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Research Infrastructure for Real-Time Computer Vision Applications in Unmanned Aerial Systems

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***Abstract*—As the use and applications of Unmanned Aerial Systems (UAS) grow, the need for rapid and efficient research and development arises. UAS aspects such as sensing, navigation, and collision avoidance need to be evaluated. To facilitate this, research infrastructure comprising a simulator and a sizeable indoor testing center has been proposed and built. The discussed infrastructure aims to boost research progress with a focus on low-power computer vision solutions for UAS applications. This research and development process optimizes available resources by eliminating suboptimal solutions early. Leveraging a motion capture system, precise and accurate metrics can be used to evaluate and compare competing solutions prior to real-world testing. Additionally, various scenarios and environments can be recreated at relatively low cost in simulation or indoors, providing researchers with rigorous testing opportunities. Competitions are currently held to pit teams from around the world to produce effective solutions for UAS tasks. Beginning with simple problems, tasks of increasing complexity will be introduced commensurate with previous successes. While it is acknowledged that simulation and indoor testing cannot completely replace real-world testing, this infrastructure setup provides an invaluable opportunity for UAS researchers.**

Keywords—UAS, trajectory tracking, computer vision, navigation

I. Introduction

The need for more testing environments has emerged as the popularity and applications of Unmanned Aerial Systems (UAS) increase. Due to safety concerns, outdoor unmanned flights are subject to a myriad of regulatory restrictions. Hence, indoor areas provide advantageous testing grounds for new developments and applications. Indoor testing areas remove the constraints of airspace regulations and allow researchers to control and simulate different environments, scenarios, and obstacles. Providing a stable testing area promotes the rapid deployment of novel approaches and solutions of computer vision problems. Additionally, UAS movement and performance can be analyzed using high-definition motion capture systems with precise and accurate metrics. The application of metrics to computer vision solutions on unmanned aerial systems can eliminate bias in determining the most effective solutions.

II. Literature Review

In recent years, UAS have been used in many civil applications due to their ease of use, low costs, and high mobility [1]. These include search and rescue, delivery of goods, security, surveillance, agriculture, infrastructure inspection, transportation, wireless communication, and remote sensing [2]. As a result, extensive research has gone into developing autonomic systems that do not require human input, leading to genuinely autonomous aerial vehicles [1]. As part of this development, UAS platforms must be able to sense, analyze, communicate, plan, decide, and control themselves independently. Challenges include power, weight, and communication limitations. Thus, a need to test and identify optimal solutions through comparisons and testing arises. While the use of simulations can estimate the effectiveness of a solution, applying such solutions to a real-world UAS would allow developers and engineers to rapidly field-test their ideas to determine compatibility with practical operating environments.

Current UAS regulations governing the United States' National Airspace System focus on improving the safety of manned aircraft and uninvolved individuals. The primary legislation governing UAS operations is Title 14 of the Code of Federal Regulations Part 107, "Small Unmanned Aircraft Systems" [3]. Part 107 outlines the procedures for UAS registration, obtaining a small UAS pilot's certificate, and airspace authorizations. However, following Part 107 procedures can complicate the conduct of research using UAS platforms. For example, following the airspace authorization regulations outlined in Part 107 can require up to 90 days in some parts of the national airspace system. In addition, UAS

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flights must have a Part 107-approved UAS operator to supervise or fly the vehicle regardless of the testing location. Many of the restrictions contained in Part 107 are applicable only to outdoor flight tests. A remote ID requirement is the next addition to UAS regulation, providing law enforcement and security personnel the ability to identify the individual operating the UAS. Similar to Part 107, remote ID only applies to UAS operators conducting outdoor flights. While performing indoor flights will remove the remote ID requirement, additional obstacle avoidance and navigation parameters can be tested based on the broadcast information from remote ID. Remote ID transmissions may allow computer vision solutions to be tested as an additional method for detecting nearby vehicles.

