Unmanned Aircraft Systems (UAS)

Broad Agency Announcement (BAA)

Call# 005

Final Report

Project Title:
Distributed Multi-Hazard Monitoring System for High-Density BVLOS Operations

Company Name:
Texas A&M Engineering Experiment Station

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1. Executive Summary

High-density Beyond Visual Line-of-Sight (BVLOS) Uncrewed Aircraft System (UAS) Operations will require services that provide comprehensive situational awareness of airspace operations. These services are expected to include distributed monitoring functions that enable detection, tracking, 3D-geolocation, track forecasting, and alerting of concerns (e.g. conflicts) for multiple heterogeneous mobile objects (UASs, birds, crewed aircraft, etc) operating in complex airspace (with uneven terrain and varying weather). The overarching goal of this project was firstly to advance the development of such distributed monitoring services, and secondly to define requirements for UAS monitoring services, to facilitate integration of high-density BVLOS UAS operations into the airspace. Toward this high- level goal, the following specific objectives were met:

1. Development of Texas A&M's ground-based distributed Multi-Hazard Monitoring System or *Multi-Object Monitoring System (MOMS)*[1], for comprehensive monitoring (detection, tracking, classification, 3D-geolocation, forecasting) of multiple heterogeneous mobile objects in complex airspace in real-time.
2. Description of Concepts of Operation (ConOps) for high-density BVLOS operations in airspace volumes and their surveillance; and planning and execution of flight tests for these ConOps.
3. Completion of two three-day flight campaigns in Alaska, to execute the developed ConOps and flight tests and deploy/evaluate MOMS. The flight campaigns were conducted at Poker Flat Research Range (March) and Nenana Municipal Airport (July).
4. Performance evaluation of detection, tracking, classification, and 3D-geolocation functions for the MOMS, via analysis of data collected from the flight tests.
5. Model-based assessments of risks to traffic control/operations due to monitoring system characteristics, as a means to develop requirements for such monitoring systems. MOMS

[1] We originally named our system "Multi-Hazard Monitoring System", but prefer "Multi-Object Monitoring System" as a more accurate description of its function.

was compared against these requirements, and ou analysis was also used to refine the requirements and assessments.

6. Demonstration and reporting to the FAA, standards bodies, and outside stakeholders with interest in high-density and BVLOS UAS operations.

As a whole, the project work indicates that ground-based distributed monitoring systems such as MOMS can provide useful, comprehensive situational awareness for high-density BVLOS UAS operations in complex airspace. The project also has yielded operational concepts, flight testing paradigms, risk and requirements analyses, and data resources that represent advances in the area of UAS-integrated aviation operations.

2. *Introduction*

2.1. *Context and Motivation*

Both civilian and military aviation operations increasingly require management of airspace with multiple heterogeneous mobile objects, including uncrewed aircraft systems (UASs), crewed aircraft, birds, and potentially balloons and projectiles, operating in close proximity within complex low- to medium- altitude airspace. These operations will require specialized real-time monitoring or surveillance capabilities, encompassing several functions: 1) fast detection of objects impinging on the airspace volume; 2) simultaneous tracking and distinguishing of multiple objects in both image and geographical frames of reference; 3) classification of objects by type or size; 4) alarming of scenarios of concern (e.g. potential collisions, stream-merging or sequencing challenges, coordinated intrusions or attacks). Such multi-object monitoring tasks are sometimes further complicated by environmental and operational factors, which may include uneven terrain, wind impacts on airspace operations and sensor measurements, cloud cover and precipitation, varying lighting profiles and background coloring/structure, radio interference, adversarial activities (e.g. jamming), size weight and power (SWaP) constraints, and potentially strong cost constraints. While a number of sensing technologies and supporting systems (computing hardware, algorithms, software, etc) have been developed for aerial object monitoring, and in particular UAS monitoring [1-10], simultaneous monitoring of multiple heterogeneous objects in complex environments remains challenging.

In civilian aviation, the growing need for ground-based multi-object monitoring is being driven by the rapid growth in low-altitude UAS operations. Specifically, while UAS operations to date have largely been restricted to line-of-sight operations and airspace with limited traffic, scaled-up operations will be BVLOS and will include busy airspace [11-13]. Recognizing this need, the U.S. Federal Aviation Administration has recently (August 2025) proposed a set of rules for BVLOS UAS operations (Normalizing Unmanned Aircraft Systems Beyond Visual Line of Site Operations) [11], which will allow for wider BVLOS operations. This rule focuses on lower-altitude airspace, and considers both small (<55lbs) and larger (<1320 lbs) UASs with a speed limit of 100mph. Importantly, the rule categorizes airspace operations into risk levels. Higher-risk operations include all operations in the part of controlled airspace that falls in the purview of the rule, and also uncontrolled (Class G) airspace in populated areas. For such higher-risk operations, UAS operators and airspace managers will be required to meet a set of requirements, which include strategic deconfliction, conformance monitoring, and Detect-and-Avoid (DAA) requirements. The rule as proposed is flexible with regard to how these requirements are met by airspace stakeholders, however it broadly formalizes the use of Automated Data Service Providers (ADSPs) which support these requirements. Implementation of the rules will require UAS flight operators and airspace managers/administrators to have a common operating picture for airspace volumes of operations, which may be a stand-alone service or part of a full UAS Traffic Management (UTM) service provided by an ADSP. Distributed surveillance or monitoring systems which can track heterogeneous airspace objects (including authorized and unauthorized UAS, crewed aircraft, and birds) in close proximity are anticipated to be a critical part of such services, as enabling technologies for DAA, tactical deconfliction, and possibly strategic deconfliction and conformance monitoring.

An even wider range of BVLOS operations in high-density airspace are expected in the long term, which are beyond the scope of the recent proposed rule. These include controlled operations near future vertiports, airspace operations which involve a mixture of crewed and uncrewed traffic, and operations involving even larger or faster UASs. Many of these future operations are envisioned in the scope of the Urban Air Mobility paradigm, Advanced Air Mobility paradigm, and/or vertiport-concepts of operations [14-17]. While the specifics of these operations are still being envisioned, surveillance systems will be needed in support of supervisory control and/or advanced DAA approaches. Both within and beyond the scope of Part 108, comprehensive monitoring of multiple objects will be needed, including fast detection, tracking/track-forecasting, classification, and alarming. We also stress that the airspace volumes requiring UAS monitoring may be quite varied, ranging from urban areas with man-made obstructions, to remote and uneven natural terrain.

While high-density UAS operations are a primary motivation for multi-object airspace monitoring, traditional aviation operations near airports also may benefit from more advanced surveillance/monitoring to support alarming and automation. In addition, incursions of unauthorized UAS (e.g., UAS without Remote ID) and bird strikes in terminal areas, which are not alarmed by traditional radar systems, are a substantial and growing concern [20]. These incidents show that additional real-time ground-based monitoring at low altitude may be helpful as supplements or backups to existing terminal-area surveillance systems. Beyond these core aviation applications, there is also a need for low-cost UAS detectors for facility perimeters, that achieve high sensitivity and specificity at reasonable cost. While RF-based detection is sometimes sufficient for this purpose, there is a growing concern about unauthorized UASs operated by malicious actors which are non-communicating, use non-authorized frequency bands, spoof or jam radio signals, or otherwise avoid detection from their radio signature. Alternate low-cost monitoring may be appropriate for these tasks.

Simultaneous monitoring of multiple mobile aerial objects is also growing in importance in military operations [22,23]. In recent conflicts in Ukraine, the Middle East, and Kashmir, UASs have been used extensively for surveillance, defense, and attack functions. Often, combatants simultaneously deploy multiple UASs, which may have complementary and/or coordinated functions in a theater-wide operation. The UASs used in military operations are diverse, with small low-cost drones engaged in one-time missions being quite common. Importantly, UASs are being used by both regular state-sponsored forces and by irregular forces, and can benefit weaker actors in asymmetric conflicts. For such high-density military UAS operations, ground-based multi-object monitoring systems are needed for a number of reasons, including protection of personnel and assets against attacks via counterUAS actions, coordinated rapid response to adversary maneuvers, differentiation of friendly and adversary UASs, and coordination of UAS-based offensive activities. Similar to civilian aviation operations, multi-aerial-object monitoring in military operations requires a comprehensive suite of algorithms for fast detection, tracking, classification, and forecasting of aerial objects. In addition, military monitoring solutions need to be low-SWaP for portability and field use, and must operate robustly in varied environments (e.g., uneven, mixed- natural and man-made terrain; communications-denied or jammed environments; etc).

These various use cases for multi-object airspace monitoring have attracted substantial recent interest from a number of aviation stakeholders, including the Federal Aviation Administration (FAA), multiple branches within the Department of Defense, the Department of Homeland Security, the National Aeronautics and Space Administration, state and local governments, airports, and the aviation industry. Although progress has been made along several tracks, a comprehensive treatment of monitoring for multiple airspace objects is of value for both civilian and military aviation (see e.g. [8,23]). This comprehensive treatment should encompass advances in hardware, computing, and algorithms for multi-faceted dense airspace monitoring (fast detection, tracking, classification, 3D-geolocation, alarming, etc). Additionally, a comprehensive treatment concurrently requires advancement of policies, standards, and cost/usability related to multi-object airspace monitoring. It also requires experimentation to evaluate the performance of airspace monitoring systems, and to support certification of monitoring and broader UAS traffic control/management systems. This project aims to advance airspace monitoring in these cross-cutting directions.

2.2. *Technical Background and Contribution*

In the last few years, a number of UAS monitoring and counterUAS systems have been commercialized, and at the same time a considerable technical literature on monitoring has been developed [1-10,24-27]. Despite this, the multiple mobile-object monitoring problem described above has not been fully addressed. The multi-object monitoring applications described above involve multiple requirements which make the problem challenging, including: 1) simultaneous monitoring of a substantial number of objects (potentially 25-50+), 2) fast detection of impinging objects (0.5s-5s in many cases, depending on operational requirements and contraints), 3) accurate tracking in a geographical coordinate system (i.e., track of 3D-geolocations (latitude, longitude, altitude) vs time) or other common coordinate system, 4) high specificity and sensitivity object classification (as determined based on operational requirements and risk assessment), 5) ability to monitor substantial volumes (0.25-10 mi^2 areas and altitudes of 0-5000ft+) and varied object types, 6) robustness to environmental and operational variations, 7) ability to provide confidence intervals for detection/classification/alarming results, 8) low cost and size/weight/power, 9) compatibility with existing civilian and military aviation systems, and 10) ability to handle significant object speed variability, among others. Current solutions each address some of these requirements, but certain requirements (e.g. object classification and track forecasting, low-SWaP, development of confidence intervals) have not been fully addressed by any solution. Specifically, in the commercial aviation space, RemoteID-based tracking of drones has been promoted as a preferred solution, but is only usable for authorized drones using RemoteID, lacks robustness at distances beyond a few hundred feet and in degraded environments, and may not be sufficiently fast for DAA. Monitoring systems that use ambient RF signals have also been developed, but they have limited capacity for geolocation and tracking, are limited only to RF-enabled UASs, and cannot handle multiple UASs. More advanced commercial systems with tracking capabilities have been developed, primarily for military counterUAS operations. Radar systems have long been used in aviation for collision avoidance and traffic control, but traditional radars often do not have the resolution to capture small UAS and birds, may be unsuitable for near-ground operations, and also may be cost-prohibitive. Recently, several advanced radar and electro-optical systems have been developed, which can allow tracking of small objects at substantial distances. However, these systems do not provide comprehensive monitoring of multiple objects within an airspace volume, with robust tracking/differentiation of objects in close proximity, classification, 3D geolocation of multiple objects, removal of spurious object tracks, and object prediction remaining challenging. They may also be bulky, susceptible to interference, and expensive.

Relative to this background, one main contribution of our work has been to develop a track-centered methodology and distributed system for monitoring multiple mobile objects in airspace volumes, which we term the multi-object monitoring system (MOMS), see Figure 1. The innovative concept of MOMS is that simultaneous monitoring of multiple mobile airspace objects can be achieved by extracting tracks from sensor data, using new video/sensor processing methods that exploit the underlying physics/dynamics of airspace mobile objects (please see Section 3.2 for details) [28]. In turn, multiple object tracks can be leveraged, again using physics/dynamics-based approaches together with limited data for calibration, to develop a comprehensive monitoring (3D-geolocation, classification, track forecasting) and alarming capability. A comprehensive development and implementation of the method and system have been undertaken in the project, encompassing 1) integration of hardware and networking for data collection and real-time monitoring with the core sensing/algorithms; 2) development and/or enhancement of the monitoring algorithms (see [10, 28-30] for our preliminary work); 3) development of software and scripts for end-to-end operation of the distributed monitoring system; 4) software development and integration for streaming-data-based and real-time monitoring, as well as visualization for a central authority. A main contribution of this project is the development of a complete distributed system for comprehensive real-time monitoring of multiple heterogeneous airspace objects, which can be used for BVLOS UAS operations in complex environments.

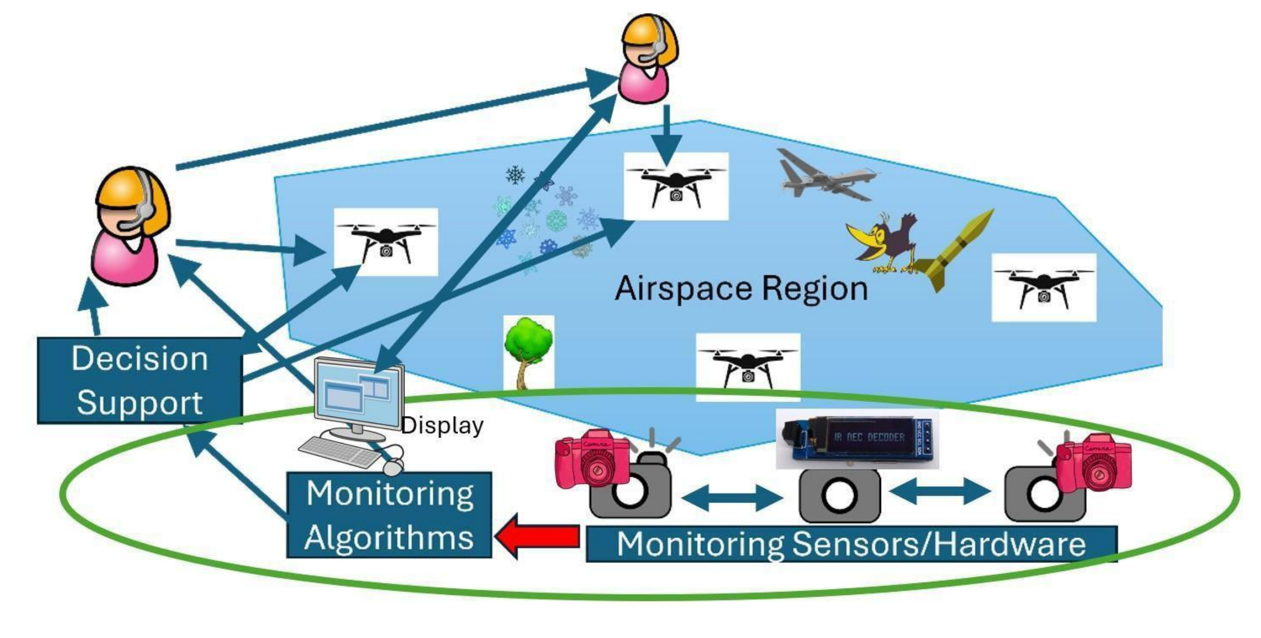


Figure 1: Illustration of the Multi-Object Monitoring System (MOMS). MOMS is a distributed system which provides ground-based monitoring services (detection, tracking, classification, 3D-geolocation, forecasting) for complex airspace with heterogeneous mobile objects. MOMS consists of multiple pods with sensors together with a command module, which are networked to provide a real-time operational picture to relevant stakeholders and decision-support systems. MOMS as implemented for the field test primarily used light-spectrum video cameras, although an infrared camera is also being tested, and the MOMS algorithms have also been tested on some radar data.

Our work is connected with a set of recent studies on track-based monitoring of multiple airspace objects, as well as a broader image-processing literature on tracking mobile objects. Some initial work on multi-track-based monitoring was developed in prior work by our group and by C. Dolph and co-workers, with a primary focus on classification of UASs vs birds in radar signatures [10,28-30]. Relative to these prior works, we focus here on developing a comprehensive solution based primarily on passive video sensors, which encompasses multi-track extraction, classification, and 3D-geolocation, and track prediction; as a starting point for comprehensive monitoring/alarming based on the tracks. These studies also align with other recent work that considers airspace object monitoring from an image or video processing perspective. The works in this direction broadly combine a number of concepts, including application of background subtraction techniques, use of learning, and trajectory-based classification [31-38]. Seidaliyeva et al. (2020) and Unlu et al. (2019) demonstrated the efficacy of background subtraction for initial detection of small distant objects [31, 32], but focused only on entirely static backgrounds. Liu et al. (2023) highlighted that good detection and tracking often requires combining multiple techniques, but focused only on single objects [33]. Opromolla et al. (2018) pursued methods for maintaining tracking accuracy across varying distances [34]. Significant contributions have also come from Srigrarom's group [36-38]. Srigrarom et al. (2020) proposed a trajectory-based classification system to distinguish drones from birds by analyzing motion patterns, including turning angles, curvature, and flight velocity [36]. This is similar in flavor to the prior efforts from C. Dolph and co-workers, and our groups, although using different feature sets. In subsequent work, Srigrarom and Chew (2020) introduced a hybrid motion-based detection system for small, fast-moving drones, combining blob detection with appearance-based verification [37]. This group's latest research (Srigrarom et al., 2021) aims to extend this to multi-camera, multi-drone tracking with trajectory-based re-identification [38]. While this work is aligned with our efforts, substantial gaps remain in tracking heterogeneous objects (different velocities, gaps), achieving monitoring for substantial distances, enabling effective classification, and practically implementing the algorithms in real-time, among other needs. Our work aims to extend the state-of-the-art through several innovations: 1) an adaptive and dynamics-informed background subtractor, 2) a robust trajectory management system maintaining object identities through occlusions, 3) dual-threshold area filtering, 4) new classification metrics and algorithms, 5) new methods for 3D-geolocation and track forecasting, and 6) GPU acceleration specifically optimized for background subtraction operations. Additionally, our physics-informed framework distinguishes between aerial objects based solely on motion patterns, and uses the same motion information to improve simultaneous geographical-coordinate localization. This enables tracking and classification without extensive training data, please see Sections 3 and 4 for further details.

Beyond the contribution inherent to the technology itself, the project also contributes to the development of operational concepts, data, and analyses for aviation systems, and specifically high-density and BVLOS UAS operations. From this perspective, we stress several advances:

1) The research effort contributes to the development of paradigms and concepts of operations for high-density BVLOS UAS operations, such as operations near future vertiports and in congested corridors [15-17]. From this perspective, a primary contribution of our effort is to pursue reduction to practice of UAS traffic management concepts/paradigms proposed in the literature, through a) definition of distinct CONOPS for specific operational needs (e.g., deconfliction of two crossing streams, sequencing) within a broader paradigm; b) definition of simplified operational scenarios (including specific airspace volumes, terrain/environment characteristics, traffic situations requiring control) for each of these specialized CONOPS, c) development of flight-test plans for each operational scenario at flight-test sites in Alaska; and d) completion of these flight tests. A second contribution has been to explicitly represent ground-based monitoring services with specific performance characteristics within a BVLOS paradigm, which allows analysis of their impacts on aviation-system performance.
2) A method has been developed for quantitatively assessing risks introduced by monitoring systems in high-density UAS operations requiring centralized management. This risk assessment has further been used to estimate requirements on monitoring systems, which are relevant to developing standards for UAS traffic control/management services (see Sections 3.5 and 4.5).
3) Flight tests have been conducted, which include repetitions (10-25+) of simplified traffic patterns requiring control actions (deconfliction, sequencing), and variations of these scenarios (at different altitudes/distances, with different UASs, etc). Extensive sensor data has been collected from these flight tests using MOMS. These flight tests and the data

collected permit statistical analysis of monitoring-system performance, and also can serve as a benchmark data set for advanced monitoring algorithm development.

4) A demonstration of the real-time monitoring capability provided by MOMS has been achieved (see Section 4).

3. Methodology

The project methodology is presented, organized according to the major objectives within the scope of work – 1) CONOPS Development/Flight Planning, 2) MOMS Assembly and Enhancement, 3) Flight Testing and Data Collection, 4) Data Analysis, 5) Requirements Analysis and Development for Monitoring Systems, 6) Demonstration, Information Sharing, and Project Administration. Figure 2 diagrams the specific work tasks and subtasks, according to the statement of work for the project, while Table 1 maps these tasks to the six objectives above. Figure 3 presents the schedule according to which the work was conducted.

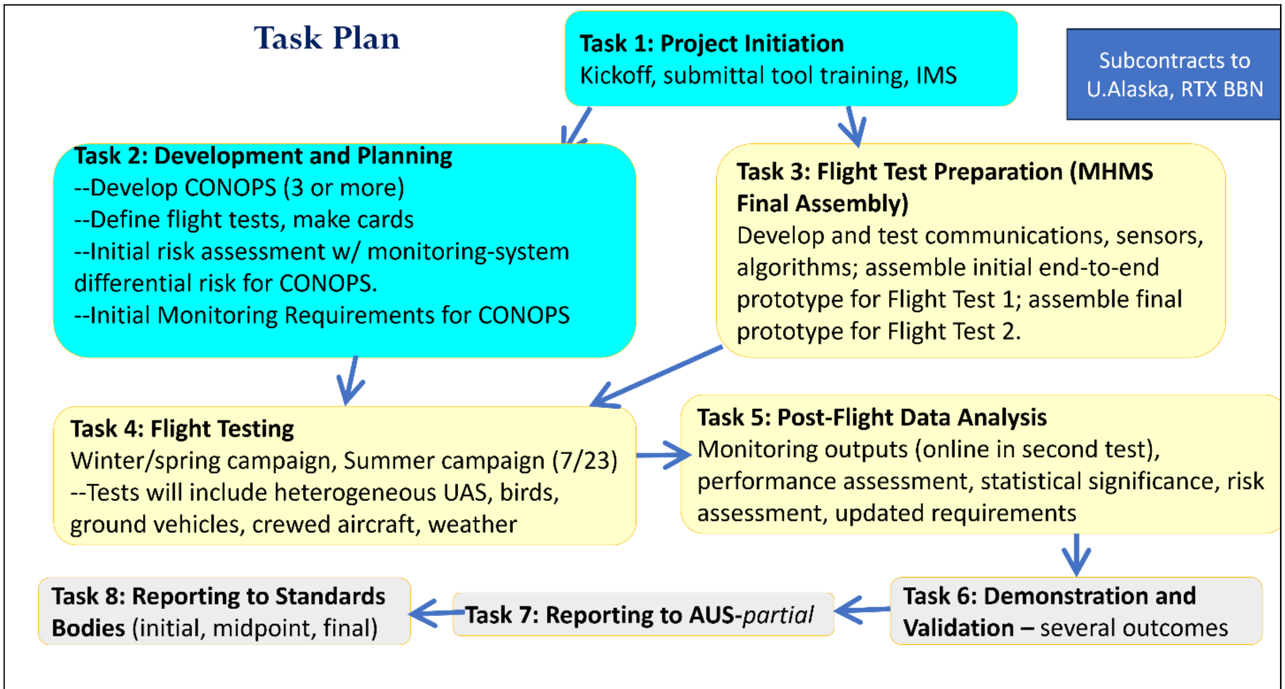


Figure 2: Task Breakdown for the Project.

Objective	Associated Tasks/Subtasks
1. CONOPS Development, Flight Planning	2.2, 2.3
2. MOMS Assembly and Enhancement	3.1, 3.2, 3.3, 3.4
3. Flight Testing and Data Collection	4.1, 4.2
4. Data Analysis	2.1, 5.1, 5.2
5. Risk Assessment and Requirements Development for Monitoring Systems	2.4, 2.5, 5.3, 5.4
6. Demonstration, Information Sharing, Project Administration	1, 6-8

Table 1: Mapping of tasks/subtasks to main project objectives.

Task	Staff
Task 1 • Project Initiation	
1.1. Contract kickoff	PI,Con
1.2. FAA deliverable tooltraining	PI,Con
1.3. Integratedmaster	PI
schedule Task 2 •	
Development and Planning	PI
2.1. Data Analysis Plan	PI,GS, UA
2.2. Flight test plan and test cards	PI,GS, UA
2.3. CONOPS for high density BVLOS ops.	PI,GS
2.4. Initialrisk assessment	PI,GS
2.5. Monitoring requirements	
Task 3 • Flight Test Preparation	
3.1. Adaptive communication functions	RTX,GS
3.2. Instantiatealgorithms in project hardware	PI,GS, RTX
3.3. End-to-endprototype	PI,GS
3.4. Refined prototype for second on-lineflight test	PI,GS, RTX
Task 4 • Flight Testing (also see below)	
4.1. Winter flight campaign	UA, PI,GS
4.2. Summer flight campaign	UA, PI,GS
Task 5 • Post Flight Data Analysis	
5.1 Performance analysisfrom data	PI, GS, RTX
5.2. Statistical significance analysis	PI,GS
5.3. Finalrisk assessment	PI,GS
5.4. Finalmonitoring requirements	PI,GS
Task 6-Validation	
6.1. Demonstration to FAA (video,snapshots)	PI,GS
6.2. Share requirementswith standards groups	PI
Task 7 • Reportingto AUS	
7.1. Monthly Progress Reports	PI
7.2. Quarterly PMRs	PI
7.3. Draft FinalReport	PI,GS, RTX
7.4. FinalReport	PI,GS, RTX
7.5. FinalProject Briefing	PI,GS, RTX
Task 8 • Reportingto Standards Bodies	
8.1. Kickoff presentation	PI
8.2. Mid-point presentation	PI
8.3. Finalpresentation	PI

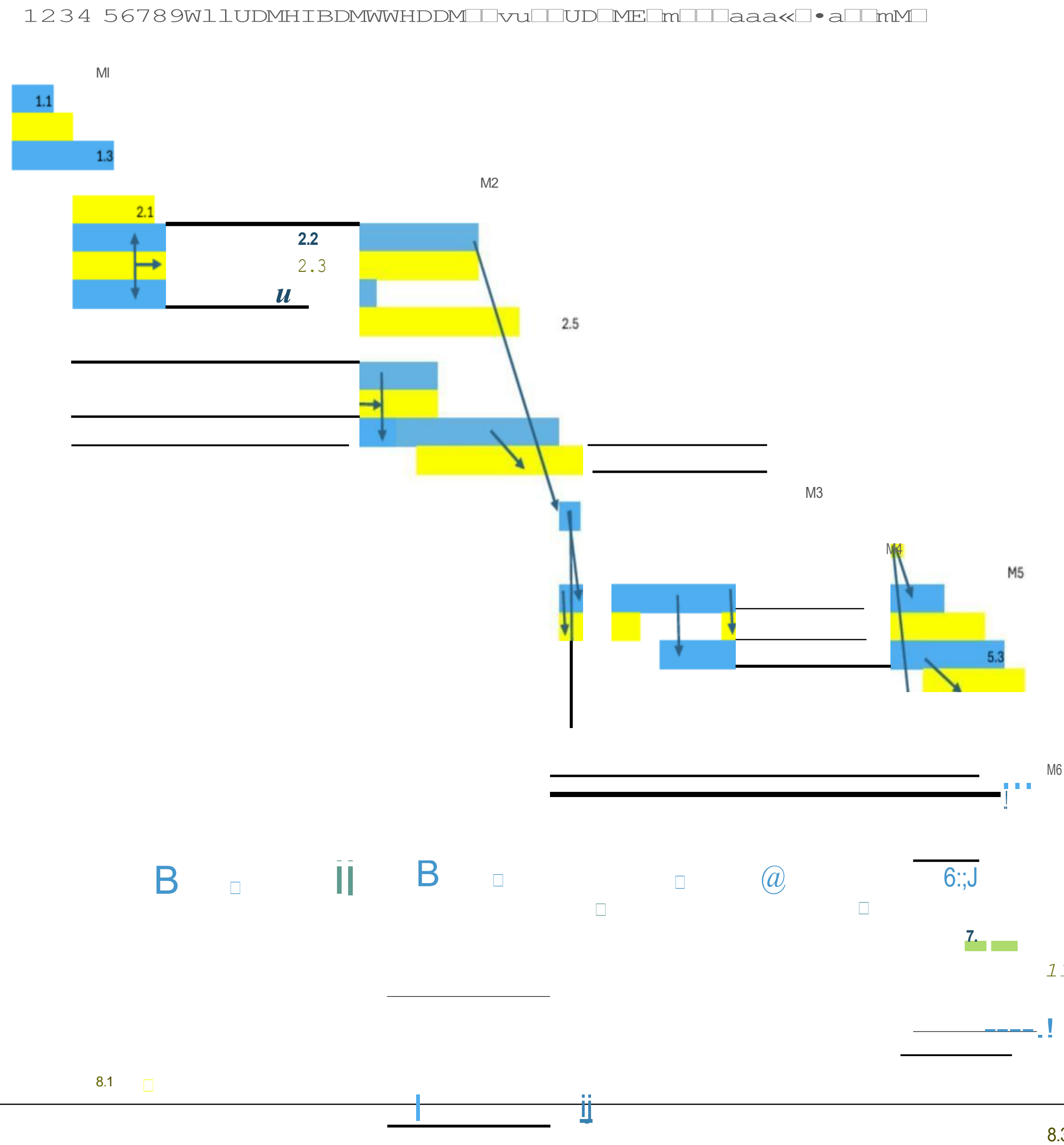


Figure 3: Integrated Master Schedule for the project.

3.1. CONOPS Development and Flight Planning

3.1.1. CONOPS Development

CONOPS for high-density BVLOS UAS operations are still under development in the aviation community [15-17,39-42], although the recent proposed rule (Part 108) provides a more comprehensive framework for some operations [11]. For this project, we have considered CONOPS where ground-based real-time monitoring is provided as a service, which is used to support airspace operational needs for UAS such as deconfliction and sequencing/guidance. This service could be used in several ways. Specifically, per the proposed Part 108 rule, a monitoring function may be a component of a situational awareness or UTM service provided by an ADSP, or a standalone service, that is used to meet operational requirements provided in the rule (DAA, strategic or tactical deconfliction, conformance, etc). Alternately, for some future BVLOS operations, such as those near an airport or vertiport, we envision that the monitoring system may be directly provided to central authority such as a Terminal Radar Approach Control (TRACON) or similar facility. In this case, the authority would use the monitoring system to achieve traffic control or operational objectives within an airspace volume. In general, operational objectives that could be supported by the monitoring system include maintenance of separation distances between different types of objects (as needed for DAA or tactical deconfliction), guidance of UAS on specified routes or patterns, situational awareness for unexpected or unauthorized traffic, and potentially conformance monitoring. We stress that ground-based monitoring may be complementary to vehicle-board sensing that is used for DAA. Similarly, the monitoring systems considered here may complement, integrate with, or encompass other technologies that help to maintain a common operating picture of an airspace volume, such as RemoteID-based monitoring of UASs. As will be described in Section 3.2, a monitoring system with multiple distributed pods, which use edge computing and networking for real-time communication with the control authority, is considered. The control authority uses data and visualizations provided by the monitoring system to pursue operational objectives.

Within this broad framework, distinct CONOPs are defined which specify types of flight patterns and operational goals for an airspace volume of interest. In this project, we have focused on three distinct CONOPs, which reflect envisioned high-density UAS operations in the future airspace system. The three CONOPS are:

1) *Congested Corridor Traffic Management,* where the monitoring system is used for surveillance and deconfliction of crossing traffic streams in congested airspace.
2) *Near-Vertiport Traffic Management,* where the monitoring system is used for traffic control near a future vertiport, including sequencing of aircraft for arrival and deconfliction.
3) *UAS Free Flight in Congested Airspace,* where the monitoring system is responsible for surveilling authorized or unauthorized maneuvering UAS in airspace volumes with substantial bird densities, weather hazards (rain, snow), and/or crewed-aircraft overflights.

The CONOPS are illustrated in Figure 4.

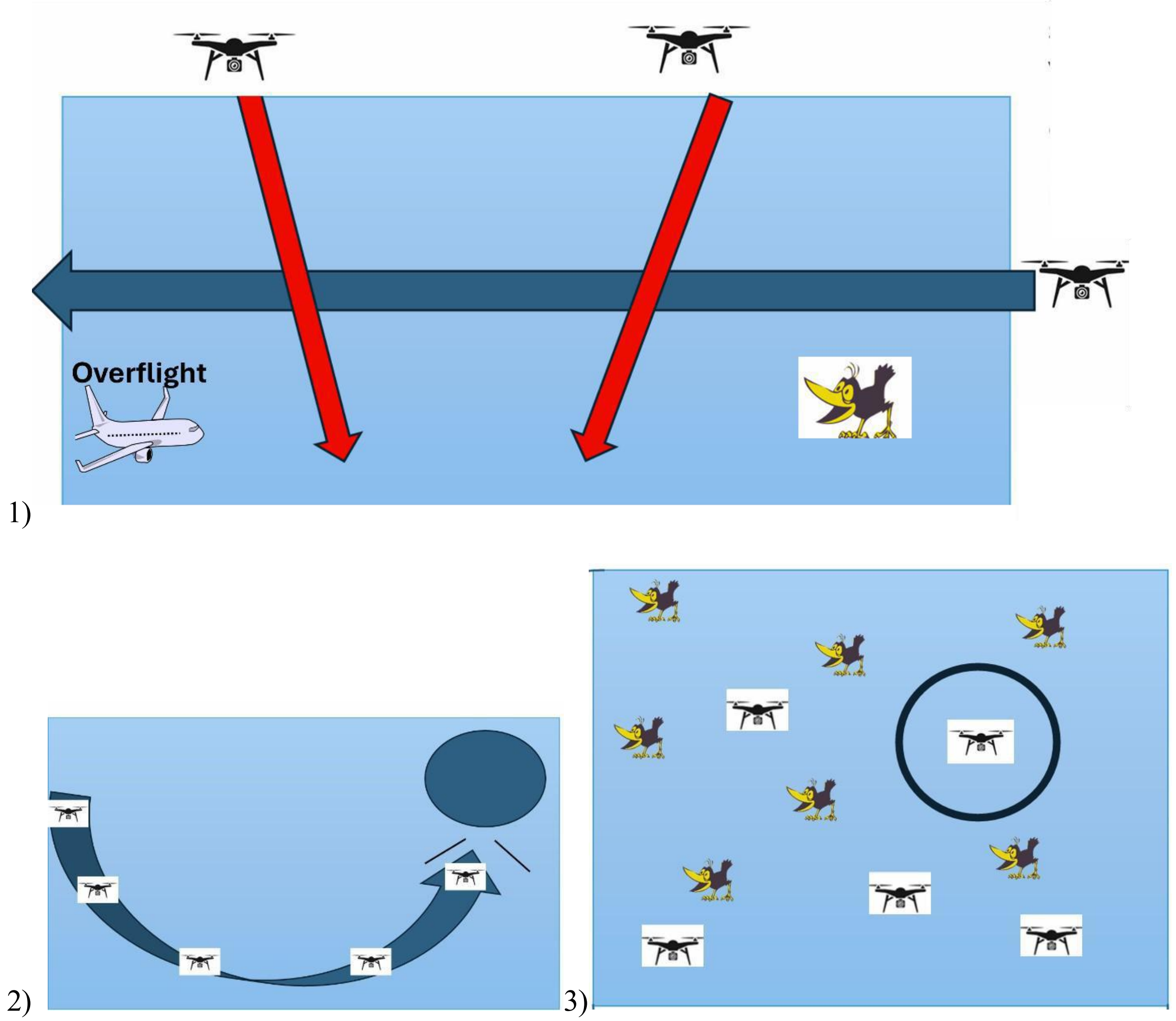


Figure 4: Illustrations of three distinct CONOPS for high-density BVLOS UAS operations, which capture different operational needs/scenarios. The CONOPS are: 1) deconfliction of a traffic stream in a congested corridor (top), arrival stream to an vertiport (bottom left), and 3) free-flight-type operations in congest airspace (bottom right).

