Exploring the technical advances and limits of Autonomous UAVs for Precise Agriculture in Constrained Environments

Meriem Ben Miled[1], Davide Grande[1], Xudong Li[2], Yuanchang Liu[1,*]

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***Abstract*— In the field of precise agriculture with autonomous unmanned aerial vehicles (UAVs), the utilization of drones holds significant potential to transform crop monitoring, management, and harvesting techniques. However, despite the numerous benefits of UAVs in smart farming, there are still several technical challenges that need to be addressed in order to render their widespread adoption possible, especially in constrained environments. This paper provides a study of the technical aspect and limitations of autonomous UAVs in precise agriculture applications for constrained environments.**

I. Introduction

Mountain agriculture is essential for multiple reasons. Firstly, mountain regions are home to about 12% of the global population providing food and employment opportunities for the local communities [1]. Secondly, it represents a significant portion of the farmland. In fact, in England, the majority of hill farming land, classified as a Less Favored Area (LFA), represents 17% of the land farmed in the country [2]. As the global population is projected to reach 9.7 billion by 2050, demand for food and agricultural products will exponentially increase [3], and mountain agriculture will play an important role in the future of food self-sufficiency. Indeed, mountain agriculture has the potential to contribute to meeting this future demand by increasing productivity and improving the efficiency and sustainability of agricultural practices in these regions. Additionally, mountain agriculture plays an important role in maintaining ecosystem services such as soil conservation, watershed protection, and biodiversity conservation. However, the geographical constraints and difficulties of farming in these regions often result in higher costs and lower productivity compared to other areas. The challenges faced by mountain farmers also include a harsh and unpredictable climate. These challenges can lead to lower work productivity, which can have a negative impact on the sustainability of mountain communities [4].

To address these challenges, there is a need for innovative solutions that can help improve the efficiency of mountain agriculture. The use of autonomous unmanned aerial vehicles (UAVs) can help address some of these challenges by providing more efficient and cost-effective ways to monitor crops, manage pests and diseases, and support decision-making [5]. The integration of UAVs into mountain agriculture (Fig. 1) has the potential to improve the viability and sustainability of these farming systems, making them more resilient to the challenges posed by the unique conditions of mountain environments. In fact, drones have the potential to revolutionize the agricultural industry. However, practical implementation of precise agriculture using drones is impeded by various technical challenges. Thus, in the following sections, the role of drones in precise agriculture for hill agriculture will be studied, along with the technical constraints of this application. The ongoing technical research and advancements aimed at addressing these challenges will also be emphasized.

II. Role of Autonomous UAVs in smart farming

In precise agriculture, drones are classified into two distinct categories (Table I.): large drones, also known as Remotely Piloted Aircraft (RPA), and small drones, referred to as Unmanned Aerial Vehicles (UAVs). UAVs lead in the drone industry as they are cost-effective. They have lower payload capacity, making them easier to operate. In addition, the data collected by small drones can be analyzed and used to optimize decision-making processes, such as determining the best time to plant, water or harvest crops, and optimizing fertilizer and pesticide application [6]. In contrast, RPAs are used for tasks that are more heavy duty. These drones are larger and have a higher payload capacity, allowing them to carry more weight and cover larger areas. They are also used to automate the spraying and seeding processes and reduce waste by only spraying specific areas [7].

TABLE I. UAVs in Precise Agriculture

	Applications	Sensors
UAV	- Crop monitoring (crop health, soil moisture, plant growth) - Field mapping - Surveillance	- Cameras (RGB, Multispectral, hyperspectral, thermal) - Soil sensor - Humidity sensor - LiDAR
RPA	- Planting - Crop pollination - Aerial seeding - Sampling - Spraying (water, pesticide, fertilizer)	- Spraying equipment: spray tank, nozzles, and a pump - Seed hoppers - Probe/ sampling tools - TLS

Currently, specific non-autonomous drones designed for smart farming are available on the market. For instance, the Matrice 300 RTK [8] is designed for agriculture, equipped with a multi-spectral camera from third party manufacturers for crop analysis and mapping, and a large-capacity battery

