Review of Autonomous UAV Methods in GNSS-Challenging Environments

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***Abstract*—Interest in autonomous UAVs has been growing due to the need in many different industries to seek a robust and efficient system that can work even in remote areas without any other intervention. This paper provides a comprehensive review of recent advancements in autonomous UAV methodologies, with a particular focus on three key areas: planning, navigation, and AI-driven algorithms. The review examines the strengths and limitations of traditional approaches, such as Kalman filters and SLAM-based methods, while also exploring the potential of AI-driven techniques, particularly deep reinforcement learning (DRL), in enhancing UAV autonomy. Although recent developments show promising results, challenges remain in scalability, computational efficiency, and adaptability to complex environments. The findings suggest future research directions toward hybrid methodologies that integrate classical and AI-based techniques to improve UAV performance in real world scenarios.**

***Index Terms*—GNSS-Challenging environments, Autonomous system, AI-driven, Antispoofing, Antijamming, Sensors, Navigation, Control, Planning, GNC.**

I. Introduction

Unmaned aerial vehicles (UAVs) play an important role in many real-life scenarios, e.g. agricultural fertilization, military missions, or wildfire location, where proper guidance, navigation and control (GNC) are critical aspects of the mission. However, many of these missions take place in remote areas, areas with GNSS-challenging environment, or even under conditions of active jamming. Therefore, UAVs must be capable of partial or full autonomy to secure a quality result.

This paper provides a review of the currently used methods deployed in autonomous UAV and multi-UAV (swarm UAV) systems, particularly those designed to function in GNSS-challenging environments. Key areas of focus include articles that delve into the development of fully or partly autonomous systems with use of traditional methods of navigation, planning or alternatives in form of AI. By examining these approaches, we will gain a fundamental understanding of the techniques currently shaping UAV autonomy. Furthermore, the aim of this article is to find gaps in these methods for further research.

Contribution

This study examines the current methodologies used in autonomous UAVs, with a particular focus on comparing classical approaches—such as SLAM, Kalman filters, and direction-of-arrival (DOA) estimation—with emerging AI-driven solutions. The key contributions of this study are as follows.

- **Description of traditional and AI-based techniques** – We describe several traditional and AI-based approaches used in UAV. We examine widely used methods, highlighting their strengths, limitations in real-life UAV operations. Simultaneously, we analyze AI-driven methods, particularly deep reinforcement learning (DRL) and neural network-based solutions, which offers new possibilities in exchange for different drawbacks.
- **Evaluation of scalability, robustness and computational efficiency** – While classical methods often offer well-established foundations and lower computational costs, AI-based approaches provide enhanced adaptability and better robustness but at the expense of increased processing requirements. This review discusses the trade-offs associated with each approach and their feasibility.
- **Identification of research gaps** - Despite recent advances, both traditional and AI-driven methods face challenges in terms of robustness, real-time adaptability, and generalization to unseen environments. This paper outlines potential research directions, presenting hybrid methodologies that integrate the reliability of classical models with the learning capabilities of AI techniques to enhance UAV performance.

The rest of the paper is organized as follows. Section II. briefly describes frequently used techniques and their fundamental logic in UAVs from both AI and traditional methods. This is followed by a review of papers that incorporate these methods while integrating innovative approaches. Section III. presents a comparison of both approaches, followed by a discussion and conclusions in Section V.

II. Methodology

When it comes to methods in UAV we need to specify the target usage of these techniques. Typically, the usage categories are split into three main categories – Guidance, Navigation, and Control. However, these three parts often overlap. If we are talking about an autonomous system, its control unit will be purely dependent on internal navigation and planning, i.e. no direct user intervention will be possible. Therefore, we can omit the Control category. The main purpose of the Guidance category is to lead the drone in its environment and ensure that the drones are on the correct path. There are numerous ways available to accomplish this.

- **Waypoints navigation** – The basic solution is to give a drone location or a sequence of locations in the form of waypoints which the drone follows. Consequently, the drone itself blindly follows linear trajectories from point A to point B.
- **Path planning** – A more sophisticated way to lead the drone is path planning. There are quite a few path planning algorithms, ranging from the state-of-the-art Dijkstra's algorithm [1], A* algorithm and their modifications to complex swarm path planning algorithms, for example Ant Colony Optimization (ACO) [2] or Particle Swarm Optimization (PSO) [3]. In general, the goal of path planning is to determine the most efficient and fastest route to a given destination. Initially, the path consists of scattered points that are later refined into a final trajectory. [4]
- **AI Path planning** – The significant increase in the use of AI-based path planning algorithms has been driven primarily by Deep Reinforcement Learning (DRL), Machine Learning (ML), or Partially Observable Markov Decision Process (POMDP). [4] Despite their long training time, these AI models perform great in complex environments and have a fast reaction time.

