IoT-enabled Unmanned Traffic Management System with Dynamic Vision-based Drone Detection for Sense and Avoid Coordination

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ABSTRACT

This paper showcases the integration of several technologies to develop an Unmanned Traffic Management System that enables the centralized coordination of unmanned ground and aerial vehicles. By addressing the need for safe and efficient autonomous vehicle operations, this system contributes to improved safety and reliability in various applications, from civilian to military contexts. Furthermore, the exploration of dynamic vision-based drone detection methods adds valuable insights into the field of real-time image processing and deep learning. In that perspective, a more in-depth computer vision development is been presented.

The system's core components include the Swarmie, an unmanned ground vehicle (UGV) guided through a wireless mesh network through radio frequency enabled (RF) markers. Simultaneously, an unmanned aircraft vehicle (UAV) is controlled by an IoT cloud platform that sends coordinates to an embedded system. The integration of wireless communication and navigation markers is a proof to the importance of circuitry and microcontrollers in developing RF markers to enhance navigation.

One of the primary objectives of this research is the development of a dynamic vision-based drone detection system for sense and avoid actions. Two different methods are explored for drone detection. The first method utilizes the Viola & Jones algorithm. The second method involves the You Only Look Once (YOLO) Real-Time Object Detection algorithm. The performance of these methods is evaluated, providing insights into the effectiveness of each approach in real-time drone detection.

Keywords: IoT-enabled, Unmanned Traffic Management System, dynamic vision-based drone detection, embedded system, sense and avoid

1. INTRODUCTION

The utilization of autonomous and controlled robotic systems has become a new commodity within our society. Such technologies helped identify and reach new innovative methods to satisfy critical needs both the industry and defense sectors. Industry 4.0 has been enhanced by the implementation of autonomous robots for infrastructure/safety inspection, surveying and mapping, precision farming and crop monitoring, last-mile delivery of packages, and warehouse inventory management among many other applications.[1] The defense of nations has been enhanced by unmanned autonomous systems in tasks such as counter-terrorism and security; intelligence, surveillance and reconnaissance; aid with combat readiness; critical infrastructure protection; border security; and overall multi-domain (sea, land, air, and space) defense.[2,3]

As more autonomous robotic systems are been deployed, there is a need for a unified or as functional as possible Unmanned Traffic Management System (UTM) within populated regions.[4] To simplify the complexity of coordinating and enabling a UTM the case of drone-based delivery systems can be utilized. Such system has the simple task of taking a product from one point to another utilizing predefined waypoints while maintaining

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Real-Time Image Processing and Deep Learning 2024, edited by Nasser Kehtarnavaz, Mukul V. Shirvaikar, Proc. of SPIE Vol. 13034, 130340C · © 2024 SPIE · 0277-786X · doi: 10.1117/12.3014009

its integrity. That mission can be summarize through the implementation of path-planning, navigation and collision avoidance tasks. Currently companies such as Wing's has demonstrated the potential and reality of delivery drones as a new commodity for society. The company has over 300,000 successful deliveries.[5]

The Federal Aviation Administration (FAA) has recognized drone application potential by allowing beyond-line-of-sight operations.[6] Phoenix Air Unmanned, Wing, Zipline, UPS Flight Forward, and uAvionix have taking advantage of new regulations and possibilities to test drone capabilities thanks to new government permits and standards.[5,7] In complement to Unmanned Autonomous Systems (UAS) becoming a new reality, many households and industrial facilities are becoming dependent of Internet of Things (IoT) capabilities to enhance quality of life and resource management. Recent implementations of IoT driven unmanned systems technologies can be review in the following sources.[8–12]

A relevant, reliant and resilient UTM has to become IoT-enabled to combine some of the best new innovations that technology provide to users. Relevant references on design, requirements and frameworks explored to develop such UTM can be find on references.[4,13] In the Collaborative Robots and Agents Lab (CORAL) an IoT-enabled UTM involving unmanned ground vehicles (UGV) and unmanned aerial vehicles (UAV) has been developed. Currently hardware has been deployed with the flexibility to continue expanding the UTM capabilities. All vehicles are task to navigate without colliding and accomplish their missions through the laboratory testbed. A UGV is guided through a land wireless mesh network enabled by RF markers that work as "breadcrumbs" to enhance the autonomous vehicle path navigation. An IoT-enable control, coordination and collision avoidance architecture is been tested and deployed for small drones. An IoT cloud platform can currently send coordinates to embedded systems withing the UTM infrastructure.

However, the main purpose of this paper is to document the work done for the Sense and Avoid (SAA) strategies implemented utilizing the UAV camera. Such SAA has an initial tasks of detection other similar or identical UAS as dynamic objects to be avoided. Two machine learning algorithms have been tested for the task with the purpose to provide options and flexibility of implementation. Through this paper it will be defined the utilization of the Viola&Jones algorithm to tests and enable a drone control strategy. Then, the detection of drone object is done with the You Only Look Once version 5 (YOLOv5) algorithm. Such algorithms are identified and utilized due to their popularity, availability, capability and its ease of application in embedded and robotic systems implementations.[14–16]

The reminder of the paper is organize as follows. Section 2 defines the problem statement with pertinent identification of the current UTM scope and constraints. Section 3 will briefly covers the method aided by open source available knowledge to implement YOLOv5 and Viola&Jones for object detection applications. The level of confidence in the detection of objects is critical for the UTM SAA implementation. Section 4 covers the experimentation and main results of the UTM SAA implementation. It also discusses the lessons learn and observations acquired to continue enhancing the proposed technology driven solution. Section 5 closes with the conclusion and future work required for a relevant, reliant and resilient UTM deployment based on initial SAA results.

