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Corridor-Wide Surveillance Using Unmanned Aircraft Systems

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16. Abstract

The motivation for this research was the lack of a protocol to apply an Unmanned Aerial Vehicle (UAV) platform for traffic data collection and effectively analyze and evaluate incidents in high-speed multi-lane and freeway corridors. The ultimate purpose of this research study was to integrate the use of drones into real-time incident detection to assist in reducing congestion and delay, improve traffic operations, and enhance overall safety in the corridor and contiguous surface transportation networks. Phase I of the research project consisted of a comprehensive literature review, selection and acquisition of drones and drone training to develop the protocol, data collection using the drone platform and dual sensing technologies, and evaluation of vehicle detection algorithms.

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ACRONYMS AND ABBREVIATIONS

AADT	Average Annual Daily Traffic
ACT	Autoridad de Carreteras y Transportación
CA	Camera Angle
CAV	Connected Autonomous Vehicles
DDR	Drone Distance from Road
DH	Drone Height
DOE	Design of Experiments
DOT	Department of Transportation
DTOP	Departamento de Transportación y Obras Públicas
DTPW	Department of Transportation and Public Works
EDC	Every Day Counts
ETC	Electronic Toll Collection
FAA	Federal Aviation Administration
FHWA	Federal Highway Administration
HPMS	Highway Performance Monitoring System
ITS	Intelligent Transportation Systems
LC	Lighting Conditions
M2EA	Mavic 2 Enterprise Advanced
NICR	National Institute for Congestion Reduction
PIC	Pilot in Command
PRHTA	Puerto Rico Highway and Transportation Authority
RGB	Red Green Blue
RLC	Red Light Camera
RM	Ramp Meter
RTK	Real Time Kinematic
sUAV	Small Unmanned Aerial Vehicle
TBD	To Be Determined
TIM	Traffic Incident Management
TIS	Traveler Information System
TMC	Transportation Management Center
TSC	Traffic Signal Coordination
TSP	Transit Signal Priority
UAG	Unmanned Aircraft General
UAS	Unmanned Aircraft Systems
UAV	Unmanned Aerial Vehicles
US	United States
USDOT	United States Department of Transportation
USF	University of South Florida
UPRM	University of Puerto Rico at Mayaguez

EXECUTIVE SUMMARY

The mission of the National Institute for Congestion Reduction (NICR) is to provide multimodal congestion reduction strategies that leverage advances in technology, "big data" science, and innovative transportation options to optimize the efficiency of the transportation system for all users, specifically those battling congestion on freeway corridors, as stated in its Fourth Pillar. NICR 4-3: Corridor-Wide Surveillance Using Unmanned Aircraft Systems (UAS) is a joint research effort formed between the University of South Florida (USF) and the University of Puerto Rico at Mayaguez (UPRM).

The motivation for this research was the lack of a protocol to apply an Unmanned Aerial Vehicle (UAV) (drone) platform for traffic data collection and effectively analyze and evaluate incidents in high-speed multi-lane and freeway corridors. The ultimate purpose of this study is to integrate the use of drones in real-time incident detection to assist in reducing congestion and delay, improve traffic operations, and enhance overall safety in the corridor and contiguous surface transportation networks.

The research approach of the project consists of a comprehensive literature review, the selection and acquisition of drones and drone training to develop the protocol, data collection using the drone platform and dual sensing technologies, and evaluation of vehicle detection algorithms.

A comprehensive literature review was conducted to document the findings of existing research relevant to the use of drones in traffic management. Transportation topics such as freeway facilities, level of service, bottlenecks, and freeway management were reviewed for a better understanding of the project. The use of UAS and their application was also reviewed, including the 14 CFR Part 107 regulation, safety concerns, restrictions, and specifications regarding the use of UAS. This literature review also included experiment design for data collection, comparison of different sensing technologies, and real-time vehicle detection algorithms.

Two types of drone capabilities were selected for this research project—Red Green Blue (RGB) camera (standard vision) and infrared (thermal) camera capabilities. The teams identified and purchased different drones that met those requirements—Autel Evo II 8K, Autel Evo II Pro 6K, Autel Evo II Dual 640T, and the DJI Mavic 2 Enterprise Advanced. The University of Puerto Rico at Mayaguez (UPRM) research team completed hands-on drone training to understand the different controls and commands to safely fly a UAS. The University of South Florida (USF) team assembled training materials for preparation in taking the Unmanned Aircraft General – Small (UAG) exam, part of the 14 CFR Part 107 requirements to become a certified remote pilot. The training also helped to develop and calibrate the before, during, and after procedures for flying a drone, which were integrated into the protocol.

The research team proposed a protocol for the safe use of small UAVs (sUAVs) that complies with 14 CFR Part 107. The protocol was developed with three main parts—before, during, and after flight. Before flight includes explaining the procedure to ensure the safety of the team in preparation for the flight. During flight, the pilot and team must be aware of the environment to be able to act appropriately. After flight, the team ensures that everything was handled

appropriately with all the safety precautions and that information collected is secure. For each part, a prompt list was developed describing the items and actions to take.

Next, a general framework was developed, which describes the experiment design for the data collection of the research project. It consists of seven steps—recognition of and statement of the problem; choice of factors, levels, and ranges; selection of the response variable; choice of experimental design; performing the experiment; statistical analysis of the data; and conclusions and recommendations. The USF team explored real-time vehicle detection algorithms for both visual and infrared cameras and conducted experiments comparing their performance. RGB videos and thermal videos were collected from a UAS platform along highways in the Tampa, Florida, area. Experiments were designed to quantify the performance of a real-time background subtraction-based method for vehicle detection from a stationary camera on hovering UAVs under free-flow conditions. Several parameters were varied in the experiments based on the geometry of the drone and sensor relative to the roadway. The results for stationary data (with UAV hovering at a fixed location) show that a background subtraction-based method can achieve good detection performance on RGB images (F1 scores around 0.9 for most cases), and more varied performance was seen for thermal images with different azimuth angles. The results of these experiments will help inform the development of protocols, standards, and guidance for the use of drones to detect highway congestion and provide input for the development of incident detection algorithms.

As part of Phase II of this project, the team will continue processing RGB and thermal video data from moving stations at different speeds and different locations in Tampa and Mayagüez and will compare the performance of vehicle detection algorithms. The team also will work on developing algorithms to identify non-recurrent congestion that could be caused by incidents. Finally, the team will discuss with local Traffic Management Centers (TMCs) the potential implementation of the drone platform for traffic data collection and algorithms for identifying incidents in real-time.

COVID-19 has greatly affected how people live and function, but UAVs have proven that they can work during a pandemic to ameliorate certain aspects of everyday life. In the first year of this research project, the progress was compromised and paused due to the four-month quarantine in Puerto Rico and Florida; starting in March 2020, citizens could not leave their homes unless it was considered necessary, such as grocery shopping and visiting pharmacies, hospitals, hardware stores, etc. However, the team worked on the comprehensive literature review, obtained 14 CFR Part 107 Remote Pilot Certificates, identified variables for the experiment design, and developed a protocol to ensure the safe use of UAS.

CHAPTER 1: INTRODUCTION

1.1 BACKGROUND

Congestion usually relates to an excess of vehicles on a portion of a roadway at a particular time, resulting in slower speeds—sometimes much slower—than normal or "free flow" speeds. Congestion often means stopped or stop-and-go traffic (FHWA 2020). Congestion generally is caused by seven factors—traffic incidents, work zones, weather, fluctuations in normal traffic, special events, traffic control devices, and physical bottlenecks. When the capacity of a highway section is exceeded, traffic flow breaks down, speeds drop, and vehicles crowd together. These actions cause traffic to back up behind the disruption (FHWA 2020). There are three types of traffic flow behavior that will cause traffic flow to break down—"bunching" of vehicles as a result of reduced speed, intended interruption to traffic flow, and vehicle merging maneuvers (FHWA 2020).

Surface transportation system users have developed strategies to deal with increased congestion and reduced reliability. For this, the use of technologies in the transportation field is critical to implement. Unmanned Aerial Vehicles (UAVs) (drones) can be such a tool for battling congestion in selected corridors. UAVs were first used for military purposes; as of 2006, the Federal Aviation Administration (FAA) allowed their use in the US civilian airspace due to the devastation caused by Hurricane Katrina (Daly, 2012-2020). Figure 1 shows the trend of the use of these vehicles throughout the years, starting in 1849 as an explosive balloon in Austria (Faraz, 2018). These vehicles currently provide a platform that can carry cameras and sensors for collecting real-time traffic information, especially for corridors under congested conditions, when traditional loop detectors do not work properly, and where there is a lack of other means of traffic monitoring. As an alternative, Road Rangers continuously patrol the roadways monitoring traffic crashes and stranded motorists to respond to those incidents. Continuously patrolling along roadways in this manner is both costly and man-power intensive.

The use of UAS has grown significantly in the US and worldwide. The FAA recognizes recreational and commercial primary classifications for drones—recreational drones are used for public enjoyment and commercial drones are used for inspection of facilities, emergency response, cinematography/film industry, traffic enforcement, incident management, medical product delivery, and military operations, among others. Figure 2 illustrates the trend of the use of UAS in the US (FAA, 2021).

On December 21, 2015, the FAA online registration system for recreational UAS went into effect, and almost 990,000 recreational UAS owners had registered as of December 2019. Commercial drone online registration opened in April 2016; since then, over 385,000 drones have been registered. In 2016–2018, commercial drone registrations increased slightly, with about 90,000 registrations, and rapidly grew in 2018–2019, with about 300,000 registrations (FAA, 2021).

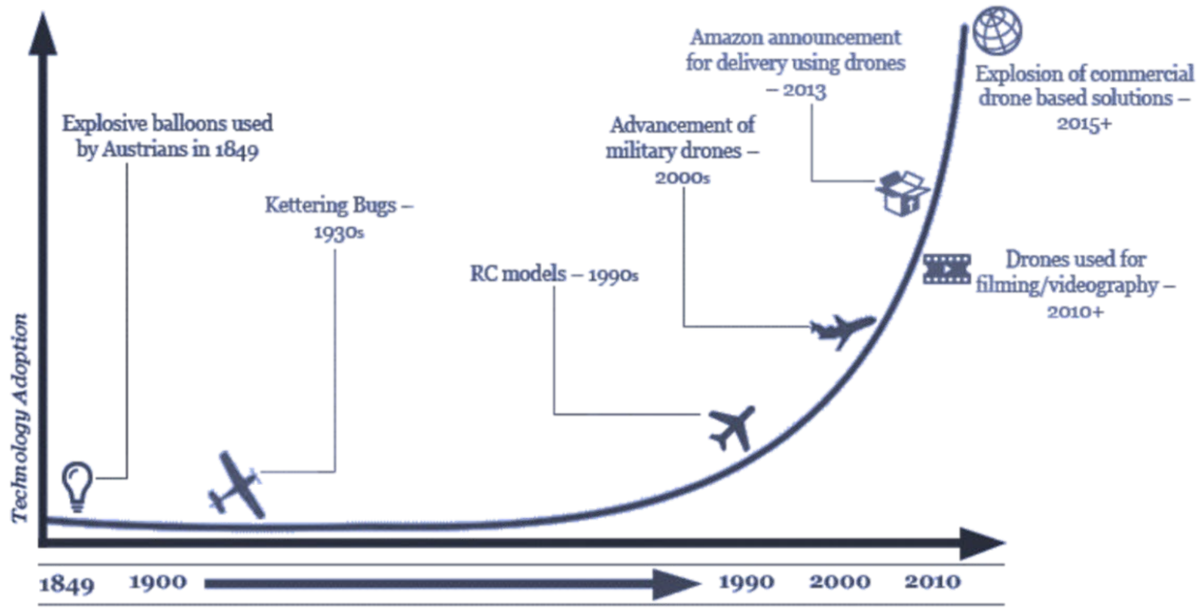


Figure 1: Timeline of Drones and Their Applications
Source: Adapted from Faraz, 2018

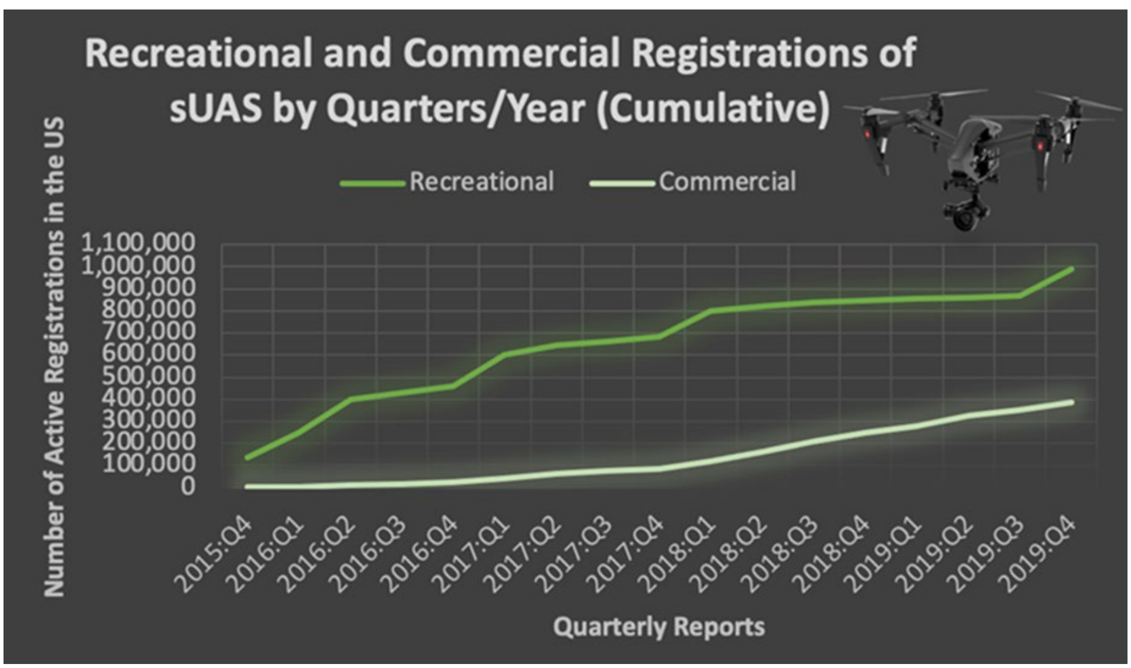


Figure 2: Cumulative Online Commercial and Recreational sUAS Registration, 2015–2019
Source: Adapted from FAA Aerospace Forecast

UAVs are increasingly being used by state and local transportation agencies for a variety of purposes. Infrastructure inspection and disaster management (e.g., rockfall inspection, damage assessment, flood/ice jam monitoring, etc.) are the most common applications of UAVs by these agencies, but there is increasing interest in using the technology to monitor traffic in real time

(Plotnikov et al., 2018). The US Department of Transportation (USDOT) developed a survey to determine how state DOTs were using UAS. The results were divided primarily into the categories of inspections, surveillance, research, studies, surveying, and data collection. Figure 3 shows all US states where UAVs are used according to that survey. By 2018, 39 of 50 states, including Puerto Rico and Florida, were using UAVs daily, primarily for bridge inspections, representing 53 percent of total inspections performed. Other uses include roadway conditions inspection at 18 percent and rockfall, airport, high mast pole, solar panel, and structural inspections at 6 percent each, as shown in Figure 4(a).

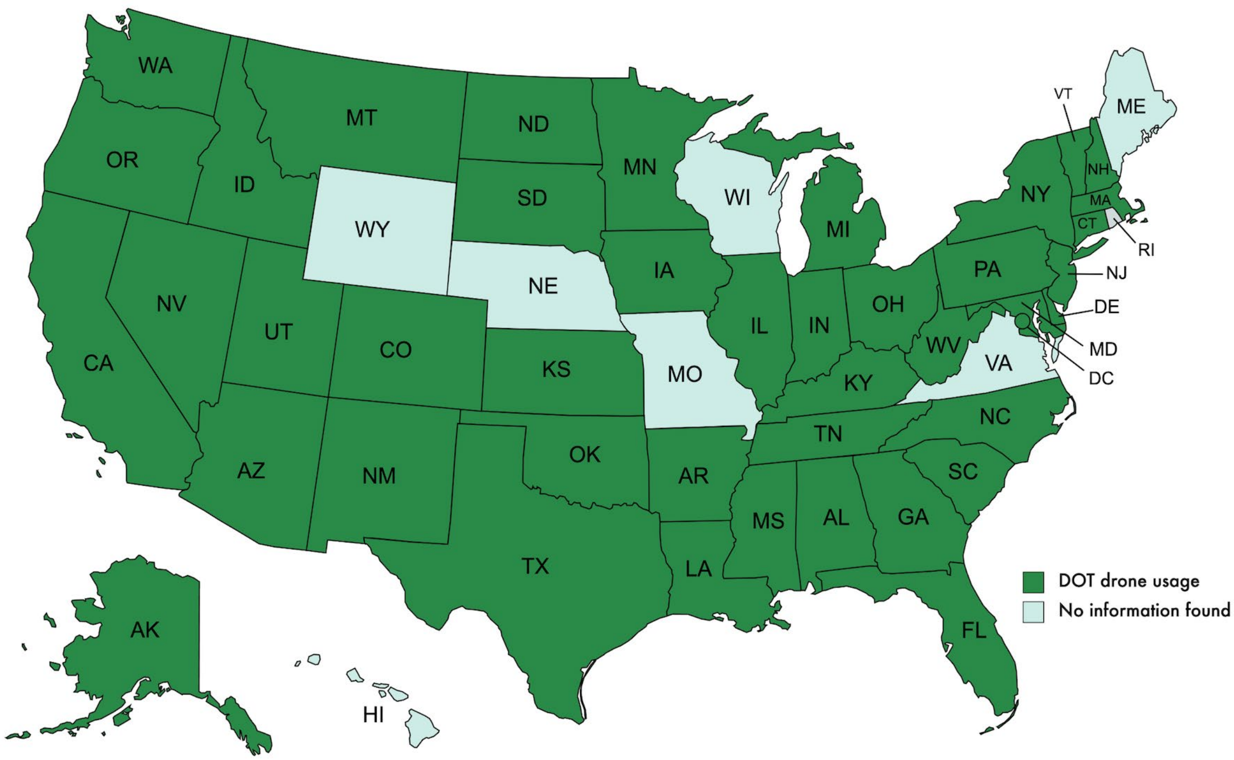
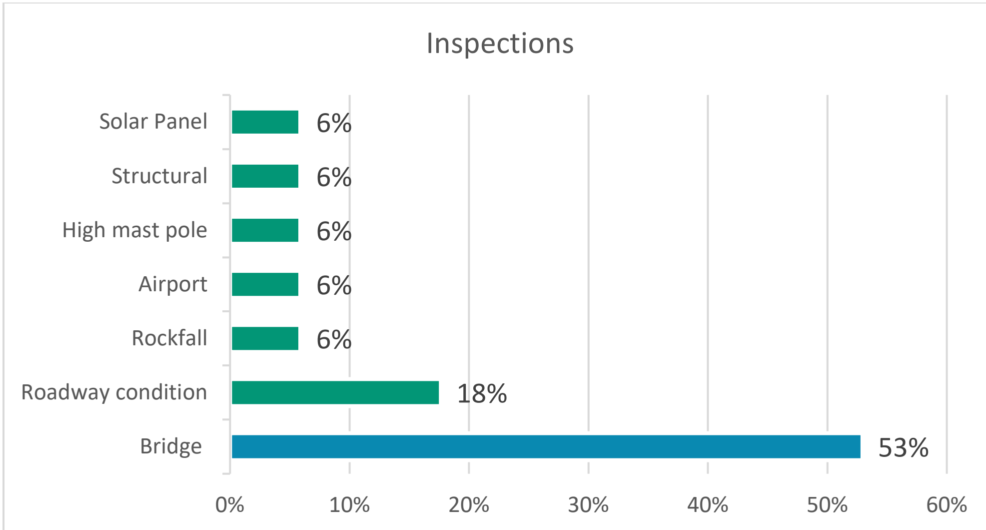
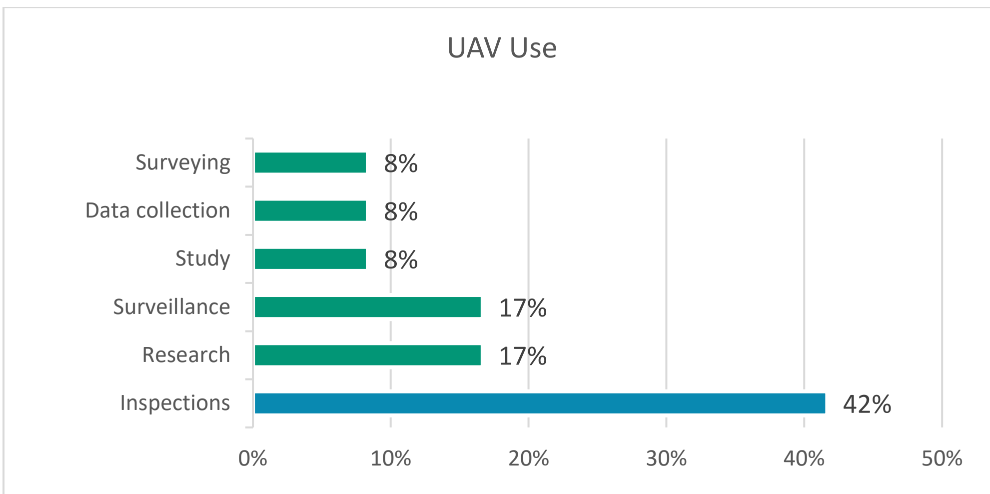


Figure 3: State DOT Drone Usage Survey
Source: Adapted from WTKN, 2021

The Southeastern region represents 29 percent of total inspections performed in the US (Figure 4 (b)), but 42 percent of the activities in that region are inspections, followed by research and surveillance at 17 percent each and study, data collection, and surveying at 8 percent each. Inspections performed in this region include bridges, on-water bridges, high mast poles, and other structures, and studies conducted are on rights-of-way and feasibility to promote traffic safety. The surveillance and monitoring performed pertained to incident scenes, namely airborne and airport obstruction assessments.



