AFRL-AFOSR-VA-TR-2016-0203

Dynamic Data-Driven UAV Network for Plume Characterization

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05/23/2016
Final Report

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AF Office Of Scientific Research (AFOSR)/ RTA2
Arlington, Virginia 22203
Air Force Materiel Command

REPORT DOCUMENTATION PAGE

Form Approved
OMB No. 0704-0188

1. REPORT DATE *(DD-MM-YYYY)*
14-06-2016

2. REPORT TYPE
Final Performance

3. DATES COVERED *(From - To)*
15 Feb 2013 to 14 Feb 2016

4. TITLE AND SUBTITLE
Dynamic Data-Driven UAV Network for Plume Characterization

5a. CONTRACT NUMBER

5b. GRANT NUMBER
FA9550-13-1-0090

5c. PROGRAM ELEMENT NUMBER
61102F

6. AUTHOR(S)
Kamran Mohseni

5d. PROJECT NUMBER

5e. TASK NUMBER

5f. WORK UNIT NUMBER

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)
UNIVERSITY OF FLORIDA
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Gainesville, FL 32611-0001 US

8. PERFORMING ORGANIZATION REPORT NUMBER

9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)
AF Office of Scientific Research
875 N. Randolph St. Room 3112
Arlington, VA 22203

10. SPONSOR/MONITOR'S ACRONYM(S)
AFRL/AFOSR RTA2

11. SPONSOR/MONITOR'S REPORT NUMBER(S)
AFRL-AFOSR-VA-TR-2016-0203

12. DISTRIBUTION/AVAILABILITY STATEMENT
A DISTRIBUTION UNLIMITED: PB Public Release

13. SUPPLEMENTARY NOTES

14. ABSTRACT
Targeted, intelligent sensor networks have important applications in a tremendous range of situations, including toxic plume characterization,
Intelligence, Surveillance and Reconnaissance (ISR), environmental monitoring, weather forecasting, and disaster management and response. Data
driven operation of a mobile sensor network enables asset allocation to regions with highest impact on the mission success. We studied a dynamic
data driven (DDD) approach to operation of a heterogeneous team of unmanned aerial vehicles (UAVs) or micro/miniature aerial vehicles (MAVs)
for toxic plume characterization or similar ISR missions in complex domains. The proposed approach consists of two DDD loops. These are the
DDD simulation loop and DDD sensor placement loop. The integrated feedback loops connect simulations and data analysis techniques with
mobile sensor data collection where simulations and measurements become a symbiotic feedback control system where simulations inform
measurement locations and the measured data augments simulations. We have developed several model reduction strategies to reduce the
computational complexity of the simulation loop.

15. SUBJECT TERMS
micro-UAV network; pollutant plume detection; ISR

Standard Form 298 (Rev. 8/98)
Prescribed by ANSI Std. Z39.18

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
a. REPORT	b. ABSTRACT	c. THIS PAGE			DAREMA, FREDERICA
Unclassified	Unclassified	Unclassified	UU		19b. TELEPHONE NUMBER *(Include area code)* 703-588-1926

Standard Form 298 (Rev. 8/98)
Prescribed by ANSI Std. Z39.18

Abstract Targeted, intelligent sensor networks have important applications in a tremendous range of situations, including toxic plume characterization, Intelligence, Surveillance and Reconnaissance (ISR), environmental monitoring, weather forecasting, and disaster management and response. Data driven operation of a mobile sensor network enables asset allocation to regions with highest impact on the mission success. We studied a dynamic data driven (DDD) approach to operation of a heterogeneous team of unmanned aerial vehicles (UAVs) or micro/miniature aerial vehicles (MAVs) for toxic plume characterization or similar ISR missions in complex domains. The proposed approach consists of two DDD loops. These are the DDD simulation loop and DDD sensor placement loop. The integrated feedback loops connect simulations and data analysis techniques with mobile sensor data collection where simulations and measurements become a symbiotic feedback control system where simulations inform measurement locations and the measured data augments simulations. We have developed several model reduction strategies to reduce the computational complexity of the simulation loop.

In the DDD simulation loop, a greedy algorithm is derived for detecting hot spots by maximizing mutual information gain. A general criterion for dynamic sensor placement will be derived to simultaneously reduce the unbias and uncertainty of the measured filed. In the DDD sensor loop, a fluid based path planning algorithm is developed where simulated atmospheric flow are used to identify corridors of transport. The developed methodologies have been tested in both simulation and in hard-ware in the loop (using micro aerial vehicles) simulation.