2. PROBLEM STATEMENT

The design and development of a safe testbed environment where autonomous aerial and ground vehicles can coincide requires for each controlled and coordinated agent to avoid obstacles, navigate effectively, be capable to simulate a mission/objective, use mobile applications to control drones through Internet of Things (IoT), and record critical telemetry data and upload it to the cloud. The current CORAL UTM started in part with previous work based on the NASA Swarmathon event specifications to design a fleet of UGV.[17] Its original purpose was for foraging applications but further work has been done in autonomous package delivery tasks. Another innovation involves the implementation of a UAS capable of coordinating with the UGV ground missions doing their delivery tasks too. A multi-domain system-of-systems is then been integrated.

Both systems are defined to navigate through waypoint definition strategies through ground and air traffic corridors. Based on a client need, the system is expected to be frequently updating the network to include new calls initiated and exclude calls suspended from its path based on the initiate and suspend calls. The updated network will send a request to the systems and methods to form a path for the UGV and UAV. The UGV path is

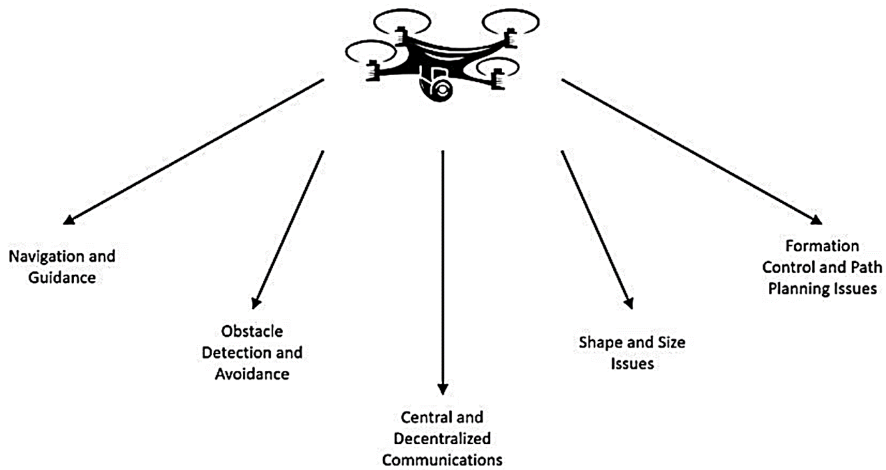


Figure 1: Challenges in UAVs[20]

constrain by established ground road infrastructure while the UAV has more freedom through a flight corridor. Navigation plans can includes multiple road options or traffic corridors along the path connecting the origin point of the vehicle and the requested destination.

The UGV is capable of handling heavy payload with high performance computing equipment. However, the drone had to be constraint by their payload and battery capabilities. Another problem with the ability to have autonomous drones' delivery system is the ability to have a viable way to manage the air traffic that the drones would have to endure. With the desire to have little to no human interaction with the drones there is a need for a management system that can minimize the intervals of incidents that are inevitable such as collisions between drones, structure, and animal strikes; all while keeping within FAA regulations.[18,19]

Although these applications are expanding daily, there are still several limitations that slow UAS integration into the National Airspace System (NAS) as seen in Figure 1. Safety and service ability become the primary concerns when considering the commercialization of UAV and UGV systems. The project objective, alongside many others, is to demonstrate how unmanned vehicles can operate safely while providing a service that is applicable and cost effective.

A main challenge is to enable a safety bubble SAA coordination as described in Ref. 21. The multi-agent coordination will require for each drone to be capable of detecting obstacles in their path. A sensor fusion strategy has to be implemented defined by proximity detection passive and active sensors. Passive sensors are the devices that need the energy to produce an output provided by the sensed physical phenomenon itself such as thermometer. In contrast, an active sensor need an external power supply to report was is been sensed such a strain gauge. Relevant work has been done into implementing diverse type of sensors to enable the detect and avoid action in drones.[22–29] However, the main constraint is identifying how many sensors can a drone handle based on their payload capabilities. An initial need that can be implemented is a drone-to-drone detection. The main adversary of a UAV within an airway is another one in a head-on collision. Similar to an automobile road infrastructure, a UAV air corridor must have enable drone to drone detection mechanism. A commercial aerial traffic management (ATM) system uses transponder and global positioning technologies (GPS) to enable a centralized traffic coordination strategy for airplanes.[30] However, it is challenging to develop a centralized system for heterogeneous swarms of UAVs with different missions and owners. There is a need to enhance each individual drone capability to detect each other in a decentralized coordination. For such detection, sensors utilizing a kind of electromagnetic (EM) field or spectra are optimal. They have the simple task to detect the proximity of incoming objects and assist the UAVs to decide how to proceed or avoid any risk of collision. Common proximity detection sensors utilize light, sound or EM waves (ex. ultrasonic sensors, lidars, time-of-flight). The other technology been implemented and studied involve the implementation of optical sensing devices such as cameras. This technology requires machine learning training data and costly computing power to efficiently operate. A