[1] University College London (UCL), Department of mechanical engineering
[2] Dalian University of Technology, School of Mechanical Engineering
(* corresponding author, e-mail: yuanchang.liu@ucl.ac.uk)

for an industry-leading flight time of 55 minutes. The Parrot Anafi USA [9] features a 32x zoom, 4K HDR camera with a 21-megapixel Sony sensor and thermal imaging capabilities, allowing users to capture highly detailed images and videos for mapping and surveillance tasks. The UAV has a flight time of up to 32 minutes and a range of up to 6900 m. The Precision Hawk Lancaster 5 [10] is equipped with a high-resolution multispectral camera and a thermal sensor, which allows it to capture images in multiple spectra for enhanced analysis and decision-making for crop health assessment, yield estimation, and precision irrigation. The drone has a flight time of up to 45 minutes and can cover up to 4000 m^2, making it suitable for covering large areas efficiently.

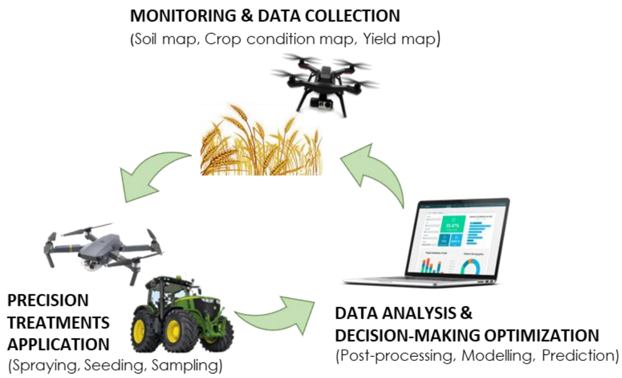

Figure 1. Precision agriculture cycle and its main phases

The literature currently available shows that autonomous drones offer several technical advantages in constrained environments such as farming in mountains:

- expand accessibility to hard-to-reach regions: UAV's ability to manoeuvre in tight spaces and over rough terrain [11], makes them well suited for working in challenging environments or densely vegetated areas;
- improved data collection speed and accuracy: UAVs can cover large areas of hilly terrain quickly and efficiently, providing farmers with high fidelity real-time data (NDVI, RGB, and LiDAR) [12];
- enhance safety for farmers: UAVs reduce the need for manual labor in challenging terrain such as steep slopes, rocky terrain, and pesticide application [13].

III. Technical Advances and Limitations of Autonomous Drones in Constraint Environments

Operating autonomously in complex environments, such as under a forest canopy, can be arduous. In this section, the major technical limitations of autonomous drones operating in challenging environment will be listed and explained.

A. State estimation

In a UAV, the state space vector is defined as:

$$\overrightarrow{x_k} = [x, \dot{x}, y, \dot{y}, z, \dot{z}, \emptyset, \dot{\emptyset}, \theta, \dot{\theta}, \psi, \dot{\psi}] \quad (1)$$

where (x, y, z) is the vehicle's position, $(\dot{x}, \dot{y}, \dot{z})$ the linear velocity, $(\emptyset, \theta, \psi)$ the roll, pitch and yaw respectively, and $(\dot{\emptyset}, \dot{\theta}, \dot{\psi})$ the angular velocity [14]. The state is found by using mathematical models and algorithms to fuse available measurements from multiple sensors [15]. Fusing GPS and IMU data using a Kalman Filter is mainly used for outdoor state estimation. However, GPS signals are often not available in many rural areas and forests, making it difficult to use GPS-based navigation and mapping solutions in these cluttered environments. To counter this challenge, UAVs can rely on alternative algorithms, such as RTK (Real-Time Kinematic) GPS [16], SLAM [17], and VIO [18] to provide accurate state estimation in GPS-denied environments [19]. Despite showing encouraging results in controlled standard environments, in constrained environment, however, their performances decrease tremendously.