(a)



(b)

Figure 4: UAV Use in US: (a) Inspections, (b) Use in Southeastern US

In Puerto Rico, the use of UAVs is growing rapidly. Government agencies and the private sector use them for inspections, assessments, photogrammetry, 3D mapping, crash reconstruction, design and construction, and emergency response. After Hurricane Maria in 2017, UAVs were an important tool for assessment of damages.

Traditionally, vehicle loop detectors, radar detectors, cameras, and other conventional sensors are used for measuring and monitoring traffic conditions; however, they are limited to fixed sites. Roadway incidents cause a reduction of road capacity and lead to significant congestion and vehicle delay if not addressed quickly. Automated detection of incidents with traditional sensors has been developed but is not applied widely. Road Rangers continuously patrol roadways, looking for collisions and stranded motorists and responding to those incidents, but continuously patrolling roadways is both costly and manpower-intensive. UAVs offer the opportunity to rapidly and autonomously reconnoiter large sections of roadway, with minor investment in fixed infrastructure. Using UAVs, sensors such as regular and infrared (thermal) cameras can collect traffic information, and real-time incident detection algorithms can be developed for prompt response to detected incidents.

The mission of the National Institute for Congestion Reduction (NICR) is to provide multimodal congestion reduction strategies that leverage advances in technology, “big data” science, and innovative transportation options to optimize the efficiency of the transportation system for all users, specifically those battling congestion on freeway corridors as stated in its Fourth Pillar. NICR funded this research project at the University of South Florida (USF) and the University of Puerto Rico Mayaguez (UPRM) to address the lack of a protocol ensuring the safe use of UAS in transportation applications, conduct an in-depth investigation of the performance of vehicle detection algorithms with data collected from different sensing technologies, and develop effective real-time incident detection methods for high-speed multi-lane and freeway corridors. The research was planned for two phases; this report summarizes the research efforts of Phase I.

1.2 RESEARCH OBJECTIVES

Phase I of the joint UPRM/USF research consists of three main objectives—1) to develop a protocol for the use of UAS; 2) to monitor freeway traffic conditions that complies with 14 CFR Part 107 of FAA regulations and ensure the effective and safe use of drones for monitoring corridor-wide traffic conditions; and 3) to identify suitable drones, sensor technologies, and operational parameters by comparing the performance of vehicle detection algorithms using the data collected via a rigorous experimental design. These objectives will serve the ultimate purpose of the research project, which is to integrate the use of drones in real-time incident detection to assist in reducing congestion and delay and to improve traffic operations and overall safety in the corridor and contiguous surface transportation networks.

1.3 ORGANIZATION OF REPORT

This report is organized in six chapters:

- Chapter 1 introduces the previously-presented objectives and scope of the research project, and the organization of the report.
- Chapter 2 discusses the comprehensive literature review of pertinent research and previous studies relevant to the use of drones in surface transportation activities; topics such as object detection, congestion reduction, incidents, bottlenecks, UAS, among others, are included.
- Chapter 3 describes the research methodology.
- Chapter 4 describes protocols and is divided into three parts: before, during and after flight. These three stages of flying a drone are described, and each has a check list to be used for the safety of the team and for the equipment.
- Chapter 5 describes the general framework and includes the selection of the drones for the research project, drone training, and data collection. The experimental data collection and analysis followed the seven step guideline described in Montgomery (2013),

including recognition and statement of the problem, choice of factors/levels/ranges, selection of variables, choice of experimental design, performing the experiment, statistical analysis of the data, and conclusions and recommendations. As noted, in practice Step 2, choice of factors/levels/ranges, and Step 3, selection of variables, are often done simultaneously or in reverse order. In this project, these two steps were done simultaneously. In Phase I, traffic data from stationary UAV (i.e., drones hovering at a fixed location) and dual sensing systems (RGB and thermal cameras) were analyzed. Performance metrics such as Precision and Recall were used to measure the performance of vehicle detection algorithms for the data collected with different heights of a drone above ground, angle of depression, and azimuth of the sensor relative to the roadway. The data analysis will be continued in Phase II in addition to other tasks to understand the impacts of other parameters, e.g., drone speed, ambient lighting, and level of traffic congestion, on the performance of learning-based vehicle detection algorithms.

- Chapter 6 includes conclusions and recommendations based on findings from the literature review, drone training, protocol developed, and data collection and analysis outcomes.

CHAPTER 2: LITERATURE REVIEW

This chapter presents a comprehensive literature review that focused on three main research areas—surface transportation topics, UAV applications and specifications, and experiment design. The technical reports reviewed consisted of studies from other professionals, researchers, federal and state agencies, web pages, regulations, manuals, surveys, and conferences proceedings.

2.1 SURFACE TRANSPORTATION TOPICS

The first research area concentrated on fundamental transportation topics associated with urban congestion, level of service (LOS), queue length, incident management, freeway segment, and capacity. It also includes the seven sources of congestion reported by FHWA (traffic incidents, work zones, weather, fluctuations in traffic, special events, traffic control devices, and physical bottlenecks). Freeway segment aspects such as their elements, major dimensions, and attributes were also considered. The main goal of this comprehensive literature effort was to gain a better understanding of the different sources of congestion and how to address it.

The *Highway Capacity Manual* (HCM) defines a freeway as a divided highway with full control of access and two or more lanes for the exclusive use of traffic in each direction (FHWA, 2017). Freeways are composed of a basic freeway, ramp junction, and weaving segments. A basic freeway segment consists of areas without the influence of a ramp or another segment. Weaving segments are formed when a merge area is closely followed by a diverge area or when an on-ramp is closely followed by an off-ramp and the two are joined by an auxiliary lane (TRB, 2000). On freeways, all entering and exiting maneuvers take place on-ramps that are designed to facilitate the smooth merging of on-ramp vehicles into the freeway traffic stream and smooth diverging of off-ramp vehicles from the freeway traffic stream onto the ramp (TRB, 2000). Figure 5 shows the segmentation of a freeway facility.

The Greenshields model, used to determine the LOS of roadway segments, was studied for possible incorporation in the proposed research study. The model, which dates to 1935 (Greenshields, 1935), is still taught in Transportation Engineering classes and explains the relationship between the variables of traffic flow, vehicle speed, and traffic density. This model is a macroscopic approach based on the hypothesis that the relationship between speed and density is linear with a negative slope—as density increases, vehicle speed decreases. As traffic flow can be described as the multiplication of density times speed, equations for the relationships between flow and density as well as flow and speed can also be developed. The latter relationship is mainly used to determine the LOS for highway segments (Hoel et al., 2008).

LOS is a qualitative measure that describes the performance of highways that are operating at volumes less than the capacity of the highway itself. It consists of a grade-system from A through F and considers how the conditions of the highway are perceived by the drivers (Hoel et al., 2008). LOS A indicates free-flow speeds and optimal conditions; thus, drivers are influenced by the geometric characteristics of the highways. As vehicle volume (i.e., traffic flow) increases, density increases as well but vehicle speeds decrease, thus changing the LOS of the highway.

LOS F indicates when the traffic volume exceeds the capacity of the highway; queues form, and the highway operations are "highly unstable."

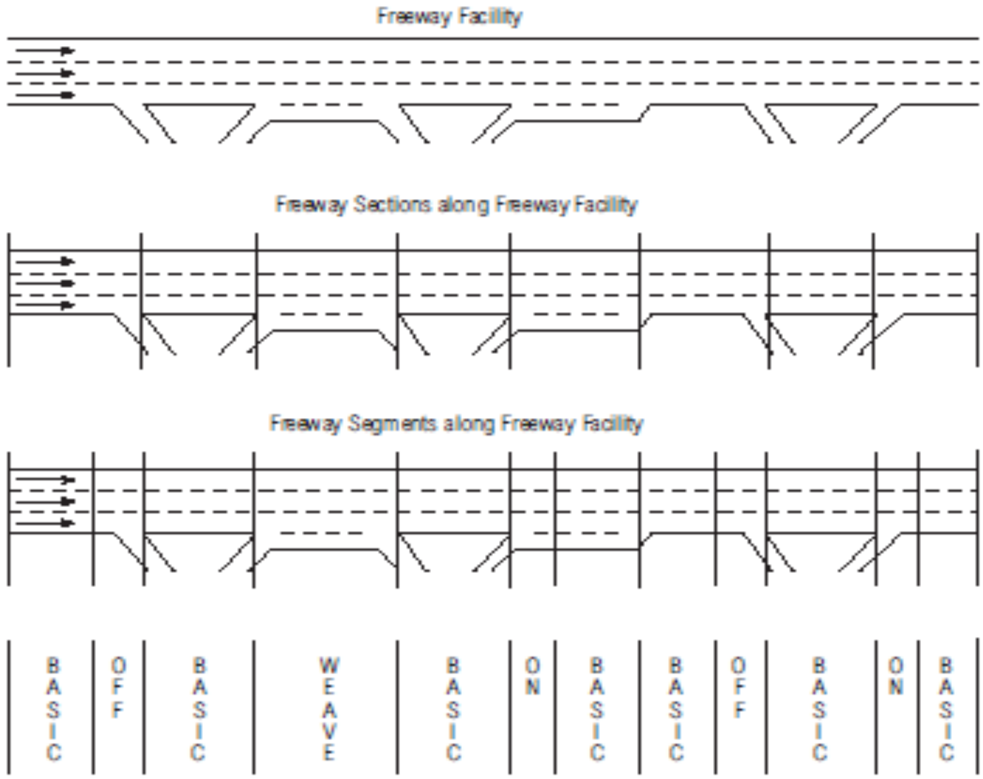


Figure 5: Conversion of Freeway Section into Freeway Segment
Source: HCM, 2000

The LOS for freeway segments is determined by the density obtained from the slope of the relationship between flow and speed, as shown in Figure 6. A range of densities corresponds to each LOS, i.e., densities of 0–11 passenger-cars per mile per lane (pc/mi/ln) represent a LOS A, 11–18 pc/mi/ln are LOS B, and so on. Once the density reaches 45 pc/mi/ln, the LOS is F and congestion forms. Incidents in freeway segments that result in a lane closure or slower speeds affect the operational performance of the highway even if traffic volume has not increased.

Traffic congestion is usually the result of traffic demand exceeding capacity. According to the HCM (2016), the definition of capacity establishes using "the maximum sustainable flow rate at which vehicles reasonably can be expected to traverse a point or uniform segment of a lane or roadway." The definition also specifies that environmental and physical conditions should be taken into consideration to calculate capacity. Therefore, a basic model to analyze traffic congestion in corridors should include determining both demand and capacity.

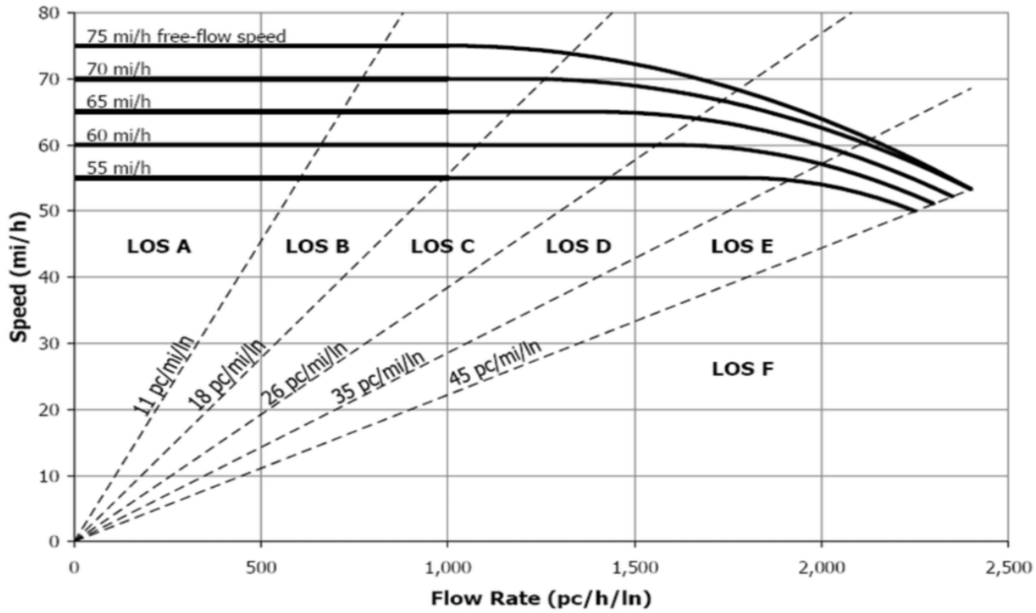


Figure 6: LOS for Freeway Segments
Source: HCM, 2010

In the context of freeway corridors, localized constrictions of traffic flow or restricted capacity segments are typically called bottlenecks (FHWA, 2020). Initially, a bottleneck can be associated with eliminating one lane or reducing other dimensions of the cross-section elements of a particular freeway segment. However, many other factors affect capacity. Therefore, it is a dynamically changing feature that needs to be estimated.

Bottlenecks represent 40 percent of the causes of congestion, as shown in Figure 7. They can be categorized as recurrent, which are predictable at a particular time of day, and non-recurrent, which are random and can happen at any time. Overdemand of volume is the signature trigger of recurrent bottlenecks. The loss of capacity triggers the non-recurrent bottlenecks that typically occur because of an incident or a short-term overdemand by a spot event. For dissipation of a bottleneck, when it is recurrent, the volume of the overdemand should return to a manageable level. In the case of non-recurrent bottlenecks, dissipation occurs when the event is over, or demand is lower than the bottleneck capacity.

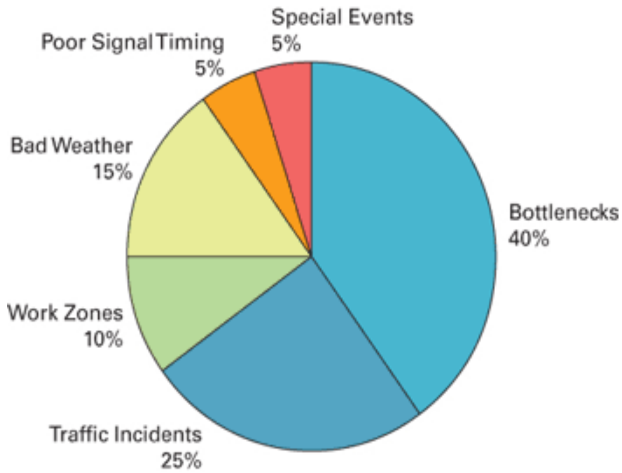


Figure 7: Causes of Congestion
Source: FHWA, 2009

A basic model can be considered to represent bottleneck analysis as presented by the classic reference by May (1999). According to this model, and considering lane reduction, traffic congestion starts in a segment of reduced capacity. A queue is formed upstream, and queue length can be determined by subtracting the number of vehicles arriving at the bottleneck to the bottleneck capacity. The queue length at each time interval for the duration of the queue, and the total delay generated during the congestion period can also be calculated. Hoogendoorn and Knoop (2013) further developed this basic model and presented examples of all these calculations and the corresponding graphical analysis.

The topic of traffic congestion in corridors has been studied for a long time. For example, Cassidy and Bertini (1999) discussed the issues related to traffic bottlenecks at freeways based on observations made in and near Toronto, Canada. Their observations confirm that the capacity of the bottleneck segment is lower during the congestion period than the flow measured before the formation of the queue. This reduction in the maximum flow rate is an interesting fact that also needs to be incorporated in the analysis of corridor congestion.

Using drones can significantly improve corridor surveillance and reduce traffic congestion related to incidents. For this research project, drones will help identify bottlenecks related to incident situations that reduce capacity. The algorithms developed will estimate traffic demand, and with those figures, the characteristics of the traffic congestion can be calculated using the basic model presented before or with even more sophisticated analyses. All this information will be received at the corresponding corridor control center to manage each situation promptly.

Freeway traffic management and operations are the implementations of policies, strategies, and technologies to improve freeway performance (FHWA, 2017). The overriding objectives of freeway management programs are to minimize congestion (and its side effects), improve safety, enhance overall mobility, and provide support to other agencies during emergencies. Technology—specifically Intelligent Transportation Systems (ITS)—is creating an environment in which management and operations can take a major leap forward. Recent advances in surveillance, communications, processing, and information dissemination technologies, with an emphasis on "real-time" applications, have proven to be a significant enabler of freeway management and operations. ITS allows for the rapid identification of situations with a potential to cause congestion, unsafe conditions, reduced mobility, etc.; and then to implement the appropriate strategies and plans for mitigating these problems and their duration and impacts on travel. Freeway management applications have had a positive effect on freeway operations leading to benefits such as increased safety, improved traffic flow, and reductions in traffic delays (FHWA, 2017).

The ITS aim is to achieve traffic efficiency by minimizing traffic problems (Choudhary, 2019). It enriches users with prior information about traffic, local convenience, real-time running information, seat availability, etc. which reduces travel time of commuters as well as enhances their safety and comfort (Choudhary, 2019). Millions of Americans experience ITS every day without even noticing (Chan-Edmiston et al., 2020). These technology tools made possible through ITS both increase efficiency for travelers across the nation and increase the value of existing transportation infrastructure. Today's emerging ITS includes automated driving systems and data exchanges, supports cybersecurity, and uses spectrum and artificial intelligence to meet traveler's needs. American travelers alone derive substantial economic and societal benefits from ITS, estimated at a value exceeding $2.3 billion annually (Chan-Edmiston et al., 2020). Some of the most prominent ITS technologies already deployed across the country include electronic toll collection, ramp meters, red-light cameras, traffic signal coordination, transit signal priority, and traveler information systems.

Among these technologies, ITS deployment appears to have the most broad-based benefit for improved mobility (US DOT, n.d.). There are six primary deployments as part of the USDOT's ITS Technology adoption—Electronic Toll Collection (ETC), Ramp Meter (RM), Red Light Camera (RLC), Traffic Signal Coordination (TSC), Transit Signal Priority (TSP), and Traveler Information Systems (TIS).

ETC supports the collection of payment at toll plazas using automated systems that increase the operational efficiency and convenience of toll collection. Systems typically consist of vehicle-mounted transponders identified by electronic readers located in dedicated or mixed-use lanes at toll plazas. ETC has the potential to significantly increase mobility on the US transportation system. High estimates for ETC's nationwide mobility benefits were over $1 billion per year at 2007 deployment levels (2009 $) (US DOT, n.d.). ETC can reduce delays through the toll area. Vehicular on-board electronic equipment interacts with fee collection infrastructure at the toll booths to automatically collect tolls, thereby reducing the time vehicles otherwise would have spent waiting in queue and at the toll booth itself (Roy et al., 2016).

RMs are traffic signals on freeway ramps that alternate between red and green signals to control the flow of vehicles entering the freeway. Metering rates can be altered based on freeway traffic conditions. Most ramp meters allow only one vehicle through each green light, creating a 4–15 second delay between cars entering the highway. This delay helps reduce disruptions to freeway traffic and reduces incidents that occur when vehicles merge onto the highway (WSDOT, 2021). Without ramp meters, multiple cars try to merge simultaneously. Drivers on the freeway slow down to allow the cars to enter and these slower speeds quickly cause backups. If cars enter the highway in controlled intervals, they are less likely to cause a disruption to the traffic on the freeway. A short wait on the ramp allows drivers to increase their average freeway speed and shorten overall freeway travel times. Ramp meters also reduce the number of collisions that often occur when multiple vehicles merge onto the highway at the same time (WSDOT, 2021).

