Generating Traffic Statistical Profiles Using Unmanned Helicopter-Based Video Data

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Abstract: **Small unmanned vertical take off and landing vehicles are used to provide the eye-in-the-sky alternative to monitoring and regulating traffic dynamically. Spatial-temporal visual data are collected in real time and they are used to generate traffic-related statistical profiles, serving as inputs to traffic simulation models. Generated profiles, which are continuously updated, are used to calibrate traffic model parameters, to obtain more accurate and reliable simulation models, and for model modifications. This method overcomes limitations of existing traffic simulation models, which suffer from outdated data, poorly calibrated parameters because of outdated data, questionable accuracy and poor predictions of traffic patterns.**

I. Introduction

Traffic simulation models are used to evaluate complex traffic behaviors and design alternative strategies to improve traffic control, minimize congestion and enlarge / modify traffic networks. They help predict future traffic demand, optimize signal timing and determine the need to improve roadway capacity.

Traffic simulation models rely on collecting data from various sources and sensors, and then processing this data to generate study and evaluate traffic patterns and profiles. An integral part of this process includes model modifications and model parameter calibration based on updated data.

Focusing on parameter calibration, simulation models are being calibrated mostly based on distribution and estimation techniques [1]. Lack of continuous and detailed real-time data and lack of frequent updates based on acquired reliable data lead to inaccurate and "not properly calibrated" traffic simulation models with questionable results. Thus, mismatch and discrepancies between predicted traffic situations (output of simulation models) and actual traffic patterns occur.

Moreover, since each traffic network component (segment) has distinct characteristics, one cannot use the same set of calibrated data and parameter values in all network components to predict traffic. Each simulation model needs be calibrated based on the specific network's unique features and traffic patterns. This may be only achieved if collected data is up-to-date, frequently updated, reliable, and data sources are readily available.

However, recent advances and progress in technology and utilization of Unmanned Aerial Vehicles (UAVs) for traffic surveillance has allowed traffic planners to consider the 'eye-in-the-sky' approach to monitor traffic, collect detailed data in real-time and process such data to evaluate traffic patterns, determine origin-destination (OD) flows, as well as for emergency response.

The advantage of using small unmanned helicopters to collect visual data is many-fold: helicopters hover over specific areas, can focus on data collection from a specific link or intersection, can cruise repeatedly over a traffic link/component and they can fly in very low altitudes. They offer a very reliable way of collecting spatial-temporal data.

As such, it is the main objective of this paper to capitalize on small unmanned vertical take off and landing (VTOL) vehicles (helicopters) to collect real-time traffic data from network segments and use this data to generate (mathematical) statistical profiles to improve accuracy, parameter calibration and reliability of traffic simulation models, thus, improving traffic prediction.

The starting point is a 'system' integrated with the unmanned helicopter that automates the process of visual data collection. This is accomplished using a controller with a dual on-board / on-the-ground processing system and a pan–and–tilt camera that collects visual data. Data may be stored on-board to be processed later on, or transferred to the ground station via secure communication channels (at 14-15 frames per second) [2].

Visual data are then converted to traffic statistical profiles that serve as input to the simulation models and are used to update, calibrate and optimize them.

Mathematical equations are derived. Parameters such as speed, density, Level of Service (LOS), OD are calculated for links/segments, while intersection analysis is performed to measure queue length, turning movement patterns and delays.

For the purpose of traffic statistics, roadways may be divided into interstates versus urban networks. This paper considers an urban network that may be further divided into links and intersections. The basic reason for differentiating links and intersections is that on links, vehicles interact only with other vehicles. That is, they need to change their behavior depending only on traffic flow or congestion. At intersections, vehicles also need to respond to signals and queue developments.

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The main contribution and novelty of the paper is the conversion of visual data to traffic statistical profiles that are used to run the simulation models. Indeed, a literature survey has shown that no similar approach exists. Parameters such as intersection delay, network usage, and turning movement that are otherwise difficult to measure can be measured directly through visual data.