In the navigation part, the UAV receives information about its position and orientation relative to a specific reference point. With this information, the drone can be located while maintaining the necessary stabilization, which is a crucial attribute for the overall system. Various methods are used to obtain this information.

- **Dead reckoning (DR)** – Is probably the oldest technique in the book. DR is a navigation technique used to estimate a vehicle's current position based on previously known positions, velocity, heading, and time elapsed. Unlike absolute positioning methods such as Global Navigation Satellite Systems (GNSS), dead reckoning relies solely on internal motion sensors and does not require external references. [5]
- **Inertial Measurement Units (IMU)** – The unit combines an accelerometer and a gyroscope to measure acceleration and angular velocity. This information is integrated to provide the current position of the UAV. Additionally, the IMU may contain magnetometer or barometer for more accurate heading information or altitute estimation. [6]
- **Global Navigation System (GNSS)** – To understand, what we lost in GNNS-challenging situations, we need to understand it. The most common and well-known method in navigation is the GNSS using one or more constellations: the US Global Positioning Signal (GPS), the European GALILEO, the Chinese BEIDOU or the Russian GLONASS. GNSS uses trilateration to obtain the correct position. To determine it, a GPS receiver calculates how long it takes for signals from multiple satellites to reach it. By multiplying this travel time by the speed of radio waves (approximately 300,000 km or 186,000 miles per second), the receiver estimates its distance from each satellite. Each measurement defines a sphere with the satellite at its center and the receiver somewhere on its surface. When signals from at least three (in reality four, due to an inaccuracy in the receiver's clock) satellites are processed in this way, the receiver's internal system pinpoints its exact location by finding the intersection of these spheres, providing precise latitude, longitude, and altitude. [7]
- **Visual Odometry (VO)** – VO refers to the process of estimating a UAV movement, including both translation and rotation relative to a reference frame, by analyzing a sequence of images captured from its surroundings. VO represents a specific application of the broader Structure-from-Motion (SFM) technique, which addresses the challenge of reconstructing a 3D representation of an environment while simultaneously determining camera poses from either ordered or unordered image sequences. Usually, the VO is split into Monocular and Stereo models where each may encounter different problems. In general, there are three estimation techniques: 3D to 3D, 3D to 2D, and 2D to 2D. [8]
- **Simultaneous Localization And Mapping (SLAM)** – As the name suggests, this techniques combine localization and mapping. Generally, SLAM algorithms work by building maps of an unknown environment from multiple sources while keeping track of their own position in it. [9] Due to many applications, the SLAM may be sorted into many categories. Yousif et al. [8] sorted the SLAM into filtering and smoothing categories with different versions of SLAM. The filtering methods focus on addressing the online SLAM problem, where only the UAV's current state and the map are continuously updated by integrating sensor data as it is received. In contrast, the smoothing approaches tackle the full SLAM problem by estimating the posterior (robot poses and map) over the entire trajectory alongside the map. The filtering category can include **Extended Kalman Filters (EKF)**, **Particle Filters (PF)**, or **FastSLAM**, which is SLAM with Rao-Blackwellized particle filter for large-scale environments. The smoothing category can include for example **Visual SLAM (V-SLAM)**, **RGB-D SLAM**, that is basically V-SLAM with RGB-D sensors, or **GraphSLAM**.
- **AI navigation** – AI-based navigation most often build on the shortcomings of classical methods. For example, ML methods can enhance navigation by improving the accuracy and robustness of the UAV's position and orientation estimation in filtering SLAM techniques (e.g. EKF-SLAM with ML model for better handle of non-linear filters, or enchancing V-SLAM technique with computer vision and ML for faster mapping). [4]

A. Solutions without AI

There are a large number of traditional methodologies, many of them are especially focused on estimation, detection, and relocation with help from visual odometry (VO), Kalman filters, DOA, or other techniques mentioned above. For active jamming situation, Zhou et al. [10] proposed a solution for communication and localization. The solution work on power frequency domain inversion, where GNSS information is sent through different RF frequency band based on the position and frequency of the jamming signal. However, this solution must meet the condition that the number of nodes in the swarm is larger than the number of jammers. This obstacle solved Zhou et al. [11] with the leverage of multi-source direct-of-arrival (DOA) estimation that applied space-time DOA matrix techniques against spoof attacks. Different antijamming solutions presented by Wang et al. [12] by power optimization and trajectory planning. In this case, the UAV managing situation through IRR characterization with a power control and transmit power based on the Stanckelberg equilibrium game framework.