To estimate the position $\overrightarrow{p_k}$ of the drone in a GPS-denied environment, the pose (x, y) in the horizontal plane is usually decoupled from the z-coordinate, which represents the altitude. In the context of precise agriculture, drones need to fly close to the ground to capture accurate and high-quality data. Nonetheless, flying at a low altitude can generate additional problems for height estimation $h_{estimated}$, as the flat ground assumption is not valid anymore when flying below 3 m [20]. One of the main issues is that the height sensor may not have a clear line of sight to the ground, especially in areas with tall vegetation or uneven terrain. In addition, in the presence of cavities and hills, it is challenging to maintain a desired minimum clearance $h_{desired}$, which is the minimum vertical distance that must be maintained between the drone and the terrain. Indeed, to maintain a constant altitude $h_{desired}$, the mainly used altitude P-controller for VTOL UAVs [21] $u(t) = Kp * (h_{desired} - h_{estimated})$ takes the difference between $h_{desired}$ and the current height sensor measurement $h_{estimated}$. Thus, if a drone is flying over a hill, the height sensor will measure the altitude of the drone relative to the slope of the hill, rather than ground clearance [22]. Similarly, if the drone is flying over holes or depressions, the UAV may descend into the depression, even if the height sensor indicates that it is maintaining a constant vertical distance above the ground. This can cause degraded performances and in the worst case scenario even lead to a crash and collision with the ground.

The main algorithm used to estimate the pose (x, y) in GPS-denied environment is 3D LiDAR Simultaneous Localization and Mapping (SLAM). 3D LiDAR SLAM [23] works by simultaneously creating a map of the unknown environment and estimating the drone's pose within the map. Despite the promising performance of the state of art 3D LiDAR SLAM in unobstructed scenarios, its accuracy and robustness in complex environments pose significant challenges [24].

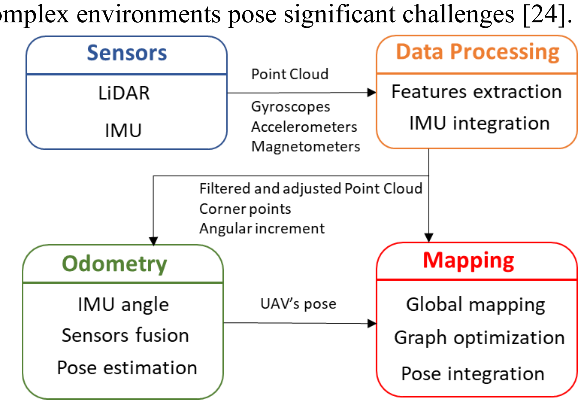

Figure 2. LiDAR 3D SLAM process overview

Indeed, to construct the Global Map for 3D LiDAR SLAM (Fig.2), IMU angles and LiDAR frames are fused to compute ${}_{i+1}^{o}\boldsymbol{T}$, the transformation from UAV's coordinate system $\{B\}$ to the world coordinate system $\{O\}$ at the time i+1 [24]:

$$ {}_{i+1}^{o}\boldsymbol{T} = {}_{i}^{o}\boldsymbol{T}\,{}_{i+1}^{i}\boldsymbol{T} \tag{2}$$

$$ {}_{i+1}^{i}\boldsymbol{T} = \begin{bmatrix} {}_{i+1}^{i}\boldsymbol{R}_{IMU} & {}^{i-1}_{i}\boldsymbol{p} \\ 0 & 1 \end{bmatrix} \tag{3}$$

$$ {}_{i+1}^{o}\boldsymbol{f} = {}_{i+1}^{o}\boldsymbol{T} * {}_{i+1}^{i}\boldsymbol{f} \tag{4}$$

where ${}_{i+1}^{i}\boldsymbol{T}$ and ${}_{i+1}^{i}\boldsymbol{R}_{IMU}$ are the translation and the rotation measured by IMU transformations between two consecutive LiDAR frames $\boldsymbol{f}$ and ${}^{i-1}_{i}\boldsymbol{p}$ is the displacement vector. In Eq. (3), the transformation between two LiDAR frames ${}_{i+1}^{i}\boldsymbol{T}$ is obtained using IMU data. Although, while LiDAR data is typically captured at a rate of approximately 10Hz, IMU data is collected at a much higher frequency of about 200Hz. To integrate the two types of data, the IMU data needs to be synchronized with the LiDAR timestamp: all IMU angular velocity measurements between two LiDAR frames are integrated to get the angular increment. However, navigating throughout a complex environment requires rapid changes in yaw pitch and roll, making the IMU data integration between two frames uninformative. In addition, certain types of UAV navigation that involve frequent and rapid changes in rotation, such as high-speed aerial maneuvers or flying in turbulent wind conditions, can increase the noise of the IMU. This is because the rapid changes in rotation can cause the inertial sensors in the IMU to experience high levels of acceleration and vibration, which can introduce additional error and bias into the measurements [26]. Thus, the inaccuracy of IMU time integration and noise augmentation make $\boldsymbol{R}_{IMU}$ invalid, and therefore the mapping unsuitable.

