ABSTRACT

POWERS, THOMAS CORNELIUS. Artificial Lumbered Flight for Autonomous Soaring. (Under the direction of Drs. Larry Silverberg and Ashok Gopalarathnam).

Soaring strategies are redefining the flight capabilities of small-class fixed-wing UAVs. This dissertation presents an autonomous soaring strategy that exploits updraft energy independent of the classification of an updraft. The strategy employs an artificial lumbered flight algorithm (ALFA) that weighs near-field updraft velocity estimates and mission priorities for navigation. This work raises the question of ALFA's ability to *handle* classified updrafts. Indeed, ALFA does not explicitly consider the classification of the updraft. Instead, ALFA measures updraft data along an aircraft's flight path, estimates updraft data ahead of the aircraft, generates candidate flightpaths ahead of the aircraft for evaluation, and then selects the best candidate flightpath based on a reward function. This dissertation describes the structure of ALFA and the tuning processes for the updraft estimator and the decision function. Flight results demonstrate the ability of artificial lumbered flight to harness atmospheric energy and complete its objectives. The flight results consider aircraft behavior in more detail, examining ALFA's effectiveness when flying among classified updrafts. They demonstrate the ability of artificial lumbered flight to navigate unclassified updrafts and harvest energy from thermal updrafts. Finally, this work highlights that autonomous flight design and control of small-class aircraft is maturing into its own flight regime that lies between the flapping flight and cruise flight regimes, and will be driven by the harvesting of energy from the atmosphere.

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Artificial Lumbered Flight for Autonomous Soaring

by
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LIST OF SYMBOLS

x, y, z	Aircraft position, m
V, φ, γ	Velocity, m/s; Heading angle, rad; Velocity pitch angle, rad
α	Angle of attack, rad
m	Aircraft mass, kg
g	Gravitational acceleration, m/s ²
W_x, W_y, U	Wind velocity components, m/s
T, L, D	Thrust, N; Lift, N; Drag, N
Δt	Iteration time, s
d	Distance to waypoint, m
$(L/D)_{est}$	Estimated glide ratio
R_p, R_K, R_U, R_N	Potential, Kinetic, Updraft, and Navigation rewards, J
w_p, w_K, w_U, w_N	Reward weighing coefficients
S_z	Vertical component of GPS velocity, m/s
F_z	Z component of fuselage elements of the direction cosine matrix
a_1, a_2, a_3, a_4	Updraft estimation coefficients
$\mathbf{e}$	Updraft estimation error, m/s
C	Updraft estimation robustness coefficient
n	Moving window size
AR	Aspect ratio
e	Span efficiency factor
C_D	Drag coefficient
K	Number of data points used for MASE calculation
e_k	Error between estimated and measured updraft velocities, m/s

Chapter 1

Introduction

An entirely new approach to autonomous flight has emerged in recent years for aircraft in the 2-55 lb. class. This approach focuses on harvesting energy from the atmosphere to keep the aircraft aloft instead of relying on onboard fuel sources as aircraft do today. The viability of harvesting atmospheric energy autonomously is no longer in question [1-4] and will likely drive aircraft design and control strategies for aircraft of this size in the future. Soaring flight is generally characterized in two ways. Static soaring refers to the use of atmospheric updrafts, which are typically classified as thermals produced by irregular ground heating and convection currents, ridges caused by air moving up over large physical objects, and waves resulting from passing over large physical features. Dynamic soaring uses wind speed gradients within the boundary layer to help propel a bird or an unmanned aerial vehicle (UAV) and increase its velocity.

While early research centered on the dynamic soaring flight of the albatross, recent work has explored the benefits of static soaring. Toward this end, methods of estimating vertical wind profiles and the development of wind exploitation strategies are being advanced. Allen [1] presented an in-flight method of tracking a thermal's center. When the thermal center is known, he applies a circling strategy that harvests energy from the thermal while taking measurements to keep track of where the thermal may be moving. Kahn [5] used an energy variometer to get more detailed wind updraft measurements to aid in the locating and centering around thermals. Langelaan et al. developed a few methods for estimating the wind field for small UAVs and tested the methods with a 3DOF model in simulation [6]. They discussed

different methods of estimating the wind field such as using vehicle dynamics and kinematics, computing wind from the vehicle response, and direct computation using GPS and airspeed measurements. Other methods of estimating the wind field that have been used include using an unscented Kalman filter, extended Kalman filter, Weibull probability density function and a vision-based camera system [7-12]. Cheng and Langelaan [13] incorporated a guided exploration component to actively search for favorable updrafts and map the wind field in various regions with a flock of UAVs. Chakrabarty and Langelaan [14] explored orographic or ridge lift with a heuristic search and created a regional energy map that the aircraft uses to locate updrafts. Other studies focus on harnessing ridge lift to soar in urban environments, the transition between multiple ridges, and using tree-based path planning approaches to navigate the wind fields [15-19]. Langelaan and Bramesfeld [20] wrote a feedback controller that enabled gust soaring, unlocking the potential of rapid wind changes to increase the energy of an aircraft. All of these strategies focus on keeping the aircraft centered around the best area of lift or developing methods for finding the next updraft quickly.

Path planning and exploration algorithms are used to incorporate wind and soaring knowledge, thereby extending the lumbering flight capability of birds to UAVs. The A* algorithm, which is used in path planning problems and aerial sense and avoid, is well suited to a general auto-soaring approach, as suggested in a preliminary study by Chakrabarty and Langelaan [14]. In that study, they used the A* algorithm to build an energy map of a region which, in turn, they used to determine a path through a set of waypoints. Silverberg and Bieber [21] imbedded the A* algorithm in a new central command architecture for large systems of UAVs and recently flight-tested this with four aircraft. Other path planning algorithms used in conjunction with auto-soaring are tree planners such as Rapidly-Exploring Random Tree

(RRT) and Look ahead Tree Search (LTS). Lawrance and Sukkarieh [22], Langelaan [23] and Nguyen et al. [24] developed these methods and demonstrated good behavior in thermal and ridge soaring applications in simulation. Gudmondsson et al. developed a lift seeking sink avoidance algorithm based on a potential flow method and best path search method and simulated flight through mountainous terrain [19]. Reinforcement learning strategies have also been applied to enable a UAV to autonomously harvest energy from the atmosphere [25-27]

Since this area of work is relatively new, most of the literature simulates soaring methods without flight-testing. However, there are several notable exceptions. Allen [1] demonstrated his circling algorithm with successful flight tests, climbing an average of 172 meters in 23 thermal encounters. Edwards and Silverberg [2] entered an autonomously soaring UAV in a soaring competition where it performed well against manually piloted gliders, demonstrating the high potential of autonomously soaring UAV. Depenbusch et al. [3, 4] showed the successful culmination of their research with autonomous soaring flights in their two-part paper series, where they demonstrated successful wind estimation, classified updraft identification, thermal mapping and exploration methods. Reddy et al. recently demonstrated successful energy harvesting using their reinforcement learning approach [27].

While the term soaring encompasses the field of atmospheric energy harvesting, it logically divides into a structured approach and a lumbered approach. The structured approach is performed in three steps: exploration – identification – exploitation. The aircraft can use knowledge of the wind field to guide exploration or can simply travel directly to its destination. The aircraft identifies updrafts by comparing updraft velocity measurements with its database of classified updrafts. Once the measurements match a classified updraft, the aircraft can exploit the encountered updraft for energy gain. This approach tailors aircraft behavior for each

type of classified updraft based on knowledge of its structure. However, it relies on the identification of a classified updraft and can only exploit updrafts that are contained in its library.

The lumbered approach is a method of soaring that explores and exploits updrafts, whether classified or not. Inspired by the lumbering flight of birds such as eagles and hawks, which can only sense the nearby updrafts, this approach uses local, real-time decision-making to navigate the wind field. The term lumbering refers to the lazy motion observed in the flight of eagles and hawks when soaring through the air rather than when they flap their wings. This approach eliminates the need for knowledge of updraft classifications and expands the scope of energy harvesting to updrafts of all kinds, including unclassified updrafts. A drawback of this method is that it does not tailor energy gain to specific updraft classifications.

Most of the literature studies autonomous soaring with the structured approach, focusing on a single updraft classification. The lumbered approach has received little attention, and its feasibility is still in question. It is uncertain how well this approach can use classified updrafts such as thermals or ridges, and whether it is able to exploit unclassified updrafts at all. For this reason, this work seeks to determine the ability of a real-time decision-making process with limited wind field knowledge to gain energy from the atmosphere. The first goal is to determine whether an aircraft can harness energy from the larger, classified updrafts commonly exploited with structured autonomous soaring methods. The second goal is to see if this method can harvest energy from the weaker, variable wind gusts, or unclassified updrafts which are found in the space between large classified updrafts. This dissertation addresses these questions using the Artificial Lumbered Flight Algorithm (ALFA). ALFA is a path planning algorithm designed to harvest atmospheric energy using the lumbered approach to

autonomous soaring. For this work, the ability to exploit energy from the atmosphere is indicated by a decrease in aircraft sink rate from a straight gliding baseline. Thus, any reduction in sink rate signifies successful updraft exploitation. This work describes ALFA's development and flight-testing and investigates the behavior and flight performance of ALFA as a test aircraft navigates various wind fields. The focus of this dissertation is on the physical implementation and flight testing of the algorithm as this allows the algorithm performance to be assessed in a real, changing wind field. This is especially important when attempting to harness the energy in unclassified updrafts. Finally, interesting flight patterns produced by the algorithm are assessed to gain understanding of ALFA's decision-making process.