Introduction. The accurate analysis and prediction of complicated phenomena behavior is a difficult issue in a variety of application domains. At fault is the segmentation between offline simulations and online sensory measurements. Offline simulations are uniquely suited for capturing trends in environmental phenomena over multiple spatio-temporal scales and under a variety of conditions. However, one or more simulations may not exactly align with real-world events, which can cause increasingly divergent predictions. There may also be some associated uncertainty about how much the predictions deviate from actual events. Online measurements offer a potential opportunity to assess the state of a phenomena. It is not always possible to have excellent spatio-temporal sensing coverage, though, especially in widespread domains.

The dynamical, data-driven application system (DDDAS) paradigm is a principled attempt to integrate both offline simulations and online measurements in a way that avoids the inherent issues with each. More specifically, the goal of a DDDAS is to dynamically incorporate meaningful sensor observations into one or more running simulations. These dynamically updated simulations are then employed to steer the measurement process so that more information about the current state of the environment can be gleaned. Ideally, the resulting predictions made by the dynamically updated simulations should better align with real-world events than those from purely offline simulations. The dynamically updated simulations should also possess a spatio-temporal resolution that is better than what can be obtained by a small collection of sensors.

Modeling and Reduction Research. Model reduction is often the first step in designing control strategies for large-scale dynamical systems. Among many model reduction techniques, proper orthogonal decomposition (POD) is the most widely used in a variety of application domains. However, POD has several shortcomings that limits its use in DDDASs. First, POD needs precomputed simulation snapshots to construct reduced systems. Second, the POD approach is not guaranteed to yield a stable reduced system, even if the original system is dissipative and stable. As a result, the predictions made by such reduced models could quickly diverge, leading to poorly performing DDDASs. Third, as a linear dimensionality reduction method, POD inevitably keeps some redundant information, which impedes the rapid prediction of environmental phenomena. Lastly, there is no notion of uncertainty associated with the POD predictions. As a result, in real-world DDDASs, investigators would have little indication of if they should trust those predictions or if the predictions are deviating and by how much.

In the past few years, we have proposed novel model reduction methods to solve these problems. In the first effort, we proposed an online manifold learning method. This method simultaneously obtains an invariant subspace and the solutions of the original system by a reduced Picard iteration [1]. A sequence of approximate solutions obtained by the reduced Picard iteration converges to the actual solution of the original system under certain conditions. In the second effort, we proposed a symplectic model reduction technique to preserve the symplectic structure present in various problems. This allowed us to achieve significant computational savings for large-scale, Hamiltonian systems [2]. Recently, we have extended this approach to address forced Hamiltonian systems [3], which encompass a variety of phenomena that would be of interest for certain applications. Our probabilistic framework allowed us to gauge the prediction uncertainty and determine when new observations needed to be included to revised the reduced model. The prediction uncertainties were also used to determine how many observations would be needed to ensure good prediction accuracies.

Dynamic Simulation and Testing Research. In [4, 5], we investigated a two-dimensional Gaussian puff evolving within a uniform background flow. The standard Kalman filter handles the data assimilation; an SPH control scheme handles navigation and collision avoidance. *Hot spots*, which are regions of high information sensitivity, are selected based on the estimated center and radius of the puff. These hot spots are used to steer the vehicles. The paper concludes with the following field test: a partially autonomous vehicle (shown in figure 1) tracking a simulated puff as it is advected downwind. Results demonstrate the advantages of employing mobile sensors for atmospheric sensor applications.

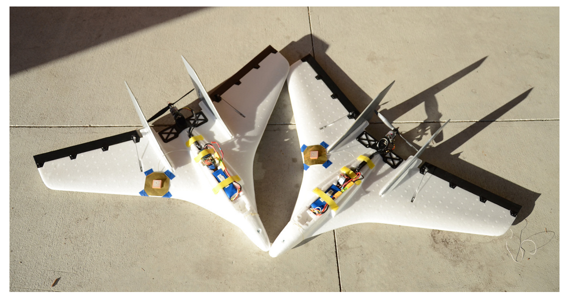

Figure 1: The delta wing UAV was used to experimental validate our DDDAS.

For the work in [6], a Gaussian puff is still employed. However, instead of evolving within a uniform background flow, the puff passes between and around two simulated buildings. The background flow is obtained through a high-resolution Naiver-Stokes simulation. The simulated measurements are obtained by pre-computing the puff concentration using a high-resolution advection-diffusion solver. When online, the DDDAS evolves the puff using a courser discretization of the advection-diffusion equation. Also developed in this work are more advanced guidance laws for the mobile sensors; however only nominal improvements in performance are achieved. This work demonstrates that a single mobile sensor in the DDDAS framework outperforms and array of nine static sensors.

