

Drones in Smart Cities: Overcoming Barriers through Air Traffic Control Research

Aislan Gomide Foina, Raja Sengupta, Patrick Lerchi, Zhilong Liu and Clemens Krainer

Abstract— Within the last decade, the recent automation of vehicles such as cars and planes promise to fundamentally alter the microeconomics of transporting people and goods. In this paper, we focus on the self-flying planes (drones), which have been renamed Unmanned Aerial Systems (UAS) by the US FAA. The most controversial operations envisaged by the UAS industry are small, low-altitude UAS flights in densely populated cities - robotic aircraft flying in the midst of public spaces to deliver goods and information. This subset of robotic flight would be the most valuable to the nation's economy, but we argue that it cannot happen without a new generation of Air traffic control and management services. This paper presents a cloud based system for city-wide unmanned air traffic management, prototype sensor systems required by city police to keep the city safe, and an analysis of control systems for collision avoidance.

Index Terms—UAV, UAS, UTM, drones, identification, traffic management system, smart cities, collision avoidance.

I. INTRODUCTION

AIRCRAFT operate in National Airspace Systems (NAS for short), which are controlled by governments worldwide. The underlying principles involving control systems and services have engaged the control and operations research community since 1950 [1]. Today, both the global and United States (US) NAS may be on the brink of a transformation in scale. In 2012, the US Bureau of transportation statistics recorded 209,000 General Aviation and 7,400 Commercial Cargo/Transit aircraft. These numbers are dwarfed by annual US drone sales, which exceeded 250,000 aircraft in 2014 and are forecast to reach on million by 2018 [2]. NAS controllers like the US FAA or EUROCONTROL are currently structured to work with an industry that sells aircraft by the hundreds each year, not by the hundreds of thousands. Are the FAA's of the world hurtling towards a change of scale?

We perform a quick thought experiment to assess the new scale. If US aircraft sales were 100,000 units per year, the US NAS would increase by one whole order of magnitude (Note:

2014 sales already surpass this value). If annual drone sales reach one million new aircraft per year, the NAS will increase to the order of 10 million operating aircraft - growth by two orders of magnitude. Systems engineers know that a change in scale by an order of magnitude changes complexity, creating pressure for new systems built on new principles. We write this paper to explore the new kind of air traffic control required for aircraft in the millions, describe new systems we have built, and integrate the current literature.

We see the contours of the new problem emerging from two salient features - low altitude flight with low cost air traffic control services. The drones driving growth are priced as consumer products in the range of \$500 to \$50,000. They are used as low altitude toys or tools for personal aerial photography. Commercial operations, still small in the US due to FAA restrictions [3], are projected an economic impact of the tens of billions [4], led by:

- Agriculture - for crop dusting and field imaging
- Motion Picture and commercial Film cinematography
- Utility and energy companies surveying hundreds of kilometers of power lines or pipelines
- Delivery services such as Amazon Prime Air, UPS or Google's Project Wing

These drone uses are also low altitude flights for various reasons. For safety reasons, no package would be dropped to a consumer from above a few meters, nor would a farm spray insecticide from high altitude. The imaging and surveying applications are low altitude because the costs of imaging sensors need to match the costs of the drones to keep the economy of operations, i.e., \$500 to \$50,000. Cameras, thermal imaging, or radar sensors at these prices have short ranges (~100 meters).

In the rest of this paper, low altitude is nominally defined as 500 feet and below (~150m), following the recent FAA NPRM [5], which highlights altitudes of 500 ft and below as the target range for these drone operations. Airspace at such low altitudes signals a major change of style for Air Traffic Control. FAA FAR 91.119 requires all aircraft to stay above 1000 feet in congested areas and 500 feet elsewhere. Excepting airports, the entire air traffic control infrastructure is designed to work above 500 feet where there is nothing but aircraft. The new airspace is

This work was supported in part by the Brazilian CNPq under Grant 232525/2013-7.

A. G. Foina is with the University of California - Berkeley, Berkeley, CA USA (e-mail: aislan@berkeley.edu).

R. Sengupta is with the University of California - Berkeley, Berkeley, CA USA (e-mail: sengupta@berkeley.edu).

P. Lerchi is with the University of California - Berkeley, Berkeley, CA USA (e-mail: patrick.lerchi@berkeley.edu).

Z. Liu is with the University of California - Berkeley, Berkeley, CA USA (e-mail: lzl200102109@berkeley.edu).

C. Krainer is with the University of California - Berkeley, Berkeley, CA USA (e-mail: clemens.krainer@berkeley.edu).

where humanity lives its life.

Low-altitude is the link to cities. Cities govern the spaces lived by dense clusters of humanity. When aircraft fly above 1000 feet, people do not notice and control can be left to national or federal agencies. However, drones flying at 50 to 100 meters behave more like cars: they will be noticed, interacted with, and feared. Cities control and regulate cars through traffic lights, signs, speed limits, speed bumps, and other measures. They hold the institutional capacity, though not the technical capacity, to govern millions of drones flying at low-altitude in densely populated areas. Organizations like the FAA, EUROCONTROL, and emerging companies like Airware hold the technical capacity or expertise. The new unmanned air traffic control enterprise needs to be a collaborative enterprise between Smart Cities and NAS Operators, renting services pioneered by Silicon Valley. We present three technical products in the paper, two of which are built with a focus on cities. The path to scale is the distribution of control over the smart cities of the future.

Two current developments indicate the emerging collaboration between the US FAA and the smarter cities of the future. 35 of 50 US states and many cities have written pending or enacted drone legislation suggesting a strong desire to have control over low altitude unmanned flight [6]. Likewise, the FAA has asked local law enforcement agencies to take responsibility for enforcing rules on unmanned flight [7]. The new volumes are too big for the current Air Traffic Control structure. The US FAA already uses 15,000 employees as controllers for 220,000 aircraft. How many employees will the current model need for 10 million drones [4]?