Chapter 2

Method

ALFA employs a 3 degree-of-freedom (3-DOF) aircraft flight model that predicts a family of candidate flight paths over an iteration in time. These predicted flight paths employ a real-time estimate of the updraft velocity that is determined from updraft measurements over current and previous iterations. A reward function weighs local (short-term) and global (long-term) goals in the spirit of the A* path planning algorithms [28]. Based on this flight model, the algorithm uses the reward function to select the best candidate flight path. This chapter first describes the 3-DOF model, the reward function, and the estimation of the updraft velocity. Then, it describes the tuning of the reward function and of the updraft estimator.

2.1 The 3-DOF Model

Over each iteration, ALFA estimates a set of candidate flight paths using a 3-DOF model. This family of candidate paths is referred to as the ALFA flower and a single flight path as the flower's petal (see Fig. 2.1). The 3-DOF model is governed by the 3-DOF equations of motion for a fixed-wing airplane, shown in Eq. (1) [29]. The current work uses a 2-meter wingspan powered glider as the test aircraft, which is described later in section 2.4, so the 3-DOF model uses the same aircraft.

Figure 2.1: The ALFA Flower.

Each petal of the ALFA flower corresponds to the predicted flight path due to a set of control inputs of pitch angle, bank angle and thrust level. The flower encompasses a range of flight paths resulting from control inputs that span the flight capabilities of the aircraft. The initial model has a set of pitch angles made up of four angles equally distributed between -15 to 15 degrees. The set of bank angles is composed of six angles spanning -60 to 60 degrees. The thrust levels considered are the no thrust, half throttle, and full throttle levels. Using these parameters, the equations of motion are numerically integrated using the second order Runge-Kutta method over a relatively small iteration time step, i.e. 0.5 – 2.5 seconds. Simulating the full ALFA flower over a 2 second iteration time step on a computer takes roughly 0.064 seconds. While simulating more candidate paths within the ranges of the parameters would smooth the total combined flight path, it would be at the cost of greater simulation time. The set of candidate paths shown here provide a good general starting point and is used in the simulation of the algorithm. For flight testing, the candidate paths were simplified based on various considerations and is described in section 3.2.

Figure 2.2: Free body diagram of the aircraft

$$\begin{aligned}
 \dot{x} &= V \cos \gamma \cos \varphi + W_x \\
 \dot{y} &= V \cos \gamma \sin \varphi + W_y \\
 \dot{h} &= V \sin \gamma + U \\
 \dot{V} &= \frac{1}{m} [T \cos \alpha - D - mg \sin \gamma] \\
 \dot{\varphi} &= \frac{1}{mV \cos \gamma} (T \sin \alpha + L) \sin \mu \\
 \dot{\gamma} &= \frac{1}{mV} [(T \sin \alpha + L) \cos \mu - mg \cos \gamma]
 \end{aligned}
 \tag{1}$$

In Eq. (1), γ is the velocity pitch angle, the heading angle, φ , is the angle between the aircraft's horizontal heading and North, and μ is the bank angle. The estimated wind velocity components are W_x , W_y and U . Fig. 2.2 shows the free-body diagram of the aircraft. The estimated updraft profile and control inputs are assumed constant over the iteration time step Δt , so the accuracy of the simulated flight path increases with a reduction in the size of the iteration time step or by increasing the discretization of the input variables. In the simulations, the iteration time step ranged from 0.5 – 2.5 seconds. During flight testing, a time step of 2 seconds was selected because it produced smooth flight paths with a turning behavior that is

common for autonomous aircraft of the selected size. When the time step was shorter than 2 seconds, the aircraft exhibited abrupt and inefficient turns. When the time step was larger than 2 seconds, the control input did not update fast enough, resulting in large turns that lasted too long and overshooting the desired turn. This turning behavior depends on the specific type of aircraft selected, and other time step values may suit different aircraft.

2.2 The Reward Function

As mentioned earlier, the reward function considers both local and global goals. Locally, the reward function considers the changes in the aircraft's potential and kinetic energies and the total "updraft kinetic energy" over the iteration time step. The updraft kinetic energy provides a measure of the usable energy available in the surrounding wind field. Globally, the reward function favors traveling toward the next waypoint. The global reward estimates the potential energy reduction during a direct glide to the waypoint. The reward function is comprised of four terms, each expressed in terms of energy.

$$(2) \quad R = R_p + R_K + R_U + R_N$$

in which

$$(3) \quad \begin{array}{l} \text{Local} \left\{ \begin{array}{ll} \text{Aircraft potential} & R_p = w_p mg (z_{i+1} - z_i) \\ \text{Aircraft kinetic} & R_K = w_K \frac{1}{2} m (V_{i+1}^2 - V_i^2) \\ \text{Updraft} & R_U = w_U \frac{1}{2} (1) (|U_{i+1}| U_{i+1}) \end{array} \right. \\ \text{Global} \left\{ \begin{array}{ll} \text{Navigation} & R_N = w_N mg \frac{d_i - d_{i+1}}{(L/D)_{est}} \end{array} \right. \end{array}$$

In Eq. (3), z is aircraft altitude, V is aircraft airspeed, U is updraft velocity, and d is distance from the desired destination. The coefficients w_p , w_K , w_U and w_N are used to tune the

priorities among the terms of the reward function, and ultimately govern the behavior of the algorithm. Notice that these weights are *not* normalized. Also notice that the individual rewards are associated with the change in energy over an iteration time step; a large reward indicates a correspondingly large improvement in the energy of the aircraft over the iteration time. The exception is the updraft term, which just considers updraft velocity. Since the updraft term reflects the kinetic energy contained in the atmosphere surrounding the aircraft, it must be given a mass to bring the expression to energy units. However, it is unclear how mass of the air should be represented in this situation. So, the mass is effectively absorbed into the updraft coefficient w_U . The tuning process sets the weights to produce the desired energy harvesting flight behavior, regardless of how the mass is included in the equations. If the mass were calculated and included some other way, the value of the updraft coefficient that produces desirable flight behavior would be different.

Lawrance and Sukkarieh [30] use a similar reward function in their paper to choose a path from the set of candidate paths they produced using an expanding tree search. That reward function uses the same potential, kinetic, and navigation terms as those shown in Eq. (3), though they scale the terms with an exponential decay function rather than with coefficients as shown here. Within the local considerations, they use an extra term which represents the instantaneous power at the end of the flight segment, $K_{\dot{E}} \dot{E}_{i+1} \Delta t$. This term uses the fixed weight $K_{\dot{E}}$ to prioritize the terminal power that can be used for further energy gain. This instantaneous power term was replaced here with the updraft term to better represent and weigh the impact of the vertical updraft velocity on the harvesting behavior. After choosing the path to fly from the set of candidate paths, the process of generating the ALFA flower and selecting

the best petal repeats every iteration to produce a flight path that harvests energy from available updrafts and can perform a desired mission.

2.3 Updraft Estimation

For successful lumbered flight, the reward function relies on an accurate estimate of updraft wind velocity. Following the approaches discussed by Langelaan [6] and Premerlani [31], the wind velocity components are estimated using the data from a typical IMU-GPS flight setup. The updraft component U of the wind is

$$(4) \quad U = \frac{S_{z,i} + S_{z,i+1} - |V|(F_{z,i} + F_{z,i+1})}{2}$$

where S_z is the vertical component of the GPS velocity, V is airspeed, and F_z is the z component of the fuselage elements of the direction cosine matrix. As indicated, they are evaluated at two consecutive data points. Using estimated updraft velocity data at points along the flight path, a fit of the wind is created from which the updraft velocity along the candidate paths is extrapolated. Several assumptions serve to simplify this fit. Since the reward function primarily differentiates between the candidate paths to the right and left of the aircraft, the updraft estimator must be able to do the same. A first order fit meets this requirement. The fit also assumes that the updraft velocity near the aircraft does not vary with altitude, which further simplifies the fit. This assumption is reasonable because the updraft velocity varies little in the direction of the flow, and the difference between the final altitudes of the candidate paths are small compared to the forward distance travelled by the aircraft. Since both the velocity changes and the distances between the path endpoints are small, any change in updraft velocity due to altitude is negligible. While these assumptions are valid over a short distance ahead of the aircraft, they degrade over longer distances. Since certain classified updrafts move spatially

over time, the fit includes a time component to account for this movement. Thus, this lower-order fit, which corresponds to a highly filtered fit, suits the ALFA application. More specifically, the updraft velocity distribution is a function of x , y , and t and is represented as a moving plane that is tilted with respect to a horizontal plane. Its general form $U = a_1 + a_2(x - v_x t) + a_3(y - v_y t)$, is written as

$$(5) \quad U = a_1 + a_2 x + a_3 y + a_4 t$$

where $a_4 = -a_2 v_x - a_3 v_y$ and in which v_x and v_y are drift velocity components of the wind field.

The coefficients a_1 , a_2 , a_3 and a_4 are calculated at each iteration using a moving window.

Employing Eq. (5), the measurement equations over the moving window are:

$$(6) \quad U_i = \mathbf{x}_i^T \mathbf{a}_i + e_i \quad (i=1, 2, \dots, n) \quad \mathbf{x}_i = [1 \ x \ y \ -t] \quad \mathbf{a}_i = [a_1 \ a_2 \ a_3 \ a_4]$$

Equation (6) is n equations expressed in terms of four unknown coefficients at step j . In matrix form, the n equations at the j^{th} step and the augmented least square function are:

$$(7) \quad U_j = \mathbf{X}_j^T \mathbf{a}_j + \mathbf{e}_j \quad E_j = \mathbf{e}_j^T \mathbf{e}_j + C(\mathbf{a}_j - \mathbf{a}_{j-1})^T (\mathbf{a}_j - \mathbf{a}_{j-1})$$

in which $U_j = [U_1, U_2, \dots, U_n]^T$ and $\mathbf{X}_j = [\mathbf{x}_1^T, \mathbf{x}_2^T, \dots, \mathbf{x}_n^T]^T$. Notice that the augmented least square function has two parts – a least square error and a robustness term that penalizes changes in the coefficients from the previous step. C is a weighing coefficient and $\mathbf{a}_{j-1}$ is the set of previously calculated coefficients. The minimization of Eq. (7) yields

$$(8) \quad \mathbf{a}_j = (\mathbf{X}_j \mathbf{X}_j^T + C)^{-1} (\mathbf{X}_j U_j + C \mathbf{a}_{j-1})$$

Notice that the weight C guarantees robustness since it guarantees that the matrix $(\mathbf{X}_j \mathbf{X}_j^T + C)$ has an inverse. The weight C also eliminates large, rapid changes in the fit of the updraft wind velocity. The reward function and the updraft estimation methods each have parameters that

govern the behavior and success of ALFA. In preparation for flight-testing, these parameters were tuned to produce desirable estimation and lumbered flight qualities, using the simulation model as described in the next two sections.

