm toward the target. The remaining omega wolves update their positions based on these leaders, mimicking the encircling and attacking of prey. This nature-inspired method uses only a few control parameters (notably, parameter A for balancing exploration and exploitation and parameter C for obstacle avoidance) to effectively guide the search process. In UAV path planning applications, each "wolf" can represent a candidate flight path (for instance, encoded as a series of waypoints), and the iterative update process helps converge toward collision-free, efficient routes with smooth nature trajectories. Although GWO is praised for its simplicity and minimal tuning, it can sometimes become trapped in suboptimal regions if the alpha wolves prematurely converge around a local optimum.

In a real-world application, Qu et al. [12] introduced a hybrid GWO algorithm called HSGWO-MSOS, which integrates a modified symbiotic organisms search (MSOS) to efficiently balance global exploration and local exploitation, thereby achieving faster convergence on optimal paths. Their analysis and simulations revealed that HSGWO-MSOS outperforms conventional GWO, the original SOS, and SA, yielding better optimal solutions and computational efficiency, which confirms the advantages of the hybrid approach.

4.8 Pigeon-Inspired Optimization (PIO)

Pigeon-Inspired Optimization (PIO) is a relatively new swarm intelligence algorithm proposed by Duan and Qiao in 2014 [13] that emulates the homing behavior of carrier pigeons, inspired by how pigeons navigate using multiple cues — the Earth's magnetic field, the sun, and landmarks. PIO balances global exploration with local exploitation in a two-phase process. In the initial phase (map and compass operator), candidate solutions update their positions in a manner akin to pigeons orienting themselves with a compass. Once a preset threshold is reached, the algorithm transitions to the landmark phase, refining solutions by converging them around a leading candidate. In a UAV context, one can imagine each pigeon in the population as a candidate flight path or set of waypoints. During the map-and-compass phase, these path solutions are guided globally (ensuring the UAV's route broadly heads toward the goal while exploring different trajectories), and during the landmark phase, the solutions fine-tune around the best-so-far route to yield a precise, obstacle-free path. PIO's inspiration from pigeon homing makes it well-suited for waypoint navigation tasks; for instance, the algorithm can integrate natural waypoints or radio beacons as "virtual landmarks" to improve convergence on a final route.

Although promising, standard PIO may lack diversity and maturity, leading to further enhancements to boost robustness and performance in UAV navigation tasks. As for instance, Hu et al. [14] proposed an Adaptive Operator Quantum-Behaved PIO (AOQPIO) that employs adaptive operators to address these shortcomings. Additionally, integrating chaotic strategies helps generate a more diverse initial population, thereby broadening the search space.

4.9 Summary of Optimization-Based Approaches

Optimization-based methods offer a structured, mathematically rigorous framework for UAV navigation. They excel in scenarios where the environment is relatively predictable or where computational resources are sufficient, presenting several advantages as well as some limitations.

Advantages:

– Deterministic Outcomes: these methods tend to produce repeatable and predictable outcomes, which is particularly beneficial for safety-critical applications;

– Established Theoretical Foundations: the underlying mathematical rigor provides a solid framework for path planning;

– Applicability in Well-Defined Environments: in controlled environments with relatively static obstacles, optimization-based methods can be highly effective.

Limitations:

– Lack of Adaptability: traditional methods are less suited for rapidly changing environments;

– Computational Demands: when extended to dynamic scenarios, the need for frequent re-planning can lead to significant computational burdens;

– Scalability Issues: the complexity of some approaches may make practical implementation difficult on UAV platforms with limited resources.

Due to these inherent limitations in adaptability and the high computational demands of dynamic re-planning, there has been growing interest in alternative approaches — particularly those based on machine learning — which will be discussed in the following section.