The second paradigm-shifting factor is the cost required for the new unmanned air traffic control services. Low cost drones will produce commerce only with low cost air traffic control services. On its web site, the FAA shows how a pilot flying from Los Angeles to Baltimore interacts with 28 air traffic controllers in 11 different flight centers. Current air traffic control is a high-touch high-cost business that processes 87,000 flights per day in US airspace. UPS alone delivers 17 million packages daily at nominally \$5 a package. A million \$5000 drone flights delivering items valued under \$50 would all need to be executed without conversing with an air traffic controller. In short, unmanned aircraft need unmanned air traffic control. Traffic lights for cars are unmanned and low-cost.

We found two national projects targeting low cost unmanned air traffic control – Australia’s Smart Skies project [8], and NASA’s new Unmanned Traffic Management program in 2014 [9]. NASA’s UTM has published a 2-page fact sheet envisaging ideas like a portable UTM box easily usable by entities without the technical expertise of NAS operators. Smart Skies prototyped and tested MATS (Mobile Aircraft Tracking System). However, neither program derives its products from the structure and economy of cities, which is why this paper prioritizes very different problems. For example, section II is about incentivizing cities and citizens to provide airspace and flight data. The Smart Skies MATS system is based on portable radar. We target even lower costs by, basing on smartphones, Wi-Fi, cellular data, and GPS. Dedicated Short-Range Communications, being driven by transportation departments worldwide, are essentially Wi-Fi and GPS based collision

avoidance communications for cars [10]. Engaging cities will bring NASA’s UTM architecture to life.

We have found one other paper on drones for smart cities [11]. They identify several challenges, of which this paper provides solutions for two – low altitude unmanned air traffic management at low-cost. There are two other papers discussing similar challenges [12], [13]. Other papers on drone air traffic control focus on reducing the operator-to-vehicle ratio [14], [15].

The aerial roboticists of the 21st century have done what Henry Ford did for automobiles, i.e. consumerized aircraft. The control engineers should now consumerize air traffic control. To this end, we present three pieces of work that we consider essential, summarized as follows.

1. The Community Drone Service for Problems of Planning: This is a cloud-based platform whose first function is to support a citizen and city process that will create low-altitude airspace. Airspace needs airways, obstructions such as building footprints and heights, landing areas and approach paths for services like package delivery, over-flight permissions or prohibitions. This is section II. The platform includes flight planning services. The current flight planning service is a routing algorithm running on the airspace model, called the Air Parcel model, computing a flight path to a destination. This service would eventually be like the direction service on Google Maps but for the air in three dimensions.
2. Management and Control Functions Coordinating Drone and Smart City Infrastructure: The systems required first are ones able to affix responsibility for every drone flight on some legal person. This is akin to reading the license plates of cars. Drones need a type of license plate readable by local police while the drone is in the air. The license plate system needs to be highly accessible, scalable, and reliable. We consider alternatives to aircraft tail numbers, and we have built two prototypes. Coordination also includes flight analysis services over a mobile cloud of boxes called Flight Integrity Units (FIU). These collect the data from each drone flight and then transfer it to the platform, which analyzes the flight for violations of FAA rules, city regulations, trespass, or assessment of flight taxes that may be city or federal.
3. Control Functions that are purely Drone based: We have started with the problem of avoiding collisions between drones and helicopters, because they fly with people at low altitudes. Our principal concern is that a helicopter far away from a drone will trigger the drone to execute a collision avoidance maneuver simply to avoid an unlikely worst-case, i.e., the helicopter might suddenly turn and fly straight towards the drone at maximum speed. This would destroy the commercial value of drone flight. The objective of analysis is to find collision avoidance protocols that minimize unnecessary interruptions to commercial drone operations, while maintaining the high level of safety expected by people in helicopters. We find that a helicopter 100 to 300 meters away can cause a drone to execute collision avoidance maneuvers. This is acceptable. The analyses also show that raising ADS-B transmit frequency from 1Hz to 2 Hz may be worthwhile. Drone-to-Drone de-

confliction services are future work.

II. COMMUNITY DRONE PLATFORM - PROBLEMS OF PLANNING

This is a cloud-based platform to be used by citizens and cities to create low altitude airspace. We present the platform and discuss how to incentivize citizens to use it.

Urban unmanned aerial commerce needs structured airspace with clearly defined airways. This is the first purpose of the Community drone platform, illustrated by Figure 1. We seed airspace structure by taking the land parcel map from the city office and extruding each land parcel to 500 feet, thus creating an Air Parcel above it. Figure 1 shows an Air Parcel Map for the Berkeley campus. Each building is assumed to be a parcel.

Ownership of the air parcel is assigned by default to the landowner, with air parcels over city roads being assigned to the city, those over parks or water bodies assigned to the park or water authorities, and so on. Each air parcel owner is empowered to login into the system and post information about her parcel. This is illustrated by the white “Change Permissions” box in Figure 1. Important information includes building height, flight restrictions, landing areas, and safe approach paths to the areas.

The landowner needs to be motivated to post information, a process we make easy by a web browser. Next, we expect that building insurance companies will motivate parcel owners to post, because publishing a building height will create an obstacle or no-fly box of the right height visible to drone operators inside the air parcel. This would reduce the risk to insurance companies, because a drone operator entering a posted no-fly box could be held liable. A second platform capability, i.e. posting trespass restrictions on the air parcel, targets privacy or environmental concerns. While the part of the parcel above the buildings may be safe to enter, we still empower the parcel owner to post trespass. Restricting access by posting trespass can protect against unwanted photography, reserve airspace for clean air or low noise drones, safer propeller guarded drones, or other characteristics. A smart city could put the force of local law behind trespass posted on such a platform, further motivating citizens to post. Each type of trespasses restriction creates new problems of sensing, violation detection, and enforcement, discussed in section III.

