A Survey on LiDAR-based Autonomous Aerial Vehicles

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***Abstract*—This survey offers a comprehensive overview of recent advancements in LiDAR-based autonomous Unmanned Aerial Vehicles (UAVs), covering on their design, perception, planning, and control strategies. Over the past decade, LiDAR technology has become a crucial enabler for high-speed, agile, and reliable UAV navigation, especially in GPS-denied environments. The paper begins by examining the evolution of LiDAR sensors, emphasizing their unique advantages such as high accuracy, long-range depth measurements, and robust performance under various lighting conditions, making them particularly well-suited for UAV applications. The integration of LiDAR with UAVs has significantly enhanced their autonomous capabilities, allowing for the execution of complex missions in diverse and challenging environments. Subsequently, we explore essential software components, including perception technologies for state estimation and mapping, as well as trajectory planning and control methodologies, and discuss their adoption in LiDAR-based UAVs. Additionally, we analyze various practical applications of the LiDAR-based UAVs, ranging from industrial operations to supporting different aerial platforms and UAV swarm deployments. The survey concludes by discussing existing challenges and proposing future research directions to advance LiDAR-based UAVs and enhance multi-UAV collaboration. By synthesizing recent developments, this paper aims to provide a valuable resource for researchers and practitioners working to push the boundaries of LiDAR-based UAV systems.**

***Index Terms*—LiDAR-based UAV, Applications on UAV, UAV Autonomy**

I. Introduction

The past decade has witnessed a remarkable surge in the development and deployment of Unmanned Aerial Vehicles (UAVs), driven by their versatility, cost-effectiveness, and ability to access hazardous or hard-to-reach areas. These aerial systems have found widespread applications in fields ranging from aerial photography [1], precision agriculture [2] to infrastructure inspection [3], search and rescue operations [4, 5]. By endowing these aerial platforms with the ability to sense, make decisions and navigate without direct human control, the scope of their applications has expanded significantly. Autonomous UAVs can execute intricate missions, such as surveying remote or hazardous areas, without exposing human operators to unnecessary risks.

For autonomous navigation, the sensing module is essential for UAVs to achieve reliable state estimation and obstacle detection. LiDAR sensors provide significant advantages, offering accurate, direct depth measurements well-suited to the high agility and mobility of UAVs. LiDAR captures 3D points at high frequencies (hundreds of thousands to millions of Hertz), enabling fast and precise motion estimation [6, 7]. With centimeter-level accuracy over long ranges (up to hundreds of meters), LiDAR allows UAVs to detect distant obstacles for high-speed flight and maneuver through narrow, cluttered environments. Its time-of-flight (ToF) mechanism supports the detection of thin objects, such as power lines, which other sensors often miss. Additionally, LiDAR's active sensing nature ensures reliable performance even in low-light conditions, such as nighttime. These capabilities greatly surpass those of traditional visual-based approaches, which often struggle with depth accuracy, motion blur, and variable lighting.

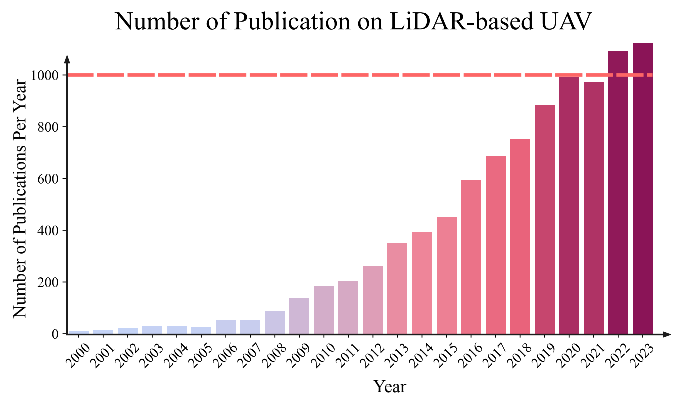

Fig. 1. Number of publications on LiDAR-based UAV since 2000. In 2023, the number of publications related to LiDAR-based UAV surpassed one thousand.

Since the 1990s, research on autonomous UAVs has gained increasing popularity, with the development of LiDAR sensors significantly enhancing UAV autonomy. This advancement has led to the emergence of various techniques and the publication of over a thousand papers annually related to LiDAR-based UAV systems, as shown in Fig.1. Although several survey papers have reviewed autonomous UAVs – such as Kendoul's comprehensive survey on UAV guidance, navigation, and control in 2012 [8], including both vision-based and LiDAR-based systems; Kanellakis *et al.*'s review of vision-based works [9]; and reviews by Gyagenda *et al.* [10] and Chang *et al.* [11] on UAV navigation techniques in GNSS-denied environments – the rapid development of LiDAR technologies driven by the autonomous driving industry since 2017 [12] necessitates a more focused and comprehensive review of autonomous UAV systems based on LiDAR sensors.

This survey is primarily motivated by the absence of a single

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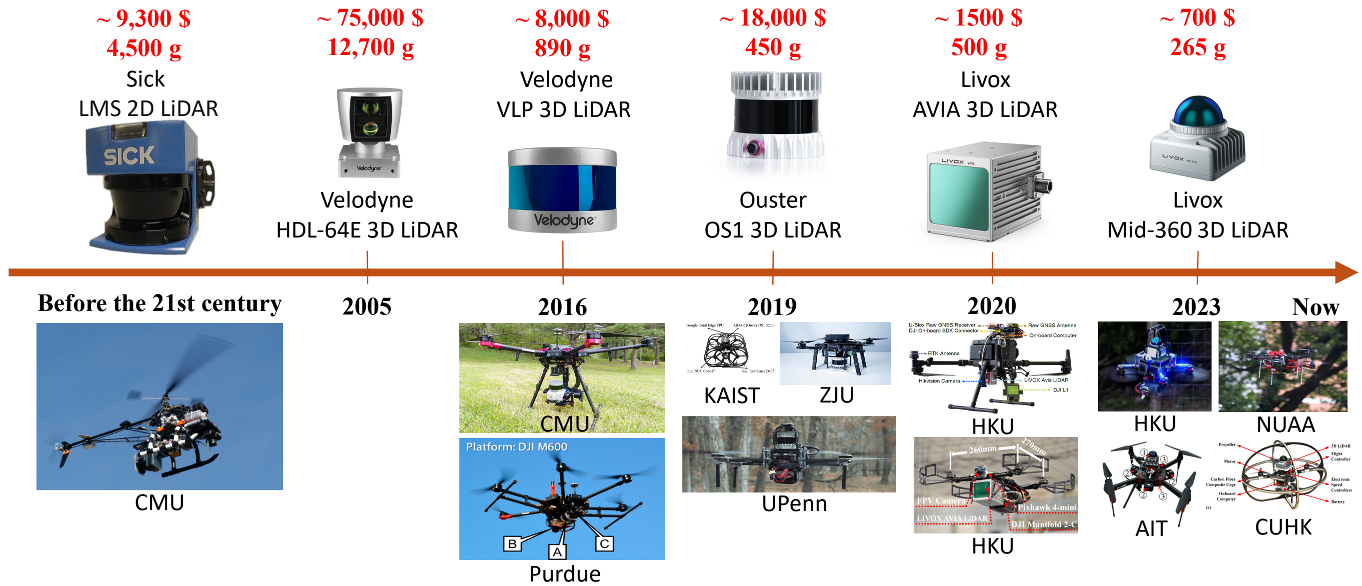