A second contribution not to be overlooked is that based on the presented approach, traffic patterns are observed and analyzed in real-time. This is helpful in case of accidents and emergency response, because traffic planners access real-time information that may be helpful to deploy backup resources, de-routing traffic and other crucial decision making.

A. Related Research

Several simulation models such as CORSIM, VISSIM, SYNCHRO and PARAMICS are commercially available and are used by the transportation industry. A set of pre-defined performance measures are used in these models to predict traffic. But since every network along with its associated links and intersections has a distinguished set of behaviors that change dynamically (peak-hours, urban/rural areas, emergency events), pre-defined measures and parameters render inaccurate results. Since most traditional data collection methods are highly expensive and time consuming to gather such extensive amounts of data, simulation models become 'outdated' and inaccurate.

Aerial monitoring is gaining momentum, becoming a well accepted way of gathering traffic data. Research ranges from platform development to deriving application specific image processing algorithms. A detailed list of on-going projects in this area is presented in Table A in the Appendix. Data collection is done using cameras mounted on the vehicle. Systems like COMETS [3] and WITAS [4, 5] are studying control architectures required to handle UAVs for traffic-related applications, while research at Ohio State [6, 7, 8] and UFL [9, 10] focuses on data collection and communication issues.

The rest of the paper is organized as follows: Section 2 describes the proposed framework for real-time traffic video data collection and implementation into traffic simulation models. Section 3 describes formulations to convert the obtained data into traffic statistical profiles and presents results. Section IV concludes the paper.

II. Framework for Real-Time Traffic Simulation and Control with UAV Video Data

Real-time traffic simulation may be incorporated in a real-time traffic control system to support optimization of traffic control strategies such as real-time intersection signal control, ramp metering or variable message signs. Traffic simulation allows one to obtain measures where direct observations are unavailable, for example, where no sensors are located, or to predict future traffic conditions. To support real-time traffic control, these simulation results must reflect reality as closely as possible. Discrepancies between simulation-generated results and real traffic conditions must be and are minimized through regular updating of simulation parameters based on real-time data. Using the traffic conditions estimated by the real-time simulation model, traffic control strategies may be optimized by maximizing throughput or minimizing delay. A block diagram of the proposed approach is shown in Figure 1. Data collection is accomplished using either VTOL vehicle mounted video cameras, or infra-red and other detectors. Video data consist of information related to the entire road network under scrutiny. Image analysis follows to obtain essential parameters such as vehicle type, vehicle density, flow, velocity, turning ratio, turning speed, queue length, queue discharge rate and other variables. Gathered video data is then interfaced with the simulation model to generate a more precise and accurate traffic model.

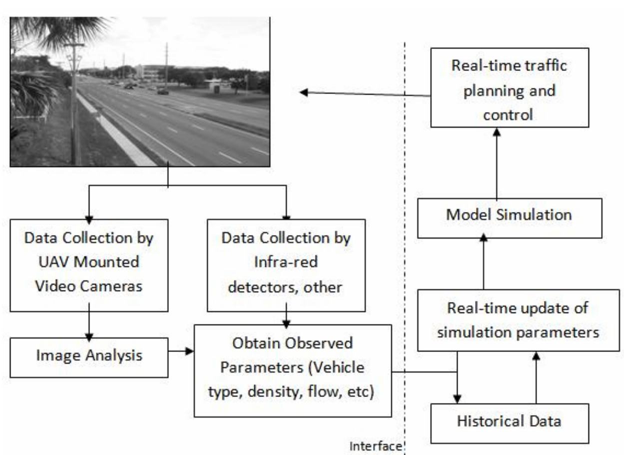


Figure 1: Flowchart of the proposed approach.