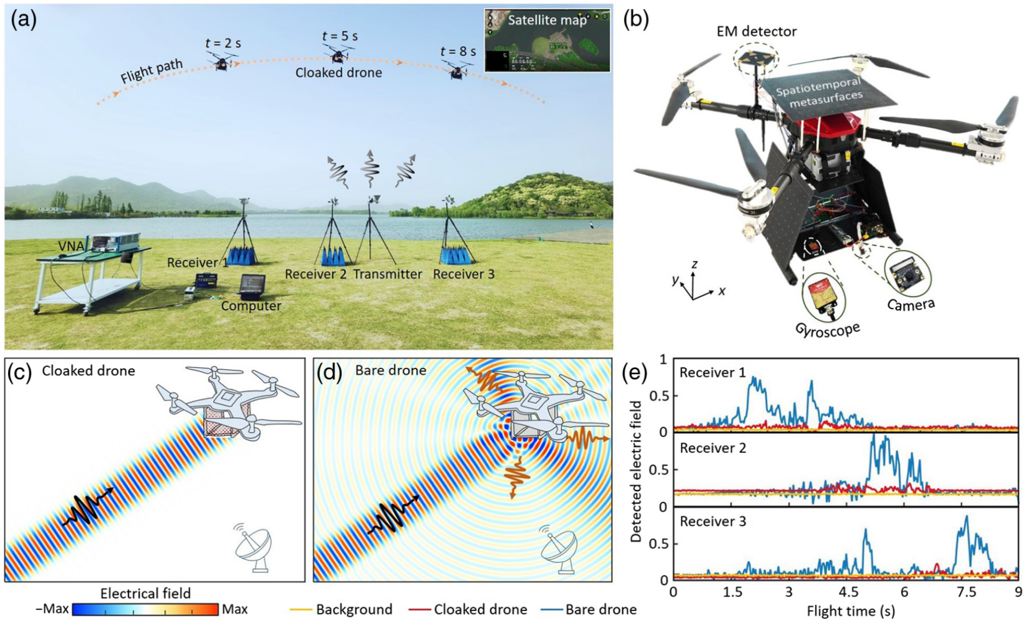


Figure 2: Autonomous aeroamphibious drone invisibility cloak operation[31]

main constraint is having a UAV capable to efficiently contain a high performance computing payload.

Not adding computationally expensive devices and cameras can still enable a UAV to properly detect incoming drones through sensor fusion. However, the recent work developed by Quian et. al. arrives as a clear warning that computer vision device must be implemented to guarantee the safety of future swarm of drones implementations.[31] In their work, they achieve the development of artificial intelligence (AI) and meta-material enable invisibility to electromagnetic (EM) detection cloaking technology. Their technology absorbs the EM incident waves. Meaning, that a radar will not received a reflected signal thus making the drone invisible as shown in Figure 2. Something that cannot be detected by a radar might be only detected to a camera. It is then imperative to identify low cost and efficient methods to add a computer vision enabled camera in UAVs SAA systems.

The purpose of this paper is to explore a simple computer vision enabled mechanism to produce simple results such as the ones from least computational intensive mechanisms. A small quadcopter drone with limited capabilities was utilized as a proof of concept. The main control strategy was initially implemented through the understanding of a face detection drone control using the Viola&Jones algorithm. Then, the object detection of a drone for SAA or collision avoidance required coordination is further implemented with the YOLOv5 algorithm with proven success. This allow to further the study of utilizing a more up-to-date YOLO, version 8. This is a work still in progress but this document seeks to inform the reader on the possibilities to achieve drone detection and collision avoidance through publicly available technologies.

3. DESIGN AND METHOD

IoT-enabled Unmanned Traffic Management (UTM) System consisted of developing a hybrid system involving UGVs and UAVs. All vehicles navigated without colliding and accomplishing their missions through a testbed environment at the Collaborative Robots and Agents Lab (CORAL). The Swarmie was guided through a wireless mesh network enabled by RF markers that worked as "breadcrumbs" to enhance the unmanned vehicle path navigation. The Tello drone was controlled by an IoT cloud platform sending coordinates to the Beaglebone Green that uploaded the data to a cloud network. The project is a proof of concept that enables future versions to scale up to larger UGVs and UAVs and allow them to carry a much greater payload.