The third platform function is flight-planning services for drone operators. Since we now have an airspace structure, a drone operator seeking to fly from an origin to a destination, can be served by solving a vehicle routing problem [16] in the Air Parcel space. The Berkeley campus air parcel map shown by Figure 1, makes airways on all campus roads. The buildings in cyan have permitted over-flights which enlarges airways, while those in red have not. As drone operators, we log into the platform, specify an origin and destination, and get a flight path compliant with all the posted restrictions.

The routing algorithm currently in the platform is simple, and overly so. We compute paths that use only the air parcels above campus roads, by abstracting the campus road network into a graph and running Dijkstra’s algorithm on it. This is sufficient because the road network is built to connect all buildings. Done this way google maps could compute all the air routes even

today. We would simply shift the computed route up.

The control community has many contributions to the Vehicle Routing Problem. Better algorithms are possible and desirable for scale. The Google directions API permits 10 requests per second from a single IP and 100,000 requests in a 24-hour period. If 10% of UPS packages eventually become drone deliveries, the company would generate nearly 2 million routing requests per day. The next routing algorithms should be 3-dimensional and exploit the Euclidean properties of airspace as done in 2-d ([17] and references therein).

III. CO-ORDINATION FUNCTIONS FOR DRONE AND CITY INFRASTRUCTURE

We anticipate management and control functions that need to be supported by smart cities for drone commerce, present work on the functions that need to be provided first, and discuss others that will be required when there are more drones in the city skies.

A. *The Unique Identifier Allocation Problem*

The airspace is only open for business when responsibility can be affixed on a legal person for every drone flight. This means each drone flight needs a unique identifier, traceable to the responsible legal person. Candidate unique identifiers include aircraft tail numbers backed by an FAA registry linking the number to a legal person; for cars, we have the VIN and license plate. In the US, the Departments of Motor Vehicles provide the service of tracing the license plate to a legal person. This is the kind of infrastructure required to put unique identifiers within reach of consumers. Drones are flying computers, meaning SIM cards or IP addresses could become possible unique identifiers. Telecommunications companies provide the tracing infrastructure for SIM cards, and ICANN with its affiliates the same for IP addresses. Unique identifiers are an expensive business because of the corporate infrastructure required to link them to legal persons.

In this paper we describe a prototype based on SIM cards. The aircraft tail number infrastructure works on the scale of thousands a year, while the SIM card infrastructure works on the scale of millions. We propose each drone carry a Flight Integrity Unit (FIU) that is essentially a flying cellphone. It should record flight data including GPS waypoints and speed, and be configured with meta-data about its drone such as its make and model number. This identifies safety and environmental impact features important to citizens. Our current FIU is a modified Android phone. One takes responsibility for a drone flight by simply inserting a SIM card into it. Our FIU then logs all the flight data with the number of the inserted SIM card and transmits it over the cellular network. The current FIU is the phone with an App. SIM cards as unique identifiers can separate a legal person responsible for a flight from the legal person owning the drone. Aircraft tail numbers could be used to identify the latter. We also use the FIU cellphone screen to broadcast the SIM number as described later for visible identification by local police.

Therefore, we propose that cities standardize the unique identifier to be used by any commercial drone operator flying

in the city, and require an FIU be mounted for any flight. The FIU must upload its flight data (non-real time) to the Community drone platform and support visible identification by city police as discussed next.

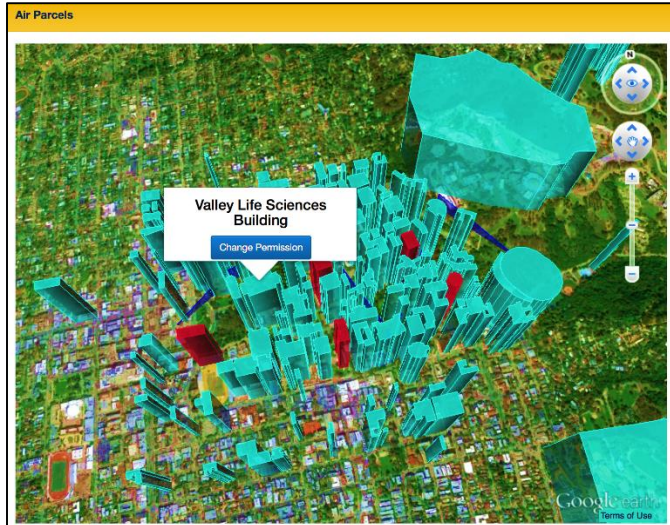


Fig. 1. Structured airspace created by us over the UC Berkeley campus. Each building is a separate Air Parcel. Owners of Air parcels in red have forbidden over-flight by posting trespass, while the cyan air parcels permit over-flight. Landowners can log in using web browsers and change permissions.

B. The Non-Real Time Identification and Flight Analysis Problem

Here we focus on the problem of enabling drone operators to fly as good citizens in compliance with local laws, and with the proper payment of taxes or fees imposed by cities for commercial operation. As drone operators, we upload flight data from the FIU to the Community Drone platform, as kml files with the SIM card number as meta-data. The platform then automatically computes any air parcel violations. The violated parcels are colored red in Figure 2. A future platform would assess any relevant taxes or fees, invoice the SIM card owner by integrating with telecommunication databases, and transfer payments to the appropriate city accounts.

C. The Real-time Drone Identification Problem

Unmanned air traffic management and law enforcement functions will require identification of a drone in real-time. The FAA’s Air Traffic Control currently solves this problem for large aircraft by using secondary surveillance radar or its modern version called ADS-B. The system delivers an aircraft position labeled with the unique identifier of the aircraft, the same data from our FIU, but in real-time. These systems are for remote operators monitoring airspace. We have focus on a city policemen wanting to identify a drone she is looking at, much like the office reads the license plate number of a car. Our two solutions are based on cellular data communications and LED’s. The two solutions could be used together. We found patents identifying UAS using RF and color codes [18], [19] without performance analyses of the kind included here.

