

Safe Autonomous Flight Environment (SAFE50) for the Notional Last “50 ft” of Operation of “55 lb” Class of UAS

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The most difficult phase of small Unmanned Aerial System (sUAS) deployment is autonomous operations below the notional 50 ft in urban landscapes. Understanding the feasibility of safely flying sUAS autonomously below 50 ft is a game changer for many civilian applications. This paper outlines three areas of research currently underway which address key challenges for flight in the urban landscape. These are: (1) Off-line and On-board wind estimation and accommodation; (2) Real-time trajectory planning via characterization of obstacles using a LIDAR; (3) On-board information fusion for real-time decision-making and safe trajectory generation.

I. Introduction

Safe and autonomous flight in urban landscape is hard due to many factors including: (1) Environmental uncertainties such as wind and dynamic obstacles; (2) Vehicle performance constraints posed by weight, size, and power limits and system failures; (3) High precision requirements for navigation and control; and (5) On-board autonomy operation in an infrastructure-free environment.

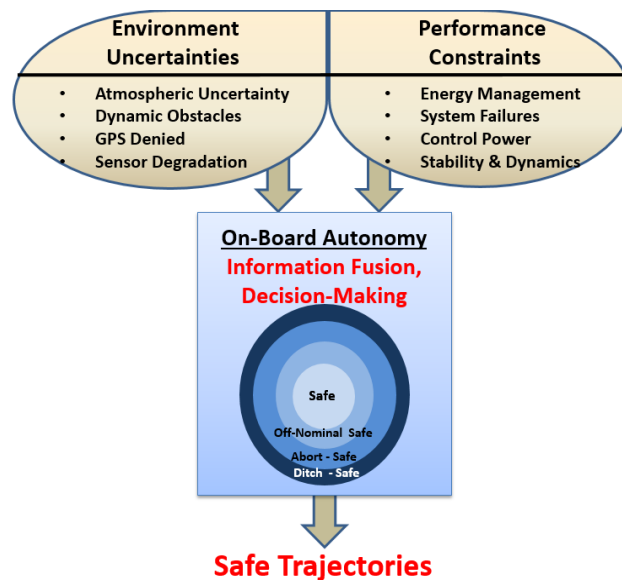


Figure 1. SAFE50 Targeted Approach for Arriving at Safe Trajectories

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According to the Sense-And-Avoid (SAA) research panel findings, the most important research needed to overcome the technology barriers for urban operations include:

- A Low-SWAP vehicle's ability to land and operate in a complex dynamic environment
- Detection of dynamic and static Obstacles (or targets), including use of datasets/databases on board
- Mission Planning for safe trajectories/different modes
- Robust wind information availability in near real-time
- Information fusion framework for decision-making
- High-fidelity drone performance models and sensor models
- 3D Models of urban cityscapes
- Novel data structures where a small UAS can store large size maps

These research topics are particularly challenging because there is a significant amount of uncertainty and system posed constraints that could be changing over time. As a result, developing focused technological solutions via a set of robust research goals is critical for future success of safe, autonomous flight. Figure 1 presents our targeted approach for solving the SAFE50 challenges. We have identified a list of uncertainties and constraints that have to be addressed and the information fusion and decision-making needed to enable safe flight. From an information fusion perspective, these uncertainties (arising due atmospheric variations, GPS denial or degraded signals, degraded sensors, dynamic obstacles, etc.) and vehicular performance constraints (arising due to Low SWAP designs, draining energy source, control authority, etc.) are mostly probabilistic in nature. The on-board autonomy via a decision-making system needs to assess these probabilistic information assimilated from the sensors and a priori prediction models, and select safe trajectories.

In the rest of the paper, we outline our approaches to three most important research objectives selected based on both the needs of the SAFE50 problem and the lack of active research in these domains. These research topics include: (1) Robust wind information, estimation and accommodation; (2) Detection of dynamic and static obstacles (or targets) for real-time mission planning of safe trajectories; and (3) Information fusion framework for decision-making.