Testing and analysis must be performed on multiple aspects of autonomous flight, one of which is collision avoidance. Essential elements of collision avoidance include object detection, object trajectory, and local path planning to avoid collision [4]. Each element of collision avoidance contains various solutions and approaches, together with benefits and drawbacks. An example of this is using cameras as passive sensors, which have low power consumption but high processing requirements. Another approach is using active sensors such as radar and sonar; these have higher power consumption but lower processing requirements. Further, each sensing method is susceptible to false-negative detection of particular objects in specific environments. Cameras, for example, are prone to glare, while radar may not provide sufficient resolution for some detection applications. In addition, ground-based surveillance methods can be relayed to UAS or integrated with ground-based command and control systems. Finally, collision avoidance solutions must be compatible with the global path planning and navigation method in use. Possible real-time metrics for collision avoidance performance can include detection constraints (velocity or object size), ability to handle dynamic environments, swarm compatibility, communication dependence, escape paths, and potential for deadlock (local minima) [4]. In practice, testing and analysis of a collision avoidance solution must be completed to ensure adequate performance prior to real-world deployment.

Regarding navigation and path planning, navigation systems are classified into three categories based on the amount of measured environmental information: the map-based system, the map-less system, and the map-building system [5]. Most general localization methods for UAS rely on inertial measurement systems or global navigation systems [6]. The map-based system applies these two navigation systems to allow UAS the capability for route planning and detours. The other two methods rely greatly on the airborne optical system. The UAS with a map-less system needs to extract, analyze and memorize the visual information to move without collision. A map-building system adds another step that compares and amends the existing map according to the actual environment sensed while operating [5]. Such vision-based navigation can be treated as an extension of ground autonomous driving. The difference is that UAS operate in three-dimensional space.

Cesetti et al. [7] proposed a vision-based guidance system that enables autonomous navigation and landing ability for UAS by detecting natural landmarks. Singh et al. [8] constructed a theoretical model by predicting the collision probability between a UAS and surrounding obstacles using an algorithm demonstrates the ability to respond to various latency constraint scenarios. Padhy et al. [9] achieved UAS navigation in the indoor corridor environment by taking the next maneuver course as a classification task. The trained Convolutional Neural Network (CNN) model processes the video information from the front camera and feedback the real-time command. Finally, Vanegas et al. [10] introduced a model that combines multiple localization algorithms into one framework. The method uses Simultaneous Localization and Mapping (SLAM) with Partially Observable Markov Decision Processes (POMDP) algorithms to navigate and explore the UAS's surroundings with the Global Navigation Satellite System (GNSS) failed situation, processing the action as "sequential decision problems under uncertainty" [10].

The successful testing and development of these UAS components can lead to the safe integration of UAS in national airspace systems. In addition, simulators and indoor/small-scale environments allow preliminary testing to be performed in controlled environments at a relatively low cost, with no need for regulatory approvals. For many smaller developers and applications, large-scale testing with national organizations, such as the National Aeronautics and Space Administration's UAS Traffic Management (UTM) National Campaigns, is out of reach and may not be suitable for early-development testing [11]. Hence, the opportunity to test solutions at an indoor test facility is invaluable to researchers.

III. Methodology

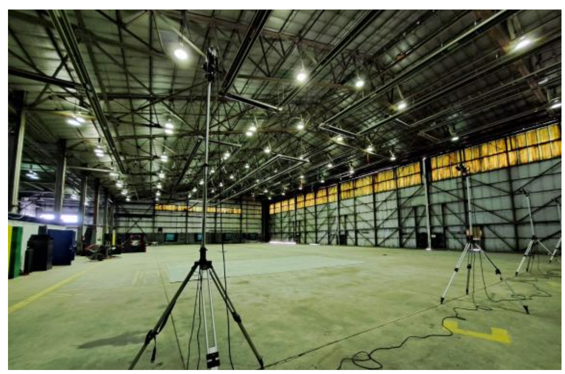

Fig. 1. Indoor infrastructure facility.