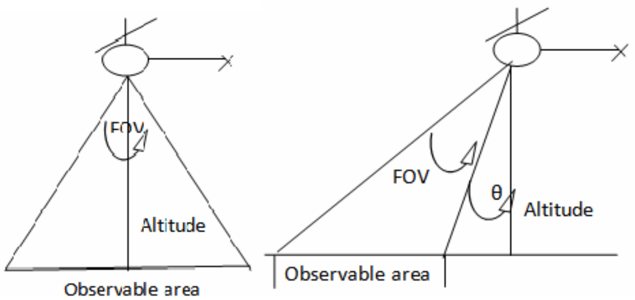
Figure 2 shows a sample traffic image with the results of key processing steps. The initial image is segmented into regions containing motion, which are then designated by superimposing minimum bounding rectangles on them.

Figure 2: Original image (top left), and regions containing motion with bounded boxes placed over vehicles.

III. Creating Statistical Profiles from Video Data

Traffic parameters are defined using detailed video information. Some parameters are similar to formulations found in traffic flow theory literature, while others have been modified keeping in mind the information that can be extracted using aerial video data.

Preliminary work has been completed keeping the unmanned helicopter in a hovering state, that is, the source (camera) is fixed at a point, and can only observe a limited amount of network area. The position of helicopter can be determined by using the on-board GPS sensor. The area that can be covered by a particular camera is called the field of view (FOV). Thus, the observable distance can be denoted by *d (FOV)*, see Figure 3.



(a) (b)

Figure 3: (a) Fixed camera pointing straight down; (b) Camera tilted at some angle. Observable area is the camera's field of view.

From figure 3(a), the area that can be observed is given by

$$ObservableArea = 2 * (Altitude) * \tan(\frac{FOV}{2}) \quad (1)$$

The specific camera that has been used (Sony block FCB-EX980S) has a horizontal Field of View of 42.2^o. Given that the maximum altitude the helicopter has flown is currently 200 ft (approx. 66m) the maximum area that can be observed is about 50.9 m.

In figure 3(b), the observable area is related to the FOV and the tilt angle θ by the equation:

$$Observable\ Area = Altitude * (\tan(FOV + \theta) - \tan\theta) \quad (2)$$

This yields a value of observable area of 165m. This value doesn't take into consideration constraints posed by the requirement to accurately detect vehicles; that is, observe the road and distinguish between overlapping / occluded vehicles. If that is taken into account the detection range is approximately 44 m.

However, to calculate this value it is assumed that the whole image is used for vehicle detection. Alternatively, if only a portion of it is used for processing, then the camera is able to monitor a sizable part of a road (500m or more).

It is important for traffic planners to know the ratio of type of vehicles on a roadway to estimate network usage. The used algorithm to identify vehicles, distinguishes between cars, trucks, and bikes. Increase in ratio of trucks on a roadway decreases the average speed of the link. Thus, a detailed information of vehicular classification is obtained using the image algorithm.

Once the counts are determined using on-board / on-the-ground processing system, the statistical features can be calculated in real-time. It is advisable to perform the statistical calculations on the ground station due to high computing requirements, which require larger infrastructure than could be accommodated on the helicopter. Figure 4 shows a section of the network depicting the two different analyses required for traffic planning. Link analysis is used to calculate speed, flow, density etc; while intersection analysis is used to calculate turning movement, queue estimation, and delay.

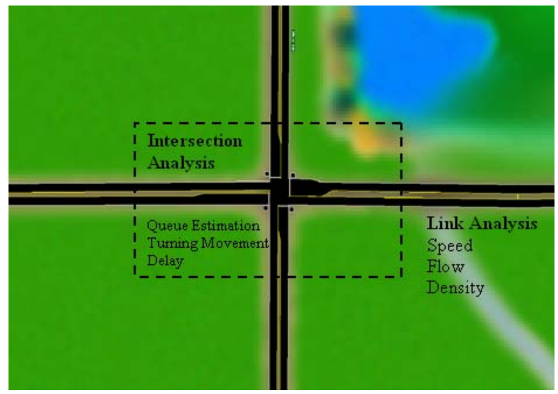


Figure 4: Performance measures on a network (link and intersection)

