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Intelligent Decentralized Survey of Volcanic Plumes from Unmanned Aerial Vehicle Platforms

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Many fields of Earth Science, including Volcanology, would greatly benefit from the ability of aerial platforms to provide coordinated high-density in situ sensor measurements near active and often dangerous physical phenomena, but the limitations of current autonomy limits the practical applicability and potential benefits of these platforms. Particularly, autonomous platforms lack the ability the ability to sense, predict, and respond to the phenomena and surrounding environments, which are often large-scale, hazardous, complex, and uncertain. In this paper we present an intelligent automated system for coordinating in situ measurements from multiple unmanned aerial vehicles to study emission, transport, composition, and in situ properties of aerosol emissions from active volcano sources. We present the hardware and software architectures that underlie NASA's swarming Dragon Eye UAS platforms, describe model based approach for modeling and predicting environmental conditions around the Turrialba volcano, describe a decentralized control approach for coordination of multiple vehicles, and present the high-fidelity simulation environment developed to evaluate this system. We present results from simulation and from initial flight test validations. These results suggest that onboard model-based autonomy with the decentralized control architecture presented will enable these vehicles to autonomously and reliably gather in situ data in conditions that were previously inaccessible to unmanned systems. Finally, this paper describes the current status of this project and research, and describes the future direction planned for this research.

I. Introduction

Volcanologists face an urgent need for greater in situ sampling capabilities in and around plumes and drifting ash clouds resulting from explosive volcanic eruptions. Current modeling efforts to detect, characterize, and track volcanic emissions are hindered by very sparse in situ validation data, a chronic and pervasive problem identified within the NASA's Earth Surfaces and Interior (ES&I) focus area and more generally within the volcanological

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literature. Collection of data is of crucial scientific importance for understanding the dynamics and chemistry of volcanic activity, particularly for validation of existing ash plume detection, retrieval, and transport algorithms[1][2][3][4].

Although unmanned aerial systems (UAS) are well-suited for performing pre-programmed remote surveys in safe locations far away from hazardous phenomena and where the survey area is fixed and well-known, collecting meaningful in situ data in and around uncertain, dynamic, and dangerous phenomena such as volcanic plumes is exceedingly difficult with current state-of-the-art technology. These data would be more readily collectable if vehicles had the ability to autonomously find and track complex non-stationary earth science phenomena, the evolution of which is usually difficult to predict ahead of time. Further hindering the utility of UAS in this application domain is the inability of on-vehicle autonomy to estimate, sense, and avoid hazardous environmental condition, making in-situ sampling near dangerous sources impossible without risking the vehicle platform. This unfortunately drives in-situ solutions to small disposable platforms which limits the scientific significance of the collected data.

In this paper we address these deficiencies, presenting an intelligent automated system for coordinating multiple unmanned aerial vehicles to locate, characterize, track, and monitor emission, transport, composition, and in situ properties of aerosol emissions from active volcanic sources. Particularly, we address two limitations of current UAS autonomy that hinders greater in situ measurement capabilities. First, UAS currently have no ability to autonomously sense, understand, and react to the hazards in the environment or the observation targets associated with payload sensors. Second, UAS are currently unable to coordinate flight activities in a scalable manner. The approach presented incorporates model-based predictions based on computational fluid dynamic (CFD) models of the system which are used as a priori predictions of the wind vector field and plume state as functions of environmental conditions. These offline CFD predictions are incorporated into an online probabilistic model that produces real-time estimates of aerosol plume location and density based on real-time data streamed from a distributed network of airborne and ground-based sensors. Predictions from this model are utilized for real-time trajectory optimization of the airborne vehicle platforms around the volcano, generating flight plans that place sensors in locations that will maximize scientific data return, identify and avoid dangerous areas of adverse winds and turbulence, take advantage of local wind patterns, and adhere to real-time constraints such as synchronizing observations with the sensor swath of thermal infrared (TIR) sensors of the NASA-MITI Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) instrument onboard the NASA Terra satellite [3]. This paper describes the requirements and challenges involved with autonomous in situ volcanic plume monitoring. An outline of the approach is presented with a description of the architectures being built for planned test-flights over and around the Turrialba volcano in Costa Rica. Preliminary results from analysis, simulation, and initial flight testing are then presented.

A. Background

The ability for autonomous airborne systems to collect systematic in situ data of eruption plumes and drifting ash clouds would address several identified urgent needs for the science community. For instance, the initial phase of volcanic eruptions are often unobserved due to considerable uncertainty in prediction models, yielding considerable uncertainty in even basic predictions, such as plume geographic extent. Remote sensing from spaceborne platforms, for instance the NASA ASTER instrument, provides crucial information for monitoring these processes but by itself is not sufficient to answer all the science questions without additional sensor data measurements provided from in situ measurements. In situ measurements provide calibration and validation, provide data not available from the vantage of a remote sensor, and is necessary for interpretation of remote sensor data. For instance, it is currently difficult to directly relate ASTER TIR measurements and UV ash-loading retrieval models to infer actual in-plume concentrations [3][4].

This paper presents methods towards enabling safe and reliable collection of high-quality in situ data around complex natural phenomena such as volcanic plumes. For this problem, we characterize these natural phenomena as large, dynamic, hazardous, uncertain, and time-varying. Uncertainty in the phenomena requires responsiveness of measurement platforms and adaptability in mission execution. Timely sampling requires systematic data collection focused around the phenomena of interest, but many of these target phenomena - such as aerosol plumes - are difficult to sense and invisible to pilots. Given the large-scale nature and rapidly evolving dynamics of volcanic eruptions, in situ sensor measurements should be taken as near simultaneously as possible throughout the entire plume, with high-density uniform samples needed at key locations of concentration that is not known a priori and will vary as the plume evolves. Sampling capability should also be persistent, allowing complete measurements to be made at regular and frequent time intervals throughout the life cycle of the volcanic process. Preprogrammed sampling flight plans would be necessarily conservative, and would not meet the desired time frequency and spatial sampling density even with a large number of aircraft. Scaling the mission to multiple independently control aircraft would help increase coverage, but would require a large number of aircraft and flight teams, posing significant challenges to logistics, mission execution, coordination, and separation assurance. Real-time adaptability in mission execution based on real-time payload sensor data is likely necessary to conduct this mission, directing the aircraft to focus flight trajectories around areas of important plume concentration, through the extent of plume concentrations is unknown difficult to estimate from individual sensor readings, requiring advanced processing to estimate the plume extent. The resulting behavior must satisfy the constraints imposed for science sampling, such as near orthogonal transects across the phenomena with uniformity in flight line spacing. Unfortunately, the environment around volcanic plumes contain inherent dangers to manned and unmanned aircraft alike, and the measurement targets (eg, aerosol and ash plumes) are located near to or collocated with these environmental hazards. For example, volcanic ash clouds pose a danger to aircraft to air-breathing engines, and the area in and around the plumes experience regions of adverse winds and extreme turbulence. Similar to the volcanic plumes of interest, the environmental hazards are also large-scale, time-varying, difficult to sense, and difficult to model and predict.