The UAVs in this project had been enhanced with a capability to lift and drop a package (Figure 3). Also, steps have been taken into implementing a object detection system though the build in camera of the drone to detect other similar drones. Working under that scope UAV technology is highly sought after in present civilian

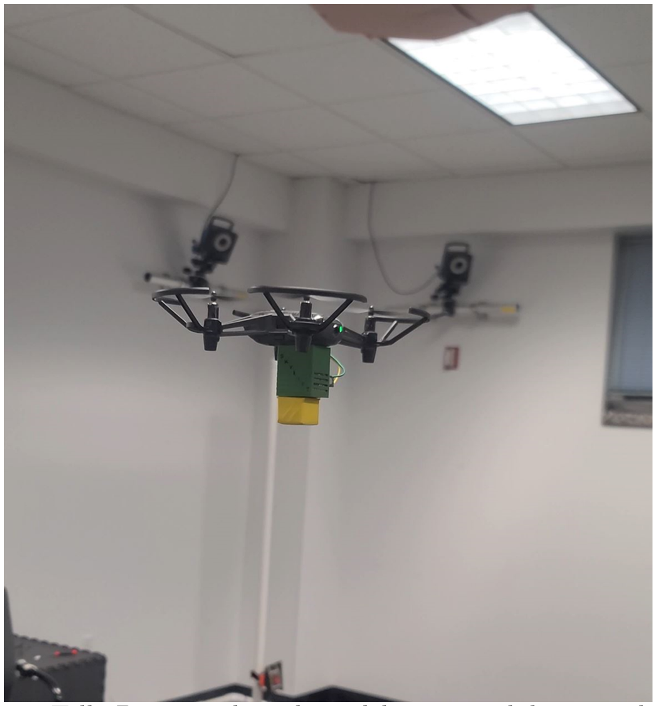


Figure 3: Tello Drone with package delivery capabilities mechanism

and military applications. There are several types of challenges to overcome when setting up UAVs to perform certain tasks such as navigation, obstacle detection/avoidance, shape/size, path planning issues, and formation control issues. Developments in UAVs have allowed for the ability to overcome these challenges with present technology. For example, Multi-Rotor UAVs have multiple propellers and motors that allow for the UAV to not require a runway for vertical takeoff.

The main UTM system required IoT enabled technology to control and record sensor fusion data for the drones and the UGV Swarmie. Both requirements were needed and meet in order to maintain an autonomous ecosystem. For the purpose and scope of this paper a emphasis is done on the Tello drone as the device under test (DUT).[32] The Tello is is a small drone with a nose-mounted camera with the capability of streaming 720p high-definition video and capture 5 megapixel photographs. Is a simple device easy to control through an smart phone application. It is simple to program through its sofware development kit (SDK). User Datagram Protocol (UDP) packets are transmitted through Wi-Fi containing the commands to enable the control of the drone. Through the DJI Tello drone controller python package it can be enabled for automated tasks.[33] Its capabilities for the testing of autonomous systems are also enhance by having the capability of utilize the OPENCV libraries through its camera.

The Tello was enhanced with the implementation of a magnetic switch package pick and drop mechanism powered with its built-in battery. This design utilizes the practice of controlled magnetism to pick-up and release metal objects. The magnetic design is made up of 7 components: the SkyLift enclosure, magnetic housing, 2 diametric magnets, a servo horn, a servo pin, and a servo motor. The drone was modified for the purpose on enabling the package delivery capability of 30-gram packages (Figure 4). The added magnetic switch mechanism (SkyLift) was designed to be small enough to fit on the underside of the Tello and outside of the its down-facing camera's range of view. However, the hardware, design and process to develop such function is out of the scope of this paper.

The testbed environment fit within the designated area of the CORAL and was made of a stable material. The testbed environment had at least 3 ft between the mock buildings in order to allow the Swarmie to pass in between. The mock buildings had a top with the minimum dimensions of 2ft x 2ft (Figure 5). The drone was tested to navigate between two positions throughout the UTM. It was tested to be able to pick-up, carry, and

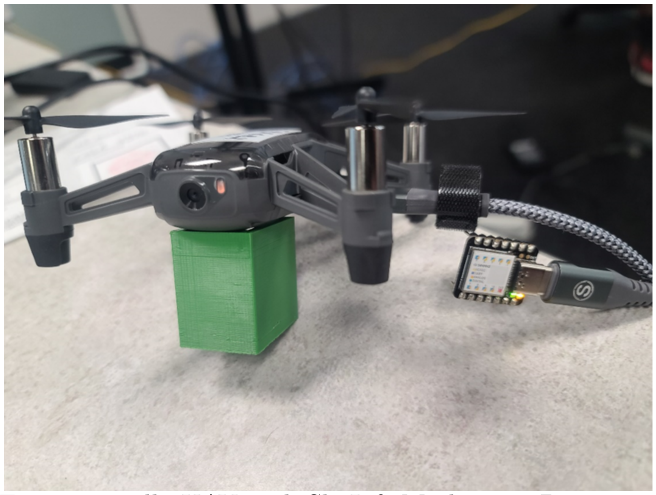


Figure 4: Tello UAV with SkyLift Mechanism Prototype

(a) Testbed Environment Prototype in Initial Position. (b) Testbed Environment Prototype with Mobile Drones.