2.4 Tuning the Reward Function

The aircraft used for simulations and flight-testing was the Phoenix 2000 powered glider. It is a standard hobby-grade remote control glider with a built-in power system. Its interior space housed the necessary equipment without being too large or having too much drag. Table 2.1 gives the aircraft's physical parameters. The purpose of the simulations described below was to tune the weights w_P , w_K , w_U and w_N of the reward function for this aircraft in the presence of a specified set of wind fields. The effect of the reward function weights and different wind structures on the effectiveness of the flight paths was examined. The most suitable weights from the simulation studies were then used in the flight-testing.

Table 2.1: Aircraft Parameters: Phoenix 2000 Powered Glider.

Weight (kg)	1.51
Average chord (m)	0.1715
Span (m)	2
Aspect ratio	11.62
C_{D_0}	0.00762

The first step was to compare ALFA behavior with gliding-flight theory. For the no-wind case, the optimum glide slope is [32]

$$(9) \quad (L/D)_{\max} = \frac{1}{2} \sqrt{\frac{\pi A Re}{C_{D_0}}}$$

For this simulation, ALFA was started for flight at an altitude of 500 m, heading east, and flying horizontally at a speed of 9 m/s. This initial condition differs slightly from the inclined speed for the best glide-slope. With these initial conditions, the reward function weights were adjusted to achieve the result shown in Fig. 2.3. In the tuning process, the weights were found to separate into a set that controls steady glide (w_P and w_K) and a set that enables energy harvesting (w_U and w_N). This separation of the reward weights simplified the tuning, allowing for greater focus on the ratio of the terms, rather than exact values each should have. Throughout this tuning process, the potential and kinetic energy weights w_P and w_K were found to have the greatest impact on the smoothness of the flight path. The ratio of w_P to w_K that produced the best glide flight path shown in Fig. 2.3 was 1.2 to 1.

Figure 2.3: The ALFA flight path matches the no-wind minimum glide slope.

As shown, the selected path with ratio 1.2 to 1 (shown in blue) oscillated slightly toward the beginning of the path. The oscillations were due to the initial flight path *not* being directed along the glide slope and due to the aircraft's initial speed *not* being identical to the speed of

the optimal glide slope. As shown, the oscillations settled down to the best glide slope, represented by the dashed black line. The settling time of the oscillation can be decreased by increasing the number of pitch angle values being considered in the AFLA flower, but at the expense of computation time. When deviating from the 1.2 to 1 ratio, the flight path showed increased oscillations and would not approach the best glide slope. When the ratio is less than 1.2 to 1, the kinetic energy of the aircraft generally dominates the path decision, causing the aircraft to trade altitude for velocity, diving down sharply with long oscillations as seen in Fig. 2.3. When the ratio was greater than 1.2 to 1, the increased role of the potential term causes the aircraft to climb while sacrificing velocity until the aircraft stalls and pitches down to regain its velocity. The aircraft then settles to a more constant slope, but one less than the best glide slope. Keeping the potential energy weight slightly higher than the kinetic energy weight stabilized the flight path and prevented small wind disturbances from having such large impacts.

After the ALFA flight paths matched optimal theory, simulated classified updrafts such as ridges and thermals, were used to determine a set of updraft and navigation weights that provide a balance between reaching the waypoint and harvesting energy. The emphasis of this portion of the tuning process was finding values that allowed the aircraft to harvest energy and gain altitude. The ratio of w_U to w_N was adjusted by changing the navigation term. In this study, ridge lift with a region of high updraft velocity of 5 m/s was simulated. The area of updraft is modeled with a parabolic updraft velocity profile that runs the length of the ridge. This simple model helps pinpoint the weight values at which the flight behavior transitions between either harvesting energy or reaching the waypoint. It narrows down the weight values that produce a flight path that both harvests energy and reaches the waypoint. This small range of values that

cause the path to harvest energy and reach the destination is the starting point for further tuning through flight testing. More elaborate ridge models have been developed for use with ridge studies such as those discussed in [14-18], but the simple model suffices for this application.

As shown in Fig. 2.4, the ridge is oriented at a 30-degree angle to the line joining the start point [at (0,0)] and navigation waypoint [at (300,0)]. When the navigation priority was set too low as is the case with the harvesting path, the aircraft remains in the favorable updraft along the ridge without proceeding to its waypoint. When the navigation priority was set too high as shown with the navigation path, the flight path passed through the favorable updraft while gaining minimal energy. The region of transition between the two behaviors is shown when the navigation weight is 11 and the aircraft exploits significant energy from the ridge before traveling the remaining distance to the waypoint. Finally, the baseline flight path indicates the energy gained when gliding along a straight-line path to the waypoint. Table 2.2 provides a summary of the differences in flight paths using flight time, final energy, distance traveled and reaching the waypoint as metrics for comparison. The flights were simulated for a maximum flight time of 100 seconds.

Table 2.2: Performance Metrics for the Ridge Updraft Simulation.

<i>Metric</i>	<i>Baseline</i>	<i>Harvesting</i>	<i>σ</i>	<i>Transition</i>	<i>σ</i>	<i>Navigation</i>	<i>σ</i>
<i>W_N</i>	----	3		11		18	
<i>Flight Time (s)</i>	48	92.3	14.87	76.9	23.35	52.8	11.51
<i>Energy (J)</i>	1193.3	4347.8	1241.8	3130.5	1460.2	1609.1	738.3
<i>Distance (m)</i>	295.3	580.5	84.2	147.8	142.5	72.8	75.5
<i>Reached Waypoint</i>	100%	12%		58%		97%

Figure 2.4: Effect of navigation weight during a 30° approach to a ridge.

ALFA's ability to ride a ridge updraft successfully also depended on its approach angle to the ridge. When the flight path approached the ridge at an angle greater than 70 degrees, the algorithm did not differentiate between the right and left sides of the aircraft well enough to turn and exploit the ridge updraft. ALFA demonstrated the ability to follow a ridge and circle to harvest energy when the navigational priority was not set excessively high.

To study the effect of the navigation weights for a thermal updraft, a simulation was conducted for a flight path that crosses a thermal (see Fig. 2.5). The set of weights that framed the transition point between harvesting and reaching the waypoint for a classified ridge is similar to the set of weights that frame the transition point for the classified thermal. This stems from basing the algorithm on the measurement of updraft strength and decoupling it from the identification of classified updrafts. For this simulation, the thermal was modeled as a vertical column with a parabolic updraft profile. Like the ridge model, a simple model for a thermal helps to narrow down the transition region between flight behaviors. More elaborate models for thermals have been developed for in-depth simulations [1-3, 33-36]. When approaching a thermal, it was found that the aircraft circled in the high areas of lift when the navigation weight

was sufficiently low. As shown, the harvesting aircraft path circles the thermal, but does not reach the destination. The navigation path travels directly to the destination without exploiting much energy from the thermal. In the transition case, the aircraft exploits the thermal before reaching the waypoint. The baseline flight path indicates the energy gained when gliding along a straight line path to the waypoint. Table 2.3 provides a summary of the performance the flights in Fig. 2.5. For these simulations, the maximum simulated flight time was 80 seconds. In the rare situation when the aircraft approaches a thermal precisely toward its center, the aircraft passes through it without engaging the thermal. Wind noise was added to this thermal model as a random distribution with magnitude extremes of -0.1 to 0.1 m/s to evaluate the role of wind noise on the flight behavior of the aircraft. Wind noise accounts for the changes in updraft velocity that are rapid compared to changes in velocity due to the structure of a classified updraft. In the first part of all three cases, the flight paths oscillated in response to rapidly changing updraft velocity. As the updraft velocity from the thermal increases, it overcomes the wind noise, allowing the updraft estimator to get better updraft measurements and smoothing out the flight paths. These examples verified ALFA's ability to achieve desirable energy harvesting behavior without identifying classified updrafts. They also provided a range of energy harvesting weights around the transition behavior of the flight paths that serve as a starting point for further tuning the algorithm with flight testing.

Table 2.3: Performance Metrics for the Thermal Updraft Simulation.

<i>Metric</i>	<i>Baseline</i>	<i>Harvesting</i>	σ	<i>Transition</i>	σ	<i>Navigation</i>	σ
W_N	----	3		6.1		10	
<i>Flight Time (s)</i>	48	99.9	0.313	91.2	17.919	54.7	5.224
<i>Energy (J)</i>	1559.3	4602.7	215.6	3839.9	1120.8	1670.6	217.2
<i>Distance (m)</i>	295.3	627.3	2.0	572.3	113.5	341.0	33.06
<i>Reached Waypoint</i>	100%	0%		20%		100%

Figure 2.5: Effect of navigation weight when encountering a thermal.