B. Related Work

Both manned aircraft and unmanned aerial system (UAS) platforms are increasingly utilized to conduct remote Earth observing science missions. While prohibitively dangerous for manned aircraft, volcanic plume sampling from small disposable low-cost UAS has been demonstrated (eg, [6][7][8][9]), where disposable aircraft are preprogrammed to fly directly through potential hazards to collect data with low-fidelity sensors. These examples show tremendous potential for autonomous in situ measurement capabilities. Unfortunately these approaches are still limited to small, low-cost, low-accuracy, disposable sensors on small disposable aircraft, where aircraft are preprogrammed to fly blindly through hazardous areas that place the vehicle and sensor payload at risk, and where useful data may not be collected. Many challenges remain towards enabling autonomous airborne in situ sampling mission concepts that require higher-fidelity instruments on more-capable UAS platforms to be reliably, safely, repeatedly, and systematically operated. Limitations in current UAS autonomy restricts these missions to pre-programmed surveys in safe locations well-clear of hazardous phenomena, where the survey area is relatively fixed and well-known, and where there is little urgency for temporal/spatial coverage. UAS missions are currently defined by flight plans composed of preprogrammed sequences of georeferenced waypoints that the aircraft is programmed to blindly fly through. Mission plan are developed by ground operators and uploaded to the vehicle's Flight Management System (FMS), which manages execution and provides appropriate input into the vehicle's automatic flight control (autopilot) system. Some level of adaptability can be achieved by having scientists in the loop. For instance, sensor data can be streamed in real-time from the aircraft to ground science observers who can monitor the data and request modified flight plans to the flight manager; in turn, the changes are preprogrammed by the ground station operators, validated on the ground, sent to the aircraft, revalidated on the aircraft, then commanded to execute by the ground operator. Unfortunately this is a relatively slow process that is difficult to achieve in practice, for instance requiring significant human involvement, reliable communication, imposing additional logistics and timing challenges, and is not easily scalable (eg, frequent long-term flight operations or multiple simultaneous flights).

Given these challenges, the areas around volcanic activity where plumes are located are unsafe and inaccessible to both manned and unmanned aircraft alike when value is assigned to these platforms. UAS platforms have a few advantages over manned aircraft; for instance, unmanned platforms can generally accept more risk than manned platforms, and electric-powered propulsion options for UAS will alleviate the risk associated with ash ingestion. However, UAS flight control systems are currently designed to fly preprogrammed pattern and are less likely to achieve mission success than a human pilot in this scenario, who can assess and adapt in real-time and can respond more appropriately to off-nominal situations and flight conditions. Unfortunately assuming platform expendability drives mission concepts to small low-cost vehicles that have severely limited range, endurance, and reliability. Payload capabilities are then highly constrained in terms of size, weight, and power, limiting sensor selection to disposable low-quality sensors and limiting potential scientific significance.

Many concepts in the research literature have been proposed to provide autonomous mission plan adaptability to environmental conditions based on payload sensor data. This Payload Directed Flight (PDF) capability would enable many future applications for airborne science [5]. Several approaches for processing sensor data through statistical or mathematical models have been proposed [10][11][12]. These approaches make no attempt to justify the underlying mathematical model form that are used to estimate the phenomena from sensor samples, and closing-the-loop around these models will provide no assurance of correctness in behavior, especially given the inherent extrapolation which must occur to plan behaviors beyond the current sensor limits. However, the complexity of phenomena models and uncertainty of predictions in this domain likely make attempts to incorporate precise models into the control system infeasible. For instance, in similar science missions, raw sensor data collected by all aircraft and platforms during a mission must be analyzed post-mission and reprocessed based on emerging underlying hypothesis and assumptions. These underlying assumptions may not be completely known until the entire data set is collected and analyzed in the context of all the information available, and changes in these assumptions can greatly alter the sensor processing models and resulting data products. Since aircraft must make automated decisions in real-time, the aircraft will likely not be able to rely on the accurate or reliability of onboard processing models. The approach presented in this paper incorporates first-principle models derived in coordination with the science domain experts specifically for autonomy, allowing the vehicle to process sensor information and make conservatively accurate predictions in real-time. We accept that onboard sensor processing pipelines and real-time model predictions generated by the autonomous control system will likely have no scientific significance beyond adapting real-time flight behaviors, and derive autonomy sensing models accordingly. For instance, it would be better to use a generally conservative estimation model that assumes more areas of sampling interest exist, rather than using a more detailed prediction model that directs the aircraft away from an area of interest and results in sensor coverage gaps. The resulting models have limited scientific utility beyond autonomy.

There are several approaches in literature for onboard autonomous decision making that use simple behaviors to direct aircraft behavior, such as gradient-following, optimal-peak-finding (e.g., [11][13][14]). These approaches are also difficult to extrapolate to this application as the resulting behaviors do not meet requirements or constraints derived from the scientific data collection objectives. Earth science sensor sampling trajectories typically needs to provide regular, uniform, high density flight lines, providing sufficient coverage to ensure that the phenomena has been sufficiently mapped, and appropriate for later offline processing and investigation by the science team. Simple random, optimizing, or gradient-following behaviors do not meet these requirements.

Many approaches in the literature provides methods for autonomously controlling behavior of groups of vehicles, including swarm-based autonomy, for instance mapping chemical clouds [13] and multi-agent search [14]. Here, we generally characterize swarming autonomy as a scenario where multiple, cooperative, self-organizing agents autonomously react to each other and to the environment based on simple interaction rules, designed such that collective emergent behavior results in global system behavior that robustly achieves specified global system objectives. Swarming concepts have a number of limitations. For instance, any concept requiring multiplicity of vehicles is inherently challenging, adding complexity and increasing overall risk. Most of the challenges faced in a single UAS science mission concept will be multiplied in a swarm mission concept. Swarm missions based on current technology introduces many unique challenges; for instance, logistic is difficult, costs are multiplied, multiple autonomous systems have shown to be difficult to monitor and control, and project resources will be dispersed and diluted across multiple instruments and platforms. Swarms themselves are a form of decentralized control strategy which are necessarily suboptimal, especially considering the utilization of simple interaction control rather than rigorously synthesized decentralized control laws. However, the tradeoff in optimality versus robustness is well suited for these mission concepts where vehicles must operate under great uncertainty, complexity, and risk. Further, given the model complexity and uncertainty for underlying phenomena models, deriving decentralization strategies that optimize over these models may not be as appropriate as designing simple interaction rules to guide swarming behavior.