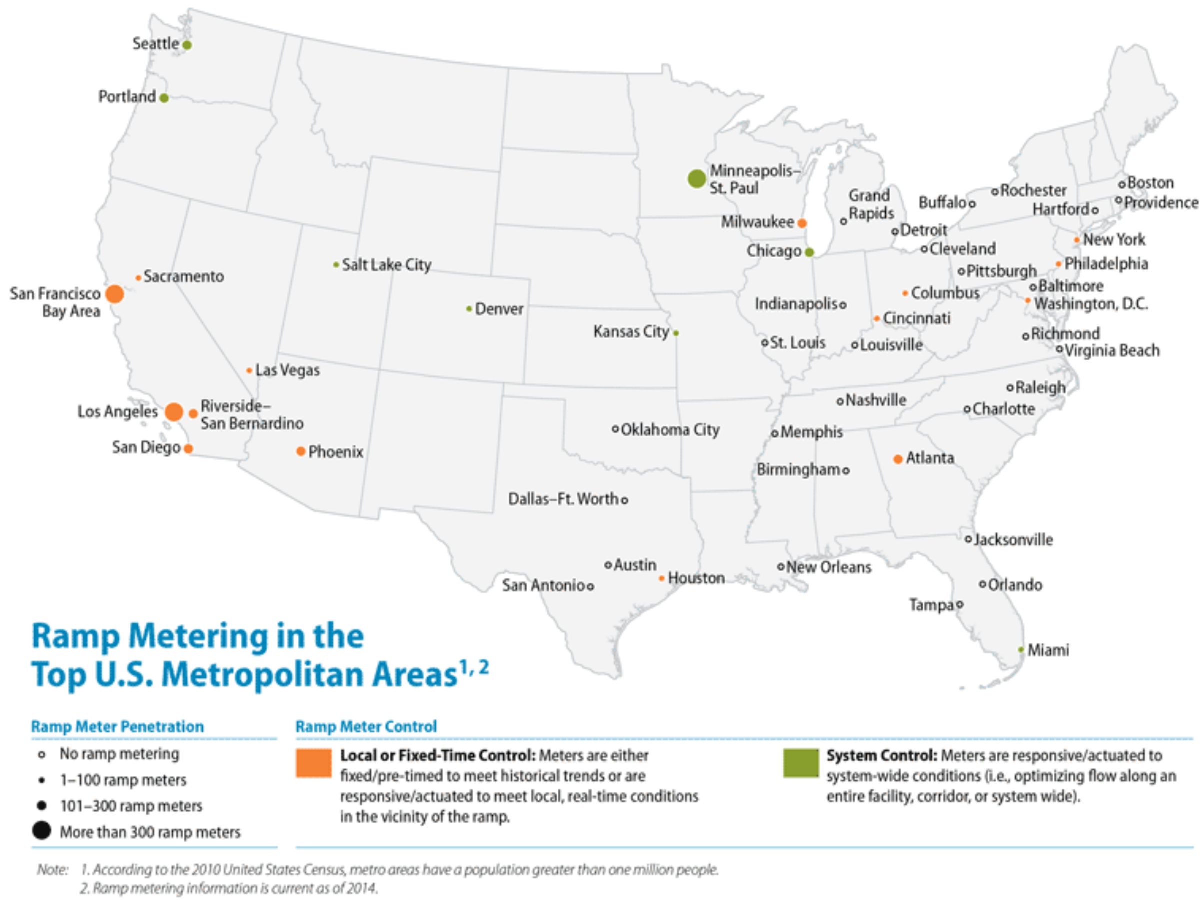


Figure 8: Ramp Metering in Top U.S. Metropolitan Areas
Source: FHWA, 2014

Without ramp meters in operation, multiple vehicles merge in tightly-packed platoons, causing drivers on the mainline to slow down and, sometimes, even stop to allow vehicles to enter. The cascading slower speeds, both on the mainline and the ramp, quickly lead to congestion and sometimes stop-and-go conditions. Ramp meters can break up the platoons by controlling the rate at which vehicles enter the mainline from the ramp (FHWA, 2014). This allows vehicles to merge smoothly onto the mainline and reduces the need for vehicles on the mainline to reduce speed. In addition to breaking up platoons, ramp meters help manage entrance demand at a level that is near the capacity of the freeway, which prevents traffic flow breakdowns. Ramp meters are shown to reduce peak-hour lane occupancies (FHWA, 2014).

RLCs detect a motor vehicle that passes over sensors in the pavement after a traffic signal has turned red. The sensors connect to computers in high-speed cameras, which take two photographs of the violation. Typically, the first photo is taken of the front of the vehicle when it enters the intersection, and the second is taken of the rear of the vehicle when the vehicle is in the intersection. Law enforcement officials review the photograph, and a citation is mailed to the registered owner of the vehicle. RLC benefits appear primarily to be in safety, with high estimates of over $1 billion (US DOT, n.d.). A series of IIHS studies in different communities found that red light violations are reduced significantly with cameras. Institute studies in Oxnard, California, and Fairfax, Virginia, reported reductions in red light violation rates of about 40 percent after the introduction of red-light cameras (IIHS HLDI, 2021). Violations occurring at least a half-second after the light turned red were 39 percent less likely than would have been expected without cameras. Violations occurring at least one second after, were 48 percent less likely, and the odds of a violation occurring at least 1.5 seconds into the red phase fell to 86 percent (IIHS HLDI, 2021).

TSC provides the ability to synchronize multiple intersections to enhance the operation of one or more directional movements in a system. Some examples include arterial streets, downtown networks, and closely spaced intersections such as diamond interchanges (US DOT, n.d.).

TSP gives special treatment to transit vehicles at signalized intersections. TSP systems use sensors to detect approaching transit vehicles and alter signal timings to improve transit performance. For example, some systems extend the duration of green signals for public transportation vehicles when necessary. Because transit vehicles can hold many people, giving priority to transit can potentially increase the person throughput of an intersection. TSP technologies had high annual mobility estimates of over $149.9 million (US DOT, n.d.).

Effective TIS are multimodal and support many categories of drivers and travelers. Traveler information applications use a variety of technologies, including Internet websites, telephone hotlines, and television and radio, to allow users to make informed decisions regarding trip departures, routes, and mode of travel. TIS technologies have had high annual mobility estimates of over $543.1 million (US DOT, n.d.).

A Traffic Management Center (TMC) is the vital unit of ITS. It is a technical system administered by the transportation authority (Choudhary, 2019). A TMC is the hub or nerve center of most freeway management systems (FHWA, 2020). It is where the data on the freeway system are collected and processed, fused with other operational and control data, synthesized to produce information, and distributed to stakeholders such as the media, other agencies, and the traveling public. TMC staff use the information to monitor the operation of the freeway and to initiate control strategies that affect changes in the operation of the freeway network. It is also where agencies can coordinate their responses to traffic situations and incidents.

The role of a TMC often goes beyond the freeway network and the responsible agency, functioning as the key technical and institutional hub to bring together the various jurisdictions, modal interests, and service providers to focus on the common goal of optimizing the performance of the entire surface transportation system. It is essential that the TMC be planned for, designed, commissioned, and maintained to allow operators and other practitioners to control and manage the functional elements of the freeway network (FHWA, 2020).

Traffic Incident Management (TIM) consists of a planned and coordinated multi-disciplinary process to detect, respond to, and clear traffic incidents and restore traffic flow as safely and quickly as possible. Applied effectively, TIM reduces the duration and impact of traffic incidents and improves the safety of motorists, crash victims, and emergency responders (FHWA, 2021). There are numerous benefits to integrating TIM into the transportation planning process at a state or regional level using an objectives-driven, performance-based approach. Transportation planners and traffic incident management professionals are two groups of professionals who traditionally have had little interaction, but there are real and sustainable benefits for incident responders, planners, and the traveling public to be gained when the connection is made. Those benefits start with safer, more efficient transportation system performance for the traveling public. With greater regional support, incidents can be cleared safely in less time, minimizing congestion and the impacts of traffic incidents on overall mobility and safety (FHWA, 2021).

From a transportation perspective, incidents tend to be classified based upon their impact on traffic operations (FHWA, 2017). Transportation agencies have their ranking systems for classifying incidents. Most of them have these characteristics for the classification—traffic flow, impact/delay, incident characteristics, and who responds. TIM has defined the traffic incident elements, as shown in Figure 9 and explained in Table 1.

Around 70 percent of states and territories in the US have TIM programs implemented. In Puerto Rico, the DTPW has the San Juan Metropolitan Area TIM Program, which consists of a planned and coordinated multi-disciplinary effort to detect, respond to, and clear traffic incidents so that traffic flow can be restored as safely and as quickly as possible. Effective TIM reduces the duration and impact of traffic incidents and improves the safety of motorists, crash victims, and emergency responders. Major natural events highlight the importance of TIM as more than a tool for increasing mobility and reducing congestion. Public safety agencies are also acknowledging their roles in responder and motorist safety and secondary incident prevention.

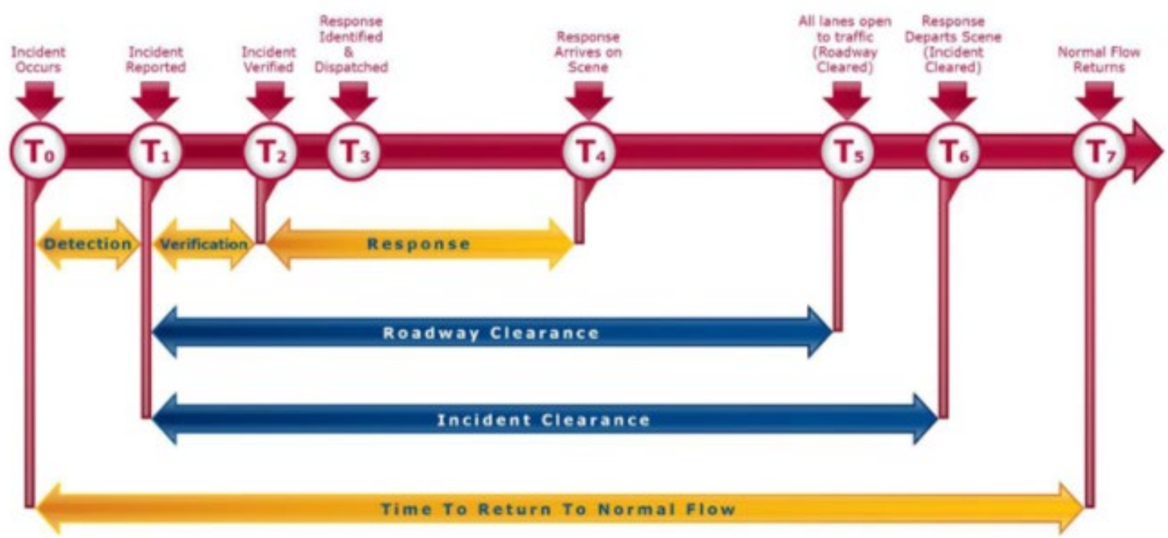


Figure 9: Timeline of Traffic Incident Elements
Source: FHWA, 2015

Table 1: Key Traffic Incident Times

Measure	Definition
Detection Time T1 – T0	Time between the incident occurring and the incident being reported. Detection time is not typically reported due to the fact that the actual time the incident occurred is often unknown.
Verification Time T2 – T1	Time between incident being reported and the incident being verified. TMCs can typically assist with verification through use of their CCTV cameras.
Response Time T4 – T2	Time between the incident being verified and the first responder arriving on scene. Law enforcement may not always be the first party to arrive on scene.
Roadway Clearance Time (RCT) T5 – T1	Time between the first recordable awareness of the incident by a responsible agency and the first confirmation that all lanes are available for traffic flow.
Incident Clearance Time (ICT) T6 – T1	Time between the first recordable awareness of the incident by a responsible agency and the time at which the last responder has left the scene.

Source: FHWA, 2015

In surface transportation, FHWA has developed a vehicle classification scheme for the purpose of counting and classifying all vehicular traffic in accordance with the classification scheme in Figure 10. This scheme separates motorcycles, passenger cars, pick-ups, buses, and different types of trucks, from single-unit trucks to multiple axle combinations. It is important that any vehicle detection algorithm developed for incident detection can distinguish between traditional passenger cars and multi-trailer/axle truck configurations.

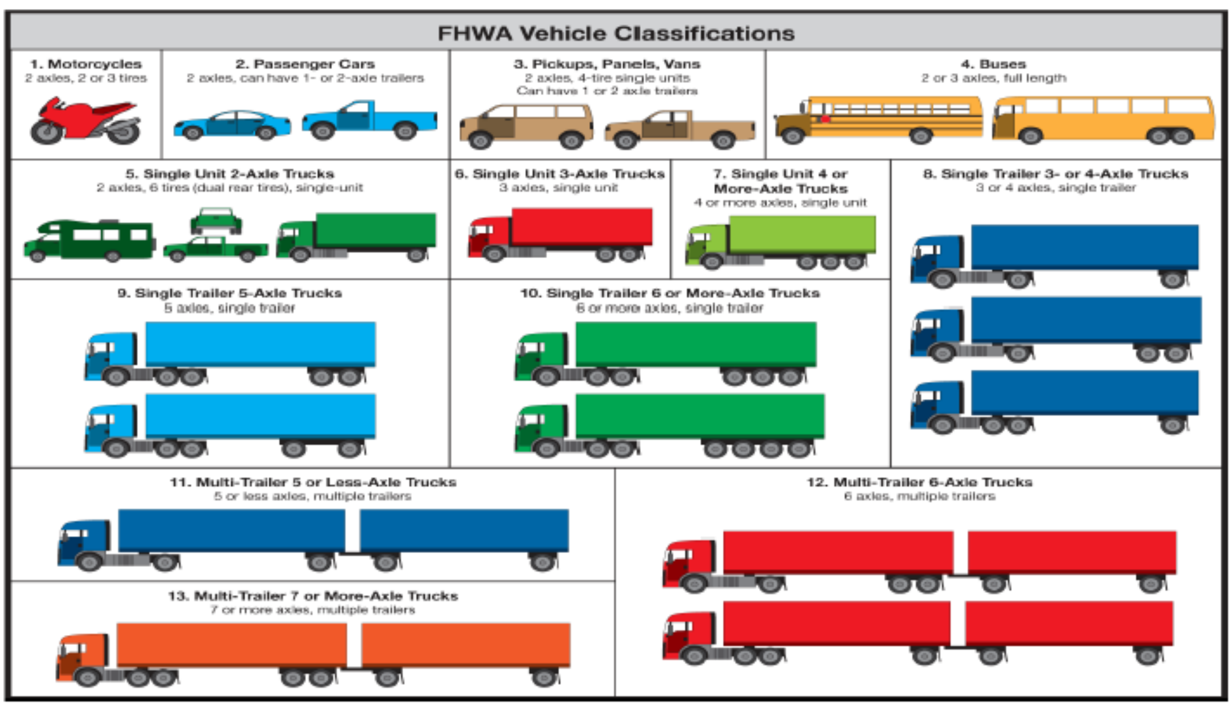


Figure 10: FHWA Vehicle Classification
Source: FWHA and Refai et al., 2014

An example of the current methods to collect these types of data is using road tubes for traffic counts. These devices are commercially available and include road tubes that are 10 ft parallel to each other, as shown in Figure 11, with the appropriate device to register the pressure imparted by vehicles as they cross. An algorithm then converts the data to a classification of the vehicle as defined by FHWA. These traditional devices have a margin of error that may be affected by irregularities of the pavement surface, the differential in tire pressure of vehicles, as well as speed. These devices are used to determine the Average Annual Daily Traffic (AADT) and other requirements established in the Highway Performance Monitoring Systems (HPMS).

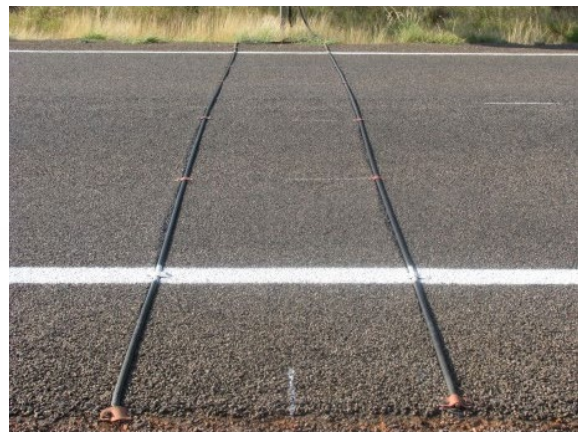


Figure 11: Road Tubes
Source: Diamond Traffic and Metro Count

The use of drones and the proposed design experiment framework will assist researchers to determine the percent of error of those commercial setups used in the lanes of multi-lane highways for permanent count stations. The effectiveness of a drone's capacity to count vehicles and classify them will be compared to traditional methods. They will be compared when measuring the traffic flow at particular periods during the day, peak and off-peak, and the efficiency of transmitting the information to the TMC for the appropriate action of traffic detour prior to an incident and other information that can be sent to other organizations such as police enforcement, emergency responders and others.

Mallela et al. (2021) stated that the aerial accessibility provided by UAVs and the availability of scalable and efficient computer vision algorithms create an excellent potential for using UASs for traffic analysis applications. UAS equipped with a high-resolution camera flying at a high altitude provides an aerial view of live traffic data. Recent advancements in computer vision can detect and analyze the speed, count, flow, and sometimes make decisions independently. Although there are limitations (e.g., altitude ceiling and short battery life), the prospect of UAS application in traffic monitoring is tremendous. Using UASs for traffic analysis could see savings of $75 million nationally (Carroll & Rathbone, 2002).

2.2 UNMANNED AIRCRAFT SYSTEMS

The second focus of the literature review concentrated on the different aspects of small UAVs (sUAV), specifically, sUAV specifications, application to surface transportation projects in urban and suburban areas, federal regulations, and protocols required as per 14 CFR Part 107. In this federal regulation, certifications that are required to fly an sUAV, the available waivers for special applications, limitations, and restrictions are explained.

2.2.1 14 CFR PART 107

Just as there are rules of the road when driving a car, there are rules of the sky when operating a drone. 14 CFR Part 107 provides the set of rules and regulations applicable to drone pilots to operate commercial drones in the national airspace (FAA, 2020). Prior to flying a commercial drone, the pilot must obtain an FAA license, and the person obtaining the license must comply with all the requirements established by the FAA. To prepare for the licensing exam, the pilot must have knowledge of regulations, national airspace systems, weather, operations, and loading and performance. The FAA's online registration system for drones went into effect on December 21, 2015, and required all UAS weighing more than 0.55 lbs (250 grams) to be registered.

The FAA has a series of operating restrictions for drone pilots (FAA, 2020), as summarized below:

- Always avoid manned aircraft.
- Never operate in a careless or reckless manner.
- Keep your drone within sight. If you use First Person View or similar technology, you must have a visual observer to always keep your drone within unaided sight (for example, no binoculars).
- You cannot be a pilot or visual observer for more than one drone operation at a time.
- Do not fly a drone over people unless they are directly participating in the operation.
- Do not operate your drone from a moving vehicle or aircraft unless you are flying your drone over a sparsely populated area, and it does not involve the transportation of property for compensation or hire.

14 CFR Part 107 provides all the requirements that pilots must follow, some of which are as follows: Pilots can fly during daylight (30 minutes before official sunrise to 30 minutes after official sunset, local time) or in twilight if the drone has anti-collision lighting. Minimum weather visibility is 3 miles from the control station. The maximum allowable altitude is 400 ft above the ground level (AGL), higher if the drone remains within 400 ft of a structure. Maximum speed is 100 mph (87 knots).

The remote pilot must be aware of all the airspace restrictions and, if needed, the waivers required for every flight. Restrictions that commonly affect UAS flights include stadiums and sporting events, airports, security-sensitive airspace, special use airspace, and the Washington, DC Special Flight Rules Area and Flight Restricted Zone. Pilots may fly specific drone operations not allowed under Part 107 by requesting an operational waiver, which allow them to deviate from certain rules under 14 CFR Part 107 by demonstrating they can still fly safely using alternative methods (FAA, 2021).

14 CFR Part 107 was amended on April 21, 2021, to allow a drone operator to fly at night, over people, and over moving vehicles without a waiver. For this to apply, the operator must meet the requirements defined in the rule. However, airspace authorizations are still required in controlled airspace. Figure 12 shows when a drone operator must request a waiver for several flying conditions.

You want to…	Part 107 regulation you need a waiver from…
Fly a small UAS from a moving aircraft or a vehicle in populated areas	§ 107.25 – Operation from a Moving Vehicle or Aircraft
Fly a small UAS at night without anti-collision lighting	§ 107.29(a)(2) – Operation at night
Fly a small UAS during periods of civil twilight without anti-collision lighting	§ 107.29(b) – Operation at Night
Fly a small UAS beyond your ability to clearly determine its orientation with unaided vision	§ 107.31 – Visual Line of Sight Aircraft Operation
Use a visual observer without following all visual observer requirements	§ 107.33 – Visual Observer
Fly multiple small UAS with only one remote pilot	§ 107.35 – Operation of Multiple Small UAS
Fly over a person with a small UAS which does not meet operational categories 1, 2, 3, or 4	§ 107.39 – Operation over human beings.
Fly a small UAS: • Over 100 miles per hour groundspeed • Over 400 feet above ground level (AGL) • With less than 3 statute miles of visibility • Within 500 feet vertically or 2000 feet horizontally from clouds	§ 107.51 – Operating limitations for Small Unmanned Aircraft
Fly over moving vehicles with a small UAS which does not meet operational categories 1, 2, 3, or 4 or other conditions	§ 107.145 – Operations Over Moving Vehicles

Figure 12: Available Waivers for Flight Operations Contrary to 14 CFR Part 107
Source: FAA (www.faa.gov)

2.2.2 UAS APPLICATIONS IN SURFACE TRANSPORTATION

Applications of sUAS in surface transportation were reviewed for potential applicability to the research project. Examples of such applications include road and bridge inspection, traffic surveillance, incident management, incident investigation, and emergency management. According to a survey by the American Association of State Highway and Transportation Officials (AASHTO), 33 state departments of transportation (DOTs) have carried out or are exploring applications of UASs in various aspects of transportation, including inspecting bridges, collecting traffic data, and assisting in motor vehicle crash clear-up (Daiheng Ni, 2017). Regulation and protocols available from other state DOTs were reviewed as part of this comprehensive literature review. Such regulations were used as a reference for the development of the NICR freeway multi-lane corridor surveillance protocol.

