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An Energy-Aware Airborne Dynamic Data-Driven Application System for Persistent Sampling and Surveillance

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Abstract

This paper describes an energy-aware, airborne, dynamic data-driven application systems for persistent sensing in complex atmospheric conditions. The work combines i.) new onboard and remote real-time, wind sensing capabilities; ii.) online models for planning based on Gaussian processes for onboard data and dynamic atmospheric models that assimilate Doppler radar data; and iii.) a hierarchical guidance and control framework with algorithms that can adapt to environmental, sensing, and computational resources. The novel aspects of this work include real-time synthesis of multiple Doppler radar data into wind field measurements; creation of atmospheric models for online planning that can be run inside guidance loops; guidance algorithms based on stochastic dynamic programming and ordered upwind methods that can adapt planning horizons, cost function approximations, and mesh representations of the environment; and throttling algorithms that manage the adaptation of the models and guidance algorithms in response to computational resources.

Keywords: dynamic data-driven application system; unmanned aircraft system; atmospheric models; planning and control

1. Introduction

Unmanned aircraft technology has advanced to the point where platforms fly sensing missions far from remote operators. Likewise, atmospheric phenomena can be simulated in near real-time with increasing levels of fidelity. Combining autonomous airborne sensors with environmental models enables the collection of data essential for examining the fundamental behavior of the atmosphere. Future airborne sampling and surveillance missions will require performance that exceeds that derived from traditional internal-combustion and gas-turbine engines. In addition to low radar cross section, low acoustic and thermal emissions from unconventional UAS designs employing electric propulsion and power systems will enable stealthiness and ease of operation. Two major challenges for small and medium UAS operating at low to medium altitudes are range and endurance, and operations in adverse weather. While traditional energy management meant monitoring hydrocarbon fuel levels, future advanced energy management systems will employ *in situ* and networked remote sensing integrated with atmospheric modeling to implement strategies to harvest energy from the environment; energy to supplement that stored onboard prior to launch. Integrated sensing and modeling coupled with autonomous low-level control will

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enable trajectory planning to revolutionize in-weather operations by detecting and avoiding mesoscale weather features that degrade performance or pose unacceptable risk to the aircraft.

The main challenge for future airborne sampling and surveillance missions is operation with tight integration of physical and computational resources over wireless communication networks, in complex atmospheric conditions. The physical resources considered here include sensor platforms, particularly mobile Doppler radar and unmanned aircraft, the complex conditions in which they operate, and targets or region of interest. Autonomous operation requires distributed computational effort connected by layered wireless communication. Onboard decision-making and coordination algorithms can be enhanced by atmospheric models that assimilate input from physics-based models and wind fields derived from multiple sources. These models are generally too complex to be run onboard the aircraft, so they will need to be executed in ground vehicles in the field or on high-performance computing in the lab, and connected over broadband or other wireless links back to the field. Finally, the wind field environment drives strong interaction between the computational and physical systems, both as a challenge to autonomous path planning algorithms and as a novel energy source that can be exploited to improve system range and endurance.

This paper describes an energy-aware airborne dynamic, data-driven application system (**EA-DDDAS**) that can perform persistent sampling and surveillance in complex atmospheric conditions. The main challenges that are addressed by the EA-DDDAS include tighter integration of sensor-based processing into online prediction tools; use of these tools inside planning loops that exploit available wind energy; and improved estimation of onboard energy states for higher degrees of autonomous learning. The EA-DDDAS presented here embodies the dynamic data-driven application system (DDDAS) concept and spans four key technology frontiers:

- Decision-making over different **application modeling layers** that include local aircraft energy and wind state dynamic models; spatio-temporal wind field models learned from onboard measurements; dual-Doppler synthesis of regional wind fields; and on-line models for atmospheric planning that assimilate (remote) dual-Doppler and (*in situ*) UAS measurements.
- **Mathematical algorithms** that provide high degree of autonomy with control loops closed over multiple spatial and temporal scales. Sampling-based optimization strategies will be combined with ordered upwind methods to create a planning framework that can adaptively balance between solution quality and computational resources devoted to the problem.
- New **measurement systems and methods** whereby multiple disparate information sources (*in situ* data from unmanned aircraft and remote dual-Doppler radar measurements) are assimilated by online models, mobile sensors are targeted to relevant measurements in real time, and data flow and processing rates are throttled in response to computation resource availability.
- Net-centric middleware **systems software** that connects multiple subsystems with computation and control resources dispersed over wireless communication networks, using multiple communication channels such as IEEE 802.11 (WiFI) or cellular broadband, while transmitting heterogeneous data sets that include high-priority commands as well as large-volume sensor measurements.