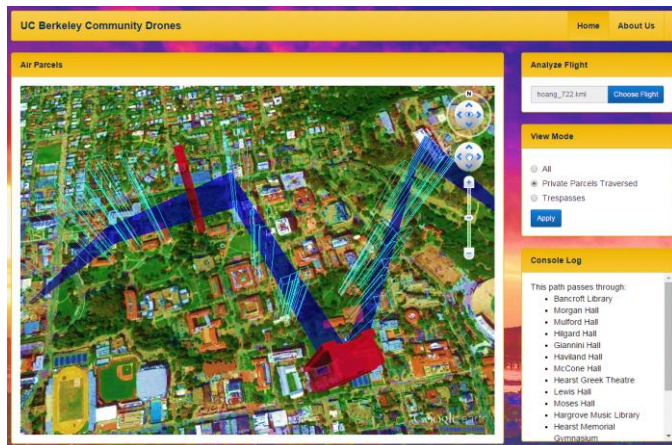


Fig. 2. The blue visualizes a drone flight path. It shows drone flight data uploaded to the platform by an FIU. All air parcel crossed are listed in the bottom right window and visualized in cyan. Air parcels trespassed are highlighted in red.

Identification by LED

The purpose is to enable a police officer looking at a drone to read its unique identifier, just as one reads the license plate of a car. This problem needs technological enhancement because the drone is smaller and further away. The LED solution requires an FIU on the drone and a camera held by the police officer, much as he uses a radar gun for cars. There is one patent using light signals to identify a UAS [20].

Our FIU cellphone screen blinks a color pattern encoding the number of the SIM card in the FIU. The phone is attached to the drone as illustrated in Figure 3a. The current prototype is for proof of concept and encodes just the last four digits of the SIM. We are also experimenting with LED arrays. See Table I for a first comparative performance assessment. Car brake lights are LED’s and visible at nearly 300 meters. Problems such as the visible ranges, the impact of solar glare, and identification reliability need further research, as do radar or laser range finder based solutions.

We have prototyped an FIU on a Raspberry PI connected to a RGB LED array and integrated with the PX4 autopilot, sending the FIU GPS coordinates through the MAVLink protocol. The Android mobile phone FIU creates a standalone solution, i.e., without the autopilot. The insurance company could install the FIU. The drone operator installs autopilots. The Android FIU can be attached to any UAS with any autopilot. The phone GPS logs the flight data and uploads it via Wi-Fi or the cellular data network.

Our current blink uses only five different colors, red, green, cyan, yellow and pink. The sequence consists of six blinks, creating 15,625 possible combinations. The FIU lights each colors for 500ms, with a 200ms pause separating blinks. At the end of the sequence, there is a one-second pause to mark the next cycle. The maximum total time necessary to capture the complete blink sequence is 4.8s. We have used a sequence of five colors flashes so a person looking at a UAS can see the colors and the complete sequence. A person would have to look at a small drones flying at 15m/s for 72m to see the complete code.

For the police officers identifying drones, we have prototyped the handheld camera device in Figure 3b. This is an android cell phone with a special attachable 12x zoom lens to increase the detection range. The cell phone camera captures the image. The phone has an App that uses the OpenCV library to detect the colors. The zoom lens increases the detection range by 30% - 104m during the day and 516m at night.

Table 1 presents all the measured distances. Using a 4" phone screen installed beneath the drone, as seen in Figure 3a, we could identify the blink sequence at 87m with the naked eye during a sunny day and at 384m at night. The daytime range rises to 150m with LED's on the drone instead of a blinking smartphone screen. The FAA's 500 ft flight ceiling is 150 meters.

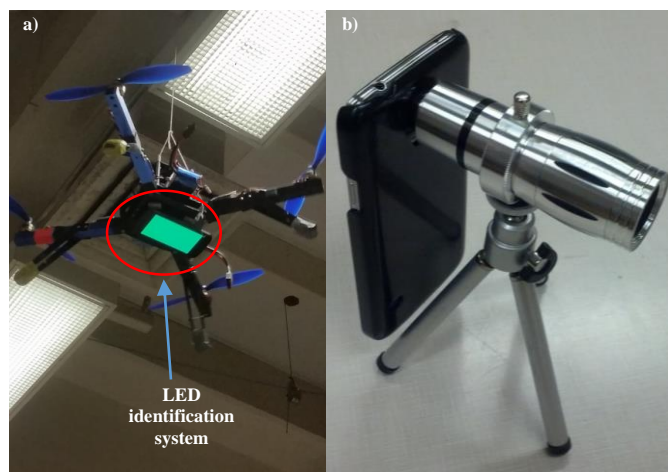


Fig. 3. a) Flight Integrity Unit (FIU) mounted on the underside of a quadrotor. The FIU logs and transmits all flight data with SIM card number over the cellular network. It also blinks a color pattern encoding the SIM number in the FIU. b) The prototype of our ground identification device which is a cellphone camera with a 12x zoom. When pointed at the blinks it decodes the color sequence and displays the SIM card number on its screen.

There are problems in the current system. For example, we could not use blue in the identification color sequence. The background sky is mostly blue during the day and the app was not able to distinguish between the license plate and the sky. Further image processing research is required.

In addition, we cannot identify the blinks when the vehicle is between the ground device and the sun. The sun is much brighter than the mobile screen. This motivated the switch from a smartphone LCD screen to LED's. Car brake LED lights are visible for more than 300 meters on roads, even against the sun. Since we are at 150m only, our image processing could get a lot better.