In this paper, we present an approach towards a self-assembling, self-organizing, self-separating swarm of vehicles that will autonomously – without user input – optimally structure itself in such a way as to detect, track, and characterize volcanic plumes. The vehicles will automatically generate in situ sampling flight lines, build maps of the environment, and re-plan to optimize sampling flight lines based on the latest plume estimates based on payload sensors. Flight lines will be planned that avoid predetermined hazardous areas of high winds and turbulence, and flight trajectories optimize over the predicted wind field to take advantage of winds aloft for greater safety and fuel efficiency. Our approach extends the Payload Directed Flight architecture developed at NASA Ames Research Center to a multi-vehicle swarm configuration. Mission designers need only provide the vehicles with the mission parameters that consist of (1) a set of mission objective functions, (2) mission constraints, and (3) mission data that the objective functions or constraints need to reference. These mission parameters codify mission objectives and science goal for the complete mission. Based on these mission parameters, each agent will automatically plan and execute the mission without the need user input. Behavior of individual aircraft is determined through automated onboard trajectory generation that optimizes the aggregate mission objective functions and constraints. Sensor data is processed by a probabilistic estimation model which provides each aircraft with an estimate of the global plume state. A CFD model is developed for the environment and used to evaluate the expected wind, hazards, and plume states given a specified condition. In this initial implementation, limited set of conditions were analyzed in the CFD study, and results were limited to steady-state condition based on constant emission rate of SO_2 and steam into the environment. The CFD model provided a priori expectations of plume location for the estimation model. The CFD results were also processed into a wind field database onboard each aircraft which was evaluated as part of the cost function for each trajectory. The implementation is an extension of previous applications in PDF, adding CFD model integration into prior distribution of the phenomena estimation, adaptation of the mission objective function, and extension to a multi-agent swarm architecture utilizing simple control laws to control behavioral interaction between agents. The concepts for swarm autonomy are implemented on an appropriate demonstration platform to show feasibility of this approach.

II. Mission Design

The mission concept is shown in Figure 1. As each vehicle is launched, the automated planner will determine the best flight lines to reach the sampling area. The a prior plume state, determined by offline CFD studies, is used to guide the aircraft to the expected area of the plume, while the mission cost function captures the sampling behavior desired. New aircraft that are introduced into the mission transmit their positions to surrounding vehicles. These positions are used to separate the aircraft through virtual repulsion forces, defined as part the aggregate mission cost function. For this initial implementation, sampling planes are predefined, and repulsion forces are defined strong enough to move vehicle flight trajectories to surrounding sampling planes, or to further regions of the sampling region on occupied planes. This approach will scale well until the number of aircraft becomes larger than the number of sampling planes, which is a constraints for this initial implementation.

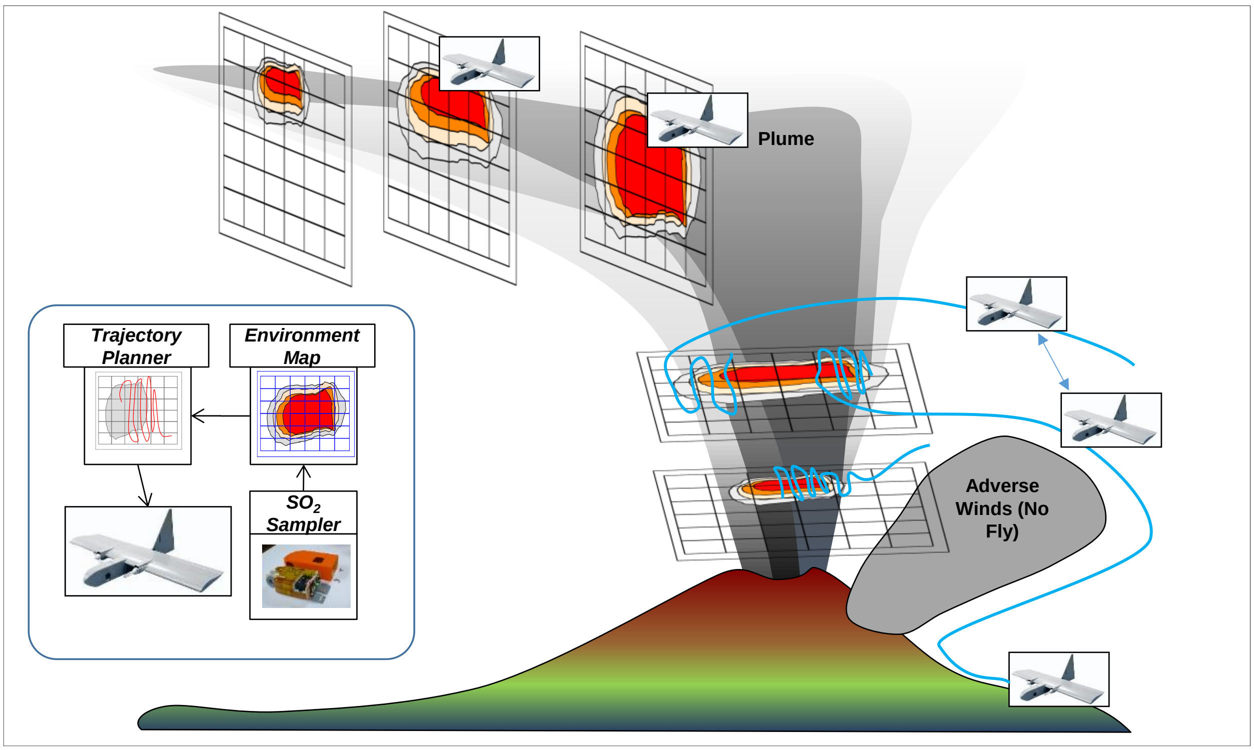

Figure 1. Mission Concept

The mission concept data processing model for swarming volcanic plume monitoring is shown in Figure 2.