3.1.2. Flight Test Planning

Flight tests were designed to evaluate the performance of the multi-object monitoring system (MOMS), for these CONOPS. The flight tests aimed to replicate, in a simple and repeatable a manner, key UAS interactions requiring surveillance (conflicts of orthogonal traffic, merging of streams for approach/landing, bird avoidance) for each CONOPS. Two flight campaigns with similar flight tests were planned and executed, one taking place in early Spring and the other in Summer, to encompass different weather and lighting conditions. The flight campaigns were focused on variations of three primary flight tests. The flight test plans are described in detail next (see Section 3.3 for details about the flight tests themselves).

3.1.2.1. Flight-Test Objectives

The main objectives of the flight tests, which drove test plan development, were the following:

- Replication of CONOPS that may arise in future high-density BVLOS UAS traffic control/management scenarios.
- Implementation and testing of the MOMS in a field setting. The baseline test goal was to for the first test was to verify that the MOMS was able to robustly collect data from at least two field sites over a multi-hour period. The baseline test goal for the second field test was the scale up the operations (more field sites, sensors, larger UASs), automate operation of the distributed system, and demonstrate real-time monitoring.
- Instantiation of algorithms that process MOMS raw data (e.g. for detection, tracking, identification, and track forecasting), in support of high-density BVLOS UAS operations.
- Statistical evaluation of the performance of MOMS, and comparison against performance requirements for specific high-density BVLOS UAS operations.
- Testing of CONOPS using different types and sizes of UASs, and in different terrains and weather conditions. Details about the vehicles used are given in the Section 3.3. The list of vehicles used included: small Autel rotorcraft, several larger rotorcraft (including the Alta-X, the Aurelia X6, and the Skyfront P8), a fixed-wing Skyrider UAS, and a vertical takeoff-and-landing Supervolo UAS.

3.1.2.2. Flight Authority.

Flights were conducted under 14 CFR part 107 or appropriate COAs already in place with University of Alaska Fairbanks.

3.1.2.3. Flight Test A: Crossing Traffic-Stream CONOPS

Description: Flight test A captures a typical traffic control need that may arise in a CONOPS where crossing heterogeneous traffic streams must be managed in high-density airspace. Such CONOPS may arise in congested corridors, where unauthorized cross traffic needs to be deconflicted from a main traffic flow. The CONOPS may also arise in the scope airport and future vertiport operations, where multiple coincident traffic streams (e.g. arrival and departure streams, or traffic flows entering via different arrival fixes) must be monitored and managed. The test is concerned specifically with replicating conflicts between traffic on crossing flows, to allow evaluation of monitoring of such conflicts for traffic control/management. The test is diagrammed in Figure 5 below. The test involves one UAS (referred to as "ownship") transiting through a corridor, with two other UASs ("path crossers") crossing the first vehicle's path at an angle (representing either alternate traffic streams or cross traffic). Several variants were planned and conducted, at different altitudes, distances, UAS types, etc.

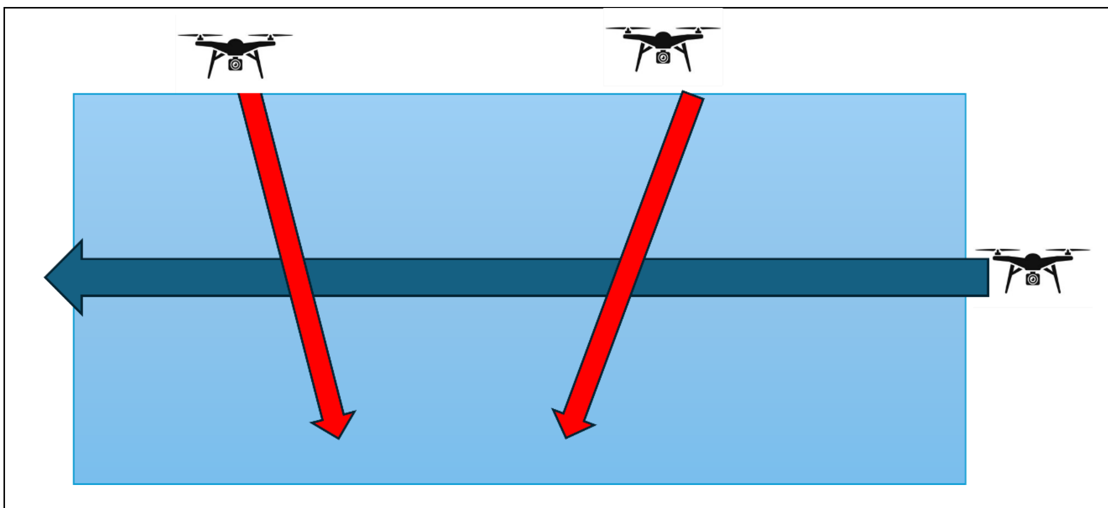


Figure 5: Cartoon diagram for Flight Test A. The test is meant to replicate a traffic control CONOPS in a congested corridor with cross traffic.

Test A Further Details

Ownship: Rotorcraft or Fixed Wing

Ownship flight path: Straight-line path at ~400 ft AGL across FoO.

Path Crossers: Rotorcraft (two)

Path Crossers flight paths: Straight-line paths at ~350 ft AGL, at an angle of 45-135 degrees relative to the ownship flight path.

Pilots: 3 in total for the three UASs

Test constraints for vehicles: Remote ID, GPS enabled

Test constraints for flight paths: vehicle speeds 15-25 knots, at least one path crosser comes within 50-250 ft of ownship. The intent is to replicate scenarios where alerting for deconfliction is critical.

Test constraints for environment: no precipitation, daytime

Data actions: RemoteID transmitter on vehicle is turned on (ACUASI is responsible) and RemoteID data capture is attempted (TAMU), flight logging enabled (ACUASI), MOMS recordings conducted as indicated in the project Data Analysis Plan (TAMU)

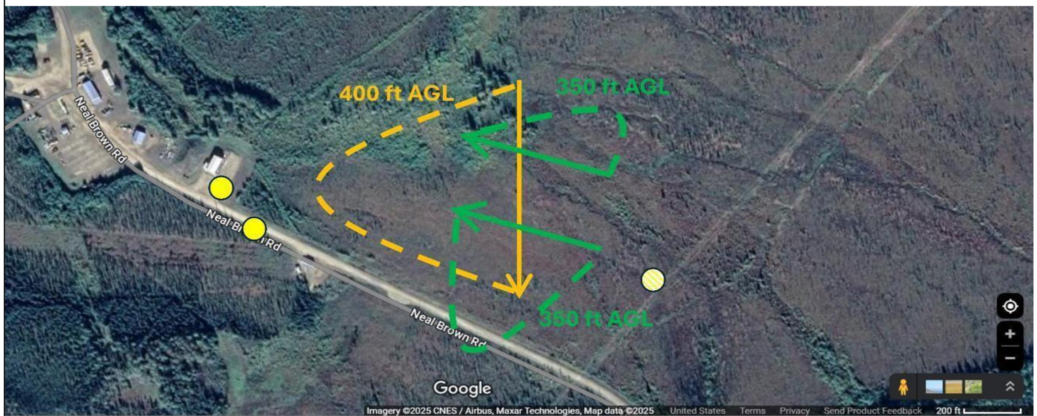
Repetitions: 10+

Note: flights will be conducted in LoS.

Variants: fixed-wing ownship, different altitudes and distances, different backgrounds/weather, with birds.

The planned flight test is diagrammed on a map of the flight test site, for each flight campaign.

Spring Flight Test Plan, Poker Flats Research Range



Summer Flight Test Plan, Nenana Municipal Airport

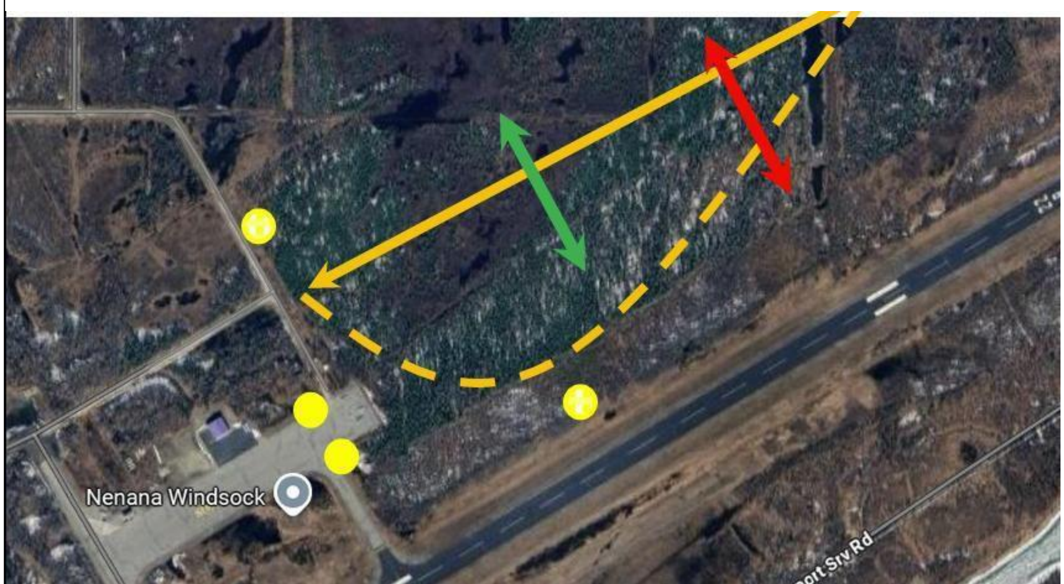


Figure 6: Map of the Fields of Operations (FoO) with Test A flight patterns shown. The UASs will fly circuits, or back and forth, for repetitions of the trials. Trials at different altitudes and distances will be conducted. The crossing-traffic will be at a different altitude (25m or 50m higher or lower) compared to the flight through the corridor.

3.1.2.4 Flight Test B: Vertiport Sequencing/Landing CONOPS

Description: Flight test B replicates a CONOPS where heterogeneous UAS are sequenced and landed at a vertiport (see Figure 7). The test involves three UAS (labeled W,X,Y) approaching on different paths to be sequenced, and then gradually descending in sequence toward a destination waypoint. The merging/descent phase includes a turn. Details are presented next.

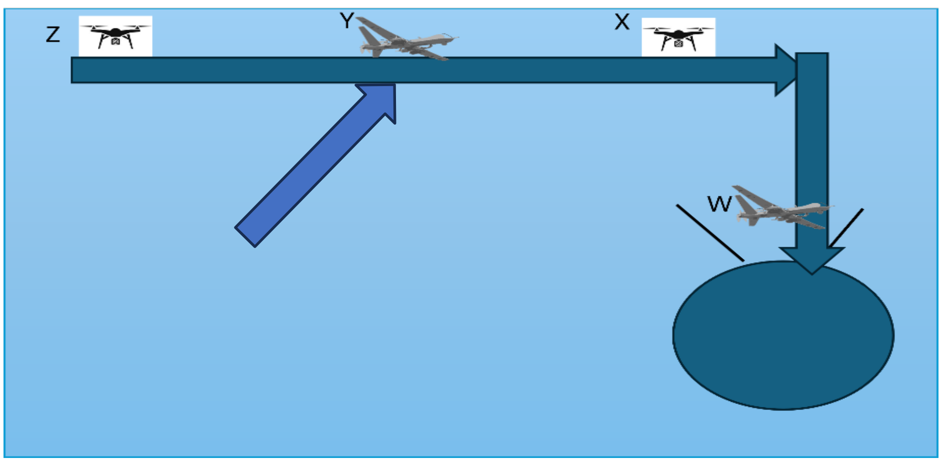


Figure 7: Cartoon diagram for Flight Test B. The flight test replicates a CONOPS for sequencing of arrivals into a vertiport.

Test B Details

UASs: Base case – 2-3 sUAS, two rotorcraft (W,Y) and one fixed wing (X); or two rotorcraft.

UAS flight paths: The sUASs will be holding at 400ft AGL in different quadrants of the FoO. The UASs will be sequenced in order, with a time of approximately 15 seconds between vehicles joining the arrival flight path. Once on the arrival flight path, the vehicle will turn, and follow a straight-line descent from 400ft AGL to 200 ft AG (see Figure 8).

UAS pilots: 2 or 3

Test constraints for vehicles: Remote ID enabled, GPS enabled

Test constraints for flight paths: vehicle speeds 25-45 knots, spacing between vehicles around 10-15 seconds.

Test constraints for environment: no precipitation, daytime.

Additional constraints: potential presence of birds

Data actions: RemoteID transmitter on (ACUASI), flight logging enabled (ACUASI), MOMS recordings conducted as indicated in the project Data Analysis Plan (TAMU)

Repetitions: 10+

Note: Flights will be conducted in LoS.

Variants: Variants using different UASs (including all fixed wing), altitudes/distances, and descent characteristics will be used.

Note: for the first flight campaign, on the day of operations, the plan was altered to a chasing pattern (each vehicle following the same circuit, with one behind the other). The descent component was maintained, but there was no merging of streams.

Note: During the second flight campaign, a mixed flight test which included two vehicles in descent patterns (Flight Test A) and also a crossing vehicle (Flight Test B) was undertaken.

Test B flight patterns on the field of operations are shown in Figure 8.

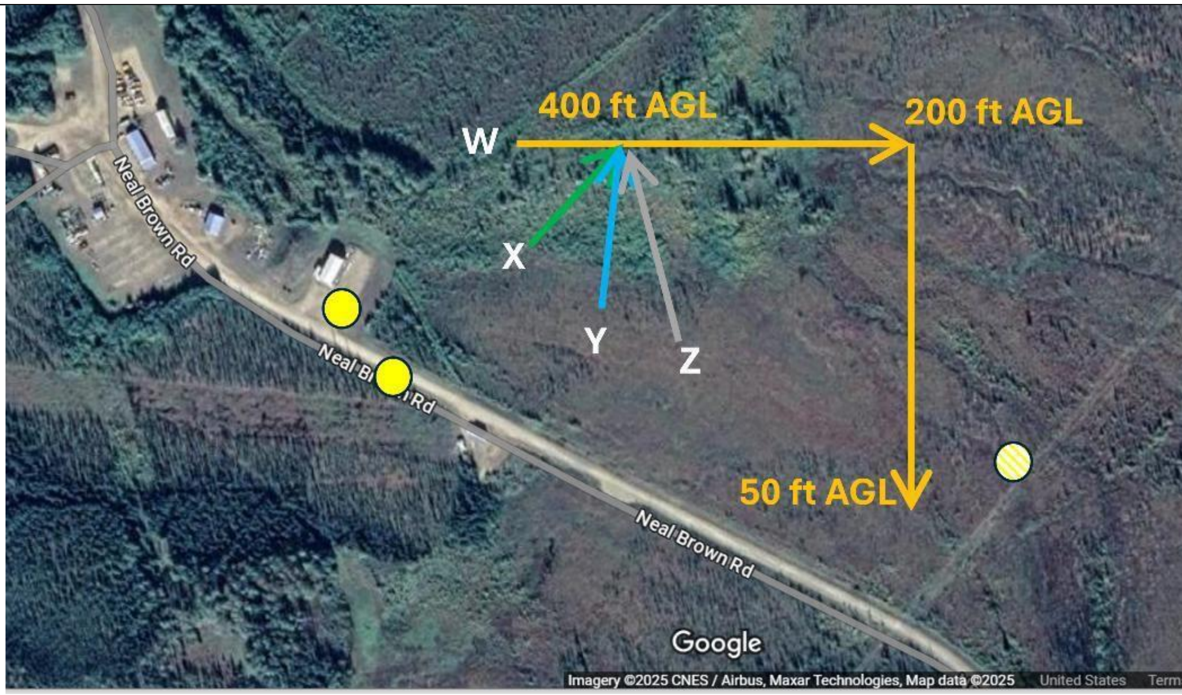


Figure 8: Test B flight patterns on a map of the Fields Of Opeation. The test emulates merging and descent of two or three UASs on different streams for arrival at a vertiport. For the first flight test, the UASs were flown in a chasing pattern to emulate the descent with a turn. For the second flight test, the two UASs followed different circuits, merging at a point and then descending.

3.1.2.5. Flight Test C: Complex Maneuvers in Degraded Airspace

Description: Flight test C replicates a CONOPS where a UAS is undertaking complex BVLOS maneuvers in airspace with confounding objects (birds, crewed aircraft overflights) and some weather impact (see Figure 9). Our focus is to evaluate the monitoring system in this setting. The test involves one UAS (labeled W,X,Y,Z) engaging in turns and elevation changes in such a degraded environment. We also considered testing the limits of the monitoring system, via flights a larger distances (up to about 1 mile) and altitudes (up to 1200 ft) away from the sensors. Details are presented next.

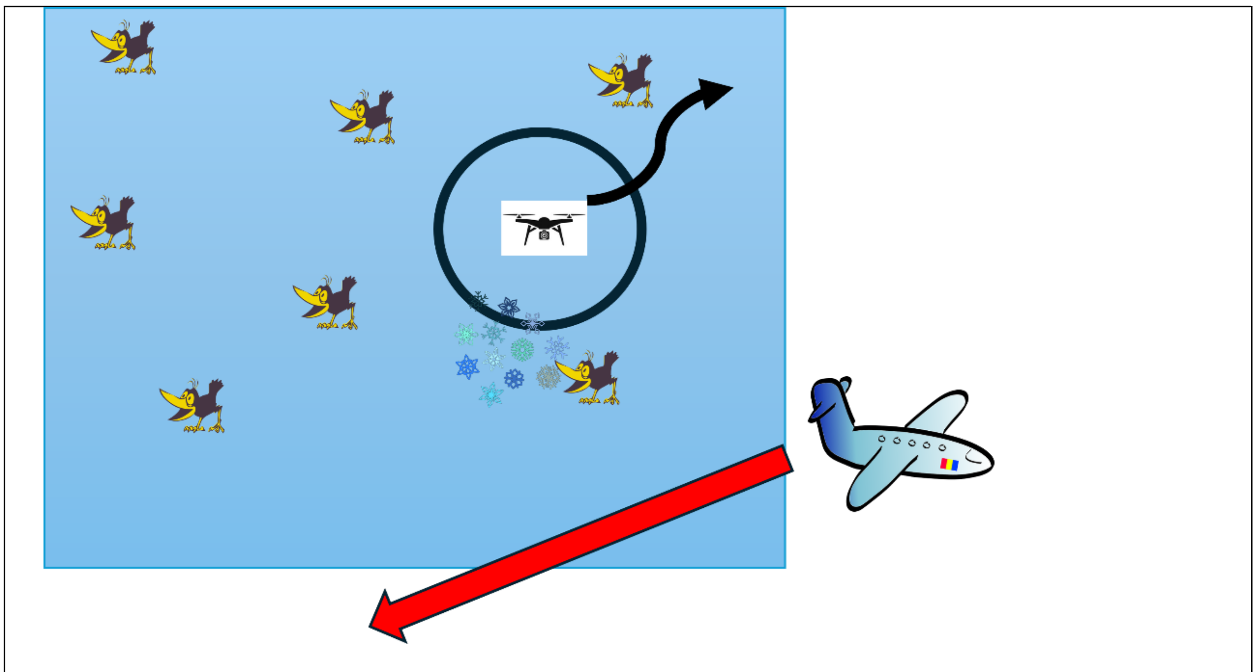


Figure 9: Cartoon diagram of Flight Test C. Complex UAS maneuvers in airspace with birds, overflights, and limited weather impact are considered.

Test C Details:

UAS: One sUAS, rotorcraft or fixed wing

UAS flight paths: The vehicle undertakes a sequence of maneuvers, which include turns at different angles and changes in elevation (Figure 10).

UAS pilots:

Test constraints for vehicles: Remote ID, GPS enabled

Test constraints for flight paths: vehicle speeds 10-45 knots.

Test constraints for environment: very light precipitation or other limited weather impact (e.g. elevated wind). Additional constraints: presence of a high density of birds, crewed aircraft overflights. Data actions: RemoteID transmitter on (ACUASI), flight logging enabled (ACUASI), MOMS recordings conducted as indicated in the project Data Analysis Plan (TAMU)

Repetitions: 10 or as many as possible Note: flights will be conducted in LoS.

Note: also will conduct a monitoring stress test to see understand the range of the monitoring system for UASs of different sizes.

The test is diagrammed on the Field of Operations in Figure 10.

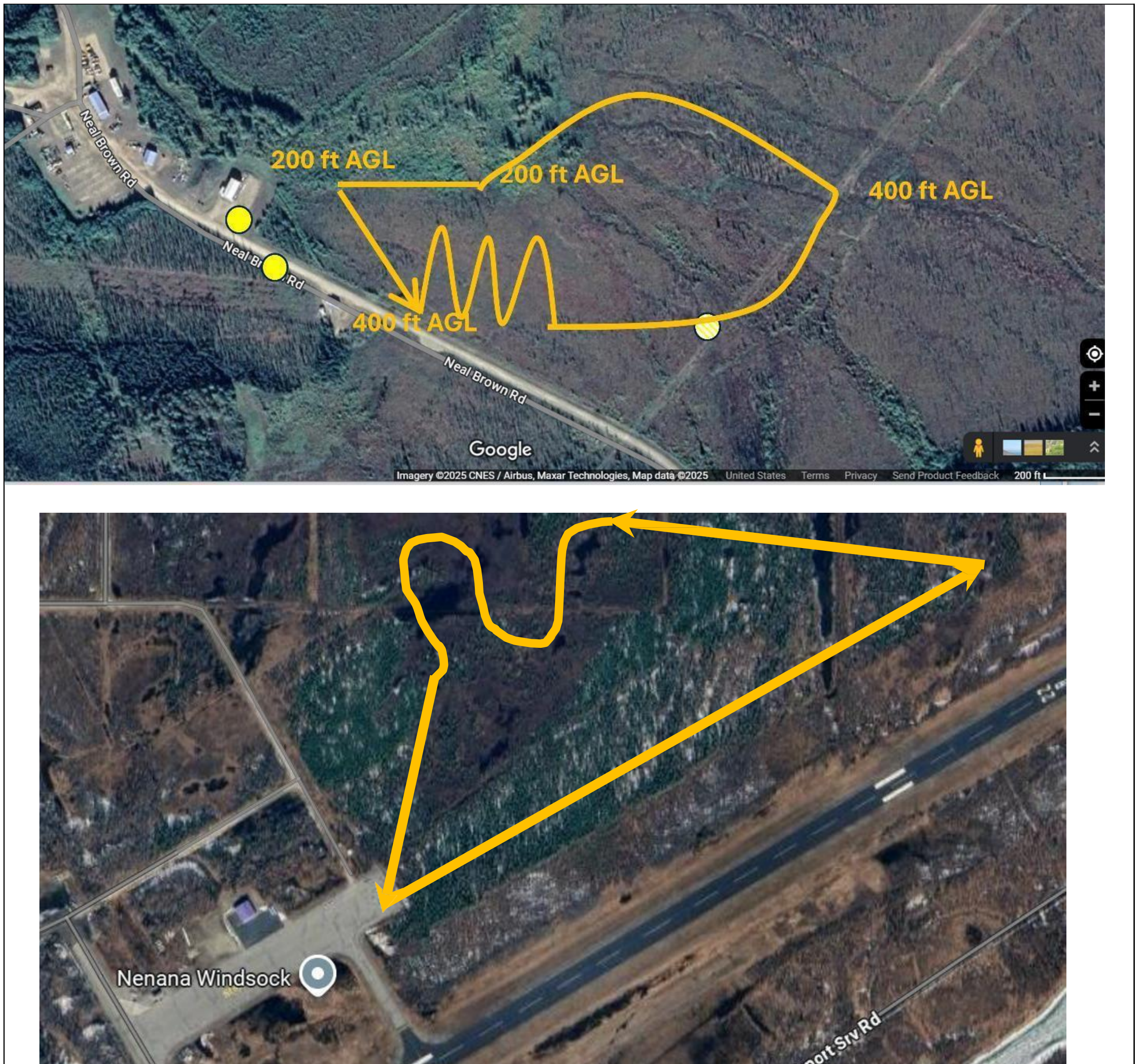


Figure 10: Test C flight patterns. A single UAS is undertaking complex maneuvers in a region of airspace. These include: straight-line ascent, zig-zag pattern, flight along a curve, curved descent, and straight-line level-altitude flight. Our interest is in monitoring the UAS in the face of various hazards and confounding factors, including a high density of birds, crewed-aircraft overflights,

3.1.2.6. Multi-Object Monitoring System (MOMS) Setup during Flight Tests

MOMS uses imaging sensors (2D and 3D cameras, infrared) to monitor airspace (see Section 3.2 for details). Each imaging sensor is wire-connected to a microcontroller or edge device (a Raspberry Pi or NVIDIA Jetson), which collects and stores the sensor data, and also has the ability to send the video data to a host computer using several modalities (WiFi, Cellular) in real time. For the field tests, communications via a local area network using WiFi were used. The host computer can process the collected data using several monitoring algorithms, including for detection, tracking, object identification, and track forecasting.

The setup procedure was focused around deploying the sensor assemblies at locations at one edge of the field of operations, setting sensor angles/directions, deploying networking, powering all devise, initiating recording for the sensors (done differently at each flight campaign), and being prepared to protect the sensors in case of rain or other inclement weather. To protect the computing devices against high temperatures, heat sinks were installed on each edge device.

Motivated by use cases of interest, the flight tests were planned to use UASs of diameters between 1.5ft-10 ft, although still within the small UAS class to allow easy conduct of multiple trials of multi-UAS operations.

3.2. MOMS Development, System Integration, and Enhancement: Methodology

The Multi- Object Monitoring System (MOMS) developed by the project team is a ground-based capability for simultaneously monitoring multiple heterogeneous mobile objects (e.g., UASs, crewed aircraft, birds, balloons, projectiles) in an airspace volume, encompassing detection, tracking, and classification functions. MOMS is a comprehensive solution which comprises: 1) a distributed architecture and hardware for sensing, computing, communications, and display; 2) a suite of algorithms that enable monitoring functions; and 3) software for data communications, device command, and instantiation of the monitoring algorithms.

Some of the track-analysis algorithms for MOMS (for classification, in-image-frame tracking), which form the conceptual foundation for our overall solution, were developed and tested in a preliminary way in prior work using data primarily from NASA-conducted flight tests [10,29,30]. All other aspects of MOMS, including integration of these algorithms with track extraction from videos, further track analytics, and all hardware and software implementation for both off-line and real-time monitoring were developed and assembled in this project [28]. Thus, we describe the MOMS solution as a whole as a means to describe our methodology for assembling and enhancing the system MOMS is overviewed at a system level first, while details and associated technical contributions are described thereafter in Subsections 3.2.1-3.2.3.

Architecture and Hardware Overview: MOMS is structured to incorporate multiple types of sensors. The sensors primarily used for monitoring the flight tests were light-spectrum imaging sensors (video camera), with one infrared camera also used. MOMS algorithms have also been applied to radar data, and the system has the capacity to include other types of surveillance such as RF signal detectors. MOMS sensors are organized in two or more non-collocated platforms which we call pods. The sensors are mounted on rotating hinges which allow easy positioning of the sensor's azimuth and elevation. Each sensor is connected by a cable with a microcontroller. A timing device is also connected with each microcontroller, which provides a synchronous global clock. A Wifi local area network is established for wireless communication among the devices on each pod, between the pods, and to/from a command-and-display node which has CPU- and GPU-based computing capabilities. We note that the command/display module may also serve as a pipe to remote authorities or stakeholders. Alternate wireless communication modalities including cellular-network-based have also been examined in the project, and can be used. Local area networking through Wifi was chosen as the preferred networking mechanism for the current instantiation, because of the speed, cost, and robustness benefits. However, alternatives (e.g. cellular) may be needed for monitoring over larger areas.

Monitoring Algorithm Suite Overview: An integrated suite of algorithms has been developed for simultaneous monitoring of multiple heterogeneous airspace objects. Broadly, the algorithm suite draws on core image processing methods available in OpenCV, but is specialized to exploit the physics-based dynamical properties of mobile airspace objects, and to allow for simultaneous monitoring of many objects. At its core, the algorithm suite is trajectory or track based, i.e. it uses dynamics-informed video processing algorithms to extract multiple object tracks from sensor data, and then achieves core monitoring functions primarily from the track data. Key algorithms are:

1. Multi-track extraction algorithms which extract and distinguish simultaneous tracks of airspace objects in each imaging sensor's field of view, in the sensor's local coordinate system.

2. Algorithms for detection of any mobile object impinging on the monitored airspace volume, using tracks from one or more sensors; and tracking of these objects within the image/video frame.
3. A 3D-geolocation algorithm which computes object tracks in the geographical coordinate system (latitude, longitude, altitude), using imaging-frame tracks extracted from multiple imaging sensors.
4. A classification algorithm which classifies mobile airspace objects by type (e.g., bird, UAS, crewed aircraft, projectile, etc), primarily based on track signatures.
5. Advanced monitoring algorithms for additional functions such as track forecasting, velocity computation, and object intent determination.
6. Visualization and alarming algorithms for providing operators with real-time information about critical concerns (e.g. potential collisions), as well as actionable situational awareness about the airspace. These are still under development.

Software Overview: Software has been developed for real-time: 1) storage and communication of sensor data including videos, 2) remote operation/command of the sensors, 3) instantiation of the monitoring algorithms described above, and 4) display of tracked objects and preliminary alarming of scenarios of concern (e.g., close proximity of objects of different types). The software is developed in the Python programming language. Specifically, code is run on each sensor's associated microcontroller (e.g. Raspberry Pi). This microcontroller archives the sensor data on the local drive and/or attached storage card, and also transmits the data via the network to the control/display module. In tandem, the control/display module has code that can be used to start and end the sensing, storage, and communication functions at each microcontroller. Additionally, code is run at the command/display module, which allows ingestion of the sensor data communicated by each sensor's microcontroller, and application of the monitoring algorithms described above on this data. The command/display module also allows display of data on request, including raw videos, tracks in a video sensor's pixel frame, and tracks in the geographical coordinate system, with object classifications overlaid. Finally, the command and display module is structured to run software which overlays and vocalizes alarms based on user-defined criteria. We note that the command/display module may be used directly by an airspace authority, or may serve as a pipe to users of the monitoring service.

3.2.1. Architecture and Hardware Details

MOMS comprises two or more pods which each may have multiple sensors, along with a central control module for visualization and alarming to operators and/or piping of data to monitoring-service users/authorities. The airspace volume of interest is monitored by the sensors deployed on each pod. Sensor data (e.g. live video streams) are stored on microcontrollers that are connected each sensor, and are transmitted through a wireless link in a local network to the central control module for centralized data processing and analysis. Figure 11 shows the overall network architecture of MOMS, including the pods and central control module.

The components within pods in MOMS, and the roles of these components, are shown in Figure 12. A list of components is provided in Table 1. Specifically, for large pods with 3-6 sensors and network routing function, a metal frame with shelves was used to house pod components (microcontrollers, networking equipment, etc). A perforated mounting platform is installed at the top, serving as the interface for sensor deployment. Standardized mounting holes are evenly distributed across the mounting platform, enabling flexible positioning of sensors via nut-secured attachments. The remaining layers of the frame are allocated for communication hardware, such as a quad-band router, and power supply units for the entire platform. The pod can be powered via a wall outlet or a power station. For our field test, a standard power station was sufficient to power a large pod for about 7 hours, with most of the power consumption associated with the router. Besides the large pods, small pods with 1-2 sensors were also developed. For these pods, the sensors were placed on a perforated mounting platform, which was then directly placed on a box or other small platform. The small pods contain only the sensors and associated microcontrollers, and a small lithium-ion battery bank that powers the devices. The pods can be networked, to allow transmission of sensor data via the local area network, but do not have a router associated with them. They can also continue to record in the event of a loss of networking. The small pods are able to record for 15+ hours on a single battery.

Sensors mounted on the perforated platform include high-resolution 2D cameras (including standard, wide angle, and night-vision cameras) and an infrared camera. Additional non-imaging sensors can be optionally deployed. The current study has included tests with three types of cameras: (1) a Raspberry Pi Camera Module 3 (CSI interface) equipped with both standard and wide-angle NoIR lenses, (2) an ultra-high-resolution Arducam IMX179 USB camera, and (3) an infrared thermal camera. A night-vision camera was also tried, although not during the field tests. All imaging sensors are controlled by a dedicated microcontroller, which handles acquisition tasks including parameter setting, recording segmentation, data communication, etc. An independently powered real-time clock (RTC) module is connected to the microcontroller via GPIO pins to provide consistent timing and accurate timestamps for the data streams. The CSI camera component, as an example illustrated in Figure 13, is connected to the microcontroller through a flexible flat cable (FFC). The camera is housed in an ABS enclosure and mounted on a hinge mechanism fixed to the platform, which allows orientation tuning through tilt adjustment of the upper arm and rotation of the base.