II. Robust Wind Information, Estimation, and Accommodation

The state-of-the-art for over 100 years, even for manned aircraft, has been the use of weather information provided by the National Weather Service. Here a mean-wind assumption is made and is applicable to large open areas like runways at airports that are many square miles in area. In measuring these wind, obstruction of the wind sensors is not permitted, hence are not applicable to urban environment that are full of obstructions. Our Computation Fluid Dynamics (CFD) approach uses the mean wind information as obtained from the weather service along with the architectural details of an urban area to arrive at a more detailed GPS-referenced wind mapping that could be utilized for trajectory planning and for on-board control. An example wind profile derived is shown in Figure 2 for the city of Indianapolis. Detailed wind profiles showcased in the figure are not obtainable using the current state-of-

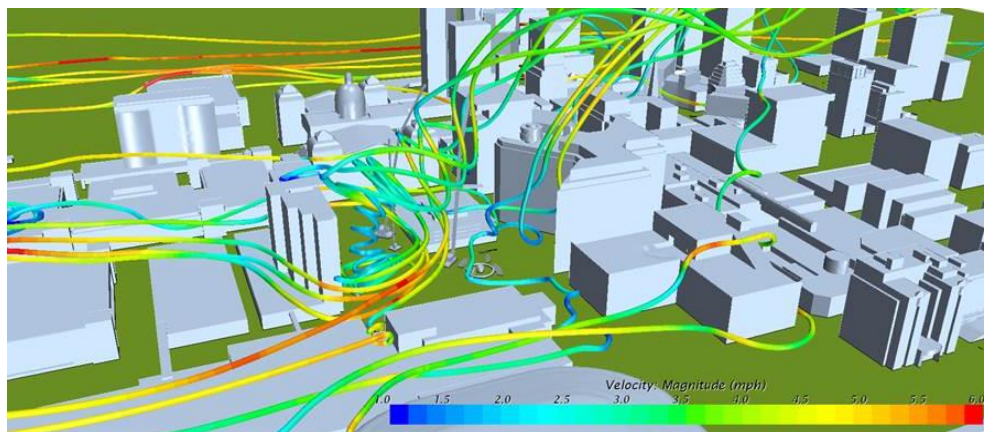


Figure 2. Urban Architecture and CFD Simulation of Wind Profiles.

the-art information services. The CFD details for the Indianapolis simulation include:

- Volume Mesh: 10.2 M cells - approximately 1 meter resolution around building corners
- Surface Mesh: 741K cells to define the buildings;
- Assumed steady flow for this prototype simulation;
- Approximated atmospheric boundary layer with hydrostatic pressure distribution
- Simplified model of downtown Indianapolis
- Navier-Stokes simulation using STAR-CCM+

The future enhancements for more accurate wind modeling could include: (1) Surface temperature distribution; (2) Unsteady flow (gusts) calculation; and (3) Improved atmospheric boundary layer;

The CFD solver utilized in our research is FUN3D [1] which is a fully unstructured Navier-Stokes solver that is developed and supported by NASA. It uses robust node-based finite-volume discretization, incompressible though hypersonic applications, and profile inflow boundary conditions to simulate the atmospheric boundary layer. Figure 3 presents a use case representing the city of Indianapolis downtown urban area with colors identifying low wind to high wind areas. It is clear that such a map will be very useful for sUAS mission planners.

Validation of this methodology was carried out using several approaches including (1) Use of Shinjuku (Tokyo) database of wind measurements collected over an eight year period [2]; (2) Indoor wind simulation using industrial size fans and wind data collected using anemometers at various locations inside the building (Ref) ; and (3) NASA Ames DART facility instrumented with anemometers wind loggers (on-going). The CFD data base is indexed to the GPS location and can be used either for off-line trajectory planning and/or as the initializing seed data for on-board adaptive wind estimation.