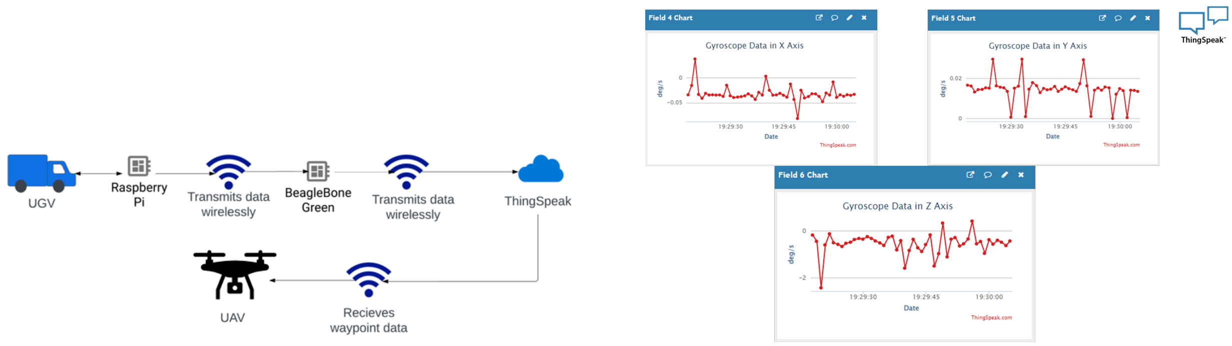
Figure 5: CORAL UAS UTM Testbed

release different objects and accomplish the set objectives. This design was decided primarily due to its light weight, small size, and ability to pick-up and transfer objects as the team intends.

Through the testing of the UTM, data was collected to determine the location of the UGVs and to plan their future paths based on velocity and time. The collected data was analyzed to generate paths that avoid any obstacles or potential hazards that may be encountered during the mission. The UGV specifics and development is out of the scope of the paper, but is of interest to identify it as the other critical subsystem into developing the UTM. UAVs used IoT provided waypoints and machine vision to generate paths that avoid any obstacles or potential hazards that may be encountered during the mission .

The IoT technology was implemented into the UTM system. First the UGVs send sensor data to the Raspberry Pi which is integrated into the UGV with an onboard accelerometer and gyroscope. This data is then transmitted to the team's BeagleBone Green which is then transmitted wireless to the cloud platform in ThingSpeak. On ThingSpeak, the team was able to generate waypoints which the UAV's were able to receive using a microcontroller and Wi-Fi. On ThingSpeak the data can be visualized on graphs or charts; whichever the user sees fit, and all data is plotted in real time (Figure 6).

The development of the Tello collision avoidance control was initially enabled by the learning the methods



(a) IoT Implementation Design. (b) Results for Gyroscope Data Through IoT.

Figure 6: IoT UTM Testbed Proof of concept.

from the Youtube Drone Programming With Python Course from Murtaza's Worshop - Robotics channel.[34] Its third project involved the development of a face detection operation in which the drone avoids and follows a human face at a user defined safe distance. And the face detection is enable through the implementation of the Viola&Jones algorithm.[35] That algorithm is a breakthrough computer vision technique implemented for object detection, specially human face recognition. It was develop by utilizing Haar-Like features that are calculated over multiple scales and positions in an image. Then, utilizing the AdaBoost for feature selection, it constructs classifiers through weak and strong features. The cascade classifiers can be implemented for functions such as facial recognition detection. However, it requires multiple positive images versus negative images. The attempt to train a Tello detection algorithm based on Viola&Jones demonstrated been inefficient and least precise that newer methods. However, the algorithm prove important and efficient as a starting point into programming the computer vision for detection in the Tello drone. A Haar cascade was downloaded from the OPENCV repository and utilized.[36] Such open-source knowledge was critical to have an initial understanding of the capabilities that a small drone can have to enable comprehensive research in autonomous systems.

From that point, the original software was modified utilizing the Deep Drowsiness Detection using YOLO, Pytorch and Python Youtube tutorial by Nicholas Renotte to implement the YOLO object detection capabilities for the drone.[37] YOLO is a modern and efficient object detection algorithm in real-time.[38] In contrast to previous methods, it utilizes a detection as a regression problem instead of a classification activity. YOLO implements single neural networks through images. The image gets divided into grid cells and bounding probabilities and boxes are created for every cell. Instead of having a folder with negative and other with positive images, the YOLO training involves bounding and labeling each positive image in the detection. YOLO has the capability to process images at 45 frames per second with high accuracy. The data repository from David Chuan-En Lin was utilized to add the trained drone detection data for the Tello detection operation.[39] The Tello was tested in the UTM and the experimental setup and results are documented in the next section.

4. EXPERIMENTATION AND RESULTS

The overall UTM experimental setup involved five key steps. First, gain a deep understanding of IoT and how it would be integrated into a UTM system. Once this knowledge had been acquired, the team developed the programs and design mechanisms that enabled unmanned vehicles to travel and pick up objects autonomously. The next step involved the hardware and circuitry implementation. With all the components in place, the team then deployed them in a testbed environment for trial-and-error examination, allowing them to identify and address any issues that arise. Finally, a live simulation of the UTM system was conducted and recorded in CORAL Lab, which served as the platform for the demonstration of the autonomous unmanned vehicle solution.