To understand the relationship between the maximum velocity of an updraft and tuning parameters, Fig. 2.6 plots the last reward value at which the aircraft both harvests energy and reaches its destination. This is indicative of the region in which transition takes place. In the transition region, the reward function is balanced with the strength of the updraft. When this happens, the stronger parts of the updraft cause the updraft term to dominate the reward value of the candidate paths, making the aircraft stay in the high lift area. For any given updraft velocity, the aircraft will stay in the region of updraft for w_N values below the transition value, and the aircraft will reach the waypoint for w_N values above the transition value. For both ridges and thermals, as the maximum updraft velocity increases, the aircraft needs a stronger navigation weight to pull the aircraft out of the updraft. When navigating real updrafts, which tend to get weaker with increasing altitude or time, the aircraft will break out of the updraft when the updraft velocity sinks below the velocity corresponding to the selected transition reward weight.

Figure 2.6: Effect of updraft velocity on the transition w_N .

2.5 Tuning the Updraft Estimation Method

To ensure that the method of fit used to estimate the updraft velocity ahead of the aircraft is accurate, the estimation of updraft velocities was simulated at five points around the front of the aircraft (see Fig. 2.7). As shown, the points formed a semi-circle of radius r around the aircraft.

Figure 2.7: Test points for updraft estimation.

The points are labeled center left (CL), front left (FL), front (F), front right (FR), center right (CR) and Aircraft. Point F is always in line with the fuselage, points CL and CR are always in line with the aircraft's wings and points FL and FR lie at 45° from the fuselage axis. Since the

aircraft can update updraft measurements at 3 Hz, and the nominal gliding speed for the aircraft is just over 9 m/s, r was set to 3 meters to simulate the distance traveled between measurements. The window size n and the weight C were tuned based on this setup.

When performing the tuning, the first simulation started with a constant updraft velocity that stepped up to a higher velocity halfway along the flight path to see the updraft estimation's peak-overshoot and settling time characteristics. This addressed the estimation problem along a straight-line flight path. Next, the estimation problem was extended to two-dimensional space. Here, the problem considered a thermal updraft with a maximum strength of 8 m/s, as shown in Fig. 2.8. Noise in the wind velocity was added to the model by adding a sinusoidal noise function to the updraft distribution. This sinusoidal noise function was given an amplitude that ranged from 0 – 0.5 m/s, and period that ranged from 0.1 meters to 2 meters. The noise is always modeled as noise in the vertical direction. The amplitude and period of the noise function were adjusted throughout the testing to simulate various noise conditions. The sampling rate along the flight path coupled with the period of the noise function produced a noise profile that appeared random. Two flight paths were simulated through the thermal, one straight, and one sinusoidal, to compare the performance of the updraft fit in the regions to the left and right of the aircraft. The sinusoidal path had an amplitude of 10 meters and a period of 40 meters. The updraft estimates along the straight flight path were compared with the updraft estimates along the sinusoidal flight path to help determine the importance of data points collected perpendicular to a straight flight path.

Figure 2.8: Updraft for testing and tuning the updraft estimation method ($U_{\max} = 8$ m/s).

The tuning process considered the updraft estimator performance at each of the six locations around the aircraft. The effect of changing the parameters n and C was studied. Increasing n and C were both found to increase lag (settling time), but there was a tradeoff between the lag and filtering the wind noise out of the signals. The primary effect of the weighing coefficient C was in preventing large overshoot errors. The primary effect of the size of the moving window n was to filter out wind noise. With the effect of the parameters identified, Monte Carlo simulations were run to choose the parameters.

Since the parameters must be suited to many flight conditions, a metric was needed to compare the estimation error during various situations. These situations considered various levels of wind noise and considered the error at the six estimation locations discussed above. Since the updraft error is dependent on the magnitude of the updraft velocity, the metric had to be normalized to eliminate that factor. The Mean Absolute Scaled Error (MASE), which normalizes the average error with the magnitude of the updraft velocity in order to weigh the data points equally, is defined as [37]:

$$(10) \quad MASE = \frac{\sum_{k=1}^K |e_k|}{\frac{K}{K-1} \sum_{k=2}^K |U_k - U_{k-1}|}$$

In Eq. (10), K is the number of total data points, e_k is the error between the estimated and measured updraft velocities, and U_k is the updraft velocity at a given point. The results show the MASE values for a range of n and C for the simulated sinusoidal flight path for all of the six locations at one level of wind noise (see Fig. 2.9). The minimum MASE score for this case is indicated by the green dot. The other simulations, which considered multiple strengths and types of noise and varying levels of sinusoidal flight, were run and the combined minimum MASE value is indicated by the green x. This combined minimum MASE value indicates the chosen parameters of $n = 15$, and $C = 0.01$.

Figure 2.9: Monte Carlo results for a single wind noise level with minimum MASE scores indicated.

Using these parameters, Fig. 2.10 shows the error between the estimated and actual updraft that has been scaled by the magnitude of the updraft velocity along the flight path. When measuring at the aircraft, the error is below 2% for 93% of this flight path. The calculated R^2 value for the flight path is 0.991. This indicates that the updraft estimator should be sufficient for extrapolating the updraft values.

Figure 2.10: The scaled error between estimated and measured updraft velocities along the flight path.

To help visualize the effect and performance of the selected parameters, Fig. 2.11 shows the measured updraft velocities (solid blue line) and estimated updraft velocities (dashed orange line) along the simulated sinusoidal flight path for each of the six locations. The updraft distribution includes wind noise with a strength up to 0.5 m/s. As shown, the estimate at the aircraft, where the sensor is located, is better than at the other 5 points. Also shown, the estimate at F is better than along the left and right sides of the aircraft. The updraft estimates at points FL , FR , CL , and CR were the least accurate. This indicates that the data is not “rich”. The “richness” of the data describes whether the data has enough points orthogonal to the flight path to generate a realistic 2-dimensional updraft model. A model that produces small errors between the measured and estimated updraft velocities would be considered rich. As discussed

later, a sinusoidal flight path improves the richness of the data, but even so, the aircraft's inability to measure data outside the flight path of the aircraft produces richness concerns. However, the data did show that there is a distinction between the left and right sides of the aircraft, which is necessary for successful energy harvesting.

Figure 2.11: Estimator performance at various locations about the aircraft.

Now that the updraft estimation parameters are set, the differentiation between left and right sides of the aircraft were analyzed to ensure the reward function could differentiate between the candidate paths. To do so, the difference between the updraft values at point *FL* and *FR* were compared to evaluate the need for a prescribed sinusoidal path, which increases the richness of data. Fig. 2.12 demonstrates the impact of the simulated sinusoidal path (orange

color) and its improvements over the simulated straight flight path (blue color). The solid lines indicate measured difference in updraft velocity between the two locations, and the dashed lines show the estimated differences. While the measured velocities of the straight path differentiated between the right and left sides, its estimated velocities did not register a difference at all. When the aircraft followed a sinusoidal path, however, the estimated velocities matched the measured velocities much better. This indicates that data richness affects the success of the estimator and, if needed, prescribing a sinusoidal flight path can produce better results. The estimates still overshoot changes in updraft velocity, but this behavior is expected. Since the algorithm only needs to differentiate between the two sides of the aircraft, the presence of exaggerated values can be beneficial.

Figure 2.12: Effect of sinusoidal flight path on updraft estimates.

Chapter 3

Flight-testing Setup and Initial Results

3.1 Flight Testing Setup

The test platform for ALFA was the Phoenix 2000 EPO Composite R/C Glider (see Fig. 3.1). It has a two-meter wingspan foam wing, with the option of landing flaps, a 1.16-meter-long blow-molded fuselage and is powered by a 1050KV brushless motor and folding propeller. A powered glider was selected for ease of launch and recovery. Its loaded flight weight was 1.51 kg.

Figure 3.1: Phoenix 2000 powered glider used for flight-testing.

A flight controller (Pixhawk Mini) was used in conjunction with an open-source ground control software (Mission Planner) to control the aircraft, and communication between the aircraft and the ground control station (GCS) was accomplished with RFD-900 telemetry units. ALFA was run with MATLAB on the GCS laptop and used Mission Planner to relay commands

to the aircraft. The flight data presented in this dissertation was collected in September 2018 at the North Carolina State University Lake Wheeler Road Field Laboratory. The flight area consisted primarily of cornfields, with some trees around the border and a couple of buildings and trees in the center. The rolling fields allowed for good thermal activity in the mornings and afternoons. Throughout flight-testing, the reward function weights were adjusted to produce desirable flight behaviors depending on the wind conditions. Several flights were conducted with a set of weight values, and based on the behavior of the aircraft, the ratio was adjusted to find the set of values that produced energy harvesting behavior. This process was repeated every flight day as the wind conditions were a large factor in which sets of weights would produce energy harvesting behavior. Over time, the parameter values were slightly adjusted until the desired energy harvesting behavior was observed. This resulted in a w_U to w_N ratio of 5 to 1. Adjusting the iteration time step to a length of 2 seconds also helped produce smooth energy harvesting flight behaviors.