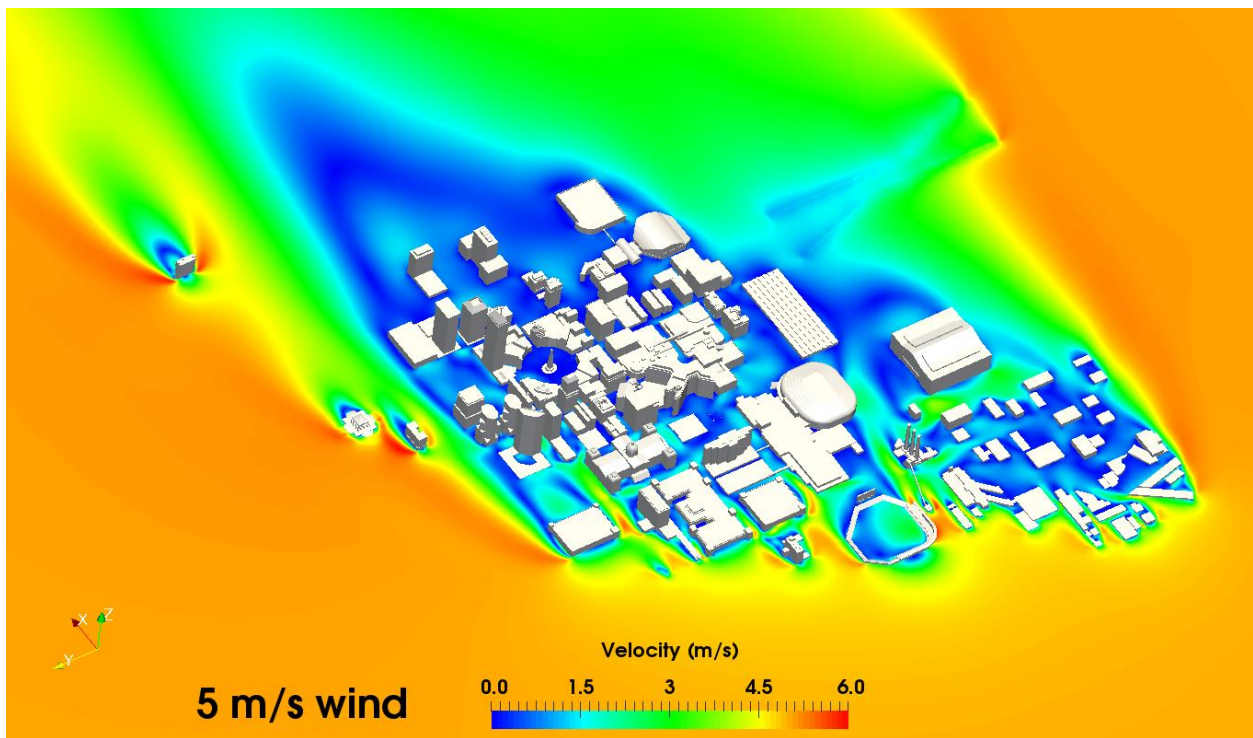


Figure 3. City of Indianapolis Wind Map

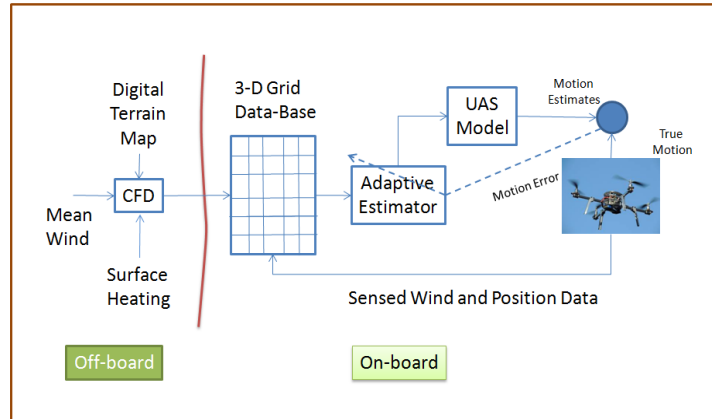


Figure 4. Off-line and On-board Adaptive Wind Estimation.

Figure 4 presents our approach for on-board wind estimation and control (See Ref [3] for more details). A compact set of CFD models are used for off-line trajectory planning, and on-board along with adaptive state estimation to arrive at real-time control solutions. The on-board estimation, navigation and control architecture consists of (1) adaptive algorithms to estimate vehicle's aerodynamic drag coefficients with respect to still air and the urban wind components along the flight trajectory, with guaranteed fast and reliable convergence to the true values; (2) navigation algorithms to generate feasible trajectories between given way-points that take into account the estimated wind; and (3) control algorithms to track the generated trajectories as long as the vehicle retains sufficient control authority for compensating for the estimated wind. All components of this on-board system are computationally efficient and are intended for real time implementation.