To test the final prototype, the team ran both the UAV and UGV to perform their specified tasks in which they picked up and delivered a payload. The UAV used IoT enabled data to have the drone fly autonomously from building to building using the SkyLift mechanism to take advantage of magnetism to accomplish this goal. The UGV used IoT data sensor fusion to navigation safely through the simulated city to accomplish this goal. Figure 7 illustrates the testing and evaluation plan used throughout the project. Throughout the project, we

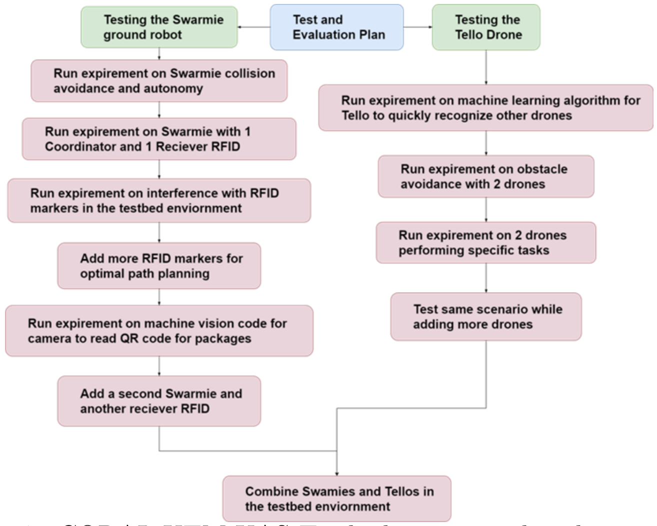
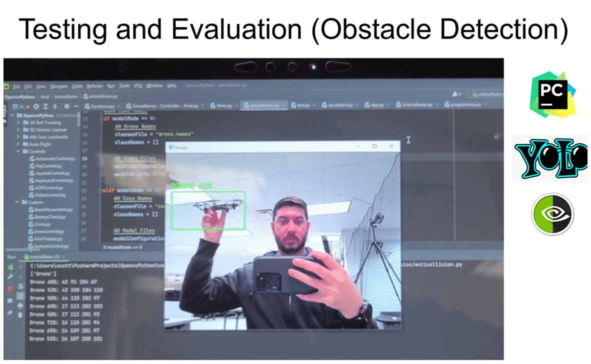


Figure 7: CORAL UTM UAS Testbed testing and evaluation plan



(a) YOLOV5 drone detection testing.

(b) YOLOV5 drone detection implementation.

Figure 8: YOLOV5 enabled drone detection for SAA.

utilized the testing and evaluation plan as a contingency plan or guide to ensure that our project remained on track and met all necessary testing and evaluation requirements.

The final prototype ran both the UAVs and UGVs to perform their specified tasks of picking up or delivering a package. The first UAV used IoT enabled data to have the drone fly autonomously from building to building using the SkyLift mechanism to take advantage of magnetism to accomplish this goal while a second UAV used anti-collision to detect the first UAV and stopped until it had passed. The first UGV used IoT data sensor fusion to navigate safely through the simulated city to accomplish this goal while a second UGV interfered with the first UGVs pathway to show it's anti-collision feature. This functionality is similar in that the first UAV and first UGV preferred that tasks as first thought of but differs in that the second UAV and second UGV do not perform in the same way. Also, the first and second UAV would have SAA features. The YOLO version 5 enhanced collision detection was implemented and observed after the initial package delivery tasks were demonstrated. The experiment was setup until a proper level of confidence was acquired through a computer built in camera Figure 8.

A follow up experimental setup was required to further evaluate the drone collision detection capabilities though computer vision sensing. The Tello was setup with five motion-capture detection markers. The CORAL 12-camera Vicon system was utilized to track the drone motion through the whole activity. The main task consisted on having a Tello drone hover in the testbed until another Tello is detected as a collision treat to be avoided. The drone had the capability to stay in place or be corrected by an operator through teleoperated