3.2 Reducing the ALFA Flower

Before conducting flight tests, there are several considerations which allow the ALFA flower to be reduced to fewer candidate paths, which in turn will improve the simulation time. Recall that the reward function consists of four terms: potential, kinetic, updraft, and navigation. The potential and kinetic energy terms primarily address the aircraft's ability to maintain a steady glide, as discussed previously. During flight-testing, the purpose of the flight controller is to maintain steady glide and govern the flying characteristics of the aircraft, effectively handling the potential and kinetic terms. This leaves the updraft and navigation terms for the ALFA algorithm to control. Letting the flight controller manage the steady glide components of the decision-making portion of ALFA does not remove the need for those terms in the reward

function, as they govern the steady glide of the aircraft in simulations. If ALFA was fully implemented on the flight controller, all four terms would be governed by the reward function as well. However, since the algorithm is run on the ground station, it is logical to let the flight controller handle the terms it already governs. This consideration in addition to the assumptions made in the updraft estimation process, namely that updraft velocity is independent of altitude, allows the ALFA flower to be reduced to one pitch value producing nearly planar flight. The second reduction is the removal of thrust levels from the candidate paths. Since the focus of this dissertation is to investigate the energy harvesting capabilities of the lumbered approach while gliding, the use of thrust is of secondary importance to this study. The thrust is used to prevent the aircraft from descending below a minimum altitude of 30 meters. When gliding at a sufficient altitude, the thrust is set to zero for all candidates and is not considered in the ALFA process. In the future, understanding the relationship between thrust levels and navigating updrafts to harvest energy will be important to determine an optimum way to incorporate energy harvesting in powered flight applications. However, these considerations do not match the focus of this work, allowing the ALFA flower to be reduced in this way. The resulting set of candidate paths considers the six nearly-horizontal flight paths produced by various bank angles spanning from -60 to 60 degrees. It is important to note that when six flight paths are equally distributed between -60 and 60 degrees there is no option for the aircraft to fly straight. Preventing the aircraft from flying straight ensures that the flight path always has a sinusoidal component to it, which is necessary to collect updraft data that is rich enough for a good updraft estimate, as described in section 2.5.

With this simplified ALFA flower, the updraft and navigation terms of the reward function govern which petal is selected. Since the updraft term experiences variations due to

wind noise, and the navigation term is, in comparison, more robust and consistent, the flight path selections can alternate between banking extremes. This would produce erratic flight patterns that change drastically and are inefficient. To prevent these rapid changes from occurring and produce a smoother flight path, the selected path number was constrained to be no more than two paths removed from the previous path number. After the reward function selects a flight path, it is compared to the previously selected path number to determine how much it changed from the previous time step. When the difference is more than two paths, the algorithm selects the path that is two paths toward the newly selected number. Thus, the new selected path is constrained to be no more than two paths from the previous path number, producing flight behavior more consistent with aircraft of this size class.

3.3 The Reward Pie

The previous section discussed ways in which the ALFA flower was simplified and that the flight controller was set to handle the reward terms governing steady glide. This leaves the updraft and navigation terms for the ALFA algorithm to use to determine the flight path. To visualize the tradeoff between the updraft and navigation terms a visual aid was developed, which is referred to as the reward pie. The updraft and navigation terms are represented in Fig. 3.2 as the green and red hatched areas respectively. The “spokes” on the pie chart represent the six petals of the reduced ALFA flower. The reward is normalized by the maximum reward value of the ALFA flower, allowing the reward values to stay between 1 and -1. As shown, the updraft values begin at the center arc, representing zero, and the navigation values start where the updraft values left off. The final reward values are represented with the bolded line, and the red star indicates the selected path having the largest reward score. The reward pie is illustrative of ALFA’s decision-making process.

Figure 3.2: The reward pie.

3.4 Navigation Baseline

The focus of this work is to determine whether this algorithm can enable the aircraft to harness energy from the atmosphere. However, the ultimate goal of an aircraft mission is to reach the waypoints and complete objectives. Using ALFA, the priority between reaching waypoints and harnessing energy from updrafts can be adjusted to produce the flight behavior required for a particular mission. The reward function priorities can be set such that the aircraft ignores all updrafts and single-mindedly follows waypoints or only focuses on harnessing updrafts and never reaching mission waypoints. Fig. 3.3 shows a flight conducted where the energy harvesting ratio was set to heavily favor navigating to waypoints with a ratio of w_U to w_N of 1 to 5. The flight indicates that the aircraft flew directly to each waypoint with minimal deviations from the straight path. The small sinusoidal motion observed along the flight path is caused by the lack of a straight flight option in the ALFA flower as discussed previously. This shows that ALFA is able to produce flight paths similar to those of a simple waypoint

following autopilot. From this point on, the updraft weight was increased so that the aircraft was able to harvest energy. The remainder of this dissertation focuses on the behaviors produced by the algorithm when set to harvest energy, and flights that harvest energy at the expense of not reaching all waypoints are considered acceptable for analyzing the soaring behavior produced.

Figure 3.3: Altitude and flight path while prioritizing navigation.

3.5 Illustrative Flight

The following flight case demonstrates the feasibility of ALFA. In this flight, the aircraft was manually hand-launched, flown to an altitude of 170 meters, and then controlled by ALFA for the remainder of the flight until landing. Fig. 3.4 shows the time variation of altitude for a portion of an ALFA controlled flight. Fig. 3.5 shows the flight path over an image of the flight field, and Fig. 3.6 shows a three-dimensional view of the flight path. The same color scale has been used in all three figures. The aircraft's mission is to fly a triangle between waypoints A, B and C, and to exploit wind conditions whenever possible. The aircraft updates its waypoint when it passes within 15 meters of the active waypoint.

As shown in Figs. 3.4 to 3.6, to describe the ALFA behavior, the flight was divided into four sections, separated by circled numbers. Section one (1 to 2) shows the aircraft gaining altitude and circling in an updraft, as well as meandering between areas of good lift heading to the first two waypoints. Waypoints are indicated by the white circles in Fig. 3.5. Section two (2 to 3) shows an area where the aircraft exits the updraft to travel toward the next waypoint and loiters in a weak area of lift. Section three (3 to 4) shows a period where there is almost no updraft present, but the aircraft still searches the region for an updraft. In section four (4 to 5), the aircraft has again found a good updraft and circles to gain altitude.

Figure 3.4: Altitude flight profile (color map represents aircraft altitude).

Table 3.1: Sink Rates for Illustrative Flight Sections (unassisted sink rate = 0.7 m/s).

Section 1 (m/s)	-0.371
Section 2 (m/s)	0.359
Section 3 (m/s)	0.663
Section 4 (m/s)	-0.544

The constant exploitation of the small updrafts and wind variations while searching for stronger updrafts allows the aircraft to fly at a reduced sink rate from that of a direct glide to its destination. Herein ALFA's potentially greatest benefit to soaring is demonstrated. For comparison, the unassisted sink rate, which is the average sink rate along portions of the flight where the aircraft glides unassisted by the algorithm, is 0.7 m/s. This value represents the average sink rate of several flights that glided directly between these waypoints without using power or ALFA to harness energy. Table 3.1 shows the average sink rates for the sections of the flight path. In all the flight path sections, ALFA performed better than the unassisted sink rate. In sections 1 and 4, the aircraft demonstrated a climb rate, which indicates the presence of a strong updraft in the area and showed that ALFA was able to harvest energy from the rising air successfully. Sections 2 and 3 brought the aircraft to a region of weaker updrafts where it lost altitude, but still flew with a sink rate less than the unassisted sink rate.

Figure 3.5: Aircraft flight path over the test area.

While traveling toward waypoint A, the aircraft utilized updrafts and executed several turns to remain in the favorable area of updraft. After reaching waypoint A, it started meandering toward the second waypoint while staying in a favorable updraft. Near waypoint B, the aircraft noticed a possible updraft south of the waypoint and executed three turns in the updraft at that location. Then the navigation term gained priority over the updraft term and the aircraft proceeded past waypoint B. Heading to waypoint C, the algorithm directed the aircraft to loiter in an area of weaker updraft, and it stayed there slowly losing altitude until it reached point 3. From point 3 to point 4, the updraft weakened or moved away, and the aircraft lost altitude more rapidly. However, at point 4, the algorithm found another region of lift, and was able to gain altitude by following the updraft and executing a couple of turns. After point 5, the pilot took manual control and landed the aircraft. Throughout this flight, the aircraft never reached waypoint C. While the ultimate goal for a soaring algorithm is to reach its objective points while harvesting energy, the purpose of this work is to demonstrate the ability an aircraft to harvest energy at all using the lumbered approach to autonomous soaring. So, while not reaching waypoint C falls short of the ideal, this flight contains energy harvesting behaviors that are valuable for this study.

Figure 3.6: Three-dimensional view of the illustrative flight.

As seen in Fig. 3.6, the flight section between points 1 and 2 shows circling behavior. The aircraft appears to follow either a thermal that rose at an angle to the ground or one that was moving along at some speed. Fig. 3.7 shows a detailed view of flight section 1. As seen in this figure, the aircraft circled three times before moving toward the next waypoint and circling again. Near the end of the climb, the updraft weakened to the point where the navigation term of the reward function influenced the aircraft to begin heading toward the next objective point. By this point, the aircraft had gained 85 meters in altitude and was heading toward the next objective.

Figure 3.7: Detailed view on the 85-meter climb in section 1 (between points 1-2).

Throughout this flight, ALFA was able to identify and remain in areas of updraft. It demonstrated an ability to meander and circle in a thermal. It was able to loiter in areas of a weaker updraft, which allowed it to sink at a slower rate than the unassisted sink rate. With ALFA, the endurance of the aircraft during this flight improved from an estimated total flight time of 180 seconds associated with an unassisted glide, to 810 seconds, an improvement of 350%. The flight demonstrates the feasibility of using the lumbered approach for autonomous soaring.

Chapter 4

Detailed Flight Analysis

In this chapter, three flights that were selected to demonstrate the feasibility of ALFA (see Figs. 4.1 and 4.2). Flight 1 was waypoint oriented, and showed the aircraft navigating the airspace with minimal deviations from direct waypoint paths. While navigating between the waypoints, the aircraft demonstrated a tendency to zigzag and avoid straight flight paths. In flight 2, the aircraft's waypoints were laid out in a triangle, but the aircraft prioritized updraft exploitation over waypoint navigation. In this case, the aircraft was able to explore and gain altitude, but only reached two of its three waypoints. In flight 3, the aircraft was given a loiter command near a thermal, and ALFA was able to exploit energy from the thermal without exploring too far from its loitering location.