The overall EA-DDDAS concept for persistent sensing is shown in Figure 1. Mission objectives determine targets or regions of interest for persistent sensing. Online simulation models are fed by *in situ* measurements from unmanned aircraft and real-time data from Doppler radar that when available are fused to provide wind field data aloft (Section 2). An autonomy architecture (Section 4) switches between algorithms that use the wind field data and simplified models (Section 3) to plan paths that guide the aircraft into the region of interest while maximizing endurance through extraction of wind energy. All of these components are combined into a hierarchical framework that can select between default or resource-driven algorithms, that can direct the sensor platforms, and that can throttle processing rates in response to changes in measurement and computational resource availability.

2. Wind Sensing and Energy Estimation

This section describes new wind sensing and onboard energy estimation capabilities. Integration of a multi-hole probe enables *in situ* wind velocity measurements that can be fused with other sensors to estimate the aircraft total energy state. Ground-based Doppler radar processing provides additional wind field measurements over a much larger scale. Novel algorithms enable on-line processing such that the derived wind fields can feed into the atmospheric models (Section 3) that then enable the guidance and control architecture (Section 4).

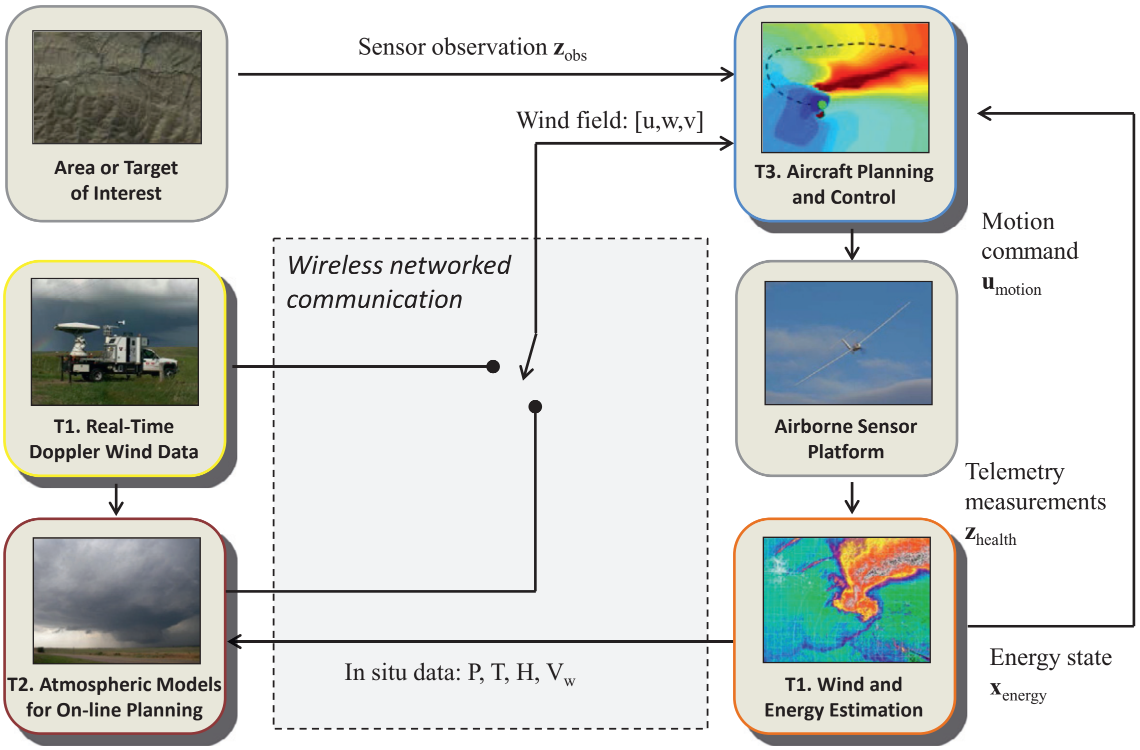

Fig. 1. An energy-aware, airborne DDDAS for persistent sensing in complex atmospheric conditions.