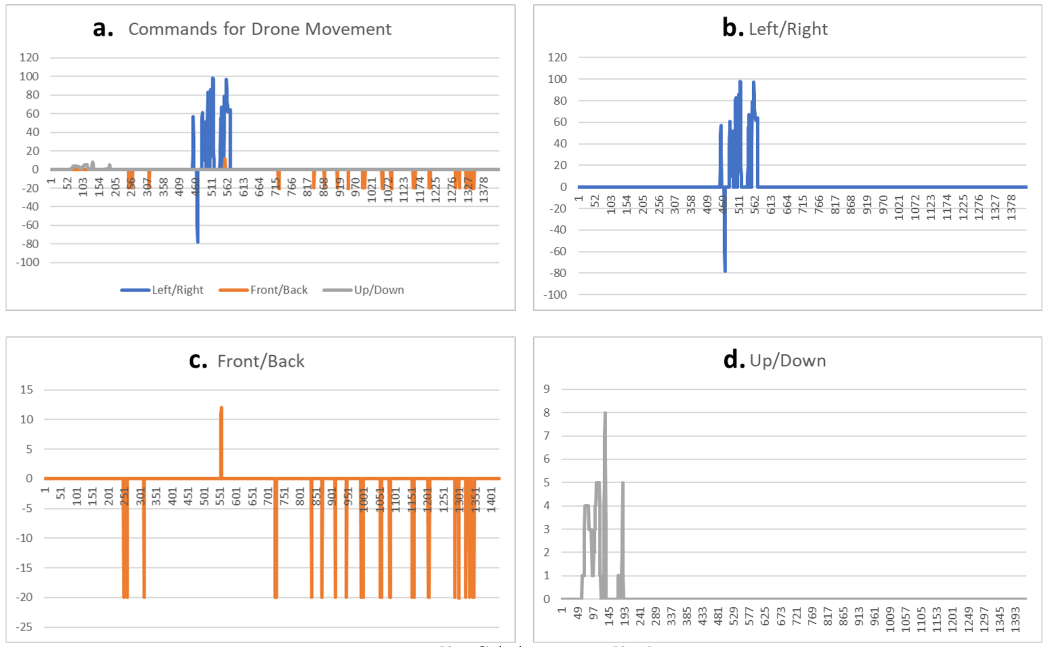
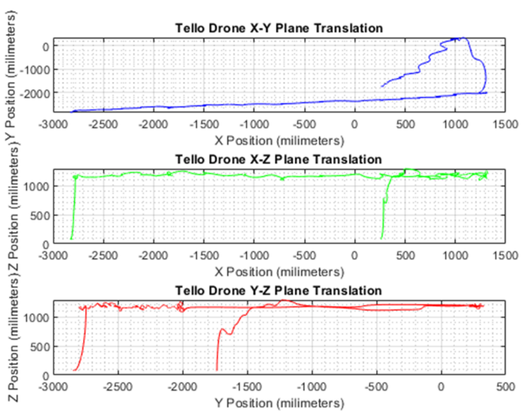
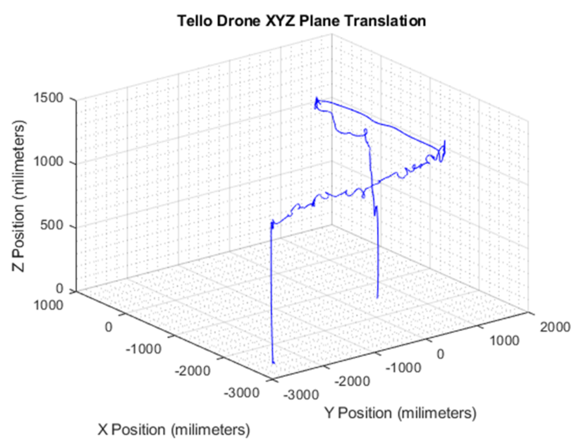


Figure 9: Tello SAA controlled motions



(a) Tello translation by planes.



(b) Tello 3D translation

Figure 10: Tello drone VICON enabled dynamic detection.

control. Another Tello drone was position safely by hand at a safety distance in front of the operational drone. As the Tello detected the drone it move back at a predefined safe distance and stay hovering in place. The SAA detection drone was push to the edge of the area enabling multiple detections. The experiment was repeated about twenty times. The python code had the capability to log every single control instruction sent to the drone. Figure 9 shows the different motions that were logged by the drone control. In Figure 9C it can be observed more that 20 positive avoidance actions (back motions). This demonstrated that a low level device such as the Tello can be enhanced with an advance object detection algorithm. To complement the analysis, the VICON drone dynamics can be observed in Figure 10. On those images in can be observed how the drone maintain a line with minimum disturbances going back to avoid the other drone position in front of it.

A further effort is been in progress into utilizing YOLO version 8 and utilizing Tello specific images for the training. After collecting about 240 images of the specific drone through a combination of internet and actual photographs taken in the laboratory, 100 epochs were trained. The results of the training can be seen in Figure 11. Such results demonstrate a good trend of losses reduction but it can also be observed that the precision

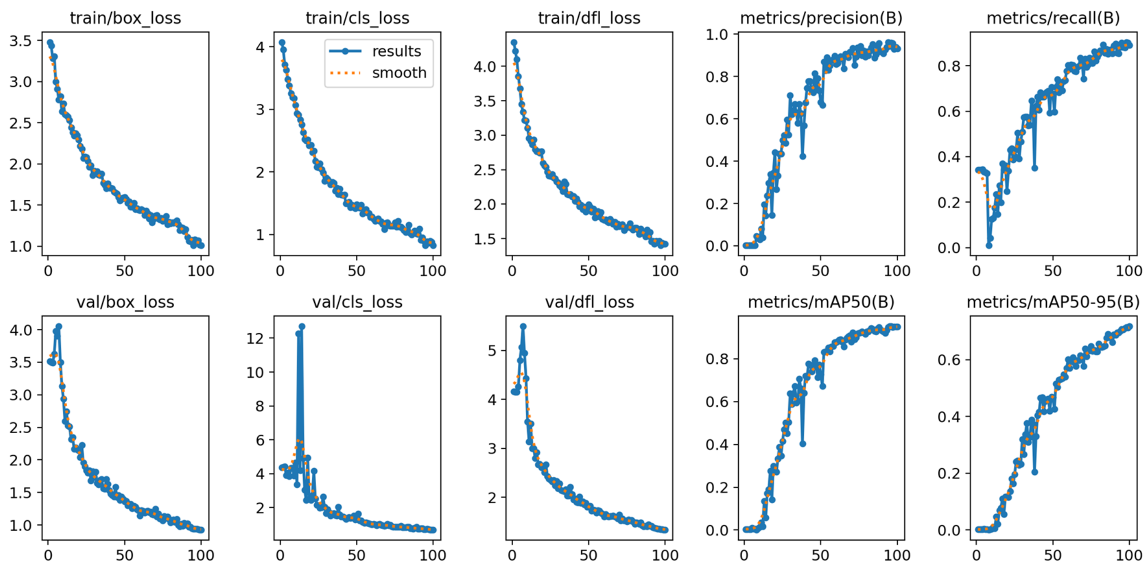
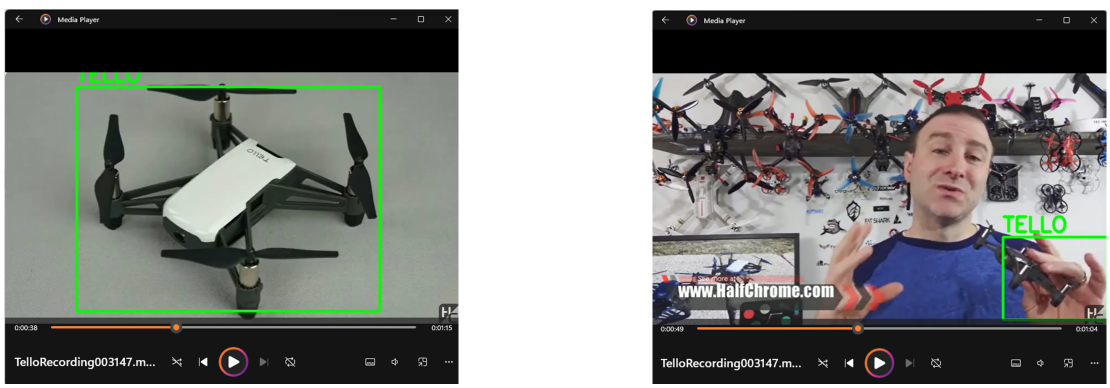