5. Learning-based approaches

Learning-based approaches focus on the traditional model-based algorithms in artificial intelligence, leveraging their adaptability and efficiency in solving complex problems. These algorithms excel at delivering near-optimal solutions for NP-hard problems while maintaining relatively low computational complexity, making them highly suitable for dynamic and resource-constrained environments. Learning-based approaches represent a shift from static, pre-determined navigation methods to adaptive, data-driven strategies capable of responding to dynamic environmental conditions. These methods leverage machine learning algorithms to improve UAV decision-making in real time. This section provides a comprehensive review of the most widely used techniques, which have been integrated into UAV systems to enhance obstacle detection, environmental perception, and real-time decision making.

5.1 Reinforcement Learning (RL)

Reinforcement Learning (RL) is a paradigm where an agent learns optimal actions by interacting with its environment and receiving feedback in the form of rewards or penalties. The agent observes the current state of the environment, takes an action, and receives a reward signal and a new state as feedback. By continually updating its policy (e.g. using algorithms like Q-learning or State-Action-Reward-State-Action SARSA to update value estimates), the agent improves its behavior. This trial-and-error learning allows the agent to autonomously discover effective strategies without explicit programming of the solution. For UAV navigation, RL has been applied to key tasks such as path planning, trajectory optimization, and obstacle avoidance. The UAV is treated as an agent that learns to choose actions — such as changes in trajectory — by maximizing a cumulative reward signal that may incorporate factors like safety, energy consumption, flight time, and path optimality. In an RL framework, the UAV observes its state (which may include position, velocity, sensor readings, etc.), selects an action according to a policy, and receives feedback from the environment. Through iterative training, the UAV refines its policy to improve performance. RL, due to its self-learning capabilities and energy efficiency, is particularly effective in dynamic scenarios where UAVs must adapt to dynamic obstacles, weather changes, and dense urban areas. RL-trained policies enable a UAV to make reactive decisions (e.g. deviating from its path to dodge an obstacle) based on local sensor inputs. Notably, these behaviors can be learned in simulation and then transferred to real UAVs, allowing the drone to autonomously navigate without requiring a pre-programmed map of obstacles.

As an instance, several Q-learning–based approaches have been developed to optimize trajectory and path planning, and power control under dynamic conditions. In indoor UAV navigation, Chowdhury et al. [15] proposed an RSS-based Q-learning algorithm that leverages received signal strength (RSS) measurements to guide navigation decisions in GPS-denied 2D environments (with constant altitude) for search and rescue missions. Their approach employs a specialized greedy method to address the exploration-exploitation dilemma, allowing the UAV to learn optimal trajectories based on dynamic RSS inputs while adapting to complex indoor settings. Simulation results demonstrate that this algorithm converges to near-optimal routes while maintaining reliable connectivity, highlighting its potential for enhancing indoor UAV navigation performance.

Similarly, Liu et al. [16] introduced a multi-agent Q-learning framework for jointly optimizing the deployment and movement of multiple UAVs, achieving faster convergence, enhanced coverage, and improved efficiency with low complexity compared to traditional methods. Their approach involves a three-step framework: first, users are partitioned using genetic K-means clustering. Next, a Q-learning based deployment algorithm forces each UAV (agent) to learn its optimal 3D placement with offline training capabilities. And finally, a Q-learning based movement algorithm adjusts UAV positions as users move. By allowing each UAV to learn a direction-selection policy through trial-and-error, the framework quickly converges to an effective configuration. In another study, Liu et al. [17] combined multi-agent Q-learning with position prediction using an echo state network, enabling UAVs to proactively adjust their paths based on predicted user movement, thereby enhancing UAV path planning.

Additionally, Hu et al. [18] developed a decentralized, real-time Q-learning algorithm for trajectory planning in multi-UAV networks. Their approach employs a "sense-and-send" protocol, whereby each UAV collects environmental data and transmits it to the BS according to a schedule that minimizes interference and ensures timely delivery. This protocol allows decentralized UAVs to adjust their trajectories based on real-time data from other UAVs, enhancing coordination and accelerating convergence. Finally, Zeng and Xu [19] applied a Q-learning approach that employs the temporal difference (TD) method combined with tile coding to effectively manage large state-action spaces in cellular-connected UAV navigation, ensuring optimal path design while reducing computational complexity and supporting both online and offline implementations. Collectively, these studies highlight the versatility and effectiveness of Q-learning variants in enhancing UAV navigation performance in complex, dynamic environments.