A. *Link Analysis*

The main performance measures that pertain to a link are speed, density, flow, volume, inter-vehicle spacing, occupancy, etc. Even though speed of each individual vehicle may be measured, mean speed is an essential parameter for traffic analysis. For speed, and almost all parameter calculations, the distance is considered as d(FOV), while the time taken for a vehicle to travel the distance d(FOV) is the time interval in which the vehicle enters the FOV until it leaves the FOV.

$$Time = t(LeavesFOV) - t(EntersFOV) \quad (3)$$

Thus, the mean speed can be calculated as

$$s = \frac{1}{n}\sum_{i=1}^{n}\frac{d(FOV)}{t_i} = \frac{d(FOV)}{n}\sum_{i=1}^{n}\frac{1}{t_i} \quad (4)$$

t_i → time taken for vehicle *i* to enter and exit the FOV,
d(FOV) → distance of observable area in FOV,
n → number of vehicles observed during a given time period.

Occupancy of a link at a given time period is calculated as the ratio of number of vehicles present on the link at the specified time period to the total capacity of the link

$$Occupancy = \frac{NumberOfVehicles}{TotalCapacity} \quad (5)$$

Although photographic techniques were employed to calculate density till the early 1960s [11], advanced techniques currently available allow for calculation of details in real time. Typically, density of a link is calculated by estimating the mean distance headway among vehicles over a length of one mile. For calculating distance headway, prior knowledge of time headway and speed of vehicle is required. In such case, it is extremely difficult to accurately obtain the value of mean distance headway. The advantage of aerial view is that we do not need to calculate distance headway, as density can directly be calculated as the total number of vehicles observed within a particular lane segment. Another advantage of this detailed data is that number of vehicles can be counted on a lane basis. Density on link approaching node n is

$$k_{i,l,n} = \frac{v_{i,l,n}}{d(FOV)} \tag{6}$$

with i being the direction of arrival (east, west, north, south); $k_{i,l,n}$ the density of vehicles entering node n from the i^{th} direction in lane l; $v_{i,l,n}$ the number of vehicles entering node n from the i^{th} direction in lane l.

Total density of a particular link in i^{th} direction is then the summation of vehicles in all lanes in the link.

$$k_{i,n} = \sum_{l} k_{i,l,n} \tag{7}$$

Thus, the total density across a node n

$$k_n = \sum_{i=1}^{i=4} k_{i,n} \tag{8}$$

LOS indicates the quality of service to travelers on a link. It is a qualitative measure of the operating conditions based on speed, occupancy, travel time, convenience, etc. The less the time taken to travel, the better the LOS. Thus, if the density on a link is low, LOS is would be higher. The highway capacity manual gives the following table to determine LOS if density is known.

LOS	Max. Density	Min. Speed	Max Service Flow Rate	Max v/c Ratio
Free Flow Speed = 55 mph				
A	10	55	550	0.24
B	16	55	880	0.39
C	24	55	1320	0.59
D	32	54.5	1744	0.78
E	45	50	2250	1
F	var	var	Var	var

Table 1: LOS measures [12]

Table 1 shows the LOS categories along with the corresponding density, speed and flow rate at free flow speed of 55 mph.

The v/c (volume-to-capacity) ratio is an important measure to estimate congestion on the link. Using the video data, volume (demand) can be calculated as the number of vehicles observed at a given time in a link. A direct way to get the volume is to pick up a static image of the link and count the number of vehicles in it. This is equal to the volume on the link at that time. Capacity can be calculated using the formulation given in [12].

Travel delay on a link may be defined as the extra time it takes for a vehicle traveling at lower speeds as compared to when it may travel at free-flow speed. Link delay is mentioned here, while intersection delay will be covered in the next section. Link delay is directly associated with the density on the link. Higher the density, lower is the vehicle speed, thus higher will be the delay.