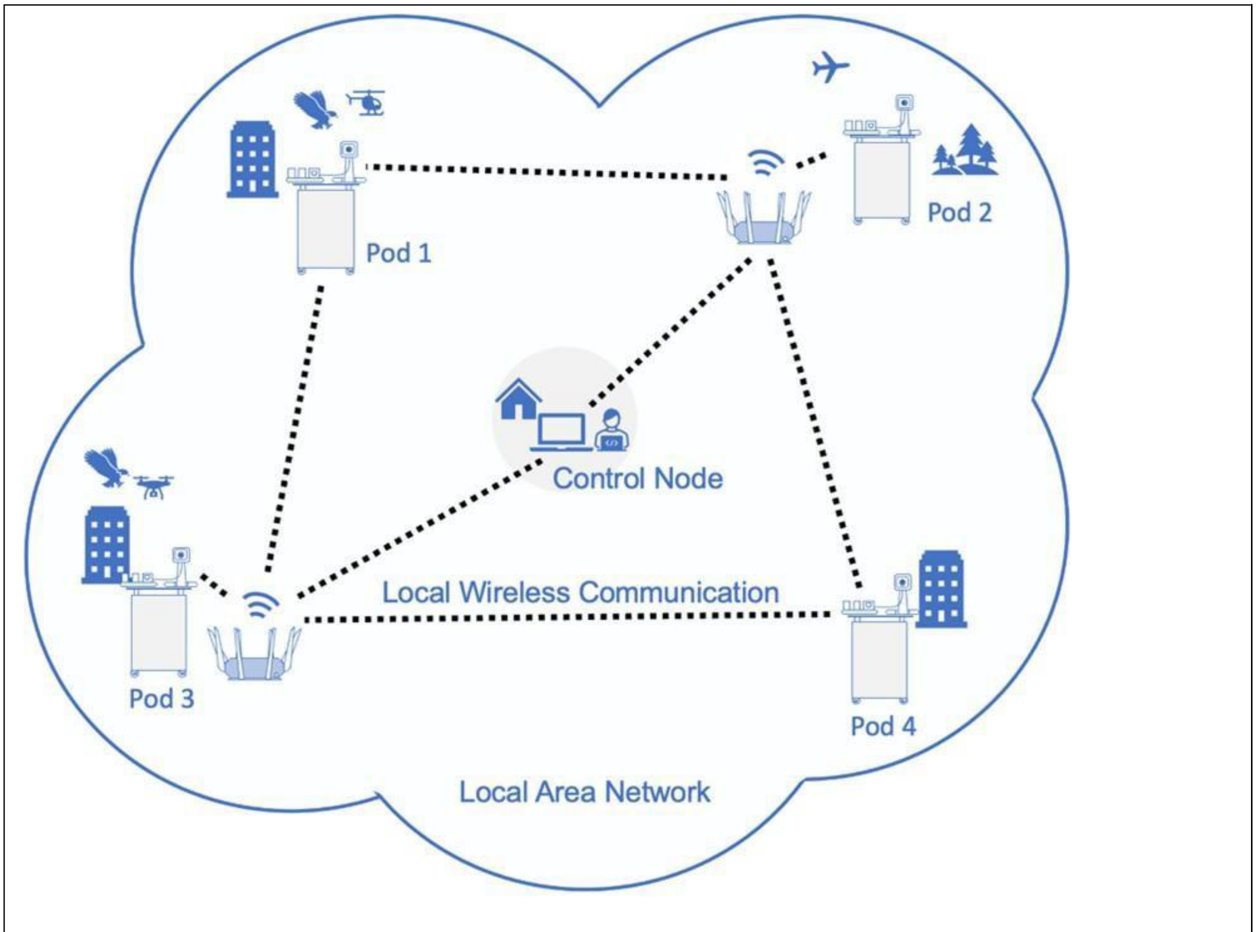


Figure 11: Illustration of the network architecture for MOMS.

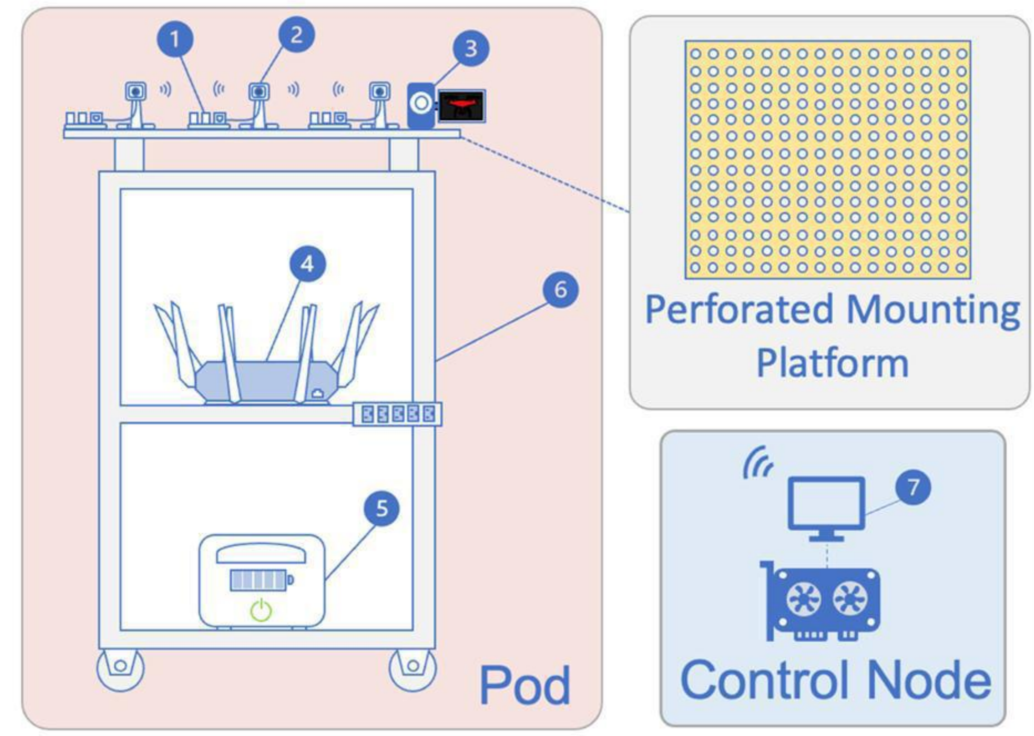


Figure 12: Pod architecture for MOMS.

The central control/display module can either be a standard laptop (Windows or Mac), or an NVIDIA Jetson microcontroller with a heterogeneous GPU–CPU computing architecture. It receives multimodal sensor data from multiple monitoring pods, performs computationally intensive detection and other monitoring-related tasks, and supports visualization and alert functionalities. It may also be directly used by authorities/stakeholders, or serve as a pipe to the users. Our software is designed to exploit GPU architectures when they are available, but also to use standard CPU-based computing otherwise.

Data transmission between the pods and the central module is enabled by a dedicated local network established using onboard microcontrollers and ASUS AiMesh gaming routers. Module nodes are interconnected through the router mesh to ensure seamless coverage. Both control signaling and data streams are transmitted over TCP/IP.

The initial test in the study demonstrated stable communications at a selected frequency in the 2.5–5 GHz range for pods in the network, sufficient for multimedia-level transmission. A quad-band router provides effective wide-range coverage (e.g., 100–150 m with the ASUS Quad-band Wi-Fi 7 Router) and employs adaptive QoS to prioritize video traffic. The central control module functions as the coordination node in a distributed system, maintaining remote access and control over all pods through Wi-Fi networking. Each router includes Gigabit Ethernet ports to enable wired redundancy when necessary. This network configuration ensures low-latency, high-reliability data transmission, and meets the stringent requirements of real-time aerial monitoring operations.

Label	Modules	Components		Devices
1	Pod	Microcontroller		Raspberry Pi 4 Model B, 8GB RAM
2		Sensor	CSI camera module	Raspberry Pi Camera Module 3, Normal & Wide NoIR
			HD USB Webcam	Arducam IMX179 USB Camera
3			Infrared Camera	TeleDyne FLR
4		Router		ASUS Quad-band Wi-Fi 7 Router
5		Power Supply Unit		Portable Power Station
6		Mechanical Frame		Removable 3-layer metal frame with mounting platform
7	Central control module	GPU-CPU based processor		NVIDIA Jetson Orin Nano

Table 2: List of hardware components used in MOMS.

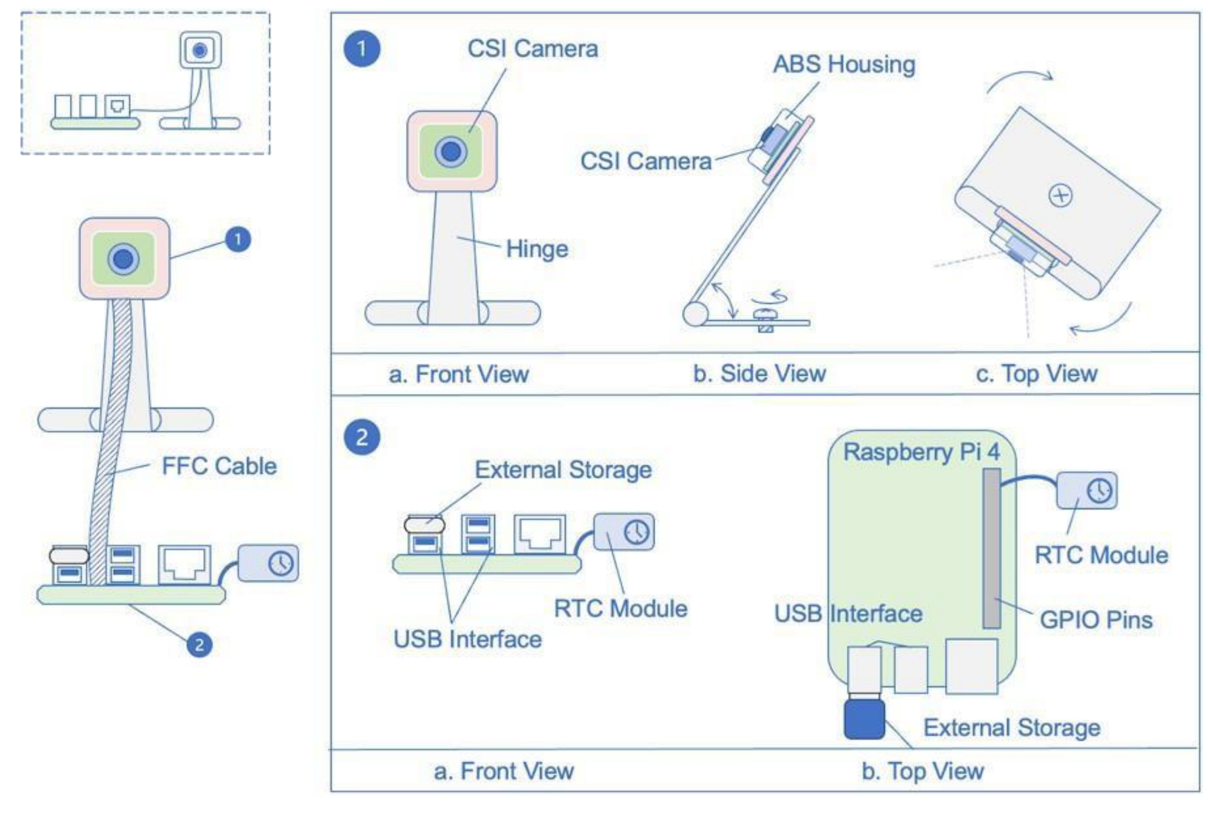


Figure 13: Camera mounted on a rotating hinge for the MOMS solution.

3.2.2. Algorithm Suite Details

A full suite of monitoring algorithms based on object-dynamics-based track-vision methods, including for in-frame track extraction from video data, detection of objects, 3D-geolocation, and classification, are included in the prototype and have been field tested. Advanced functions for track cleaning/filling and predictions have also been developed. The architecture of the algorithm suite is illustrated in Figure 14.

Specifically, giving the video stream input capture by image sensors, the track-extraction algorithms use background subtraction together with a dynamics-based time-space search and filtration for simultaneous multi-track extraction. The dynamics-based algorithms are structured to allow for simultaneous tracking of multiple objects with low computation, and to effectively distinguish objects including ones that are in close proximity or crossing. The track-extraction algorithms use limited filtering based on object size and other characteristics, to exclude tracks that obviously do not correspond to airspace objects (e.g. cars on a road in the field of vision).

Once tracks have been extracted, these are processed in a sequence of steps to implement the monitoring functions of interest (detection, in-image-frame tracking, classification, 3D-geolocation, prediction). First, an exclusion process is used to remove any additional tracks that correspond to features outside the airspace region of interest, such as foliage or man-made materials that are blowing in the wind. This exclusion process is based on removal of tracks that are jumpy but highly localized in the image frame. Tracks corresponding to cloud cover can largely be excluded in similar ways, although some tracks remain and need to be further processed based on slow movement in the frame.

After exclusion, the extracted tracks are used for detection/in-frame-tracking, classification, 3D-geolocation, and more advanced functions. The detection algorithm simply recognizes new tracks, which are originated when an on object impinges on the field of view or begins moving within the field of view, and provides in-image tracks for each such object.

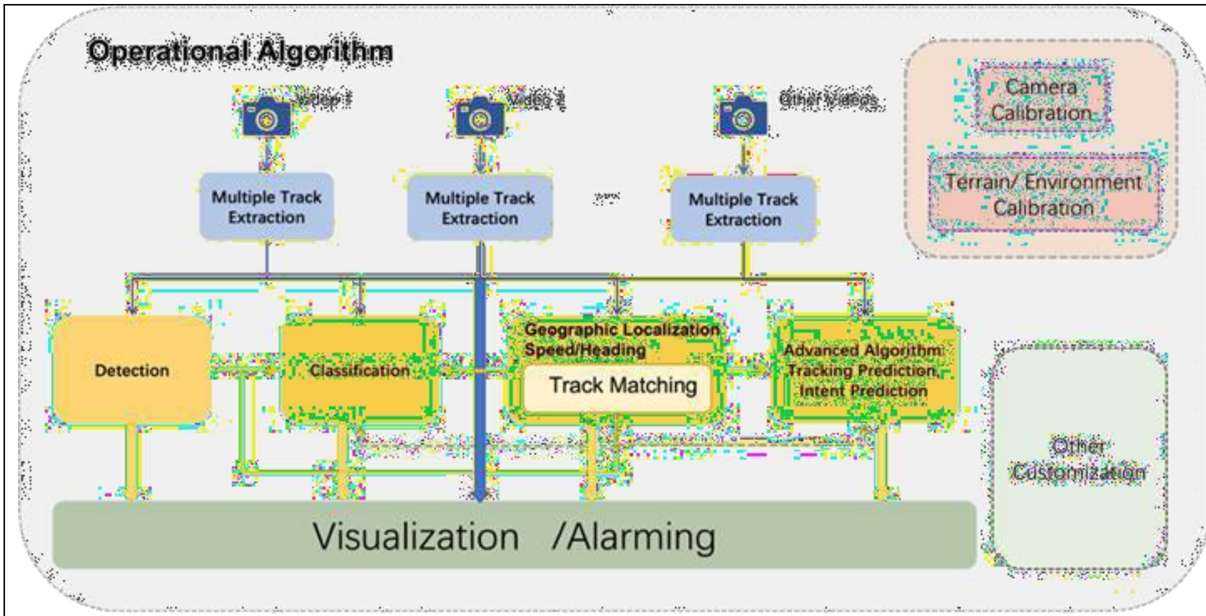


Figure 14: The architecture for our suite of algorithms is shown.

The classification algorithm, which is able to differentiate various types of aerial objects (UASs, birds, crewed aircraft overflights, unpowered objects like balloons), is based on track features. In particular, the classifier leverages differences in the inertial dynamics and reference-signal structure of these objects, which reflect in these features. A basic classification function that distinguishes crewed and uncrewed aircraft from birds implemented within MOMS is based on determining correlation coefficients (closeness to linearity) of the tracks over short intervals (2-8 seconds), and then averaging these coefficients with time. Aircraft tracks, because they are inertial and also often defined by straight-line reference signals, have persistently high correlations while bird tracks have lower correlation coefficients for most time windows. The correlation coefficient signal is used to get an initial estimate of the object type, and its persistence is then used to ascertain the type with higher certainty. Additional metrics based on low-level trajectory fluctuations and non-straight-line sparse fits have been used to further improve the estimate. Specifically, a second metric for classification uses the average amplitude and temporal autocorrelation in the trajectory deviation from linearity over very short intervals (0.2s-1s), to further distinguish cloud tracks from UASs and large birds. This further classification analysis derives from an advanced track-cleaning algorithm which corrects some artifacts in the image-processing algorithms, and then uses a detection rule for inertial objects introduced in [28,45].

The 3D geolocation algorithm finds tracks for each UAS in the airspace volume in geographical coordinates, based on triangulation from cameras on two pods. Of note, the triangulation process is able automatically to distinguish track pairs for multiple objects within the field of view, based on the mismatch distance between rays from each imaging sensor to the object. This approach for localizationof multiple discrete objects within the field of view represents a fundamentally different approach from 3D point cloud approaches which aim to recreate the entire scene, but require feature-based same-object identification on multiple images, substantial training, and large computation. Our approach permits a solution for real-time localization of far-away objects, in contrast to point cloud approaches which are appropriate for clearly-resolved near-field scenes (e.g. [46]). Our methodology uses a one-shot calibration based on the known location of a single object, and is being extended to exploit characteristics of the inertial dynamics for improved and smoother 3D-geolocation.

An initial algorithm for track forecasting and intent determination, as well as filling gaps in trajectories, has been developed. As noted above, a track smoothing algorithm which corrects artifacts in the video-generated tracks has been developed based on linear interpolation over short windows. This smoothing algorithm also allows filling of gaps in the track. In addition, a function that predicts track futures for up to 5 seconds has been developed, based on a sparse regression of track data. The concept underlying the forecasting method is that object tracks of interest are approximately sparse with respect to common bases (e.g., polynomial and sinusoidal bases) over time intervals, reflecting the piecewise sparsity of reference signals and the smoothness of the tracks; therefore, sparse regression of the tracks via an algorithm such as Least Absolute Shrinkage and Selection Operator (LASSO) can allow for effective forecasting behavior over an interval of time. Further, the sparse representation encodes notions of object intent or behavior, which are identified through the regression. Finally, alarming functions for different use cases are under development.

3.2.3. Software Details

The distributed software includes scripts run on the micro-controllers associated with each sensor (Raspberry PIs and NVIDIA Jetsons) for controlling sensors and storing/ sending data streams. It also icludes Python code run on the display+ control module which implements the track-vision algorithm suite, controls devices on pods across the system, and allows on-demand display of tracks and other algorithmic outcomes to operators. Fig. 5 shows the software details deployed across different modules in MOMS.

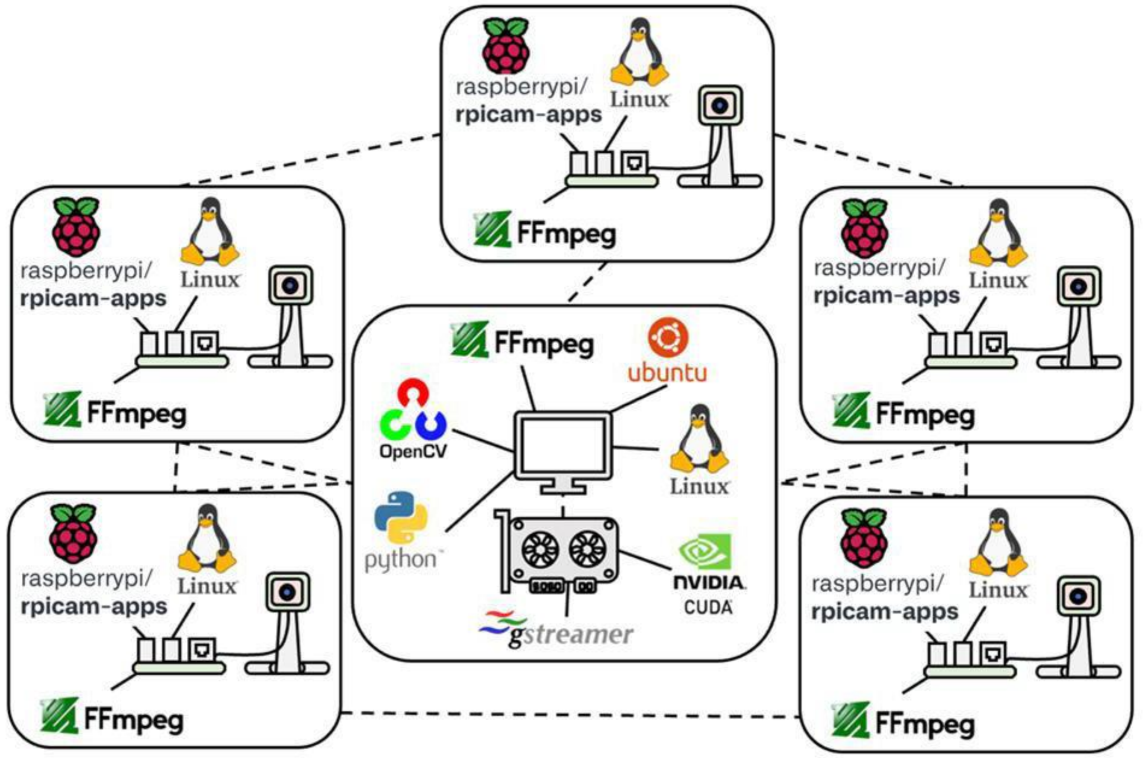


Figure 15: Software used in the MOMS solution. The center box corresponds to the control module which is implemented on a laptop, while the others are the edge devices (microcontrollers) connected with each sensor.

Specifically, in each microcontroller edge node, rpicam-apps is applied for camera interfacing and initial image capture. The core functionality pipeline is implemented through shell scripts, where the captured video stream is duplicated for dual-purpose handling: one branch is passed to FFmpeg for format conversion and segmented recording in local storage, while the other is wirelessly transmitted to the central processor. In the central processing node, FFmpeg is utilized for stream ingestion, including decoding and format packaging. Alternatively, GStreamer is considered when the control node is deployed on platforms based on NVIDIA's heterogeneous computing architecture. The image processing-related algorithms are primarily developed using OpenCV. Our method further integrates OpenCV with CUDA support, leveraging GPU acceleration on Jetson-class devices to improve computational throughput and real-time responsiveness. The core monitoring algorithms are implemented in Python for distributed real-time use, with C code used as needed to speed up processing. We note that the edge-computation challenges associated with real-time processing of video or radar data for track extraction/characterization have been studied in prior work (e.g. [47-48]). Relative to this work, the contribution of this study is to customize the computation based on airspace object dynamics and airspace-monitoring needs, to enable robust low-latency monitoring.

The deployed software allows for real-time command of distributed-system components, data storage and processing, instantiation of basic monitoring algorithms (track extraction, in-frame tracking/detection, classification) and display to an operator at the control module. In addition, the basic monitoring algorithms can be applied to already-saved stream data. Indeed, they were instantiated for post-facto stream data inputs first, and then optimized for real-time use. Basic and advanced monitoring algorithms, including experimental variants, are implemented for off-line use in Matlab.

3.3. Flight Testing: Methods

Two three-day flight campaigns were conducted, in late winter / early spring (March 19-21, 2025), and again in mid-summer (July 19-21, 2025). Both flight campaigns were managed by the Alaska Center for UAS Integration (ACUASI) at the University of Alaska Fairbanks, which was a subcontractor on this project. ACUASI operates the FAA's Alaska UAS field test site, and operates flight campaigns in multiple locations in Alaska and beyond. In the scope of this project, ACUASI guided the prime contractor in selecting test locations, entirely conducted the test flights, provided support for monitoring system setup/deployment (power, limited Internet backhaul), provided vehicle-board "truth" data to the project team, and engaged with appropriate authorities to ensure safety. Three ACUASI pilots and a program manager were involved in each flight test. Three members of the Texas A&M team (the PI, and two graduate students working on the project) attended each flight test. The Texas A&M team set up the monitoring system at the monitoring site on each flight-test day, managed the monitoring system during the test, interfaced with the ACUASI team about repetitions and modifications of the test, and disassembled the monitoring system at the end of the test. Engineering support was also made available by ACUASI for the flight tests. Further details regarding each flight test are listed below. This information is presented in bulleted lists, for clarity.

3.3.1. Mar. 19-21 Flight Test Details

- Location: Poker Flat Research Range north of Fairbanks.
- UASs

- Rotorcraft: X6 (4ftx4ftx3ft), Multiple Autels (length~1.25ft)
- Fixed Wing: Skyrider (6ft wingspan, 4.5ft nose-to-tail, 1ft height)
- X6 and Skyrider flight paths were preprogrammed; Autels were hand-flown using mounted camera.

- Flight Operations
  - Three CONOPS described above, using various combinations of the above UASs (and various distances/altitude). CONOPS were: 1) multiple conflict avoidance, 2) sequencing, and 3) maneuvering/limit-testing.
  - 13 flights – Durations: 20-45 minutes; Each flight consisted of 11-25 repetitions of a CONOPS. Day 1 – 4 flights; Day 2 – 6 flights; Day 3 – 3 flights.
  - Distance: up to 1700 m (~1 mi)
  - Altitude: between 15m-400m
  - Speeds: between 12 m/s- ~30 m/s (and hovering for rotorcraft).
- Environment
  - Terrain: Valley, surrounded by hills/low mountains
  - Coloring: Forested/snow-covered
  - Weather: clear – mostly cloudy (ceilings mostly >5000ft), no precipitation; temperatures 0-30 degree F.
  - Winds: negligible-~7mph at monitoring sites, potentially higher near hilltops on some days.
  - Overflights and road traffic: ~12 events during the flight tests (Cessna, helicopter, 4-engine military aircraft, 2 weather balloons); cars driving between 10-40 mph on road.

    - Birds: No (too early in the season); we gathered more bird data locally in Texas, at a demonstration in Virginia, and also at the second field test.
- Monitoring System
    - At three locations along a road by the field-of-operations.
        - Location 1: Location of flight takeoffs; six cameras of the platform, including homemade 3d camera.
        - Location 2: 200ft along the road from Location 1; four cameras on the platform.
        - Location 3: ~600ft along the road from Location 1; one camera.
    - Sensors on double hinges for positionability; angles measured.
    - Sensors turned on and off via command scripts applied locally to each device, with assistance from a portable monitor.
    - Data stored on drives/machines on the platforms.
        - Transferred to laptops and storage devices afterwards
    - ~10 hours of imaging data collected from each sensor over the three days; total data size ~1TB
    - Local area network for coordinating and checking the cameras.
    - Algorithms: for detection, in-image tracking, 3D-geolocation/tracking, and classification. The algorithms were implemented off-line, and are being tested on collected data.
    - Other data collected: flight logs, public flight-tracker data on overflights (ADS-B), tried remote ID– but this failed miserably.

3.3.2. July 23-25 Flight Test Details

- Location: Nenana Municipal Airport, along the George Park Highway ~50 miles south of Fairbanks.
- UASs
    - Rotorcraft: Freefly Alta X (4ftx4ftx3ft), Aurelia X6 (4ftx4ftx3ft), Skyfront P8(6.5ftx6ftx2ft), Autel (diam~1.25ft)
    - Fixed Wing: Skyrider (6ft wingspan, 4.5ft nose-to-tail, 1ft height)
    - VTOL: SuperVolo (9ftx6ftx1.5ft)
    - All UASs except the Autel were guided by preprogrammed flight paths, the Autel was joystick-flown using mounted cameras.
- Flight Operations
    - Three CONOPS described above, using various combinations of the above UASs (and various distances/altitude). CONOPS were: 1) multiple conflict avoidance with crossing patterns, 2) sequencing/descending, and 3) maneuvering/limit-testing. Mixed CONOPS with two vehicles descending and being sequenced, and a third vehicle on a crossing pattern, were also flown.
    - Note: for flight test 2, the vehicles for CONOPS2 used different approaches to a waypoint and then descended, rather than being in a chasing pattern.
    - 14 flights – Durations: 20-45 minutes; Each flight consisted of 15-35 repetitions of a CONOPS. Day 1 – 5 flights; Day 2 – 4 flights; Day 3 – 5 flights. The P8 and SuperVolo were able to remain airborne for multiple flights in a row.
    - Distance: up to 1700 m (~1 mi)

    - Altitude: between 67m-300m
    - Speeds: between 12 m/s- ~55 m/s (and hovering for rotorcraft).
- Environment
    - Terrain: regional airport with flight tests starting from an aircraft parking area / taxiway. Flights were mostly over a forested area with relatively flat terrain, with small hills in the background, and a runway as well as riverine landscape surrounding.
    - Coloring: Forested, with areas of pavement and grass.
    - Weather: partly – mostly cloudy, with somewhat low ceilings (<2000ft?) at times; drizzle causing stoppage and very light drizzle during a couple of tests; temperatures 55-75 degrees F.
    - Winds: 5-15 mph at monitoring sites, potentially higher near hilltops on some days.
    - Other mobile objects in the field of view: ~30 events during the flight tests (~5-6 crewed aircraft operations at the airport, 1 helicopter landing/takeoff, 6 overflights, at least 15-20 birds in total including larger birds at distance and small birds near the camera); motorcycle and crewed aircraft on tarmac.
- Monitoring System
    - Five locations on or at the edge of the tarmac, with two full pods with persistent networking and remote access, 2 small pods with partial networking access, and 1 single-camera, weather-protected pod placed further away and not networked.
        - Location 1: ~25 m away from the flight takeoff location; three cameras on the platform.

- Location 2: ~30 m away from Location 1, further away from the flight takeoff location along a line; three cameras on the platform
    - Location 3: ~50 m away from Location 2, roughly along the same line as locations 1 and 2 and further away from the takeoff location. Two cameras including a wide-angle camera.
    - Location 4: ~65 m away from Location 1, in an orthogonal direction from the line with Locations 1-3; closer to the main flight operations Two cameras including a wide-angle camera.
    - Location 5: ~150 m away from Locations 1-3, directly under or closer to key flight operations. Single camera
- Sensors on double hinges for positionability; angles measured.
- Sensors turned on and off remotely from a host machine, using a local area network.
- Any two sensors at Locations 1 and 2 can be run in an online mode at the host machine, with video and selected monitoring analytics (e.g., tracking) being displayed on the host machine's screen.
- Data stored on drives/machines on the platforms.
    - For online cases, track data is directly recorded on the host machine.
    - All other data transferred to laptops and storage devices afterwards
- ~10 hours of imaging data collected from each sensor over the three days; total data size ~1TB
- Local area network for full operations (turning on and off sensors, checking sensors, online monitoring).

- Algorithms: for detection, in-image tracking, 3D-geolocation/tracking, and classification. Detection and in-image tracking done in real-time for on-line sensors. The classification algorithm was programmed for streaming data by the flight test, but not fully implemented for real time operations. Geolocation and more advanced functions are done off-line.
- Other data collected: flight logs, public flight-tracker data on overflights (ADS-B).

3.4. Data Analysis Methodology

3.4.1. Overview and Research Questions:

Project data analysis was focused on assessing the performance of the ground-based MOMS monitoring system. Specifically, data analysis sought to answer two sets of questions:

1) What is the performance of the MOMS in completing aerial-object monitoring tasks, including detection, classification, 3D-geolocation, and information communication to a control center? How does this performance depend on operational and environmental parameters (number of tracks, type of sensor, distance from the sensors, data horizon, weather)?

2) Does the MOMS meet requirements on ground-based monitoring needed for high-density BVLOS CONOPS?

3.4.2. Data Collection and Basic Processing

The following raw data collection and data processing/calculations for monitoring were undertaken during field tests, including the tests conducted at the Alaska test site (Alaska Center for Uncrewed Aircraft System Integration).

1) Raw data from imaging and other sensors of airspace objects, including 2D cameras, night-vision cameras, and infrared cameras is collected and stored.
2) Trajectory (track) data extracted from raw sensor data is calculated (either online or offline), and stored. Trajectories or tracks in this context refer to measurements of the location of an object in a coordinate system, taken at uniformly-spaced time points over an interval. Specifically, a track is defined for a point of reference on an airspace object (e.g., a centroid, or a particular identified point on the object). For this point of reference, the location of the object in a coordinate system is recorded along with a timestamp, at

uniformly-spaced time points over an interval. Typically, the interval of recording is between the initial detection time of an airspace object based on raw sensor measurements, until the object leaves the field of view of the sensor. Depending on the imaging/sensing device used, object locations may be specified in either two- or three- dimensional coordinate systems. For our purposes, tracks are extracted in in the frame of reference of the imaging systems, for all collected data. Data recording is at 25Hz. The timestamp for each measurement is recorded relative to the start of the recording period, and the recording start time is also recorded. Additional tracks relevant to monitoring (e.g., velocity tracks) are also computed and stored as needed.

3) Cleaned track data is computed and stored. This process consists of removing spurious tracks related to ground clutter, objects outside the field of operations (e.g. cars along a road), and environmental artifacts (e.g. cloud edges). In addition, filtered tracks with imaging artifiacts removed are calculated.

4) Features in the track data or raw data determined to be relevant to detection, classification, 3d geolocation, and track forecasting are calculated and stored. Broadly, the term “feature” refers to a scalar or vector quantity that can be computed from the track data or raw data, which may be useful for detection, classification, or track forecasting needs. Per the proposed methodology, detection and tracking within image coordinates is based on standard methods for detecting object motion from imaging data. These methods use pixel comparison or masking methods in imagery data for detection. The project team’s methodology involves application of these algorithms for detection, with specialization and refinements which use the specific physical characteristics of the object’s motion, as a starting point for trajectory (track) extraction and further monitoring functions (see also

Algorithms discussion in Section 3.2). For the purpose of data analysis, detection indicators and metrics are computed and stored. Object classification and track forecasting is based on features derived from object tracks, potentially supplemented by additional features extracted from the raw data (also see Section 3.2). In prior work [1-4], a number of track features have been identified as being useful for classification, including: 1) variance/autocorrelation of object speed, 2) variance/autocorrelation of other object velocity characteristics (e.g. the velocity projection in the vertical direction), 3) smoothness of location or velocity track projections (see [???] for multiple specific metrics used), and 4) variance and mean-crossing counts of object headings, 5) errors in object track linear fits, among several other parameters. 3D-Geolocation is based on ray-to-object intersections from multiple imaging systems. Track forecasting is anticipated to be based on direct filtering of track data together with object classification outcomes, but may also use features such as track velocity or location autocorrelations. Features determined to be relevant for object classification and track forecasting are calculated and recorded from the track data. Due to the compressed project time line, calculation and recording of track features was limited to a subset of the flight-test data.

5) There was an intention to record RemoteID data from UASs used in field tests, however the transmitter and receiver strength were insufficient for effective recording beyond about 10m, and further collection of this data was abandoned. ADS-B data from crewed aircraft overflights and nearby crewed operations were recorded manually.