5.2 Deep Reinforcement Learning (DRL)

Deep Reinforcement Learning (DRL) extends the capabilities of classical RL by integrating deep neural networks (DNNs) as function approximators instead of relying solely on Q-tables. This approach allows UAVs to handle high-dimensional state inputs and continuous action spaces that traditional RL methods struggle with. In DRL, a DNN represents either the policy or the value function, enabling the agent to generalize across similar states rather than explicitly storing every state-action pair. For UAV navigation, DRL has been applied to tasks such as path planning, trajectory optimization, and obstacle avoidance. DRL has been instrumental in enabling UAVs to process high-dimensional sensory data — such as images from onboard cameras, point clouds from LiDAR, and other environmental inputs — and directly convert them into control commands. This capability allows UAVs to make reactive decisions and plan complex maneuvers in real time, even in dynamic or cluttered environments. Such architectures allow UAVs to learn robust policies even in the presence of noisy, high-dimensional inputs. Unlike traditional methods, which often fail in unpredictable environments, DRL leverages real-time visual data to improve collision avoidance, decision-making capabilities, and adaptive path planning. However, the computational requirements and need for extensive training data remain significant challenges for UAVs with limited onboard processing power.

Generally, RL utilize some decision-making process to be able to properly react input data. DRL can utilize the Markov Decision Process (MDP), which represents the environment. Due to the continuous state space in an MDP — which yields an infinite number of state-action pairs — traditional Q-learning is impractical. Instead, deep reinforcement learning (DRL) is employed to approximate the Q-function using a DNN. In particular, a dueling double deep Q network (dueling double DQN) architecture augmented with multi-step learning is utilized. As an instance, Zeng et al. [20] implemented an MDP-based dueling Double Deep Q-Network (DDQN) algorithm that concurrently facilitates UAV navigation and radio mapping in 3D environments. The approach discretizes the action space and uses a neural network to approximate the UAV's flying direction, while UAV signal measurements are used both to train the DQN and to construct a radio map for predicting outages. Similarly, Abedin et al. [21] developed an MDP-based DRL framework for UAV-BS navigation that improves energy efficiency and maintains data freshness. In their work, the UAV trajectory optimization is formulated as an NP-hard problem, and a DRL with experience replay is used. This approach enables UAV base stations to adapt their trajectories in real time, ensuring robust connectivity with IoT devices. Simulation results demonstrate that the proposed framework outperforms both greedy and baseline DQN approaches in terms of energy efficiency.

Additionally, He et al. [22] introduced a DRL algorithm for UAV navigation that formulates the problem as an MDP and utilizes a Twin Delayed DDPG (TD3) approach enhanced with demonstration data. By integrating imitation learning with TD3, proposed approach accelerates training and improves policy performance for 3D UAV navigation using depth camera inputs, yielding robust and energy-efficient navigation policies in dynamic environments. Collectively, these studies demonstrate that MDP-based DRL methods can significantly enhance UAV navigation in complex 3D scenarios.

Additionally, Maciel-Pearson et al. [23] developed a vision-based DRL algorithm employing an Extended Double Deep Q-Network (EDDQN) that leverages a double state-input strategy to fuse raw image data with positional maps. This design enables UAVs to effectively navigate complex outdoor environments under challenging conditions. Collectively, these Partially Observable MPD (POMDP)-based approaches demonstrate that explicitly accounting for environmental uncertainties can substantially enhance UAV navigation performance in dynamic, partially observable scenarios.