III. Obstacle Detection and Real-Time Trajectory Planning

One main challenge in urban deployment of autonomous sUAS is the need to rapidly plan collision-free trajectories in cluttered uncertain environments (See Figure 5). The vehicle in transit must navigate through a given environment to a goal position. The vehicle is required to sense and maintain minimum separation distance from static ground objects (SGO). SGO's include buildings, towers, power-lines, trees, and billboards. The vehicle is required to sense dynamic ground objects (DGO). The vehicle is required to adjust flight trajectories to maintain a minimum risk exposure to DGO's. This precludes, for instance, direct over flight of cars and people, or flight in a manner in which inflight failures would result in a trajectory that would endanger the DGO. This can be accomplished by maintaining a hazard footprint, and safe motion paths that are planned to ensure the hazard footprint does not result in a probability of hazard to the DGO above a specified threshold.

For detection, the sensor considered in our research is a 3-D scanning LiDAR. The object reconstruction architecture utilizes techniques derived from the Voxel-based Piece-wise Line Detector (VPLD) [4]. Our approach (outlined in detail in Reference [5]) utilizes 2-D methods based on transformation of the 3-D points per voxel to the (x,y) plane. The search region was defined per voxel to include the points in the eight surrounding and immediately adjacent voxels. After initial voxel-based clustering process, a Hough-Transform filter of the 2-D projected LiDAR points per voxel, an Eigenvalue classifier, and a point density classifier are applied.

Simulation studies were conducted to evaluate the real-time implementation details of such an algorithm. Figure 6 presents (a) on the left a time instant snapshot of the voxel creation process for a simulated octocopter flight in downtown Indianapolis and (b) on the right a voxel map of a power-line as detected and reconstructed using an octocopter hardware testbed instrumented with the LiDAR sensor.

In addition to detection, methods for autonomous real-time path planning using voxel-referenced waypoints generated using trajectory planning techniques such as A* and RRT [6] are under investigation. Reference [7] details our approach and presents an application to urban sUAS application.

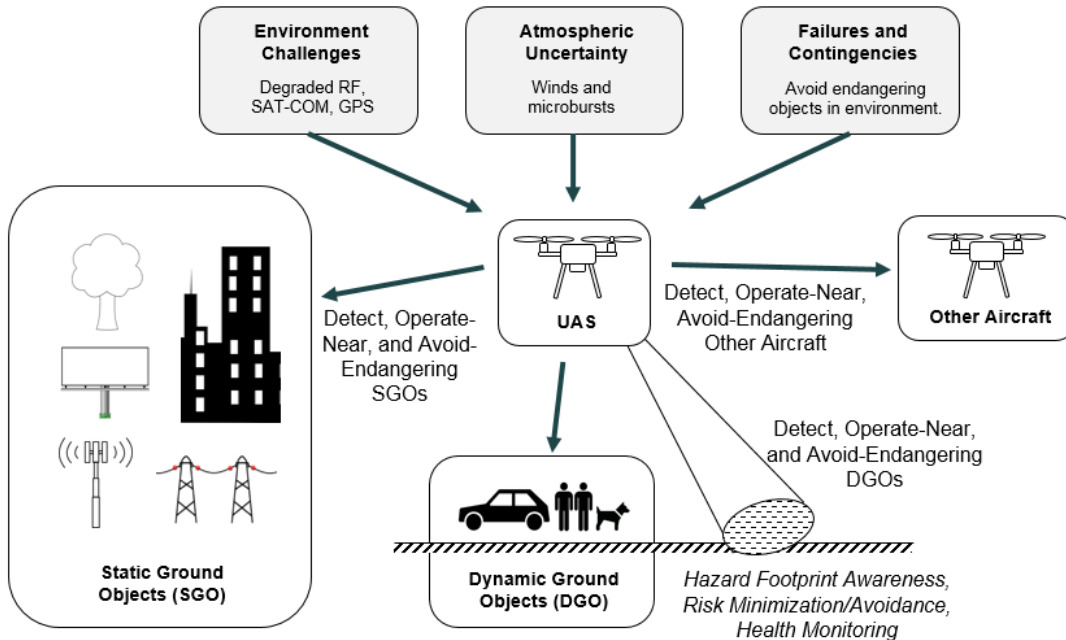


Figure 5. Navigational Hazards in Urban Environments

The benefits of using voxel-referenced waypoints provide collision-free trajectories in real-time with the drawback of higher computational requirement. The performance measures for trajectory planning, in addition to keeping a safe distance from the obstacles, also includes wind accommodation. Once waypoints are generated, trajectory-tracking control can be utilized (see Reference [3] for details) to realize the planned trajectories.