2.1. *Energy Estimation*

The total energy state of the EA-DDDAS is determined from the sum of the kinetic (based on true airspeed), potential (based on altitude), and internal (based on onboard storage) energy. As was obvious during the VORTEX2 field campaign [1], one of the major energy-monitoring challenges is a strategy to accurately monitor instantaneous power draw and stored-energy level (battery charge for the Tempest UAS used in VORTEX2). The total energy state of the EA-DDDAS, including instantaneous power consumption and stored-energy levels, must be accurately determined for any energy-management control algorithm. The principal sources of error in determining the energy state are based on the accuracy in the measurement of airspeed, altitude, and battery charge.

2.2. *Airborne In Situ Wind Measurement*

The true airspeed of a low-speed aircraft is computed from the dynamic pressure measured with a pitot-static probe, standard equipment in most UAS autopilots. The aircraft velocity in the fixed-ground reference frame is estimated from the autopilot inertial measurement unit (IMU) data, supplemented with GPS. Air-data probes are used for *in-situ* sampling of the local wind. An “alpha-beta” probe combines a conventional pitot-static probe with mechanical vanes to measure angle-of-attack and side-slip. The system developed here uses a miniaturized multi-hole probe, a pitot-static probe with additional pressure ports to sense angle-dependent differential pressures. Compared to the alpha-beta probe, the multi-hole probe provides superior wind-field resolution [2]. Subtracting this *in-situ* air velocity measurement from the IMU velocity estimate gives the local wind velocity.

2.3. *Real-time Dual-Doppler Wind Field Retrieval*

A robust initial wind field is essential to any atmospheric model for online planning tasked with the prediction of the 3D winds. Mobile Doppler radars can collect radial velocity data capable of resolving meso-γ scale and even micro-scale phenomena. When the data from multiple radars are combined, triangulation of radial velocities can yield 2D (x-y) wind fields and through mass continuity, the vertical component can also be deduced. The

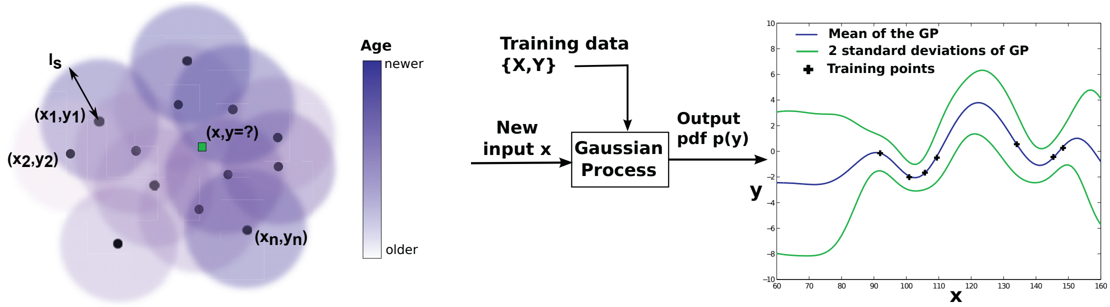

Fig. 2. a.) Training points $\{x_i, y_i\}$, new input x, and correlation distance l_s for a Gaussian process (GP). b.) The output of the GP is a probability distribution function of the measurement at input x.

techniques of computing 3D wind fields from two or more Doppler radars are well established [3]. However, these analyses have never been produced in near realtime in the context of mobile radar operations. To accomplish this objective, Doppler radial velocity measurements will first be passed through automated algorithms to detect and remove data artifacts such as non-meteorological returns ("ground clutter") and aliased velocities. The latter amounts to placing the velocity in the correct Nyquist interval. The velocity data will then be mapped to a Cartesian grid, along with radar pointing angle information, using a two-pass Barnes analysis [4, 5, 6]. The grid resolution will be tailored to the available communications bandwidth in the mobile platforms, as the gridded data from all radars will then be communicated to the mobile ground station. The gridded data from each radar will then be combined through triangulation, utilizing an upward integration of the mass continuity equation [7], followed by a final quality check of the analyzed velocity. The computed 3D velocity field will then be communicated to those processes that require near real-time velocity data, such as the models described below. The main technical challenges of this approach include sufficient automated removal of artifacts in the raw radar data (a step typically performed by a human analyst), and communication of the gridded data between platforms.

3. Models for Online Planning

This section describes the modeling approaches that provide predictions of the complex atmospheric conditions to closed loop guidance and control algorithms. Gaussian processes are used onboard the aircraft to provide near-term predictions based on correlations with previous measurements. The representational power of these methods tend to diminish with the age of the previous measurements, but provide sufficient predictions for myopic planning. When Doppler radar data is available, atmospheric models for online planning are used to predict the evolution of the wind field over larger temporal and spatial scales. These approaches require sufficient computation resources so they are run only on dedicated systems on the ground.