5.3 Asynchronous Advantage Actor-Critic (A3C)

Asynchronous Advantage Actor-Critic (A3C) is a DRL algorithm that extends the actor–critic framework by training multiple agents asynchronously. In A3C, each agent comprises an actor network, which selects actions based on the current state, and a critic network, which evaluates the state and computes advantage signals to guide learning. By asynchronously updating a shared global network using gradients from diverse agent experiences, A3C decorrelates training data and accelerates convergence [24]. This makes it particularly effective in complex, multi-agent environments like UAV navigation, where it has been applied to tasks such as path planning and obstacle avoidance. However, despite its efficiency and robustness, A3C requires careful hyperparameter tuning and extensive simulation data to ensure reliable performance in safety-critical operations. Moreover, while parallel training improves speed, it can introduce variability in updates (as each agent explores different experiences), ensuring the learned policy is robust may require extensive testing.

Wang et al. [25] developed an integrated DRL approach for autonomous UAV navigation in mobile edge computing (MEC) environments. In this framework, each UAV is equipped with an actor network and a critic network. All actor networks are trained on shared data from the entire UAV network, while each critic network is trained on its UAV's individual data via a multi-agent deep deterministic policy gradient approach. The framework jointly optimizes UAV trajectories, user association, and resource allocation, thereby enhancing geographical fairness, balancing UAV user loads, and reducing overall energy consumption for user equipment. As an additional instance, Wang et al. [26] introduced Fast-RDPG, a fast recurrent deterministic policy gradient algorithm based on the A3C framework. This approach formulates the navigation problem as a POMDP and employs an online DRL algorithm based on an actor–critic framework. Unlike traditional techniques, the method directly maps raw sensory data to control signals. Experimental findings indicate that the approach adapts well to increasingly intricate, expansive, and three-dimensional environments.

5.4 Deep Learning (DL)

Deep Learning (DL) refers to neural network models with many layers that learn rich feature representations from data. In UAV navigation, DL models can be trained on large datasets obtained from sensors (camera images, LiDAR, etc.) to accurately perceive and interpret complex environments which is critical for autonomous navigation. Essentially, a DL in the UAV's navigation pipeline acts as a highly non-linear function approximator that can predict outcomes (such as collision risk, optimal direction, or path cost) by generalizing from training examples. For example, Convolutional Neural Networks (CNNs) have become a standard tool for processing visual data, such as images and sensor data, enabling UAVs to detect obstacles, classify terrain, and generate detailed environmental maps. By integrating data from cameras and other onboard sensors, CNNs can identify potential hazards and distinguish between different types of obstacles, providing the UAV with a detailed understanding of its operating environment. This capability is particularly valuable in GPS-denied environments, such as dense urban areas or remote locations. However, the computational resource requirements of CNNs can strain lightweight UAV systems. As an instance, Lv and Tu [27] proposed a DL-based navigation system for UAVs that employs CNNs for target detection and integrates techniques such as particle filtering and probability density functions to locate navigational markers and predict the UAV's position.

The main advantage of deep learning in UAV navigation is its ability to process complex sensor data and learn intricate patterns. A well-trained deep network can recognize obstacles and terrain types with high accuracy, outperforming classical vision algorithms in many cases. However, training such models requires large datasets or extensive simulation, and limited flight data can lead to overfitting or poor generalization. In practice, DL provides UAVs with powerful perception and reactive control capabilities, but it must be carefully trained, validated, and sometimes paired with classical approaches to ensure reliable and safe navigation.

5.5 Summary of Learning-Based Approaches

Learning-based methods have revolutionized UAV navigation by enabling systems to learn from experience and adapt to dynamic environments. They offer significant flexibility and robustness compared to traditional approaches, although their computational and energy demands remain challenging. These methods provide several advantages:

– Adaptability: learning-based methods can continuously improve through training and adapt to new or unforeseen environmental conditions;

– Real-Time Decision Making: once trained, these methods can process incoming data and update navigation decisions in real time;

– Enhanced Perception: deep learning techniques allow analysis of complex visual data, improving obstacle detection and environment mapping.