There are multiple existing solutions, vehicles, and regulations for the use and operation of UAS. Conducting UAS research and testing within a large, enclosed space allows researchers better control over external variables. The infrastructure under development provides a UAS research framework impacted less significantly by airspace regulations. The indoor infrastructure is built into a hangar with 20,000 square feet (1,858 square meters) of floor space with 30-foot ceilings (10-meter), allowing ample room for UAS movement in all three dimensions as seen in Fig. 1. In addition, the hangar allows for the permanent operation and installation of motion capture cameras. Camera operation in indoor conditions improves lighting, temperature, and visual conditions. The current camera array comprises sixty Oqus 7+ motion capture cameras mounted into the hangar's ceiling. The motion tracking system allows multiple objects, individuals, or vehicles to be tracked simultaneously with six degrees of freedom. The motion capture system can easily track ground and air vehicles with the attachment of compatible reflectors.

While large spaces are helpful for beginning applications and research, many projects require the ability to control external conditions to represent the real world accurately. For example, the controlled addition of buildings, trees, or other structures that block camera sight lines creates an accurate representation of real-world conditions. Flexibility in the location, size, and number of buildings is critical. Therefore, diverse environments can be emulated using modular building blocks, such as Everblocks as seen in Fig. 2 [12]. Multiple vehicles are available for testing computer vision solutions, including ground vehicles which can be used as tracking targets. Maintaining multiple vehicles capable of operating on the same motion capture system allows for changing the flight or target vehicle with minimal system downtime.

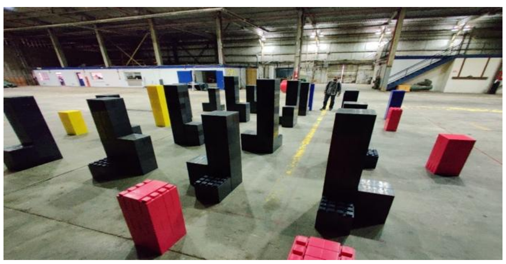

Fig. 2. Everblocks representing an urban landscape.

In addition to the large indoor space for UAS testing, a computer simulator for computer vision package testing comprises the discussed research framework. The simulator can be easily adjusted to represent the current state of the hangar or modified to future states with and without the Everblock obstacles. Multiple existing simulator platforms are available; however, the selected simulator is based on Aerial Informatics and Robotics Simulation (AirSim) and Unreal Engine as seen in Fig. 3. The primary use of the simulator is to increase efficiency by reducing real-world issues such as costs and implementation on different platforms [13]. The simulator provides the first layer of efficiency by allowing rapid deployment and testing of various computer vision solutions. Once successful solutions are validated, they can be deployed at the testing facility, reducing resources wasted from testing suboptimal solutions in person as illustrated in Fig. 4. In addition, testing the solution at the indoor facility provides a safe and controllable environment free of regulatory burdens during the development process.

Fig. 3. Sample image of simulator.

As a result of the combined simulation and indoor-testing infrastructure, novel solutions can be tested efficiently, and competing computer vision solutions can be rapidly evaluated. The use of the motion capture system available in the facility provides recordings for performance analysis based on quantitative metrics. For metrics such as navigation, the distance from programmed waypoints and actual location can be measured with precision and accuracy. The motion capture system can also be used to emulate the Global Positioning System (GPS) by feeding precise location information for the drone to its command system. Data fed from aircraft surveillance systems such as Automatic Dependent Surveillance-Broadcast (ADS-B) or Traffic Information Service-Broadcast (TIS-B) can be emulated by artificially adding latency in the data transmission. Random errors similar to those experienced in practice can also be added to the data passed on to the UAS to enhance the testing environment further.

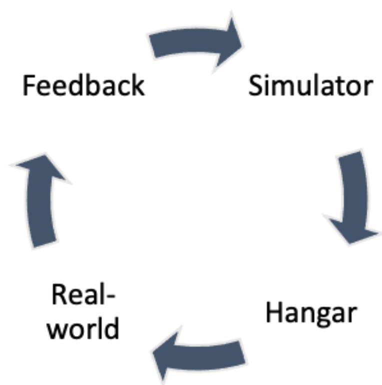

Fig. 4. Development cycle.

Using the motion capture system, the minimum distance from a vehicle to a conflicting object or other vehicle can be easily measured when testing object detection systems and algorithms. In addition, avoidance trajectories can be compared between computer vision solutions. High-speed interactions and tests can also be performed with the ability to capture data at frequencies greater than 1,000 frames per second. Solutions can be evaluated for applications such as object tracking by setting objectives such as maintaining a 3-foot distance from the object being tracked. A UAS's collision avoidance system, and its ability of the solution to track and follow a moving object can be evaluated. Further, the stability of drone flights can be easily measured by tracking multiple points on the vehicle.