An effective strategy for multi-UAV outdoor operations involves a hierarchical structure, often referred to as a father-son or leader-follower configuration. This approach presented Causa et al. [13] with a generalized dilution of precision (generalized DOP) and setting the optimal father position based on the needed position of the son. The generalized DOP performed well under difficult conditions and significantly improved the achieved accuracy. The idea of generalized DOP (geDOP) was extended in a follow-up paper [14] with added Extended Kalman Filter for estimation of son's navigation state and may perform well in almost real-time scenarios.

The previously mentioned article by Causa et al. [14] introduced the first of the partly autonomous system, which works independently. Minervini et al. [15] presented a different approach to altitude estimation using adaptive Kalman filters and the V-SLAM algorithm with Mahanalobis distance for the detection of inconsistencies. This system works well in restricted indoor areas with various obstacles in the way of the drone, but is not suitable for estimation in larger fields and longer mission duration. Mugnai et al. [16] applied a similar approach with vision-based framework which operates on the basis of finite-state machine planner. This solution was tested in an indoor real environment in the Leonardo Drone Contest.

Horyna et al. [17] proposed visual-based estimation for a decentralized multi-robot system. In this research, a group of UAVs perform a multi-robot state estimation with the use of a velocity estimator fused with the optical flow data. The velocity estimation contains fused data from IMU and UVDAR that enhances the estimation precision during dynamic maneuvers.

In a follow-up article for fast swarming UAVs Horyna et al. [18] presented a decentralized approach heavily based on the visual perception of individual UAVs on board without communication. The main contributions are the flocking controller, which represents the stabilization and collective velocity of the UAVs in the swarm, enhanced Multi-Robot State Estimation (MRSE) for safe deployment in unknown environments, and overall swarming framework. The velocity estimation is proposed through the state feedback control rule, which causes some inaccuracies. Finally, this framework was compared with state-of-the-art solutions and achieves better results in terms of speed and reliability without explicit communication.

Mishra et al. [19] proposed a complex and highly scalable framework for full-autonomy UAVs. The framework contains four main blocks: sensing, perception, planning, and controls. These blocks are made up of various subtasks which are responsible for correct function in all essential aspects of GNC. The computer vision-based algorithm for autonomous flight was introduced by Kuroswiski et al. [20], using the Ardupilot suite for flight control and integrates a Raspberry Pi for processing. A computer vision algorithm identifies landmarks from preloaded geo-referenced images to correct errors accumulated by inertial systems.

B. AI-driven solutions

Similar approach applied to the UAV swarm position and formation control presented by Ma et al. [21]. The vision-based approach is enhanced with hierarchical architecture using the deep learning object detection algorithm YOLOv7 and advanced real-time tracking DeepSORT, which introduces the Mahalanobis distance and utilizes the cosine distance in the SORT algorithm. Subsequently, this system was simulated in Rflysim software. After simulation, the real flight test takes place with three position tasks. However, the paper does not consider the complicated outdoor task, but mentions their implementation in follow-up work with a proposal for more UAVs in the swarm.

The use of machine learning does not have to be limited to detection or distance estimation. In contrast, total autonomy can be built on machine learning or other AI algorithms. Imanberdiyev et al. [22] presented a high-level model-based reinforcement learning algorithm called TEXPLORE. TEXPLORE consists of three main parts, which are action selection, model learning and planning. While planning and model learning run in the background, the action selection part interacts with the environment by taking actions as fast as required. The model is learning based on trial-and-error interactions in 3-4 decision trees based on the C_{4-5} algorithm, which will eventually create the final model. To avoid misunderstanding of environmental conditions, the models of the environment are learned by forming a random forest, which naturally causes uncertainties in the models. This model significantly outperforms the previously used Q-learning method, with only a few iterations in the learning process and real-time operation.