Fig. 2. Overview of LiDAR developments and corresponding UAV demonstrations in recent years, including Sick LMS 2D LiDAR [13], Velodyne VLP 3D LiDAR [14, 15], Ouster OS1 3D LiDAR [16]–[18], Livox AVIA solid-state 3D LiDAR [19, 20], and Livox MID-360 solid-state 3D LiDAR [21]–[26]

survey specializing in LiDAR-based autonomous UAV systems, despite LiDAR sensors being proven to be ideal sensing units for aggressive, fast UAV motions. This paper covers key technologies in two aspects: LiDAR-based perception, including state estimation and mapping, and LiDAR-enabled planning and control approaches. The central objective of this paper is to provide an overview of the history, state of the art, milestones, and unsolved problems in the area of LiDAR-based autonomous UAVs. The rest of the paper is organized as follows: First, the advantages and development of LiDAR sensors and LiDAR-enabled autonomous UAVs are introduced in Sec. II. The perception technologies based on LiDAR that are suitable for UAV applications are presented in Sec. III. Sec. IV introduces the planning and control technologies that leverage LiDAR technology to enable a higher level autonomy of UAVs. In Sec. VI, we discuss various applications of LiDAR-based UAVs. Finally, Sec.VII-G provides discussions and possible future directions for LiDAR-based autonomous UAVs.

II. Development of LiDAR Sensors and LiDAR-based UAVs

A. Development of LiDAR Sensors

LiDAR's origins date back to the 1960s, when it was initially invented for satellite tracking [27]. In the 1970s, LiDAR began seeing early applications in measurement and mapping. A notable example was its use in the Apollo 15 mission for lunar surface mapping [28], while airborne bathymetric sensors equipped with LiDAR were deployed for near-shore reconnaissance [29]. From the 1960s to the 1980s, LiDAR technology rapidly advanced, particularly in military applications such as missile guidance and tank rangefinders [30]–[32].

In the 1980s, LiDAR made significant inroads into civilian applications, especially in mapping and surveying. It became a valuable tool for airborne elevation mapping and monitoring environmental changes, such as erosion, deforestation, and polar ice sheet melting [33]–[36]. By the 1990s, advancements in high-speed computing and algorithms further facilitated the processing and analysis of LiDAR data, expanding its applications to coastal mapping, urban planning, and laser-based speed guns [35, 37, 38].

In the 21st century, advancements in optics and sensor technology transformed LiDAR into its modern form. A key milestone was the use of LiDAR by the Stanford Artificial Intelligence Laboratory (SAIL) in the second DARPA Grand Challenge, showcasing its potential for autonomous navigation. By the 2007 DARPA Urban Challenge, the multi-beam Velodyne HDL-64E [39] had become standard equipment for nearly all participants [40], further driving LiDAR's development. In addition to traditional mechanical scanning LiDARs, new types such as rotating mirror LiDARs, Risley prism LiDARs, and MEMS LiDARs emerged. The growing demand in autonomous driving and robotics pushed LiDAR technology toward miniaturization and lower power consumption. Products like the VLP-16 [41] and Ouster OS1-128 [42] stand out for their lightweight, compact designs, making them well-suited for UAV applications, though their costs remain high (i.e., 8000~20000 USD).

However, solid-state LiDARs have significantly advanced UAV technology with their lighter weight, smaller size, and more affordable prices. For instance, the Livox Avia [20, 43], released in 2020, weighs only 500 g and costs a mere 1500 USD—substantially lower than traditional rotating LiDARs. Livox further released the MID360 [44] in 2023, which weighs just 265 g, measures $65\times65\times60$ mm, and costs only 700 USD. The lightweight and low-cost features of these LiDAR sensors have played a crucial role in promoting the development of LiDAR-based UAVs, as illustrated in Fig. 2.

B. Development of LiDAR-based UAVs

The integration of LiDAR sensors on UAVs (i.e., airborne LiDAR systems) can be traced back to the 1990s when Miller *et al.* [45] equipped a 2D LiDAR on an unmanned helicopter for site mapping. From 2003 to 2006, similar works [46]–[48] used 2D LiDARs on unmanned helicopters for environmental modeling [46], obstacle avoidance [47], and autonomous landing [48]. At that time, the combination of LiDAR and helicopters was the most common platform for LiDAR-based UAVs. However, these platforms were large (over 3 meters in size), heavy (60-90 kg), and complex, limiting their applicability in dense forests, underground mining, or indoor environments due to their cost and logistical challenges.

In addition to helicopters, 2D LiDARs also enabled autonomous flight for fixed-wing UAVs. For example, Bry *et al.* [49] equipped a 2D LiDAR on a fixed-wing UAV for state estimation using an Extended Kalman Filter (EKF) framework. As multi-rotor UAVs became more popular, LiDAR-based UAVs gained traction. In 2008, Angeletti *et al.* [50] successfully combined 2D LiDAR, vision sensors, IMU, and ultrasonic sensors for autonomous hovering in indoor environments. In the same year, He *et al.* [51] developed a complete system that used 2D LiDAR and IMU for onboard state estimation and planning. By splitting the laser beam for horizontal and vertical planes, they achieved 3D localization and successfully demonstrated autonomous navigation [51] and target tracking [52] in GNSS-denied environments. Since then, 2D LiDARs have become one of the most popular sensing modalities for autonomous multi-rotor UAVs [53].

A significant milestone in LiDAR-based UAV systems occurred in 2015 with the release of the VLP-16 [41], a 16-beam 3D LiDAR small and light enough to be equipped on multi-rotor UAVs. In 2016, Gao *et al.* [54] applied the VLP-16 on a quadrotor UAV to achieve fully autonomous navigation, including state estimation, obstacle avoidance, and control in GNSS-denied environments. This combination quickly gained popularity in academia [55]–[61]. In 2017, Liu *et al.* demonstrated autonomous navigation at speeds exceeding 5 m/s in unknown environments using the VLP-16. In 2018-2019, Zhang *et al.* [56, 57, 59] combined the VLP-16 with the DJI Matrice 600 Pro UAV to develop a point cloud-based planning and control system, enabling quadrotor UAVs to fly at speeds of 10 m/s in unknown environments. Gao *et al.* [58] further achieved fully autonomous UAV navigation in unknown environments with a more compact design. Despite the advantages of the VLP-16, its limited point cloud density and field of view led researchers to explore alternatives like the Ouster OS1-128 LiDAR [42], which offers higher point density and a wider field of view. In 2022, Wang *et al.* [16] and Cheng *et al.* [17] used the OS1-128 LiDAR on quadrotor UAVs to achieve autonomous navigation in unknown environments.