6) Environmental data relevant to monitoring is recorded manually, including 1) wind speed and direction, 2) rainfall/snow indicators based on processing of imaging data and/or visual observation, and 3) temperature.

7) Connectivity and latency data for the monitoring system is recorded, during checks of the monitoring system. Specifically, the monitoring system is designed to send data from edge devices with sensors attached to a host computer. Pings are used to establish connectivity and latency of each edge device with the host computer, at check times.
8) Flight details are recorded. Manual observations are made of unexpected flight characteristics, airspace object behavior, and environmental factors.
9) Sensor data was recorded on edge (embedded microprocessor) platforms, or directly on a dedicated project laptop. Manual observations are recorded on laptops used during the project.

3.4.3. Data Management

Data recorded on edge platforms was transferred to project laptops, and also stored on an external hard drive. Thus, all data was and remains available for the purpose of data analysis. In addition, data has been backed up on desktop machines at the Global Cyber Research Institute's laboratory at Texas A&M, which is directed by the principal investigator. Appropriate data security methods have been applied.

To allow for easy manipulation and use of the data by our group and others, a Structured Query Language (SQL) database was created for the project, and is being populated with the flight test data.

3.4.4. Proposed Data Analyses:

Algorithms for detection, classification, 3D-geolocation, and track forecasting for airspace objects established by the project team are applied to the collected data (either for the full data set, or selected portions). The outcomes of these algorithms are used to:

1) Determine the performance of the MOMS with respect to a set performance metrics, for the high-density BVLOS concepts of operations for which field tests have been conducted and data collected (as defined above). Assessed performance metrics include: detection probability (the probability that an moving aerial object within the monitored airspace is detected); time until detection (time interval between the entry of the object into the monitored airspace and its detection), classification sensitivity and specificity (true positive rate and false positive rate), time until classification (time interval between the entry of the object into the monitored airspace and its classification), and track error (deviation between the actual object location and the one indicated by the MOMS at the measurement time, both in the relative coordinates of a monitoring device and in absolute coordinates). Probabilistic characterizations of these performance metrics (e.g., the probability of detection vs time from object entry) are considered. Further, performance metrics related to the ability of the MOMS to give real-time confidence intervals on monitoring outcomes are considered. Due to the time constraints, the statistical analyses are restricted to subsets of the data, with substantial data used for in-frame tracking and classification goals, but very limited data analysis on 3D-geolocation conducted.
2) Pursue a preliminary analysis of the effectiveness of the MOMS with respect to usability, in terms of providing situational awareness to traffic controllers and UAS operators via displays or information streams. This usability analysis is more limited than originally planned, due to the compressed time schedule after the second field test. The usability

analysis is primarily centered around qualitative understanding of the types of information that can be provided to users, via the system's visualization capability. The usability analysis also includes a qualitative assessment of the timeliness and robustness of real-time information gathering/display using the MOMS.

3) For the tested CONOPS, characterize the dependence of the performance metrics on monitoring-system, operations-related, and environmental parameters. Specifically, we aim to study if/how these metrics depend on the number of simultaneous tracks that are processed, weather conditions, distance of object from sensors, type of object (e.g. bird vs UAS vs crewed aircraft), types of sensors used, etc. Again, due to time constraints, only an initial qualitative analysis is conducted here.

4) Evaluate whether our monitoring system meets the requirements on ground-based monitoring systems to meet an acceptable risk threshold. To the best of our knowledge, such requirements have not yet been defined, and attendant risk analyses and thresholds have not been defined. In this effort, the acceptable risk threshold is defined in terms of the chance of violation of a set of airspace requirements for high-density BVLOS operations, including inter-vehicle spacing requirements, traffic rate requirements, etc. Requirements on the monitoring system to meet this risk threshold are determined through model-based analysis (see Section 3.5). The requirements are phrased in terms of: a) the number of objects that can be simultaneously tracked, b) the tracking error, c) classification sensitivity and specificity, d) track forecasting accuracy, e) measurement horizon required for tracking and classification, and f) communication delay incurred by the monitoring system. The performance of our monitoring system is compared with these requirements.

3.4.5. Statistical Methods

The proposed analyses of performance metrics and performance-metric dependencies provide point estimates. Standard statistical methods can be applied to develop confidence intervals around these estimates. In particular, Normal and refined Student's t Distribution approximations are used to obtain confidence intervals, assuming sufficiency of the sample size; the assumption of sufficiency is also checked via standard methods. The evaluation of requirements (item 3 in the "Proposed Data Analyses" section) resolves to a hypothesis testing problem. Therefore, the one-tailed T-test analysis is appropriate to determine statistical significance of the result. We note that only a portion of the data has been processed, and so only very statistical analyses can be completed at this point. Further statistical analysis will be pursued as the data is more fully processed.

3.5. *Monitoring-System Risk Assessment and Requirements Development*

A secondary aim of the project was to undertake an assessment of the risk introduced by limitations in ground-based monitoring systems (e.g., errors or delays in detection and classification, 3D-location errors, etc). A model-based method was developed and applied for risk assessment, and the risk assessment was then used to determine requirements. The risk-assessment methodology and requirements development were refined based on observations from the field testing of our monitoring system, and the performance of our monitoring system was also compared with the requirements.

There is a considerable literature on developing risk assessments for UAS operations within the airspace (e.g. [50-53]), which has had a primary focus on assessing risks to ground assets and commercial/general aviation due to UAS integration. Assessments of risk have been central to developing policies and requirements for UAS operations, including the recent Part 108 proposed rule, and they are considered within processes for certifying or excepting airspace entrants. Relative to this background, the focus of our work is to: 1) assess specifically the risk to airspace operations due to surveillance-system degradations; and 2) assess risk from the perspective of violations to airspace operational requirements (e.g., spacing requirements) rather than risk to ground and other assets. We take this approach to allow the development of requirements for monitoring systems which are provided as services.

3.5.1. *Risk Assessment Method*

The risk-assessment methodology is concerned with evaluating the potential risk to airspace operations due to performance limitations in the monitoring system, for a particular high-density

BVLOS CONOPS and operational scenario. We stress that the risk assessment methodology is specific to a particular CONOPS (e.g., the three CONOPS introduced above) and the operational scenario (particular airspace volume, aircraft density/speed limits, presence or absence of other sensing/communications features, etc).

The risk assessment procedure is initiated with the selection of a CONOPS and specific operational scenario. For this CONOPS/scenario, airspace operational requirements (e.g., aircraft spacing requirements, guidance/routing requirements, etc) are specified. These requirements may either originate from standards defined for the Concept of Operations, or may be specialized for the particular scenario. Besides requirements, additional constraints on the operational scenario (e.g., the type of UASs or crewed aircraft that are of concern in the airspace, weather characteristics allowed) may be specified. One operational scenario, related to management of crossing traffic streams, is illustrated in Figure 16.

For the purpose of risk assessment, the monitoring system is represented as a service that provides information to a central authority (traffic controller) or a set of decentralized stakeholders about mobile objects (UASs, crewed aircraft, birds, balloons) that are in the airspace volume. Specifically, the monitoring system detects objects when they impinge on the airspace volume, tracks object locations in imaging- system coordinates and geographical coordinates, and classify object types (UAS vs bird vs crewed aircraft). For the purpose of risk assessment, it is assumed that traffic controllers are able to effectuate control actions that prevent airspace operational requirement violations, once the monitoring system provides correct information about mobile objects in the airspace. Each of the functions of the monitoring system has a set of performance parameters, which may include delay (until detection or classification), correctness probability (for detection or classification), or error (for geolocation, or possibly classification). Values of these performance parameters for a particular monitoring system, such as ours, may be specified distributionally, or an upper bound or notional value may be specified.

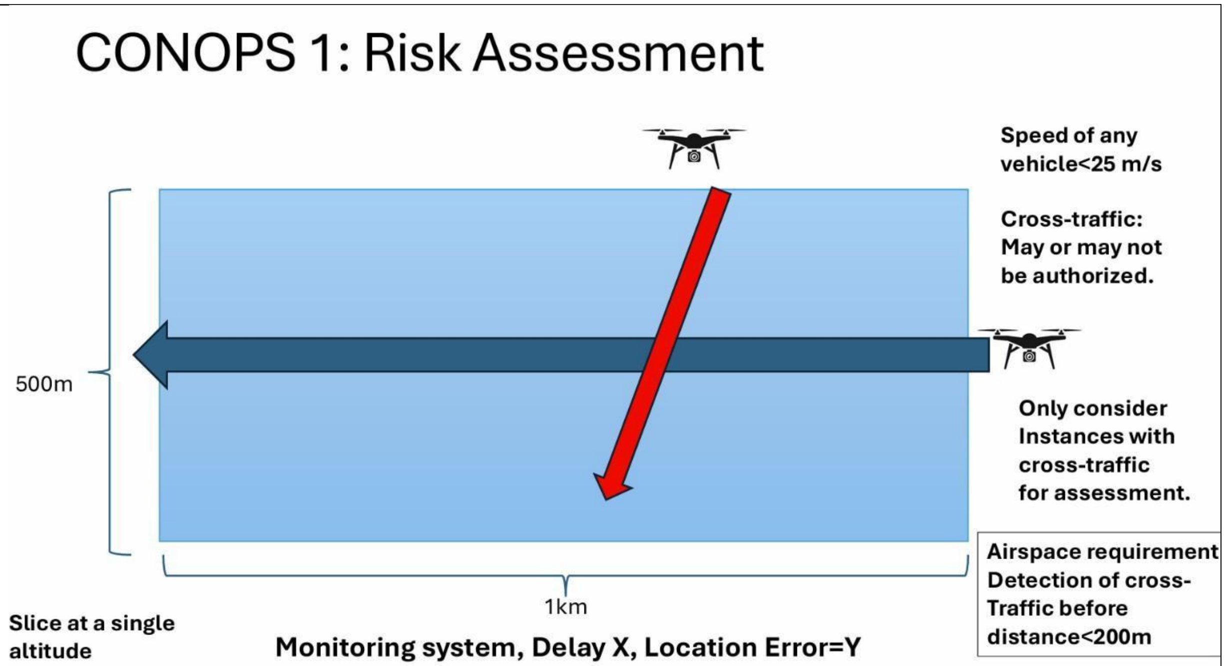


Figure 16: A CONOPS and operational scenario on management of crossing UAS traffic streams is extended to include operational constrains and airspace requirements.

The purpose of the risk assessment is to evaluate the likelihood of an airspace operational-requirement violation, given the performance parameters of the monitoring system. To undertake the risk analysis, we develop a simplified stochastic simulator for the CONOPS/scenario. Our simulations, developed in Matlab, are minimalized representations of operations, which are focused on replicating flight paths while excluding finer-grained details. For instance, for the CONOPS/scenario shown above, the simulator considers UASs traversing the region on the major flow, and models crossing traffic as impinging on the airspace at a randomly-selected boundary location, time, and angle to potentially create a conflict. Monte Carlo simulations are used to assess the probability of an operations-requirement violation, for sets of monitoring-system performance parameters. The dependence of the requirements violation probability on the monitoring performance parameters is plotted, to get an idea of the impact of monitoring on risk. The described risk analysis is complicated by incomplete development of and knowledge about high-density UAS CONOPS. For instance, for the CONOPS/scenario described above, it is unclear whether ground-based monitoring would be supplemented by vehicle-board data (e.g., ADS-B or RemoteID data), and if so what fraction of vehicles would provide such data to the traffic controller. Likewise, the likelihood that operational requirement violations would be resolved by detect-and-avoid mechanisms is difficult to model. For our risk assessment, we primarily consider the risk incurred when only centralized control based on the ground-based monitoring is used.

3.5.2. Requirements Development

The risk analysis is used to develop requirements on ground-based monitoring systems. The methodology for requirements-development is as follows. First, a collection of CONOPS and associated operational scenarios is chosen, each with specified requirements. Then, the monitoring-system performance parameters that are germane to this collection of scenarios are listed. For a given set of bounds on these monitoring performance parameters, risk assessments are conducted for each of the scenarios in the collection, and the maximum among the calculated risks is used as a measure of overall risk. Then, a scan over the monitoring performance parameter bounds is performed, to determine a set of bounds such that overall risk is below a threshold. For instance, bounds may be identified such that the overall risk is less than 0.25%, which corresponds to the monitoring system by itself failing to adequately alarm four out of one-thousand potential requirements-violation scenarios.

3.5.3. Refinement of the Risk Assessment and Requirements Development

The flight tests conducted during the project inform the risk assessment and requirements development process in a couple of ways.

First, broadly, the flight tests can provide insight into the risk analysis in the following ways:

1) The tests can give insight into whether our representation of monitoring-system performance for the purpose of risk assessment is adequate.

2) The tests allow focus on operational scenarios/requirements and monitoring-system parameter limits that are more realistic, in conducting the risk assessment.

The following are some specific insights into the monitoring system from the flight testing and data analysis effort, that are relevant to the risk assessment.

1. Consistent fast detection of mobile objects as they enter the field of operations is realistic.
    - Combining image-frame detection and communication delays, we believe that detection with almost 100% accuracy within 0.5s is realistic.
    - This also suggests that, for the purpose of risk assessment, modeling detection as a single delay with an upper bound is reasonable.
    - Detection does depend on object size and distance, so minimum object size should be specified.
    - Although more data analysis needed, it appears that track fidelity for UASs within the field of operations is high. The vast majority of gaps in tracks were very brief

(<0.15s), although about 15-20% of tracks had gaps in the 1-2.5s range (at least on a day with fast-moving clouds).

- We anticipate that the image-frame location/timing caused by these gaps can be suppressed through short-duration track forecasting. Our initial efforts to fill gaps show promise.
- Given this, we believe that the gaps can be modeled as adding a delay with a small upper bound, and possibly a small error in the frame location, for the purpose of risk assessment.

2. Our initial results suggest that good classification is possible, but classification time and possibly accuracy may depend on operational conditions, size/speed/type of vehicles, background conditions, etc.
   - The worst-case model may be overly conservative. A stochastic model of delays may be appropriate for risk assessment.
   - This also means that airspace policies need to be appropriately defined to address possible false positives or true negatives (including with human intervention if needed/possible).

3. 3D-Geolocation needs further study. Initial results suggest that an error bound that is dependent on distance can be realistically be assumed. Therefore, based on the number of sensors used, an error bound on the 3D-geolocation can be obtained for the purpose of risk assessment. However, this analysis may require refinement in several ways, to account for setting and object dependent variations, influence of the calibration process, etc. Thus, a more sophisticated model for object geolocation errors potentially may be needed for risk assessment.

The flight tests also indicate that the airspace operational requirements may need to refined, for the purpose of risk assessment. Specifically, collision-related risks may vary widely based on object speeds, sizes, propulsion types, and other factors. Thus, it may not be feasible or natural to define spacing requirements in terms of fixed hockey-puck-like volumes, and instead such operational requirements may be need to be specialized for different object types, speeds, and other characteristics. The flight tests also highlight that characterizing the performance of a monitoring-system, for the sake of risk analysis or certification, is a non-trivial task.

In the project, we have undertaken one initial refinement of the risk assessment, to include a distributional model for the classification delay. Specifically, rather than modeling the time required for classification as being fixed, we model a monitoring system as being able to achieve classification with some probability after different delays. For this revised monitoring-system parameterization, we have undertaken a risk assessment for a CONOPS and operational scenario requiring classification for deconfliction of crossing-streams. Results of this analysis are presented in Section 4.

The flight-testing effort also informs development of monitoring system requirements in a couple of ways. First, it provides insight into the types of performance that monitoring systems can reasonably achieve, and hence facilitates the development of requirements that are practical. Second, the refined risk assessments developed based on the flight tests can be carried through to develop refined requirements, which account for more sophisticated representations of the monitoring system's performance.

3.6. Demonstration and Reporting Activities Methodology

A number of demonstration and reporting activities have been conducted in the scope of the project, with the broad aim of disseminating information about our technology, and also more generally about paradigms and requirements for new monitoring systems for dense UAS operations, to stakeholders. Demonstration and reporting was focused in the following directions:

1) Reporting to FAA program officers and technical staff about project outcomes, through quarterly project reviews as well as written reports and deliverables.
2) Communication with the appropriate standards groups at ASTM and RCTA about project activities, focusing especially on risk analysis and requirements monitoring requirements development in support of standards development.
3) Demonstration of MOMS as well as information-sharing regarding flight test results to government, industry, and academic stakeholders who are interested in aviation monitoring. One key activity of this sort was participation in a BVLOS flight test organized and conducted by NASA Langley in early July, which was concerned with the flight of two UASs across a forested area to a remote destination, with another UAS near the destination point. The Texas A&M team demonstrated the MOMS solution at small scale (four sensors in two pods, placed near the takeoff locations for the UAS). The demonstration included the real-time capability.

4. Results and Discussion

Project results are presented and discussed. The presentation of results is also organized according to the six objectives listed in the methods section. For each objective, the results are presented primarily as a sequence of figures, with the captions of the figures used to give a discussion about our main findings. Some text is interspersed as needed to give further context about results.

4.1. CONOPS Development and Flight-Test Planning: Results

Frameworks and paradigms for BVLOS UAS traffic have been introduced in several prior works, with a primary focus on DAA, but also a growing interest in more organized traffic control for high-density and complex operations (e.g., near vertiports). The development of such frameworks and paradigms remains an area of active research & development. Relative to the literature, the work done in this project has resulted in two main outcomes:

1) Specialization of overarching BVLOS UAS operations paradigms into distinct CONOPS capturing particular operations of significance in high-density airspace (e.g., deconfliction of orthogonal traffic streams, arrival merging/sequencing); and, in turn, specialization of these CONOPS into specific operational scenarios, which are then realized in flight plans and ultimately in flight tests. Since example CONOPS, operational scenarios, and flight plans have already been diagrammed in the methods section, they are not repeated here; please see Figures 4-12 for these diagrams. These flight plans were successfully instantiated using UAS flight controllers (for Alta-X, X6, P8, SkyRider, and SuperVolo), and also joystick-based flight controls (Autel). As an illustration, Figure 43 in Section 4.3 shows

simultaneous flights of the Alta-X, X6, and P8 as recorded by the onboard flight controller. The UASs were replicating a crossing-traffic-streams CONOPS. We note that mixed CONOPS, which include crossing streams and arrival patterns, were also flown.

2) The developed CONOPS make explicit the use of passive ground-based monitoring services for high-density BVLOS UAS traffic control, and specify performance parameters for these monitoring services (see also Section 4.3 for more details).

We believe that the CONOPS are a useful starting point for assessing monitoring services for UAS traffic, and also for hazard (bird, unauthorized UAS) avoidance near airports. An important outstanding task is to develop CONOPS which comprehensively integrate different monitoring systems, including ground-based, vehicle-board, and regional radar systems.

4.2. Results for MOMS Assembly

The MOMS was assembled in our laboratory at Texas A&M University (the laboratory of the Global Cyber Research Institute, located in Blocker Building Suite 241), and deployed for the project flight tests. A real-time instantiation was also completed and deployed for the second field test. Photographs and screenshots of the MOMS solution are included in this report, as the outcome of the assembly process. Hardware, algorithmic, and software components are shown.

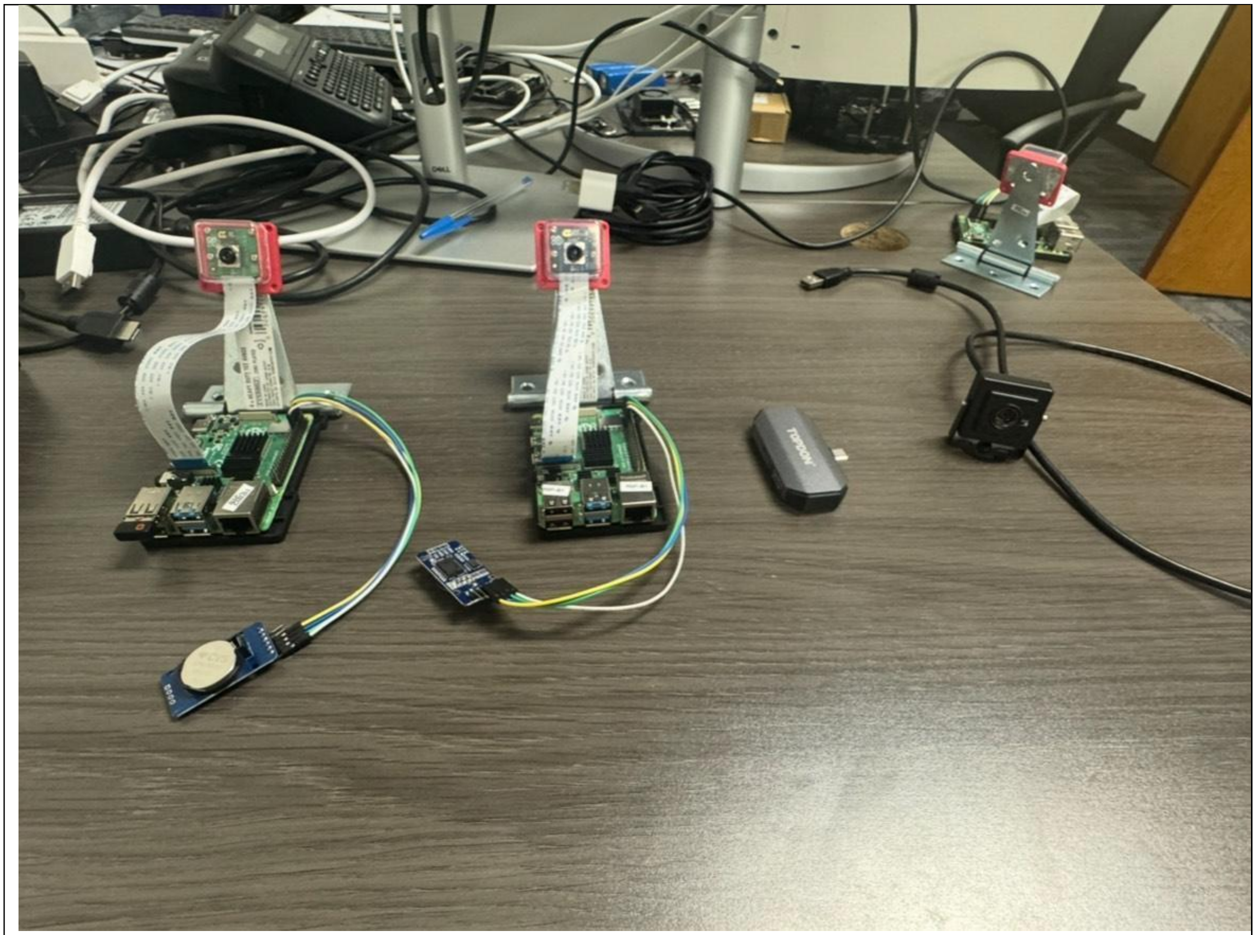


Figure 17: Two MOMS sensors placed on rotating hinges, and connected with microcontrollers are shown. A clocking circuit is also connected with each microcontroller, to allow maintenance of a global clock in the absence of external power.

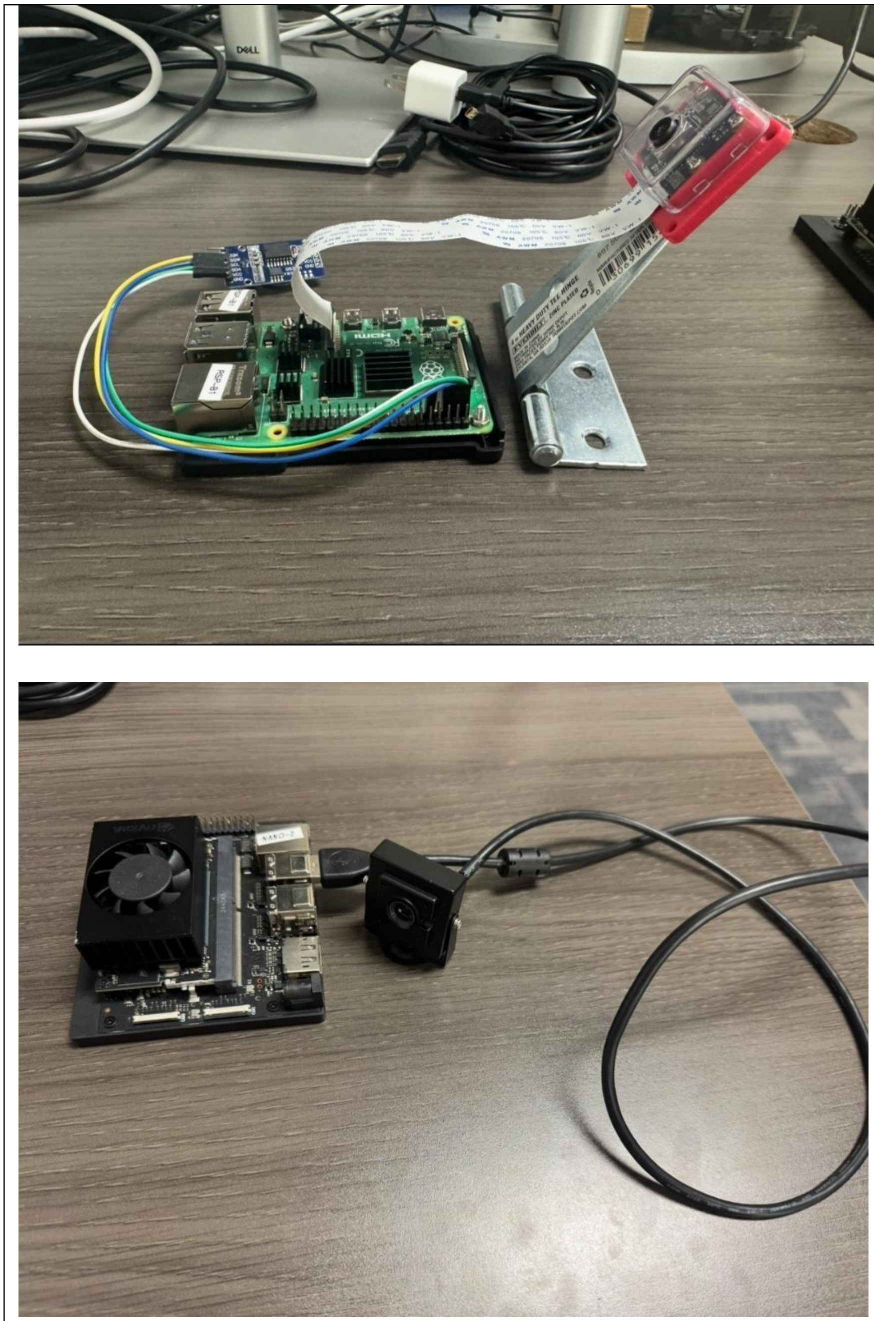


Figure 18: Two types of microcontrollers used in the MOMS – Raspberry Pi 4 and NVIDIA Jetson – are shown. A side view of the rotating hinge is also shown, to help visualize the mechanism. We note that heat sinks are also attached to each microcontroller as needed, and allowed long duration operation in hot weather.

Figure 19: Two MOMS pods are shown, at the July Flight campaign at Nenana municipal airport in Alaska. The first pod is a full assembly with three sensors, while the second pod is a weatherized mini-assembly.

Figure 20: One of the routers used in our MOMS instantiation is shown. Either one or two routers were used for networking of up to 11 sensors, at 3-5 locations. A laptop that served as a command module for the MOMS is also shown. The photograph of the command module was taken during a demonstration at a flight test conducted by NASA Langley.

Algorithm 1: Object Tracking - Offline

```
Input: video_file_path
Output: Trajectory history
cap ← VideoCapture(video_file_path);
Extract x_max, y_max, fps, f_max;
t_max ← f_max/fps;
fgbg ← MOG2(history=30, threshold=20);
Initialize traj_history, last_time, corr_history, labeled, etc.;
Set frame position to CurFrame;
while video is open do
    Read frame;
    fgmask ← ApplyBackgroundSubtractor(frame);
    Morphologically clean fgmask;
    contours ← FindContours(fgmask);
    centpoints ← [];
    foreach contour in contours do
        if area is valid then
            Compute centroid (cx, cy);
            Append to centpoints;
    foreach point in centpoints do
        assigned ← False;
        foreach id in traj_history do
            if trajectory outdated then
                continue;
            if distance to last point < threshold then
                Append point to traj_history[id];
                Update last_time[id];
                assigned ← True;
                break;
        if not assigned then
            traj_history[newid] ← [point];
            last_time[newid] ← current time;
            newid ← newid + 1;
```

Figure 21: Pseudocode of one of the algorithms used in the MOMS is shown, as an illustration of algorithm development/implementation. This pseudocode is for the basic track-extraction algorithm.

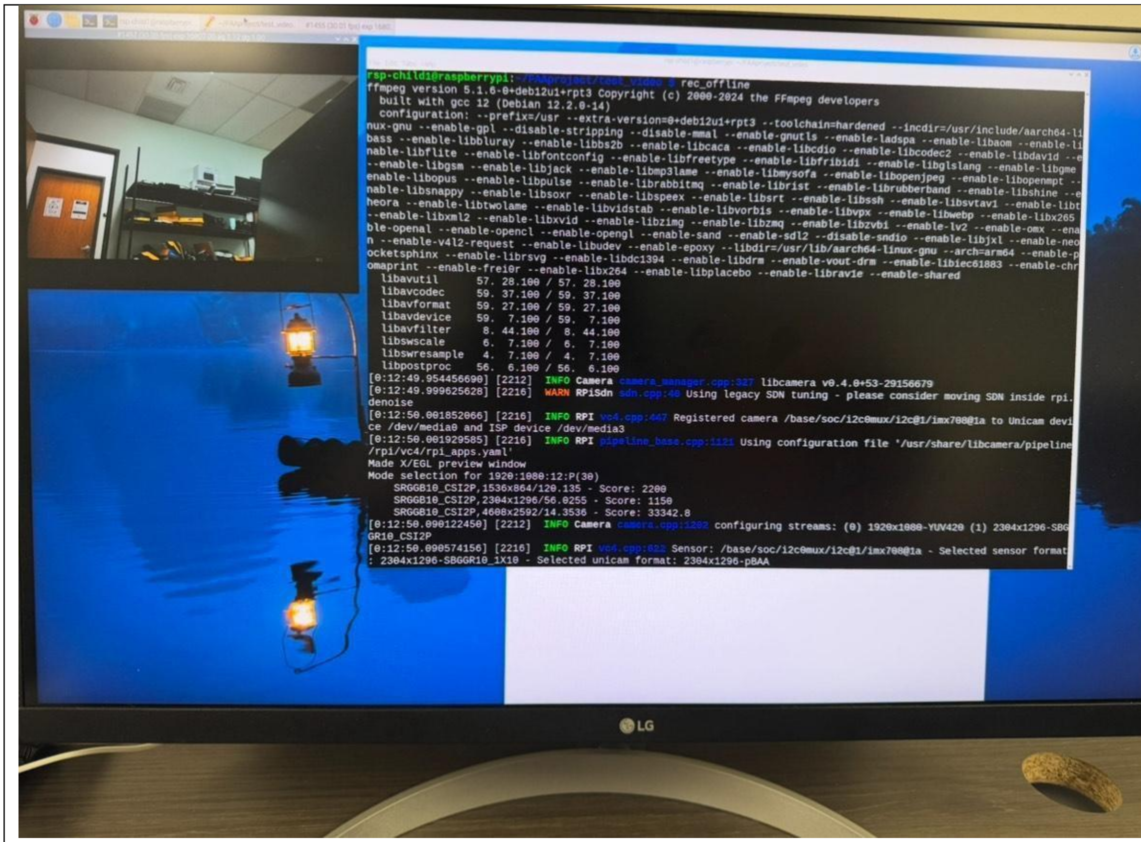
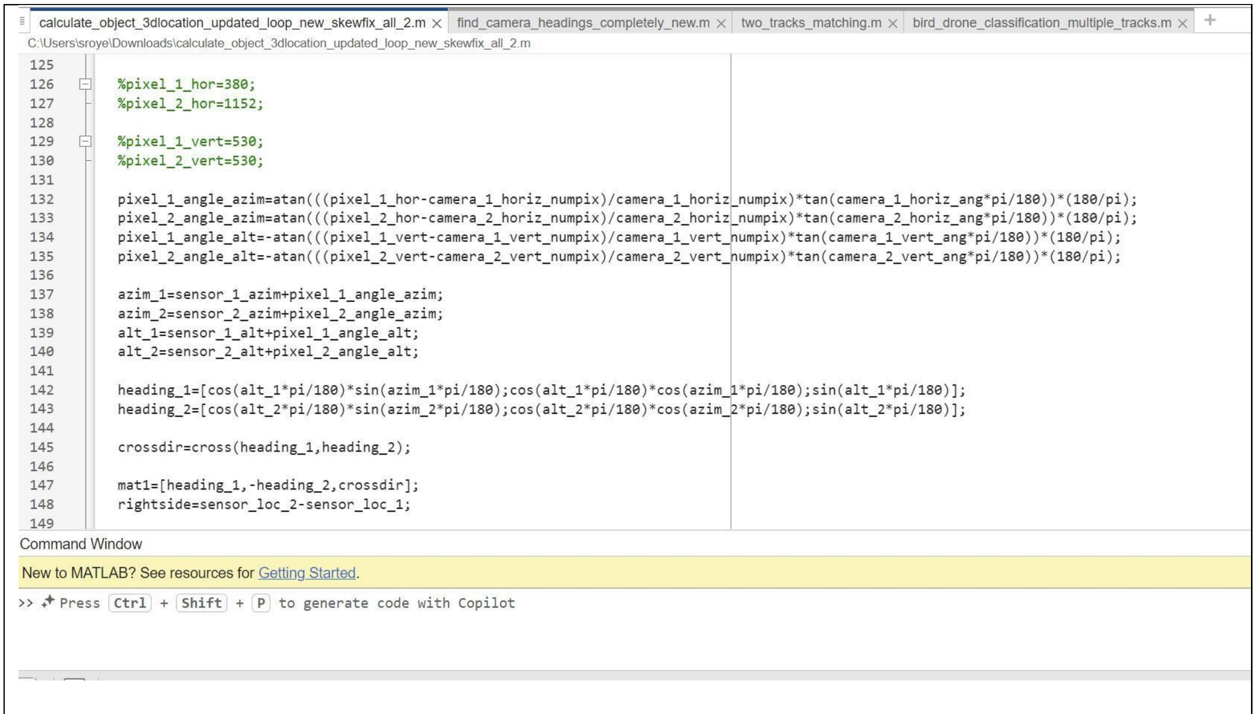


Figure 22: Software for command of the microcontrollers and data recording are shown in operation, during a live test in our laboratory.


calculate_object_3dlocation_updated_loop_new_skewfix_all_2.m × find_camera_headings_completely_new.m × two_tracks_matching.m × bird_drone_classification_multiple_tracks.m ×

C:\Users\sroye\Downloads\calculate_object_3dlocation_updated_loop_new_skewfix_all_2.m

```
%pixel_1_hor=380;
%pixel_2_hor=1152;

%pixel_1_vert=530;
%pixel_2_vert=530;

pixel_1_angle_azim=atan(((pixel_1_hor-camera_1_horiz_numpix)/camera_1_horiz_numpix)*tan(camera_1_horiz_ang*pi/180))*(180/pi);
pixel_2_angle_azim=atan(((pixel_2_hor-camera_2_horiz_numpix)/camera_2_horiz_numpix)*tan(camera_2_horiz_ang*pi/180))*(180/pi);
pixel_1_angle_alt=-atan(((pixel_1_vert-camera_1_vert_numpix)/camera_1_vert_numpix)*tan(camera_1_vert_ang*pi/180))*(180/pi);
pixel_2_angle_alt=-atan(((pixel_2_vert-camera_2_vert_numpix)/camera_2_vert_numpix)*tan(camera_2_vert_ang*pi/180))*(180/pi);

azim_1=sensor_1_azim+pixel_1_angle_azim;
azim_2=sensor_2_azim+pixel_2_angle_azim;
alt_1=sensor_1_alt+pixel_1_angle_alt;
alt_2=sensor_2_alt+pixel_2_angle_alt;

heading_1=[cos(alt_1*pi/180)*sin(azim_1*pi/180);cos(alt_1*pi/180)*cos(azim_1*pi/180);sin(alt_1*pi/180)];
heading_2=[cos(alt_2*pi/180)*sin(azim_2*pi/180);cos(alt_2*pi/180)*cos(azim_2*pi/180);sin(alt_2*pi/180)];

crossdir=cross(heading_1,heading_2);

mat1=[heading_1,-heading_2,crossdir];
rightside=sensor_loc_2-sensor_loc_1;
```

Command Window

New to MATLAB? See resources for Getting Started.