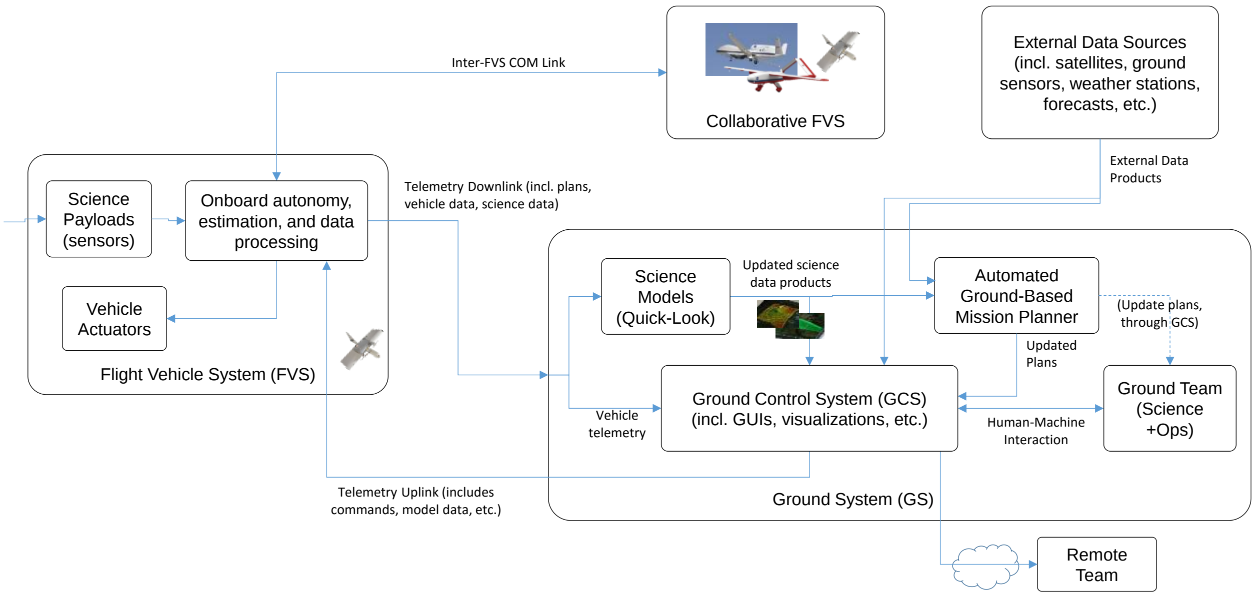

Figure 2. Data Processing Architecture

A general data flow architecture for coordinating multiple Dragon Eye vehicle systems is shown in Figure 3. An adaptive mesh radio modem allows vehicles to address other vehicle directly with point-to-point communication, allowing low-latency data sharing between vehicles during the flight mission over a remote location that does not rely on a reliable data link to a ground control station, as is expected in the given flight condition. Further, with scaling to multiple vehicles operating at large distances to the ground station, communication from each vehicle to the ground becomes an issue that an airborne mesh network may address. In previous flights over Turrialba conducted with the Dragon Eye, the vehicles experience degraded communication link with point-to-point RF modems due to environmental conditions over the Turrialba that included high humidity, cloud and fog cover. The flight operations model in Figure 3 show the major ground components and staffing/personnel requirements.

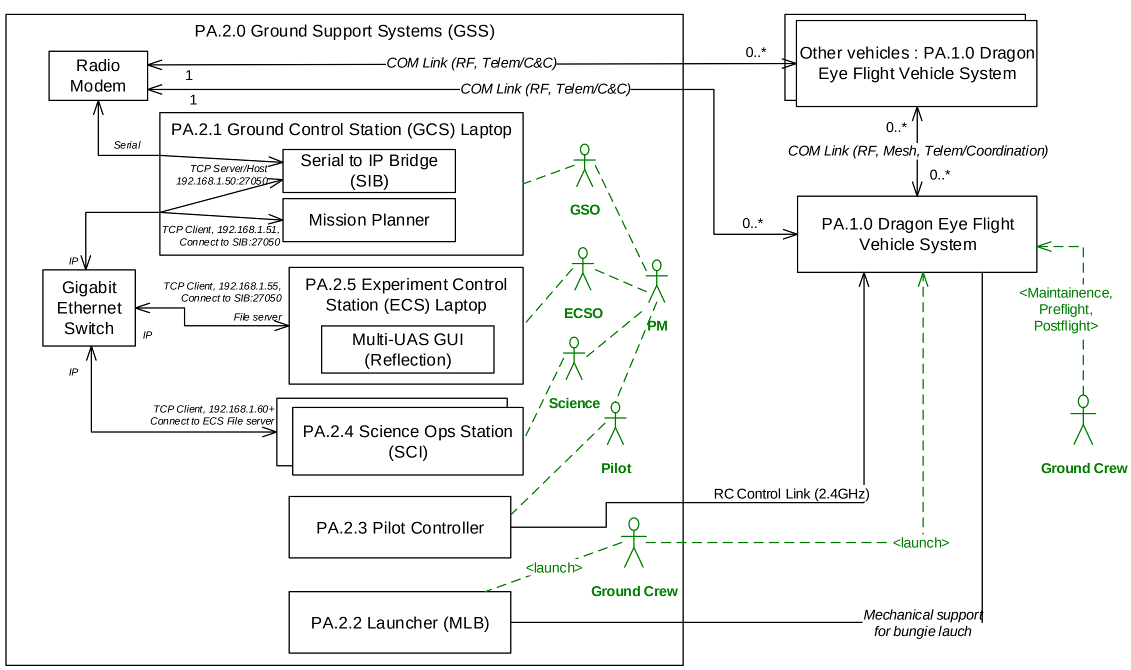

Figure 3. Flight Operations Model

C. Demonstration Flight Vehicle Design

An appropriate demonstration platform was selected based on a number of criteria. The vehicle had to be able to survive the volcanic plume environment while demonstrating low-TRL research autonomy. We desired rugged, compact, dynamically stable, and must use an electric propulsion system. The vehicle had to be capable of peer-to-peer communication, which was designed and implemented as part of this project's development. The vehicle platform had to be capable of fielding a representative sensor, which was selected and built as described below. The vehicle had to be capable of hosting the autonomy algorithms and be representative of larger platforms, which led to the team designing custom avionics based on an open-source hobby-grade autopilot system with a secondary processor. The autonomy demonstrator vehicle had to be disposable, replicable, fieldable within the constraints of the project budget, already operational, and should have low design/development costs to field the demonstration.

The Dragon Eye UAS platform, developed by Aeroenvironment, Inc., was selected as the demonstration platform for this mission as shown in Figure 4 below. A large number of Dragon Eye UAS had been acquired by NASA Ames Research Center as military surplus items, and they are small, compact, rugged, all-electric, and feature a sufficient nose section for hosting payloads. The flight time and range was sufficient to demonstrate at the selected test site. Unfortunately the vehicles featured closed military-grade export-controlled avionics, limited single-string/limited redundancy, limited end-user extensibility, and no peer-to-peer communication functionality.

Figure 4. NASA Ames Dragon Eye UAS deployed at the Turrialba Volcano in Costa Rica in 2013 (left), and the SO2 sensor payload developed at NASA Wallops Flight Facility (right).

To meet the demonstrator requirements, Dragon Eye vehicle avionics were redesigned. The closed export-controlled hardware was removed. The replacement control system utilized the open-source Ardupilot autopilot system with custom software and integrated with a high-power mesh communication radio modem operating in the ISM 900Mhz band at 1 watt transmission power. The Adapteva Parallella-16 computer was installed as a secondary processor for autonomy and higher-level processing. The swarming vehicle avionics hardware architecture (Rev C) is shown in Figure 5.