3.1. Models Learned from Onboard Data

When the wind field is measured onboard the aircraft but Doppler radar data is not available, a wind field model can be derived based on stochastic learning. Rather than derive a physics-based model, geospatial regression techniques are utilized to correlate predicted values with previous measurements. In complex weather phenomena wind velocity will depend on a variety of effects that lead to local variations in time and location, which will be captured by a spatio-temporal Gaussian process (GP). Spatio-temporal GPs use correlation between training samples (Figure 2a) to model the underlying process [8]. The relationship between the training samples and their corresponding measurements is captured by learning the hyperparameters of the GP. Using these hyperparameters, the probability distribution (Figure 2b) of the wind velocity at an unseen location at another time can be predicted by computing its correlation with the training samples [8, 9]. As the environment evolves (i.e. the operating region and time of interest changes), the correlation of the test samples with the training samples decreases. Consequently the applicability of the GP decreases, and sample collection and GP training can be repeated.

Gaussian processes have been shown to model wind fields well enough for aircraft path planning for energy extraction while performing exploration missions [10]. One of the main benefits of the GP is that it provides a probability distribution function for future measurements, not just a single mean value. This output enables planning approaches to consider the risk involved with predictions of future wind energy availability.

3.2. Atmospheric Models for Online Planning

As with most dynamic systems, the principal sources of error in forecasts of the atmosphere emerge from the observations used to define the initial state and the models used to develop the forecast. Errors in the initial observations notwithstanding, it is the paucity of atmospheric data that has the most control over forecast accuracy. This is particularly true when the focus is on small, rapidly-evolving atmospheric phenomena that need to be resolved for energy-aware UAS. Even if a perfect initial state can be assumed, model errors must also be considered. When constrained by the need to produce timely predictions, the computational expense of a forecast model places an implicit restriction on model complexity/accuracy and thus an implicit restriction on the predictability that can be expected. Therefore, model errors will also degrade forecast skill. Data and model errors become convolved when data limitations prevent the explicit modeling of certain properties or scales. Such conditions necessitate the parameterization of these unresolved features which introduces additional errors.

Remotely-sensed observations of the atmosphere collected by instruments such as Doppler radars have the potential to provide the dense observations required to initialize predictions for use in path planning. This potential is embraced by the warn-on forecast initiative (http://www.nssl.noaa.gov/projects/wof/) which aims to develop a system for assimilating surveillance observations of the atmosphere into numerical weather prediction models for the purpose of generating real-time guidance for short-term forecasts of meteorological phenomena, particularly thunderstorms and their attendant hazards [11]. The efficient and accurate assimilation of surveillance data into numerical weather prediction models for warn-on forecasting is a challenge whose horizon is years away [11]. Furthermore, the forecast skill required to predict the weather is likely much higher than the skill required to guide autonomous path planning. Thus, advances can be made incorporating Doppler radar observations into numerical weather prediction models to provide sufficiently accurate guidance for UA path planning.

Even with a successful technique for assimilating Doppler radar-derived wind fields into a dynamic model, predicting the evolution of the 3D wind field requires an initial mass (pressure, density) field as well. Surveillance observations of mass do not possess the spatio-temporal resolution to initialize a weather prediction model. UAS have the potential to fill the data void in the thermodynamic/mass variables observed within the lowest 2 km of the atmosphere with a sufficient density to enable ex post facto analysis of the structure and evolution of atmospheric phenomena. However, the data collected by a single UA alone cannot be used in dynamic models for the purpose of online UA flight planning. Ultimately, omission of the mass field renders the governing equations of any dynamic model open, and thus, predicting the evolution of the 3D wind field requires inventive ways of diagnosing the poorly-resolved mass fields.

We are examining five approaches to modeling the atmosphere for the purpose of UAS flight planning. Each of the methods, referred to as atmospheric models for online planning (AMOP), contain three components: 1) a strategy for diagnosing the mass field, 2) a method used to initialize the dynamic model with the available data, and 3) the dynamic model. While the schemes are presented in order of increasing complexity, there is no assurance that AMOP accuracy scales directly with complexity. Since the computational cost of each method is likely to scale directly with complexity, performance throttling requires careful consideration of the sacrifices in accuracy that must be made in the presence of dynamic communication and computational resources.