However, these benefits come with a set of challenges:

– High Computational Demand: the training processes for deep learning models require significant computational resources, which can be a limiting factor on resource-constrained UAV platforms;

– Data Dependency: effective learning relies on large, diverse datasets that may be difficult to obtain for all operational scenarios;

– Energy Efficiency: the increased processing load often results in higher energy consumption, limiting UAV flight times and scalability.

6. Results

When analyzing the differences among existing methods, it is important to highlight the specific characteristics of each approach. Tables 1 and 2 provide detailed rundown, separating the methods into optimization-based and learning-based categories. These tables summarize their objectives (for Learning-Based approaches) and time complexities (measured in terms of the number of operations, m), as well as the number of hyperparameters, offering a comprehensive comparative analysis of these AI approaches.

Moreover, many methods offer a range of variations and modifications — even beyond navigation — as researchers incorporate additional conditions, elements, or layers to better suit specific applications [28], so it is important to carefully select the most appropriate approach for a given problem. While some of these methods can be applied interchangeably, each one tends to excel at addressing particular tasks or operating under certain conditions.

Table 1

Comparison of Optimization-Based Approaches

Algorithm	Type	Complexity	Hyperparameter Count
Dijkstra and A*	Dijkstra [3]	$O(mn + mn^2)$	-
	A* [4]	$O(2mn^2)$	5
Particle Swarm Optimization	MPSO [5]	$O(mn^2)$	6
Ant Colony Optimization	DACO [6]	$O(mn^2)$	9
Differential Evolution	ADE [7]	$O(mn + mn^2)$	4

Simulated Annealing	Multi-UAV SA [8]	$O(mn)$	4
Genetic Algorithms	GA [9]	$O(mn^2)$	5
	HR-MAGA [10]	$O(mn^2)$	7
Grey Wolf Optimization	HSGWO-MSOS [12]	$O(mn + mn^2)$	2
Pigeon-Inspired Optimization	AOQPIO [14]	$O(2mn^2)$	6

Table 2

Comparison of Learning-Based Approaches

Algorithm	Type	Goal	Complexity	Number of layers	Hyperparameter Count
Reinforcement Learning	RSS-based Q-learning [15]	Indoor search and rescue missions	$O(mn^2)$	-	3
	Multi-agent Q-learning [16, 17]	Multiple UAV trajectory optimization to maximize data transfer efficiency	$O(mn)$	-	3
	“Sense-and-send” Q-learning [18]	Perform sense and send tasks to adjust the trajectories of decentralized UAVs	$O(mn)$	-	3
	TD learning [19]	Cellular-connected UAVs navigation in complex urban environments	$O(mn^2)$	-	4
Deep Reinforcement Learning	MDP-based dueling DDQN [20]	UAV navigation and radio mapping in 3D environments	-	4+5	3
	MDP-based DQN with experience replay [21]	UAV-BS navigation	-	4	8
	MDP-based DRL with TD3 [22]	UAV obstacle avoidance for navigation in dynamic environments	-	10	8
	POMPD-based EDDQN [23]	Autonomous outdoor UAV navigation and exploration under challenging conditions	-	14	7
Asynchronous Advantage Actor-Critic	A3C-based DRL [25]	Trajectory planning for multi-UAV assisted MEC	-	6	5
	Fast-RDPG [26]	Autonomous UAV navigation in complex environments	-	6	7
Deep Learning	CNN [27]	Visual system for autonomous UAV navigation	-	N/A	N/A

Nevertheless, significant challenges remain. The high computational requirements of deep learning models and the energy inefficiencies of AI-based systems limit scalability and practical implementation. Additionally, reliance on extensive training data, advanced communication protocols, and rigorous real-world validation continues to obstruct widespread deployment. Addressing these issues is crucial for fully harnessing the potential of AI in UAV navigation.