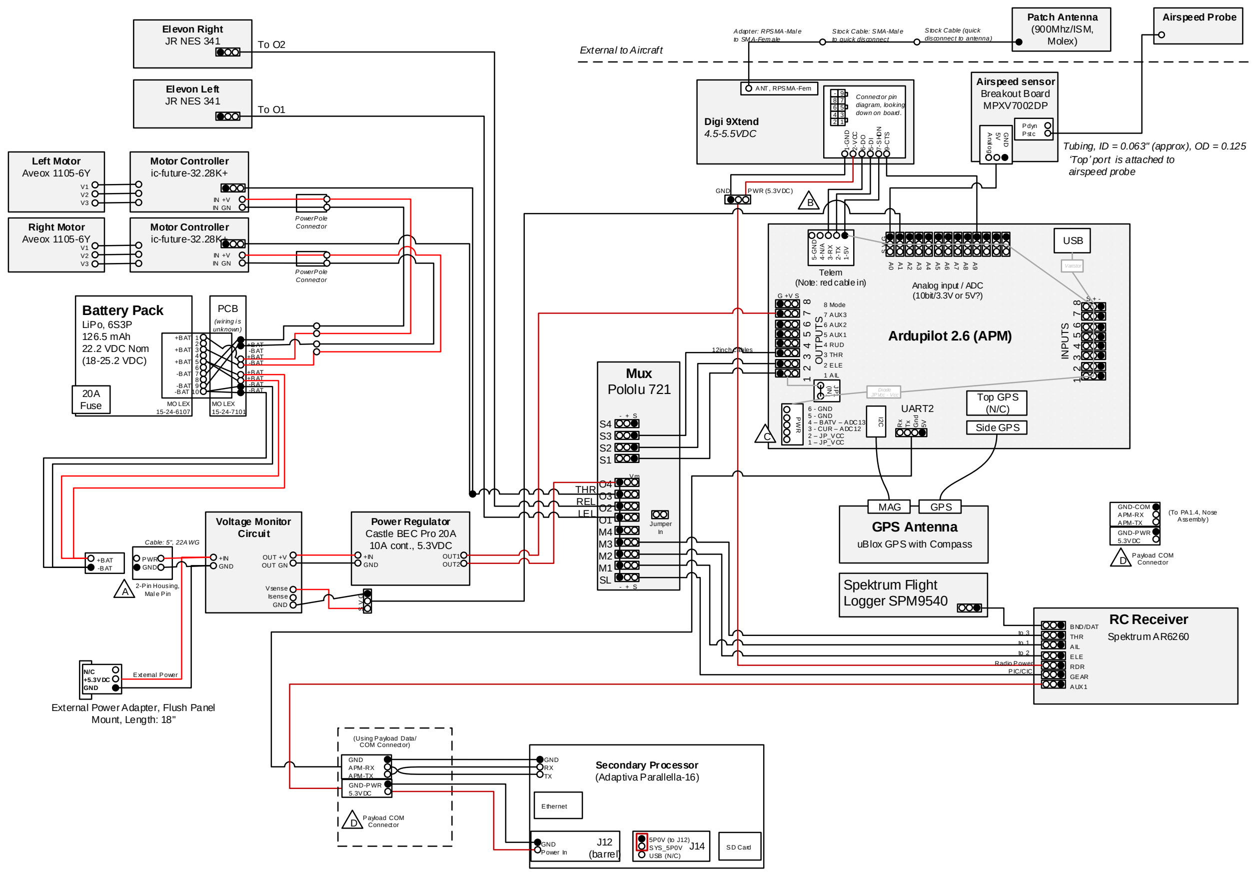

Figure 5. Electrical Schematic of the Dragon Eye Vehicle, Rev C.

The sensor payloads were selected, designed and built at NASA Wallops Flight Facility to fit into the nose of the Dragon Eye platform. The payload system consists of a Pace XR440-M data logging system with a CityTech SO2 sensor in addition to temperature, humidity, and pressure sensors. The payload system schematics are shown in Figure 6.

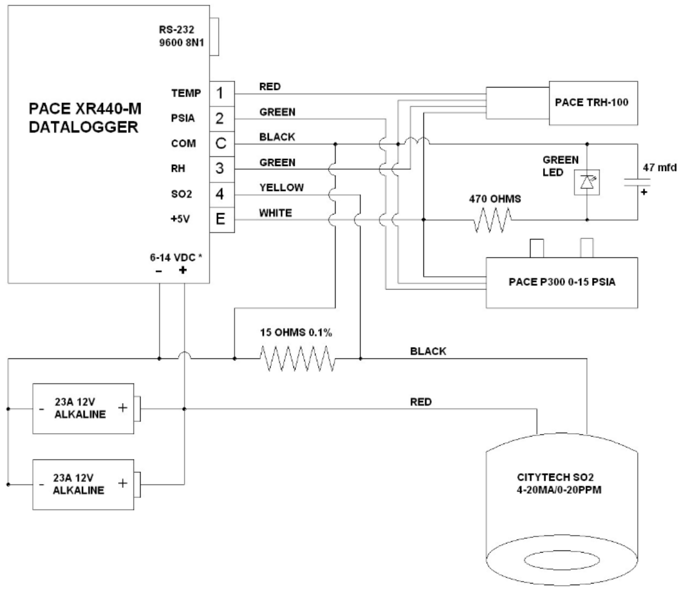

Figure 6. SO2 Sensing Payload System

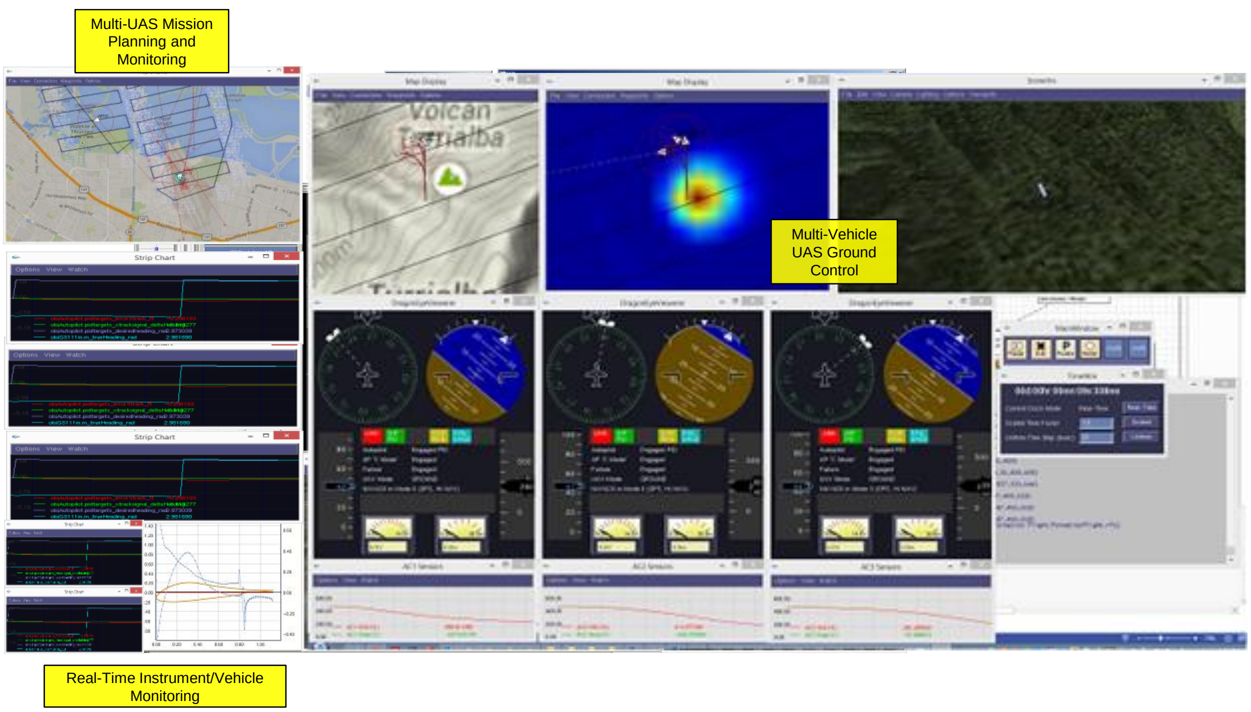

Figure 7. Multi-Vehicle Simulation Environment

A multi vehicle simulation environment was created for the evaluation of the system, as shown in Figure 7. The simulations assumed three Dragon Eye vehicles operating over Turrialba. A ground control station was developed that allows a single operator to monitor the resulting trajectories of each vehicle, with the ability to manually override the onboard autonomy with manual commands. The CFD results for a given condition were compiled into a wind field database and added to vehicle simulation dynamics.