>> Press Ctrl + Shift + P to generate code with Copilot

Figure 23: Example software for testing out advanced monitoring algorithms (3D-geolocation, forecasting, etc), experimenting with basic monitoring algorithms (cleaning, detection/tracking, classification), and doing data analysis is shown. These off-line programs are written in Matlab. This code is for 3D-geolocation of objects.

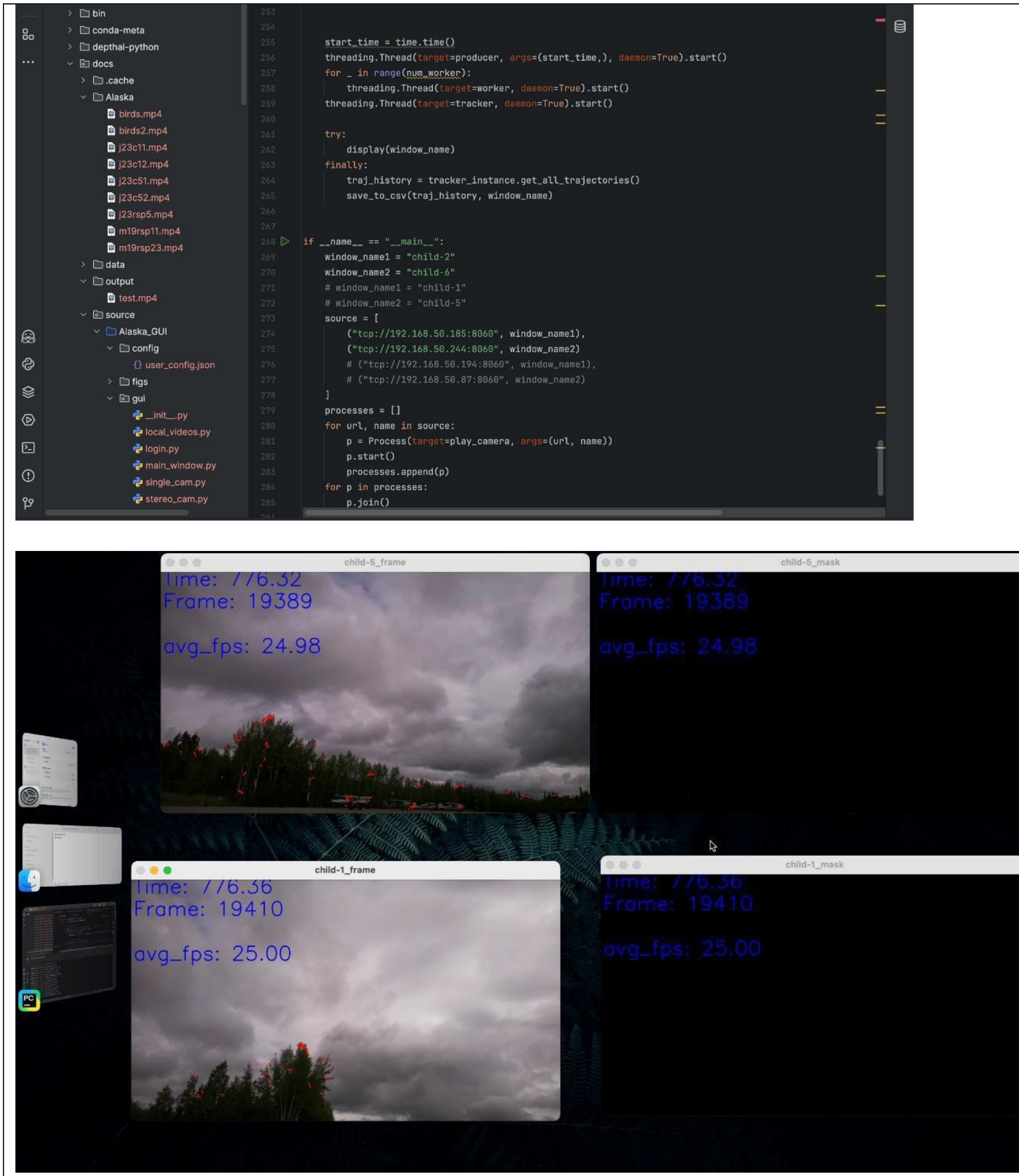
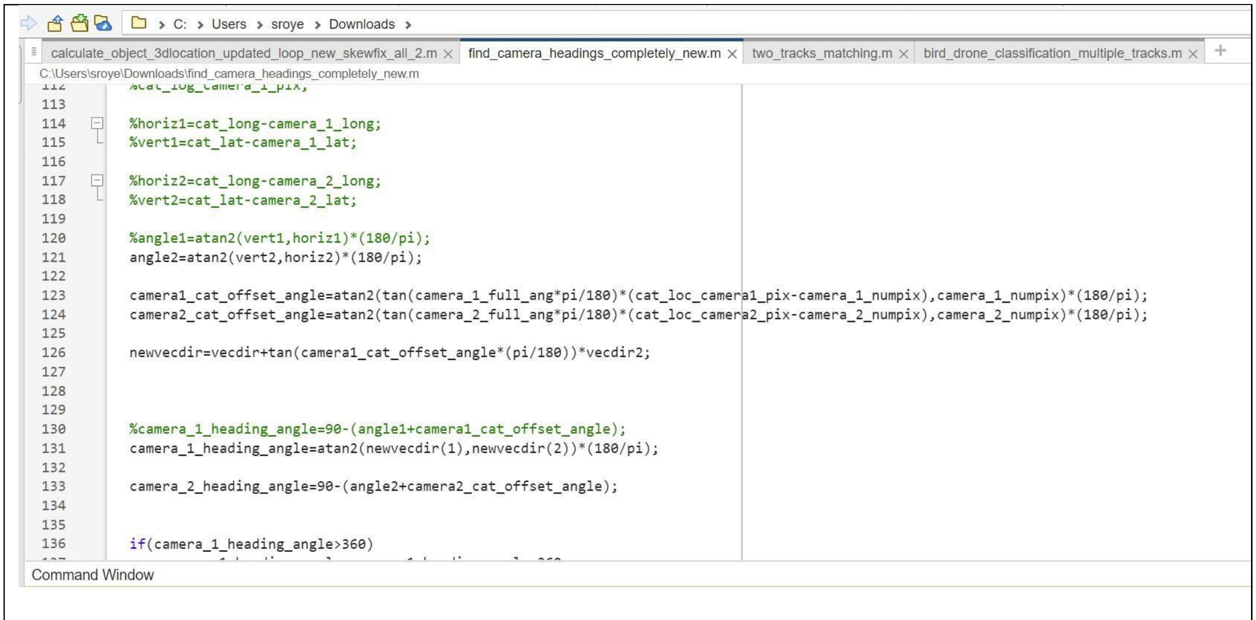


Figure 24: Example software for implementing streaming and online monitoring functions is shown, and a real-time display produced by the software is shown (with videos from two cameras and overlaid identified tracks and the corresponding background subtraction shown).



C: > Users > sroye > Downloads >

calculate_object_3dlocation_updated_loop_new_skewfix_all_2.m × find_camera_headings_completely_new.m × two_tracks_matching.m × bird_drone_classification_multiple_tracks.m ×

C:\Users\sroye\Downloads\find_camera_headings_completely_new.m

```
%cat_log_camera_1_pix;

%horiz1=cat_long-camera_1_long;
%vert1=cat_lat-camera_1_lat;

%horiz2=cat_long-camera_2_long;
%vert2=cat_lat-camera_2_lat;

%angle1=atan2(vert1,horiz1)*(180/pi);
angle2=atan2(vert2,horiz2)*(180/pi);

camera1_cat_offset_angle=atan2(tan(camera_1_full_ang*pi/180)*(cat_loc_camera1_pix-camera_1_numpix),camera_1_numpix)*(180/pi);
camera2_cat_offset_angle=atan2(tan(camera_2_full_ang*pi/180)*(cat_loc_camera2_pix-camera_2_numpix),camera_2_numpix)*(180/pi);

newvecdir=vecdir+tan(camera1_cat_offset_angle*(pi/180))*vecdir2;



%camera_1_heading_angle=90-(angle1+camera1_cat_offset_angle);
camera_1_heading_angle=atan2(newvecdir(1),newvecdir(2))*(180/pi);

camera_2_heading_angle=90-(angle2+camera2_cat_offset_angle);


if(camera_1_heading_angle>360)
```

Command Window

Figure 25: Matlab software for calibration of multiple cameras, for the purpose of 3D-geolocation, is shown.

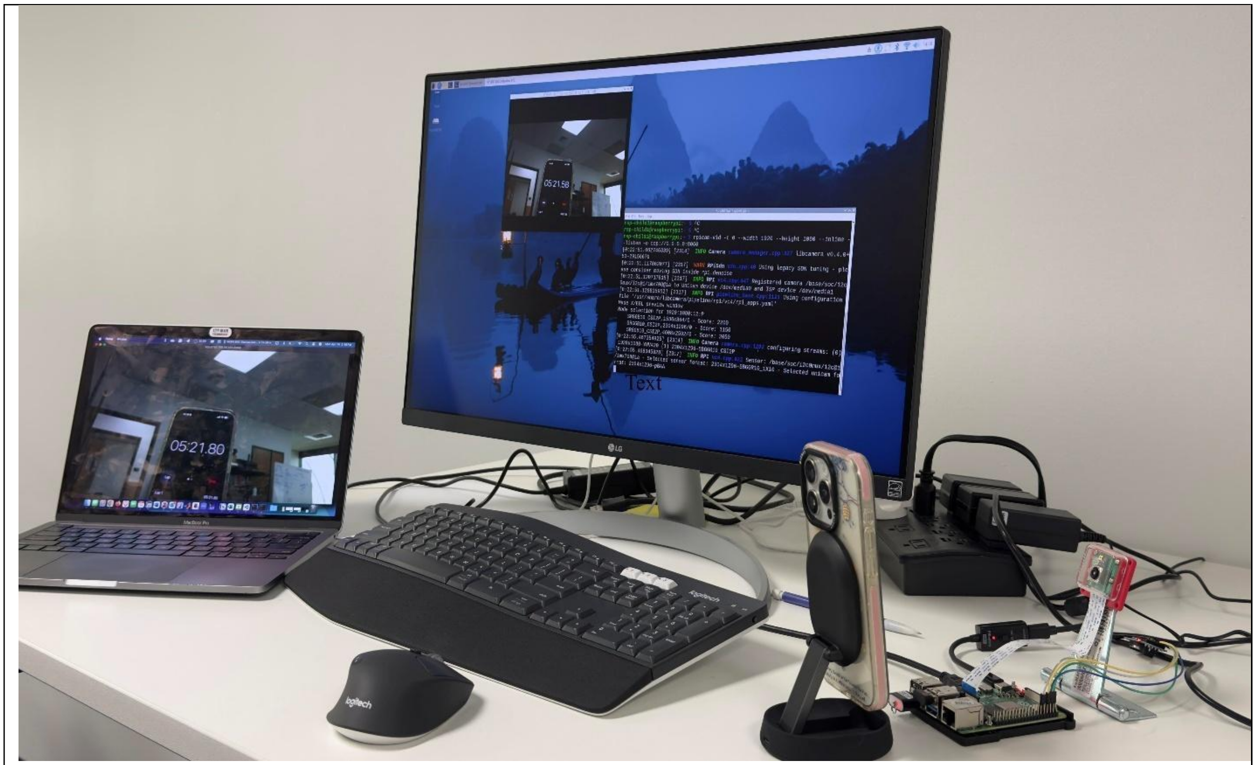


Figure 26: A test of the real-time software suite, to determine the communication and processing delay. The delay was found to be 22 ms in this test. In the field, delays were variable but largely were on the order of 10-100 milliseconds. For online processing and visualization of complex scenes, delays were sometimes larger at the initiation of the online recording, but settled to small values after 1-2 minutes.

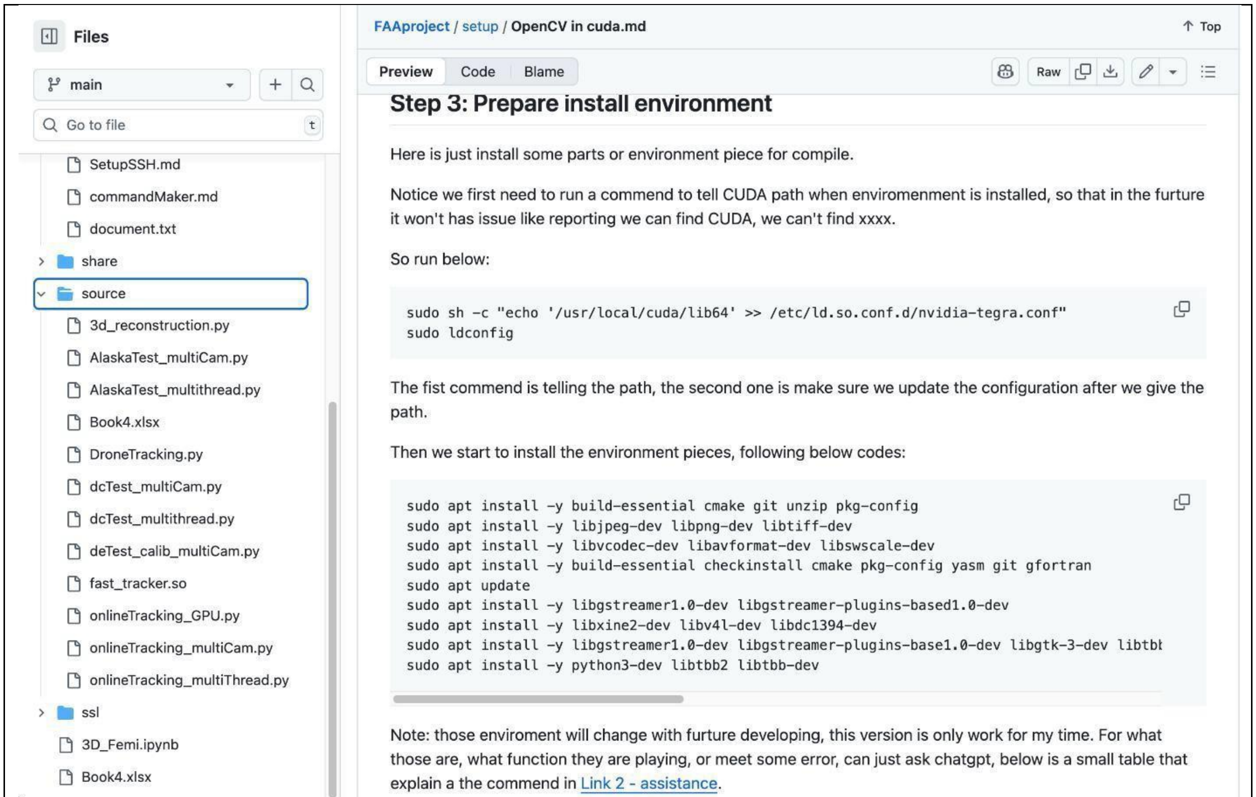


Figure 27: A GitHub repository for project software is shown.

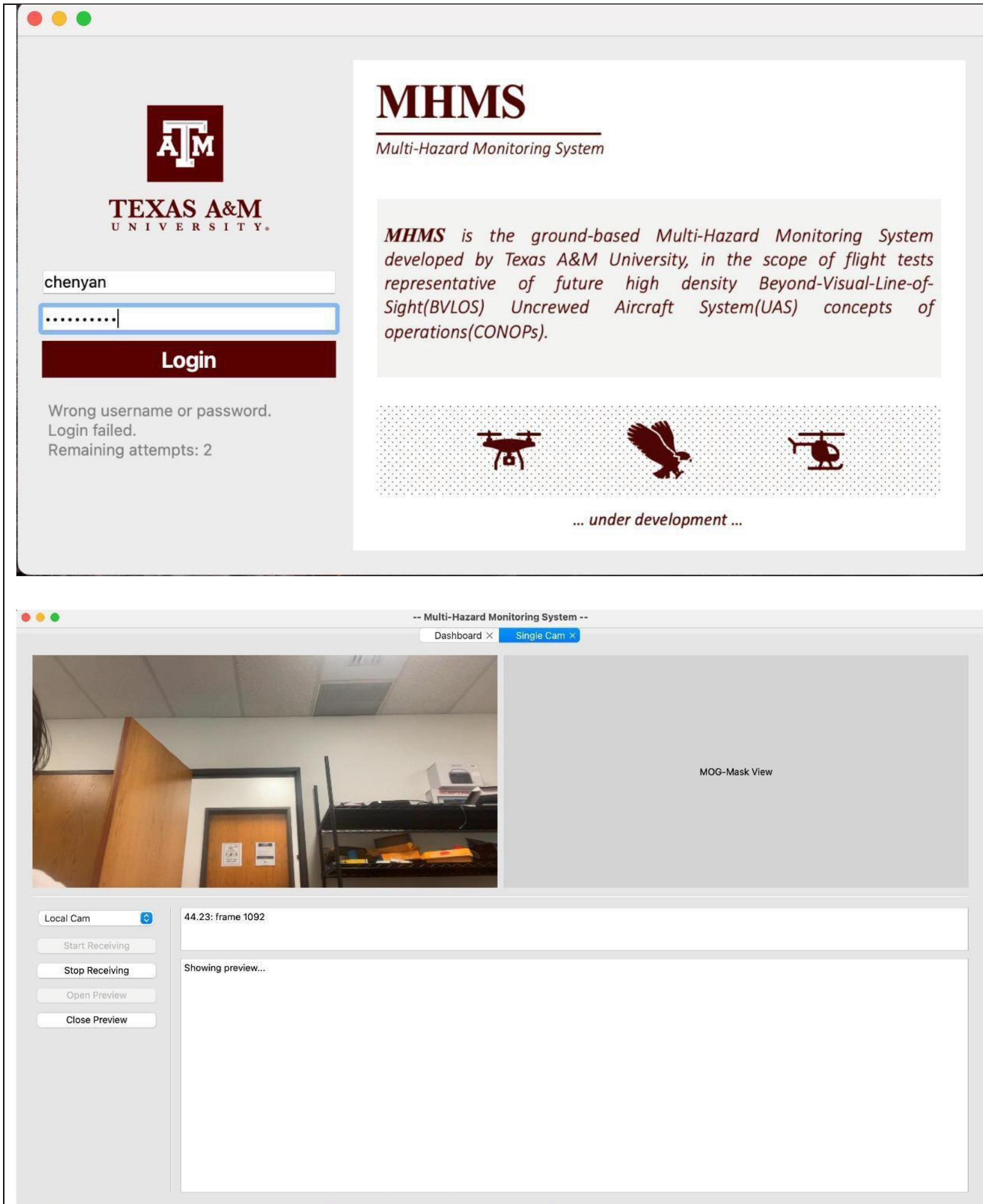


Figure 28: Two screenshots of the graphical user interface for the MOMS is shown. The user interface is currently being integrated with the full online monitoring software suite for the MOMS.

Function	Status
Video data collection, storage, and transmission to control authority	Integrated, streaming, real time
Track extraction and tracking in image frame	Integrated, streaming, real time
Track cleaning	Some methods are integrated, streaming, and real time; still working on further methods.
Visualization of in-frame tracks for control authority	Integrated, real time
Classification	Integrated, streaming, real time
3d-locationing/tracking	Integrated as an add-on module, working on streaming and real-time
Calibration for 3d-locationing/tracking	Partially integrated but is still manual, working on automation.
Track forecasting	Initial algorithm developed, not integrated.
Aviation alarming	Starting to develop/implement

Table 2: The development statuses of the monitoring functions which will be included in MOMS are shown.

4.3. Results from Flight Tests

Results from the two three-day flight campaigns (May 19-21, July 23-25) are shown. For both flight campaigns, the flight tests were successfully conducted according to the plan (as discussed in the Methods section), and the MOMS solution was successfully used to collect long-duration data (3-6 hours per day per sensor) across all flight tests, from 10 or more sensors. The collected sensor data included extensive data with multiple UASs in simultaneous flight (~10 hours per flight campaign), bird data (approximately 20-30 in the second flight campaign), overflights (approximately 10 in each flight campaign), nearby runway operations with crewed aircraft (approximately 5 in the second flight campaign), and balloons (2-3 in the first flight campaign). In addition, long-duration data from large birds, and further data with simultaneous birds+UASs, was collected during a flight test at NASA Langley where our team was demonstrating the technology. Short flight tests in College Station, Texas, also included interesting data, including high-density bird flights and bird flocks. Command of the MOMS sensors through the network was demonstrated, and real-time implementation was robustly achieved in the second field test. We note that the field tests have quite varied temperatures and weather conditions, and the MOMS solutions as well as its monitoring functions performed robustly across these conditions. Highlights from each flight campaign are shown. Then, monitoring functions applied to flight test data are shown.

4.3.1. Flight Campaign 1 results

Figure 29: Photographs of the field-of-operations at Poker Flat Research Range north of Fairbanks, Alaska, for Flight Campaign 1. Winter weather conditions are observed, with temperatures between 0-30 degrees Farenheit. The weather was clear at times, and partly cloudy with fast-moving clouds at altitudes around 3000-5000ft during the flight campaign.

Figure 30: Map with sensor locations indicated, and box roughly outline the field of operations, for Flight Campaign 1.

Figure 31: Photographs of two types of UASs used for Flight Campaign 1, a SkyHunter fixed wind and an X6 rotorcraft. These two aircraft had diameters around 5-6 ft. Smaller (1.5ft-2ft diameter) Autel UASs were also flown.

Figure 32: Example vehicle flight trajectory for Flight Campaign 1, as recorded in vehicle-board log data. This log data was collected for all flight tests, and provides a baseline for comparison for our algorithms (especially, the 3D-geolocation algorithm).

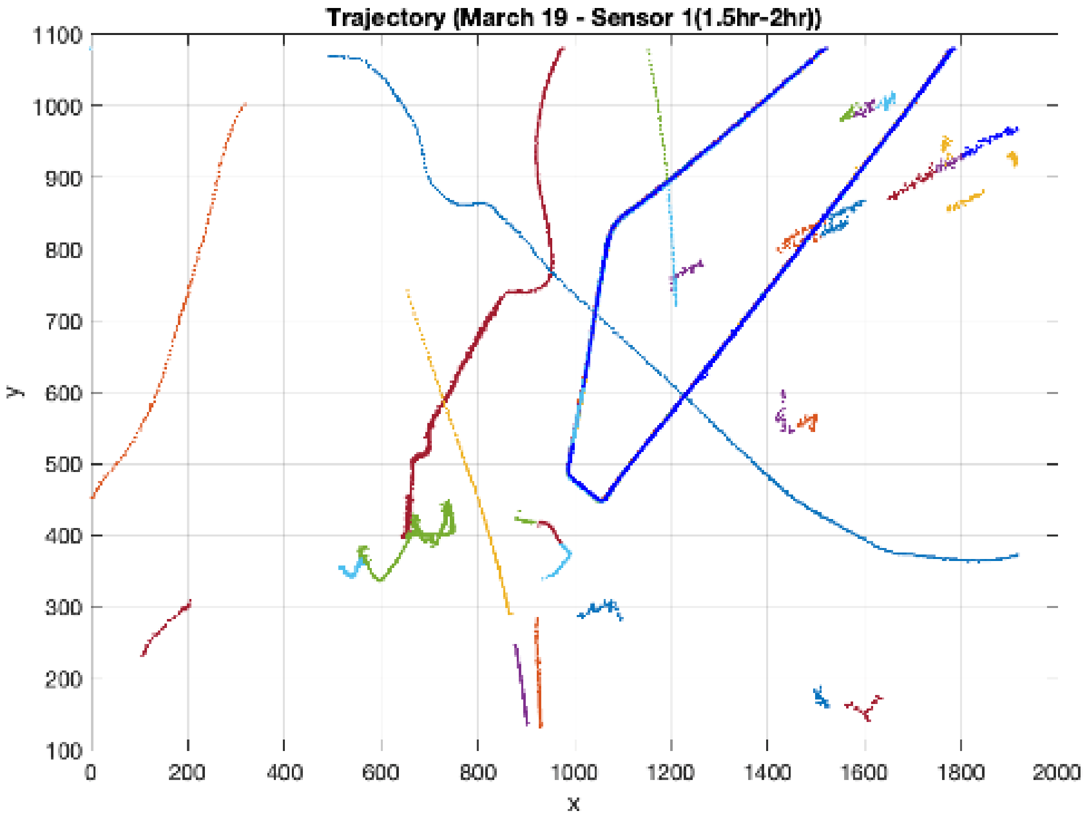


Figure 33: Example compendium of tracks extracted (after the fact) from video recordings for a single sensor over a 1 hour flight, during Flight Campaign 1. This data corresponds to a flight test with crossing streams (Flight Test A). The ownship follows a trapezoidal or quadrilateral shape (in Blue), with multiple repetitions of the path covered. One of the crossers can be seen as going back and forth at slightly different locations. An overflight of a helicopter at 5600 ft is also present.

Figure 34: Example UAS tracks extracted from video recordings, shown in post-facto streaming mode, for Flight Campaign 1.

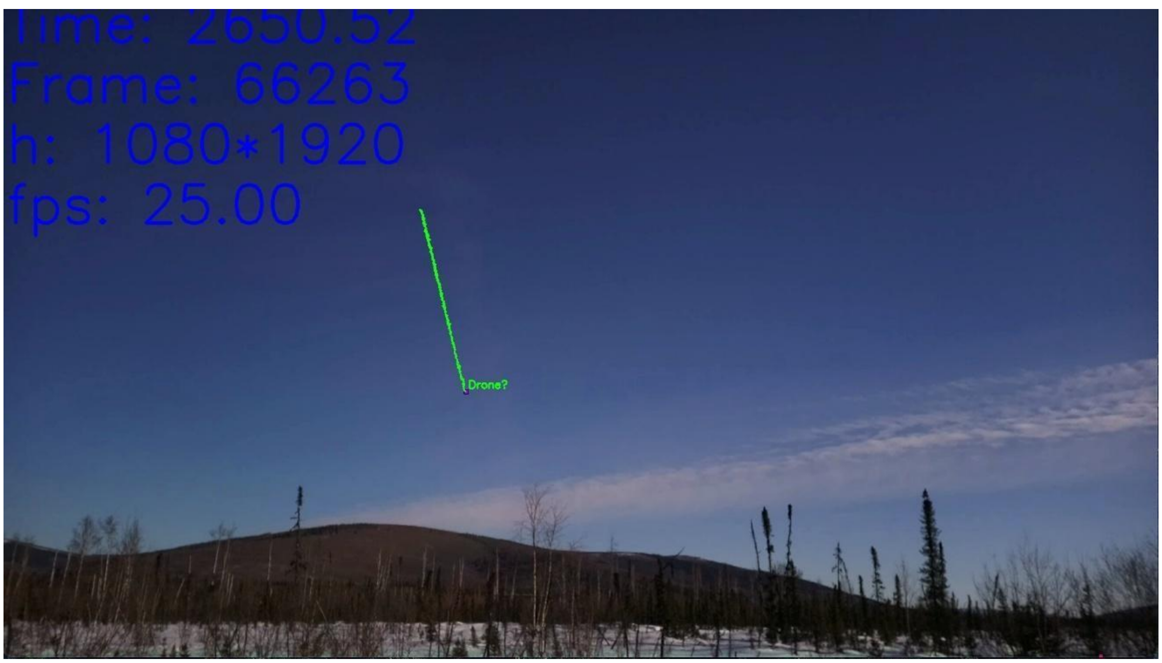


Figure 35: Example non-UAS tracks extracted from video recordings, shown in Streaming mode, for Flight Campaign 1. The track is for an overflight: a jet at altitude near 10,000 feet. Of note, the bird-UAS classifier was also applied. The track is classified as an aircraft, but our basic classifier does not distinguish between UASs and crewed aircraft. An analysis of the object's distance would allow for differentiation: we expect to develop this refinement later.

Figure 36: Photograph of Flight Test 1 participants (two pilots from ACUASI, and a graduate student from Texas A&M) and setup.

4.3.2. Flight Campaign 2 results

Figure 37: Photograph of the field-of-operations for Flight Campaign 2. The flight campaign was at Nenana Municipal Airport south of Fairbanks, Alaska. The photograph is a still from a wide-angle video camera, which was one of the MOMS sensors. The wide-angle camera uses a special light filter, which causes the image to have an unnatural pinkish coloring.

Figure 38: Map with GPS sensor locations and box indicating the field of operations, for Flight Campaign 2. Five sensor pods (2 full size, 3 mini-pods) were used. Regular, wide-angle, and night-vision cameras were tested during the flight test. A subset of four cameras (Cameras 1, 2, 5, and 6 on the two full pods) were used for online visualization and recording for parts of the flight test. Data from all cameras was recorded for off-line processing.

Figure 39: Some photographs from Flight Campaign 2.

Figure 40: Photographs of UASs used for Flight Campaign 2. An Alta-X (rotorcraft), P8 (rotorcraft), and SuperVolo (fixed wing) were used. The X6, Skyhunter, and Autel used in Flight Campaign 1 were also used in Flight Campaign 2. The P8 and SuperVolo are larger and heavier vehicles, which may give insight into monitoring (detection, classification) at a greater distance.

Figure 41: An infrared photograph of the Alta-X taken by the project team is shown. The MOMS solution is able to use infrared sensors, although we have not collected substantial data using infrared yet.

Figure 42: Views of the field of operations on July 23rd for Flight Campaign 2 from two Sensors – Sensor 1 and Sensor 5—are shown. These two sensor streams were used for 3D-geolocation for a test case.

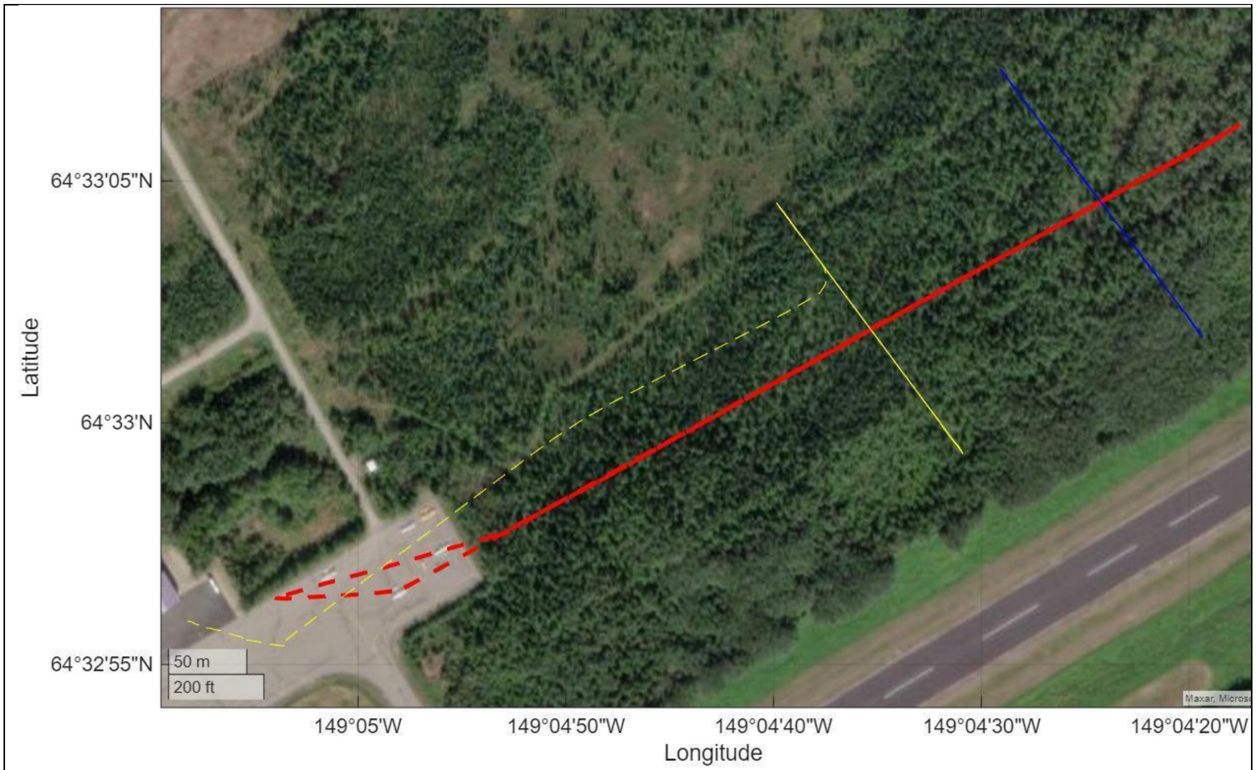


Figure 43: Example vehicle flight trajectories for Flight Campaign 2, taken from vehicle-board logs. Three vehicles' trajectories are shown, for a crossing-pattern Flight Test (Flight Test A) from July 23rd. The vehicle altitudes are between 150-200 meters above ground.