Thus, delay on a link may be calculated as

$$Delay = t_f - t_d \tag{9}$$

t_f → travel time with free-flow conditions
t_d → travel time with delays

$$t_f = \frac{d(FOV)}{s_f} \tag{10}$$

s_f → free-flow speed

$$t_d = \frac{d(FOV)}{s} = \frac{d(FOV)}{\frac{d(FOV)}{n} * \sum_{i=1}^{n} \frac{1}{t_i}} = \frac{n}{\sum_{i=1}^{n} \frac{1}{t_i}} \tag{11}$$

Thus,

$$Delay = \frac{d(FOV)}{s_f} - \frac{n}{\sum_{i=1}^{n} \frac{1}{t_i}} = \frac{d(FOV) * \sum_{i=1}^{n} \frac{1}{t_i} - n * s_f}{s_f * \sum_{i=1}^{n} \frac{1}{t_i}} \tag{12}$$

B. *Intersection Analysis*

The most important performance measure pertaining to intersections is queues and delay. An issue with current data collection method at intersection is that vehicles are measured when they pass a stop bar (served traffic), while the queue backup (demand traffic) is ignored [13]. Also, turning movement is hard to determine using loop detectors. Visual data is very helpful to calculate the queue length as well as turning movement. A polygon-based methodology is described to determine queue length at a given intersection.

C. Queue Estimation

The definition of queue length differs across literature, and different formulations are used by simulation models to implement queues [14]. For the purpose of our research, queue length at an intersection is defined as the number of "stopped" cars at an intersection at the instant the signal turns from red to green. At this time, the stopped cars start to dissipate, clearing away the queue. One of the problems with such definition is that it takes some time for the vehicles at the end of the queue to start moving, in which time some more vehicles enter the queue. The method described in this paper does not include these "moving" vehicles as part of the queue, as these vehicles do not stop due to the signal, but due to vehicular interaction only.

At the moment when the signal turns from red to green, a polygon-based area can be detected. Such type of analysis has also been used in [15]. Figure 5 shows one such scenario.

Figure 5: An intersection queue scenario.

The average spacing between two cars, or gap, at halt can be calculated prior to queue length estimation. This value can be taken directly from previous literature or an analysis of gap distance can be done for the particular intersection. Let l_1 and l_2 be the length of the polygon, and w be the width of the total number of lanes. Also let g_a be the mean acceptable gap between two vehicles. Thus,

$$v = \frac{A}{g_a + v_a} \tag{13}$$

$$A = \frac{1}{2}(l1 + l2) * w \tag{14}$$

v is the number of vehicles in the queue, g_a is the mean acceptable gap, v_a is the area of one vehicle.

The above equation is helpful to find the total number of vehicles in queue in all lanes. The problem with such method is that even though the gap between adjacent vehicles in the same lane is considered, we ignore the gap between adjacent vehicles in adjacent lanes. To solve this, it is important to mention here that v_a (area of one vehicle) should actually be considered to be equal to the multiple of the vehicle length v_l and the width of the lane w_l.

$$v_a = v_l * w_l \tag{15}$$

This simply means that one vehicle occupies the entire width of the lane.

Turning movement on an intersection can be easily determined using aerial video. Each vehicle is tracked individually through the intersection. As the vehicle passes through the intersection, a counter can be incremented for through, left turn and right turn respectively. Alternatively, points can be setup on the turning lanes, and a counter gets incremented whenever a vehicle crosses that point.

The novelty of aerial data can be utilized for otherwise hard-to-calculate parameters such as intersection delays. Intersection delay consists of control delays, delays occurring due to deceleration and acceleration at the intersection. It is extremely hard to estimate intersection delay analytically. With help of video data, each vehicle can be followed through the intersection, the time taken can be noticed, and thus, the delay that the vehicle experienced can be calculated.