In [7], we proposed a novel DDDAS for the problem of predicting plume behavior. The objective of this work is to locate the source of the plume, to track informative sensing locations as the plume evolve, and to incorporate measurements of the plume concentration to improve a running simulation of the event. In this work, we consider the use of POD together with its discrete empirical interpolation method (DEIM) extension for creating reduced-order models. We also consider a smoothed particle hydrodynamics vehicle control strategy [8, 9] to drive vehicles to the hot spots such that the main POD modes are captured. Both the assimilation method and the control strategies are very computationally efficient and can be carried out in real time. The simulation results verify the utility of the proposed DDDAS. Specifically, three UAVs are able to approach three hot spot locations and produce a greatly improved estimate of plume concentration when compared to the use of static sensors.

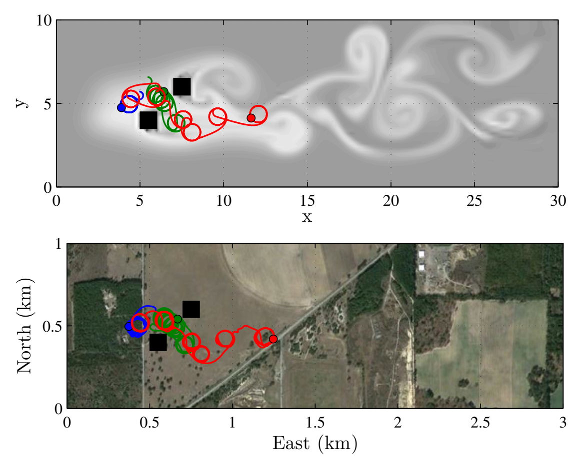

Figure 2: Real UAVs were deployed to test the feasibility of our DDDAS. Simulations and experiments showed remarkable agreement.

The work in [10] is an extension of our previous work in [7]. We use proper orthogonal decomposition to replace a high-dimensional Kalman filter with a reduced Kalman filter (RKF) while preserving the dominant

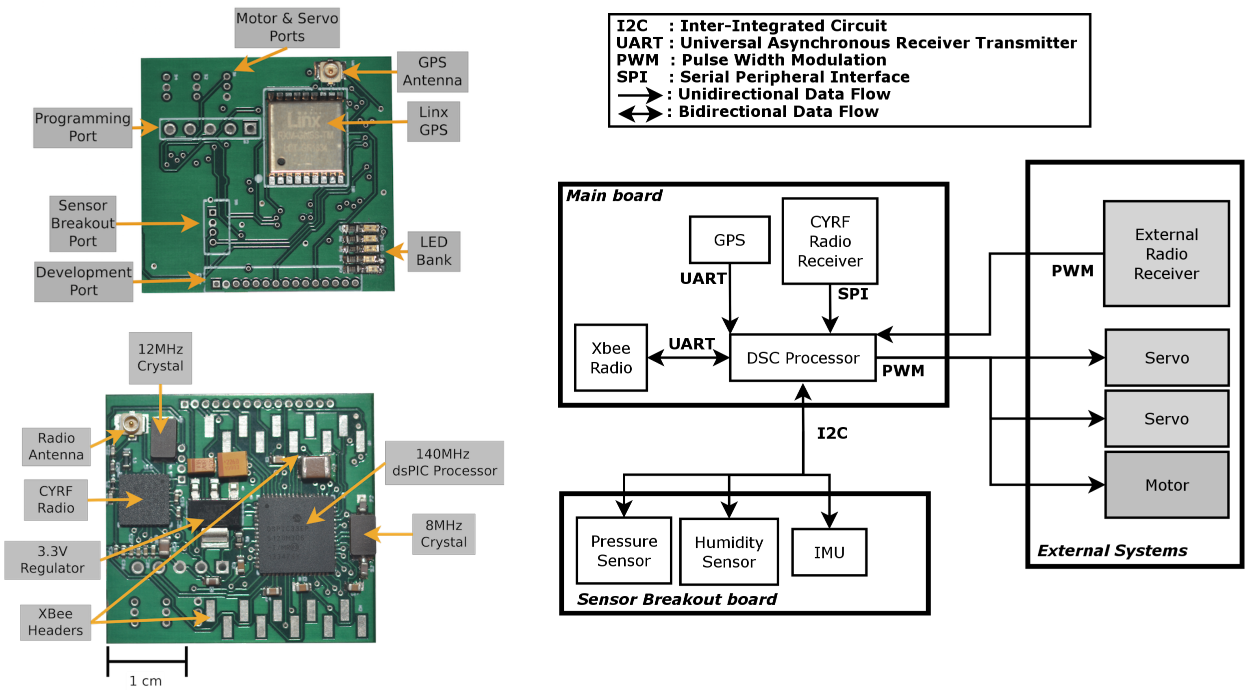

Figure 3: (left) The autopilot developed as a result of this research grant. (right) The system architecture of the new autopilot board.