The emergence of solid-state LiDARs, starting in 2020, marked another breakthrough in UAV technology. Solid-state LiDARs, being smaller, lighter, and less expensive than traditional mechanical LiDARs, are particularly well-suited for UAV applications. Kong *et al.* [19] first applied the Livox Avia solid-state LiDAR [43] on a small quadrotor UAV with a 280 mm wheelbase, achieving obstacle avoidance in dynamic environments. In 2022, the release of the Livox MID360 [44] further advanced UAV capabilities, thanks to its small size and lightweight design, enabling unprecedented agility and high-speed navigation. Ren *et al.* [21] demonstrated high-speed autonomous flight in cluttered environments with a compact quadrotor equipped with the MID360, reaching a maximum speed of 13.7 m/s. In 2023, they further achieved agile flight through narrow gaps [62] with fully onboard sensing, planning, and control. Since then, MID360-based UAVs have become increasingly popular in research, including both single UAV systems [23]–[25, 63]–[66] and UAV swarms [67]–[69].

III. LiDAR-based Perception

A. State Estimation for UAVs

State estimation aims to optimally determine the UAV's state, including attitude, position, and velocity. It serves as the foundation for autonomous UAV systems, supporting upper-layer modules such as planning and control. LiDARs are widely used for high-quality state estimation due to their unique advantages, including long-range detection, precise distance measurements, and robustness to varying lighting conditions. As LiDAR-based state estimation is closely tied to advancements in LiDAR technology, we separately discuss algorithms using 2D and 3D LiDARs.

1) 2D LiDAR-based State Estimation: While UAVs equipped with LiDAR (including 2D laser range finders) emerged in the late 20th century [45], LiDAR-based state estimation for UAVs gained momentum in the early 21st century [46, 48]–[52, 70]. In 1998, Miller *et al.* used a 2D laser range finder for environmental mapping, but due to the lack of reliable localization algorithms, the state estimation relied on GPS, IMU, and compass sensors. By 2003, Thrun *et al.* [46] implemented a probabilistic SLAM framework using 2D LiDAR, GPS, and compass data on a helicopter, employing the Iterative Closest Point (ICP) algorithm [71] for reliable pose estimation. In 2006, Theodore *et al.* [48] combined 2D LiDAR with monocular camera images and IMU data for precise landing, using LiDAR to ensure accurate positioning near the ground. Initially, 2D LiDARs were auxiliary to GPS, suitable only for outdoor environments with strong GPS signals. However, GPS-denied scenarios, such as indoor environments, demanded alternative solutions. In 2008, Angeletti *et al.* [50] achieved indoor autonomous hovering by matching 2D LiDAR scans to estimate horizontal position and yaw angle, while ultrasonic sensors and IMU provided vertical position and attitude data for 6-DOF pose estimation. That same year, He *et al.* [51] used a redirected 2D LiDAR scan for downward range measurements, enabling geometric beacon tracking [72] to achieve GPS-free autonomous flight. In 2012, Bry [49] introduced a hybrid filter that tightly coupled IMU and 2D LiDAR data for localization on a prior map. The approach used an IMU-driven Extended Kalman Filter (EKF) for prediction, with Gaussian Particle Filter (GPF) updates [70], resulting in robust and efficient state estimation.

2) 3D LiDAR-based State Estimation: While 2D LiDARs offer precise distance measurements, their limited vertical field of view restricts their effectiveness for UAVs with 3D motion. The introduction of the VLP-16 in 2015 [41] marked a major milestone in LiDAR development, quickly gaining popularity in fields such as autonomous driving, robotics, and UAV technology. Since then, numerous 3D LiDAR models with varying densities, fields of view, weights, and prices [42]–[44] have driven significant advancements in UAV state estimation.

One of the earliest and most influential 3D LiDAR SLAM algorithms, LOAM, was introduced by Zhang *et al.* in 2014 [73]. Unlike traditional point-to-point ICP methods, LOAM extracts plane and edge features from point clouds and optimizes state estimation through point-to-plane and point-to-edge ICP. Using estimated poses and undistorted points, LOAM incrementally maintains a global map in a 3D KD-tree structure. This framework has been widely adopted in UAV applications [54, 55, 58], with later enhancements integrating IMU and cameras for robust performance during aggressive UAV maneuvers [56, 57, 59, 74, 75].

The emergence of solid-state LiDARs like Livox Avia and Mid360 [43, 44] in the 2020s further accelerated the development of LiDAR-based UAV state estimation. Many innovative algorithms have since emerged [6, 7, 67, 76]–[79]. In 2020, Lin *et al.* [76] proposed LOAM-Livox, which pioneered a LiDAR odometry system for small field-of-view solid-state LiDARs by introducing a scan-to-map registration approach. In 2021, Xu *et al.* [77] introduced FAST-LIO, an efficient LiDAR-inertial odometry framework based on ESIKF, featuring a new formula for Kalman gain calculation to manage large-scale point clouds and enhance computational efficiency. FAST-LIO2 [6] extended this framework with the ikd-tree [80], optimizing nearest-neighbor search and enabling direct point registration, improving both robustness and efficiency. These advancements have been widely adopted in UAV research [19, 21, 62, 63, 66, 81]. He *et al.* [7] further enhanced the FAST-LIO framework by implementing point-wise state estimation, dramatically increasing output frequency and enabling robust performance during extreme maneuvers, even with saturated IMU measurements. When utilizing these LIO methods as the state estimation module of UAV systems, accurate temporal-spatial calibration between LiDAR and IMU sensors is always required. To solve this problem, Zhu *et al.* [82] proposed a real-time initialization framework that is able to estimate the LiDAR-inertial temporal-spatial extrinsic and initial states accurately.

The camera is an excellent complementary sensor to 3D LiDAR due to its low cost and rich color information. In recent years, many state estimation methods that integrate LiDAR, camera, and IMU sensors have emerged [83]–[85]. In 2024, Zheng *et al.* introduced FAST-LIVO2 [84], which improved upon FAST-LIVO [83] by enhancing computational speed, memory management, and localization accuracy. This method was successfully applied to UAV systems, enabling autonomous navigation.

Recent work has focused on aerial swarm systems. In 2022, Zhu *et al.* [67] introduced a fast LiDAR-inertial odometry framework optimized for swarm systems using Livox LiDARs, enabling real-time ego and mutual state estimation for collaborative missions [68]. In 2023, Pritzl *et al.* [86] demonstrated the use of 3D LiDAR for relative localization, effectively mitigating visual-inertial odometry drift through LiDAR measurements.