Simple Translation of Linear Boundary Layer Structures: The convective boundary layer is often characterized by coherent meso-γ-scale circulations organized into linear structures with lifetimes on the order of 10s of minutes. These lifetimes enable a level predictability that can be exploited with even simple dynamic models. In this first AMOP, linear boundary layer structures (LBLS) are identified at both $t = t_0$ and $t = t_0 + \delta t$, each LBLS is tracked using well-established feature tracking algorithms, and the mean motion is used to advect the features forward in time. The 3D wind field derived from multiple Doppler radars is not used in this AMOP, thereby greatly simplifying the logistics of field deployments and data processing time required for initialization.

Persistence of 3D Wind Field: In contrast to the previous AMOP, this approach predicts the evolution of the full wind field. As such, this model requires the wind field derived through synthesis of multiple Doppler radars. In this AMOP, the wind field is assumed to remain unchanged in time. Each new update of radar data (1 min

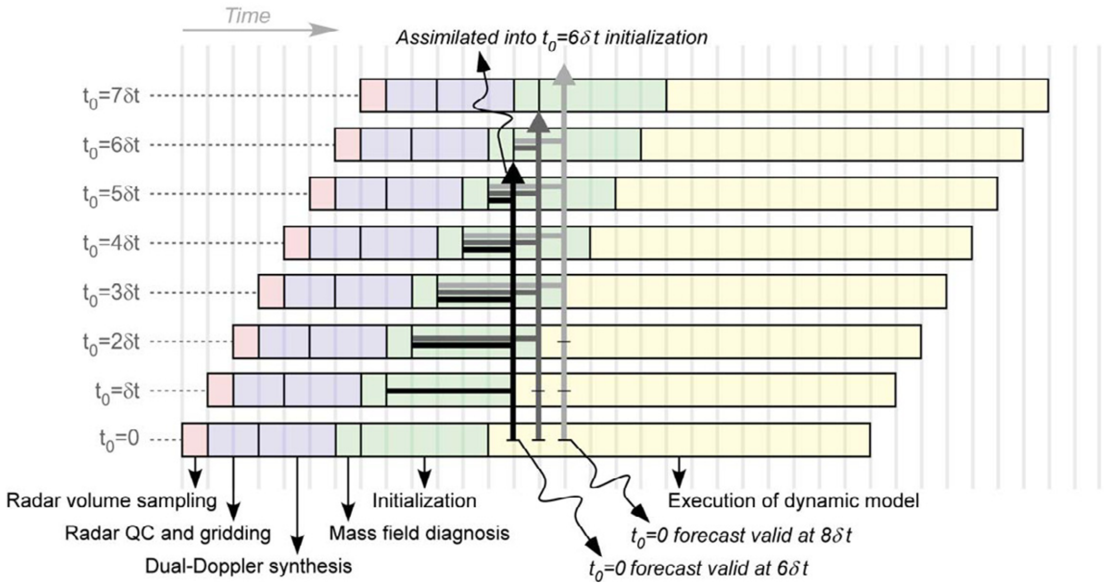

Fig. 3. Full Prediction of the 3D Wind Field AMOP

interval) will be used to initialize a new prediction based on a new distribution of the wind field. As in the Simple Translation of LBLS AMOP, each execution of the Persistence AMOP will be independent of prior predictions.

Simple Translation of the 3D Wind Field: In this AMOP, the feature identification and tracking used in the Simple Translation of Linear Boundary Layer Structures AMOP is used to advance the 3D wind field derived through synthesis of radial velocity data collected by multiple Doppler radars. The feature-relative wind field does not change in time. Eulerian changes in the winds are therefore a consequence of the advection of the wind field by an imposed flow equivalent to the translation of the LBLS. As in the Simple Translation of Linear Boundary Layer Structures AMOP, each new update of radar data will be used to initialize a new prediction but each execution of this AMOP will be independent of prior predictions.

NAS Translation of the 3D Wind Field: As in the Simple Translation of the 3D Wind Field AMOP, the NAS (not as simple) Translation AMOP is based on the assumption that a balanced flow field involving mass is present and juxtaposed upon the initial wind field. As such, the NAS Translation method adopts the same strategy for feature identification and adopts the same dynamic model that were used in the Simple Translation of the 3D Wind Field AMOP and also neglects the diagnosis of mass. However, the NAS method develops an initial field that is constrained by solutions from prior forecasts. That is, not only is the dual-Doppler derived wind field used for both feature identification and for creating the initial state at $t = t_0$, but data from previous forecasts (initialized at $t - n\delta t$) and valid at t_0 are also used. Blending observed data and forecast data is standard procedure for operational numerical weather prediction models.