Figure 11: YOLOv8 Tello detection training results



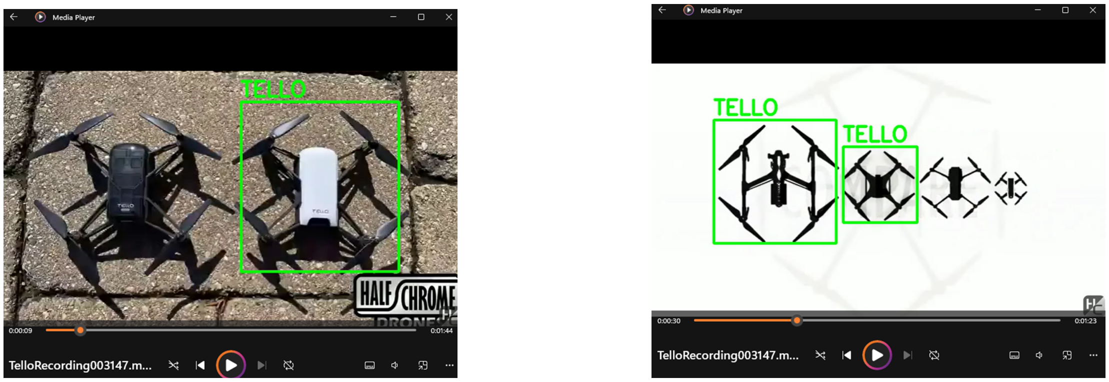
(a) Test result: Tello detected. (b) Test result: Tello detected on human hand.

Figure 12: YOLOv8 accurate Tello detections.

still required more training. Some spikes decreasing the precision can be seen between epochs 40 and 60. A video from Youtube was then utilized as a dynamic sample to test the YOLOV8 enabled detection. Correct or accurate results can be observed in Figure 12. While inaccurate of incomplete detections can be seen in Figure 13. The plan is to further enhance the efforts and create more training data to be program into the Tello. A benchmark procedure is in progress and is intended to catalog all different training efforts and document the levels of efficiency for collision avoidance operations.

5. CONCLUSIONS

The UTM system was able to fulfill its intended functionality with both UAVs and UGVs. While the scale was different in the testbed, the result of the robots operating cooperatively was similar to the real-world use of this project. The various impacts of implementing IoT into the system was seen in many parts of the project, including the computational components that communicate with the vehicles and the markers that lead the vehicles to their intended destinations. The computer vision implementation for collision avoidance operations show promising results. The utilization of a limited device such as the Tello drone and having a level of success shows promise of integration in more advance technologies. With the development of drone cloaking technologies, EM only dependent sensing technologies will not have the capability enable more comprehensive collision avoidance operations. Through the utilization of multiple hands-on knowledge and resources it was



(a) Test result: Only one Tello detected.

(b) Test result: non Tello drone frames detected

Figure 13: YOLOv8 inaccurate or incomplete Tello detections.

demonstrated that is possible to develop a full UTM coordination in a limited research environment. Following the process within a national laboratory or an entity with further resources can greatly increase the results from experimenting with hardware beyond software simulations. The final integration of unmanned autonomous systems into the national airspace and other domains within the nation will depend on hands-on experimentation rather than just algorithm development and testing through software.

Some recommendations for future phases of this project include using a larger quantity of unmanned vehicles, increasing the scale for the environment and size of the unmanned vehicles and finally adjusting the obstacle avoidance algorithms to include outdoor interference's.

ACKNOWLEDGMENTS

This work is been supported by the National Science Foundation CNS Division of Computer and Network Systems, NSF AWARD #2131263 titled: CISE-MSI: DP: SaTC: Dynamically Enforcing User-Oriented Geospatial Restrictions for Drone Fly-Overs."

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