Different drone operation manuals were analyzed as part of this task. It was found that each drone acts differently; therefore, a remote pilot must evaluate different drone manuals to gain insight into their processes. Common activities and tasks related to drone operation include different flight modes, Return-to-Home, warning lights, battery safety, storage, and maintenance. Several quotes from local and national sUAV suppliers were evaluated in terms of the specifications and capabilities required for our research project. For example, camera resolution, battery life, stability in adverse weather conditions, software for thermal detection, and other attributes that will be required to transfer data from the urban corridor freeway evaluated in real-time.

Focal length and the field of view were reviewed as part of understanding the influence of the drone height and the camera in the video resolution. Field of view defines the maximum area of a sample that a camera can cover, determined by the focal length of the lens and sensor size. The focal length of a lens converges light so that the image of an object is focused on the sensor. This determines the angular field of view, a parameter of the overall field of view (Field of View and Angular Field of View, n.d.).

UAS have historically been used for military, aerial photography, search and rescue efforts, mapping, and law enforcement applications (O'Neil-Dunne & Estabrook, 2019). Technological advancements over the past decade have brought many improvements and features to UAS to the point at which consumer-grade UASs can be obtained for a relatively low price. Some of these advances include autonomous flight, safety features such as a return-to-home feature, and obstacle avoidance. UASs are evolving quickly given how much technology has already changed in the past several years.

At the Innovative Applications in Transportation Infrastructure using Unmanned Aerial Systems Congress on May 12 and 13, 2021, several professionals from the public and private sector presented how they are integrating UAVs in their daily routines. The use of UAVs was a key component in the assessment of damages due to Hurricane Maria in 2017, from getting aerial images to helping in calculating the debris generated.

The Municipality of Bayamon in Puerto Rico used sUAS as a measuring platform for the reports of the volume of debris that was required by the Federal Emergency Management Agency (FEMA) after the hurricane (Flores Rivera, 2021). Klein Engineering worked on landslide projects for the PRHTA and FHWA. The projects consisted of island-wide assessments and repair recommendations. The UAS was used for the measurement and calculation of areas and volumes to assess the extent of the damages (Klein, 2021). The Puerto Rico Police Bureau is integrating UAVs into their ranks to help them in crash investigations and reconstruction, traffic control, traffic incident monitoring, hazardous materials spill, inspection of bridges and structures, and landslip inspections (Hidalgo, 2021). PRHTA's Soils Engineering Office is implementing the UAVs for the Geotechnical Asset Management Program, emergencies of weather, natural events, design and construction, route planning, and rating asset conditions (Barbosa-Vélez, 2021).

In Missouri, studies and inspections using UAVs have been completed. Trial tests indicate that UASs can significantly reduce the total man-hours on bridge inspections (WTKN, 2021). Larger bridge inspections may often require a team of up to seven people, whereas a team of only three is required when using a UAS. In addition to reduced personnel and man-hours, the use of UASs to inspect bridges will not require any maintenance of traffic activities, nor an inspection vehicle (boom truck), nor additional vehicles to carry traffic cones; therefore, significant cost savings due to less gasoline usage are expected (WTKN, 2021). More importantly, the use of UASs to inspect bridges will result in fewer traffic interruptions due to lane closures, which is vital to the general motoring public's quality of life and reduces the safety risks to inspection personnel.

The NIMBUS Laboratory at the University of Nebraska has been developing drones that have the unique ability to dig holes in the ground and then fill those holes with sensors. The drone needs to be able to carry a portable digging system a useful distance, locate a diggable spot, land, verify that the spot it thought was diggable is, in fact, diggable, dig a hole and install the sensor, and then fly off again (WTKN, 2021).

In Wyoming, a survey was performed to identify the economic impact of sUAS. Camp Guernsey Integrated Training Area Management employs UAS as a tool to quantify and identify damage from military maneuvers in training areas that can be as large as 7,000 acres. Operational, maintenance, and fuel costs are reduced significantly with UAS (WYDOT, 2020). The uses are distributed into aerial photography/videography, agricultural/forestry related, natural resources inspection, engineering/surveying, local government, military, UAV manufacturing, among others. It was also found that a total of 87 different organizations or entities were identified as being active drone operators. These entities have 159 employees devoting at least part of their time to UAS/UAV activities (WYDOT, 2020).

In Jacksonville, Florida, UAVs are used to accurately repeat flights over a specific area, which allows users to monitor change over time. It can be used to monitor environmental conditions such as flooding, beach erosion/restoration, changes in vegetation or wildlife utilization, the success or failure of mitigation projects, and pre-storm and post-storm conditions. It could also be used to track land-use changes or monitor construction progress (USACE, n.d.).

Pertinent findings of the use of drones in India, the United Kingdom, Japan, and Switzerland are briefly described, but recognizing that their flying protocols are not under the jurisdiction of 14 CFR Part 107. When drones are used along with traditional ground-based sensors, more absolute data can be collected for traffic monitoring and management (Archana, 2018). UAV was essential for the accurate estimation of longitudinal and lateral gaps between vehicles (Afzal Ahmed, 2021). UAVs are preferred over other technologies due to their mobility and the significantly lower cost of operation compared with manned systems (Raj, 2017). UAVs can be sent quickly to find accident victims without risking human lives. Furthermore, acquiring data from an aerial view is exceptionally useful as it solves essential issues when evidence is spread out, and it is difficult to get a good point of view from ground level (Raj, 2017).

As a pilot project, the Government of Maharashtra in India has deployed two drones to monitor weekend rush hour traffic and crashes on the 95-km stretch between the Lonavala Exit and Khalapur Toll Plaza and on the six-lane Mumbai-Pune Expressway (PwC, 2018). Information collected with the help of drones eases identification of defects, patches on roads, the traffic situation at different times of the day, obstructions, etc. (PwC, 2018).

In the United Kingdom, Khan (2017) organized UAV-based traffic studies and prepared a framework that can be utilized for general drone-based studies. The framework includes seven components—scope definition, flight planning, flight implementation, data acquisition, data processing and analysis, data interpretation, and optimized traffic application. In scope definition, the main objectives of the study were defined, and a specific focus was established corresponding to the expected results. The Flight Planning Stage involved preparation for the implementation of the actual UAV flight for the collection of the required data. During the flight implementation stage, the UAV flew over an area of interest as per the planned flight path/route. This flight was conducted based on the parameters established during the flight planning stage. The acquisition of data from the UAV was also a critical step of the proposed framework and was largely dependent on the scope of the study. Data to be acquired from the UAV included video footage of the region of interest along with any other data from sensors (infrared, thermal, ultrasonic, etc.) mounted on the UAV. Data acquisition can be real-time or offline depending upon the requirements of the project. Analysis of the UAV-based traffic footage involved some pre-processing and stabilization procedures, which were necessary to make the video ready for the actual analysis steps. Interpretation of the processed video data was the next step in the framework and was done with the help of different types of graphs and charts that are generated as an output of the data analysis procedures. The proposed steps in this framework were directly dependent on the scope of the study. The optimized conclusion of the traffic study in accordance with the scope was the final step in the proposed UAV-based traffic analysis framework. The study-specific traffic parameters determined during the analysis and interpretation steps were employed to improve the existing traffic models which ultimately help in solving the real-world traffic situations.

Komatsu, a Japanese construction company, has begun creating Smart Construction, a team of robotic vehicles that scoops rock and pushes dirt without the need of a human behind the wheel. They are guided in their work by a fleet of drones, which map the area in three dimensions and update the data in real-time to track how the massive volumes of soil and cement are moving around the site (Popper, 2015). Before switching to drones, Komatsu had been experimenting with autonomous dump trucks, bulldozers, and excavators, but they lacked the ability to see and understand the environment around them with enough precision to be useful on their own. Komatsu used teams of human surveyors to create detailed maps of the job site, a process that left a lot of room for improvement. With Skycatch drones, Komatsu says it has dramatically reduced that margin of error while dramatically cutting the time it takes to complete a sitemap.

In Switzerland, architect Ammar Mirjan has been conducting experiments in a laboratory to prove that drones will be able to build structures soon (Hobson, 2015). Although drones are unlikely to replace traditional techniques in most cases, their unique capabilities will lead to them being used for specific applications in construction. Using drones to build tensile structures follows on from an earlier project by Gramazio Kohler Architects and Raffaello D'Andrea, in which UAVs were used to build a tower out of 1,500 polystyrene bricks at the FRAC Centre in Orléans, France.

2.2.3 UAS CHALLENGES

UASs have many benefits related to transportation activities, but they also has limitations and challenges that need to be considered (O'Neil-Dunne & Estabrook, 2019) . The primary limitations of UAS are weather and battery life; typical UAS platforms and sensors cannot be flown under rainy conditions since the platform and sensors are not water-resistant. UASs also cannot be flown in high wind or gusty conditions; wind speed maximums are specific to UAS platforms, as some are better in wind than others. Battery life is the second major limiting factor in UAS, as batteries limit flight times to typically less than an hour, limiting the amount of data that can be captured in a single flight (O'Neil-Dunne & Estabrook, 2019).

Barmpounakis et al. (2017) compared the challenges of using static cameras, manned aerial vehicles (MAV), and UAV for monitoring. Collecting visual information for large networks can be a challenging procedure. Installing stationary cameras to monitor the extent of a transportation facility has been a successful practice for years. Nevertheless, several practical issues may emerge; for example, there are cases where the area to be monitored is large and cannot be covered from static cameras. Moreover, installing stationary cameras and supplementary infrastructure can sometimes be too costly, especially when an area does not need to be monitored anymore. Even if costs could be reduced, the problem of acquiring imagery and gathering data under the emergence of unexpected events is still not addressed. An extreme event may occur at any place and at any time. The response to such events should be made promptly to reduce their effects on the surface transportation system. From an emergency response perspective, it is evident that a set of static cameras fails to provide a clear picture of the unexpected extreme event, as the setting is specific, usually with limited ability to cover a surface transportation system (Barmpounakis et al., 2017). Table 2 compares the attributes of static cameras, MAV, and UAV for traffic monitoring.

Table 2: Comparison of Static Cameras, MAVs, and UAVs

	Static cameras	MAV	UAV
Length coverage	Low	High	High
Security/Privacy	Medium	Medium	Low
Cost (acquiring and maintenance)	Low	High	Low
Multiple uses	Low	High	High
Energy efficiency	Low	Low	High
Deployment	Low	High	Low
Operational time	High	High	Low
Operation under adverse weather	Medium	Low	Low
Risk	Low	High	Medium
Endurance	High	High	Low
Video post-processing skills	Medium	High	High
Data transfer, communication and storage	Low	High	High
Operation skills	Low	High	Medium
Training requirement	Low	High	Medium
Complexity	Medium	High	Medium

Source: Barmpounakis et al., 2017

2.3 COMPARISON OF RGB AND THERMAL CAMERA IMAGES

Sensors are an important part of any data collection apparatus. UAVs already use a suite of sensors for flight control and navigation and are often equipped with Global Positioning System (GPS), Inertial Navigation Sensors (INS), Micro-Electro-Mechanical Systems (MEMS) gyroscopes and accelerometers, Altitude Sensors (AS), and one or more sensors for their primary task of video recording or other type of data collection (Yao, Qin & Chen, 2019). UAVs can acquire very detailed information of observed objects by using a wide range of cameras such as Red Green Blue (RGB) sensor cameras, infrared, or thermal cameras that can be useful for obtaining aerial images of vehicles and tracking them (Jin et al., 2016).

The most widely used sensors for data collection with UAV are RGB cameras (Chun et al., 2019). These cameras provide multiple features such as high-resolution images and video recording. Lightweight RGB cameras provide the flexibility of using them with UAVS where weight is an issue. RGB cameras and thermal cameras have been used in surveillance, agriculture, inspection, filmmaking, and many other industries (Samaras et al., 2019). For use in traffic monitoring systems, the focus of this paper, RGB cameras are useful as flight aids and as data collectors to detect and process scenes involving vehicles (Nagai et al., 2012). RGB cameras also have limitations; the quality of the RGB visual data is highly dependent on the light present at the scene—the more intense the surrounding light, the better the quality of the image.

Another image sensor is the infrared (thermal) camera, which detects the infrared radiation emitted by objects in its field of view. The energy of the radiation mainly depends on the object temperature. This can be useful when flying UAVs in different weather and light conditions. Compared to RGB cameras, thermal cameras have more flexibility when capturing videos with low levels of lighting. Thermal cameras provide enough information for object detection even though they typically provide lower resolution images with fewer details; this can be useful when privacy is important, as thermal images do not reveal vehicle license plates or the face of a person (Ma et al., 2016). Using thermal cameras also assist in reducing the pre-processing time of the frame before any real-time object detection and tracking algorithms, as the step of blurring part of the frames to obscure private information can be eliminated. Thermal cameras, therefore, have great potential for traffic monitoring purposes with the correctly calibrated algorithms in place.

2.4 VEHICLE DETECTION ALGORITHMS

Motor or electric vehicles on the freeway or in a high-speed multi-lane facility first need to be detected and classified to accurately extract traffic-related information. Then, based on the detected results, traffic flow parameters can be estimated. Vehicle detection is often regarded as an application of object detection, which is a computer technology related to computer vision and image processing that has been studied abundantly. Object detection involves two main tasks—localization and classification (Vaddi, 2019). Localization is locating the object in the form of bounding box coordinates, and classification is predicting the object class. If all vehicles are deemed a single class, the object detection needs to deal only with the task of localization. This problem can be treated as a moving object detection problem, assuming cars are moving on the ground. The methods applied in object detection and moving object detection are discussed below.

Methods for object detection can be categorized into neural network-based or non-neural network approaches. For non-neural network approaches, features such as histogram of oriented gradients (HOG), Haar, and scale-invariant feature transform (SIFT) are first computed and then fed into a classification model such as a support vector machine (SVM) to create classifiers (Lienhart, Rainer & Maydt, 2002; Dalal & Triggs, 2005; Lowe, 1999). After the rise of deep learning, neural network-based approaches were developed to provide a higher detection accuracy based on the convolutional neural network (CNN), among which there are two major categories—two-stage or region-based detector and single-stage detector. The region-based convolutional neural networks (R-CNNs) are models that involve a region proposal stage to extract a region of interest (ROI). R-CNN applies selective search algorithms to extract 2,000 region proposals, or ROIs, from the image. Each region proposal is then warped and fed into a CNN before the classification module and bounding box regression are applied (Girshick et al., 2014). The major problems of R-CNN are that inference time is very slow and the training process is very complex, as it requires training of three separate modules. To improve the speed of R-CNN, the same author built a faster detector, named Fast R-CNN, by passing the input image directly to the CNN to extract features before region proposals in such a way that only one CNN needs to run, as opposed to running 2,000 CNNs over 2,000 proposals (Girshik, 2015). Faster R-CNN further improved speed by replacing the selective search algorithm with a small convolutional network—a region proposal network—and achieved an end-to-end deep learning network (Ren et al., 2015). Faster R-CNN is hundreds of times faster than Fast R-CNN, with a frame rate of 5 FPS on a GPU, but it can perform real-time detection tasks.

Single stage architectures have been created in the last few years to address the inference time limitation of the R-CNN family. The two state-of-the-art single-stage detectors are single-shot detector (SSD) and You Only Look Once (YOLO). Different from region-based detectors that first generate region proposals and then feed them to classification/regression heads, single-stage detectors use a single convolutional network to make predictions of the bounding boxes and the class probability in one shot. YOLO has evolved to version 4 (YOLOv4) with a real-time speed of over 65 FPS and 43.5 percent mean average precision (mAP) for the MS COCO dataset. SSD321 can achieve 28.0 mAP and over 16 FPS. Both YOLOv4 and SSD can outperform Faster R-CNN in mAP (Liu et al., 2016; Bochkovsky, Wang & Liao, 2020; Redmon & Farhadi, 2018).

Some classic approaches to detect moving objects include consecutive frame difference, optical flow, and background subtraction (Chapel & Bowmans, 2020; Kulchandani & Dangarwala, 2015). Consecutive frame difference methods suffer robustness issues, and optical flow methods usually require many calculations, making real-time detection challenging. Background subtraction methods achieve a good balance between robustness and real-time detection, making them the most popular method in the literature. Background subtraction methods extract the moving foreground from the background and output a binary mask that separates the foreground and background pixels. To extract the foreground, background models are first created. The main difference between different types of background subtraction models is how the background model is built. Researchers have proposed approaches based on statistical models, machine learning models, and signal processing models. Statistical models such as single Gaussian, Mixture of Gaussians (MOG), and Kernel Density Estimation have been widely used in the literature (Stauffer& Grimson, 1999; Godbehere, Matsukawa & Goldverg, 2012; Bouwmans et al., 2018). Representation learning (e.g., GRASTA, incPCP) and neural networks (e.g., CNNs) have also been applied to background modeling He, Balzano & Szlam, 2012; Rodriguez & Wohlberg, 2016; Wang, Luo & Jodoin, 2017). Based on signal processing, researchers used signal estimation models, transform domain functions, and sparse signal recovery models to model the background Chang, Gandhi & Trivedi, 2004; Cevher et al., 2008; Kuzin, Isupova & Mihaylova, 2015).

2.5 SPECIFICATIONS OF POTENTIAL SUAS

The USF and UPRM teams researched available drones with different capabilities and specifications. The specifications and features of the DJI Mavic 2 Enterprise Advanced and Autel Evo II Pro 6K (Figure 13) are shown in Table 3 and Table 4, respectively. The Mavic 2 has dual sensors, a 640 x 512 px high-resolution thermal sensor, and a 48MP visual camera, that can work separately or at the same time. It has a maximum flight time of 31 minutes and a speed of 45 mph. It offers a stable connection between the remote controller and the drone at a maximum distance of 6.2 miles. It is capable of centimeter-level positioning accuracy with the Real-Time Kinematic (RTK) module (DJI, 2021). Also, the lightweight and portable Mavic 2 can take off in less than a minute. Additional features include discreet mode, self-heating batteries, password protection, and a working temperature from -10°C to 40°C (DJI, 2021).

The Autel Evo II Pro 6K has a maximum flight time of 40 minutes. The range of the transmission between the controller and the drone is about 5.6 miles. Additionally, its bright color makes it easier to maintain visual contact. Autel Robotics puts a color display into the controller itself so that the user can fly, frame photos, and record video without an extra device (Fisher, 2021). The EVO II has a maximum speed of 22mph and offers all-around obstacle detection. It is very useful for working lower to the ground, where trees or other obstructions may be an issue. When the user is flying higher, above the trees, switching to the Ludicrous mode gives footage more sense of motion (Fisher, 2021).

Figure 13: Examples of Researched Drones:
DJI Mavic 2 Enterprise Advanced (*top*), Autel Evo II Pro 6K (*bottom*)

Table 3: DJI Mavic 2 Enterprise Advanced Features

Aircraft		Thermal Camera	
Takeoff Weight (without accessories)	909 g	Sensor	Uncooled Vox Microbolometer
Max Takeoff Weight	1100 g	Focal Length	Approx. 9mm
Dimension (LxWxH)	Folded: 214x91x84 mm		35 mm format equivalent: Approx. 38 mm
	Unfolded: 322x242x84	Sensor Resolution	640x512 @30Hz
Diagonal Distance	354 mm	Accuracy of Thermal Temperature	Measurement: ±2°C or ±2%, whichever is greater
Max Ascent Speed	6 m/s	Digital Zoom	16 ×
Max Descent Speed	5 m/s	Pixel Pitch	12 μm
Max Speed	72 kph (S-mode, without wind)	Spectral Band	8-14 μm
	50 kph (P-mode, without wind)	Photo Format	R-JPEG
Max Service Ceilling Above Sea Level	31 min	Video Format	MP4
Max Wind Speed Resistance	10 m/s	Metering Method	Spot Meter, Area Measurement
Internal Storage	24 GB	FFC	Auto/Manual
Visual Camera		**Battery**	
Sensor	1/2" CMOS, Effective Pixels: 48 M	Capacity	3850 mAh
Lens	FOV: 84°	Voltage	15.4V
	35 mm format equivalent: 24 mm	Max Charging Voltage	17.6V
	Aperture: f/2.8	Battery Type	LiPo
	Focus: 1 m to ∞	Energy	59.29 Wh
ISO Range	Video: 100-12800 (auto)	Net Weight	297g
	Photos: 100-1600 (auto)	Charging Temperature	5°C - 40°C
Digital Zoom	32×	Operating Temperature Range:	-10°C - 40°C
Max Image Size	8000×6000	Heating Methods:	Manual Heating, Auto Heating
Still Photography Modes	Single shotInterval: 2/3/5/7/10/15/20/30/60 s	Heating Temperature	-20°C - 6°C
	Panorama: Sphere	Heating duration	500s (Max)
Video Resolution	3840×2160@30fps	Heating Power	55W (Max)
	1920×1080@30fps	Charging Time	90 mins
Photo Format	JPEG	Max Charging Power	80W
Video Format	MP4		

Source: Adopted from DJI, 2021

Table 4: Autel Evo II Pro 6K Features

Aircraft		Visual Camera		Battery	
Takeoff Weight	1191 g	Image Sensor	1" CMOS	Battery	7100mAh
Max Takeoff Weight	1999 g	Pixels	20MP	Transmission Power (2.4G)	13.2
Aircraft Battery	7100 mAh			Battery Type	LiPo 3S
		Perspective	82°	Battery Energy	82Wh
Max Flight Time	40 min	Lens	EFL: 28.6 mm Aperture: f/2.8–f/11 Focus Distance: 1m to any distance (with autofocus mode)	Weight (g)	365 g
Max Level Flight Speed	45 mph (20 m/s)	ISO Range	Video: 100-6400 (auto)	Charging Temperature Rang (°C)	5~45°C
Max Ascent Speed	8 m/s		Photo: 100-12800 (auto)	Storage Temperature & Humidity	-10~30℃, 65±20%RH
Max Descent Speed	4 m/s	Zoom	1-8x (Max 3x lossless)	Max Charging Power Consumption (W)	93W
		Video Format	MP4 / MOV (MPEG-4 AVC/H.264, HEVC/H.265	Charging Time	90 min
Operating Environment	14-104 °F	Video Resolution	6K		
Working Frequency	2.4~2.4835 GHz	Max Bitrate	120 Mbps		

Source: Adopted from (Autel, 2020)

The USF team further explored two versions of the Autel Evo II series—the EVO II with an 8K single camera and the Evo II Dual 640T with an 8K RGB camera and a 640x512 pixel thermal camera. Specifications for the Autel Evo II are shown in Table 5, and thermal camera specifications for the Dual 640T are shown in Table 6. All other specifications for the dual drone are the same as in the Evo II model. The drones are shown in Figure 14.