Eight segments were selected from these three flights to demonstrate specific flight behaviors produced by the algorithm (see Fig. 4.1). Before reviewing the individual flight segments more closely in the next section, notice that the aircraft consistently performed better with ALFA than when unassisted by the algorithm. Table 4.1 compares aircraft sink rates over each of the flight segments and shows that the sink rate with ALFA was lower than the unassisted sink rate of 0.7 m/s. Recall that this value represents the average sink rate of the aircraft over several flights when set to navigate the waypoints while gliding, without using the algorithm. Segment 2, which had the highest sink rate of the segments, still shows a sink rate less than the unassisted sink rate. The best sink rates were actually climb rates, and these occurred near classified thermals. By reducing the sink rate around unclassified updrafts,

ALFA exhibited great energy savings in addition to gaining energy from the classified updrafts.

Table 4.1: Sink Rates for Detailed Flight Sections (unassisted sink rate = 0.7 m/s).

Segment 1 (m/s)	0.3
Segment 2 (m/s)	0.5
Segment 3 (m/s)	0.4
Segment 4 (m/s)	-0.6
Segment 5 (m/s)	-0.2
Segment 6 (m/s)	-0.4
Segment 7 (m/s)	-0.4
Segment 8 (m/s)	-0.2

Figure 4.1: The altitude profile of the flights.

Figure 4.2: Aircraft flight paths.

4.1 Observed Behavior

The segments introduced above illustrate eight flight behaviors exhibited by the ALFA controlled aircraft. ALFA flight behavior is made up of three simple behavior elements, a circle, a straight line and a random line. These elements combine to produce various flight behaviors, such as the eight behaviors identified below. Flight segment 1, Search and Return, shows how the aircraft transitions from waypoint following to exploration behavior. In segment 2, Circle Away, the aircraft executes several loops in response to the wind conditions. In segment 3, Regional Loiter, the aircraft exhibits loitering behavior. In segment 4, Sine Climb, it zigzags toward its waypoint while gaining altitude approaching a thermal updraft. These four flight segments show how ALFA responds to rapidly changing, and often weaker, unclassified updrafts, while demonstrating exploration behavior. In segment 5, Loiter, the aircraft maintains and slowly increases its altitude while loitering near a point. In segment 6, Thermal Loiter, the aircraft executes a nice circling pattern to gain altitude in a thermal. Segment 7, Angled Thermal, shows the aircraft circling up a thermal that is angled. In segment

8, Stationary Thermal, the aircraft circles to remain in a stationary thermal. These last four segments illustrate how ALFA behaves near classified thermal updrafts. Fig. 4.3 shows a snapshot of each of the flight segments. Throughout this chapter, the figures for each flight segment use a unique color scheme that indicates altitude. Using the reward pie, this chapter evaluates ALFA's performance in each of the eight segments and observes the priority management between terms of the reward function.

Figure 4.3: Eight common flight behaviors.

4.2 Search and Return

In Search and Return, the aircraft transitions between navigating toward a destination and exploring a wind field and then continues to reach the destination. As shown in Fig. 4.4, the aircraft maintained an altitude above 150 meters while traveling toward the waypoint, before descending and settling at a new altitude of 125 meters. The dashed black line indicates the aircraft's unassisted glide slope of 0.7 m/s. This glide path serves as a baseline for the slope of the actual flight path to demonstrate the energy gained using ALFA in regions with unclassified updrafts. Fig. 4.5 shows the aircraft flight path with the reward pie indicating reward term values at several points along the flight path. The reward behavior at these points is indicative of the decision-making process for all the decision points in the flight segment. At the first four points along the flight path, the updraft term governed aircraft behavior, and was negative in most cases. This suggests that the algorithm primarily avoided areas of sink, rather than followed areas of updraft. Especially near point 4, the reward function guided the aircraft away from a direct path to the destination to avoid areas of strong sink. This led the aircraft to explore other options to reach its destination and maintain a lower sink rate. The navigation term governed the aircraft behavior at points 5-8, enabling ALFA's global priorities to navigate the aircraft back toward its destination. If the navigation term had been set to a higher priority, the aircraft could have travelled directly to the waypoint indicated by the red circle (see Fig. 4.5). Recall that the reward weights were held constant for the whole flight. Thus, the well-tuned reward weights must allow for both energy harvesting behavior and reaching a destination. In this case, the aircraft would have lost less altitude if it had traveled straight to the waypoint from point 4 instead of avoiding sink and traveling further around the waypoint. However, if the navigation weight had been set to produce that behavior, the sections of the flight path

where the aircraft harvested energy would have been negatively affected, and less energy would have been harvested along the whole path. This situation illustrates the benefits that a strategy which updates reward weights throughout the flight could have, though that is not investigated in this dissertation. This segment demonstrates how the reward function balances mission priorities and how this affects flight path behavior.

Figure 4.4: *Left:* Altitude profile for Search and Return. *Right:* Top view of flight path.

Figure 4.5: The flight path for Search and Return, with the reward pie at eight points along the path.

4.3 Circle Away

Next, consider the flight segment in which the aircraft exhibits circling behavior while traveling away from its waypoint. In this segment, the aircraft descends over the majority of the flight but is able to maintain its altitude of around 75 meters for 30 seconds (see Fig. 4.6). In Fig. 4.6, the dashed black line indicates the unassisted glide slope of the aircraft to act as a baseline. After reaching point 3, the aircraft consistently traveled away from its destination, occasionally circling in response to updraft stimuli. Taking a closer look at the reward breakdown (see Fig. 4.7), notice that the updraft term dominated the reward at all points. The updrafts in the area guided the aircraft away from the waypoint, and the navigation term was not large enough to guide the aircraft back to its destination. The circles indicate a temporary increase in the strength of the updraft so that it briefly captured the aircraft, as seen at point 4. Near the end of this segment, at points 6 and 7, the updraft term became less dominant, and at point 8, both the updraft and navigation terms guided the aircraft back toward its objective. This behavior suggests the presence of either a weak and moving classified thermal updraft, or a noisy unclassified updraft. This segment illustrates the energy saved while navigating weak or unclassified updrafts.

Figure 4.6: *Left*: Altitude profile for Circle Away. *Right*: Top view of flight path.

Figure 4.7: The flight path for Circle Away, with the reward pie at eight points along the path.

4.4 Regional Loiter

Now consider the segment in which the aircraft loiters and remains in a confined area. During this flight segment, the aircraft slowly descended while exploring, and did not make progress toward the destination in the North (see Fig. 4.8). Once again, the dashed black line indicates the unassisted glide slope of the aircraft. At the first point, the navigation term controlled the reward to turn the aircraft left toward the destination, even though the updraft term opted for a right turn (see Fig. 4.9). The remaining points show that the updraft term dominated the reward, leading the aircraft to pursue updrafts away from its destination. At points 3, 4, 6, 7, and 8, which lie on the edge of the loiter region, Fig. 4.9 shows negative updraft velocities on one side of the aircraft. This trend suggests that the aircraft loitered in an updraft inside a region of sink. Once again, the exploration behavior resulted from noisy unclassified updrafts producing

large updraft rewards to overcome the navigation term. In this instance, ALFA prioritized reducing aircraft sink rate over passing through the area of sink toward the destination.

Figure 4.8: *Left*: Altitude profile for Regional Loiter. *Right*: Top view of flight path.

Figure 4.9: The flight path for Regional Loiter, with the reward pie at eight points along the path.

4.5 Sine Climb

Next, consider how ALFA makes decisions when exploring an area leading up to a classified thermal. In this 40 second flight segment, the aircraft zigzagged toward a classified thermal, climbing the entire time (see Fig. 4.10). The section started at point 1 with a dominant navigation term and an updraft term that was negative at each petal (see Fig. 4.11). After this initial state, the updraft term took control of the reward, and guided the aircraft toward the classified thermal. As the aircraft continued, the updraft term kept the aircraft directed toward the center of the updraft, essentially “climbing” up to the region of strongest updraft velocity. This segment highlights the sinusoidal motion that is observed to intermittently occur during the flights. Several factors contributed to this behavior. The first was simply that the ALFA flower does not contain the option of flying straight. Secondly, the selected path number was constrained to be no more than two paths removed from the previous path number, as discussed previously. Another factor causing the sinusoidal behavior was the algorithm iteration time step Δt . Changing the iteration time step affected the frequency of the meandering behavior of the flight path because it governed how quickly the flight path updates. These last two factors dictated the period of a sinusoidal flight of six steps. Given an iteration time step of 2 seconds, the minimum period became 12 seconds. The relationship between the frequency of the sinusoidal flight path and the richness of data used to estimate updraft velocities was considered when tuning the updraft estimator. After completing this segment, the aircraft reached the top of the thermal, and began the circling behavior that is commonly observed in thermal soaring.

Figure 4.10: *Left*: Altitude profile for Sine Climb. *Right*: Top view of flight path.

Figure 4.11: The flight path for Sine Climb, with the reward pie at seven points along the path.

4.6 Loiter

In this 63-second portion of the flight when the aircraft loitered around its waypoint, the aircraft showed only a ten-meter increase in altitude, as seen Fig. 4.12. Starting near the bottom the map in Fig. 4.12, the aircraft executed two circles before flying a figure-8 in search of better

updrafts. During the two circles, the aircraft maintained its altitude at around 87 meters. Then, as it disengaged from circling, it gained some altitude before returning to the loitering waypoint indicated by the red circle, which ensured that the aircraft did not explore too far. During the first two circles, the navigation term controlled the reward, as seen at points 1 – 3 in Fig. 4.13. Points 4 – 6 indicate that control of the reward shifted to the updraft term as the aircraft disengaged from the circling behavior. When the reward function prioritized the navigation term, the aircraft stayed in a tight circle around the loitering waypoint. However, when the aircraft encountered a favorable updraft, it adjusted its behavior to search for and remain in that updraft. This segment illustrates ALFA's ability to balance competing objectives while loitering to determine a beneficial flight path, even in the absence of a strong updraft.