3) Discussion: The advancement of LiDAR-based state estimation methods is closely tied to the development of LiDAR sensor technology. Compared to 2D LiDARs, 3D spinning LiDARs offer a wider field of view, while the advent of solid-state LiDARs introduces benefits like reduced cost and lighter weight. Each sensor innovation has spurred new state estimation algorithms, expanding LiDAR applications from ground robots to UAVs and even aerial swarms. As LiDAR technology evolves, emerging sensors like Frequency Modulated Continuous Wave (FMCW) LiDAR, which provides velocity measurements for each point, are expected to inspire more advanced algorithms, further advancing autonomous drone capabilities.

Due to motion distortion and performance degradation in low-structured environments, most LiDAR-based state estimation methods rely on multi-sensor fusion, integrating data from IMU, GNSS, and other sensors. This trend is expected to continue, with future systems incorporating additional sensors, such as cameras and radar, to enhance state estimation accuracy and robustness.

B. Occupancy Mapping

Occupancy mapping tackles the challenge of building consistent maps from noisy and uncertain sensor data, assuming the robot's pose is provided by an odometry algorithm [87]. These maps classify space into occupied, free, and unknown regions, enabling UAVs to navigate effectively in uncharted environments. This section discusses discrete and continuous occupancy representations, followed by an overview of popular map structures used to manage occupancy information.

1) Occupancy Rerepsentations: Discrete representations are popular in occupancy mapping for their simplicity and efficiency. A common approach divides the space into evenly distributed 2D grids or 3D voxels, each represented by a Bernoulli random variable indicating occupancy probability. By assuming spatial independence between neighboring voxels, occupancy probabilities can be efficiently updated. This technique, known as occupancy grid mapping, was introduced in early research [88, 89] and formalized in [87]. Octomap [90] extended this framework to 3D using octrees and a log-odd function to reduce computational complexity. Most subsequent works have focused on optimizing memory usage and computational efficiency, with minimal changes to the underlying probability model.

Another discrete method is the Euclidean Signed Distance Field (ESDF), which computes the Euclidean distance from each voxel to the nearest surface. While most ESDF representations are derived from occupancy grids, Voxblox [91] constructs ESDF maps directly from TSDF data. However, Voxblox suffers from distance estimation inaccuracies due to the approximated TSDF-to-ESDF conversion [92].

Continuous representations assume spatial correlation between neighboring spaces, reflecting real-world physical structures. Early attempts [93, 94] modeled boundaries and occupancy probabilities using curves and polygons. Later, O'Callaghan and Ramos [95] proposed a non-parametric approach using Gaussian processes (GPs) to estimate continuous occupancy in 2D space. However, GPs require storing all N measurements and performing $\mathcal{O}(N^3)$ operations for each query, making them computationally expensive. Although clustering local measurements can reduce the dataset size, each query still requires constructing a new covariance matrix. Extensions like GPmap [96], GPOctomap [97], and BGKOctomap-L [98] applied GPs to 3D spaces using octrees [99], but they continued to rely on raw measurements for predictions.

Semi-parametric methods mitigate the storage burden by clustering data into parameterized functions, such as Gaussians or kernels. NDT-OM [100] divided space into voxels, with each voxel storing a Gaussian, though it struggled with discretization errors in unstructured environments. Confidence-rich mapping [101] accounted for measurement uncertainty within sensor cones to improve planning and exploration. The Hilbert map [102] and its variants [103]–[105] employed kernel approximations to reduce inference complexity to $\mathcal{O}(N)$. Additionally, occupancy maps based on Gaussian mixture models have been explored, with hierarchical structures [106] and variable resolutions [107] providing further flexibility.

2) Occupancy Map Structures: As discrete representations divide the space into evenly distributed 2D cells or 3D voxels, the early research utilized arrays to store grids, typically known as uniform grid maps [108]. However, a critical drawback of the uniform grid maps is their tremendous memory consumption, which prevents their application in high-resolution and large-scale mapping. Nonetheless, uniform grid maps offer the strongest efficiency in updating and querying compared to other map structures to be discussed in this section, due to their continuous memory allocation. Thus, uniform grid maps are well-suited for occupancy mapping in a local space, such as the ROG-Map [63].

To reduce the memory consumption in uniform grid maps, hashing techniques were introduced to organize the cells (or voxels) [109]. Rather than pre-allocating memory for each cell (or voxel), the hashing-based grid map allocates a smaller array. The hashing technique uses a hash function to generate a hash value for each voxel to indicate its index in the array. The design of the hashing function is critical to minimizing the conflict rate, and a smart strategy is also required to deal with possible conflicts to avoid information loss. The hashing grid map allows dynamic map resizing through rehashing and reallocation, thus not requiring knowledge of the mapping area beforehand [91]. Compared to uniform grid maps, hashing grid maps possess higher memory efficiency and better dynamic ability. However, the computational efficiency of hashing grid maps is lower than that of uniform grid maps due to hash conflicts and a lower cache hit rate [110].

Quadtrees and octrees are useful data structures for organizing voxels at various resolutions and have become popularly used in occupancy grid mapping [90, 111]. These tree-based map structures exhibit superior memory efficiency compared to uniform grid maps and hashing grid maps, making them favorable for high-resolution maps and large-scale environments. However, the time complexity for updating occupancy probabilities in a tree structure is logarithmic, while that in grid maps is constant. Consequently, subsequent research has focused on enhancing update efficiency without compromising original accuracy and memory efficiency [81, 112]–[116]

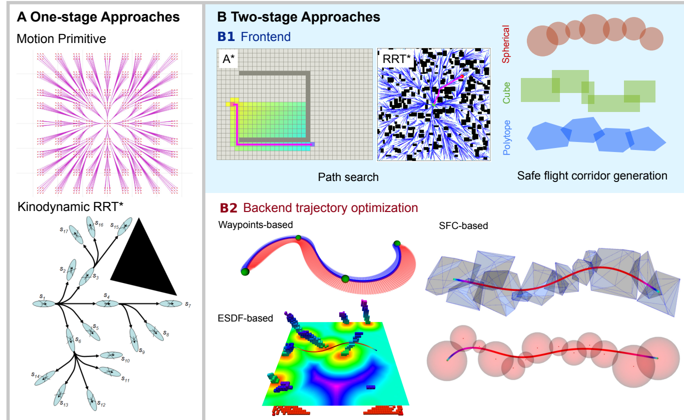

Fig. 3. Existing planning approaches can be categorized into two types: (**A**) One-stage approaches directly generate a collision-free, dynamically feasible trajectory from the current state to the goal. (**B**) Two-stage approaches involve a front-end path planning module and a back-end trajectory optimization module.

The occupancy map structures for continuous representation are similar to those for discrete representations. Grid maps and tree-based maps are used to store raw measurements [96]–[98] or parameterized clusters of raw measurements [100, 101, 106, 107]. Another data structure worth mentioning is the R-tree [117] which is used to organize GMMs without evenly partitioning the space, thus avoiding discretization errors [118].