Table 5: Autel Evo II Specifications

Camera	
Attribute	**Specifications**
Image Sensor	1/2" CMOS
Pixels	48MP
Perspective	79°
Lens	Equivalent focal length: 25.6 mm
	Aperture: f/1.8
	Focus Distance: 0.5m to any distance (with autofocus mode)
ISO Range	Video: 100-6400 (auto)
	Photo: 100-3200 (auto)
Zoom	1-8x (Max 4x lossless)
Still Photography Modes	Single Shot
	Burst shooing: 3/5 frames
	Automatic Exposure Bracketing (AEB) :
	3/5 bracketed frames at 0.7 EV Bias
	Timelapse :
	JPG: 2s/5s/7s/10s/20s/30s/60s
	DNG: 5s/7s/10s/20s/30s/60s
	HyperLight: support (under 4K JPEG format)
	Long Exposure: Max 8s
	HDR imaging: (under 4K JPEG)
Still Photography Resolution	8000*6000 (4:3)
	7680*4320 (16:9)
	4000*3000 (4:3)
	3840*2160 (16:9)
Video Format	MP4 / MOV (MPEG-4 AVC/H.264, HEVC/H.265)
Video Resolution	8K 7680*4320 p25/p24
	6K 5760*3240 p30/p25/p24
	4K 3840*2160 p60/p50/p48/p30/p25/p24
	2.7K 2720*1528 p120/p60/p50/p48/p30/p25/p24
	FHD 1920*1080 p120/p60/p50/p48/p30/p25/p24
Max Bitrate	120Mbps
Aircraft	
Takeoff Weight	2.5 lbs (1150 g)
Max Takeoff Weight	4.4 lbs (1999 g)
Diagonal Wheelbase	15.6 inches (397 mm)
Aircraft Battery	7100 mAh
Max Flight Time (standard)	40 min
Max Hovering Time (standard)	35 min
Max Level Flight Speed (Standard)	45 mph (20 m/s) (Ludicrous)

Max Ascent Speed	18 mph (8 m/s (Ludicrous)
Max Descent Speed	9 mph (4 m/s) (Ludicrous)
Max Service Ceiling Altitude	4.3 miles (7000 m) MSL
Max Wind Resistance	Force 8 wind
Operating Environment Temp	14-104°F (-10-40°C)
Working Frequency	2.4~2.4835GHz
Transmission Power	2.4~2.4835GHz
	FCC/ISED：≤27dBm
	SRRC/CE/MIC/RCM：≤20dBm
Hover Precision	Vertical:
	± 0.1m (with visual positioning in normal operation)
	± 0.5m (with GPS in normal operation)
	Horizontal:
	± 0.3m (with visual positioning in normal operation)
	± 1.5m (with GPS in normal operation)
Sensing System	
Sensing System Type	Omnidirectional Binocular Sensing System
Forward	Accurate Measuring Range: 0.5 - 20m
	Detection Range: 0.5 - 40m
	Effective Sensing Speed: < 15 m/s
	FOV: Horizontal: 60°, Vertical: 80°
Backward	Accurate Measuring Range: 0.5 - 16m
	Detection Range: 0.5 - 32m
	Effective Sensing Speed: < 12 m/s
	FOV: Horizontal: 60°, Vertical: 80°
Upward	Accurate Measuring Range: 0.5 - 12m
	Detection Range: 0.5 - 24m
	Effective Sensing Speed: < 6 m/s
	FOV: Horizontal: 65°, Vertical: 50°
Downward	Accurate Measuring Range: 0.5 - 11m
	Detection Range: 0.5 - 22m
	Effective Sensing Speed: < 6 m/s
	FOV: Horizontal: 100°, Vertical: 80°
Sides	Accurate Measuring Range: 0.5 - 12m
	Detection Range: 0.5 - 24m
	Effective Sensing Speed: < 10 m/s
	FOV: Horizontal: 65°, Vertical: 50°
Service Environment	Textured/patterned ground and adequate illumination (> 15 lux, normal indoor environment with fluorescent lamp on)
	Upward: diffuse reflecting surface with reflectivity above 20% (wall, tree, human, etc.)
	Downward: textured/patterned ground and adequate illumination (> 15 lux, normal indoor environment with fluorescent lamp on)
	diffuse reflecting surface with reflectivity above 20% (wall, tree, human, etc.)

Gimbal	
Operation Range	Pitch: -135° to +45°
	Yaw: -100° to +100°
	Pitch: -90° to +30°
	Yaw: -90° to +90°
Stability	More stable with 3 axes
Max Control Speed (Tilt)	300°/s
Angular Vibration Range (°)	±0.005°
Remote Controller and Transmission	
Max Signal Transmission Distance	5.5 miles (9km) FCC, 3.1 mi (5km) CE
Working Frequency	2.4~2.4835GHz
Transmission Power	2.4~2.4835GHz
	FCC/ISED：≤27dBm
	SRRC/CE/MIC/RCM：≤20dBm
Real-Time Transmission Quality	720p@30fps / 1080p@30fps
Max Bitrate of Real-time Transmission	40Mbps
Remote Controller Battery	5000mAh
Operating Hours	3h
Charging Time	2h Fast Charging
Display	3.26-inch OLED screen
	854 (W)*480 (H) pixels
	Preview video without need for connecting to mobile phone
Power Consumption	1.7A@3.7V
Battery	
Battery (mAh)	7100mAh
Voltage (V)	11.55
Transmission Power (2.4G)	13.2
Battery Type	LiPo 3S
Battery Energy	82Wh
Weight (g)	365
Charging Temperature Range (°C)	5~45℃
Storage Temperature & Humidity	-10~30℃，65±20%RH
Recommended Storage Temperature	22~28℃
Max Charging Power Consumption (W)	93W
Charging Time	90min

Source: Adopted from Autel, 2020

Table 6: Autel Evo II Dual 640T Thermal Camera Specifications

Infrared camera sensor	Uncooled VOx Microbolometer
Sensor resolution	640x512
Pixel pitch	12 μm
Wavelength range	8～14 μm
focal length	13mm
FOV	H33°V26°
Zoom	1 ~ 8x
Camera resolution	Infrared mode: 640*512
	Picture in Picture: 1920*1080, 1280*720
Photo shooting mode	Single shooting, continuous shooting, time-lapse shooting
Video Resolution	640*512 30fps
Video format	MOV / MP4 (support H.264/H.265)
Temperature	±3°C or ±3% of reading (whichever is greater)
Measurement accuracy	@ambient temperature -20°C~60°C
Temperature range	High gain mode: -20° to +150°C
	Low gain mode: 0° to +550°C
Accurate temperature measurement distance	2-20 meters

Source: Adopted from Autel, 2021

Figure 14: Autel Evo II (left) and Autel Evo Dual 640T (right)

2.6 EXPERIMENT DESIGN

The last focus of the literature review was experiment design. In an experiment, one or more process variables or factors are deliberately changed to observe the effect and the changes it has on one or more response variables. The statistical design of experiments is an efficient procedure for planning experiments so that the data obtained can be analyzed to yield valid and objective conclusions.

The split-plot design is a special case of a factorial treatment structure. This type of experimental design was selected for this project. It is used when some factors are harder (or more expensive) to vary than others. Much of the cost of running a split-plot experiment is tied to changes in the hard-to-change factors (Jones et al., 2009). A split-plot design consists of two experiments with different experimental units of different "sizes" (Lukas Meier, n.d.). One randomization is conducted to determine the assignment of block-level treatments to whole-plots (Jones et al., 2009). It is difficult to analyze due to the random errors of split block and whole blocks consisting of a lack of repeatability and too much variability.

The design consists of five options—two-level full factorial designs, two-level fractional factorial designs, mixture and response surface designs, split-plot designs for robust product experiments, and optimal designs (Jones et al., 2009). The two-level factorial is a completely randomized design in the whole-plot factors that is conducted and, within each whole plot, a completely randomized design in the split-plot is also conducted (Jones et al., 2009). It replicates the split-plot within a given whole-plot giving an estimate of the split-plot error variance, whereas for the fractional factorial every whole-plot treatment combination is run in combination with every split-plot treatment combination (Cartesian-product designs) (Jones et al., 2009). However, this does not guarantee a maximum resolution in the design (Jones et al., 2009).

CHAPTER 3: RESEARCH METHODOLOGY

The research methodology is described in the chapter and shown in Figure 15. The first step in the process consisted of a comprehensive literature review on transportation topics, UAS regulations and specifications, and experimental design concepts. In the second step, various drones were analyzed through their specifications and attributes to determine which UAS would be appropriate for the experiment. As part of the 14 CFR Part 107 requirements, members of the UPRM and USF teams took the Unmanned Aircraft General - Small (UAG) exam to become certified drone pilots. Members of both teams also took hands-on drone training to learn to safely fly UAS. The next step consisted of the development of the experiment design where the variables and different scenarios were established.

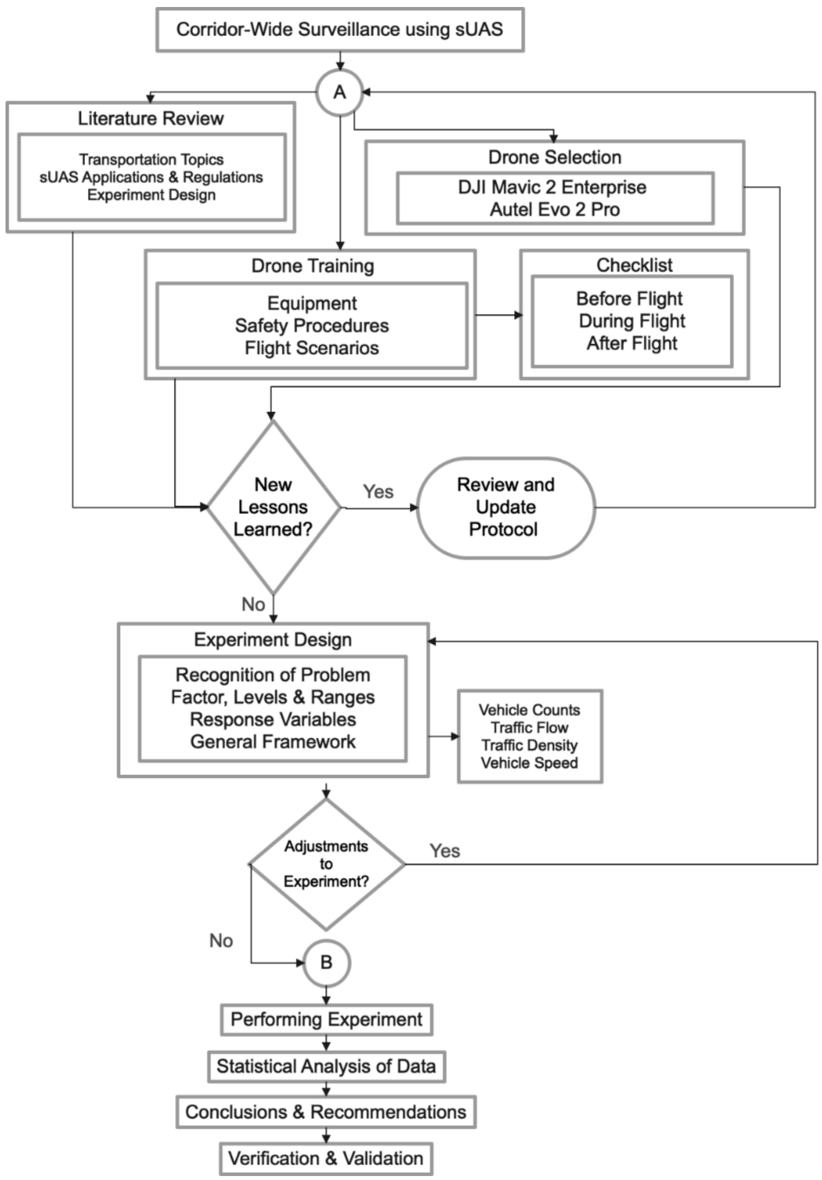


Figure 15: UAS Research Methodology

3.1 SELECTION OF SUITABLE DRONES

The purchasing budgets of UPRM and USF were similar, but timelines was different for the two teams. The final selection of the drones was done separately. Based on review of specifications of different drones, the UPRM team selected the DJI Mavic 2 Enterprise Advanced and the Autel Evo II Pro 6K. The USF team acquired two versions of the Autel Evo II series—the EVO II with an 8K single camera and the Evo II Dual 640T with an 8K RGB camera and a 640x512 pixel thermal camera.

3.2 DRONE TRAINING

Both USF and UPRM research teams performed hands-on training exercises to acquire experience with drones before collection of data for the project and obtaining pilot-in-command licenses for drone operations.

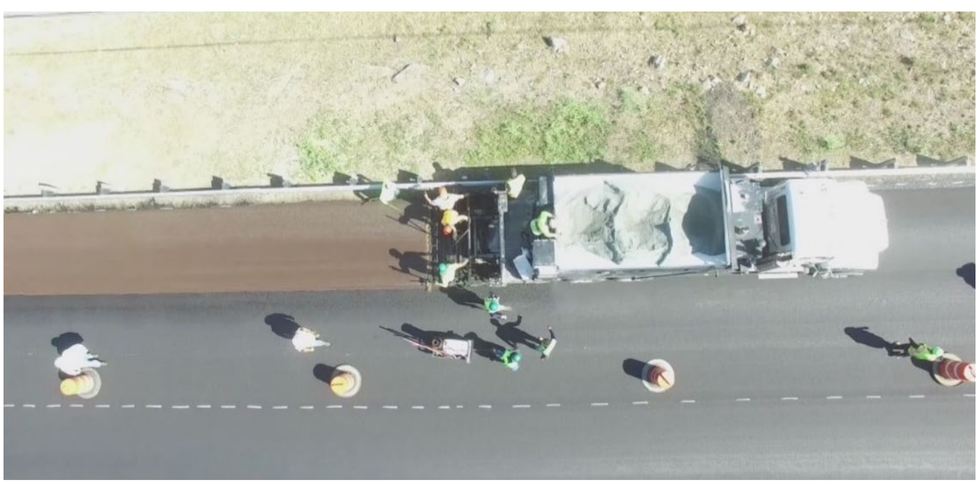
In the first three hands-on training exercises at UPRM (Figure 16), the drone used was the DJI Phantom 3 Professional provided by the Puerto Rico Transportation Technology Transfer Center from the Department of Civil Engineering and Surveying at UPRM, which are partners in this research project in the technology transfer task. The first training was on March 12 in the Civil Engineering Building in UPRM at Mayaguez, where the pilots in command tested the controls of the drone. The drone reached no more than 200 ft in height near the parking of the building. The second training exercise was on March 27 in Guayama, where the team made a detailed tutorial on how to use the remote control while flying the drone. The drone reached a height of 400 ft in intervals of 100 ft. This tutorial was made as part of the outreach activities of the research project. The third one was on April 21, 2021, in Lajas. This exercise was an invitation from the Puerto Rico Highways and Transportation Authority (PRHTA) to image a road segment before and after implementing the micro-surfacing treatment in an existing flexible pavement as part of FHWA’s Every Day Counts (EDC) initiative.

The training exercise with the research project selected drones took place on June 15. The DJI Mavic 2 Enterprise Advanced and the Autel Evo II Pro 6K were elevated at a maximum height of 100 ft as the airspace restrictions permitted. The DJI Mavic 2 recorded video with the normal and thermal camera at the same time (Figure 17). The video of the Evo II (Figure 18) shows the Civil Engineering Building and the green area behind it. Figure 19 shows the locations where the different drone training was executed in the island.

Each of these training experiences contributed to the development and calibration of the before, during, and after procedures of flying a drone for integration into the protocol. During the hands-on training experience in Lajas, the pilots encountered difficulties regarding wind, connectivity, and visibility. Wind prevented the UAVs from being stable, thus causing them to lose control and not able to record data accurately. Also, as the unmanned vehicle kept moving away from the pilot, the screen froze, and the pilot was not able to see what was being recorded. For this, the observer was attentive and kept watch of the UAV so there would be no problems. The third drone training encountered visibility problems during a segment where a curve impeded the view of the UAV to record traffic flow. The UAV was able to capture a small portion of the corridor. From the training with the Mavic 2 and Evo II, it was learned that the drones do not detect the altitude restrictions associated with the airspace classification; they detect only the 400 ft height limit above ground level (AGL).

(a)

(b)



(c)

Figure 16: Drone Trainings

Figure 17: DJI Mavic 2 Enterprise Advanced Video Images, UPRM Campus

Figure 18: Autel Evo II Pro 6K Video Images, UPRM Campus

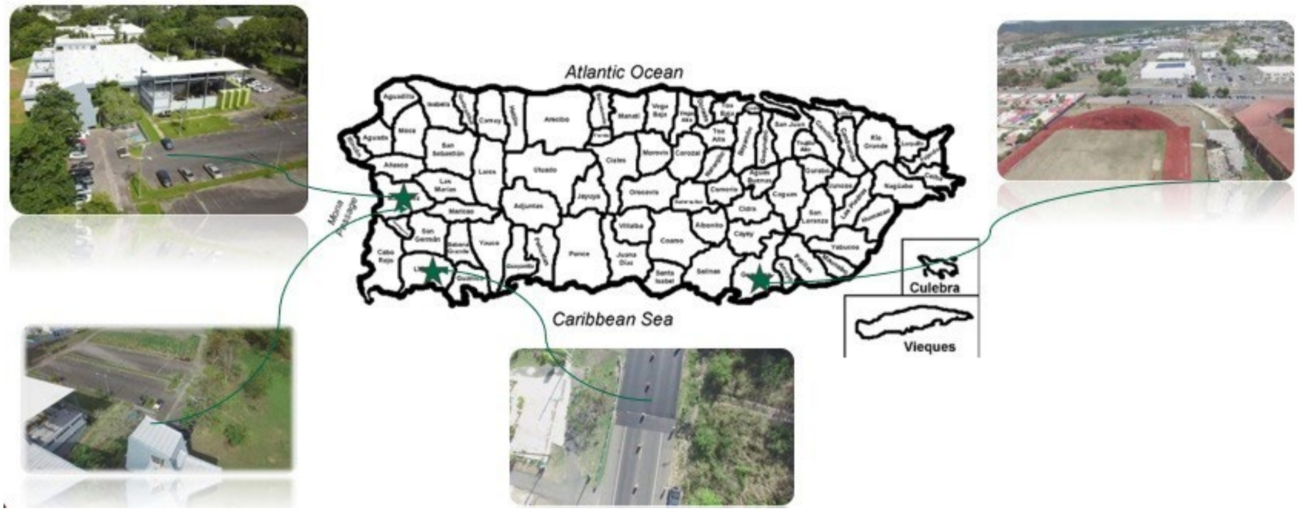


Figure 19: Locations of Drone Trainings

The USF team conducted drone training first using a Potensic D58 FPV Drone with a 2K camera. This drone is an RC quadcopter for beginners, with GPS auto return. Research team members also registered for drone flight training with 3rd Rock Air, a local company offering hands-on training. A series of training materials was developed, and meetings were scheduled for team members to prepare for the Unmanned Aircraft General – Small (UAG) exam.