features of the original filter. The RKF is applied to incorporate point observations into coupled dynamic systems to simultaneously estimate plume concentration and plume source distribution. Compared with the method that was applied in [7] for plume estimation, the RKF can obtain more robust and accurate results, because all the historical data is accumulated for current plume estimation. This work also features a field test involving three small-scale unmanned aerial vehicles in order to verify the feasibility of this DDDAS in a real world applications (see figure 2).

In preparation for these field tests, we constructed a new autopilot system (see figure 3) for our unmanned aerial vehicles. This new autopilot system weighs 6.25 grams and takes up 1.9 square inches of space. It was specifically designed for use on micro-aerial vehicles and can also be installed on large-scale platforms. This system incorporates a 16-bit 140MHz processor, GPS, dual radios, inertial measurement unit, pressure sensor, humidity sensor, and temperature sensor. Through these components, the autopilot system is capable of vehicle state estimation, localization, and wireless networking. The system is designed to be paired with a Matlab based ground station, enabling uplink/downlink communication, real-time data display, hot spot navigation, and data replay.

State feedback of the autopilot system was validated through a series of bench tests. Such tests included dynamic attitude estimation in a wind tunnel, using a model position system that was developed in-house, comparing GPS values to a known path, and comparing pressure derived altitude to multiple known heights. Flights tests with the autopilot system were performed on our group's Delta Wing and SWAMP micro aerial platforms to confirm system wide validation.

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1.

1. Report Type

Final Report

Primary Contact E-mail

Contact email if there is a problem with the report.

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Primary Contact Phone Number

Contact phone number if there is a problem with the report

352-273-1834

Organization / Institution name

University of Florida

Grant/Contract Title

The full title of the funded effort.

Dynamic Data-Driven UAV Network for Plume Characterization

Grant/Contract Number

AFOSR assigned control number. It must begin with "FA9550" or "F49620" or "FA2386".

FA9550-13-1-0090

Principal Investigator Name

The full name of the principal investigator on the grant or contract.

Kamran Mohseni

Program Manager

The AFOSR Program Manager currently assigned to the award

Frederica Darema

Reporting Period Start Date

12/01/2012

Reporting Period End Date

02/15/2016

Abstract

Targeted, intelligent sensor networks have important applications in a tremendous range of situations, including toxic plume characterization, Intelligence, Surveillance and Reconnaissance (ISR), environmental monitoring, weather forecasting, and disaster management and response. Data driven operation of a mobile sensor network enables asset allocation to regions with highest impact on the mission success. We studied a dynamic data driven (DDD) approach to operation of a heterogeneous team of unmanned aerial vehicles (UAVs) or micro/miniature aerial vehicles (MAVs) for toxic plume characterization or similar ISR missions in complex domains. The proposed approach consists of two DDD loops. These are the DDD simulation loop and DDD sensor placement loop. The integrated feedback loops connect simulations and data analysis techniques with mobile sensor data collection where simulations and measurements become a symbiotic feedback control system where simulations inform measurement locations and the measured data augments simulations. We have developed several model reduction strategies to reduce the computational complexity of the simulation loop.

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D. Lipinski and K. Mohseni, Micro/Miniature Aerial Vehicle (MAV) guidance for hurricane research, IEEE Systems Journal (accepted for publication), 2015,

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B. Hodgkinson, D. Lipinski, L. Peng, and K. Mohseni, High resolution atmospheric sensing using UAVs, Distributed Autonomous Robotic Systems, 104, 31-45, Springer Berlin Heidelberg, 2014,

There are several journal articles submitted but not published yet.

Changes in research objectives (if any):

Change in AFOSR Program Manager, if any:

Extensions granted or milestones slipped, if any:

AFOSR LRIR Number

LRIR Title

Reporting Period

Laboratory Task Manager

Program Officer

Research Objectives

Technical Summary

Funding Summary by Cost Category (by FY, $K)

	Starting FY	FY+1	FY+2
Salary			
Equipment/Facilities			
Supplies			
Total			

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Appendix Documents

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