A venue for testing such solutions has been and continues to be competitions hosted at the facility. During the first competition, participants were tasked to program a drone equipped with a camera to track a red ball mounted on an autonomous rover as it maneuvered a city constructed of Everblocks. Teams qualified for hangar testing by completing the challenge in the simulator. Succeeding in the competition, the solution must have been able to track the object, command the drone to follow the object, search for the rover if the line of sight is lost, and avoid the obstacles. In addition, all competitors were limited to the same drone, fairly pitting low-power computer vision solutions against each other. During the first competition, only one team completed this task. For future competitions, additional challenges such as the goal to maintain a specified distance from the object will be added to add layers of complexity to judge different solutions.

Flight analysis metrics and evaluation tools have been created to reduce the arbitrary assessment and evaluation of object tracking and computer vision. The metrics include:

- The average error from the target tracking distance
- Duration of flight target in the camera frame
- Duration of matching orientation between the test vehicles;
- Number of risky incidents regarding the distance between obstacle and vehicle (based on a minimum threshold)
- Speed of the tracked object
- Predicted versus the true location of vehicles
- Average detection time per frame [14]

The metrics proposed may not be applicable or appropriate in all cases. Hence, relevant metrics should be carefully selected before use for evaluation and comparison. More restrictions, such as expressly forbidden airspace control, can be added to the hangar site to simulate real-world conditions as closely as possible.

The metrics will be used to evaluate performance in the low-power computer vision competition. In addition, the tools should give any researcher the capability to perform an overall comparison between multiple computer vision solutions.

For collision avoidance evaluation, UAS are tasked to fly from one point of a mock city to another while encountering other cooperative and non-cooperative vehicles. Global and local path planning solutions can be simultaneously tested with metrics such as the number of collisions/missed traffic, closest distance with conflicting traffic, the average time to clear the course, and the ability to handle various speeds and levels of complexity. Interactions between drones of the same solution running different tasks in the same environment can also be tested to simulate an active airspace environment.

In addition to the Low Power Computer Vision competitions, the testing and research facility discussed within this paper is open for any researcher to develop and test UAS solutions. Data from the motion capture system is then available for the researcher to utilize while also kept for analysis by the infrastructure team. Data gathered from the facility will also be shared publicly on request for others to analyze.

IV. Limitation and Proposed Additions

As the facility continues to develop, multiple additions are planned. These additions include a weather testing component (wind/mist/rain), increasing the complexity of tasks and requirements for UAS, an open category competition where other hardware can be used to compete, and the implementation of scenarios that simulate air traffic conflicts. Object identification and search-and-rescue scenarios are also planned for other researchers to test and display their solutions. These additions are contingent on competitors' success with the current competition setup and the needs of researchers who utilize the facility. The complexity of tasks and tests performed at the facility must be reasonable and achievable by its users.

Efforts to create a simulation environment representative of the hangar facility and the hangar facility representative of real-world environments and scenarios, constraints on the simulator, and hangar fidelity to real-world environments must be acknowledged. The ideal environment that makes simulator and hangar testing valuable leads to the exclusion of some real-world considerations. For example, the variability of real-world weather, such as high winds and precipitation, can also significantly impact performance. Additionally, objects represented in simulation or the hangar are simplified representations of real-world objects. Therefore, computer vision methods used in the simulation or hangar will likely need significant adjustments and testing in real-world environments prior to deployment.

V. Conclusion

The described infrastructure provides a unique and valuable way for UAS users and researchers to develop, test, and evaluate solutions for problems faced by UAS systems now and in the future. Using a simulator, solutions can be tested rapidly and at almost no cost, followed by hangar testing that eliminates regulatory constraints while providing a safe and controllable environment to test and measure solutions in a near-reality environment with actual drones. The hangar's motion-capture system is the largest of its kind, offering unmatched opportunities for research. This should increase the quality and efficiency of the drone development process.

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