Once the transformation matrix ${}_{i+1}^{o}\boldsymbol{T}$ is obtained, it is used to transform the point cloud data $\boldsymbol{f}$ from the vehicle's coordinate system to world coordinate system Eq. (4). Mathematically, $\boldsymbol{f} = \{\vec{x}_1 \dots \vec{x}_n\}$ is a set of LiDAR points $\vec{x}_n = (x_{Lidar}, y_{Lidar}, z_{Lidar})$ in the drone's coordinate system. Changing point cloud's coordinate system is computationally expensive, especially for large point clouds. To optimize the computation complexity and cost, various techniques can be used. One technique is to use approximation algorithms like Iterative Closest Point (ICP) [27] or Coherent Point Drift (CPD) [28] to provide an estimation of the transformation matrix with reduced computational complexity. Another technique is to rely on certain libraries. Point cloud processing libraries, such as Point Cloud Library (PCL) [29] and Robot Operating System (ROS) [30], provide optimized functions for point cloud transformation. These functions can take advantage of hardware acceleration, such as Graphics Processing Units (GPUs), to speed up the computation. GPUs are specialized hardware designed for parallel processing and are capable of processing large amounts of data in parallel. For example, PCL provides a GPU-based implementation of the ICP algorithm, which can be used for point cloud registration. This implementation, called GPU-ICP [31], can achieve significant speedups over the CPU-based implementation. Additionally, ROS also offers a GPU-accelerated point cloud library called PCL CUDA (Compute Unified Device Architecture), which provides optimized functions for point cloud processing on NVIDIA GPUs [32]. 3D LIDAR SLAM algorithms, while optimized, remain resource-intensive due to the large datasets involved. Forest mapping with 3D SLAM involves two methods: single-scan and multiple-scans mode. The former entails LiDAR scanner placement at a single point within a forest plot, allowing unidirectional tree visibility acquisition. Despite its simplicity and speed, single-scan mode suffers from lower detection rates due to occlusion effects. Conversely, multiple-scans mode enables full stem surface coverage through data acquisition from multiple scanner positions, necessitating more extensive observation. This results in heightened temporal and preprocessing requirements, taking 1 to 10 hours depending on plot size and forest type. For instance, a 30m x 30m plot requires approximately 1 hour, while a 100m x 100m plot demands around 10 hours, exceeding typical drone flight durations [33].

As the LiDAR frames in forest measurements are complex and dense with an irregular or non-uniform terrain within a forest ecosystem, matching two consecutive LiDAR frames for global mapping becomes challenging. One used technique for matching frames is the Implicit Moving Least Squares (IMSL) [25]. The IMLS algorithm uses ICP algorithm to find the transformation that best alignment. This transformation is then used to update the position and orientation of the sensor in the map. Another proposed method involves linear interpolation for point cloud processing where each measurement is correctly re-projected in the map reference frame by considering a continuous time trajectory [35-36]. Despite the promising results of the state of art algorithms cited above, global ground consistency assumption (the property of a 3D reconstruction that ensures the ground surface is correctly identified across different segments or scans) restricts its use to flat terrain and uneven terrains cannot be adapted, making their performance poor in constrained environments. In addition, the range and accuracy of sensors used, such as LIDAR, can be limited in dense environments, particularly in the presence of obstacles that interfere with their signals [37] or dust. Furthermore, in dense environments like forest canopy, the data association problem, which involves matching features in consecutive frames, can become more challenging due to the presence of similar-looking features [38].

B. Control system

The limits of control systems for UAVs in precise agriculture can be attributed to several factors. As mentioned in section III.A, drones need to fly at low altitude to be able to capture detailed information about crops and soil at a closer range. Although, flying close to the ground creates "ground effect disturbances" [39]. This phenomenon is generated due to the interaction between the terrain and the UAV, which produces turbulences including vortexes. These additional disturbances can cause severe impacts on a drones' flight, especially during the vertical takeoff and landing. Indeed, these disturbances can affect the stability and control of the drone, leading to difficulty in maintaining stable flight [40].