Full Prediction of the 3D Wind Field: In contrast to the Simple and NAS Translation of the 3D Wind Field AMOPs, the Full Prediction of the 3D Wind Field AMOP retains the essential terms in the governing equations used to predict the state of the wind field. The dynamic model used in this AMOP is the anelastic form of the Navier-Stokes equations in an inviscid, inertial frame of reference, along with the anelastic continuity equation and adiabatic thermodynamic energy equation. The initial mass field required to apply this dynamic model will be diagnosed from the forecasts of the Rapid Refresh numerical weather prediction model [12]. The initialization of the dynamic model in the Full Prediction of the 3D Wind Field AMOP will rely on a variational method that develops an initial state that is based on the objectively analyzed data but constrained by both the governing equations and a background state from previous forecasts (Figure 3). By using data from prior forecasts, a dynamically consistent solution, one that has developed from the adjustment of mass to momentum and vice versa, is used to inform subsequent forecasts.

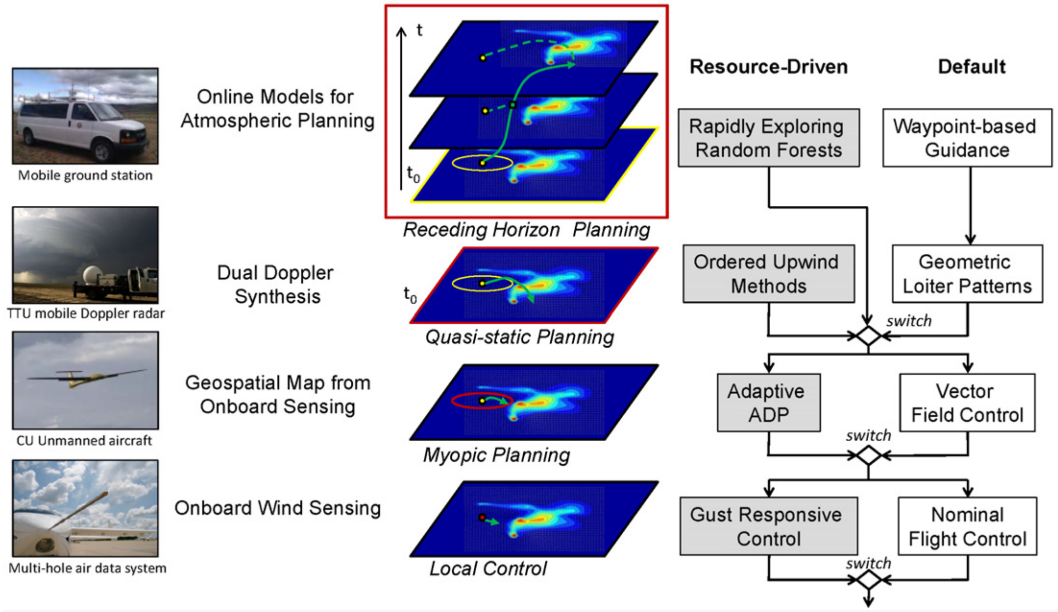

Fig. 4. Hierarchical guidance and control architecture with different modeling abstractions feeding control laws that act on different temporal and spatial scales based on resource availability.

4. Hierarchical Guidance and Control

Aircraft guidance and control provides mission-specific autonomy while accounting for the different temporal and spatial scales in the measurements and models described in Section 2 and Section 3, respectively. A hierarchical control approach (Figure 4) is implemented whereby different planning algorithms are run at the different scales using different abstractions of the system, with the output of each level serving as input to the next. The novelty of the approach derives from the overall hierarchy as well as new algorithms for mid- and long-term planning in complex atmospheric phenomena. Embedded in these algorithms are approaches to mission enhancement from wind-energy extraction.

For more than a decade, wind-field estimation has been a focus for small UAS applications, both for atmospheric science and for energy extraction strategies to enhance small UAS mission capabilities [13, 14, 15, 16, 10, 17, 18]. Inspired by soaring birds, static and dynamic soaring are well established methods to extend the endurance of unpowered gliders, of both manned and unmanned aircraft, and radio-controlled model aircraft. Static soaring refers to the use of columns of rising air created by atmospheric waves, local ground heating, or the deflection of winds by orographic features such as the windward side of hills. Dynamic soaring opportunities are created in regions with vertical gradients in the horizontal wind component created in the atmospheric boundary layer (ABL), leeward-slope separated flow, and gusts [18]. Langelaan [16] extends the notion of wind-field energy extraction to include that from short-duration turbulent wind gusts, showing simulation results for an unpowered glider, slightly larger than the Tempest airframe, that implement feedback control laws for energy extraction, without the need for full *a priori* knowledge of the gust field.