Figure 4.12: *Left:* The altitude profile for Loiter. *Right:* Top view of the flight path.

Figure 4.13: A 3D view of the Loiter flight path with the reward pie at six points along the path.

4.7 Thermal Loiter

This section looks at ALFA's decision making when the aircraft appeared to be circling in a thermal. In this case, two rotations of a longer stretch of thermal circling serve to illustrate the reward behavior. In this 30 second flight segment, the aircraft climbed 20 meters. Fig. 4.14 shows that the reward function was primarily controlled by the updraft term. This is what one would expect to see while the aircraft is thermal soaring. At point 4, the updraft term was greater toward the left, but the navigation term reduced the reward on the left side and increased the reward on the right side so that the aircraft continued its circling behavior. Point 4 illustrates a location in the circling pattern where the reward is vulnerable to interference from the navigation term. This vulnerability occurs whenever the updraft is weak enough to bring its reward values within the range observed in the navigation term. The navigation term is more consistent and robust because it relies on the distance from the waypoint, whereas the updraft

term relies on the velocity of the wind, which changes rapidly (Eq. 3). This results in much higher updraft rewards during favorable winds, and similar values to the navigation term near weaker or unclassified updrafts. These vulnerable locations encourage progress toward the aircraft's destination. In this case, the navigation term helped the aircraft maintain its thermal soaring behavior instead of breaking it out of the circle.

Figure 4.14: A 3D view of the Thermal Loiter flight path with the reward pie at five points along the flight path.

Taking a broader look at Thermal Loiter behavior, allows the visualization of the classified thermal's location and strength. Fig. 4.15 shows the aircraft flight path when the aircraft circled in a tight area including a few times when it meandered away from a perfect spiral. The measured updraft data marked in blue created the second order curve fit of the thermal. The red data points were omitted. The contour plot in Fig. 4.15 shows that the selected data points were able to approximate the location of the thermal. Regarding the strength of the thermal, the updraft velocity exhibited high variability. The maximum measured updraft velocity was

2.8 m/s and the minimum measured velocity was -1 m/s, while the average maximum updraft velocity was 0.8 m/s. This variability reflects the instability of the thermal shape and strength over time, which is filtered when fitting the data. Despite the variation in measured updraft velocities, the projected center of the thermal agrees with the behavior of the aircraft and demonstrates ALFA's successful navigation of a classified thermal updraft.

Figure 4.15: *Left*: Top view of the updraft measurement points and the contour of the thermal. *Right*: A 3D view of the aircraft flight path.

4.8 Angled Thermal

The Thermal Loiter behavior was observed when the loitering waypoint was located near a thermal. However, when the aircraft is not constrained to be near a waypoint, it can follow a thermal as it moves around. The Angled Thermal is a flight behavior that occurs when a thermal moves in space, or when the thermal is angled so that its center shifts with altitude. Fig. 4.16 shows the aircraft traveling south while circling in an updraft. The aircraft seemed to reach the top of the thermal near 200 meters in altitude. Fig. 4.17 shows the behavior of the reward function throughout this flight segment and indicates that the updraft term dominated the reward in most locations and caused the aircraft to maintain its circling behavior. At point 2, the updraft term was consistent for all candidate paths, and the navigation term prompted

the aircraft to turn back toward the waypoint and the thermal updraft. The reward pies at points 3, 4, and 5 show that the updraft term was much stronger than the navigation term. This is typical reward behavior when exploiting a classified thermal. The non-concentric circles are a characteristic of this flight behavior. This behavior demonstrates that ALFA can exploit thermals of various shapes and can do so in areas away from navigation waypoints.

Figure 4.16: *Left:* The altitude profile for Angled Thermal. *Right:* Top view of the flight path.

Figure 4.17: A 3D view of the Angled Thermal flight path with the reward pie at seven points along the path.

4.9 Stationary Thermal

The last of the eight identified flight behaviors is the Stationary Thermal. Here, the aircraft has found a stationary, vertical thermal, and flies circles in the updraft. In this case, the thermal appears to top out at around 250 meters as the aircrafts climb slows down so that the aircraft only maintains its altitude. Fig. 4.18 illustrates that this circling behavior did not occur around a navigation waypoint, and that ALFA is able to exploit a classified thermal updraft while traveling to a mission objective. Fig. 4.19 shows a three-dimensional view of the flight path with seven locations where the reward pie indicates reward behavior. At the first two points, the navigation reward has a significant impact on the reward values of the candidate paths. At point 1, the navigation term is not strong enough to overcome the updraft term, and the aircraft turns away from the destination waypoint. At point 2, the navigation dominates and causes the aircraft to maintain its turn. The remaining points in this flight segment show a strong influence from the updraft term that the navigation term is not able to overcome. At points 6 and 7, the updraft influence became weaker, but was still dominant. The circling behavior near the top of the thermal updraft demonstrates ALFA's continued ability to harvest energy from a classified updraft without knowledge of its classification.

Figure 4.18: *Left*: The altitude profile for Stationary Thermal. *Right*: Top view of the flight path.

Figure 4.19: A 3D view of the Stationary Thermal flight path with the reward pie at seven points along the path.

Chapter 5

Conclusions

This dissertation introduced the Artificial Lumbered Flight Algorithm, presented its development, described the tuning of its estimator and reward functions, and analyzed the flight behavior of the algorithm as a test aircraft flew through both classified and unclassified updrafts. Decoupled from the required knowledge of classified updrafts, ALFA unlocks the potential of bird-like soaring behavior, i.e. meandering flight behavior used to exploit favorable updrafts. It accomplished this by guiding its decisions with a reward function that incorporates energy states which balance the need for energy gain and mission completion. Using a first order curve fit to approximate the wind field, by which updrafts are exploited, the feasibility of the lumbered soaring approach was demonstrated in several flight tests, one of which showed a flight endurance increase of 350%. Throughout the flight testing, the wind conditions were observed to have a large impact on the aircraft's ability to harvest energy. The selected reward function parameters were able to produce energy harvesting behaviors with certain wind conditions, and so need to be tuned based on daily wind conditions. This study did not establish a relationship between wind conditions and reward function parameters, but instead focused on the behaviors produced when the parameters match the wind conditions to enable energy harvesting.

ALFA produced several flight behaviors, which were identified and studied regarding the decision process. Flight segments 1-4 highlighted the factors contributing to the exploring and loitering behavior in unclassified updrafts. In Search and Return, the effect of sink caused the aircraft to take a longer route to its destination, resulting in a greater energy loss. This

behavior is a side effect of keeping the algorithm sensitive to beneficial updrafts that enable altitude gain. Circle Away and Regional Loiter showed that weak and variable unclassified updrafts produce frequent changes in the updraft term that led the aircraft to exhibit exploring behavior. Regional Loiter revealed that the aircraft would loiter in a weak updraft when surrounded by a sink. In Sine Climb, the emphasis was on the zigzagging behavior commonly exhibited by the algorithm. This zigzagging pattern aids the algorithm in obtaining rich data for the updraft estimator. In Loiter, when the navigation term controlled the path decision, the aircraft followed the waypoints more closely. A strong updraft term led to searching for favorable updrafts. Thermal Loiter showed that, upon encountering a strong classified updraft, the updraft term produced the thermal circling behavior that is commonly associated with soaring, including centering in the updraft. While circling, the navigation term helped the aircraft stay in the thermal since the loiter waypoint was near the updraft. When the updraft is not sufficiently strong, the aircraft would continue toward its destination, and find stronger updrafts. This allowed the aircraft to remain on task and prevented it from following updrafts too far from its objective. Angled Thermal showed that the algorithm can identify and exploit areas of lift that move around and are not located in a single location. Stationary Thermal confirmed that a thermal updraft will be exploited while traveling toward a navigation waypoint, and not only when a loiter command is in effect. Thermal Loiter, Angled Thermal, and Stationary Thermal all showed that the lumbered approach to autonomous soaring can sufficiently use thermal updrafts as demonstrated by the observed climbing pattern and the curve fit of the updraft measurements. It also showed the success of the method used for measuring and extrapolating updraft velocity from the nearby wind field. All the flight segments showed reduced sink rates compared to the unassisted sink rate of the aircraft and

demonstrated ALFA's ability to exploit unclassified updrafts. The reported flight did not require human intervention beyond launch and recovery.

The purpose of this study was to assess the feasibility of using the lumbered approach to autonomous soaring and to demonstrate the flight behaviors produced when using this method. Now that the feasibility of the lumbered approach has been demonstrated in flight, the development of a good wind model for use in related studies should become the focus for further research. The wind models currently used for autonomous soaring focus on specific updraft types and a model has yet to clearly describe the wind behavior in the regions between updrafts. Another useful relationship that should be modeled is how the quality of wind on a given day relates to the meteorological parameters such as pressure, temperature, wind conditions and overcast level used in weather forecasting and historic data. This would help with the training learning methods in simulation. With a complete, more accurate wind model several other concepts can be developed such as a strategy for using adaptive weights throughout the flight, and integrating the use of thrust throughout the energy harvesting process. The results reported in this dissertation demonstrate the effectiveness of artificial lumbered flight when navigating classified and unclassified updrafts. It is hoped that additional research and development efforts will be undertaken in this area toward finding some future utility for lumbered flight in the aviation industry.