Architecture for Swarming PDF Autonomy

A. Computational Fluid Dynamics Model

Model based estimation of the wind fields and expected dispersion pattern of the emitted aerosol plume was developed through CFD evaluation. A computational fluid dynamics (CFD) model of the Turrialba volcano was develop as shown in Figure 8 below, which was generated from a digital elevation map with elevations at 3 meter spacing. The resulting wind vector field is shown in Figure 8 (b) which showing the complex wind patterns which matched expectations for this area. Two species, SO2 and CO2, were modeled as emitted from a point source from the approximate caldera location, and the predicted plumes are shown in Figure 8 (c). The model results were processed and used the prior expectation in the belief map.

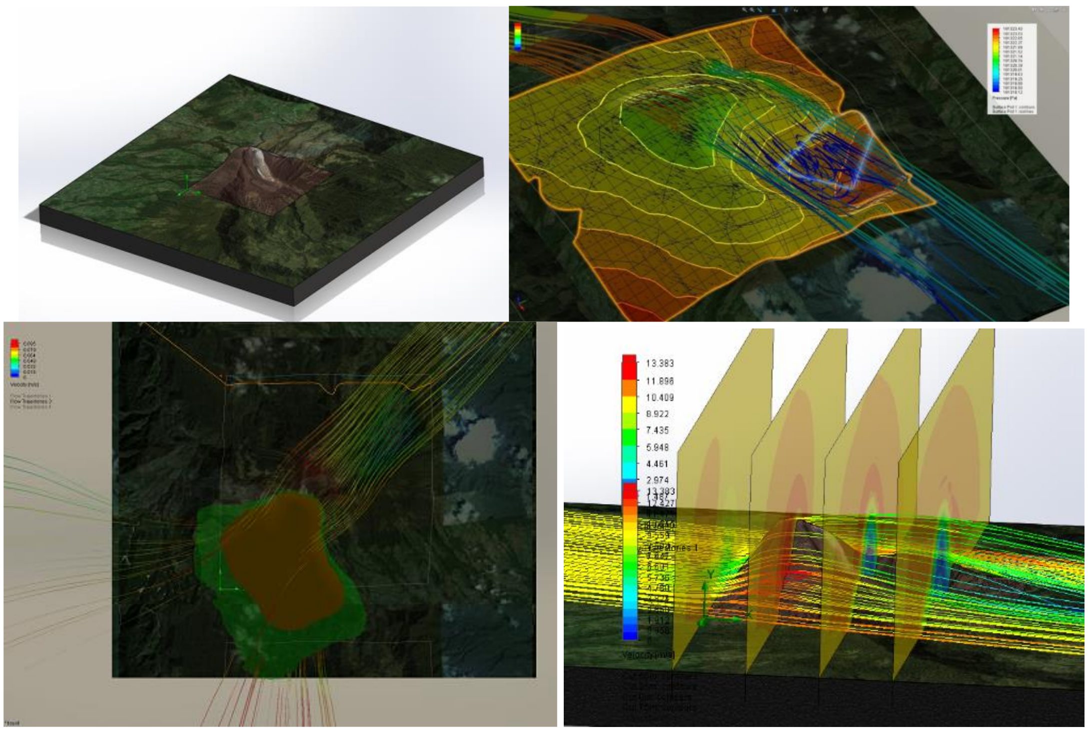

Figure 8. (a) Turrialba Volcano in the CFD Environment (top-left). (b) CFD predictions for wind vector (top-right). (c) SO2 and CO2 plume concentration predictions (bottom-left). (d) Vertical cross section expectations (priors for belief map).

B. Autonomy Architecture

The high level autonomy loop is shown in Figure 9. Data collected at the UAS is filtered locally to estimate the local plume concentration, then integrated into a probabalistic occupancy grid model of the plume, where a priori distributions were loaded from the CFD model estimates. This provides a belief map of the plume for each vehicle. Based on the latest belief map, the vehicle constructs a 2D cost map that is used for trajectory generation based on a random search tree optimization. Neighbor vehicle positions are transmitted between vehicles. At this time, a simple repulsion force law was implemented to push the vehicle to distant sections of the map and keep vehicles from coming within in the vicinity of each other. The repulsion force is added to the cost function in the trajectory planner. The resulting trajectory is used to generate a sequence of waypoints that are sent to the primary vehicle control system. Trajectories are generated at a rate of once every 10-30 seconds.

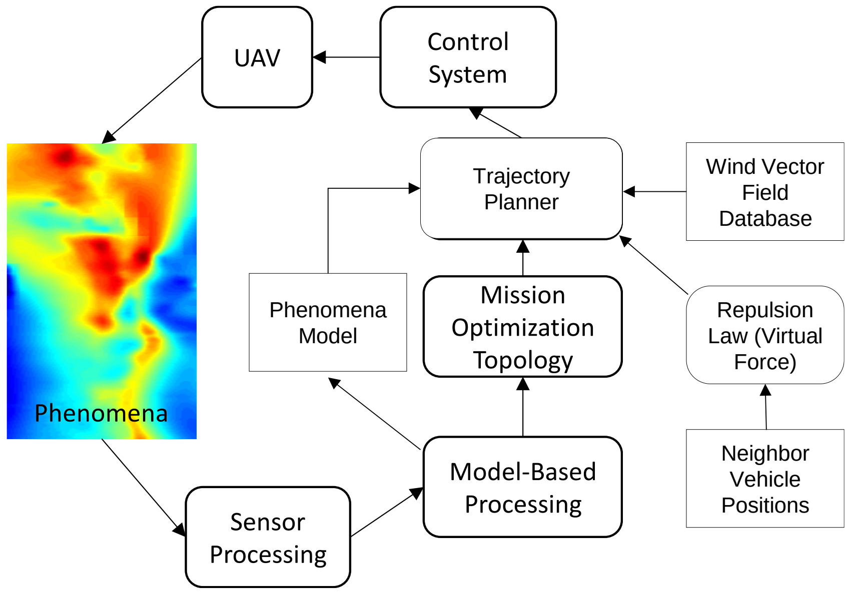

Figure 9. Optimization Loop

The vehicle autonomous control system architecture is built on the PDF architecture developed at NASA Ames Research Center [15]. The PDF architecture allowing vehicles to sense, predict, and control relative to complex phenomena through processing of payload sensor data injected at various feedback paths. The architecture is shown in Figure 11.