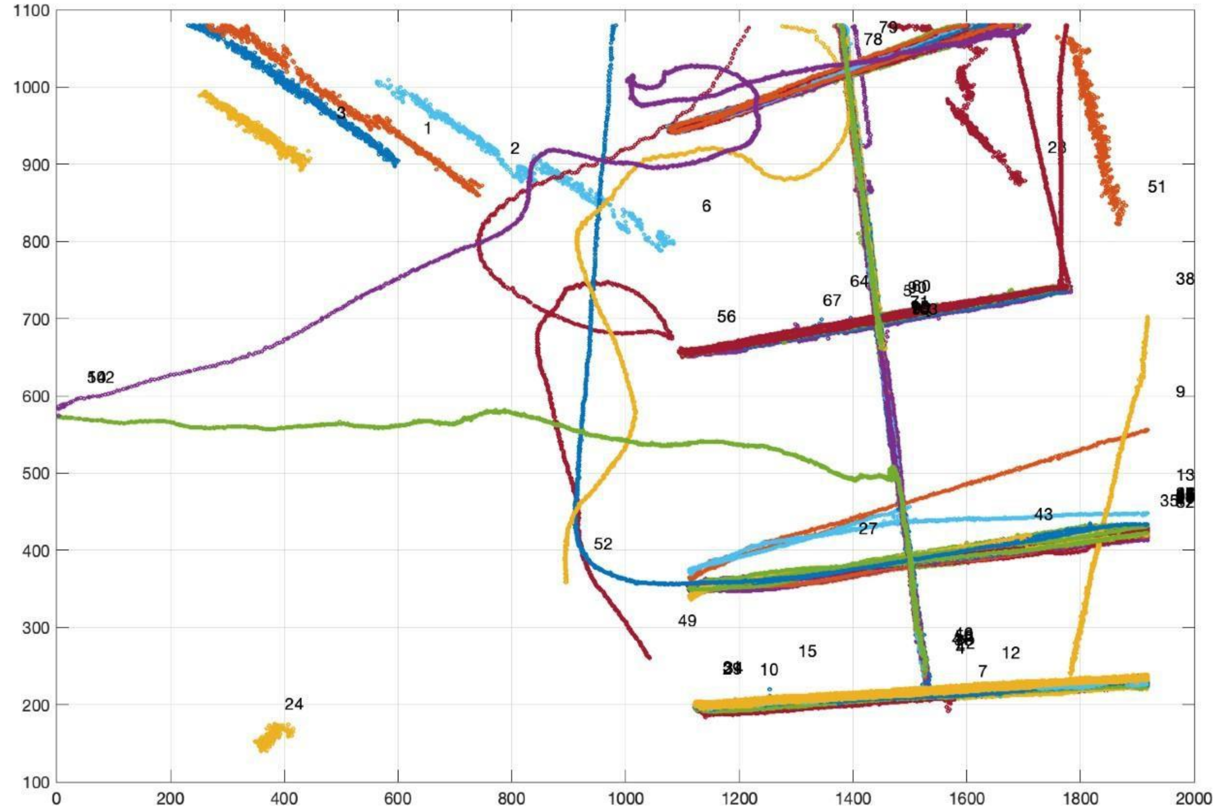


Figure 44: Compendium of tracks extracted from video recordings from one sensor over 1/2 hour, during flight campaign 2 (July 23rd). Crossing patterns at a couple of altitudes, with UASs going back and forth as the major and crossing flows, are captured.

Figure 45: Example UAS tracks extracted from video recordings, shown in Streaming mode (post facto), for Flight Campaign 2.

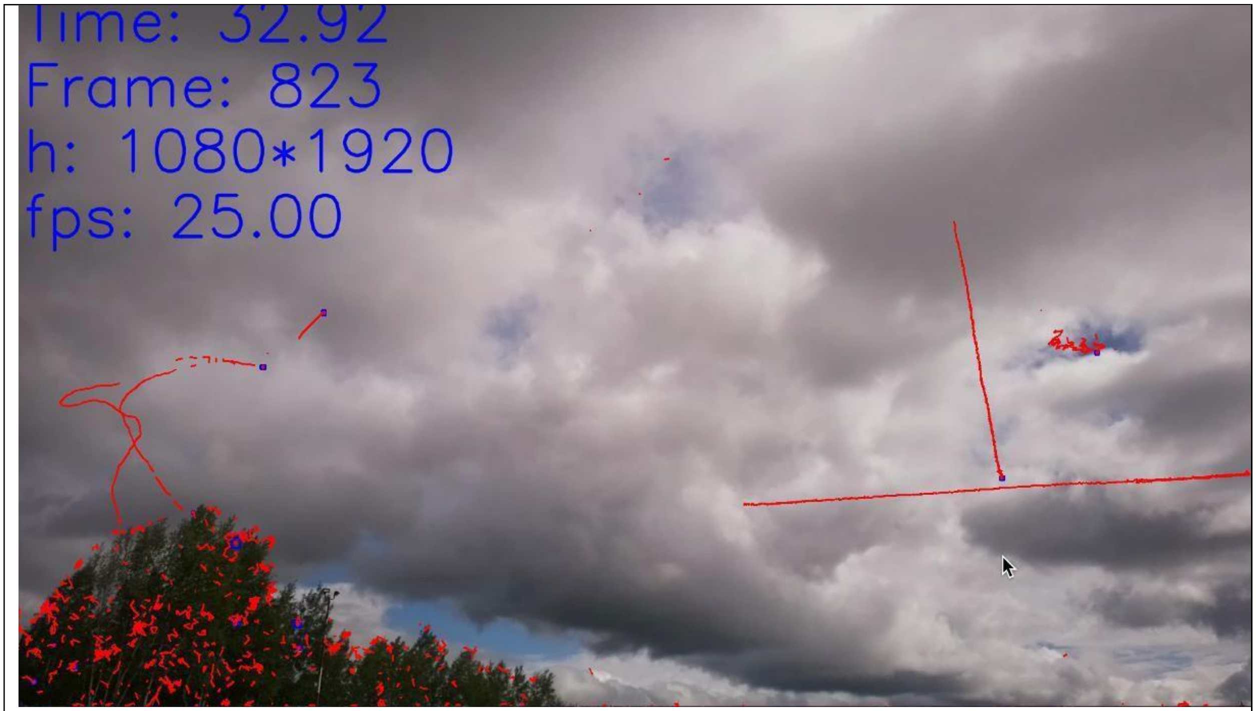


Figure 46: Example UAS and non-UAS tracks extracted from sensor video recordings, shown in Streaming mode, for flight test 2. Two UAS tracks in a crossing pattern and two bird tracks are seen in this sensor view.

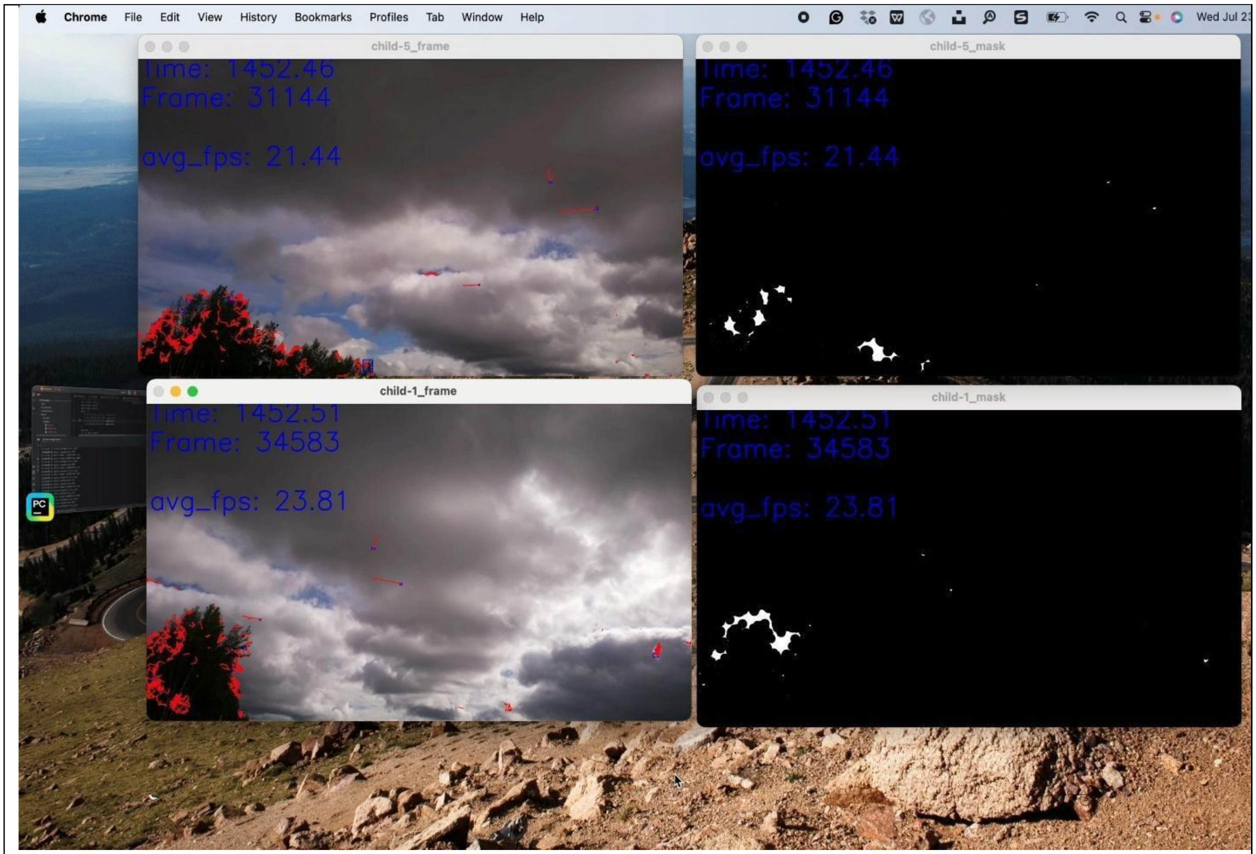


Figure 47: Real-time visualization of tracks from Sensors 1 and 5 on the command-module laptop during Flight Campaign 2. A screenshot of the laptop is shown. A UAS track can be seen in the middle of each sensor's view.

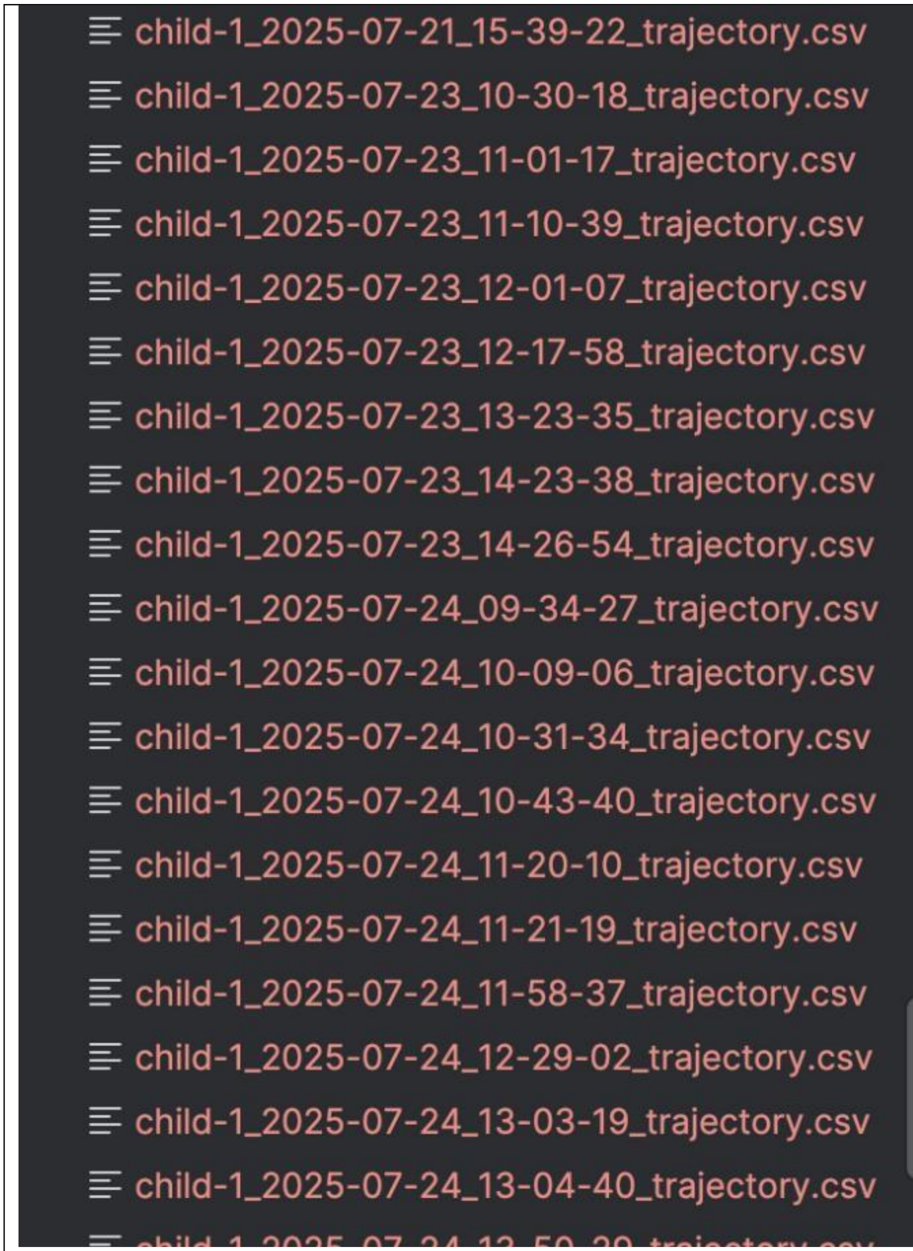


Figure 48: Real-time track-data collection at the command module laptop during Flight Campaign 2.

Figure 49: Photograph of Flight Test 2 participants and setup. The three members of the Texs A&M team are in the upper photograph. The three pilots for the flight test are in the lower photograph.

4.3.3. *Monitoring Functions Implemented on Flight Test Data*

Figure 50: Detection of a UAS impinging on a sensor's field of view, at the right of the image. Tracks are established quickly when a vehicle enters the field of view, and indexed and maintained as the vehicle moves through the field of view. An object that starts moving within the field of view will also be detected.

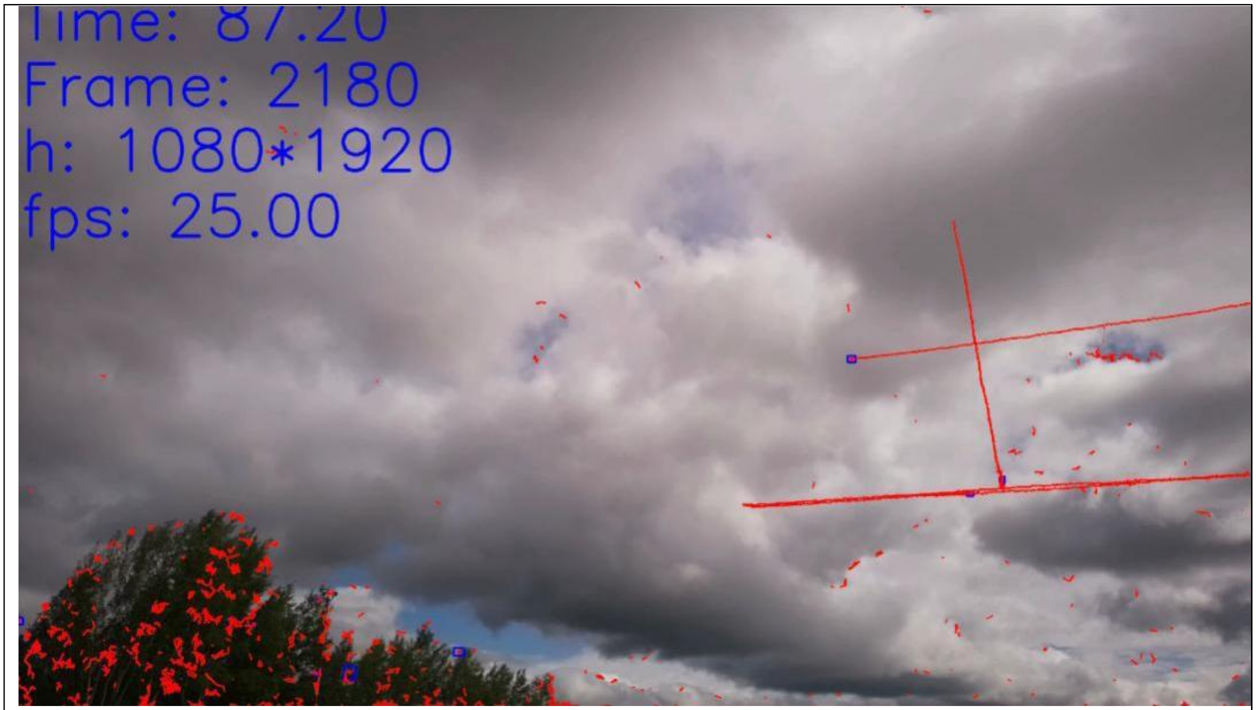


Figure 51: Simultaneous UAS tracks that cross on a sensor's field of view are shown. Such crossings can be alarmed using the MOMS. Distance estimates from 3D-geolocation or comparison on sensor's field of view can then be used to determine whether a conflict is indeed imminent.

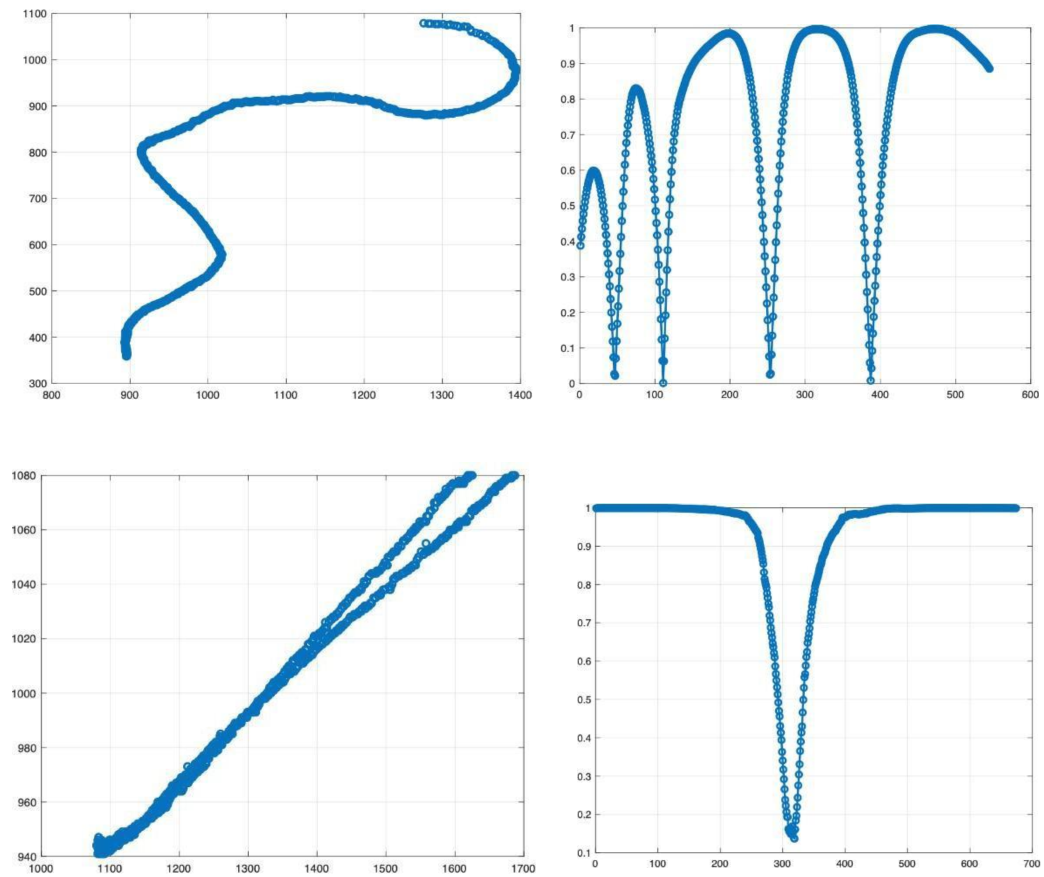


Figure 52: Time courses of a metric that is being used for classification are shown, for a UAS track and a bird track. The metric is the correlation coefficient of a short (3s) track segment on the sensor image, capturing the closeness to linearity of the track segment. The bird's track (top) has correlation coefficients substantially less than 1 for most segments, while the UAS's track has correlations near 1 except during turns.

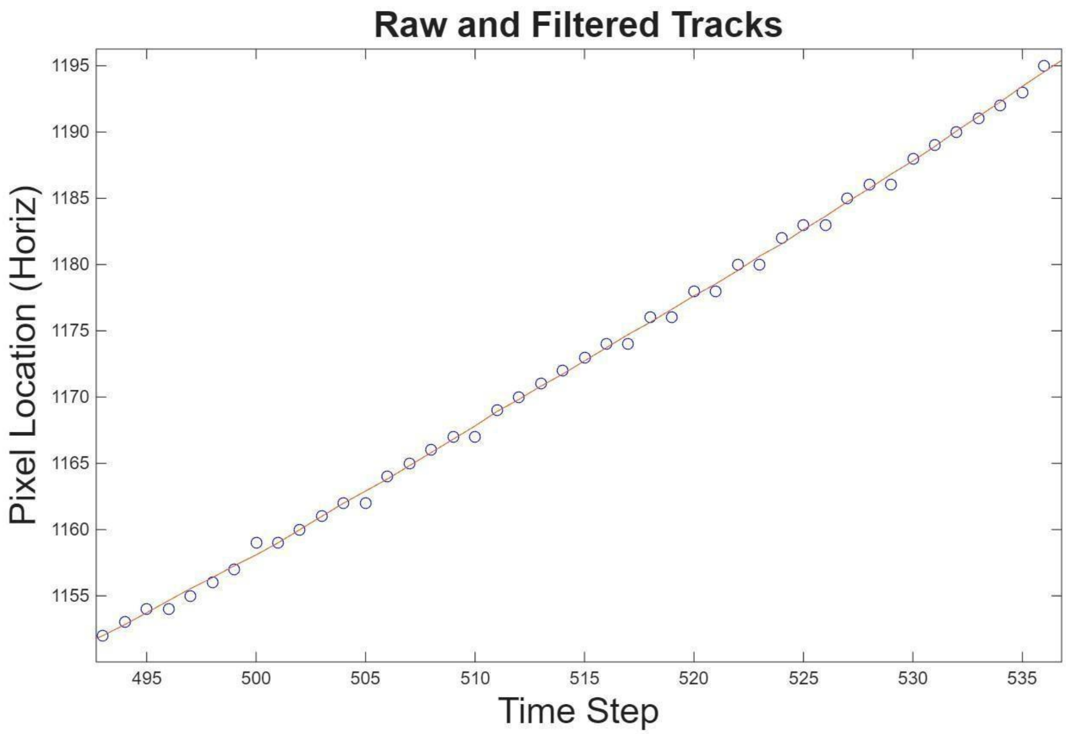


Figure 53: An advanced track filtering/cleaning method is shown. The raw tracks show a stair-step artifact (blue circles), because the background-subtraction-based image processing associates the object location with a single pixel. The artifact is eliminated using a short-horizon linear fit. This cleaning process also yields better estimates for track variations, which can be used for classification.

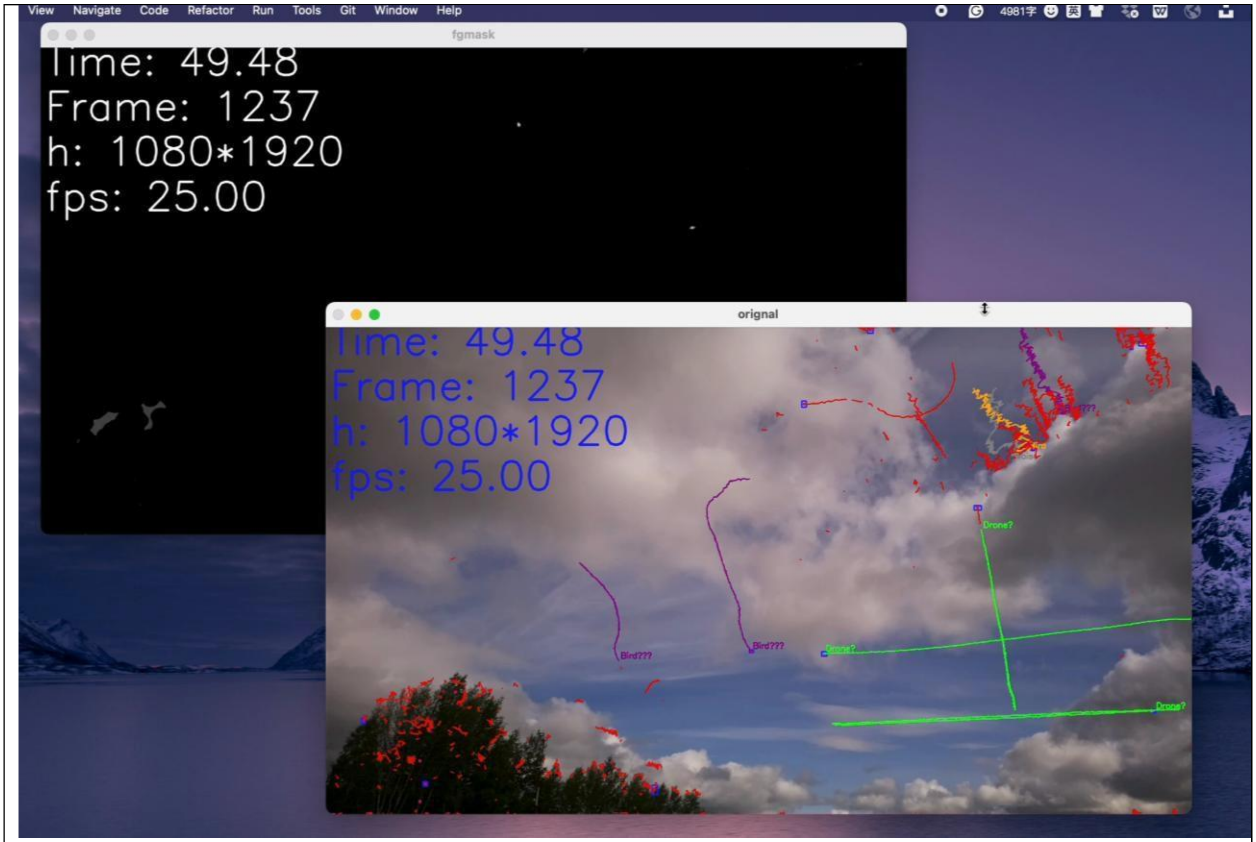
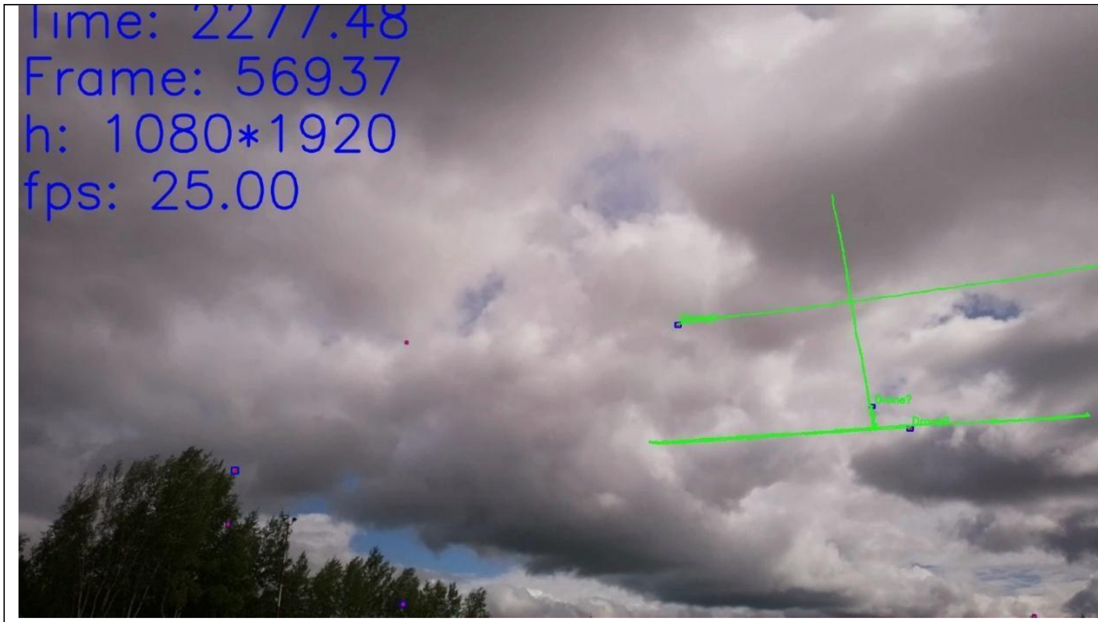


Figure 54: Classification of multiple UAS and bird tracks within a field of view, using the classification metric. Three UASs are tentatively identified, and two birds are identified with confidence, at this time point.



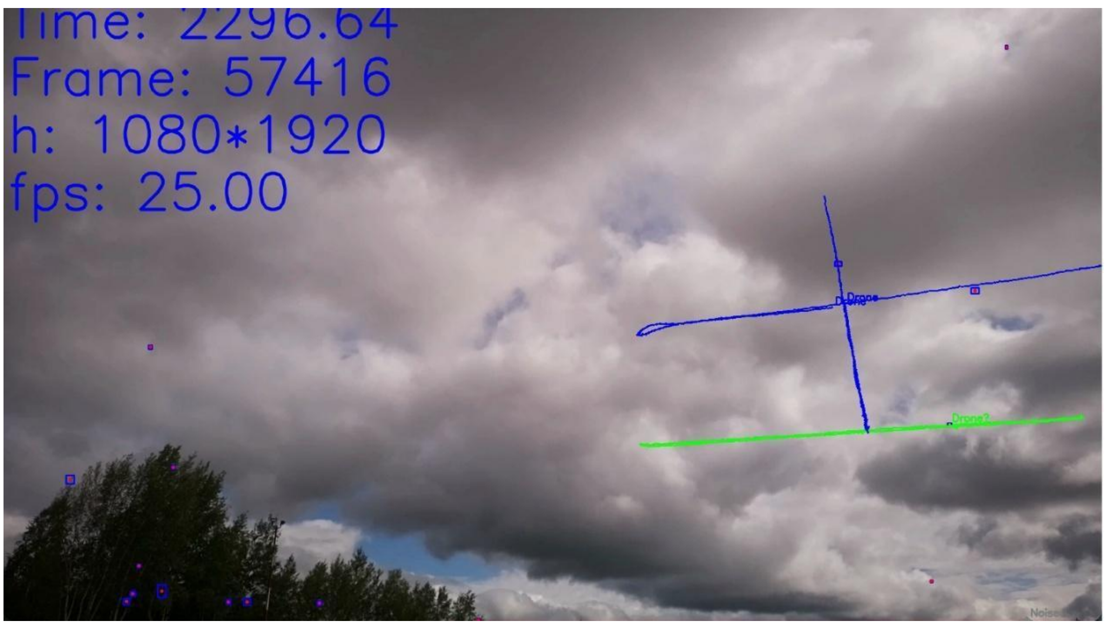


Figure 55: The classification algorithm also provides a determination of confidence. In the top image, the tracks are classified with low confidence after a short data segment. The confidence increases after a short further time interval, as shown in the bottom image.

Figure 56: A test point at a known location – in this case, the top of a tree – was used for calibration of the cameras, for the purpose of 3D-geolocation. Alternatively, "true" UAS location data from flight logs were also used. The flight log data provided somewhat better estimates of tracks thereafter, although the two estimates were relatively comparable.

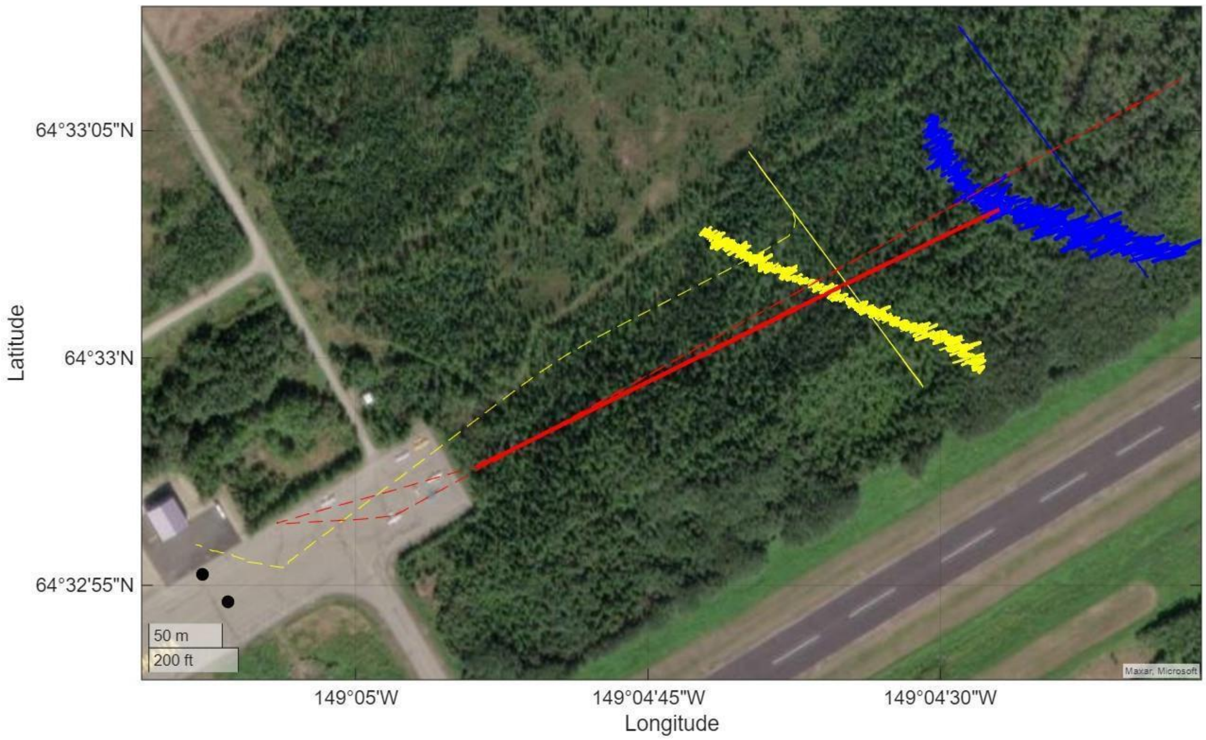


Figure 57: 3D geolocation of UAS tracks, for a crossing-pattern Flight Test from July 23rd. The track estimates are compared with log data of the locations, and are found to be reasonably accurate. Altitude (not shown) was also estimated successfully. We note that the two sensors used for geolocation (the black dots) are quite close in this case; further-spaced sensors can perform better. We are also undertaking different calibrations, including correcting for distortion and sensor location errors, to understand if estimates improve. We note that the vehicles were approximately 0.5 km away from the sensors in this case.