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APPENDIX

Appendix A

Summary of Collected Flight Data

This appendix summarizes the flights conducted with the ALFA algorithm to tune reward weights and demonstrate energy harvesting. The data represented here only includes flights where the aircraft was controlled by the algorithm. Flights conducted to set up the communications between software and hardware, test failsafe behavior, establish baselines and test general air-worthiness of the aircraft are not included in Table A.1. The flights conducted prior to September 7, 2018 contained a bug in the algorithm, but were still useful in tuning the parameters of the algorithm. The flights used in this dissertation were flown on September 7 and 19. Throughout the flight testing, the wind conditions had a large effect on the ability algorithm to harvest energy. A relationship between wind conditions and the parameters that allow energy harvesting was not established. In the Energy Harvesting column of Table A.1 the duration of altitude hold and climbs reflect the totals for the flight. The flight time includes times when the pilot took manual control over the aircraft to bring it back to a starting altitude and is therefore not indicative of an increase in flight endurance due to energy harvesting.

Table A.1: Summary of ALFA Controlled Flights.

Date	Flight No.	Start time (EST)	Flight Time (sec)	Energy Harvesting?	w_U	w_N	Δt (sec)	Location
2/22/2018	1	AM	194	Reduced Sink Rate	10	3	1	Dorothea Dix
	2	PM	297	No	10	3	1	Dorothea Dix
	3	PM	300	Climbed 110 m	10	3	1	Dorothea Dix
	4	PM	372	Alt Hold 50 sec	10	3	1	Dorothea Dix
2/23/2018	1	PM	266	Alt Hold 50 sec	10	3	1	Dorothea Dix
	2	PM	206	Reduced Sink Rate	10	3	1	Dorothea Dix
	3	PM	216	No	10	3	1	Dorothea Dix
	4	PM	159	No	10	3	1	Dorothea Dix
	5	PM	742	No	10	3	1	Dorothea Dix
3/5/2018	1	PM	329	No	10	3	1	Dorothea Dix
4/5/2018	1	PM	160	No	10	3	1	Dorothea Dix
	2	PM	247	No	10	3	1	Dorothea Dix
	3	PM	846	Held alt for 50 sec in 2 sections. Climbed 40 meters total.	10	3	1	Dorothea Dix
4/11/2018	1	PM	342	No	10	3	1	Dorothea Dix
4/18/2018	1	PM	620	No	20	3	1	Dorothea Dix
4/20/2018	1	PM	575	Alt hold 20 sec	20	3	1	Midpines
	2	PM	522	Alt hold 60 sec	30	3	1	Midpines
	3	PM	645	Climbed 300 m	50	3	1	Midpines
	4	PM	458	Climbed 200 m	50	3	1	Midpines
4/21/2018	1	PM	662	Held alt for 100 sec, climbed 40 m	50	3	1	Midpines
	2	PM	618	Held alt for 50 sec , climbed 20 m	60	3	1	Midpines
	3	PM	508	Held alt for 20 sec, climbed 20 m	60	3	1	Midpines
	4	PM	471	Held alt for 50 sec	70	3	1	Midpines
	5	PM	450	Held alt for 20 sec	50	3	1	Midpines
5/2/2018	1	PM	419	Climbed 40 m	50	3	1	Midpines

Table A.1 (continued)

	2	PM	577	Held alt for 40 sec	50	3	1	Midpines
	3	PM	454	No	100	3	1	Midpines
5/5/2018	1	AM	551	Climbed 15 m	50	3	1	Midpines
	2	AM	484	Held alt for 100 sec	70	3	1	Midpines
	3	PM	575	No	100	3	1	Midpines
	4	PM	883	Held alt for 100 sec	50	0.3	1	Midpines
	5	PM	287	No	50	0.3	1	Midpines
	6	PM	457	Reduced sink rate	50	3	1	Midpines
	7	PM	630	No	200	3	1	Midpines
	8	PM	690	Reduced Sink Rate	50	0	1	Midpines
5/9/2018	1	PM	440	Climbed 70 m	50	0	1	Midpines
	2	PM	708	Climbed 50 m	50	0	1	Midpines
5/12/2018	1	PM	540	Held alt for 40 sec	50	3	1	Midpines
	2	PM	989	No	50	0	1	Midpines
	3	PM	641	Held alt for 60 sec, climbed 40 m	70	2	1	Midpines
	4	PM	764	No	70	1	1	Midpines
5/22/2018	1	PM	701	No	70	1	1	Midpines
5/25/2018	1	AM	395	Held alt for 20 sec	50	1	1	Midpines
	2	AM	640	Held alt for 20 sec	50	3	1	Midpines
7/9/2018	1	PM	590	Climbed 30 m	50	3	1	Midpines
7/20/2018	1	AM	803	Held alt for 30 sec	50	3	1	Midpines
	2	AM	689	No	50	3	1	Midpines
	3	AM	419	Climbed 45 m and reduced sink rate	10	3	1	Midpines
	4	AM	188	Reduced Sink Rate	1	3	1	Midpines
7/22/2018	1	PM	1100	Climbed 120 m, Crash	1	3	1	Midpines
7/30/2018	1	PM	392	Reduced Sink Rate	1	3	1	Midpines

Table A.1 (continued)

7/31/2018	1	AM	540	Held alt for 50 sec	1	3	1	Midpines
	2	AM	520	No	6	3	1	Midpines
8/4/2018	1	PM	670	No	3	3	1	Midpines
	2	PM	456	Held alt for 20 sec	6	3	1	Midpines
	3	PM	385	No	6	3	1	Midpines
	4	PM	503	No	10	3	1	Midpines
	5	PM	685	No	30	3	1	Midpines
8/5/2018	1	PM	567	Held alt for 150 sec	10	3	1	Midpines
	2	PM	519	Helo alt for 30 sec	10	3	1	Midpines
	3	PM	502	No	20	3	1	Midpines
	4	PM	301	No	5	3	1	Midpines
	5	PM	528	No	10	3	1.5	Midpines
	6	PM	776	Reduced Sink Rate for 20 sec	10	3	1.5	Midpines
8/6/2018	1	PM	678	No	10	3	1	Midpines
	2	PM	586	No	10	3	1.5	Midpines
	3	PM	669	No	10	3	1.5	Midpines
	4	PM	529	No	15	3	1.5	Midpines
	5	PM	579	No	15	3	1.5	Midpines
8/7/2018	1	PM	606	No	15	3	1	Midpines
8/8/2018	1	AM	1007	Held alt for 200 sec, climb 30 m	15	3	1	Midpines
	2	AM	748	Reduced Sink for 200 sec	15	3	1	Midpines
	3	AM	318	Held alt for 60 sec	15	3	0.8	Midpines
	4	PM	479	Held alt for 60 sec	15	3	1	Midpines
	5	PM	637	No	20	3	1	Midpines
	6	PM	168	No	20	3	1	Midpines
	7	PM	743	Circle climbed 20 m	15	3	1.5	Midpines
	8	PM	613	Held alt for 40 sec	15	3	1.5	Midpines
8/9/2018	1	AM	1078	Held alt for 60 sec	15	3	1.5	Midpines
	2	AM	855	No	15	3	1.5	Midpines

Table A.1 (continued)

	3	PM	737	Held alt for 20 sec	15	3	1.5	Midpines
	4	PM	300	No	15	3	1	Midpines
	5	PM	836	Held alt for 50 sec	15	3	1.5	Midpines
	6	PM	988	Held alt for 500 sec, Climbed 100 m	15	3	2	Midpines
	7	PM	1231	Held alt for 300 sec, Climbed 60 m	15	3	2	Midpines
	8	PM	1211	Held alt for 90 sec	15	3	2	Midpines
	9	PM	733	Held alt for 30 sec, Climbed 20 m	15	3	2.5	Midpines
8/10/2018	1	AM	873	Held alt for 100 sec	15	3	2.5	Midpines
	2	AM	486	Held alt for 50 sec	15	3	1.5	Midpines
	3	PM	803	Held alt for 180 sec	15	3	2	Midpines
	4	PM	801	No	15	3	2	Midpines
	5	PM	458	Held alt for 60 sec	15	3	2	Midpines
	6	PM	909	Held alt for 60 sec	15	3	2	Midpines
	7	PM	672	Climbed 20 m	12	3	2	Midpines
	8	PM	252	No	12	3	2.5	Midpines
	9	PM	353	No	12	3	2.5	Midpines
	10	PM	232	No	15	3	2	Midpines
	11	PM	613	Held alt for 60 sec	15	3	2	Midpines
	12	PM	998	Circle climbed 170 m	15	3	2	Midpines
	13	PM	830	No	15	3	2	Midpines
	14	PM	631	No	15	3	2	Midpines
	15	PM	655	No	15	2	2	Midpines
8/16/2018	1	PM	794	Held alt for 80 sec	15	2	2	Oregon Inlet
	2	PM	940	Held alt for 100 sec	15	2	2	Oregon Inlet
	3	PM	518	No	15	2	2	Oregon Inlet

Table A.1 (continued)

8/17/2018	1	AM	1406	No	15	2	2	Pea Island
	2	AM	1279	Held alt for 30 sec	15	2	2	Pea Island
	3	AM	754	No	15	2	2	Pea Island
	4	AM	603	No	15	2	1.5	Pea Island
	5	PM	502	No	15	2	1.5	Hatteras Island
	6	PM	751	No	15	2	1.5	Hatteras Island
9/7/2018	1	AM	781	No	10	2	1.5	Midpines
	2	AM	1163	Held alt for 60 sec	10	2	2	Midpines
	3	AM	769	Held alt 20 sec, climbed 10 m	10	2	2	Midpines
	4	AM	545	No	10	2	2	Midpines
	5	AM	588	No	15	2	2	Midpines
	6	AM	1588	Circle climbed 200 m, reduced sink rate	15	3	2	Midpines
9/19/2018	1	PM	1416	Climbed 150 m	15	3	2	Midpines
11/4/2018	1	PM	358	Baseline flight	10	30	2	Midpines