The PDF inner layer in Figure 11 represents the fastest response control law, and updates at a rate of 50 Hz. The inner layer must simultaneously control the aircraft to follow the trajectory commands provided by the middle layer while meeting the fast-time response tracking control requirements needed to track the phenomena. The nature of the control system at this layer depends on the requirements for both of these objectives. General trajectory-based control is needed when aircraft must follow precision 6DOF trajectories; this is the case, for instance, trajectories are calculated to maximize the placement of a body-fixed imager viewing a target. Generally, a trajectory-based control scheme is required, such as the trajectory-linearized control outlined in [16]. For this application the control requirements are less stringent. The sensors in the current payload system (Figure 6) include an SO_2 gas sampler, temperature sensor, and pressure sensor, none of which place constraints on the vehicle attitude, relaxing the requirements to position 3DOF control. We further assume the phenomena dynamics are slowly evolving relative to the vehicle dynamics, we assume inter-vehicle separation assurance can be assured at the trajectory planning (strategic) level, and we assume there are no sensor pointing requirements on the vehicle attitude dynamics. Therefore, real-time sensor control feedback to the inner-layer was not needed, and the inner layer control mode is a simple "track-to" waypoint-following feedback control mode, fed by waypoints computed by the middle layer trajectory. Waypoint management and mission execution is managed by the FMS. The lateral mode control system structure is shown in Figure 10 below.

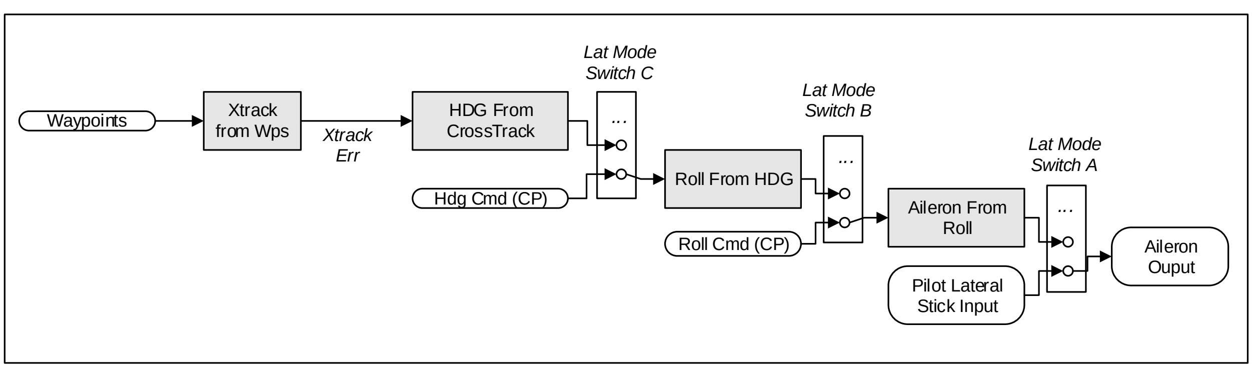

Figure 10. Inner Layer Lateral Mode Control System

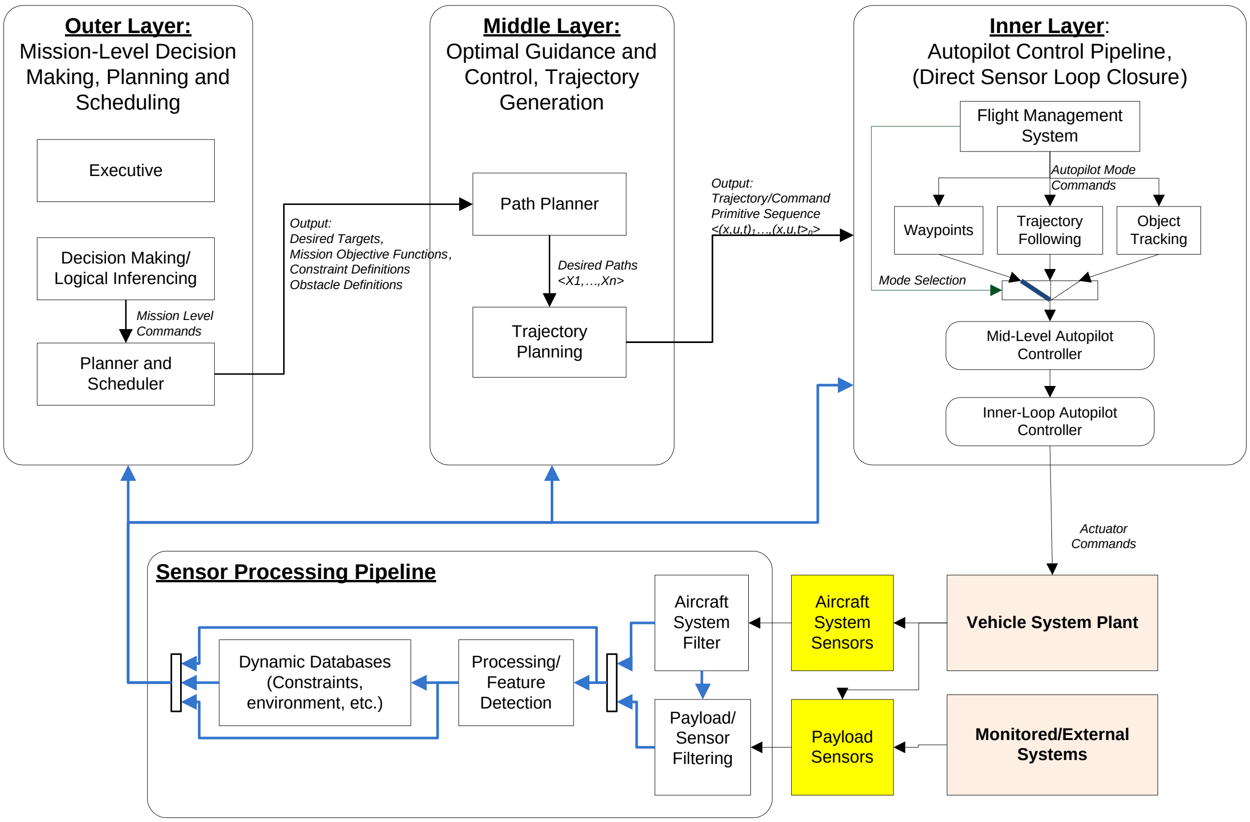

Figure 11. Payload Directed Flight Control System Architecture

The PDF architecture's middle layer (see Figure 11) is responsible for generating trajectories in the form of waypoints for the inner layer and updates at a period of 10-30 seconds. The optimization algorithm utilizes an optimization-based framework and numerical optimization algorithm first presented in [15] and conceptually shown in Figure 12. The middle layer optimization engine [15][17]. For this project, all control objectives for PDF control and inter-vehicle swarm coordination are implemented as additional constraints to this middle layer.

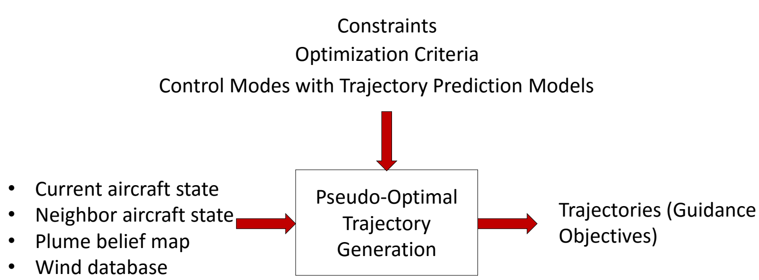

Figure 12. Middle Layer Optimization Engine

The original cost functions in [15] were augmented with a mission objective cost function c(s) of the following form.

$$c(s) = \left(\frac{v_{max} - V(closest(s))}{v_{max} - v_{min}} - 1\right) * [\, 0.5 * \cos\,(A * distance\,(s, closest(s)) + B\,) + 0.5) + 1) \tag{1}$$

Here, the function closest(s) returns the closest visited node in a 2D spatial partition grid. The function distance(a,b) returns the distance between two nodes. The cost function map from (1) returns in the following topology, which is added to the other cost functions. The constant parameters A and B can be adjusted to the desired grid spacing, as specified by the science mission requirements.