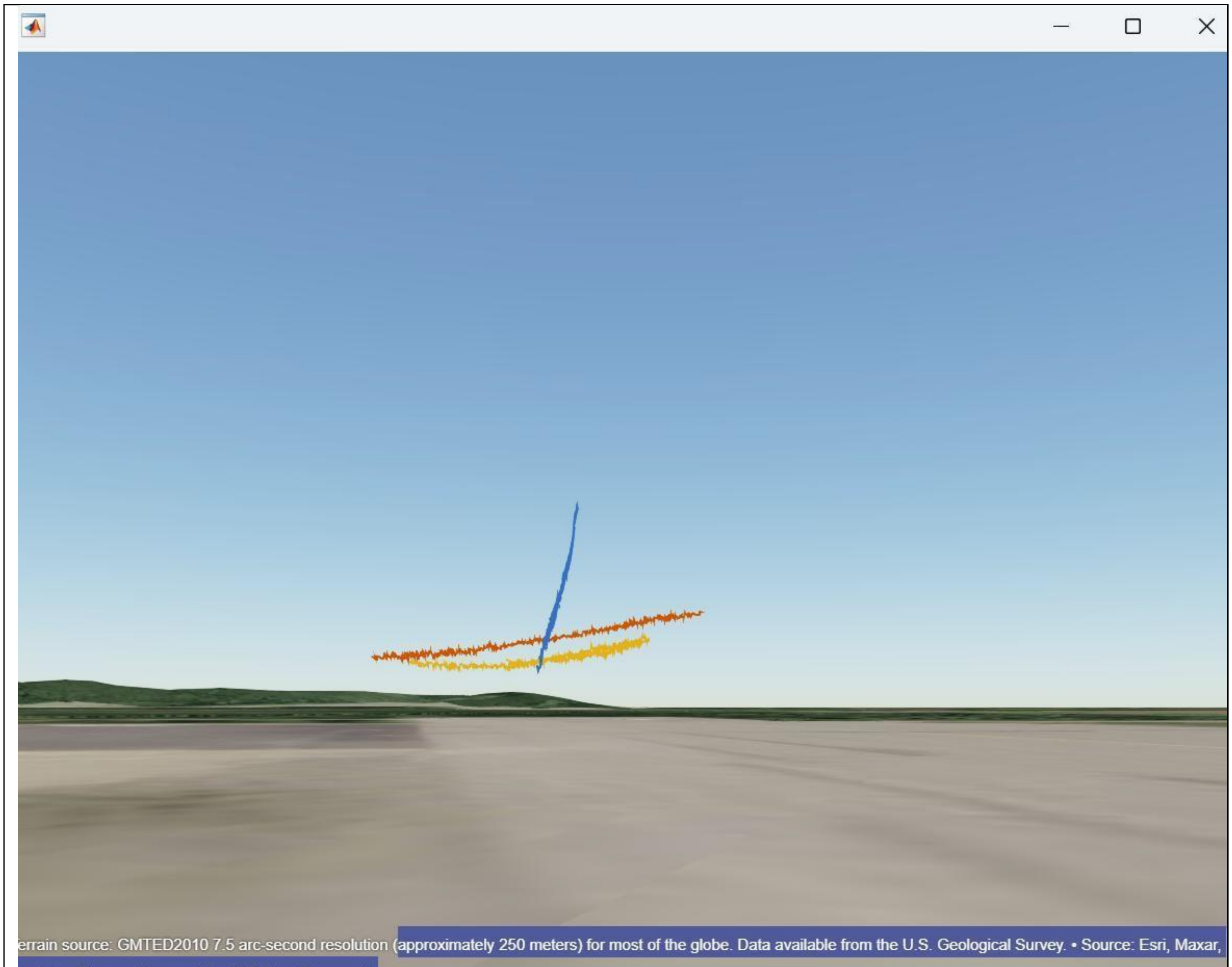


Figure 58: 3D-Geolocation location estimates are now shown in three dimensions, from a sensor point of view.

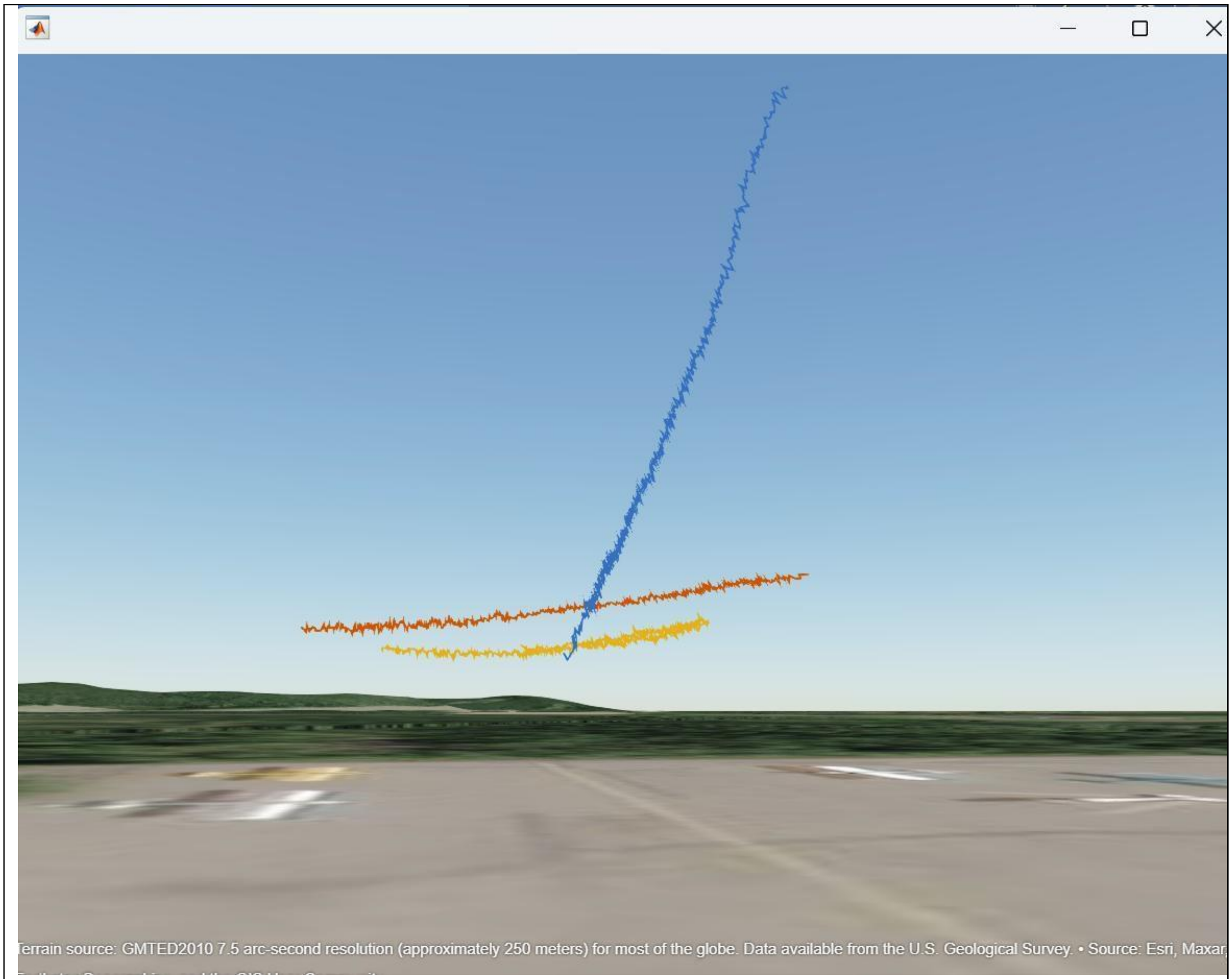


Figure 59: The 3D-geolocation estimates are shown again, but from a closer viewpoint along the ray from the sensor to the UAS crossings.

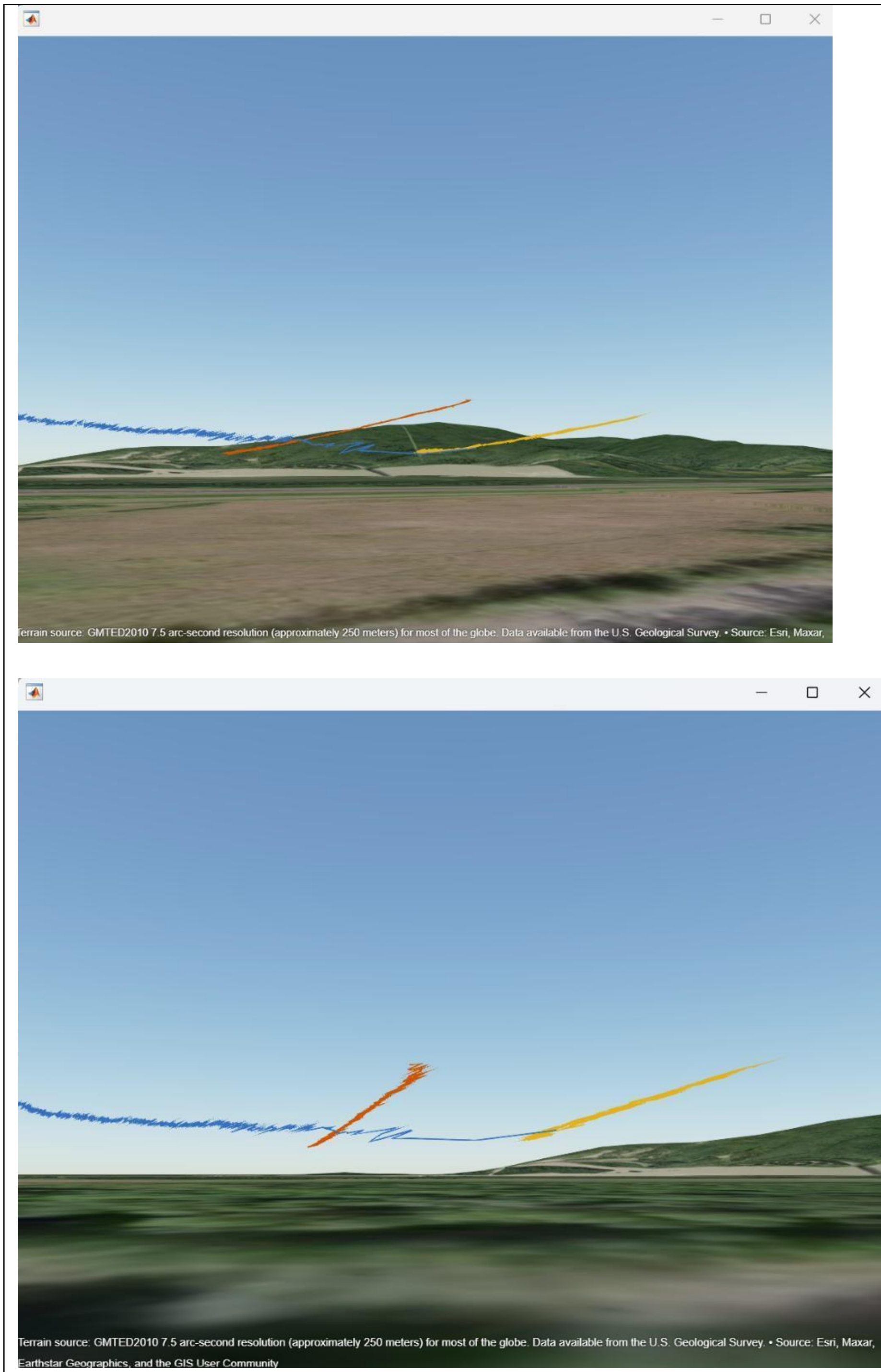


Figure 60: Side views of the 3d geolocation estimates, from near the runway at the municipal airport site, are shown. The tracks are seen to come quite close to each other, as is indeed the case.

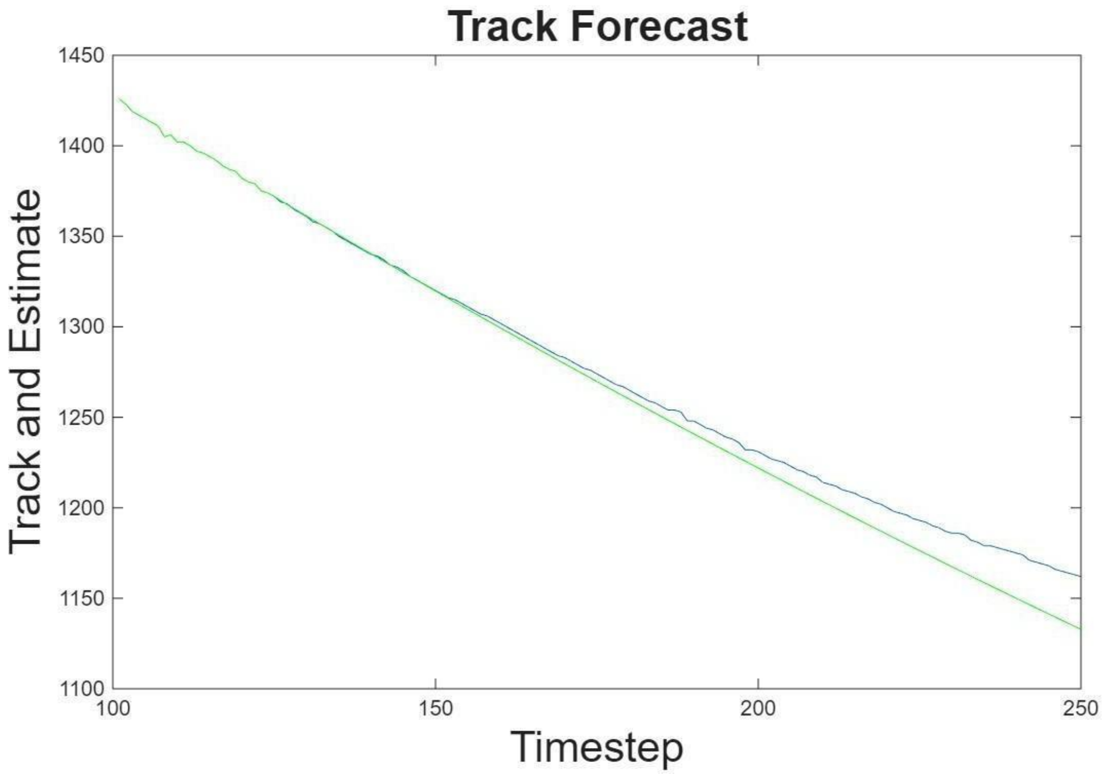


Figure 61: Preliminary effort at track forecasting. Track data over 1 second (Timesteps 101-125) is used to find a sparse regression model, which is then used to forecast the track over 5 seconds (Timesteps 125-250). The actual track (blue) is compared with the forecast (green). In this case, a straight-line track is forecasted based on the sparsification. When the algorithm is turn data from a fixed-wing UAS, this motion and intent is correctly captured via the sparsification algorithm.

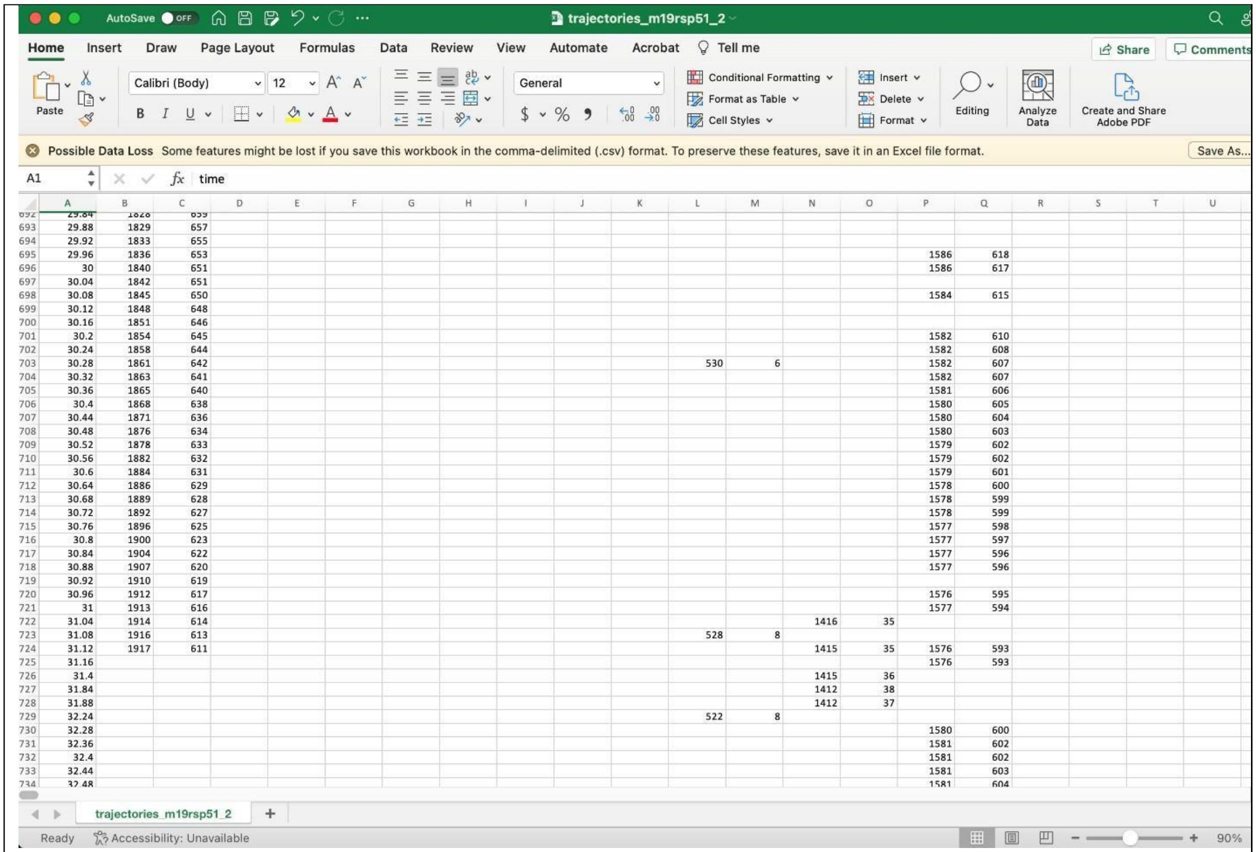
4.4. Data Analysis Results

The data analysis method described in Section 3.4 has been applied to the sensor data recorded by MOMS during the two flight campaigns. Because of the compressed timeline after the second field test, the data analysis has focused on particular flight tests within the data rather than the full data set, and is preliminary in a number of respects. Specifically, the following analyses have been completed.

1) For both flight campaigns, image-frame tracks have been extracted and cleaned from all sensor data captured during the flight campaign. As an example, one data file with extracted tracks is shown in Figure 62. Overall, the flight campaign generated approximately 8300 tracks of interest (cleaned tracks), out of around 1 million unprocessed tracks and approximately 8 million motion signatures detected by the background subtraction algorithm. Unprocessed and cleaned tracks from 1 hour of data from one sensor (7/23, beginning at 14:14:43 PM CT) are shown in Figure 63.
2) The time required to detect an object enter a sensor's field of view was analyzed, using the one-hour data set (Sensor 5, 7/23, 14:14 PM CT). This data set contained 122 incursions. All incursions were tracked within 3 pixels of the edge of the image (73 at the edge, 13 at one pixel from the edge, 30 at two pixels from the edge, and 6 at three pixels from the edge). All incursions were tracked within 0.25s of the object entering the field of view.
3) Track fidelity for UASs and birds within the field of view was assessed statistically, for one-half hour of data on 7/23 (part of the data from sensor 5 at 14:14 PM). One-half hour data on 7/25 was also analyzed, during which fixed-wing UASs were being flown. Sample data analyses are shown in Figures 64 and 65.

4) Track classification algorithms have been applied to one hour of data from a single sensor (7/23. Sensor 5, at 14:14 PM). During this hour, there were 225 tracks after track cleaning. Of these, 113 UAS tracks and 112 non-UAS tracks (5-7 birds, the remaining cloud edges) were recorded. A basic classification algorithm based on track correlation coefficients calculated over rolling windows was tested; this algorithm has been implemented in our real-time tool. A more advanced algorithm that uses both track correlation coefficients and short-duration linear-fit errors was also tested. Sample results from the statistical analyses, focused on counting true positive and false positive rates, are shown in Figures 66 and 67.
5) The performance of the 3D-geolocation algorithm was compared with truth data, as obtained from vehicle logs, for three simultaneous tracks during an approximately 2 minute period on 7/23. Data from sensors 1 and 5 were used for geolocation as described above. The performance is shown on Figure 68.

A table summarizing main findings of the statistical analysis is given, as Table 3.



	A	B	C	L	M	N	O	P	Q
693	29.88	1829	657						
694	29.92	1833	655						
695	29.96	1836	653					1586	618
696	30	1840	651					1586	617
697	30.04	1842	651						
698	30.08	1845	650					1584	615
699	30.12	1848	648						
700	30.16	1851	646						
701	30.2	1854	645					1582	610
702	30.24	1858	644					1582	608
703	30.28	1861	642	530	6			1582	607
704	30.32	1863	641					1582	607
705	30.36	1865	640					1581	606
706	30.4	1868	638					1580	605
707	30.44	1871	636					1580	604
708	30.48	1876	634					1580	603
709	30.52	1878	633					1579	602
710	30.56	1882	632					1579	602
711	30.6	1884	631					1579	601
712	30.64	1886	629					1578	600
713	30.68	1889	628					1578	599
714	30.72	1892	627					1578	599
715	30.76	1896	625					1577	598
716	30.8	1900	623					1577	597
717	30.84	1904	622					1577	596
718	30.88	1907	620					1577	596
719	30.92	1910	619						
720	30.96	1912	617					1576	595
721	31	1913	616					1577	594
722	31.04	1914	614			1416	35		
723	31.08	1916	613	528	8				
724	31.12	1917	611			1415	35	1576	593
725	31.16							1576	593
726	31.4					1415	36		
727	31.84					1412	38		
728	31.88					1412	37		
729	32.24			522	8				
730	32.28							1580	600
731	32.36							1581	602
732	32.4							1581	602
733	32.44							1581	603
734	32.48							1581	604

Figure 62: Archive of all tracks extracted from raw data, after Flight Campaign 1. One track data file (csv) is also shown.

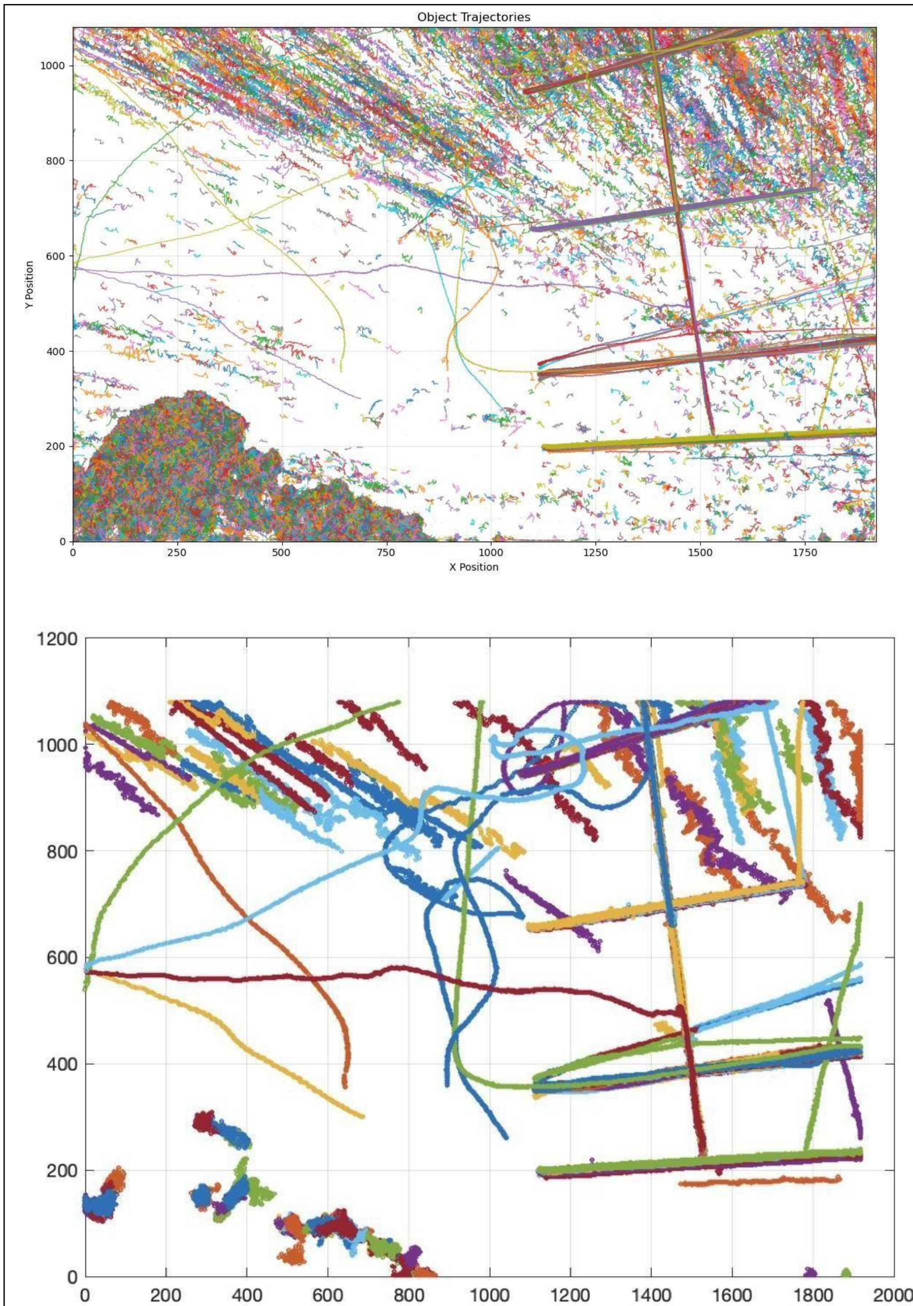
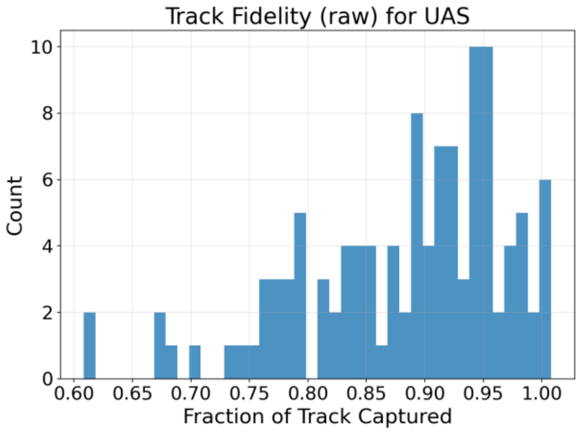
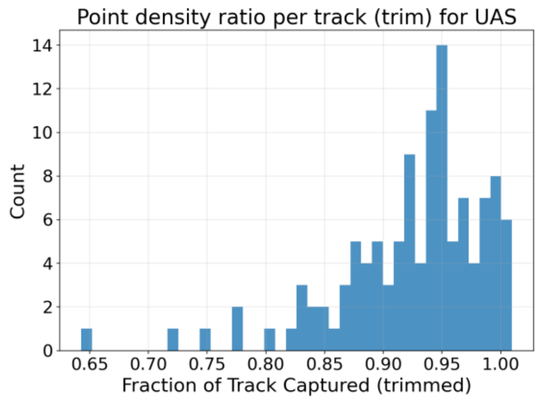
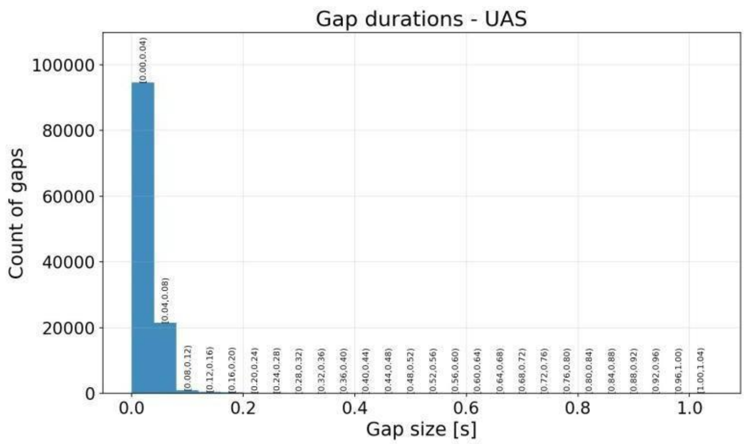


Figure 63: Unprocessed and cleaned tracks from one hour of data (7/23, 14:14 PM CT) from one sensor (Sensor 5) are shown. The cleaned tracks include 113 UAS tracks and 112 other tracks (birds, long cloud edges, and some long-duration ground clutter movement).







mean density (trim)	0.9249
median density (trim)	0.9401

Figure 64: In-frame track fidelity is characterized for UAS and bird tracks using data from Sensor 5 during a ½ hour interval on 7/23. The fractions of data points between the initial and final time of the track that are captured (for the whole track and with 1s trimmed from each end), as well as the durations of gaps on the tracks, are considered. Histograms of each are shown.

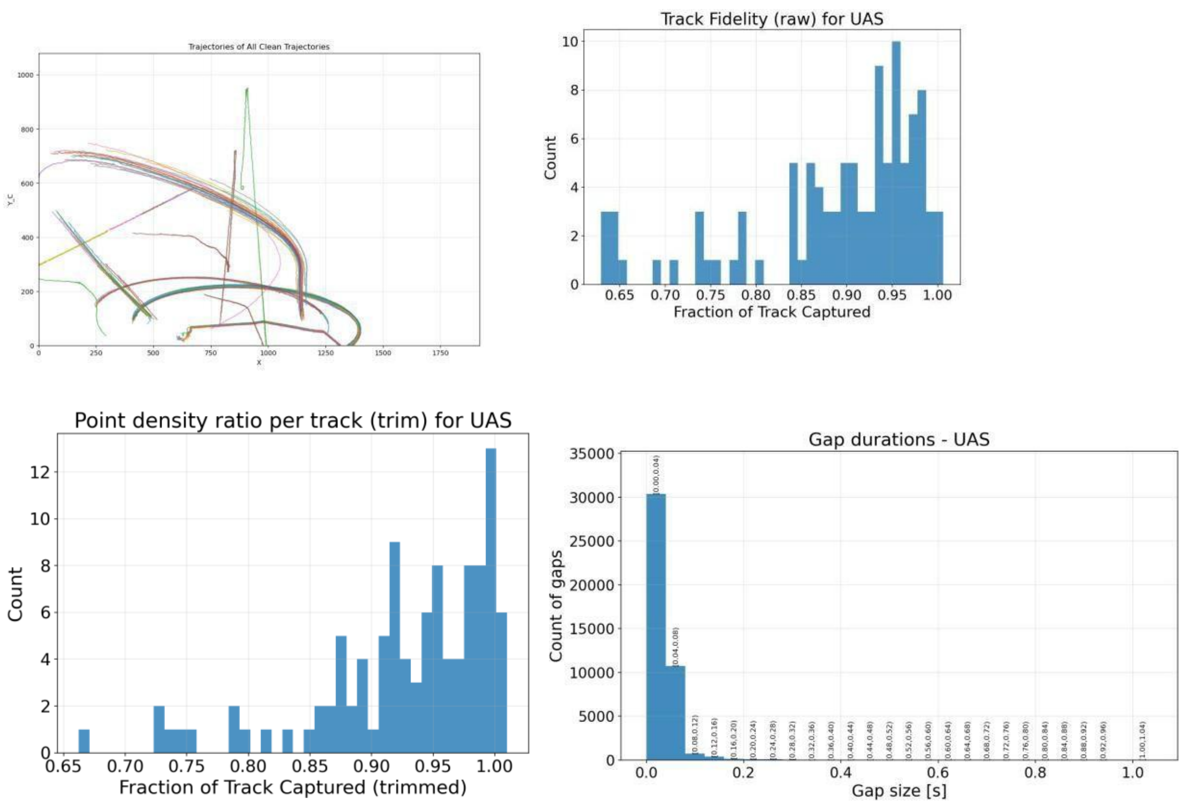
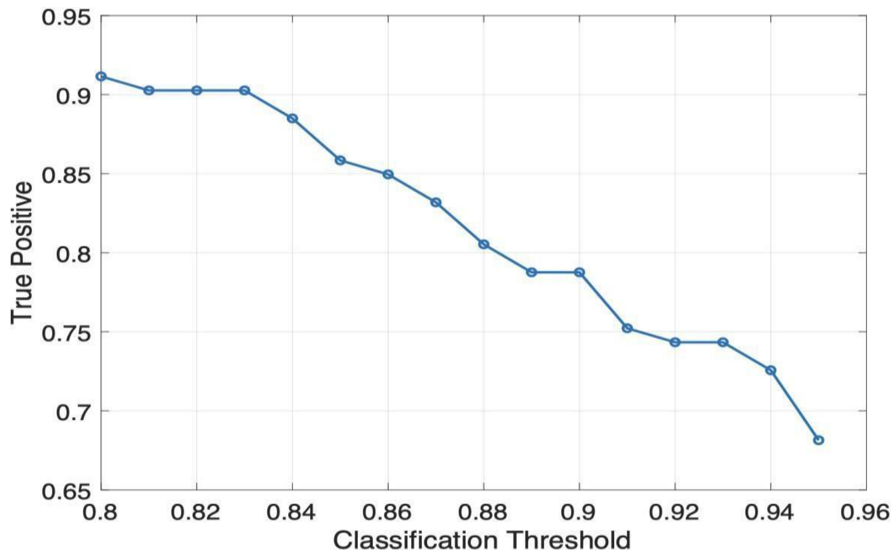


Figure 65: In-frame track fidelity is characterized for UAS and bird tracks using data from Sensor 1 during a ½ hour interval on 7/25. The fractions of data points between the initial and final time of the track that are captured (for the whole track and with 1s trimmed from each end), as well as the durations of gaps on the tracks, are considered. Histograms of each are shown.