However, this approach offers only partial autonomy. The fully autonomous system presented by Wang et al. [23] directly enables mapping of the measurements of the raw UAV sensor to the control signals for navigation, which enables full autonomy in more complex environments. The system uses a deep reinforcement learning framework to solve the partially observable Markov decision process (POMDP). The framework integrates the Fast-Recurrent Deterministic Policy

Gradient algorithm (Fast-RDPG) with hierarchical planning to provide UAVs with a dual-layer decision-making process. This combination allows for high-level strategic goal setting and low-level reactive behaviour to dynamically adapt to obstacles and environmental changes.

Lei et al. [24] proposed a different and very interesting framework based on digital twin intelligent cooperation for UAV swarm situations. This framework combines a high-fidelity digital twin model of the physical system with a machine learning-based decision-making model to enable optimal real-time decision-making. Despite the unique idea, the implementation suffers from a lack of speed in updating the digital model.

III. Comparison of the solutions

This section provides a comparative analysis of traditional and AI-driven UAV methodologies based on key performance criteria: implementation complexity, scalability, robustness, and computational efficiency.

A. Implementation Complexity

Traditional approaches, such as Kalman filters and SLAM-based methods, require significant domain expertise and precise sensor calibration. These methods rely on predefined models and accurate environmental information. In contrast, AI-driven solutions, such as deep reinforcement learning (DRL), reduce dependency on predefined models but require extensive training datasets and computational resources.

B. Scalability

Classical approaches often face scalability issues due to their reliance on fixed models and assumptions. Multi-UAV systems using methods like DOA estimation require centralized coordination, limiting their ability to scale in dynamic environments. AI-driven methods, particularly those that leverage deep learning frameworks, offer greater adaptability, making them more suitable for large-scale UAV swarms. However, their deployment is constrained by the need for extensive computational power and training.

C. Robustness

Traditional methods exhibit robustness in structured and predictable environments but struggle with complex and unpredictable conditions, such as GNSS spoofing or jamming. AI-based approaches demonstrate enhanced adaptability by learning from diverse datasets and dynamically adjusting to environmental changes. For example, DRL-based navigation techniques outperform classical methods in highly dynamic and partially observable conditions. However, AI-driven solutions may suffer from reliability issues when faced with completely new or adversarial scenarios.

D. Computational Efficiency

Kalman filters and SLAM-based techniques are computationally efficient and feasible for real-time applications. However, these methods lack the flexibility to handle complex real-time decision-making scenarios. AI-based approaches, such as Fast-RDPG and model-based reinforcement learning, require significant processing power, which can be a limiting factor for real-time UAV operations, especially on resource-constrained platforms. Hybrid approaches that integrate classical methods with AI-driven enhancements present a promising direction to balance computational efficiency and adaptability.

In summary, while traditional methods remain valuable for specific applications that require efficiency and reliability, AI-driven techniques provide enhanced adaptability and decision-making capabilities. The optimal approach depends on the specific operational constraints and mission requirements of UAV systems in GNSS-challenging environments. Future research should focus on hybrid methodologies that integrate the efficiency of classical methods with the adaptability of AI-driven frameworks and their optimalization.

IV. Conclusion

This review highlights the advancements in methods for enabling UAV autonomy in GNSS-challenging environments. The surveyed methods span traditional GNC methods and upcoming AI-driven systems. Classical approaches such as Kalman filters, SLAM, V-SLAM and other estimations remain essential for tasks requiring localization and path planning in visually rich environments. However, these methods face limitations in scalability and adaptability to large-scale or dynamic conditions.

AI-driven methods, particularly those that leverage deep reinforcement learning (DRL), demonstrate significant potential to address these limitations. Fast-RDPG-based frameworks, which effectively manage the partially observable Markov decision process (POMDP), enable robust navigation and decision-making by integrating high-level strategic planning with low-level reactive capabilities. These advancements open the door for fully autonomous systems capable of operating in complex and unpredictable environments, outperforming traditional algorithms in terms of adaptability and scalability.

Despite these innovations, several challenges remain. Many state-of-the-art solutions lack robustness in extreme environmental conditions or require significant computational resources, limiting real-time applications. Additionally, collaborative multi-UAV operations with minimal communication overhead require further exploration to ensure efficiency in large-scale swarm deployments.

Future research should focus on the integration of computationally efficient algorithms with enhanced decision making capabilities. Expanding the robustness of vision-based and AI-driven frameworks to handle adverse conditions, such as severe weather or cluttered environments, is also crucial. Finally, a unified approach that combines the strengths of classical and AI-based methods could provide the adaptability, efficiency and reliability required for UAV operations in GNSS-challenging environments.

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