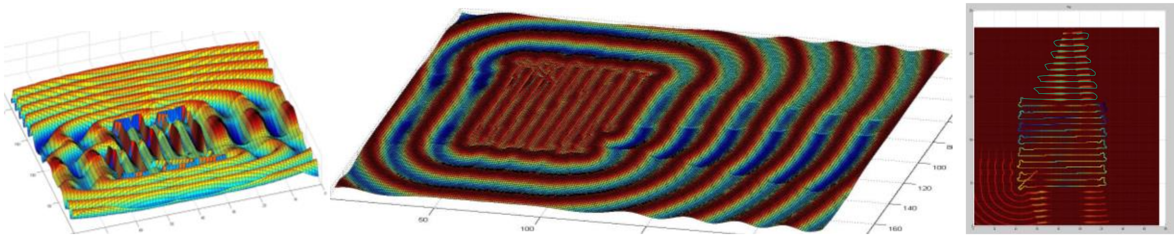

Figure 13. Mission Cost Function Topologies. (a) Initial topology, (b) shown for case 3 in Figure 14, (c) showing optimization trajectory output.

The plume estimation model is based on the Lee model for vision-based plume tracking [18]. This algorithm was implemented as described with a few modification. For this demonstration, the plume model was limited to several 2D cross-sections at various distances above the volcano. The prior probabilities on the model is seeded with the results from CFD evaluation. The estimation model has a number of limitations, including a quasi-static environment assumption, stubbornness to modifications once a solution has locked in, and currently utilizes a single static CFD solution for this initial implementation. Extension for plume dynamics are additional CFD solutions are planned for future research

Preliminary simulation results are shown in Figure 14. As the mission progresses and SO2 intensity data is collected, an environment map is generated based on this previously collected data. This environment map is processed into a cost function which encodes mission level objectives to map and follow the extent of the plume with a minimum spacing dictated by the mission requirements (10 meters). The resulting trajectory optimization algorithm generates a plan that guides each individual aircraft along the path that maximizes the mission objective to maps areas of highest SO2 concentration.

The results shown are still preliminary based on the initial simulation and flight system implementation. The project planned flight testing at the Turrialba volcano in 2015. This test site was selected based on a consistent low-level of activity and SO2 emission, making it an ideal candidate for this demonstration. These tests have been postponed due to renewed volcanic activity at Turrialba in early 2015, making the area surrounding the volcano inaccessible. The simulation results have been promising, and the project is continuing local flight testing with the SO_2 payload sensors and swarming Dragon Eye system. A number of challenges have emerged in the hardware system. Utilization of IEEE 802.15.4 mesh sensor network as an airborne peer-to-peer communication system has proven difficult, as the all communication is currently serviced through these modems, and the system in flight tests experienced bandwidth saturation, high packet loss and error rates, high latency, and inability for the mesh network to adapt in flight. Additional research would be needed to address these issues, but this project is moving to a new revision (Rev D) that forgoes peer-to-peer mesh in factor of a static point-to-multipoint (ground-to-multi-aircraft) topology that provides more reliable communication. The system originally planned to broadcast information on the belief map between vehicles, but given limitations of Rev D, this was reduced to simple position updates. This information could be served with small low-cost ADS-B type receivers that are currently available for small UAS. Additionally, the secondary processor experienced overheating issues despite the addition of active cooling in the payload bay, reducing effective flight experiments of the autonomy system to around 20 minutes. Future revisions of the aircraft hardware will likely replace the processor with a lower-power processing board to address this issue.

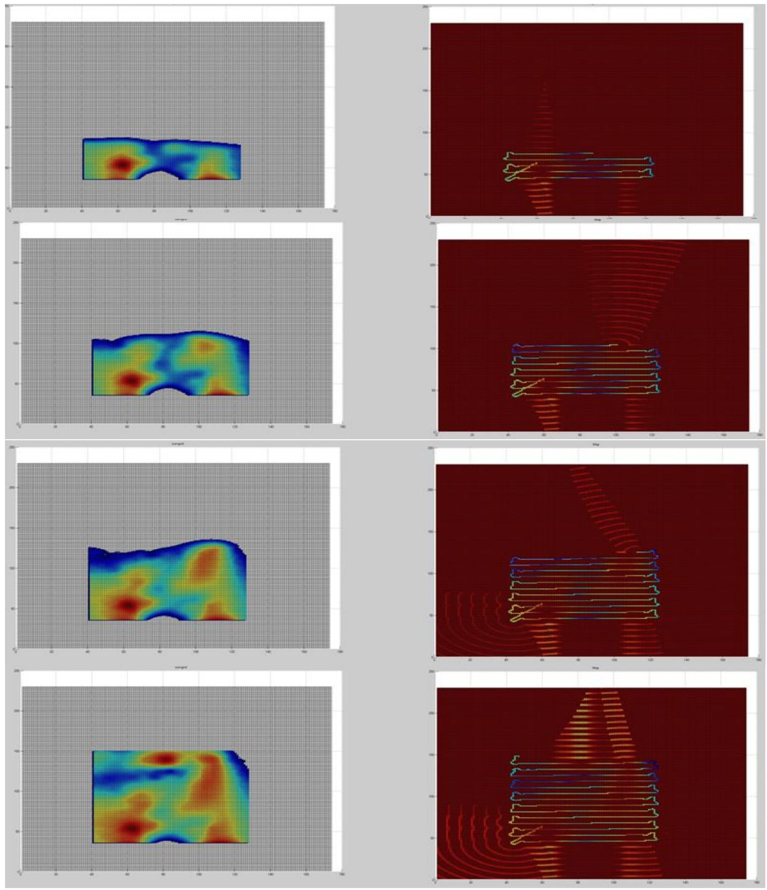

Figure 14. Evolution of the plume belief state (left) and the resulting cost map with optimized trajectory (right) during simulation evaluation.

Conclusion

In this paper we present research toward enabling high-quality in situ data collection near large-scale, dynamic, complex, and hazardous phenomena. If successful, this work would lead towards the ability to collection high-resolution data in locations currently inaccessible to autonomous vehicles, providing an urgent and identified gap in Earth science that cannot yet be filled by traditional airborne methods. Currently, the project team is continuing to conduct local flight tests and looking to advance the framework to address additional challenges posed in this problem, such as incorporating time-varying dynamics to the model and CFD evaluation. The initial autonomy implementation is an extension of the Payload Directed Flight architecture, augmented for the requirements of this mission and control laws to guide multi-vehicle coordination using simple control schemes. The simulation results have been promising but have not yet been validated through flight testing. Flight test demonstrations over an alternative SO2 source are in the planning stages, to be scheduled at the next window of opportunity for the team to conduct this deployment.

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