The overall guidance and control approach employed here will combine the energetics and informatics of the sensing platforms into a single dynamic optimization framework. We will consider objective functions of the form $J(x) = \alpha J_{erg}(x) + (1-\alpha)J_{info}(x)$ where $J_{erg}(x)$ and $J_{info}(x)$ are energy and information costs, respectively, and $\alpha \leq 1$ is a parameter that balances between them. Lawrance [9] showed that this approach yields good performance when the sensing task is to recreate the wind field itself. In this work we will extend our own previous work developing autonomous information-gathering algorithms to derive $J_{info}(x)$ while leveraging other work to derive $J_{erg}(x)$ for a general wind field, i.e. without focusing on a specific type of wind energy [13, 14, 15, 16, 10, 17, 18]. The exploration/exploitation trade-off that is inherent is environmental prediction problems [19, 9] can be addressed by including energy model terms in the information-gathering cost and by formulating information-gathering tasks in terms that depend on the energetics, e.g. total mission duration.

EA-DDDAS guidance and control is accomplished via a hierarchical control architecture (Figure 4). The lowest, bottom layers assume the entire wind field is unknown and rely on feedback control based on local state information. They require the least amount of processing and can be performed using information available onboard the aircraft. The higher, top layers of the hierarchy can exploit wind field data and atmospheric models for longer-term predictions. Default algorithms are defined for the aircraft that can be run onboard based on high-level commands that specify the mission area or target of interest. At each layer in the hierarchy the *Default* algorithm can be replaced with the *Resource-Driven* algorithm when sensing and computational resources are available. Issues of stability as different sensor measurements and computational resources are made available are mitigated by using the default algorithms, by running the algorithms at different (slower) rates toward the top of the architecture, and by passing outputs at one layer to inputs of the next.

At the lowest, inner-most level, local flight control algorithms will respond to wind estimates derived from the new onboard measurements in order to reject gust disturbances while reacting to rising air and periodic wind shear to extract energy. At the next layer, geospatial estimation algorithms are used to convert the local wind measurements into predictive maps of the local wind field. Spatio-temporal Gaussian processes [20] will provide probability distribution functions of the wind as inputs into myopic stochastic dynamic programming algorithms for computing local control policies. The third layer combines real-time wind field data from dual Doppler synthesis with quasi-static ordered upwind planning methods [21]. Here, planning occurs via interpolation over the Cartesian grid provided with the Doppler radar data. Adaptive grid refinement [21] will be used to throttle communication and computational effort in response to available resources while maintaining mission-level performance requirements. At the outer layer, sample-based planning methods will utilize the AMOP to generate trajectories over a receding time horizon. The ordered upwind methods of the previous layer are too computationally expensive for planning into the future, so sample-based methods will be used that trade expensive, optimal solutions for efficient, feasible results. Existing methods such as Rapidly-exploring Random Trees (RRT) will be augmented with new schemes that adapt plan length, search time, and the representations of uncertainty in the system models. Recent work has shown that sample-based methods can approach optimal results by properly reforming the tree after new nodes are added [22], and that distributed approaches that generate a forest of trees that can achieve super-linear efficiencies [23, 24]. Adaptation will be based on available computational resources as well as new "information acceleration" measures that provide predictions of the rate of change of the belief state of the planner.

4.1. Activating and Throttling Algorithms

The guidance and control algorithms are activated and throttled based on a combination of available resources. In this work all modeling and control layers are activated during system execution. The different atmospheric models are instantiated based on the availability of environmental, sensing, computation, and communication resources. For guidance and control, *Default* algorithms are switched for *Resource-Driven* algorithms based on resource availability.

For the EA-DDDAS considered here, the main separation of resources occurs between layers onboard the aircraft and layers executed on the ground. As a result, communication factors include the presence of a wireless link between multiple dispersed Doppler radar and the quality of the link between the aircraft and the ground control station. It is assumed that command and control of the UAS is maintained at all times, so the air-to-ground link is not a significant bottleneck for the EA-DDDAS framework. Plans are generated on the ground and transmitted to the aircraft as low bandwidth commands. The most significant communication bottleneck is the link between the radar, as it enables the calculation of wind field data from the radar measurements. Table 1 lists the type of communication required for each sensing and control layer.