3) Discussion: When comparing continuous representations with discrete ones, continuous occupancy mapping approaches effectively consider spatial correlation and provide mapping with infinite resolution as well as uncertainty estimation. However, a notable limitation lies in their computational efficiency, which currently hinders their practical application in real robotic systems, especially in aerial systems with limited computational resources. Consequently, discrete representations are currently preferred, but the full potential of continuous mapping could be unlocked with advanced onboard computational resources and the exploration of new designs in map structures utilizing parallel computation architectures.

IV. Planning and Control

A. Trajectory Planning

The trajectory planning module generates safe, collision-free, and dynamically feasible paths toward mission goals based on the mapping results and the UAV's current state, while minimizing flight time and energy consumption. Trajectory planning is typically divided into two approaches: one-stage and two-stage. The one-stage approach directly produces a feasible trajectory from the current state to the goal, while the two-stage approach uses a front-end to find a collision-free path or safe flight corridor and a back-end to optimize the trajectory. Over the years, UAV planning techniques have matured significantly. In the following sections, we will review existing trajectory planning methods for both vision-based and LiDAR-based platforms and explore their application to LiDAR-equipped UAVs.

1) One-stage approaches: One-stage approaches, illustrated in Fig.3A, evolved from traditional path-search methods and have been extensively applied in both ground and aerial vehicles. In 1999, LaValle *et al.* [119] introduced the Kinodynamic RRT (RRT*) algorithm, later extended in [120]–[122]. These methods replace the steering function in RRT* with a dynamically feasible one by solving optimal control (OC) or boundary value problem (BVP) formulations, ensuring the generated path respects the vehicle's dynamics. In 2009, Likhachev *et al.* [123] proposed a Multi-resolution Lattice State Space approach, discretizing the configuration space into states connected by dynamically feasible paths. MacAllister *et al.* [124] applied this method to UAVs in 2013 using the AD* algorithm to generate smooth, feasible trajectories. Pivtoraiko *et al.* [125] further enhanced UAV navigation by integrating a motion primitive library into an online replanning framework for unknown environments. For LiDAR-based UAVs, Zhang *et al.* [56, 57, 59] utilized motion primitive-based methods to achieve high-speed flight (over 10 m/s) in unknown environments. In contrast, Liu *et al.* [55] introduced a trajectory search method based on the Linear Quadratic Minimum Time (LQMT) problem and extended it by considering the UAV's shape for whole-body motion planning, enabling precise maneuvers through narrow gaps [126].

2) Two-stage approaches: Compared to one-stage approaches, two-stage approaches—comprising front-end and back-end modules—have gained traction in UAV planning (Fig. 3B). The front-end generates a collision-free path or safe flight corridor without considering dynamic feasibility, while the back-end optimizes a dynamically feasible trajectory to minimize factors such as time or energy.

Mellinger *et al.* [127] achieved UAV navigation by generating geometric waypoints and optimizing the trajectory using Quadratic Programming (QP) to minimize energy consumption (snap) while ensuring the UAV passes through all waypoints. Richter *et al.* [128] extended this by proposing a closed-form solution for minimum snap trajectory optimization, using RRT* for the front-end path and refining it through trajectory optimization. A similar approach is used by Ji *et al.* [129], where a mapless front-end is combined with alternating minimization [130]. However, deviations between the path and optimized trajectory often require iterative waypoint insertion, reducing computational efficiency and trajectory quality. To address this, Ding *et al.* [131] introduced elastic optimization to enforce collision-free constraints during optimization. Other methods use Euclidean Signed Distance Fields (ESDFs) [132]–[135] to maintain collision-free paths, though building and updating ESDF maps can be computationally expensive. Zhou *et al.* [136] proposed a gradient-based method that eliminates ESDFs, offering a more efficient solution while maintaining dynamic feasibility.

Safe Flight Corridor (SFC)-based approaches have also been widely studied. These methods use convex 3D shapes to represent collision-free corridors, constraining trajectories to ensure safety. Spheres [21, 58], axis-aligned cubes [137], and polyhedra [55, 62, 138, 139] are common representations. Gao *et al.* generated spherical SFCs using RRT*, while Ren *et al.* [21] used sample-based methods to generate them around a collision-free path. Chen *et al.* [137] developed axis-aligned cubes using octree structures, and Deits *et al.* [140] proposed IRIS to generate large polyhedra with Semi-Definite Programming. Liu *et al.* [55] introduced the more efficient Region Inflation with Line Search (RILS), and Wang *et al.* [141] developed the Fast Iterative Regional Inflation (FIRI) algorithm for high-quality polyhedra.

Although sphere- and cube-based SFCs are easy to generate, they may underrepresent free space, leading to suboptimal trajectories. Polyhedron-based SFCs better approximate free space but are computationally more expensive. The back-end optimization typically formulates SFCs as constraints to ensure collision-free trajectories. Chen *et al.* [137] and Liu *et al.* [55] solved the optimization using QP, Gao *et al.* [58] applied SOCP, and Tordesillas *et al.* [138, 139] used MIQP for trajectory optimization. In 2022, Wang *et al.* [16] introduced MINCO, a spatial-temporal deformation method that optimizes both spatial and temporal aspects of trajectories efficiently. The problem is reformulated as an unconstrained nonlinear optimization and solved using the quasi-Newton method.

3) Discussion: The one-stage and two-stage approaches each have distinct advantages and limitations. One-stage approaches are more efficient for short planning horizons but require simplifications to manage computational complexity, often leading to suboptimal solutions. As the planning horizon increases, their time consumption also rises. In contrast, two-stage approaches generate more accurate and dynamically feasible trajectories in less time. The front-end efficiently finds a collision-free path or flight corridor without considering UAV dynamics, while the back-end optimizes the trajectory within a smaller solution space, reducing complexity and time. Moreover, the two-stage approach can incorporate various constraints, such as energy efficiency, time minimization, and safety, making it highly adaptable.

For LiDAR-based UAVs, the challenge lies in leveraging LiDAR's long-range, high-rate 3D measurements to enhance navigation and control. Effective planning must capitalize on LiDAR's long sensing range to enable obstacle avoidance and high-speed flight. Two-stage methods are better suited for this, and we explored three types: 1) Waypoint-based, 2) Distance field-based, and 3) Safe Flight Corridor (SFC)-based methods.

Waypoint-based methods are simple but rely on heuristic waypoint placement, which can yield suboptimal results. Distance field-based methods, such as those using ESDF maps, offer smooth gradients for optimization but are computationally expensive, with non-convex costs prone to local minima. In contrast, corridor-based methods enforce collision-free constraints through convex-shaped SFCs, ensuring efficient, high-quality optimization. With advances in differentiable optimization, such as MINCO [16], SFC-based methods have become ideal for LiDAR-based UAVs. For example, Ren *et al.* [21] demonstrated a LiDAR-based UAV navigating cluttered environments at over 13.7 m/s using spherical SFCs and MINCO-based optimization. Additionally, corridor-based methods integrate seamlessly with MPC backends [65], enabling low-latency navigation and real-time obstacle avoidance for sudden threats.

B. Control

Once a collision-free and dynamically feasible trajectory is generated, the control module is responsible for executing the commands from the planning process. Trajectory tracking control methods have been extensively studied over the past decades. Thanks to the high-accuracy and low-latency state estimation enabled by LiDAR sensors, trajectory tracking control can achieve the precision necessary for most applications.

The most commonly used control method for UAVs is the Proportional-Integral-Derivative (PID) controller [142, 143]. The PX4 Autopilot software [144], widely adopted in UAV systems, employs a cascaded control architecture that combines P and PID controllers. This method is straightforward, easy to tune, and extremely efficient, making it ideal for running on embedded systems.

Beyond PID, the Linear Quadratic Regulator (LQR) [145]–[147] is another widely used optimal control method. LQR operates by minimizing a specific cost function, typically providing better performance than PID. Model Predictive Control (MPC) is also commonly used in UAV control due to its ability to handle system constraints and uncertainties, making it especially effective in the presence of disturbances. Hanover *et al.* [148] proposed an adaptive nonlinear MPC for high-accuracy trajectory tracking during high-speed flights, while Fang *et al.* [149] developed a nonlinear MPC followed by an Incremental Nonlinear Dynamic Inversion (INDI) block to enhance robustness. Sun *et al.* [150] incorporated aerodynamic forces into a nonlinear MPC (NMPC) and INDI-based control framework for quadrotors, and Lu *et al.* [151] introduced a singularity-free, on-manifold MPC framework with minimal parameterization for trajectory tracking. In this approach, the system state is mapped to local coordinates around each reference point on the trajectory, transforming the manifold-constrained control problem into a standard quadratic programming (QP) form that can be solved efficiently.

With advances in onboard computing and numerical optimization techniques, MPC-based methods are becoming increasingly popular for UAV control, offering superior tracking performance while being computationally feasible in real time.

C. Integrated planning and control

Beyond classical planning and control methods, integrated planning and control approaches have also been developed. Lindqvist *et al.* [152] modeled obstacles as spheres and proposed a nonlinear model predictive control (NMPC)-based method for obstacle avoidance. However, their method assumes that obstacle locations are known, limiting its applicability in unknown environments. Liu *et al.* [22, 65] introduced Integrated Planning and Control (IPC), which incorporates polyhedron-shaped SFC constraints into an MPC framework, enabling collision-aware real-time control. In this approach, the front-end generates polyhedron-shaped SFCs based on LiDAR point cloud data, while the back-end directly generates control commands using an MPC-based framework. The IPC method is efficient, accurate, and robust, making it particularly suitable for LiDAR-based UAVs.

V. Open Source Projecs for LiDAR-based Autonomous UAVs

Building an autonomous LiDAR-based system from hardware to software is a complex, system-wide task. Open-source resources provide a valuable foundation for researchers and developers. In TABLE I, we present a curated list of open-source resources relevant to LiDAR-based autonomous UAVs, including hardware, software stacks, simulators, calibration tools, localization, mapping, planning, control, and autopilot systems. Part of the table is adapted from [175], with additional recent resources specifically focused on LiDAR-based UAVs.

A typical pipeline for building an autonomous UAV involves:

1) Designing the hardware structure, incorporating essential sensors, computational units, and actuators.
2) Calibrating sensors such as LiDAR and IMUs, including both spatial and temporal alignment.
3) Deploying navigation software, covering perception, planning, and control modules.
4) Testing the software stack in simulation to evaluate performance.
5) Integrating the software with hardware and conducting real-world tests.

The open-source resources listed in TABLE I cover each of these stages, offering a comprehensive framework for building LiDAR-based autonomous UAVs.

VI. Applications

A. Industrial Applications

Autonomous LiDAR-equipped UAVs have been used in many industrial applications, including inspection [176]–[181], agriculture [176]–[181], search rescue [182, 183], and package delivery [184].

1) Inspection: Inspection tasks can be categorized into areas such as wind-turbine blades [176, 177], bridges [178, 179], and power lines [180, 181]. LiDAR sensors serve as primary tools for measuring geometric data and creating accurate 3D models of structures for analysis. Additionally, LiDAR can support inspections where cameras struggle, such as detecting thin power lines. Accurate LiDAR measurements combined with point cloud classification techniques can aid UAVs in power line-following tasks [185].

2) Agriculture: Thanks to the accurate measurement of LiDAR, the users can pinpoint structures or zones of interes and highlight surface degradation or vegetation growth, which makes the use of LiDAR popular in application of precision agriculture [186]. By processing and utilizing the data acquired by the LiDAR-equipped UAV, many tasks like the estimation of yield [187], health monitoring [188]–[190], height monitoring [191, 192], or tree detecting & digitisation [193, 194] can be done automatically, leading to a smarter and preciser agriculture.

3) Search rescue & package delivery: Currently, most UAVs used for search and rescue and package delivery rely on vision-based systems. However, LiDAR sensors show an advantage because they are not affected by lighting conditions

TABLE I
OPEN SOURCE RESOURCES FOR LIDAR-BASED AUTONOMOUS UAVS

Name and Reference	Category	Year	Link
OmniNxt [153]	Hardware & Software Stack (Vision)	2024	https://github.com/HKUST-Aerial-Robotics/OmniNxt
UniQuad [154]	Hardware (LiDAR & Vision)	2024	https://github.com/HKUST-Aerial-Robotics/UniQuad
Agilicious [155]	Hardware & Software Stack (Vision)	2023	https://github.com/uzh-rpg/agilicious
PULSAR [156]	Hardware (LiDAR)	2023	https://github.com/hku-mars/PULSAR
Fast-Drone-250	Hardware& Software Stack (Vision)	2022	https://github.com/ZJU-FAST-Lab/Fast-Drone-250
Aerial Gym [157]	Simulator	2024	https://github.com/ntnu-arl/aerial_gym_simulator
MARSIM [158]	Simulator	2023	https://github.com/hku-mars/MARSIM
flightmare [159]	Simulator	2021	https://github.com/uzh-rpg/flightmare
AirSim [160]	Simulator	2020	https://microsoft.github.io/AirSim/
rotorS [161]	Simulator	2016	https://github.com/ethz-asl/rotors_simulator
CLEARLAB [162]	Software Stack	2024	https://github.com/Zhefan-Xu/CERLAB-UAV-Autonomy
CMU [59]	Software Stack	2020	https://github.com/HongbiaoZ/autonomous_exploration_development_environment
DVLC [163]	Calibration	2023	https://github.com/koide3/direct_visual_lidar_calibration
LI-Init [82]	Calibration	2022	https://github.com/hku-mars/LiDAR_IMU_Init
LVI-ExC [164]	Calibration	2022	https://github.com/peterWon/LVI-ExC
lidar-camera-calib [165]	Calibration	2021	https://github.com/hku-mars/livox_camera_calib
Kalibr [166]	Calibration	2016	https://github.com/ethz-asl/kalibr
FAST-LIVO2 [84]	Localization	2024	https://github.com/hku-mars/FAST-LIVO2
Swarm-LIO2 [79]	Localization	2024	https://github.com/hku-mars/Swarm-LIO2
Point-LIO [7]	Localization	2023	https://github.com/hku-mars/Point-LIO
FAST-LIO2 [6]	Localization	2022	https://github.com/hku-mars/FAST_LIO
LIO-SAM [167]	Localization	2020	https://github.com/TixiaoShan/LIO-SAM
A-LOAM	Localization	2020	https://github.com/HKUST-Aerial-Robotics/A-LOAM
ROG-Map [63]	Mapping	2024	https://github.com/hku-mars/ROG-Map
D-Map [81]	Mapping	2024	https://github.com/hku-mars/D-Map
FIESTA [92]	Mapping	2019	https://github.com/HKUST-Aerial-Robotics/FIESTA
Voxblox [168]	Mapping	2017	https://github.com/ethz-asl/voxblox
OctoMap [90]	Mapping	2013	https://github.com/OctoMap/octomap
PMM [169]	Planner	2024	https://github.com/ctu-mrs/pmm_uav_planner
GCOPTER [16]	Planner	2022	https://github.com/ZJU-FAST-Lab/GCOPTER
mintime-replan [170]	Planner	2022	https://github.com/uzh-rpg/sb_min_time_quadrotor_planning
FASTER [139]	Planner	2021	https://github.com/mit-acl/faster
time optimal [171]	Planner	2021	https://github.com/uzh-rpg/rpg_time_optimal
TRR [172]	Planner	2020	https://github.com/HKUST-Aerial-Robotics/Teach-Repeat-Replan
FastPlanner [135]	Planner	2020	https://github.com/HKUST-Aerial-Robotics/Fast-Planner
EGO-Planner [136]	Planner	2020	https://github.com/ZJU-FAST-Lab/ego-planner
IPC [65]	Planner & Controller	2023	https://github.com/hku-mars/IPC
Geometry Control	Controller	2021	https://github.com/yorgoon/minimum-snap-geometric-control
PMPC [173]	Controller	2018	https://github.com/uzh-rpg/rpg_mpc
RPG Quad Control [174]	Controller	2018	https://github.com/uzh-rpg/rpg_quadrotor_control
QuadRotor-Control	Controller	2018	https://github.com/srikantrao/QuadRotor-Control
PX4	Autopilot	-	https://github.com/PX4
Betaflight	Autopilot	-	https://github.com/betaflight/betaflight
ArduPilot	Autopilot	-	https://github.com/ArduPilot/ardupilot

and can provide precise measurements even during high-speed flights. This capability enables UAVs to perform essential functions such as obstacle avoidance, environmental mapping, and autonomous navigation even in crowded or low-light environments, which are important for successful search and rescue as well as efficient package delivery. So far, the LiDAR-equipped UAVs are already used in search rescue [182, 183] and package delivery [184]. With the performance improvement and cost reduction of LiDAR sensor, more LiDAR-equipped UAVs will be used in these applications.

B. Autonomous Aerial Platforms

Leveraging LiDAR's strengths has driven major advancements in navigation, environmental perception, and flight speed. These advancements have unlocked new aerial platforms that were not achieved before. This section examines two notable types of autonomous aerial platforms—self-rotating UAVs and vertical take-off and landing (VTOL) UAVs—that utilize LiDAR technology to achieve higher levels of autonomy.

1) Self-rotating UAV: The self-rotating UAV has a continuous body rotation during flight. This characteristic can generally achieve higher flight efficiency than common quadrotor and obviously extend the limited field of view of the visual sensors (e.g., camera, LiDAR). Most of the existing UAVs [195]–[203] cannot achieve autonomous navigation since they have no sensor onboard the UAV to observe the environment and onboard computer for online calculation, mainly due to the low payload capacity. One self-rotating UAV [204] installed a camera for attitude estimation but it cannot realize autonomous navigation because it has no position and velocity estimation and no mapping ability. Another UAV that can estimate the full states during self-rotating uses down-facing event camera [205]. Down-facing camera ease the state estimation but it is not beneficial for autonomous navigation since its field of view is limited downward and also cannot be extended by the self-rotation.

The only one exception is a LiDAR-based self-rotating UAV named PULSAR [156]. It achieved compete autonomous flight in an unknown GNSS-denied environment by only using the LiDAR sensor. At the same time, the limit conical field of view of the LiDAR sensor is extended through self-rotation to cover most area around the UAV, which obviously improved the mapping efficiency and obstacle perception ability. Unlike the camera may have image motion blur caused by fast self-rotation resulting in harder state estimation and mapping, the LiDAR sensor can realize accurate state estimation and mapping during high-speed self-rotation. For each LiDAR point measurement, the time interval is very short such that the self-rotation of the UAV can be neglected, and hence the LiDAR sensor is more suitable for autonomous self-rotating UAVs.

2) Vertical Take-off and Landing UAVs: Vertical takeoff and landing (VTOL) UAVs can take off and land vertically like typical multi-rotor UAVs and achieve long-range and high-speed flight with high efficiency similar to fixed-wing UAVs at the same time. Since their aerodynamics are highly nonlinear with large variation of angle of attack during transition and high flight speed, achieving the autonomy of VTOL UAVs is a very challenging task. A LiDAR-based VTOL UAV platform is proposed in [206] for potential terrain-following flight, but the autonomous flight is not achieved so far. In [207], the differential flatness of tail-sitter VTOL UAV with quadrotor configuration is proofed and verified, which is a huge advance to realize high-speed autonomy of this type of UAV. The first tail-sitter VTOL UAV that achieves fully autonomous flight ability is reported in [208]. It equips a LiDAR sensor to estimate states and to build environmental map as well as uses an efficient feasibility-first solver to optimize flight trajectory within complex aerodynamic constrains during a short time interval. As a result, this LiDAR-based VTOL UAV achieved 15-m/s high-speed flight in clustered environments such as underground parking lot and ourdoor park, fully autonomously.

C. UAV Swarm Applications

Multi-UAV systems offer significant advantages over single-UAV systems, including enhanced fault tolerance, high scalability, and increased coverage and efficiency. The failure of one UAV does not compromise the mission, as others can continue operating, ensuring reliability and mission success. Additionally, these systems enable comprehensive data collection from multiple perspectives, facilitate cooperative behaviors for improved task execution, and can reduce operational costs despite a higher initial investment. Overall, the robustness and flexibility of multi-UAV systems make them essential for various complex applications in the evolving landscape of autonomous aerial operations, such as swarm aerial tracking and swarm exploration.