Secondly, as mentioned in section II., RPAs for precise agriculture are equipped with spraying systems including a tank. This added system generates an additional disturbance called "sloshing effect". Sloshing is the movement of liquid inside the tank due to the motion of the UAV, which can result in a shift in the Center of Gravity (CoG) of the drone. Indeed, phenomena can have significant negative impact on the stability and performance of the vehicle [41]. This can affect the UAV's stability and increase the challenges of the control system. Thus, standard controllers as PID might not be suited for this application and more advanced techniques paired with accurate dynamics are rendered necessary. In detail, sloshing effects significantly increase the modelling complexity as the impact of the shifting CoG and mass variation need to be accounted for. The authors in [42] developed a nonlinear dynamic model for the quadrotor, taking into account the impact of center of gravity and mass variations on the vehicle's behavior. Thus, the model includes an additional reference frame of the tank attached below the drone as seen in Fig. 3. Indeed, the modified translational and rotational motion of the UAV become:

$$\begin{bmatrix}\ddot{x}\\ \ddot{y}\\ \ddot{z}\end{bmatrix} = \begin{bmatrix}0\\ 0\\ -g\end{bmatrix} + \frac{1}{m}\left((f_T(X) + g_T(X)u_1) \begin{bmatrix}x_L\\ y_L\\ z_L\end{bmatrix} + \begin{bmatrix}R_{13}(\eta)\\ R_{23}(\eta)\\ R_{33}(\eta)\end{bmatrix} u_1 \right) \tag{5}$$

$$\begin{bmatrix}\ddot{\emptyset}\\ \ddot{\theta}\\ \ddot{\psi}\end{bmatrix} = \begin{bmatrix}f_4\\ f_5\\ 0\end{bmatrix} + \begin{bmatrix}g_4 & \frac{1}{I_{xx}} & 0 & 0\\ g_5 & 0 & \frac{1}{I_{yy}} & 0\\ 0 & 0 & 0 & \frac{1}{I_{zz}}\end{bmatrix} \begin{bmatrix}u_1\\ u_2\\ u_3\\ u_4\end{bmatrix} \tag{6}$$

$$\begin{cases} f_4 = l(x_L R_{12}(\eta) + y_L R_{22}(\eta) + z_L R_{32}(\eta)) f_T(X) \\ f_5 = l\big(x_L R_{11}(\eta) + y_L R_{21}(\eta) + z_L R_{31}(\eta)\big) f_T(X) \\ g_4 = l\big(x_L R_{12}(\eta) + y_L R_{22}(\eta) + z_L R_{32}(\eta)\big) g_T(X) \\ f_5 = l(x_L R_{11}(\eta) + y_L R_{21}(\eta) + z_L R_{31}(\eta)) g_T(X) \end{cases} \tag{7}$$

where $\overrightarrow{x_k}\ [x, \dot{x}, y, \dot{y}, z, \dot{z}, \emptyset, \dot{\emptyset}, \theta, \dot{\theta}, \psi, \dot{\psi}, x_L, \dot{x}_L, y_L, \dot{y}_L, z_L, \dot{z}_L\ ]$ represents an augmented state space vector with respect to the one introduced in Eq. (1) with 18 variables including the position and the velocity of the CoG of the tank [f], X represents $(x, \dot{x}, y, \dot{y}, z, \dot{z})$, $f_T(X) + g_T(X)u_1$ the sloshing dynamics, $-g$ the gravity and m the total mass. In Eq. (7), l represents the offset between the CoG of the drone and the tank, R_{ij} the transformation matrix between [B] and [E], η the attitude, [I] the moment of inertia, u_1 the total thrust and $u_{2,3,4}$ the roll, pitch and yaw moments.