Identification by Cellular Data Communication

The FIU is able to transmit aircraft position and velocity while flying over the cellular network. Test data in Table 2 at UC Berkeley shows most end-to-end ping delays are under 150 ms with minimal loss at least in areas with good cellular coverage. Thus a citywide FIU integrating server could display a map of drones with current GPS positions and heading to enforcement officers. If the officer knows her own GPS location and the compass direction of the drone being observed, the map could help the officer identify that drone.

TABLE I
LICENSE PLATE COLOR IDENTIFICATION RANGE

Light Emitter	Environment Light	Light Receiver	Range
Smartphone Screen	Day	Camera	15m
		Camera 12x	104m
		Eyes	87m
	Night	Camera	42m
		Camera 12x	516m
		Eyes	384m
RGB Ultrabright LEDs	Day	Camera	24m
		Camera 12x	158m
		Eyes	101m
	Night	Camera	55m
		Camera 12x	516m
		Eyes	461m

This FIU based system would not be blinded by the sun as might happen to the LED-detecting camera. On the other hand, the camera and LED solution would work in areas with poor cellular coverage. The two approaches could be integrated.

Our tests measured the received signal strength and the network latency for FIU data transmitted over the cellular network. The test was conducted at 100m for 10 minutes. The signal strength during the flight is 7.6% better than on the ground. However, the average communication latency is 2.6% better at the ground level.

Real-time drone identification solutions need to work with high reliability in the following sense. If an officer cannot identify the drone by the prescribed combination of tools, it must be true with high probability that the drone is deliberately flying without identification and is subject to law enforcement. High-speed tolling systems for cars miss less than 1 in a million cars, meaning incorrect citation rates are extremely low. Our prototypes have not yet reached this level of reliability. Thus research into the sensor, image processing, and cloud-based integration systems for real-time identification is interesting and worthwhile.

The next generation of problems in the city-drone coordination will arise as flight volumes increase. Drones will conflict at intersections, creating the need for de-confliction executed purely drone-to-drone [21], or with the equivalents of traffic lights and stop signs in the air [8]. The drone-drone free flight de-confliction algorithms work for four vehicles or less flying indoor. The need for virtual traffic lights in the air might arise at higher volumes.

IV. DRONE-BASED CONTROL FUNCTIONS

Real-time functions required for safe flight should be based purely on the drone, similar to the architecture for automated highway systems [22]. We see the first required function being collision avoidance with manned aircraft below 500 feet or 150 meters. These are helicopters. A manned helicopter ambulance could be flying to pick up a patient while an unmanned aircraft is autonomously delivering packages. Next come systems for collision avoidance with property and people, and still later

TABLE II
SIGNAL STRENGTH AND COMMUNICATION LATENCY WHILE FLYING

Altitude	Parameter	Average	Standard Deviation
Ground Level	RSSI (dBm)	-55.93	1.83
	Ping Latency (ms)	74.47	23.20
100m	RSSI (dBm)	-51.68	0.98
	Ping Latency (ms)	76.47	26.12

separation services for drone and drone, or virtual traffic lights. Our approach to avoiding buildings is as described in section II. It complements sense and avoid. Here we focus on drones avoiding collision with helicopters. Our main concern is the distances at which a helicopter will cause a drone to execute collision avoidance maneuvers quantified as the Worst-Case Minimum Maneuver distance (WCMMD). This is intended to be an upper bound in the sense that in practice the distance between helicopter and drone should be smaller at initiation of avoidance maneuvers. Overly large distances may be safer but uneconomical.

The literature discusses cooperative and non-cooperative solutions. The non-cooperative rely on sense and avoid for collision avoidance. We focus on a communication-based cooperative solution using a technology like Automatic Dependent Surveillance-Broadcast (ADS-B). The ADSB-Out transponder broadcasts aircraft GPS position and velocity data at one Hz, which is then received in real-time by nearby aircraft with ADSB-In [23]. The FAA has mandated that any aircraft flying in the US must be equipped with an ADS-B transmitter by 2020. As one might expect, this ruling has sparked a rapid growth in ADS-B technology for drones. Manufacturers have started producing lightweight ADS-B transponders tailored specifically for small UAS, such as XPG-TR from Sagetech and ADS-B ONE from NextGen UAS Transponders.

Following the literature, we model an aircraft as a ADSB equipped point mass and leverage the optimal control approach developed in [24] and [21]. We seek an avoidance maneuver executed by the drone alone, i.e., the drone is responsible for avoiding collision with a helicopter carrying people. The helicopter will cooperate only by transmitting position and velocity as ADSB-Out data.

We adapt the work in [21] to achieve a single vehicle optimal maneuver. The mathematics in [21] shows the optimal control is the maximum acceleration with a constant optimal heading. We derive the heading expression. The control law is optimal in the sense of letting the vehicles get as close as possible before triggering an avoidance maneuver. A real-time avoid set can be computed.

We address the following scenario: a small quadrotor, equipped with (ADS-B)-In must avoid a manned helicopter with (ADS-B)-Out. The maneuver is performed exclusively by the quadrotor. We assume the worst-case behavior of the helicopter. It flies at maximum velocity at each heading including the one straight towards the quadrotor. We restrict optimal control to be two-dimensional for simplicity.

The basic configuration is shown in Figure 4. The quadrotor and the helicopter are vehicles 1 and 2, respectively. Let $k = \{1,2\}$, then the vehicle positions and velocities are (x_k, y_k) and (\dot{x}_k, \dot{y}_k) in the world frame. The avoidance maneuver, expressed as the pair $\mathbf{u}_1 = [a_1 \theta_1]^T$, is the quadrotor's acceleration vector \mathbf{u}_1 with magnitude a_1 and direction θ_1 , where θ_1 is measured from the positive x-direction in the body frame of the quadrotor.