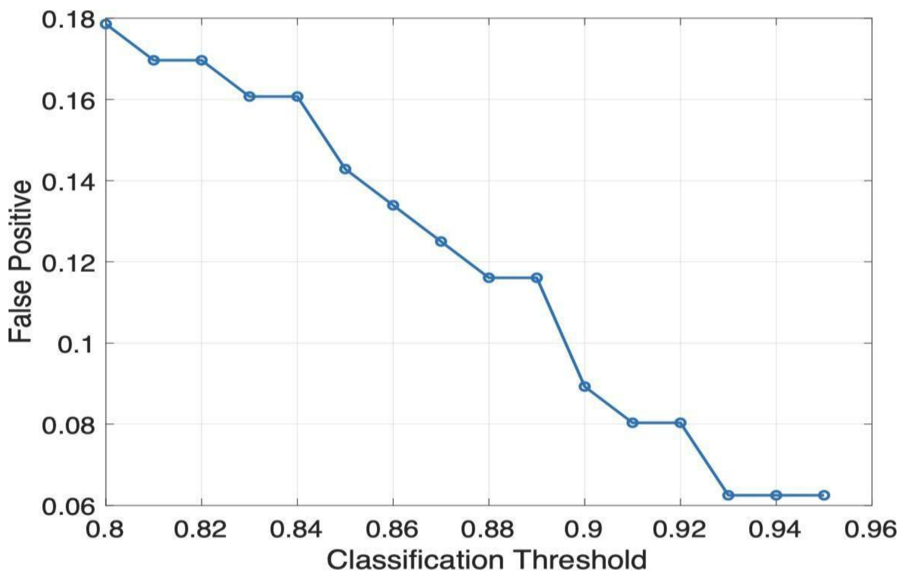


Figure 66: True positive and false positive rates for UASs for a basic object classifier, which uses the correlation coefficient in track segments (3s windows) and then averages this metric over a longer window (7s total starting from detection).

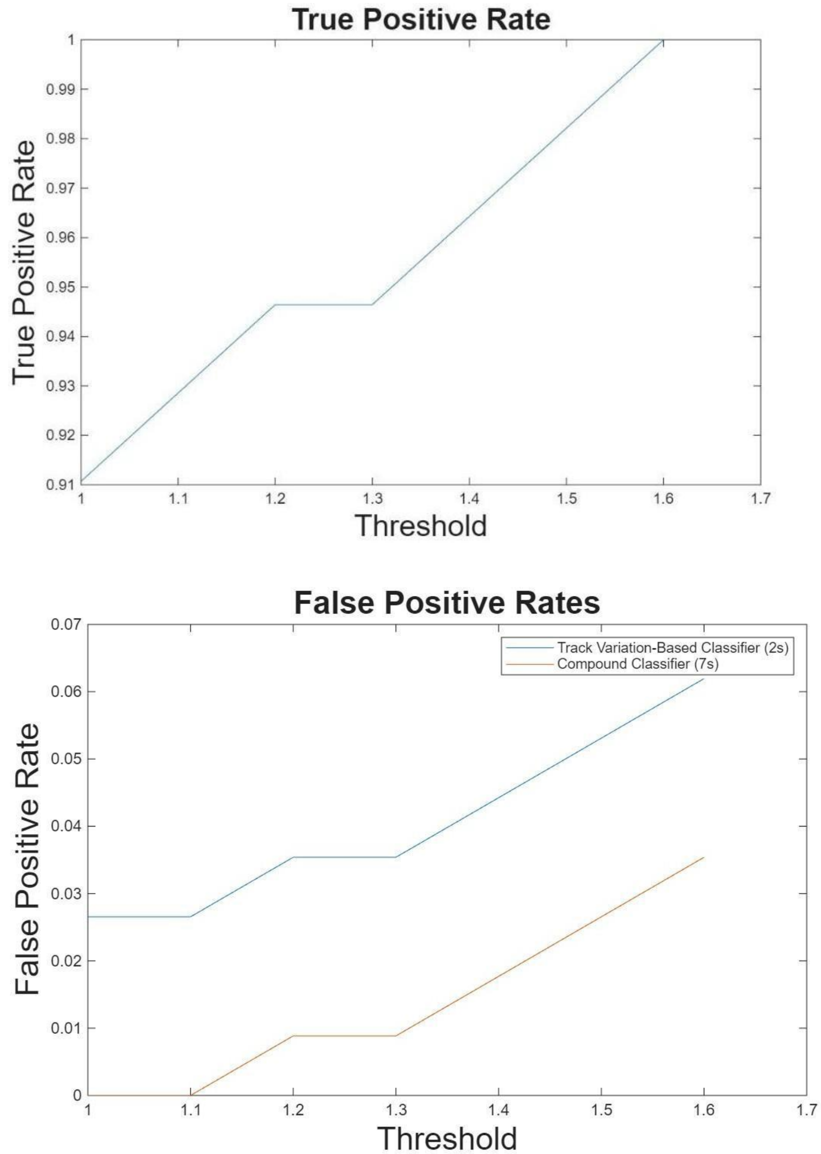


Figure 67: True positive and false positive rates for advanced classifiers. First, a classifier that uses track deviations from straight line motion over 2s intervals is used (blue lines). This classifier is able to effectively distinguish UAS/bird tracks from cloud edges and other background tracks. By combining this classifier with the correlation-coefficient-based classifier, we are also able to fully differentiate UAS and bird tracks using 7s of data.

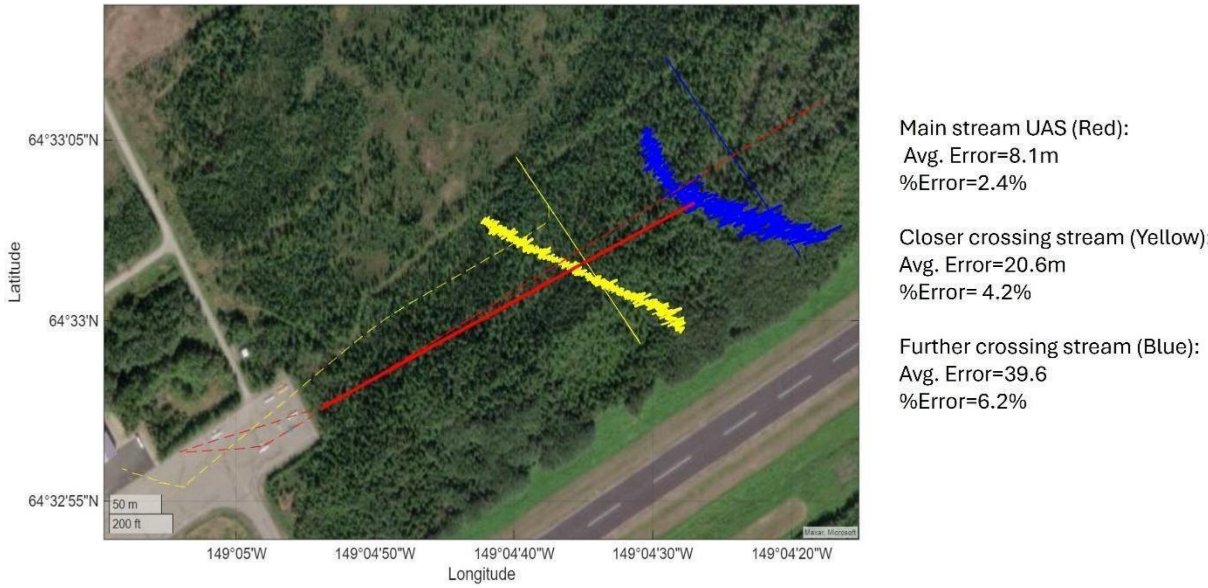


Figure 68: A preliminary performance evaluation of the 3D-Geolocation function is undertaken, via comparison with GPS log data from on board the UASs. Specifically, the mean square errors in the 3D location are evaluated for three UAS tracks. More extensive analysis of the geolocation performance, and its dependence on monitoring-system and UAS/airspace characeristics, is needed.

Metric	Performance
Detection Time	<0.25s for 100% of UASs/birds (+0.25s comm delay)
Track fidelity (in frame)	Tracks maintained for 94% of time points, Almost all gaps (99.5%) are less than 0.2s
Classification (Drone vs Bird/other)	95% TP with 3.5% FP rate in 2s, 98% TP with 1.5% FP in 7s.
3d geolocation (sample tracks)	Average track errors range from 8.1m-39m, at distances between ~300m-800m

Table 3: Monitoring system performance summary. The performance evaluation was conducted from 1 hour of data, from a crossing-traffic flight test on July 23rd.

4.5. Risk-Assessment and Requirements-Development Results

Outcomes of the risk assessment and requirements development for monitoring services are shown.

4.5.1. Risk Assessment Outcomes

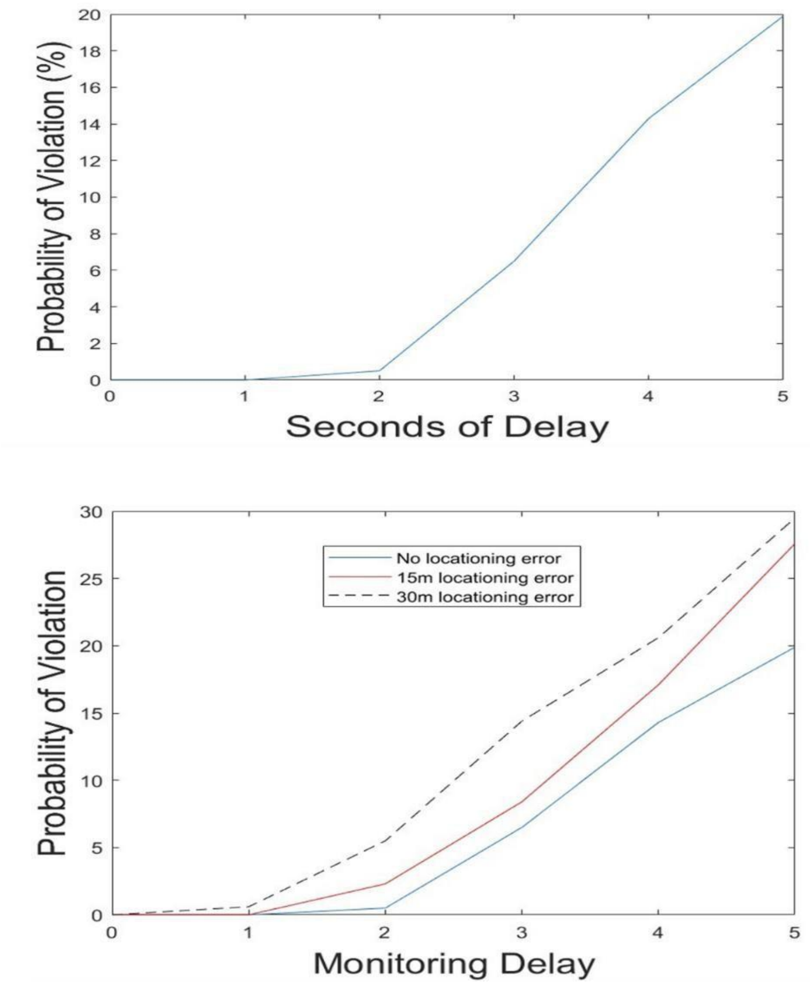


Figure 69: A risk assessment is done for the CONOPS / operational scenario with airspace constraints/requirements developed in Section 3.5 (focused on crossing traffic, see Figure 15) In particular, the probability of a spacing violation is shown as a function of UAS detection delay, for a baseline case and for cases where there is also location error.

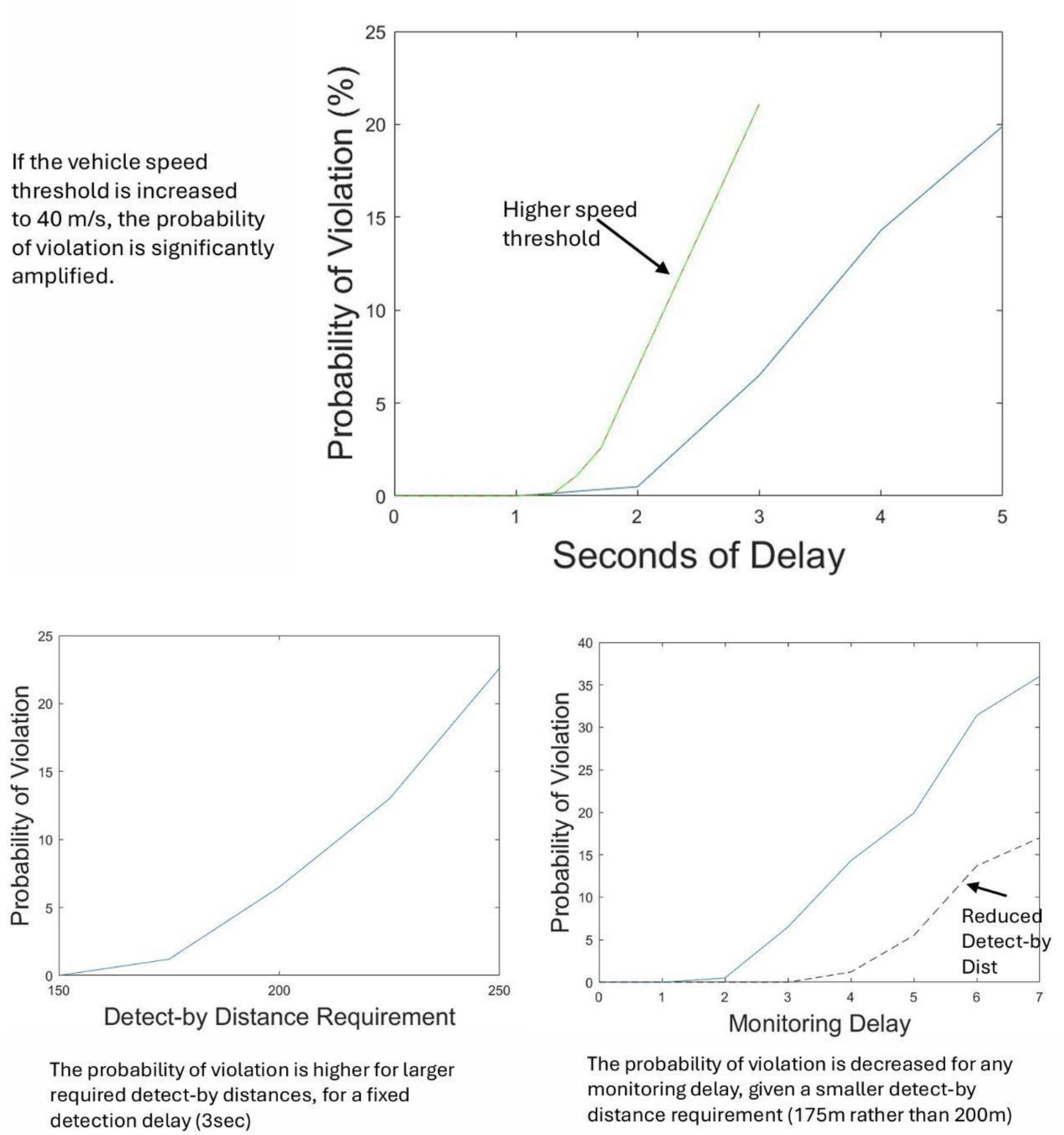


Figure 70: The dependence of the risk on operational parameters and requirements is explored. In particular, the impacts of higher vehicle-speed thresholds (top plot) and detect-by distance requirement (bottom plots) are examined.

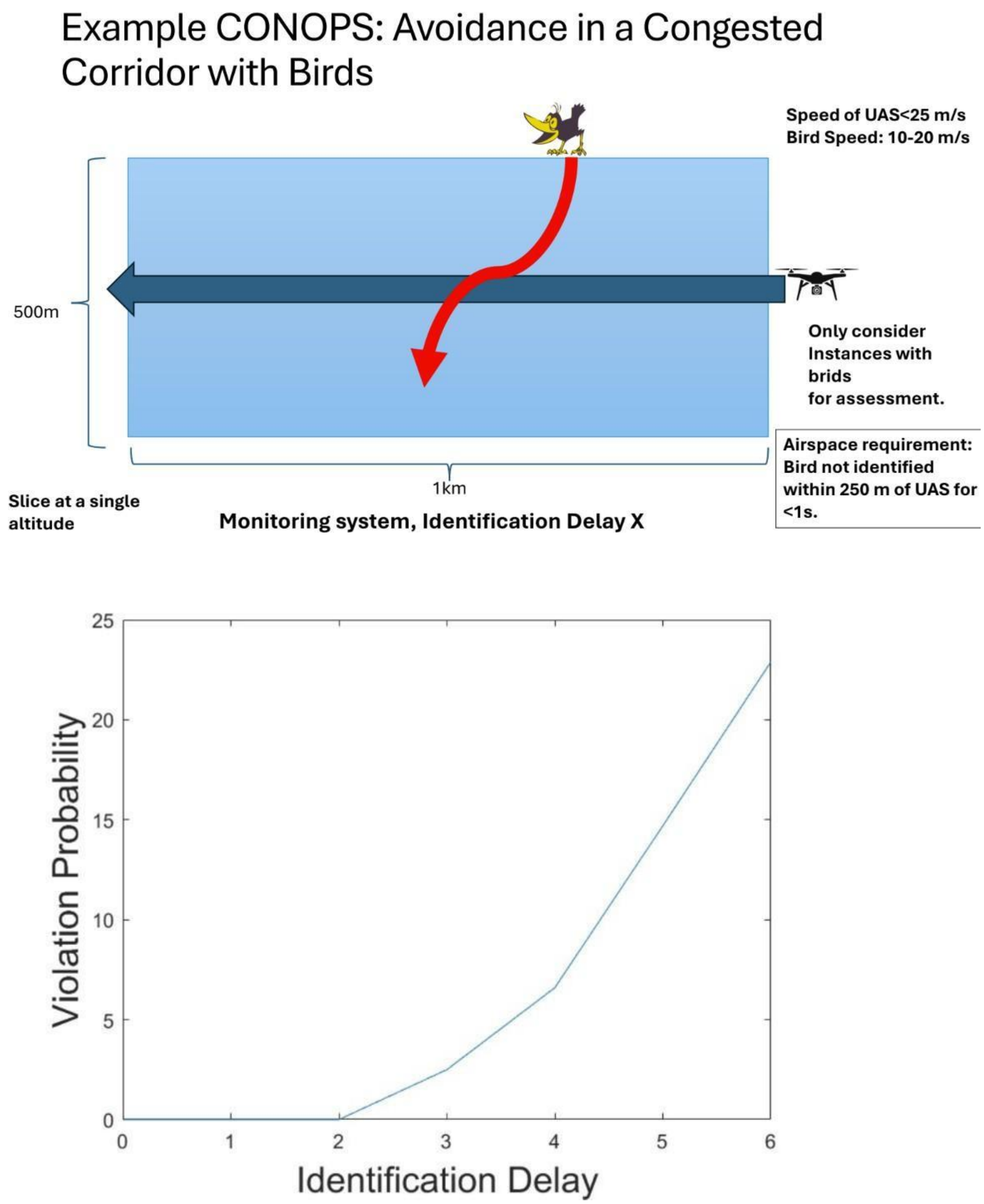


Figure 71: A second CONOPS and operational scenario where bird interactions are also a concern, in addition to UAS cross traffic, is considered. Here, the key airspace requirement is that a bird that is close (within 250m) to a UAS does not remain unidentified for long (more than two seconds). The dependence of the requirements violation probability on classification or identification delay is shown.

4.5.2. Requirements Development Outcomes

- Flight Operations Specifications (across multiple CONOPS/scenarios):
  - Field of operations
    - Convex region, up to 1mi x 1mi
    - May have uneven terrain, obstructions, background road traffic
    - Altitude slice: up to 500 ft AGL, above 50 ft AGL.
  - UASs
    - >2ft in length, <15 feet in length
    - May or may not be be using RemoteID; may or may not be in contact with traffic control (unauthorized).
    - Up to 10 UASs. Up to 2 UASs are unauthorized/non-reporting, requiring monitoring.
    - Maximum speed: 80 mph
  - Additional constraints
    - Birds—yes, up to 10. Birds over 1ft in length are of concern.
    - Crewed aircraft – overflights, but not in field of operations.
  - Air Traffic Control Specs
    - Need to deconflict UASs that come within 250 ft of each other.
    - Need to deconflict UASs from large birds within 100ft.
    - Need to sequence, route, and maintain separation among authorized UASs on a flow.

Figure 72: A comprehensive list of operational requirements and constraints/characteristics is assembled, based on multiple high-density BVLOS CONOPS and associated operational scenarios (specifically, scenarios like the ones considered in Sections 3.5.1 and 4.5.1).

- Monitoring system performance parameters are considered:
  - Volume of airspace monitored (i.e., for which the following performance parameters are considered).
  - Detection performance
    - Z% of UASs detected within Y seconds.
    - X% of other aerial objects (birds, overflights, background traffic) detected with W seconds
  - Classification performance
    - V% of UASs are identified within U seconds
    - T% of other aerial objects identified within S seconds.
  - Tracking performance
    - Max Locationing error < R feet
    - Track forecasting error: Average Location estimation error Q at a look-ahead of P seconds
  - Communication Delay< O seconds

Figure 73: A comprehensive list of monitoring system parameters that are germane to the airspace operational requirements is assembled, and used to create a template for monitoring-system requirements.

- The following are estimates for monitoring system performance requirements, based on quantitative risk assessments of several operational scenarios.
  - Volume of airspace monitored: Field of Operations Slice with 300 ft buffer in each direction
  - Detection performance
    - 99.5% of UASs detected within 1 seconds.
    - 98% of other aerial objects (birds, overflights, background traffic) detected with 2 seconds
  - Classification performance
    - 95% of UASs are identified within 2 seconds
    - 90% of other aerial objects identified within 4 seconds.
  - Tracking performance
    - Max Locationing error < 50 ft
    - Track forecasting error: none set
  - Communication Delay<0.5 s

Figure 74: Preliminary monitoring-system requirements were determined, based on integrative risk assessment of multiple CONOPS/operational scenarios.

4.5.3. Refined Risk Analysis and Requirements Development: Results

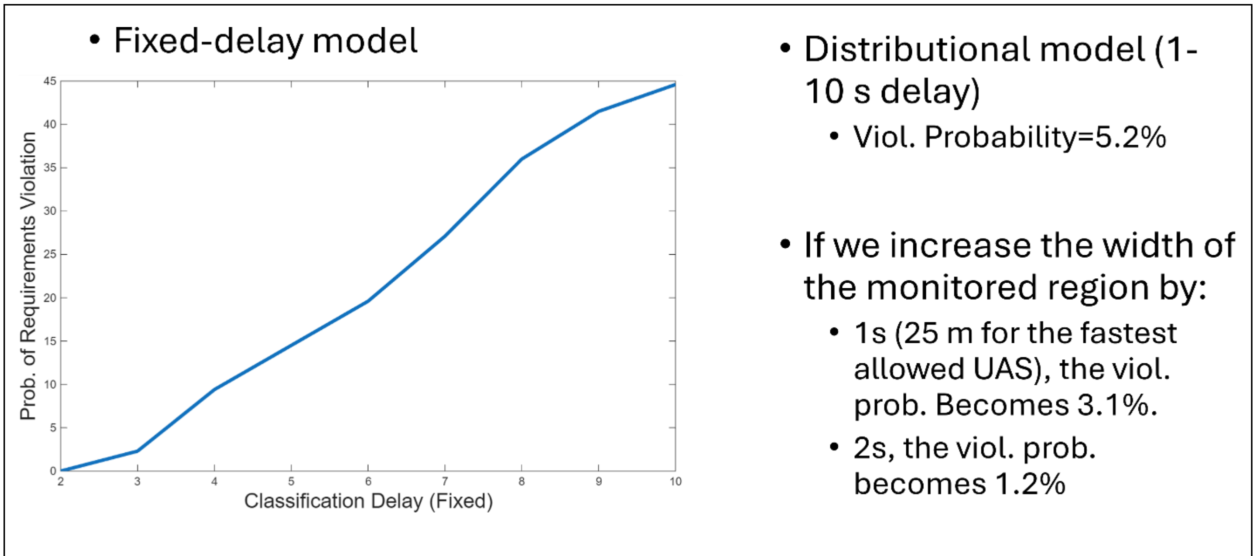


Figure 75: A refined risk assessment is conducted, for the CONOPS and operational scenario where objects near a UAS need to be detected within a short amount of time (see Figure 71). Specifically, rather than assuming a fixed classification delay, we consider a distributional model for classification delay (40% error at 2s, 20% at 4s, 10% at 8s, 5% at 10s). For the distributional-delay case, there is a lower risk for an airspace-requirements violation as compared to a fixed delay equal to its mean.

- The following are estimates for monitoring system performance requirements, based on quantitative risk assessments of several operational scenarios.
  - Volume of airspace monitored: Field of Operations Slice with 300 ft buffer in each direction
  - Detection performance
    - 99.5% of UASs detected within 1 seconds.
    - 98% of other aerial objects (birds, overflights, background traffic) detected with 2 seconds
  - Classification performance
    - 95% of UASs are identified within 2 seconds
    - 90% of other aerial objects identified within 4 seconds.
  - Tracking performance
    - Max Locationing error < 50 ft
    - Track forecasting error: none set
  - Communication Delay<0.5 s

- Classification requirements loosened but specified distributionally.
  - 60% of UAS classified by 2s.
  - 80% by 5s.
  - 90% by 8s.
  - 95% by 10s.
- Buffer area increased to 600ft in each direction.
- Minimum UAS size constraint of ~2ft in diameter.

Figure 76: Modifications to the airspace monitoring system requirements, based on the refined risk assessment and performance evaluation of our monitoring systems. The blue-colored requirements on the right are the modification relative to the prior requirements (shown in black on the left).

4.6. Demonstration and Information Sharing Outcomes

Key demonstration and information-sharing outcomes include:

Outcome 1 – Demonstration of the MOMS at a BVLOS flight test organized by NASA Aeronautics personnel at NASA Langley. Data collection and comprehensive implementation of monitoring functions was demonstrated. A basic online capability was also demonstrated. These test was conducted in hot weather (temperatures >90F, heat index around 100F, direct sunshine with very limited cloud cover), showing that the MOMS operated correctly in hot temperatures. The field test also provided substantial track data of large birds (e.g. eagles, ospreys), include birds in close proximity with UASs. Figure 77 shows tracking and classification of heterogeneous objects based on data collected during the test.

Outcome 2 – Project results were shared with relevant ASTM and RTCA standards groups and/or their cognizant FAA representatives at the beginning, midpoint, and end of the project. These discussions were very helpful for our team to gain insight into the current vision for high-density BVLOS operations. Conversely, we believe that the development of monitoring-system requirements in this project, as well as the specific characterization of our monitoring system, will assist in envisioning services and developing standards for high-density BVLOS UAS operations.

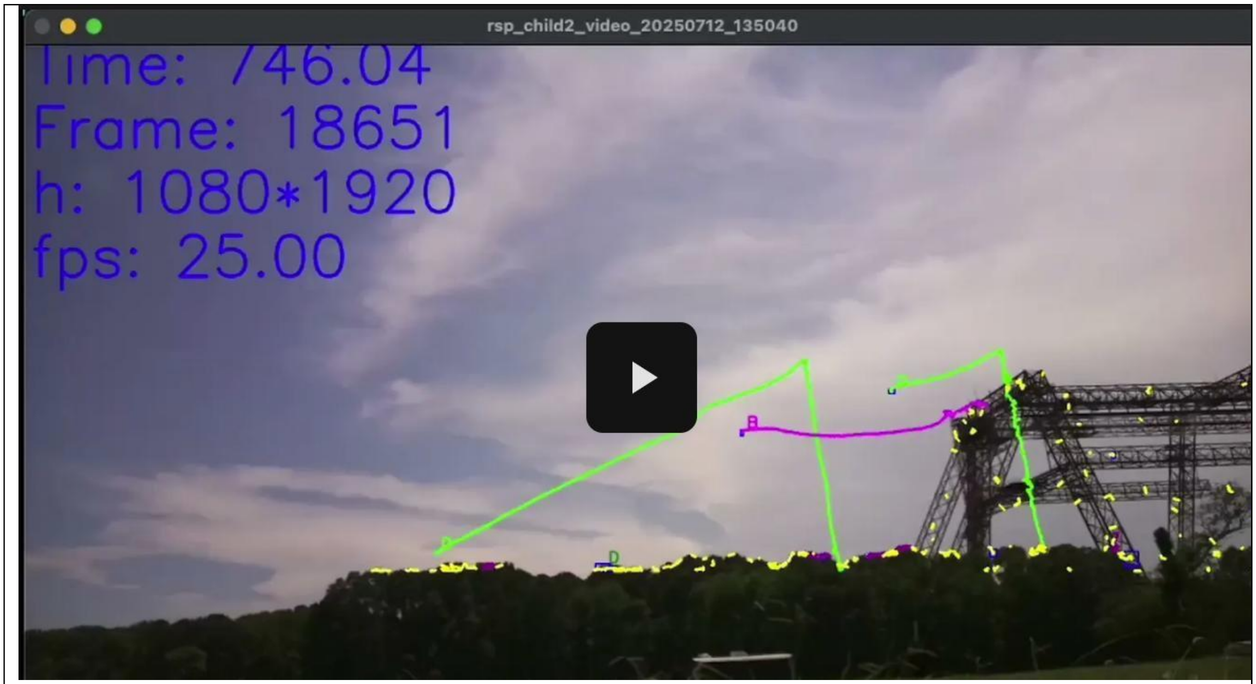


Figure 77: A screenshot of a video from the NASA Langley BVLOS Flight Test is shown, with tracks and classifications overlaid. Two UAS tracks and one bird track are identified. Many long-duration large-bird tracks (e.g. eagles, with wingspans of 4-6 feet) were recorded in this data set.

5. *Conclusions and Recommendations*

The main achievements of this project were the following:

1) The successful development, demonstration, and evaluation of MOMS, a distributed system for monitoring (detection, tracking, classification, 3D-geolocation, prediction) of multiple heterogeneous objects in close proximity in airspace volumes.
2) Completion of flight tests that replicated BVLOS CONOPS requiring deconfliction and sequencing of multiple UAS, such as merging of traffic flows near a future vertiport and crossing-streams management. The flight tests were conducted in complex environments/terrains with varied weather conditions, and multiple repeats as well as variants of each test were conducted. MOMS was evaluated for these flight tests.
3) A risk assessment methodology was developed for monitoring systems used for high-density BVLOS UAS operations, and in turn requirements for monitoring systems were developed.

This research contributes to an already-crowded market of solutions for UAS traffic management and Counter-UAS. Indeed, a number of solutions are available for UAS detection and tracking, which use a variety of sensing and communication technologies (radar, camera, radio-frequency-emission-based, Remote-ID-based, etc). In a complementary direction, several vendors have developed distributed communication/data infrastructures that are enabling technologies for UAS traffic management and counter-UAS. Relative to this marketplace, the direct contributions of the research to UAS surveillance are: 1) enabling simultaneous monitoring of a multiple (2-25+) heterogeneous objects in an airspace volume; 2) supporting advanced monitoring functions beyond detection/tracking including object classification, track/intent prediction, and 3D-geolocation; 3) supporting monitoring in complex terrains and environmental conditions; and 4) providing a systems solution that enables these advanced functions in real time. These contributions reflect a new sensor-agnostic, algorithms-centered approach, which is based on physics- informed extraction of heterogeneous object tracks, followed by track processing to implement advanced monitoring functions. Computations and communications are also customized for track-based analytics, to support a real-time solution. These methodological advances also represent contributions of the work.

Beyond the multi-object monitoring system itself, the project research has also yielded complementary contributions to the broader UAS traffic management domain. These include: 1) development of flight tests that replicate multi-UAS CONOPS in complex environments, with repeated UAS interactions requiring deconfliction; 2) a corpus of data from these flight tests, that can be used for development and evaluation of advanced monitoring algorithms; 2) methods for evaluating the risk introduced by surveillance or monitoring systems within UAS traffic management systems; and 4) initial requirements for monitoring systems used in UAS traffic management.

It is also worthwhile to highlight key lessons learned from the research effort, which point toward directions of future work. One lesson learned is that technology development and evaluation for UAS monitoring systems must be flexible to the varied CONOPS being envisioned, and the range of technologies being used already for UAS operations (e.g., RemoteID, vehicle-board sensing systems, etc). From this perspective, an important direction of future work is to understand how ground-based surveillance can be combined with other situational-awareness modalities for deconfliction and other UAS traffic control needs in high-density airspace. In particular, flight tests that allow for evaluation of multi-technology situational awareness are of importance, as are risk assessments that account for multi-technology integration. A second lesson learned is that real-time monitoring of multiple small mobile objects in outdoor environments is a multi-faceted technical challenge, which requires advances in algorithms, architectures/hardware, and software. The project research achieved advances in these directions toward a comprehensive solution, but much remains to be done to optimize the design across algorithmic, software, and hardware components.

The report is concluded with a few recommendations, based on project outcomes and experiences:

1) Ground-based monitoring can robustly provide accurate, timely, and useful information on heterogeneous mobile objects (authorized and unauthorized UASs, crewed aircraft, birds) flying in close proximity in complex airspace. Therefore, monitoring should be considered as a necessary or important service for airspace situational awareness and traffic control/management for high-density BVLOS operations, regardless of the specific paradigm chosen for future UAS operations.
2) Situational awareness and risk management for high-density UAS operations require a holistic approach, which encompasses sensor design and selection, algorithms, data & communications, hardware, computing/software, and UAS traffic system modeling and analysis. Innovation in these directions has been somewhat siloed and vendor-driven, which has left technical gaps in a practical and comprehensive solution. Research & development should be focused on filling these gaps, by taking an airspace-operations-centric approach.

3) To enable high-density BVLOS operations, aviation authorities and neutral stakeholders crucially need to develop testing and evaluation processes as well as data resources for UAS-enabled airspace operations.

Acknowledgments

Two remarkable graduate students at Texas A&M University, Ms. Chenyan Zhu and Mr. Oluwafemi Ajeigbe, were primarily responsible for developing the MOMS solution, deploying it for field tests, collecting and processing data, and evaluating the its performance. RTX BBN under the direction of Dr. Mengran Xue developed advanced monitoring algorithms for improved classification and for track prediction, and also provided advice in developing MOMS hardware and software. The Alaska Center for UAS Integration (ACUASI) team, led by program manager JR Ancheta and chief pilot Jason Williams, ably planned and managed the two flight campaigns and provided useful piloting experience that helped to refine the flight tests. The FAA staff and contractors involved in the project have provided exceptional technical, conceptual, and administrative support for the work described here.

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