Figure 20: Training Drone – Potensic D58 FPV

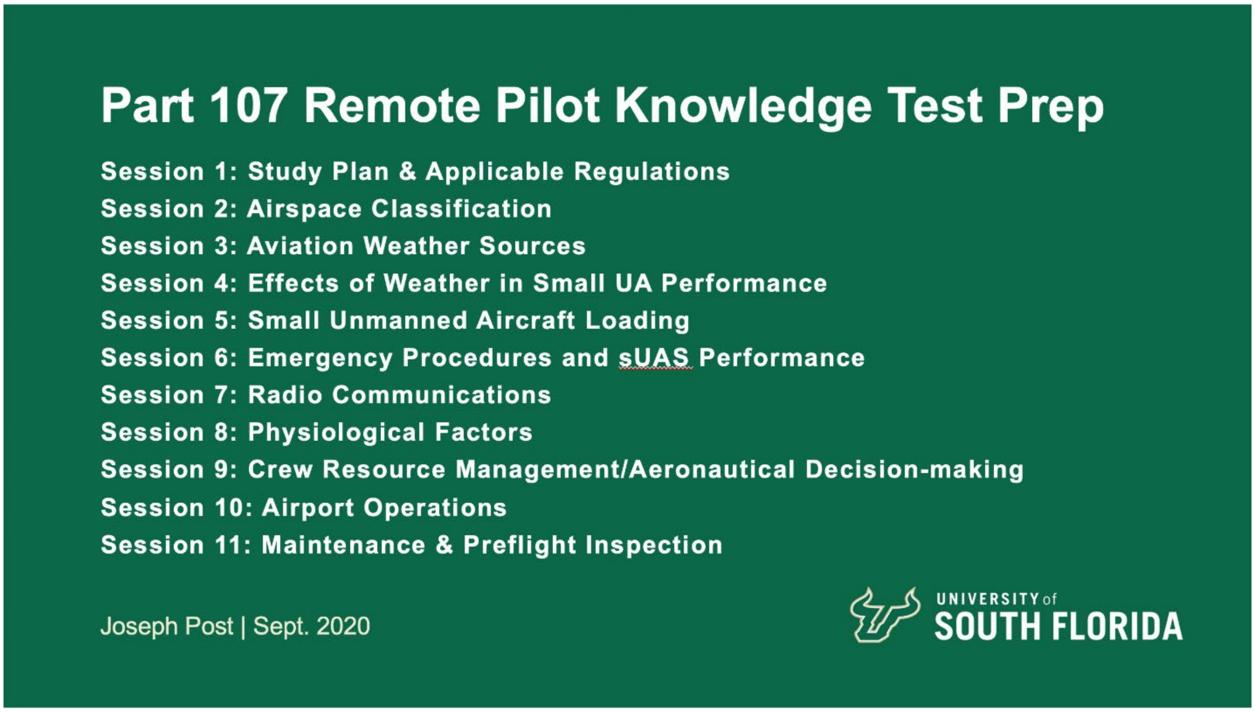


Figure 21: Content of Training Materials

CHAPTER 4: PROTOCOL

4.1 INTRODUCTION

This chapter focuses on the development of NICR sUAS protocol for freeway and multi-lane high-speed corridor surveillance and incident detection. The protocol considered the recommendations from UAS manufacturers, 14 CFR Part 107 regulations, best practices, and lessons learned from DOTs applied to different projects in transportation. It also considered experiences with weather conditions applicable in a tropical region and other locations in the US and Puerto Rico, and the collective experience of experts in surface transportation traffic operations and safety-related areas. Using this collective judgment and knowledge, prompt lists were divided into three major categories—Before, During, and After flight. The following sections describe the steps crew members took to ensure the safety of the drones and the research team.

4.2 BEFORE FLIGHT

Before every flight, the remote pilot in command must have a prompt list to ensure the safety of each member of the team, as shown in Table 7. Before the flight, the pilot must verify that all documentation regarding the 14 CFR Part 107 Remote Pilot Certificate is valid and that the drone has an up-to-date and visible FAA registration. The pilot also must verify airspace clearance to determine the need to obtain the necessary waivers during the operations in the area selected. Prior to the flight, the site area must be evaluated for possible hazards that can interfere with operations. Weather conditions must be monitored on the day before and the day of the flight; this item is key to knowing if the date of operations must be rescheduled.

At least one member of the team must be in charge of having emergency contact information for all team members, emergency responders, and the drone manufacturer and just have a first aid kit available. The remote pilot must have a written flight plan that describes the purpose of the operation and airspace classification, location, list of crewmembers, and primary and alternative launch and land sites. The flight plan also determined how the experiment would be performed. It must be revised by the remote pilot in command, as that person who oversees flight operations. Appendix C provides an example of the Flight Plan template. The pilot must verify that the drone has all the necessary updates; if not, this must be done with sufficient time days before the flight. After all these items are verified, the pilot proceeds to inspect all parts of the drone to ensure that everything is ready to proceed with the flight.

Table 7: Prompt List for Before Flight

	ITEM	ACTION
BEFORE	Remote Pilot in Command Credentials & Information	Valid Part 107 Remote Pilot Certificate. Drone flight operations records.
	Airspace Clearance	Verify regulations and airspace restrictions that may apply to the area of study. Request a waiver if it applies to the Airspace Classification of the area.
	Evaluate Site Area	Identify possible hazards in the site area that may affect the drone operations.
	Weather Conditions	Keep track of the weather conditions. This should be done several days in advance and the on day of the flight.
	Emergency Contingency	Information of emergencies contacts, agencies (e.g., police, fire department), drone manufacturers. First aid kit available always.
	Flight Plan	Purpose, airspace classification, location, list of crewmembers, primary and alternative launch and land sites.
	Drone Inspection	Verify updates needed that take time before the flight Verify drone manuals, inspect drone parts (e.g., batteries, propellers, remote control, camera).

4.3 DURING FLIGHT

A visual observer must be attentive to the drone at all times for interferences. The pilot can change the flight plan if an encounter with challenges occurs, such as a change in weather conditions, visibility problems, technical difficulties, among others. The team must always maintain proper communication during the flight. As part of good crew resource management, a crew member must oversee preparing for weather conditions (e.g., on a hot day, have water available). The pilot must monitor the battery levels of the drones during the flight; high temperatures can reduce battery use time. The pilot and team must follow the procedure established for data collection. In case of an incident, the pilot can deviate from the procedure if needed.

Table 8: Prompt List During Flight

	ITEM	ACTION
DURING	Interference/Manual Operations	Visual observers must be attentive and always keep watch.
	Challenges Encountered	Visibility problems, technical difficulties, and weather conditions.
	Data Collection	Follow the procedure established.
	Battery Level	Monitor battery levels.
	Crewmembers	Prepare for weather conditions (e.g., in a hot day have water available).

4.4 AFTER FLIGHT

After the flight, the pilot must inspect the drone parts again to make sure everything is in order. Following the recommendations of the manufacturer, all parts must be stored in a safe place. In case of any incidents, a report must be completed with a detailed explanation of what occurred.

The report must detail the persons involved and their observations of the incident. Appendix C provides an example a report. If the cost to replace or repair damages caused by the incident exceeds the limits established in 14 CFR Part 107, it must be reported to the FAA. After every drone flight operation, the remote pilot must write a report that details everything done during the flight.

UAVs will be used to transmit data in real-time; however, data will also be recorded for later analysis. The collected data from the videos will then be used for different study purposes. There will be programs implemented so that the data can be manually counted. The type of algorithm or application used to process the raw data fully depends on the data collected.

All algorithms for this research project are being implemented in Python. USF developed software to perform vehicle counts frame by frame so UPRM can use it for the same purposes. A tutorial was provided so students at UPRM could understand how the code works and apply it to the corridor selected in Puerto Rico.

Table 9: Prompt List After Flight

	ITEM	ACTION
AFTER	Drone Inspection	Inspect all parts
	Storage Considerations	Storage properly following the guideline provided by the manufacturer.
	Incidents	The remote PIC must redact a report containing details of the incident. If the cost to replace or repair the damages caused by the incident exceed the limits established in 14 CFT Part 107, it must be reported to the FAA.
	Flight Report	Detail all the flight.
	Data Analysis	Store data in the corresponding place and analyze according to purpose of flight.

4.5 LESSONS LEARNED

The research team identified the following limitations during the training exercises—connectivity problems at great distances of flight, capturing on video a long segment, and problems with sight distance on curved road segments. Depending on the capabilities of the drone, it can experience difficulties transmitting a clear image when being far away from the controller. To mitigate this, the crew must locate a strategic area where the drone is relatively close to the area of interest and themselves. When operating a drone in a long or curved segment, one should consider that the drone must be always visible by at least two members of the crew. Certain topography, such as mountainous terrain, can restrict the visibility of the pilot in command and the crew of the drone at long or curved distances. As a recommendation to treat this issue and as part of effective crew resource management, the pilot in command and visual observers can position themselves at certain distances between them to cover the whole segment. The use of walkie-talkies or other communication devices can be used for continuous communication between the crewmembers. For safety reasons, when operating alongside a freeway corridor, the crew should use a safety vest and helmets.

CHAPTER 5: EXPERIMENTS OF TRAFFIC DATA COLLECTION AND ANALYSIS

Montgomery (2013) provides guidelines for designing an experiment. The steps suggested are the following:

1. Recognition of and statement of the problem
2. Choice of factors, levels, and ranges
3. Selection of the response variable
4. Choice of experimental design
5. Performing the experiment
6. Statistical analysis of the data
7. Conclusions and recommendations

This chapter describes the data collection and analysis experiments following Montgomery's seven steps. As noted, in practice, Step 2, choice of factors/levels/ranges, and Step 3, selection of variables, are often done simultaneously or in reverse order. In this research project, these two steps were done simultaneously.

5.1 RECOGNITION AND STATEMENT OF THE PROBLEM

The reliability and validity of traffic measurement data become a cardinal aspect, especially when UAVs are used for obtaining such information. Current techniques for these count data, such as manual counting and counting masts, have certain disadvantages such as limited range of action, degradation of equipment, and high maintenance costs (Brahimi et al., 2020). Drones with different sensing technologies present an opportunity to overcome these limitations by collecting and processing traffic data in real-time. Nonetheless, the quality of data gathered with drones and the accuracy and precision of vehicle detection algorithms must be assessed. Thus, the research team carefully designed the experiments, collected the data, and evaluated the performance of vehicle detection algorithms.

5.2 CHOICE OF FACTORS, LEVELS, AND RANGES AND SELECTION OF RESPONSE VARIABLES

To inform operational concepts for the use of drones for traffic monitoring, this project explored the effectiveness of drone congestion detection as a function of the geometry of the drone and sensor relative to the highway. Flying at higher altitudes and viewing the roadway at oblique angles can make more of the roadway visible to the sensor and, thus, might increase the rate at which the drone can cover a road. On the other hand, the accuracy of the detection algorithms may be negatively affected. There also are many drone operating restrictions, some imposed by the FAA, such as altitude limits and operations over people, and others relating to obstacle avoidance, such as radio towers, power lines, overpasses, etc., that can restrict the drone's viewing perspective.

Figure 20 illustrates the geometry of a drone and sensor relative to a monitored highway and defines some of the experimental parameters. In this project, height above ground DH, depression of the sensor relative to the horizontal plane α, and azimuth of the sensor relative to the roadway ψ were varied. RGB and infrared imagery for free-flowing traffic conditions with a stationary camera were collected.

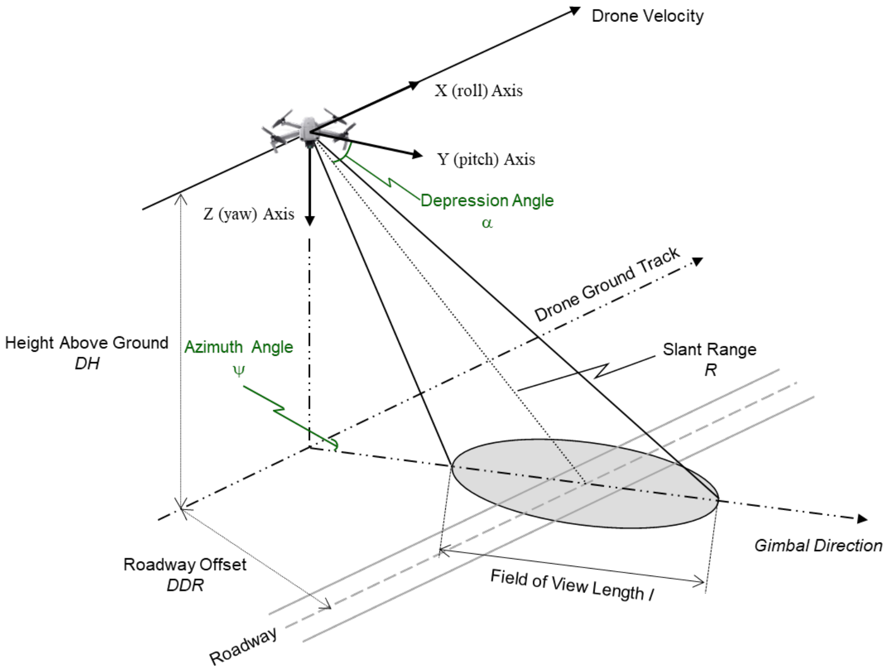


Figure 22: Drone and Sensor Geometries

5.3 CHOICE OF EXPERIMENTAL DESIGN

5.3.1 Combinations of Response Variables in Experiments

Table 10 presents the combinations of response variables for these experiments. For all experiments, the horizontal distance between the drone and the roadway (roadway offset DDR) was fixed at 100 ft.

Table 10: Combinations of Response Variables in Experiments

Traffic Intensity	Height Above Ground DH (ft)	Azimuth (deg)	Depression (deg)
Free-Flowing (without Congestion) or with Congestion	50	45	45
		90	70-90
		135	45
	100	45	45
		90	70-90
		135	45
	200	45	45
		90	70-90
		135	45
	300	45	45
		90	70-90
		135	45
	400	45	45
		90	70-90
		135	45

5.3.2 Selection of Image Processing Algorithms

The pros and cons of representative vehicle detection algorithms documented in the literature are summarized in Table 11. First tested were algorithms on free-flow traffic, the focus of this study. Although background subtraction-based methods cannot apply to moving cameras, their fast computation time and ease of implementation make them a desirable option for detecting moving vehicles in real-time when the camera is static. The vehicle detection algorithms will be tested on congested traffic and with a moving camera during ongoing work not included in this report. Learning-based methods will be used, as they work well with low-speed objects and moving cameras. Single-stage deep neural networks (YOLO v4) will be used to conduct detection for congested traffic and a moving camera due to their higher accuracy and faster inference time.

Table 11: Representative Methods and Their Pros and Cons in Vehicle Detection

Method	Background Subtraction-based Methods		Machine Learning	Two-stage Deep Neural Networks	Single-stage Deep Neural Networks	
Algorithms	Gaussian Mixture-based background/ foreground segmentation algorithm	Statistical background image estimation and per-pixel Bayesian segmentation	Cascade classifiers	R-CNN family	SSD	YOLO
Camera	Stationary		Stationary/moving			
Pros	Low computation time, easy to implement		Training relatively short compared to deep learning; low CPU power requirement	High accuracy	Trains faster than R-CNN; real-time detection; good balance between accuracy and speed	
Cons	Not for moving or vibrating camera; difficult to detect slow-moving objects; many parameters to tune, often tricky		Object shape needs to be consistent; change in rotation will affect performance	High computation time; lengthy training time; GPU required	GPU required; may be less accurate than R-CNN	

5.3.3 Summary of Research Approach

Figure 21 describes the steps applied to detect vehicles in free-flow traffic with a stationary camera using an approach based on the background subtraction method. A Gaussian Mixture-based Background/Foreground Segmentation Algorithm is used to create the background model (Zikovic, 2004). Input frames are fed into the background model to separate the foreground (moving objects) from the static background. A binary image is output, with the foreground mask representing the moving objects. The binary image is further processed by two morphological transformations, opening and dilation. The opening removes noise by conducting the erosion operation, followed by the dilation operation. Closing (reverse of opening, dilation followed by erosion) is applied after opening to remove small holes in the foreground objects. Contours are then generated based on the foreground masks. Noise is further filtered out by using a contour area threshold; any contours smaller than the threshold value are removed. Finally, the bounding boxes of detected vehicles are obtained according to the contour's coordinates.

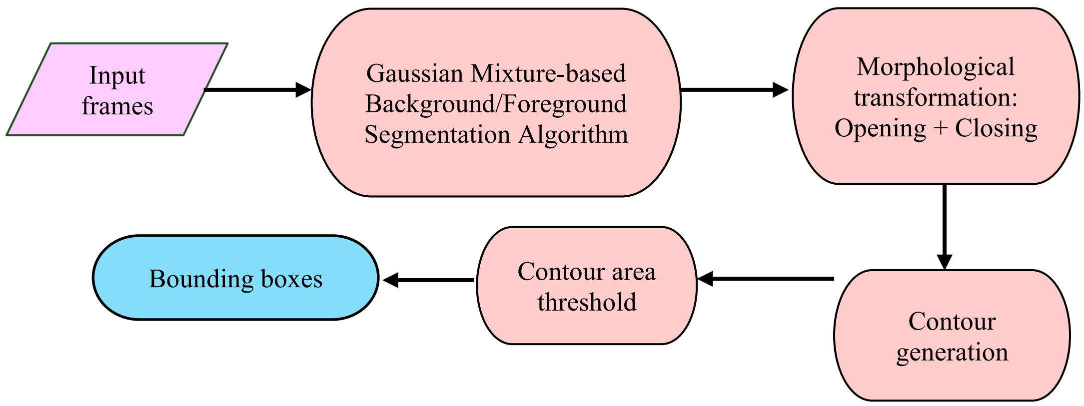


Figure 23: Background subtraction-based approach

5.3.4 Performance Metrics

To evaluate the performance of the image processing algorithms, performance metrics of precision and recall were calculated using the true positive (TP), false positive (FP), and false negative (FN) counts. The definition of precision and recall are as follows:

$$precision = \frac{TP}{TP+FP} \quad (1)$$

$$recall = \frac{TP}{TP+FN} \quad (2)$$

The F1 score was also calculated, which is the harmonic mean of precision and recall, taking both metrics into account.

$$F1 = 2 \times \frac{precision \times recall}{precision + recall} \quad (3)$$

5.4 PERFORMING THE EXPERIMENTS

5.4.1 Data Collection Sites

The first step was determining the freeway and/or high-speed multi-lane road segments that would be suitable for data collection. Although the purpose of the study was to apply UAV video to identify non-recurrent congestion caused by incidents, it was difficult to capture such events with the limited time and effort of data collection. Thus, first investigated were historical crash data to identify freeway sections with higher historical crash rates. Small freeway segments in these sections where recurrent congestion is likely to occur during peak hours due to roadway capacity changes were then identified.

In addition to the crash and congestion analysis described above, the sites had to meet specific requirements for flying a UAS. As it was not desirable to go through the process of obtaining a Certificate of Authorization from the FAA, which can be time-consuming, test locations outside of controlled airspace were selected. Figure 22 is an extract from the Visual Flight Rules

(VFR) Terminal Area Chart for Tampa. Tampa International Airport is the largest airport in the area and occupies the most airspace; no operations could be conducted in its Class B airspace, which extends down to the surface, limiting test site locations.

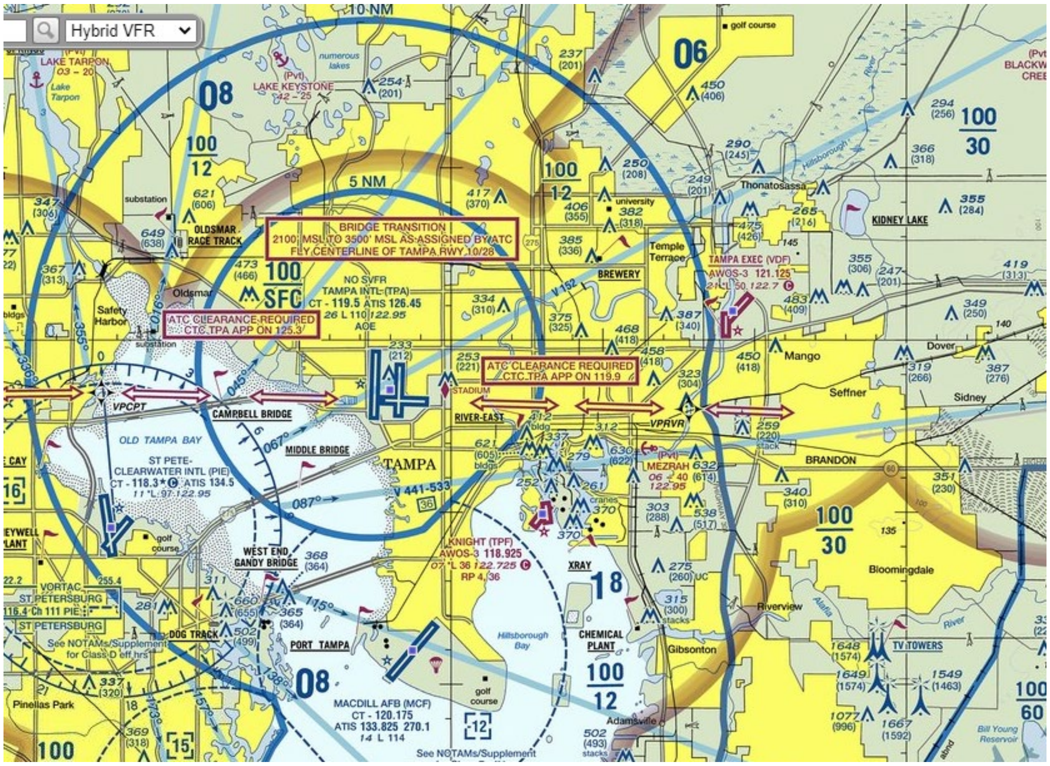


Figure 24: VFR Terminal Area Chart of Tampa—
Used to Ensure No Airspace Rules Broken During Data Collection

The first road segment selected for data collection was along I-75, as shown in Figure 25. The team used an empty parking lot of a nearby establishment to launch the UAS. The location was north of exit 279 on I-75, which offered a clear space for visual line-of-sight operations and proximity to the interstate lanes. This location was used for data collection under free-flowing traffic conditions. Videos were recorded on Saturdays between 12:00–4:00 PM on clear days to ensure good video quality. This location was not used for congested conditions.