OD matrix is essential to analyze the travel behavior of network. Estimating the OD path for vehicles is extremely difficult using loop detector data. Fortunately, in case of aerial video data, vehicles can be tracked from the moment they enter the network till they leave it. Figure 6 shows one such network. Each link acts as both an origin and a destination. When a vehicle enters the network, it gets tagged by its source of origin. Its path is followed, and finally when it leaves the network, it gets assigned with the destination point. Travel time of each vehicle for every OD pair is observed and tabulated.

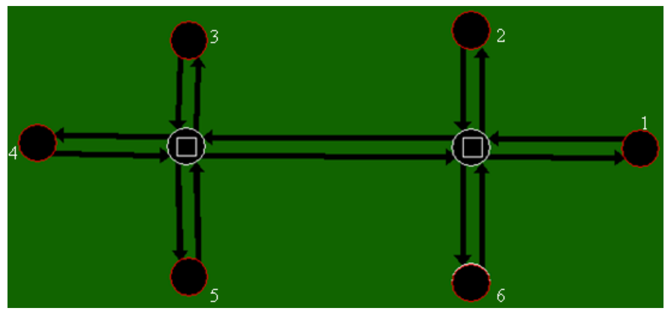


Figure 6: A network with multiple OD nodes

Assuming $n_{o,d}$ be the number of vehicles with origin o and destination d. Table 2 shows the OD matrix that can be formed. Similar of table can used to represent the travel time $t_{o,d}$ for vehicles to enter and exit the network using a set of OD paths.

		ORIGIN					
DESTINATION	Node	1	2	3	4	5	6
	1	0	$n_{2,1}$	$n_{3,1}$	$n_{4,1}$	$n_{5,1}$	$n_{6,1}$
	2	$n_{1,2}$	0	$n_{3,2}$	$n_{4,2}$	$n_{5,2}$	$n_{6,2}$
	3	$n_{1,3}$	$n_{2,3}$	0	$n_{4,3}$	$n_{5,3}$	$n_{6,3}$
	4	$n_{1,4}$	$n_{2,4}$	$n_{3,4}$	0	$n_{5,4}$	$n_{6,4}$
	5	$n_{1,5}$	$n_{2,53}$	$n_{3,5}$	$n_{4,5}$	0	$n_{6,5}$
	6	$n_{1,6}$	$n_{2,6}$	$n_{3,6}$	$n_{4,6}$	$n_{5,6}$	0

Table 2: OD Matrix for small network

In case of large networks, each origin or destination node for a zone is considered as a centroid of the zone. With current technology, estimating this centroid point is not accurate. With help of aerial data, it is easier to accurately calculate centroid of the zone based on density of the zone.

IV. FUTURE WORK

Current study is done considering a stationary camera, assuming that the UAV is in hovering state, with a fixed FOV. In Figure 7, some sample graphs of number of vehicles detected over time for each direction of interest are shown. Future work needs to be done for a moving camera source, when the UAV is in cruise state. Since the environment changes dynamically, identification and monitoring of vehicles becomes more challenging. Communication channels using 802.11 requires high bandwidth and secure connections between the helicopter and ground station to ensure high quality 30-frames per second video transfer. Also, mathematical formulations for parameters will need to incorporate the global axis along with the local axis of the moving camera.

Extended work needs to be done to calculate more useful parameters such as inter-vehicle spacing, extended delay analysis, capacity analysis, etc.