Following [21] the optimal maneuver has constant acceleration. Figure 5 highlights some position trajectories in solid red lines under optimal control. The quadrotor is at the origin, and the helicopter has relative position $(x_{12}(t), y_{12}(t))$

and is heading toward the quadrotor. The quadrotor starts the avoidance maneuver at some initial time $t = t_0$ in the past and advances to the present time $t = 0$, with initial position $(x_{12}(t_0), y_{12}(t_0))$ and final position $(x_{12}(0), y_{12}(0))$. The trajectories are parabolas since the acceleration vector stays constant. The set of all possible $(x_{12}(t_0), y_{12}(t_0))$ that come as close as possible generate the boundary of the avoid set ∂K , which is indicated by the dashed red curve in Figure 5. Within the avoid set K , optimal control is applied. A safety set S is defined by the solid gray circle with radius r_{min} around the quadrotor. The set of all $(x_{12}(0), y_{12}(0))$ lies on the boundary of the safety set ∂S . The helicopter should never enter S . The largest distance to start optimal maneuver is defined as $\|x_{12}(t_0), y_{12}(t_0)\|_2|_{x_{12}(t_0)=0}$ on ∂K , we call it the worst-case minimum maneuver distance (WCMMD). Note that the relative frame is rotated such that $\dot{x}_{12}(t_0) = 0$ and $\dot{y}_{12}(t_0) < 0$. Therefore, points on ∂K have purely downward velocities. A backward rotation should be made after the optimal control angle θ_1^* is computed. For details, refer to [21].

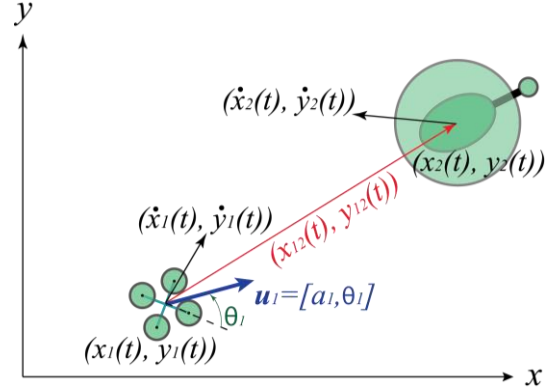


Fig. 4. The collision avoidance scenario.

There are two goals in this section. First, we derive the constant optimal acceleration vector $\mathbf{u}_1^* = [a_1^* \theta_1^*]^T$, which minimizes $\|x_{12}(t_0), y_{12}(t_0)\|_2$. Second, we graph WCMMD as a function of several parameters.

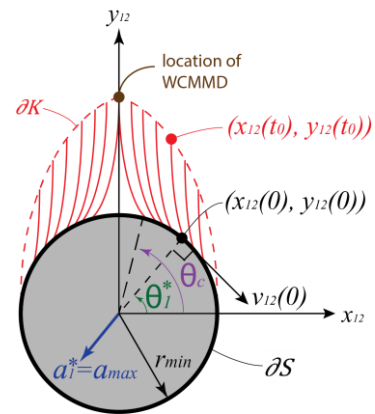


Fig. 5. The avoidance set is in red and the safety set is in gray.

If a_{max} is the maximum achievable acceleration of the quadrotor, then \mathbf{u}_1^* has magnitude $a_1^* = a_{max}$ [18]. This leaves the optimal direction θ_1^* as the only unknown control variable, which we derive.

Given the relative position of the two vehicles $[x_{12} \ y_{12}]^T$, as is indicated in Figure 4, the relative dynamics are given by

$$\frac{d}{dt} \begin{bmatrix} x_{12} \\ y_{12} \\ \dot{x}_{12} \\ \dot{y}_{12} \end{bmatrix} = \begin{bmatrix} \dot{x}_{12} \\ \dot{y}_{12} \\ -a_1 \cos \theta_1 \\ -a_1 \sin \theta_1 \end{bmatrix} \quad (1)$$

With (1), it is possible to derive θ_1^* by following the non-cooperative pursuit-evasion game formulation in [21].

$$\theta_1^* = \tan^{-1} \left(\frac{y_{12}(0)}{x_{12}(0)} \right) + \pi \quad (2)$$

Intuitively, θ_1^* is optimal because at this angle, all available acceleration is used to decrease the relative velocity component along the radial direction of the safety set S at time $t = 0$. By the time the helicopter touches ∂S , this particular velocity component is zero. Consequently, the helicopter will fly with velocity $v_{12}(0)$ tangent to ∂S and not enter S .

From Figure 5, we can see that θ_1^* is only defined on certain parts of ∂S : $\theta_1^* \in [0, \theta_c] \cup [\pi - \theta_c, \pi]$ for some unknown θ_c . At $\theta_1^* = \theta_c$, we have the worst-case minimum maneuver distance at which collision avoidance has to start, corresponding to when the helicopter flies directly at the quadrotor.

To find the critical angle θ_c and WCMMD, we need to find the parabola starting at $x_{12}(t_0) = 0$ on ∂K . To do so, we first derive the relative position $(x_{12}(t_0), y_{12}(t_0))$ on ∂K by tracing the dynamics backward in time. For a particular θ_1^* on ∂S , we have

$$\begin{aligned} x_{12}(t_0) &= \left(r_{min} - \frac{v_{12}(t_0) \sin^2 \theta_1^*}{2a_{max}} \right) \cos \theta_1^* \\ y_{12}(t_0) &= \left(r_{min} + \frac{v_{12}(t_0)}{2a_{max}} (1 + \cos^2 \theta_1^*) \right) \sin \theta_1^* \end{aligned} \quad (3)$$

where $v_{12}(t_0) = |\dot{y}_{12}(t_0)|$ is the relative speed at time $t = t_0$. The derivation of (3) is in Appendix I. Lastly, we solve for $\theta_c \triangleq \theta_i^*|_{x(t_0)=0}$,

$$\theta_c = \sin^{-1} \frac{\sqrt{2a_{max}r_{min}}}{v_{12}}, \quad 2a_{max}r_{min} < v_{12}^2 \quad (4)$$

Now we know when to apply optimal control. Excepting $x_{12}(t_0) = 0$, each point on ∂K maps uniquely to a θ_1^* on ∂S . Therefore, we first generate ∂K using (3) for a set of $\theta_1^* \in [0, \theta_c] \cup [\pi - \theta_c, \pi]$, then compare the helicopter's position $(x_{12}(t), y_{12}(t))$ to points on ∂K . If $(x_{12}(t), y_{12}(t))$ equals to a particular point on ∂K , then we find the corresponding θ_1^* and apply optimal control $\mathbf{u}_1^* = [a_{max} \theta_1^*]^T$.