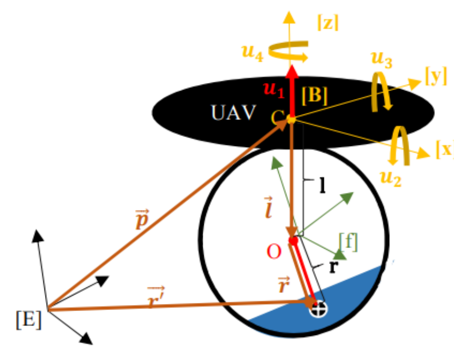

Figure 3. UAV Free Body Diagram with Sloshing [42]

Given the variability of the mass *m* (spraying decreases the weight of the tank and, therefore the total weight) and the unpredictable ground effect disturbance, robust controllers represent a suitable choice. A robust controller [43] is a type of controller that is designed to maintain system stability and performance despite parameter uncertainties, while aiming to maximize stability and performance over a wide range of operating conditions and disturbances. For instance, if the drone has limited computational power onboard, H2/H∞ could be employed. The goal of H2 [44] controller is to minimize the effect of disturbances on the system output while satisfying target performance specifications, while H∞ [45] main idea is to minimize the maximum gain from the disturbances to the output of the system. While these robust controllers show several advantages, they also present some disadvantages and limits. In fact, H2 and H∞ require the estimation of the envelope of dynamic parameters of the UAV that can be cumbersome to carry out in practical applications. Additionally, when the model estimate carries high degree of uncertainty, the designed control system can lead to a suboptimal performance. This is particularly relevant in the aforementioned application, as significant mass and CoG location variations can occur leading to an over-conservative control law. Therefore, finding the trade-off between disturbance rejection and control performance can require significant tuning effort and expert knowledge.

If sufficient computational power is available onboard, robust Model Predictive Control (MPC) [47] could be implemented to overcome the challenges cited above. Robust MPC is a nonlinear optimal controller that is well suited for controlling systems with constraints: a model-based approach that uses a mathematical model of the drone to predict its behavior over a finite time horizon, and then chooses the control inputs that optimize a certain performance criterion subject to constraints on the system inputs and outputs. However, robust MPC relies on accurate models. Any errors or inaccuracies in the dynamic models can lead to suboptimal control performance or instability [48]. In addition, robust MPC works well for systems with slow dynamics, but it may not be suitable for fast-changing systems, such as those with high-speed dynamics or rapidly changing constraints. Model Predictive Control (MPC) necessitates constant online updating of the system model with newly acquired data. However, as drones operating in confined spaces require swift and frequent movements, leading to sudden changes in both dynamics and disturbances that rapidly need to be updated online, deploying MPC may result in instability [49].

C. Communication

Wi-Fi network is mainly used in the drone industry as the primary system to exchange data with the ground station or with the remote control. The latter enables the UAV equipped with the right antenna to transmit live footage and telemetry data in real time to the terrestrial-based facility. It also allows the drone to communicate with other drones in a multi-agents system, connect to internet (Internet of Things - IoT) or to receive commands from remote control. Thus, the operator can switch to manual flight and take control of the drone for safety reasons [50] or in case of emergency. However, the communication range and reliability of UAVs using Wi-Fi in constrained environments can be limited due to multiple factors related to the structure of the surroundings itself. Physical obstacles such as trees or hills is the major factor for communication loss. In this context, cluttered environments and presence of obstacles can obstruct the line-of-sight between the drone and the ground station or the remote control, leading to signal attenuation or loss [51]. In addition, other electronic devices using the same frequency band can cause interference and degrade the quality of the communication link. The interference phenomena has, indeed, a severe impact on the performance of multi-agents systems (swarm of drones deployed) [52]. The communication glitch between drones in the same swarm can lead to collision and crash as agents will not be updated with other agents' latest positions. Moreover, the limited transmission power of Wi-Fi can limit the effective communication range, especially in environments with high levels of noise or congestion [53].

The communication latency and bandwidth constraints of Wi-Fi can also be a limiting factor for the real time performances of the drone. The latency of the communication link can affect the responsiveness and stability of the drone's control system [54], especially in applications that require real-time parameters online update. The limited bandwidth of Wi-Fi can also limit the amount of data that can be transmitted between the drone and the ground station, which can be a significant issue for applications that require high-resolution image or video data. For example, the UAV may need to store and transmit images generated by Hyperspectral cameras. A hyperspectral camera with 224 spectral bands and a spatial resolution of 1 meter can generate approximately 67 GB of data per hour for a single flight. Assuming an average transfer rate of 50 Mbps (which is a reasonable estimate for a constrained environment), it would take approximately 2 hours 58 minutes to transmit 67 GB of data over Wi-Fi. Thus, the real-time performance of the UAV will be impacted by the network latency, connectivity, and data transmission speed, which can reduce the ability of the drone to perform complex tasks or respond quickly to changing conditions.