The second segment, on I-275, was selected primarily for its high likelihood of congested conditions, as shown in Figure 26. The location was an empty parking lot adjacent to I-275 and next to an exit ramp that leads to E Bird St. Due to the location of the ramp, congestion was expected during afternoon peak hours on the right-side lanes. The road has an overpass and is elevated at the location due to the Hillsborough River and an arterial road underneath. Drone data showed an elevation difference of 30 ft from the parking lot to the surface of the interstate. This elevation was added to the height parameters so the height above the roadway was accurate.

The parking lot next to I-275 was used as a launch site for all data collection under congested conditions. A ramp between the parking lot and the interstate added distance to the roadway from the drone. Data collection occurred on three Fridays between 4:00–6:00 PM during peak hours.

Figure 25: Location of Drone Operations for Uncongested Data Collection of I-75 Traffic
"X" depicts location of drone operator and launch site; yellow line shows path of drone during collection at speed

Figure 26: Location of Drone Operations for Congested Conditions on I-275
"X" marks location of drone operator; yellow line shows path of drone during collection at speed

Data Collection Parameters

To collect data needed for evaluation of the algorithms, the team created a set of parameters that would vary to establish comparison metrics for the different algorithms used. Each combination of parameters created a scenario, and video of traffic was recorded so the algorithms could be exercised and compared. Table 12 shows the selected parameters varied for the scenarios. Video was captured at heights of 50, 100, 200, 300, and 400 ft; azimuth angles of 45°, 90°, and 135°; drone velocities of 0 and 5 mph; and depression angles 45–90°. All videos were collected during clear sky conditions and in the afternoon. The offset from the road was kept at 100 ft, and each video was recorded for 2 min. The combinations of these parameters resulted in 48 different scenarios under free-flow conditions and another 48 under congested conditions. Both RGB and thermal cameras were used for collecting video data for these scenarios.

Table 12: Scenarios for Data Collection

<table>
<tr><th>Scenario No.</th><th>Height (DH)</th><th>Azimuth (ψ)</th><th>Velocity (v)</th><th>Time of Day/Light Conditions</th><th>Depression Angle (α)</th><th>Offset (DDR)</th><th>Video Length (min)</th></tr>
<tr><td>1</td><td rowspan="3">50 ft,
100 ft,
200 ft,
300 ft,
400 ft</td><td>45</td><td rowspan="3">0–
20 mph</td><td>Afternoon–sunny</td><td>45</td><td>100 ft</td><td rowspan="3">2 min each
(96 min
total)</td></tr>
<tr><td>.
.
.</td><td>90</td><td>Afternoon–sunny</td><td>45</td><td>100 ft</td></tr>
<tr><td>48</td><td>135</td><td>Afternoon–sunny</td><td>70–90</td><td>100 ft</td></tr>
</table>

5.5 STATISTICAL ANALYSIS

This Phase I final report presents the experimental results for a fixed station and free-flow traffic condition, comparing the performance of RGB and thermal sensors using the background subtraction-based approach described in the experimental design.

When the drone was at a lower level, namely 100 ft or 200 ft AGL, with $\psi = 45°$ or $135°$, the field of view from the camera could go as far as to the horizon, which made the vehicles very far from the drone. However, due to the small size of the far-away vehicles, the capability of the algorithm to identify the vehicles was reduced. Trial-and-error efforts were conducted to restrict the field of view length, and it was determined that the frame should be cut off by two fifths, with detection conducted only on the bottom three fifths of the frame. Traffic from both directions was detected, and a mask was used to cut off the frame and separate road directions. Figure 27 shows an example of detections on images with an azimuth angle $\psi = 135°$ from 50–400 ft AGL after using a mask to cut off the frame and separate road directions.

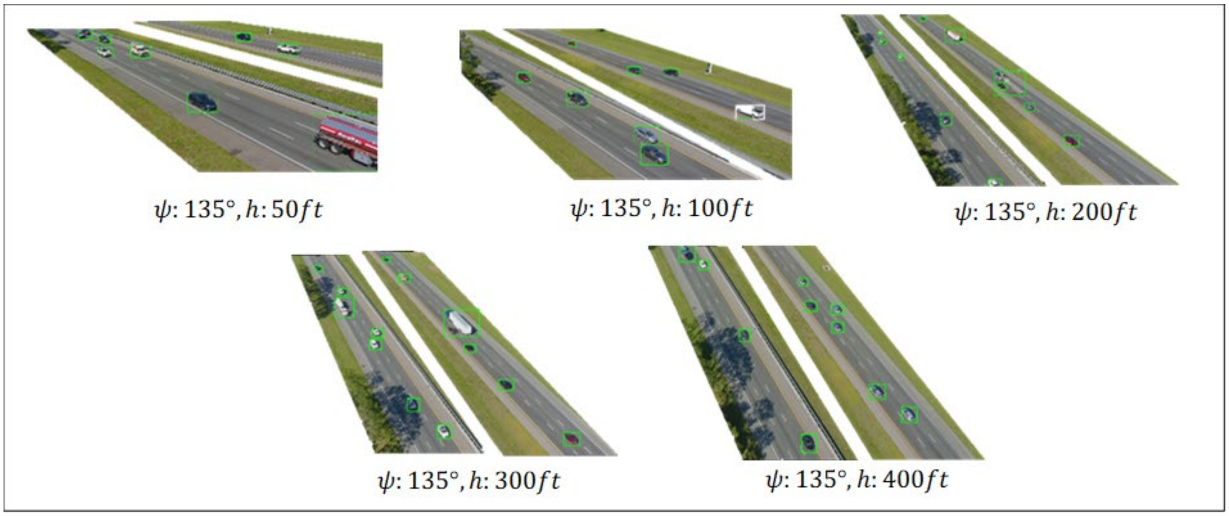


Figure 27: Detection on Images (azimuth angle $\psi = 135°$)
After Using Mask to Cut Off Frame and Separate Road Directions

Tables 13 and 14 show the comparison of RGB and thermal videos of 15 experimental scenarios (five heights 50ft, 100ft, 200ft, 300ft, 400ft AGL and three azimuth angles $45°, 90°, 135°$). Detection results were collected on every 5th frame from the 200th to 700th frame for each video/scenario, and performance metrics were computed. For example, for a video of height h_1 and azimuth angle ψ_1, we first manually counted ground truth (TP+FN) and TPs at each frame and collected the number of detected vehicles (TP+FN) using a background subtraction algorithm. Precision and recall could then be calculated, as could an F1 score given precision and recall:

$$Precision_{h_1,\psi_1} = \frac{\sum_f TP_f}{\sum_f (TP_f + FP_f)} \quad f = \{200, 205, 210, \dots, 700\} \tag{4}$$

$$Recall_{h_1,\psi_1} = \frac{\sum_f TP_f}{\sum_f (TP_f + FN_f)} \quad f = \{200, 205, 210, \dots, 700\} \tag{5}$$

Comparison of F1 scores for RGB and infrared images from different scenarios is shown in Figure 28.

Table 13: Performance Evaluation Outcomes of RGB Images

RGB	50ft–45°		100ft–45°		200ft–45°		300ft–45°		400ft–45°	
Metrics	South	North	South	North	South	North	South	North	South	North
TP	247	238	52	258	181	238	199	126	110	286
FP	16	10	2	7	1	1	5	25	0	0
FN	109	40	12	22	8	7	63	27	5	15
Precision	0.939	0.960	0.963	0.974	0.995	0.996	0.975	0.834	1.000	1.000
Recall	0.694	0.856	0.813	0.921	0.958	0.971	0.760	0.824	0.957	0.950
F1	0.798	0.905	0.881	0.947	0.976	0.983	0.854	0.829	0.978	0.974
	50ft–90°		***100ft–90°***		***200ft–90°***		***300ft–90°***		***400ft–90°***	
Metrics	South	North	South	North	South	North	South	North	South	North
TP	87	67	128	108	56	79	115	71	100	319
FP	8	8	2	12	8	13	0	0	0	6
FN	7	4	8	12	1	2	1	1	1	18
Precision	0.916	0.893	0.985	0.900	0.875	0.859	1.000	1.000	1.000	0.982
Recall	0.926	0.944	0.941	0.900	0.982	0.975	0.991	0.986	0.990	0.947
F1	0.921	0.918	0.962	0.900	0.926	0.913	0.996	0.993	0.995	0.964
	50ft–135°		***100ft–135°***		***200ft–135°***		***300ft–135°***		***400ft–135°***	
Metrics	South	North	South	North	South	North	South	North	South	North
TP	307	206	144	45	286	155	138	253	136	257
FP	7	3	3	2	5	12	5	2	0	7
FN	61	103	2	1	9	18	7	10	19	58
Precision	0.978	0.986	0.980	0.957	0.983	0.928	0.965	0.992	1.000	0.973
Recall	0.834	0.667	0.986	0.978	0.969	0.896	0.952	0.962	0.877	0.816
F1	0.900	0.795	0.983	0.968	0.976	0.912	0.958	0.977	0.935	0.888

Table 14: Performance Evaluation Outcomes of Thermal Images

IFR	50ft–45°		100ft–45°		200ft–45°		300ft–45°		400ft–45°	
Metrics	South	North	South	North	South	North	South	North	South	North
TP	167	234	54	237	174	223	221	144	111	251
FP	7	13	0	2	0	0	0	1	1	12
FN	184	43	8	40	15	20	41	9	4	48
Precision	0.960	0.947	1.000	0.992	1.000	1.000	1.000	0.993	0.991	0.954
Recall	0.476	0.845	0.871	0.856	0.921	0.918	0.844	0.941	0.965	0.839
F1	0.636	0.893	0.931	0.919	0.959	0.957	0.915	0.966	0.978	0.893
	50ft–90°		***100ft–90°***		***200ft–90°***		***300ft–90°***		***400ft–90°***	
Metrics	South	North	South	North	South	North	South	North	South	North
TP	73	67	107	98	55	72	94	57	85	287
FP	14	39	1	0	13	23	25	49	2	30
FN	17	3	21	20	3	9	21	16	16	47
Precision	0.839	0.632	0.991	1.000	0.809	0.758	0.790	0.538	0.977	0.905
Recall	0.811	0.957	0.836	0.831	0.948	0.889	0.817	0.781	0.842	0.859
F1	0.825	0.761	0.907	0.907	0.873	0.818	0.803	0.637	0.904	0.882
	50ft–135°		***100ft–135°***		***200ft–135°***		***300ft–135°***		***400ft–135°***	
Metrics	South	North	South	North	South	North	South	North	South	North
TP	261	183	129	35	165	100	134	244	140	261
FP	40	2	2	0	33	1	3	24	5	4
FN	107	124	2	0	161	96	10	10	13	52
Precision	0.867	0.989	0.985	1.000	0.833	0.990	0.978	0.910	0.966	0.985
Recall	0.709	0.596	0.985	1.000	0.506	0.510	0.931	0.961	0.915	0.834
F1	0.780	0.744	0.985	1.000	0.630	0.673	0.954	0.935	0.940	0.903

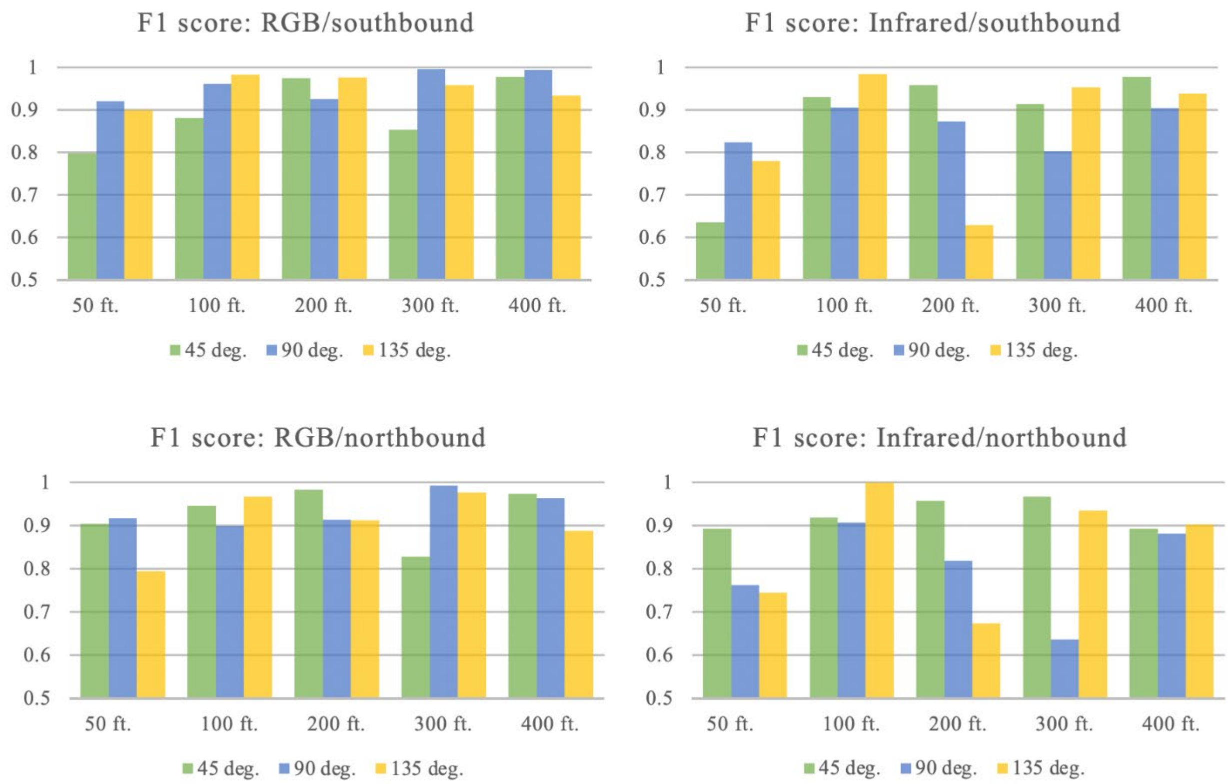


Figure 28: F1 Scores of Different Scenarios by Road Direction and Video Band

5.6 CONCLUSIONS AND RECOMMENDATIONS

5.6.1 Conclusions

The performance metrics statistics show overall that the background subtraction-based method applied in this project can achieve good detection performance on RGB images with most F1 scores around 0.9. The lowest height (at 50 ft) tends to have the worst performance for different azimuth angles; this may be caused by the restricted frames that the camera can capture when the drone is low. When the height of the drone is higher, the performance of the algorithm gets better and is consistent for different angles, except 45° at 300 ft. The research team will scrutinize the video data and further study this result.

Compared to RGB images, the results of F1 scores on infrared images show more variation from different azimuth angles at different drone heights. Overall, the performance was similar compared to the RGB images when the drone was hovering at 100 ft and 400 ft AGL. However, when the drone was hovering at 200 ft and 300 ft AGL, some of the azimuth angles show very low F1 scores, which could be caused by infrared images being more sensitive to noise than RGB images when applying background subtraction-based methods. In the Gaussian Mixture-based Background/Foreground Segmentation Algorithm, there is a parameter that sets the threshold on the squared Mahalanobis distance between the pixel and the model. This parameter was used to decide whether a pixel is well-described by the background model. To remove additional noise from infrared images, this parameter needs to be increased to include the noise in the background rather than outputting them as foreground; as a result, some vehicles that should output as foreground would be mistakenly labeled as background, leading to declining recall values. On the other hand, precision may be impacted when achieving a higher recall by decreasing the threshold. In the end, F1 scores are likely to be impacted by a reduction in recall or precision due to noise.

5.6.2 Recommendations

Based on the literature review, practitioners lack a tool that can provide real-time incident detection without violating privacy protection. Therefore, this study explored real-time vehicle detection algorithms using both visual and infrared cameras. The application of UAS with different sensing technologies for obtaining real-time traffic operational information of freeways was explored. Video data in both visual and infrared bands were collected along interstate highways in the Tampa area, and experiments were conducted to quantify the performance of a real-time background subtraction-based method in vehicle detection from a stationary camera (drone hovering at a fixed station) under free-flow conditions. Finally, the relationship between experimental parameters and performance metrics was analyzed.

The experiment outcomes show that, overall, the background subtraction-based method applied in this study can achieve good detection performance on RGB images, with most F1 scores around 0.9. Compared to RGB images, the performance of infrared images had more variations from different azimuth angles, with only some F1 scores better than or comparable to RGB images. This is because infrared images are more sensitive to noise, which affects precision. To reduce noise, the threshold on the squared Mahalanobis distance could be increased to include those noise to the background, which will improve the precision but will inevitably impact recall. For background subtraction-based methods, the detection performance of infrared images has the potential to outperform RGB images if the camera is stable and there is little noise. Additional trial-and-error efforts need to be conducted to investigate the most effective way to minimize noise when using thermal images.

CHAPTER 6: CONCLUSIONS OF PHASE I AND NEXT STEPS IN PHASE II

State DOTs are using UAS for different purposes in all the US states and territories, with inspections being the most common at 53 percent of total activities and only 18 percent dedicated to roadway conditions. Haynes (2021), at the Innovative Applications in Transportation Infrastructure using Unmanned Aerial Systems (UAS) Congress, presented surface transportation programs using UAS in the USDOT-initiated experimentation in 2010. Currently, wide-scale deployment of drones is implemented in 100 percent of USDOT surface transportation activities. A potential saving of 40–70 percent in these activities can be reached using drones. By 2023, the use of drones in surface transportation programs is expected to triple the current market of 2.7 million, with significant improvements in accuracy and overall worker safety.

A valuable application of UAS in surface transportation is traffic monitoring and incident detection, as emphasized during the ongoing pandemic. COVID-19 has greatly affected how people live and function, and UAVs have proven that they can work during a pandemic to ameliorate certain aspects of everyday life. An example not related to transportation is that UASs have been used for monitoring the streets for compliance with community quarantine guidelines so task forces do not compromise their health and for patrolling the streets in a safe manner (Hinthorn, 2020). Similar functions could be achieved in transportation by flying UASs with sensors and applying efficient algorithms to detect abnormal conditions of traffic operations.

In Phase I of the corridor monitoring project, the research team developed a protocol of using UASs to ensure the safe operations of UASs in surface transportation applications, specifically for freeway and high-speed multilane facilities. The protocol is constantly being calibrated with the procedures and safety requirements that must be implemented in the before, during, and after of flying a drone with the pilot drone training. The research team also developed training materials, trained operators, and obtained pilot-in-command licenses. After careful comparison, the research teams purchased drones within the budget of the project. Following guidelines for designing an experiment, the research team designed the experiments (data collection sites, response variables) and collected RGB and thermal videos in the Tampa Bay area and conducted performance evaluation of Gaussian Mixture-based Background/Foreground Segmentation Algorithm for both RGB and thermal image data. Based on the outcomes of the experiments, for achieving better performance of processing thermal image data, the research team recommends exploring more effective ways of reducing noise while analyzing thermal images.

In Phase II of the project, the research team will identify additional sites in both Tampa and Mayagüez, collect more RGB and thermal image data, and explore ways of improving the image processing algorithm, not only the background/foreground segmentation algorithm but also a learning algorithm that could be used for analyzing images collected from moving platforms. The team also will develop algorithms to detect non-recurrent congestion possibly caused by incidents. The team will work closely with local TMCs and incorporate their comments and suggestions into the project development.

Specifically, four objectives of the Phase II research will be as follows.:

- Advance the current state of the art in freeway automatic incident detection using image data from RGB cameras and thermal sensors and compare the performance of different sensing technologies.
- Develop a protocol for integration and implementation of UASs in Traffic Incident Management (TIM) at a district TMC into existing incident detection systems.
- Identify barriers and challenges of implementing emerging technologies in automatic incident detection and provide suggestions and future research directions.
- Strengthen mutual collaboration and lessons learned associated with incident management with TMCs in both Puerto Rico and Florida for the benefit of reducing recurrent and non-recurrent traffic congestion and improving corridor safety for all present and future road users.

ACKNOWLEDGMENTS

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APPENDIX A: DEFINITIONS

14 CFR Part 107: The pilot must have a valid Part 107 Remote Pilot License and Airworthiness Certificate for a drone. Before flying a commercial drone, the operator must obtain an FAA license. The FAA online registration system for drones went into effect on December 21, 2015, and required all UAS weighing more than 0.55 lbs (250 grams) and less than 55 lbs to be registered.

Average Annual Daily Traffic (AADT): Traffic on a typical day of the year.

Capacity: Capacity changes dynamically based on the degree of weather (e.g., ponding, snow drifts, wind debris, etc.), degree of work zone interference, degree of traffic incident severity, and other nonrecurring events. The HCM defines capacity as "The maximum sustainable flow rate at which vehicles or persons reasonably can be expected to traverse a point or uniform segment of a lane or roadway during a specified time period under given roadway, geometric, traffic, environmental, and control conditions."