Next, we would like to graph the WCMMD for a set of parameters. The parameters include the minimum separation distance r_{min} , the maximum quadrotor acceleration a_{max} , the relative speed $v_{12}(t_0)$ defined above in (3), and the ADS-B communication delay Δt . The nominal values of the parameters are chosen as follows.

First, r_{min} is chosen such that the safety set is twice the size of a typical helicopter, around 15m in diameter. By convention, a typical quadrotor is designed to lift twice its own weight. In this case, the quadrotor could tilt up to 60° , which is very unlikely in real-flight scenarios. Instead, a maximum tilting angle of 45° is more practical, generating a maximum acceleration a_{max} of around $10m/s^2$. The relative speed v_{12} is

dominated by the helicopter speed, which we consider a value of $70m/s$ for commercial helicopter. The quadrotor speed is assumed to be $10m/s$. Thus the parameters are: $r_{min} = 20m$; $a_{max} = 10m/s^2$; $v_{12} = 80m/s$.

Around this nominal condition, a range of a_{max} and v_{12} is simulated. The required WCMMD is shown in Figure 6. The most common cases are encapsulated in the lower-right corner, with the WCMMD ranging from 100 to 150 meters. The optimal maneuver duration vary from 1.8 to 2.5 seconds from simulations. Under extreme conditions, such as high wind, when a_{max} is small and v_{12} is large, the required distance could increase to around 200 meters.

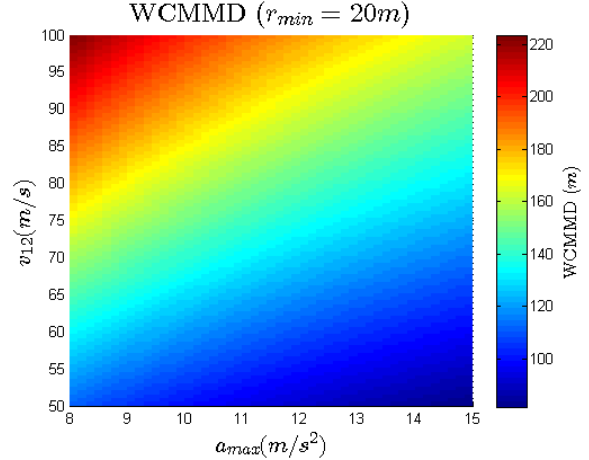


Fig. 6. The worst-case minimum maneuver distances (WCMMD).

Additionally, the delay from the ADS-B communication could be as high as one second. The amount of delay increases the avoidance distance linearly by $v_{12}\Delta t$, which is roughly 100m. Assuming a WCMMD of 150m without delay, this extra delay could yield up to 67% uncertainty in the result, which is quite significant. If the ADS-B transmitting frequency were higher, say 2 Hz, the uncertainty due to delay would be significantly reduced.

V. CONCLUSION

Drone evolution and integration into NAS's is currently challenging the air traffic management community. We need new processes and platforms for low-altitude UAS flight. This paper proposes solutions for widespread UAS flight at low-altitudes through a community platform engaging cities and tools for city law enforcement officers. Our discussion breaks down the new flight problems into three broad areas, the first of which is citizen engagement via a community platform that will create airspace, which would be a product of city planning. The second focuses on vehicle-city coordination problems. To provide communication between aerial vehicles, we prototype a system of Flight Integrity Units mounted on drones and integrated using cloud server databases and cellular networks. This infrastructure will be able to handle the exponential network growth in the unmanned aircraft market. The third area is vehicle-to-vehicle coordination. To ensure safe interactions between a growing population of vehicles, each machine should be both readily identifiable and capable of avoiding collision

without human intervention. We described our visual identification system using LED color sequences as well as an identification and tracking system using the cell phone network.

We analyzed controls enabling unmanned aircraft to avoid collision with manned vehicles and showed that drones might start avoidance maneuvers 100 to 300 meters away from a helicopter. This seems acceptable, and 50 meters of this could be cut by taking ADS-B up to 2 Hz.

In short, the exponentially increasing density of aircraft in the NAS brings several new challenges open to the control community. Their solutions will demand a multidisciplinary team since the large-scale and required low-costs suggest technologies and services that are uncommon in the current airspace or aircraft control systems.

VI. APPENDIX

In the relative frame, we can keep the quadrotor at rest, and apply $-a_{max}$ to the helicopter. Figure 7 shows the trajectory from $(x_{12}(t_0), y_{12}(t_0))$ to $(x_{12}(0), y_{12}(0))$. Decompose the trajectory into d_1 along the direction θ_1^* and d_2 along the orthogonal direction. d_1 can be calculated from the Work-Energy principle, with initial speed $v_i = v_{12}(t_0) \sin \theta_1^*$, final speed $v_f = 0$, and constant force $-ma_{max}$.

$$d_1 = \frac{(v_{12}(t_0) \sin \theta_1^*)^2}{2a_{max}}$$

In the orthogonal direction, the helicopter is undergoing constant velocity motion, thus

$$d_2 = (v_{12}(t_0) \cos \theta_1^*) \left(\frac{v_{12}(t_0) \sin \theta_1^*}{a_{max}} \right)$$

with the second term being the time elapsed. Lastly, by simple geometry,

$$\begin{aligned} x_{12}(t_0) - d_1 \cos \theta_1^* + d_2 \sin \theta_1^* &= r_{min} \cos \theta_1^* \\ y_{12}(t_0) - d_1 \sin \theta_1^* - d_2 \cos \theta_1^* &= r_{min} \sin \theta_1^* \end{aligned}$$

which results in (3).