1) Swarm Aerial Tracking: Swarm tracking empowers UAVs to autonomously identify, follow, and monitor specific targets in real time. Camera-based multi-UAV tracking has drawn increasing attention in the recent literature [209]–[212], which fully leverages the advancement of camera-based detection. Compared to cameras, LiDAR sensors can provide more accurate measurements on environments and targets . In 2020, Bonatti. *et al.* [213] presented an aerial tracking UAV which mounted a VLP-16 LiDAR for environmental sensing. However, the target in [213] is still measured with a camera, and the system only contained a single UAV. In 2023, Yin. *et al.* [68] proposed a swarm tracking system that solely utilizes Mid360 LiDARs as the sensors. The proposed system achieved visibility-aware tracking upon a high-reflective-tape-marked drone as the target in cluttered scenes, which validated the practicability of LiDAR-based cooperative tracking.

2) Swarm Exploration: Swarm exploration refers to the coordinated use of multiple UAVs to autonomously explore and gather information about an environment. This approach leverages the strengths of swarm robotics and distributed systems to achieve simultaneous data collection and hence higher efficiency than single-UAV exploration. Compared to the camera-based swarm exploration [214], LiDAR-based ones can provide superior sensing ranges and discover the detailed geometry of the environments, which helps render more accurate frontiers for exploration [69, 215]. Yu. *et al.* [216] proposed a multi-robot multi-target potential field model to select the best frontier goal and validated the method physically with two ground vehicles equipped with 2D-LiDARs. However, this work only considered 2D spaces. Yan. *et al.* [217] focused on addressing swarm exploration with unknown initial positions and verified the framework with simulated Velodyne LiDARs. However, no real-world experiment was carried out. In [69], a voronoi partition strategy was presented for task allocation and a real-world swarm of five Mid360 UAVs was deployed to validate the proposed method.

VII. Discussion and Future Directions

The rapid advancement of LiDAR technology has significantly enhanced UAV autonomy, enabling a wide range of tasks. However, there is still a considerable gap to perfection, with room for improvement in both LiDAR hardware and corresponding algorithms. Future research should focus on overcoming these challenges to fully unlock the potential of LiDAR-based UAVs. The following sections outline key challenges and future directions for enhancing the autonomy, perception, and performance of LiDAR-equipped UAVs through sensor advancements and algorithmic innovations that could elevate their capabilities to the next level.

A. Enhancing LiDAR Sensors and Multi-Sensor Fusion

Current LiDAR sensors face limitations related to weight, cost, and difficulties in detecting certain surfaces, such as glass and water, which impact UAV performance. Future research should prioritize the development of advanced LiDAR technologies, such as MEMS-based and METASURFACE LiDAR [218, 219], to reduce weight and enhance the payload capacity of UAVs.

An emerging area of interest is the development of pure solid-state LiDARs, such as flash LiDAR. Flash LiDAR offers significant potential due to its compact size, reduced weight, and simplified design with no moving parts. This technology allows for further miniaturization, which is particularly beneficial for UAVs where weight and space are critical constraints. Additionally, future enhancements in detection range, resolution, and point frequency could greatly expand the capabilities of UAVs equipped with flash LiDAR, enabling more precise and long-range sensing.

Integrating LiDAR with other sensors (e.g., GPS, radar, and cameras) in a unified perception framework can further improve robustness and sensing capabilities. Adaptive sensor fusion algorithms that dynamically adjust to environmental conditions can enhance UAV reliability, effectively addressing corner cases involving reflective or transparent surfaces.

B. Addressing Challenges in Dust and Adverse Weather Conditions

Dust, rain, and fog pose significant challenges for LiDAR-based UAVs, as these conditions can disrupt LiDAR measurements and degrade system performance. Future efforts should focus on developing adaptive filtering algorithms and signal processing techniques to mitigate noise and scattering effects caused by such adverse conditions. Integrating sensor fusion methods that combine LiDAR with radar and thermal imaging can further improve UAVs' ability to perceive and operate reliably. Additionally, machine learning-based correction models and robust data pre-processing strategies may enhance LiDAR data accuracy, ensuring dependable navigation and obstacle detection under challenging weather.

C. Improving High-Precision Real-Time Mapping and Perception Algorithms

The long detection range and high accuracy of LiDAR sensors present challenges for real-time mapping and perception algorithms [81]. Optimizing computational performance in mapping algorithms, such as occupancy grid mapping, is crucial to fully leverage LiDAR's capabilities. Future research should prioritize more efficient update methods and data compression techniques to enhance memory efficiency. Exploring continuous mapping [118] and decremental mapping [81] could further boost real-time performance. Additionally, deep learning-based approaches, such as implicit mapping, could be employed to process extensive LiDAR data while preserving maximum information in real-time.

D. Advanced Obstacle Avoidance for Small and Dynamic Obstacles

In real-world applications, small and dynamic obstacles present significant challenges for UAV navigation. The high accuracy and direct 3D measurement capabilities of LiDAR have enabled UAVs to detect and avoid obstacles that are difficult for vision-based navigation frameworks [19]. However, challenges remain in handling fast-moving and low-reflective small obstacles. To effectively avoid these, LiDAR sensors need higher point rates, greater resolution, and improved sensitivity to low-reflective materials. Additionally, algorithms must be robust to noise and capable of efficiently processing large volumes of data. For avoiding fast-moving obstacles, LiDAR sensors should operate at higher frequencies, with algorithms optimized for rapid data processing (e.g., [220]). Future research should prioritize the development of advanced obstacle avoidance algorithms capable of handling fast-moving and small obstacles, ensuring UAVs can navigate safely in dynamic environments.

E. Exploring Learning-Based Methods

Learning-based methods have demonstrated significant potential in enhancing visual UAV navigation through depth images [221]. Integrating LiDAR's long-range, high-accuracy measurements with learning-based approaches could enable UAVs to achieve more agile, high-speed flight. These methods can leverage LiDAR's rich spatial data to optimize planning and control strategies, improving adaptability in complex and dynamic environments. However, compared to vision sensors, LiDAR measurements are relatively sparse, which may limit the performance of learning-based approaches and must be systematically addressed. Future research should focus on developing algorithms that overcome this limitation, unlocking the full potential of learning-based methods for enhanced UAV performance.

F. Enhancing Environmental Interaction Capabilities

Currently, aerial robots primarily serve as passive observers, avoiding obstacles in their environment with limited capability for interaction to ensure flight safety. Future research should explore enabling LiDAR-based UAVs to actively interact with and even change their surroundings to achieve specific navigation tasks. Integrating robotic manipulation technologies could allow UAVs to perform operations such as opening doors [222] or moving obstacles. Additionally, bio-inspired designs and the incorporation of flexible sensors could further expand UAVs' operational capabilities, enabling active environmental interaction beyond mere obstacle avoidance.

G. Multi-UAV Cooperation and Swarm Intelligence

Most research to date has focused on individual UAV autonomy, but significant potential exists for exploring multi-UAV cooperation in complex missions [67, 68, 79, 214]. Developing collaborative perception and decision-making frameworks will enhance the task planning and adaptability of UAV swarms. This can facilitate efficient mission execution in large-scale, challenging environments, leveraging LiDAR's capabilities for comprehensive, cooperative operations.

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