Corridor: A corridor is a set of essentially parallel and competing facilities and modes with cross-connectors that serve trips between two designated points. A corridor contains several subsystems of facilities—freeway, rural highway (also called two-lane highway), arterial (also called urban street), transit, pedestrian, and bicycle. Each subsystem is composed of one or more facilities that, in turn, are composed of segments and points. The procedure requires the division of the facilities within each corridor into subsections, or segments, with points at the end of each segment. Traffic demand and capacity conditions are relatively constant over the length of a segment. Points are places where traffic enters, leaves, or crosses the facility, such as intersections or ramp merges.

Congestion: Congestion results when traffic demand approaches or exceeds the available capacity of the roadway system. It should be considered in two dimensions: spatial and temporal, including the where and when. Predicting this can be the first step in combating congestion. Results from one or the interaction of several of the seven sources on the roadway system. This interaction can be complex and can vary greatly from day-to-day and roadway-to-roadway. The seven sources are traffic incidents, work zones, weather, fluctuation of normal traffic, special events, Traffic Control Devices, physical bottlenecks.

Density: Density is the number of vehicles occupying a given length of a lane or roadway at a particular instant, a critical parameter for uninterrupted-flow facilities because it characterizes the quality of traffic operations. It describes the proximity of vehicles to one another and reflects the freedom to maneuver within the traffic stream.

Focal Length and Field of View: Focal length has an inverse relationship with the field of view (FOV). As the focal length is shorter the field of view is larger and vice versa. (Understanding Focal Length and Field of View, n.d.)

Freeway Facilities: An extended length of a single freeway composed of a set of connected basic freeways, weaving, and merge and diverge segments. Basic Freeway: The portions of a freeway outside the influence area of any on- or off-ramps. Weaving: The portions of a freeway where an on-ramp is closely followed by an off-ramp and entering or exiting traffic must make at least one lane change to enter or exit the freeway. Ramps: A length of roadway providing an exclusive connection between two highway facilities; the facilities connected by a ramp may consist of freeways, multilane highways, two-lane highways, suburban streets, and urban streets. Merge and Diverge: The portions of a freeway where traffic enters or exits without having to change lanes to enter or leave a through traffic lane.

Highway Performance Monitoring System (HPMS): FHWA define the HPMS as national level highway information system that includes data on the extent, condition, performance, use and operating characteristics of the nation's highways. It contains administrative and extent of system information on all public roads, while information on other characteristics is represented in HPMS as a mix of universe and sample data for arterial and collector functional systems. Limited information on travel and paved miles is included in summary form for the lowest functional systems.

Incidents: The transportation literature, transportation agencies and officials tend to define incidents differently. Traffic Incident Management Handbook defines an incident as "any non-recurring event that causes a reduction of roadway capacity or an abnormal increase in demand." Under this definition, events such as traffic crashes, disabled vehicles, spilled cargo, highway maintenance and reconstruction projects, and special non-emergency events (e.g., ball games, concerts, or any other event that significantly affects roadway operations) are classified as an incident. (Federal Highway Administration, 2000). Traffic Management Data Dictionary (TMDD), as published by ITE and AASHTO, defines an incident as "an unplanned randomly occurring traffic event that adversely affects normal traffic operations." Developers of the TMDD distinguish incident conditions from planned activities, such as roadwork or maintenance activities by defining different data elements and message sets for both incident and planned roadway events. ((MS/ETMCC), n.d.). The 2000 *Highway Capacity Manual* defines an incident as being "any occurrence on a roadway that impedes normal traffic flow" (Transportation Research Board, 2000). These definitions are very similar, they tend to suggest that within the transportation community, different officials tend to define incidents slightly differently. The *Manual on Uniform Traffic Control Devices* (MUTCDs) classified traffic incidents into three categories—Major Traffic Incident – any traffic incident terms as the major incident if it takes more than 2 hours to clear the traffic; Intermediate Traffic Incident – incident duration 30 minutes to 2 hours; Minor Traffic Incident – incident duration less than 30 minutes.

Level of Service: The *Highway Capacity Manual* (2010) defines level of service as a quantitative stratification of a performance measure or performance measures that represent quality of service. Quality of service describes how well a transportation facility or service operates from a traveler's perspective. LOS is a mechanism used to determine how well a transportation facility is operating from a traveler's perspective. Typically, six levels of service are defined, and each is assigned a letter designation from A to F, with LOS A representing the best operating conditions, and LOS F the worst. Volume-to-capacity (V/C) ratio for traffic can be used for generalized planning, such as that used in the RTP to identify study areas. When using a V/C ratio, demand (volume) is compared to the estimated capacity of each roadway during the evening peak period. The V/C ratio is separated into six levels and assigned a letter from A to F (TRPC, 2016).

Queue (Bottleneck): A localized constriction of traffic flow; a localized section of highway that experiences reduced speeds and inherent delays due to a recurring operational influence or a nonrecurring impacting event.

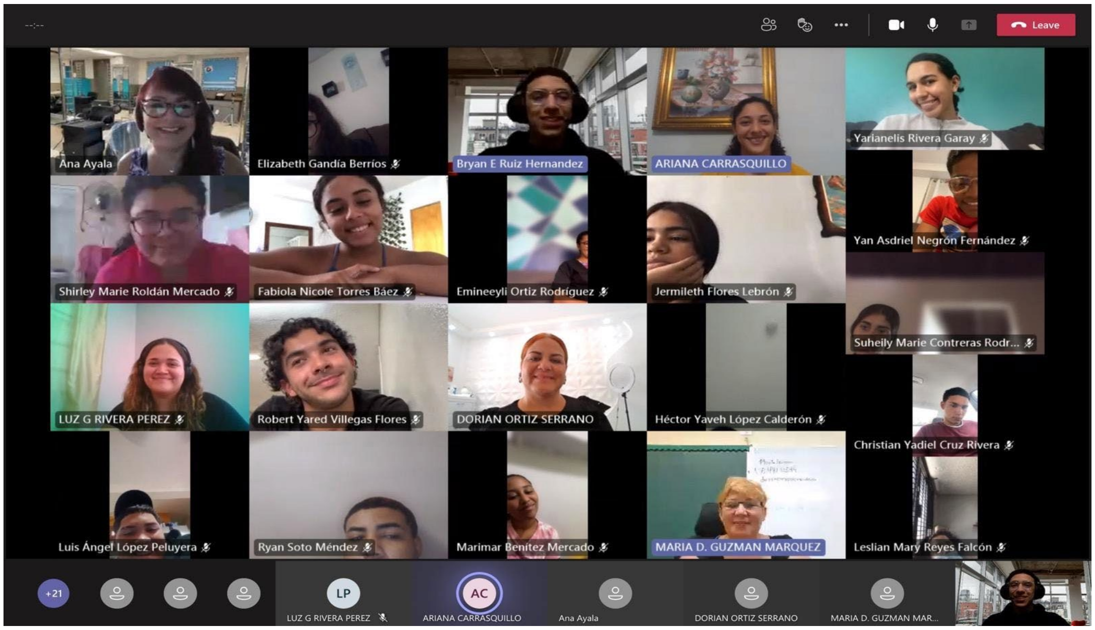
Split Plot Design: A special case of a factorial treatment structure. It is used when some factors are harder (or more expensive) to vary than others. A split plot design consists of two experiments with different experimental units of different "size" (Lukas Meier, n.d.).

Traffic Management Center (TMC): A vital unit of ITS, mainly a technical system administered by the transportation authority. This center works detecting traffic incidents, coordinating the response to address these events, monitoring, and managing vehicle congestion, and distributing information to users of transit conditions on public roads. A TMC may be responsible for managing freeway operations, arterial highway operations, heavy rail operations, transit operations, or a combination of these. A TMC's focus may be urban or rural, regional, or statewide. It may be single or multi-jurisdictional. TMC staff also may partner with other agencies to cover these variety of transportation networks, including police and transit. (Alan Toppen, 2019) Here all data is collected and analyzed for further operations and control management of the traffic in real time or information about local transportation vehicle.(Choudhary, 2019)

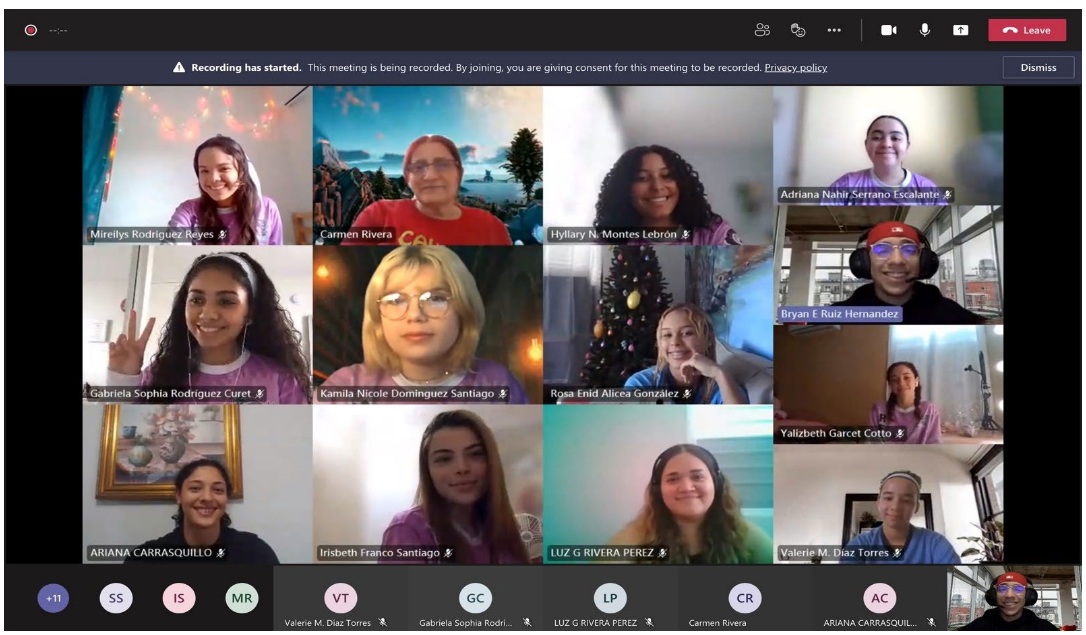
UAS (Drones): Small aircraft that can be easily controlled from a smartphone, capable of carrying cameras or other electrical devices and sensors, which is why they are used in countless scientific and commercial projects.

Uninterrupted Flow Facilities: Freeways, pure uninterrupted flow**,** multilane highway: sections of multilane highways (4 or 6 lane) that are more than two miles from the nearest point of fixed operation; rural two-lane highways: sections of two-lane highways (one lane in each direction) that are more than two miles from the nearest point of fixed operation

APPENDIX B: VIRTUAL MEETINGS

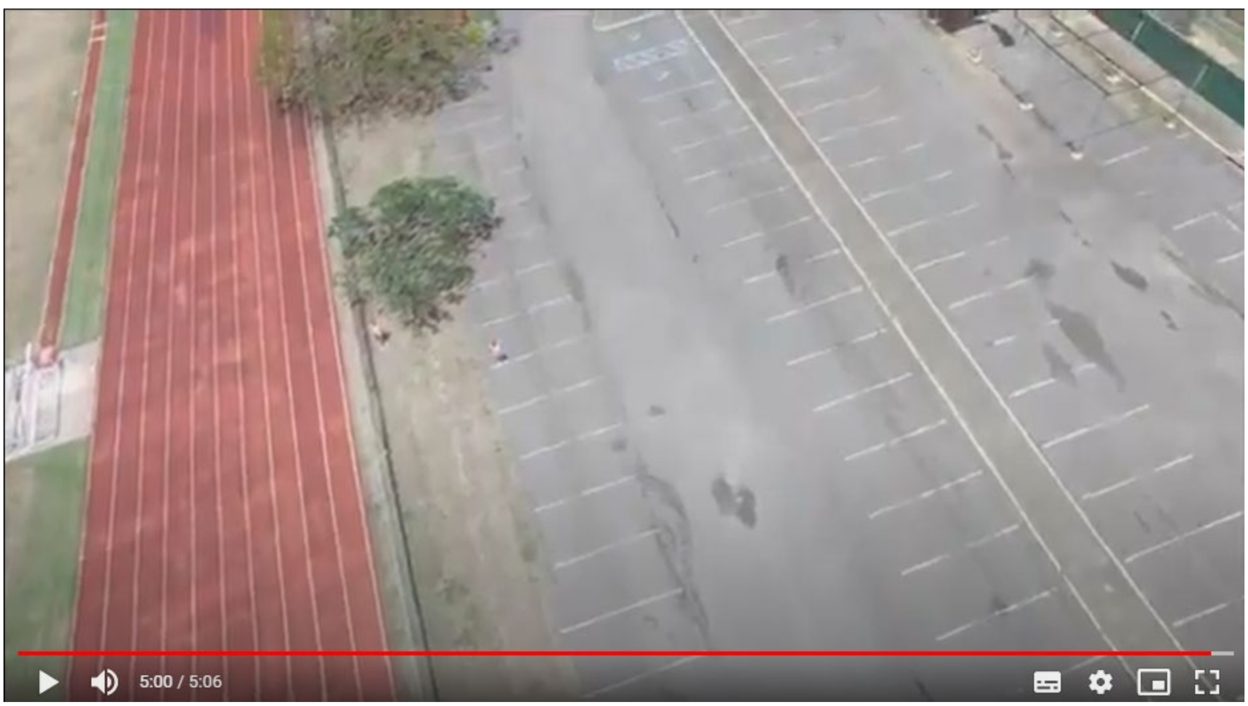


NICR 4-3 Outreach Activity: Presentation for High Schools Students, Aguas Buenas High School, March 30, 2021

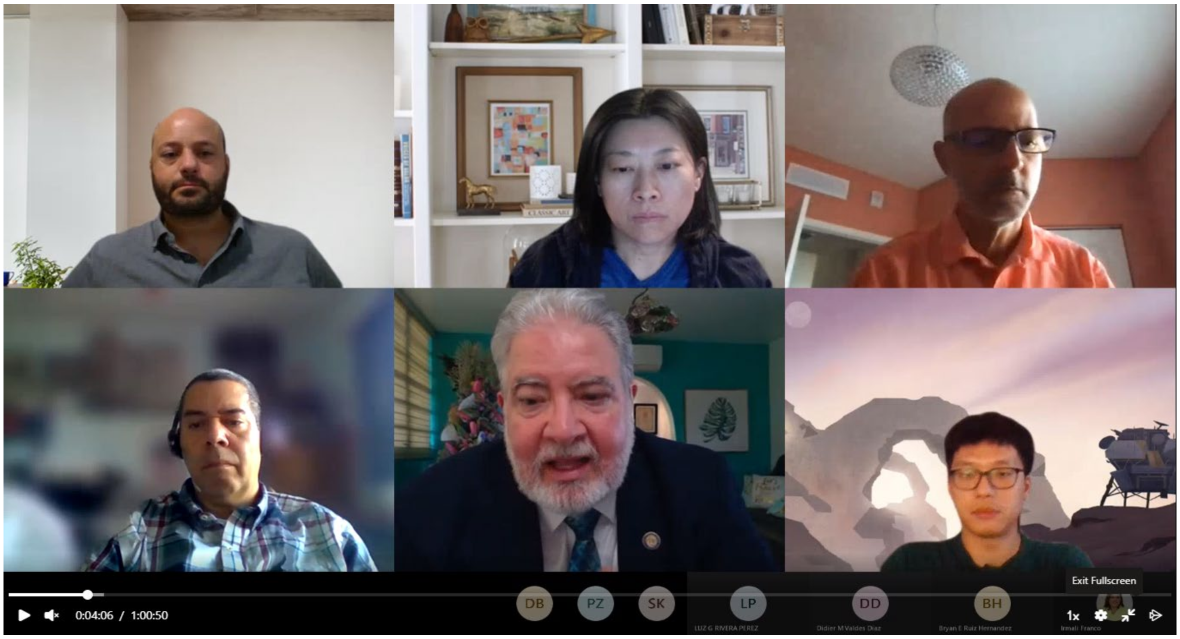


NICR 4-3 Outreach Activity: Presentation for High Schools Students, Genaro Cautiño Specialized School in Science and Mathematics, April 8, 2021

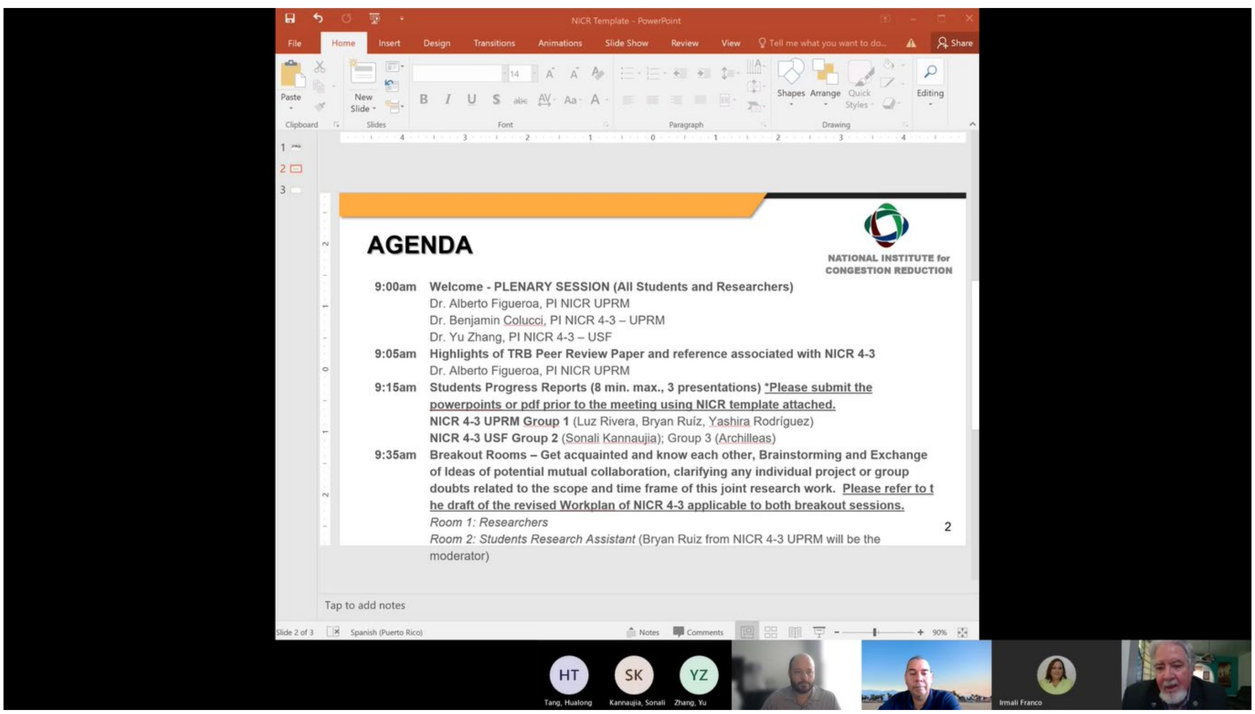
Sample Frame from Drone Video for NICR 4-3 High Schools Outreach Activities



Sample Frame from Drone Video for NICR 4-3 High Schools Outreach Activities



Joint NICR 4-3 USF-UPRM Monthly Meeting



Joint NICR 4-3 USF-UPRM Monthly Meeting Agenda

APPENDIX C. FLIGHT DOCUMENTS

FLIGHT PLAN TEMPLATE

FLIGHT PLAN

CLIENT: PROJECT DURATION:
PROJECT: REMOTE PILOT IN COMMAND:

PROJECT DESCRIPTION

PURPOSE:

LOCATION:

FLIGHT DATES:

AIRSPACE CLASSIFICATION:

Revised by:

FLIGHT PLAN

CLIENT: PROJECT DURATION:
PROJECT: REMOTE PILOT IN COMMAND:

PROJECT DESCRIPTION

OPERATING ALTITUDE:

WAIVERS:

CREW MEMBERS:

Revised by:

FLIGHT PLAN

CLIENT:
PROJECT:
PROJECT DURATION:
REMOTE PILOT IN COMMAND:

PROJECT MAP

LOCATION MAP :

Revised by:

FLIGHT PLAN

CLIENT:
PROJECT:
PROJECT DURATION:
REMOTE PILOT IN COMMAND:

PROJECT MAP

PROJECT AREA:

UAS OPERATING AREA:

Revised by:

FLIGHT PLAN

CLIENT:
PROJECT:
PROJECT DURATION:
REMOTE PILOT IN COMMAND:

PROJECT MAP

TAKE-OFF, LANDING AND
BACKUP LANDING AREAS:

Revised by:

INCIDENT REPORT TEMPLATE

INCIDENT REPORT

CLIENT: PROJECT DURATION:
PROJECT: REMOTE PILOT IN COMMAND:

DATE AND TIME:

LOCATION:

EQUIPMENT:

DESCRIPTION:

Revised by:

INCIDENT REPORT

CLIENT: PROJECT DURATION:
PROJECT: REMOTE PILOT IN COMMAND:

CREW MEMBERS INVOLVED:

DESCRIPTION BASED ON OBSERVATIONS OF THE CREW:

Revised by:

INCIDENT REPORT

CLIENT: PROJECT DURATION:
PROJECT: REMOTE PILOT IN COMMAND:

ACTIONS TAKEN BY CREW MEMBERS:

DESCRIPTION OF INTERACTION BETWEEN CREW AND NON-CREW MEMBERS INVOLVED:

Revised by: