LiDAR-Centric Aerial Robots: From Advanced Navigation to Swarm Intelligence

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I. Introduction

Birds have long fascinated humans with their ability to navigate swiftly and precisely through cluttered environments, demonstrating remarkable coordination and cooperation. Similarly, multi-rotor micro air vehicles (MAVs)—among the most agile robots ever created—can replicate bird-like flight and collective behaviors. These capabilities offer promising potential across a variety of applications, including logistics [3], inspection [2], search and rescue [14], autonomous exploration [20], and 3D reconstruction [21]. However, given that MAVs typically have limited payloads, restricting the sensors and computational units they can carry, leveraging these constrained resources to enable advanced autonomy, and even swarm behaviors, remains a significant challenge.

Over the past decade, vision-based navigation has been widely adopted in autonomous MAVs due to the Small size, light Weight, and low Power consumption (SWaP) of visual sensors [23, 7, 22, 9, 15]. However, vision sensors come with several limitations, including a limited sensing range (typically 3 to 5 meters), low dynamic range, and susceptibility to motion blur. These drawbacks significantly restrict the achievable flight speeds and overall safety of MAVs. Additionally, vision-based systems are highly sensitive to lighting conditions, creating further challenges in real-world applications with insufficient or variable illumination.

In contrast, light detection and ranging (LiDAR) sensors offer direct, accurate (centimeter-level), and long-range (tens to hundreds of meters) depth measurements. The extended range enables MAVs to detect and avoid obstacles from greater distances, supporting high-speed flight. Furthermore, the precise measurements allow MAVs to navigate through tight spaces in cluttered environments. LiDAR sensors operate at extremely high point rate, ranging from hundreds of thousands to millions of Hertz, allowing for the estimation of rapid MAV movements [18]. Additionally their time-of-flight-based active detection ensures robust performance across diverse lighting conditions, including complete darkness.

With the advancement of LiDAR technology and the emergence of new, lightweight, and compact LiDAR sensors, my research focuses on designing a LiDAR-based autonomous MAV system, along with planning and control algorithms, to fully leverage the sensing capabilities of LiDAR and the agility of multi-rotor MAVs. I aim to address the following two key questions:

Fig. 1: (**A**) High-speed and safe navigation in unknown environments. (**B1**) Swarm intelligence in autonomous delivery application. (**B2**) The online mutual state estimation and mapping for swarm robots.

Research Question 1: *How can we fully leverage the agility of MAVs to enable high-speed, agile, and safe navigation in challenging environments?*

Research Question 2: *How can we achieve swarm intelligence in multi-MAV systems for complex real-world scenarios?*

II. Current Research

A. High-speed, Agile and Safe Navigation for MAVs

In the first part of my research [12, 10, 11], I focus on developing an advanced navigation system for a single MAV to address **Research Question 1** (Fig. 1**A**). Unlike existing vision-based methods, we use LiDAR as the primary sensor. As demonstrated in [18], LiDAR-IMU-Odometry achieves accurate state estimation at over 100 Hz, enabling aggressive movements during high-speed flight. We further develop a fast, point-cloud-based mapping system that eliminates the need for computationally heavy occupancy grid or Euclidean distance field maps [23, 22, 15].

While using point-cloud maps for LiDAR sensors is intuitive, planning effectively on such maps is challenging. In [10], we use an incremental K-dimensional tree (iKD-tree)[1] to maintain obstacle point clouds and propose a novel method for generating safe flight corridors (SFC) from the iKD-tree map. Within the SFC, we apply an efficient spatiotemporal trajectory optimization method[16] to generate high-quality trajectories in just a few milliseconds. Our system achieves a flight speed of 13.7 m/s in unknown wild forests, relying solely on onboard sensing and computation.

We extend this work to enable real-time whole-body motion planning for MAVs, allowing agile navigation through narrow gaps in unknown environments [11]. Unlike existing methods requiring offline computation [6] or prior knowledge of gap features [4], our approach utilizes LiDAR measurements and a novel problem decomposition strategy to achieve online, real-time detection and motion planning for gap traversal without prior environmental data.