One promising solution is to adopt a hybrid approach that combines learning-based methods with optimization-based techniques. While learning-based methods can process real-time data, they may require solid computational resources for processing. For example, using a CNN for sensor data processing and then providing its output as input for an optimization-based approach, which computes an approximate optimal solution within a reasonable time, could give a good result, leveraging the strengths of both paradigms to enhance overall UAV navigation performance. This synergy not only addresses the limitations inherent in each individual approach but also paves the way for future innovations in autonomous UAV systems, ultimately leading to safer, more efficient, and scalable navigation solutions. At present, however, the consensus is that combining methods, even not necessarily learning-plus-optimization approaches is the most practical path to high-performance, reliable UAV navigation in the near term [29].

Future research should focus on the development of robust, energy-efficient, and scalable AI frameworks. Hybrid approaches that combine two or more foundational algorithms offer promising opportunities to overcome existing limitations. Additionally, it is crucial to continue optimizing and improving existing algorithms, which was also emphasized during the review of existing approaches. We must also remain open to new methods and novel navigation strategies that may be applied to UAV systems in the future.

7. Existing challenges

While AI algorithms have advanced UAV navigation, several challenges remain unresolved:

- Energy Efficiency: UAVs rely on batteries as their primary power source to support various functions, including flight, communication, and onboard processing. However, the limited capacity of UAV batteries often restricts their flight duration and operational range. To address these challenges, researchers have explored several strategies to optimize energy usage, including: implementing sleep-and-wake-up schemes to minimize energy consumption during idle periods, leveraging mobile edge devices for external computing to offload processing tasks, and integrating renewable energy sources like solar power [30];
- Dynamic Environments: most existing algorithms, struggle with highly dynamic environments involving moving obstacles and variable weather conditions. This limitation restricts their applicability to real-world scenarios;
- Scalability and Real-World Validation: many AI algorithms are tested in controlled environments but face scalability challenges when deployed in large-scale networks. Real-world validation is essential to ensure the reliability and robustness of these algorithms under diverse operating conditions;
- Legal and Ethical Challenges: the integration of AI with UAVs raises significant legal and ethical challenges, particularly in areas such as human privacy, safety, and the potential misuse of data [31]. Privacy concerns primarily appear from the capability of UAVs to enable surveillance and monitoring, raising fears of intrusion into personal spaces. On the other hand, security concerns arise from vulnerabilities to hacking and data breaches, which could compromise sensitive information and systems.

8. Conclusion

The rapid evolution of UAV technology has significantly transformed the field of autonomous navigation, making it a critical component across various applications — from surveillance and environmental monitoring to infrastructure inspection and beyond. However, the success of UAV navigation systems fundamentally depends on reliable and adaptive methodologies that can handle the complexities of dynamic real-world environments. Traditional navigation methods, while useful in static scenarios, fall short when applied under the dynamic challenges of real-world environments. In contrast, AI offers transformative solutions through optimization-based and learning-based approaches that can adapt to rapidly changing conditions, optimize energy consumption, and enhance safety.

This article provides a comprehensive review of current AI methodologies for UAV navigation, highlighting both the achievements and challenges associated with these techniques. Optimization-based approaches offer structured frameworks for path planning with predictable outcomes, while learning-based approaches provide the flexibility required to adapt in rapidly changing scenarios. Comparative analyses indicate that while each method has its merits, hybrid strategies that combine the deterministic precision of optimization techniques with the adaptive strengths of learning-based methods hold significant promise for future UAV navigation systems. Nevertheless, challenges such as high computational demands, energy inefficiencies, and the need for extensive training data persist.

Future research should focus on the optimization of lightweight computational models, developing energy-efficient and scalable AI frameworks, and conducting extensive real-world testing. These efforts will be crucial for transitioning these technologies from the laboratory to large-scale, operational environments. Moreover, addressing legal, ethical, and privacy concerns associated with AI-based UAV navigation will be essential for achieving public acceptance and ensuring regulatory compliance. Overcoming these challenges will lead the way for robust, efficient, and scalable UAV navigation systems that can meet the evolving demands of modern applications.

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