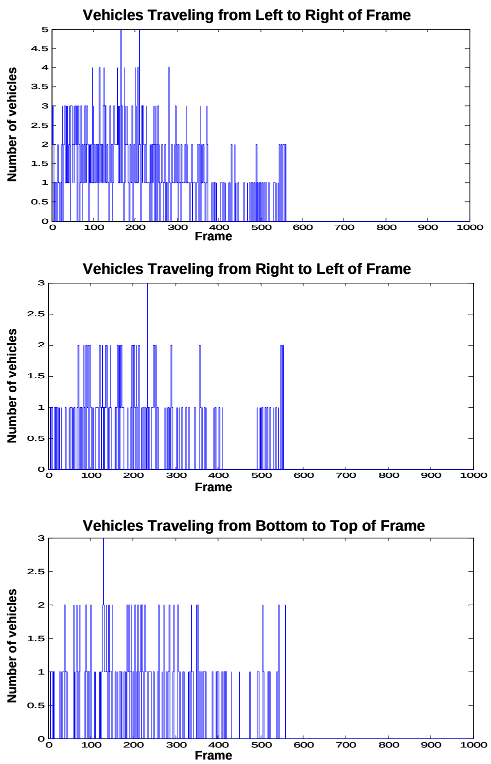


Figure 7: Converted video data

V. Conclusion

This paper presents a novel framework to gather traffic data using video camera mounted on an UAV, and an automated procedure to extract detailed measures which can be incorporated into traffic simulation models. Further, effort has been put to calculate some useful traffic parameters using the available data. These can be very useful to update and optimize simulation models in order to minimize the discrepancies between simulated data and real-world data.

Appendix

Table A shows list of current research work on UAVs related to traffic surveillance.

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Research	Team	UAV	Objective
Ohio [6,7,8]	Ohio State University Ohio DOT NCRST	MLB BAT3 (Fixed Wing)	Application of UAV for surface transportation surveillance Collecting Information on freeway conditions, intersection movements, network paths, and parking lot monitoring. Traffic parameters measured
ATSS (UFL) [9,10]	University of Florida Florida DOT Tallahassee Commercial Airport RWIS Research Team	Aerosonde (Fixed Wing)	Use of UAV with video for data collection Define communication links using current FDOT microwave system Timely information on transportation networks -both rural and urban
WITAS [4,5]	Linkoping University, Sweden	Scandicraft Apid Mk 3 (Rotary wing)	Develop technologies for deployment of fully autonomous UAV Integrate autonomy with active vision system Identifying complex patterns of behavior (vehicle overtaking etc)
COMETS [3]	LAAS CNRS Real-time Systems & Robotics ADAI CVL HELIV	MARVIN (Rotary) Karma Blimp (Fixed) Remotely Piloted helicopter (Rotary)	Design and implement a distributed control system for cooperative detection and monitoring using heterogenous UAVs. Control architecture and technique of real-time control. Integrating distributed sensing techniques with real-time imaging
Arizona [15,16]	University of Arizona NCRST-F	Manned	Use of Manned Helicopter Deriving vehicle trajectories from video Traffic parameters measured
Minnesota [17]	University of Minnesota	Unknown	Autonomous traffic monitoring Determining traffic parameters
Traffic Surveillance Drone [18]	Georgia Tech Research Institute Georgia DOT Federal Highway Administration's Priority Technology Program	Customized Drone (Rotary wing)	Development of generic VTOL, advanced controllers. Fault-tolerant and Autonomous operation algorithms. Achieve dynamic performance and flight control command generation.
Ultimate Auto-Pilot [19]	University of California, Berkeley Office of Naval Research's AINS Program	(Fixed Wing)	Intelligent guidance systems for UAV Strategies of path-planning Augment GPS with machine vision
Bridgewater State [22]	USDOT's RSPA NASA Bridgewater State College University of Massachusetts MLB Company	MLB BAT 3 (Fixed Wing)	Autonomous UAV to collect and interpret real-time traffic data Gather multi-modal data using road-following capabilities
ETH Zurich [20]	ETH	Customized UAV	Traffic Surveillance
ORCA [21]	Carnegie Mellon University	Customized UAV (Rotary)	Develop a vision-based robot helicopter which can operate autonomously to carry out well-structured mission goals.

Table A: List of current research work being undertaken at various universities along with their objectives.