IV. PROMISING STATE-OF-ART RESEARCH PROGRESS

The research is showing new techniques, technologies, and algorithms being developed and tested to address the technical challenges listed above.

A. Navigation and state estimation

Navigation and state estimation in complex and dense environments remain major challenges for autonomous UAVs. However, recent studies have shown promising results. One approach is to integrate deep learning techniques with SLAM algorithms, which has demonstrated improved feature detection, data association, and mapping accuracy in SLAM algorithms. This integration has showed increase in state estimation's robustness in constrained environments. In [59], the authors introduced a deep-learning-enhanced visual simultaneous localization and mapping (DF-SLAM) system that utilizes neural networks for descriptor generation and feature extraction and matching. DF-SLAM employs a TFeat network [60] and Visual Vocabulary [61] to learn deep local features from the input images and uses them to generate descriptors, which uses DBoW [62] to match them. VIO is then used to estimate the vehicle's motion. The results showed that DF-SLAM achieves better accuracy and robustness than other methods, especially in challenging environments with low lighting conditions. In [63], the authors present a novel convolutional neural network (CNN) based monocular dense SLAM system for real-time UAV exploration in emergency conditions. The proposed method uses ORB-SLAM [64] to extract feature, then uses Single Image Depth Estimation (SIDE) [65] to scale the reconstruction delivered by SLAM in the object space and to densify the 3D reconstruction by fusing the sparse depth map generated by SLAM with the CNN. The localization relies on CNN-based visual odometry network to estimate the UAV's motion. The system also employs a loop closure detection module to correct the drift and a 3D map optimization module to improve the chart quality. The results show that the proposed system can generate accurate and dense maps in real-time while outperforming existing state-of-the-art monocular SLAM systems in terms of accuracy and efficiency.

Another approach is the use of incremental SLAM algorithms, which incrementally build a map of the environment as the UAV moves through it, reducing the computational complexity of traditional SLAM algorithms. The riSAM algorithm proposed in [66] uses a robust optimization framework to handle outlier measurements and improve the accuracy of online incremental SLAM. The algorithm is based on the Graduated Non-Convexity method, which gradually decreases the convexity of the optimization problem to avoid local minima and converge to a globally optimal solution. The riSAM algorithm incorporates also several strategies to improve its performance and computational efficiency. For example, it uses a Scale Invariant Graduated (SIG) kernel that admits a known constant number of GNC iterations, iSAM2 algorithm [67], and Powell's Dog-Leg (PDL) [68]. The algorithm demonstrated its efficiency through benchmarking datasets, surpassing existing online approaches, and matching or exceeding the performance of current offline methods.

B. Control system

Recent research has witnessed a shift from classical control systems towards more embedded and holistic methods by utilizing Deep Reinforcement Learning (DRL) approaches. In contrast to traditional control systems that rely on hand-crafted controllers and receive desired waypoints from a navigation algorithm such as SLAM, DRL-based controllers learn the control policy directly from perception sensors and output the UAV control signal. This approach eliminates the need for human-designed robust control strategies and allows the controller to adapt to changing environments and new scenarios. When partial models of the environment are available, transfer learning approaches can be exploited to train baseline agents in a simulated domain and later updated upon deployment in the real world.

Different kinds of reward functions can be employed to tune the controller. Typical goals in UAV applications encompass maximizing the proximity from a given target whilst rejecting disturbances, or following a series of successive waypoint or a trajectory. Continuous reward signals minimizing either the negative sum error from the desired target, or the cross-track error with respect to the target trajectory, weighted with Gaussian or exponential penalties, are delivering state-of-the-art performance [73]. Due to the limited energy resources available onboard UAVs, additional penalty terms related to the minimization of power consumption are usually embedded in the reward function.

When the application entails navigating through constrained environments while avoiding obstacles, approaches combining DRL and memory-based methods can be employed [34]. The latter control system is based on a variant of the deep Q-learning algorithm, incorporating a memory module that allows the agent to remember past experiences and exploit them to make decisions in the present. In addition, to account for the drone's limited knowledge of the environment, the authors model the task as a Partially Observable Markov Decision Process (POMDP), where the system's state is not directly observable, and the agent receives observations that provide partial information about the state.