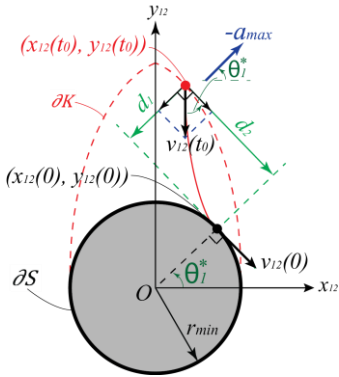


Fig. 7. Backward dynamics derivation diagram.

REFERENCES

- [1] E. G. Bowen, "Operational Research into the Air Traffic Problem," *J. Navig.*, vol. 1, no. 04, pp. 338–341, Oct. 1948.
- [2] L. Downes, "America can't lead the world in innovation if the FAA keeps dragging its feet on drone rules," *Washington Post*, 08-10-14.
- [3] "Operation and Certification of Small Unmanned Aircraft Systems," Available: <http://www.regulations.gov/#!documentDetail;D=FAA-2015-0150-0017>.
- [4] "AUVSI's The Economic Impact of Unmanned Aircraft Systems Integration in the United States."

- [5] "Small UAS Notice of Proposed Rulemaking (NPRM)." [Online]. Available: <https://www.faa.gov/uas/nprm/>. [Accessed: 24-Mar-2015].
- [6] Rich Williams, "Current Unmanned Aircraft State Law Landscape." 29-Dec-2014.
- [7] "Law Enforcement Engagement with Suspected Unauthorized UAS Operations." Available: https://www.faa.gov/uas/law_enforcement/.
- [8] R. Clothier, R. Walker, R. Baumeister, M. Brunig, J. Roberts, A. Duggan, and M. Wilson, "The Smart Skies project," *IEEE Aerosp. Electron. Syst. Mag.*, vol. 26, no. 6, pp. 14–23, Jun. 2011.
- [9] P. H. Kopardekar, "Unmanned Aerial System (UAS) Traffic Management (UTM): Enabling Low-Altitude Airspace and UAS Operations," NASA/TM—2014–218299. Apr. 2014.
- [10] J. Harding, G. Powell, R. Yoon, J. Fikentscher, C. Doyle, D. Sade, M. Lukuc, J. Simons, J. Wang, "Vehicle-to-Vehicle Communications: Readiness of V2V Technology for Application," Aug. 2014.
- [11] F. Mohammed, A. Idries, N. Mohamed, J. Al-Jaroodi, and I. Jawhar, "UAVs for smart cities: Opportunities and challenges," *International Conference on Unmanned Aircraft Systems (ICUAS)*, 2014.
- [12] M. DeGarmo and G. Nelson, "Prospective Unmanned Aerial Vehicle Operations in the Future National Airspace System," in *AIAA 4th Aviation Technology, Integration and Operations (ATIO) Forum*.
- [13] A. J. Simpson and J. Stoker, "Safety Challenges in Flying UAVs (Unmanned Aerial Vehicles) in Non Segregated Airspace," *1st Institution of Engineering and Technology International Conference on System Safety, 2006*, 2006, pp. 81–88.
- [14] D. Liu, R. Wasson, and D. A. Vincenzi, "Effects of System Automation Management Strategies and Multi-mission Operator-to-vehicle Ratio on Operator Performance in UAV Systems," *J. Intell. Robot. Syst.*, vol. 54, no. 5, pp. 795–810, Nov. 2008.
- [15] M. L. Cummings, S. Bruni, S. Mercier, P. J. Mitchell, "Automation Architecture for Single Operator, Multiple UAV Command and Control," 2007.
- [16] B. L. Golden, S. Raghavan, and E. A. Wasil, *The Vehicle Routing Problem: Latest Advances and New Challenges: latest advances and new challenges*. Springer Science & Business Media, 2008.
- [17] S. Rathinam, R. Sengupta, and S. Darbha, "A Resource Allocation Algorithm for Multivehicle Systems With Nonholonomic Constraints," *IEEE Trans. Autom. Sci. Eng.*, vol. 4, no. 1, Jan. 2007.
- [18] J. A. Matos, "Systems and methods for detecting and managing the unauthorized use of an unmanned aircraft," US20120022719 A1, 26-Jan-2012.
- [19] D. V. Limbaugh, D. H. Barnhard, T. H. Rychener, "Unmanned aerial system position reporting system," US8386175 B2, 26-Feb-2013.
- [20] I. Kymissis, "Friend or foe detection," US20100266126 A1, 21-Oct-2010.
- [21] G. M. Hoffmann, C. J. Tomlin, "Decentralized cooperative collision avoidance for acceleration constrained vehicles," in *47th IEEE Conference on Decision and Control, 2008. CDC 2008*, 2008.
- [22] P. Varaiya, "Smart cars on smart roads: problems of control," *IEEE Trans. Autom. Control*, vol. 38, no. 2, pp. 195–207, Feb. 1993.
- [23] R. Y. Gazit and J. D. Powell, "Aircraft collision avoidance based on GPS position broadcasts," in *15th AIAA/IEEE Digital Avionics Systems Conference, 1996*, 1996, pp. 393–399.
- [24] J. Krozel, T. Mueller, and G. Hunter, "Free flight conflict detection and resolution analysis," AIAA GNC.