Environmental conditions, available sensor measurements, and computational resources play a more varied role in the EA-DDDAS framework. Table 1 lists the environmental, sensing, and computing conditions and resources needed to activate the different layers. At the lowest layer, the presence of the wind sensor is the only significant resource. The estimation and control algorithms can be incorporated into existing autopilot schemes and hence require minimal additional computation. The presence of wind gusts are not needed as the control laws automatically act like the default algorithms in the absence of gust disturbances. Modeling and control at the next layer requires more computation and the presence of environmental features that can be exploited. The Gaussian

Table 1. Conditions and resources needed to activate the different model and control layers.

	Environment	Sensing	Computation	Communication
Energy Estimation	None	Onboard wind	Micro-processor	Internal
Gust Responsive	None	Onboard wind	Micro-processor	Internal
Gaussian Process	Non-uniform wind	Onboard wind	Embedded proc.	Internal
Adaptive RHC	Non-uniform wind	GP	Embedded proc.	Internal
Wind Field	"Dirty" air	Doppler radar	Workstation	Wireless R2R
Dynamic OUM	Non-uniform wind	Wind field	Workstation	Wired G2G, wireless G2A
AMOP	Atmos. Features	Wind field	Workstation	Wired G2G
Planning Forest	Non-uniform wind	AMOP	Workstation	Wired G2G, wireless G2A

Fig. 5. Layered design approach for NetUAS architecture.

process model and adaptive receding horizon control will not be useful if there is not significant variation in the wind field. A constant background wind can be represented without the complexity of the GP and the adaptive receding horizon control algorithm requires vertical wind as a minimum for energy extraction. The next layer is executed on the ground using output from multiple Doppler radar. The radar require "dirty" air in order to generate a signal and significant computational processing to derive wind fields in real-time. The ordered upwind methods require this wind data and features in the wind to make the computation worthwhile. Finally, the highest layers require the output of the Doppler radar processing and even more computational resources. It should be noted that the presence of the Doppler radar and ground-based computational resources can be known in advance of mission execution. However, the EA-DDDAS architecture does not rely on this fact and still waits until execution to determine the system configuration.

Guidance and control algorithm throttling will be based exclusively on computational resources. A novel feature of the hierarchical guidance and control framework described here is the ability to throttle computation of the adaptive receding horizon controller, the dynamic ordered upwind method planner, and the rapidly-exploring random forest planner. The exact computational requirements for each algorithm are unknown and will be measured empirically. For given field hardware the computational resources are fixed, so planning time will be used as the metric for computation. Variations in planning time will be recorded over multiple guidance and control loops, and the algorithms will adapt in response to averages over rolling time windows.

5. Net-Centric Middleware

The dispersed sensing, modeling, and planning resources within the EA-DDDAS are connected by net-centric middleware software. The Networked Unmanned Aircraft System Communication, Command, and Control (NetUASC3) software is designed to automate communication of system messages and parameters between individual subsystems and so that each node can easily recognize the capabilities of other components in the environment [25, 1]. NetUASC3 is distinguished by its ability to manage mobile ad hoc networking and service discovery protocols that integrate different network tiers and heterogeneous platforms [25, 1]. Telemetry and payload sensor data are provided in a publish-subscribe manner, and can be subscribed to by any network participant.

To address the difficulties associated with communications in complex UAS, the development of an inter and intra-vehicle network has been decomposed using a bottom-up layered design approach [25, 1]. This approach allows for the design of UA and supporting systems to reflect and enhance design decisions made at the lower layers. Given that the success of a UAS is based heavily on networked communications, this approach ensures the mission level control algorithms can be implemented on the underlying network architecture. Subsequent decisions at higher levels of the design process are based in part on the decisions made below. The layers designed here include: Physical / Transport; Data Routing and Network Configuration; integration of intra-vehicle communication for Sensor, Communication, and Control Fusion; application layer communication protocols for Service Implementation and Discovery with data stream publication; and Mission Level Control [25, 1].

6. Conclusion

This paper described an energy-aware, airborne, dynamic data-driven application systems for persistent sensing in complex atmospheric conditions. The work combines i.) new onboard and remote real-time, wind sensing capabilities; ii.) online models for planning based on Gaussian processes for onboard data and dynamic atmospheric models that assimilate Doppler radar data; and iii.) a hierarchical guidance and control framework with algorithms that can adapt to environmental, sensing, and computational resources. Strategies for activating different algorithms based on computational resources, communication performance, and environmental conditions were discussed. Net-centric middleware software needed to implement the energy-aware, airborne, dynamic data-driven application system was also presented.

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