A novel approach for safe autonomous motion control of a UAV in the presence of disturbances and moving obstacles combines a backstepping-based control design approach with obstacle avoidance [72]. To ensure safety, a Barrier Lyapunov Function (BLF) is directly incorporated into the translational control to keep the vehicle outside of a safety sphere constructed around the obstacles, while directing it towards a desired position. The BLF allows for the direct inclusion of obstacle position in the control design, for both known and unknown obstacles' velocities. This approach has the potential to be applied in various fields, including robotics, autonomous vehicles, and aerospace systems, where safety is critical in navigating in complex and dynamic environments.

C. Communication and IoT

Advancements in mobile communication technologies, such as the introduction of 5G networks, have significantly improved the use of drones in precision agriculture. The integration of drones with other technologies such as autonomous ground vehicles and Internet of Things (IoT) devices has opened new possibilities for precision agriculture in constrained environments. Multiple studies have been conducted to explore potential solutions to overcome the limits of the standard Wi-Fi communication as seen in section III.C, in order to enable the efficient use of autonomous drones in precise agriculture in hill farming. In [69], the authors discuss the use of LTE and 5G technologies for UAV communication, including the use of small cells, massive MIMO-NOMA (Multiple Input Multiple Output - Non-Orthogonal Multiple Access) and beamforming to improve coverage and capacity. It also discusses the potential of millimeter-wave and terahertz communications for UAVs, which can provide even higher data rates transmission. However, the drone may requires more advanced signal processing and antenna technologies onboard. The paper also highlights the importance of network slicing and virtualization for swarm communication, which can enable each drones in the system to share network resources with other devices and applications while ensuring reliable and secure communication. The authors also highlighted some of the key research challenges and future directions for UAV communication, including the integration of drones into 6G networks, the use of machine learning and AI for communication and the development of new communication protocols specifically designed for drones. In [70], the authors proposed a solution that integrates IoT devices and UAVs in a 5G hybrid network using satellite communication. This communication protocol allows drones to communicate with IoT devices and other drones in the network. Indeed, it uses a distributed algorithm to optimize the communication links, taking into account the battery life of the UAVs and the bandwidth requirements of the each devices. In [71], the authors introduced a PLS-based security scheme for communication networks as security challenges are raised nowadays. The proposed scheme uses beamforming and cooperative jamming to protect against eavesdropping and unauthorized access.

V. DISCUSSING FUTURE PERSPECTIVES

In this paper, the major challenges and limitations of autonomous drones in precise agriculture in constrained and dense environments has been explored. Scientific progress and state-of-art technology to overcome these challenges have been mentioned. However, there are still several technical and economic hurdles that need to be addressed in order to make their widespread adoption possible:

- *development of advanced sensors*: to improve the accuracy and reliability of state estimation and path planning in complex and dense environments, there is an urgent need to design new sensors taking into account the requirements needed to operate in constrained environments, such as lightweight high-resolution LIDAR sensors resisting dusting.
- *improving dynamic obstacle avoidance*: to navigate safely and efficiently in dynamic environments (drones, workers, animals), robust UAV algorithm for detecting moving targets are still to be developed. This can be particularly challenging in cluttered environments with complex topology, such as in mountainous or hilly areas.

- *cost reduction*: to make drones more accessible and affordable to small and medium-sized farmers and other users, the cost of sensors and computational resources must be decrease, while maintaining or improving their performance
- *regulation*: regulatory approval significantly impacts the adoption of autonomous drones in agriculture [55-58]. The intricate and lengthy process of obtaining permission for UAV operation is regulated by various government entities, resulting in substantial regional and national variance in drone usage ordinances for agriculture. This lack of standardization in UAV regulation generates confusion and uncertainty among farmers and drone operators.

VI. Conclusion

In summary, precision agriculture utilizing autonomous UAVs, although promising, faces several technical and economic challenges. These drones can provide farmers with vital data on crop health and soil conditions, aiding in optimization of farming practices. However, performance of these technologies often declines in challenging environments like under forest canopies or on hills. Economically, the high implementation cost can be prohibitive for smaller farmers, and the need for regulatory approval and investment in the technology present further barriers. As we overcome these limitations and the technology evolves, precision agriculture is expected to become the norm in the near future.

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