Although previous methods enable relatively high-speed and agile flights in unknown environments, most of them adopt an optimistic strategy, treating unknown areas (due to sensor range limitations or obstacle occlusion) as free. As a result, these methods often have low success rates at high speeds. Some strategies prioritize safety by enhancing the visibility of unknown areas [22] or treating them as occupied [9], but these tend to be overly conservative, compromising flight speed.

To achieve both high-speed and safe flight, we adopt two trajectory planning frameworks [15] and propose a novel method to efficiently distinguish known-free areas directly from point clouds, enabling the use of an efficient point-cloud-based mapping module. We also introduce a two-trajectory optimization formulation using a differentiable trajectory optimization tool [16]. As a result, our system [12] can leverage LiDAR's extended sensing range while maintaining low latency. The system has been validated in unknown, cluttered environments, achieving high-speed flights exceeding 20 m/s, relying solely on onboard sensing and computation. Thanks to the advanced sensing capabilities of LiDAR, the system can avoid thin wires with diameter less than 2 mm and navigate through varying lighting conditions, including total darkness. Additionally, our method has been applied to other unmanned aerial vehicle (UAV) types, such as in [8], where we enabled high-speed and safe navigation for a tail-sitter UAV in unknown environments. This advanced navigation capability for agile, high-speed, and safe micro air vehicle (MAV) flight serves as a foundational component for applications in delivery, inspection, and search and rescue.

B. Swarm Intelligence in the Wild

In the second part of my research, I aim to extend our MAV system to a swarm and address **Research Question 2**, focusing on achieving swarm intelligence for MAVs in real-world environments.

The first challenge we address in [24] is achieving accurate and robust ego and mutual localization for swarm robots. While existing methods have tackled localization for vision-based swarm systems [17], they are not suitable for LiDAR-based sensors and are constrained by the limitations of visual sensors, which struggle in high-speed movements, large-scale missions, and low-light conditions.

To overcome these challenges, we propose a novel LiDAR-based online mutual state estimation and mapping system for swarm robots (Fig. 1**B2**). To the best of our knowledge, this is the first LiDAR-based odometry system specifically designed for swarm robotics. Our system is fully decentralized and includes an online initialization module that calibrates the spatiotemporal extrinsics of each robot, and able to provide centimeter-level ego and mutual state estimation. Additionally, the system supports plug-and-play functionality for new robots, making it highly scalable for large-scale missions. Thanks to its decentralized architecture, our system is resilient to single-point failures. After solving the localization and mapping problem, we demonstrated in [24] and [19] that our approach enables a wide range of swarm applications, including autonomous navigation in wild forests, mutual collision avoidance in cluttered environments, and multi-MAV target tracking.

III. Future Work

My future research interests are centered around the goal of developing field robotics that can operate effectively in real-world scenarios. Two key directions for this research are: (**i**) advancing higher-level swarm cooperation and (**ii**) combining model-based with learning-based approaches to achieve greater autonomy in complex tasks.

The first one focuses on advancing swarm intelligence for real-world applications, such as our ongoing project on autonomous delivery (Fig. 1**B1**). This task requires MAVs to operate in a tightly coupled manner, as they are connected by cables, meaning that any movement of one MAV directly affects the entire swarm system. One potential solution is to draw inspiration from bird flocks and develop smarter individual MAVs capable of estimating external forces and the mutual states of other MAVs with minimal communication. This approach would enhance the system's resilience to communication failures and enable operation in more complex environments, even with larger swarm sizes. Beyond delivery missions, this swarm system could also be applied to autonomous exploration, target searching, and other tasks.

The second area one is combining model-based planning and control methods with learning-based approaches, such as imitation learning [7] and reinforcement learning [13]. Learning-based methods can effectively learn complex mappings from sensor data to control commands, achieving superior performance in tasks that are difficult to model. However, these methods are often data-hungry and may struggle with generalization in certain cases. In contrast, model-based methods can provide physical constraints and optimal solutions for simplified problems. Similar to [5], our ongoing project demonstrates that by leveraging model-based methods as prior knowledge and learning a residual model from the data to compensate for the unmodeled aspects of the model-based approach, we can combine the strengths of both methods, resulting in a more robust and efficient system. By integrating these approaches, we aim to develop a system that capitalizes on the best of both worlds.

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