IV. Information Fusion Framework for Decision-Making

The desired outcome of a decision-making algorithm, which autonomously works in conjunction with the real-time path planner, is to identify whether a given trajectory is safe or not. To achieve this goal, the decision-making algorithm leverages information available from various sources as shown in Figure 7 in which a trajectory is classified as follows:



Figure 6. Obstacle Characterization using a Voxel Map

- Nominally safe: The likelihoods of risk-factors are extremely low, hence continue with the current trajectory
- Off-nominal but safe: The likelihood of risk-factors are higher than the nominal scenario, but still low enough to be considered safe with a modified trajectory
- Unsafe: The likelihood of risk-factors are high. Abort the mission and return the sUAS safely to a landing site
- Unsafe: The likelihood of risk-factors are high. Abort the mission and ditch the sUAS without any damage/loss to private and/or public property

Given a trajectory, and a risk-factor, we determine whether the trajectory is safe or not using the so-called limit state function [8], i.e., a curve of demarcation between a predefined “safe region” and an “unsafe region”. In simple scenarios, the idea of the limit state can be viewed in terms of capabilities (C) and requirements (R). When capabilities of a system are more than its requirements, then the system is said to be safe; otherwise, the system is considered to be unsafe. The limit state is then represented by the equation that implies capabilities are equal to requirements $C - R = 0$. In our application, which represents more realistic scenarios, the limit state is represented as a generic function $G(X) = 0$, where X represents the vector of quantities that affect the limit state. In the context of our work, X potentially includes (depending on the risk-factor under consideration) wind information, obstacle information, vehicular information (including motion, dynamics, and properties), energy information, and trajectory information, as shown in Figure 7. Without loss of generality, the region represented by the curve $G(X) > 0$ can be assumed to be the safe region, and the region represented by the curve $G(X) < 0$ can be assumed to be the unsafe region. Reference [9] details our approach and presents an algorithm representing a generic probabilistic framework to define events that correspond to: Safe, Off-nominal safe, Abort unsafe, and Ditch unsafe. The approach uses a framework to predict the probability for each of the above scenarios by linking with cost and calculate associated risk to aid decision-making under uncertainty.

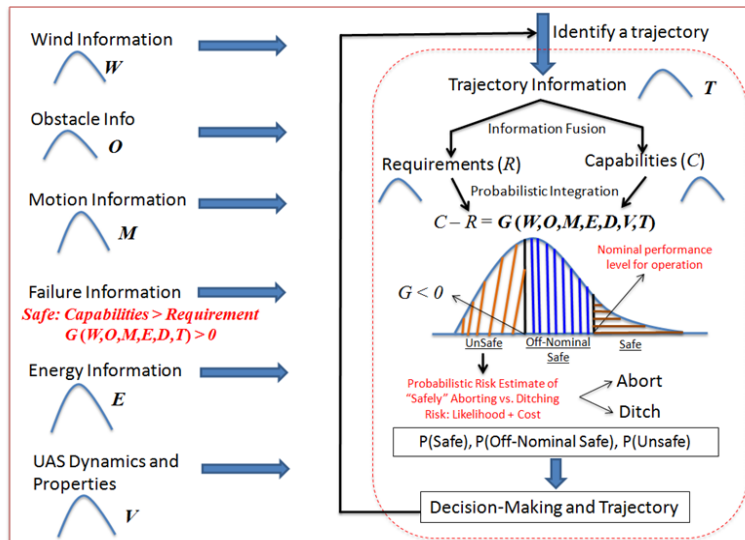


Figure 7. Framework for Decision-Making.

V. Summary

This paper outlined several areas of research and development needed for the most difficult phase of autonomous small UAS (Unmanned Aerial System) deployment in urban landscapes. We outlined three key areas of research currently underway which address some of the challenges for flight in the urban landscape. These areas are: (1) Robust wind information, estimation and accommodation; (2) Detection of dynamic and static obstacles (or targets), including use of datasets/databases on board for mission planning of safe trajectories; and (3) Information fusion framework for decision-making. Many of the details are discussed in accompanying papers as referenced. Efforts are underway to systematically evaluate these technologies in high-fidelity simulation and via flying an octocopter with integrated avionics in realistic environments.

Acknowledgments

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