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Adaptive Path Planning for Autonomous UAV Oceanic Search Missions

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This paper presents an autonomous mission architecture for locating and tracking of harmful ocean debris with unmanned aerial vehicles (UAVs). Mission simulations are presented that are based on actual weather data, predicted icing conditions, and estimated UAV performance degradation due to ice accumulation. Sun position is estimated to orient search and observation maneuvers to avoid sun glare. The planning algorithms are based on evolutionary computation techniques combined with market-based cooperation strategies for multiple UAVs. Both single vehicle and multiple autonomously cooperating UAVs cases are demonstrated.

I. Introduction

Ocean debris in the North-East Pacific Ocean is a growing problem for wildlife.[1,2] The biggest threat comes from abandoned fishing nets which catch diverse marine species while drifting until they eventually become lodged on coral reefs. These nets cause significant damage to the reef and have to be cut out by divers for disposal, a dangerous operation. The mission goal is to locate and track these nets so that they may be recovered before they reach the reefs. Using ocean circulation models and satellite measurements, scientists can estimate regions where swirling eddies can cause mass accumulations of debris. Given these estimates, scientists have conducted overflights with aircraft equipped with visible and thermal imagers to find the actual location of the nets. The theatre of overflight operations is in the North-East Pacific Ocean, where weather conditions can create significant risks for manned operations. The use of small inexpensive long endurance unmanned aerial vehicles (UAVs) offers significant advantages. The use of UAVs for these missions requires autonomous path planning capabilities that respond to environmental dynamics and changes in the targeted survey regions, e.g. the path planner must account for existing and predicted wind fields, avoid the possibility of sun glare, and consider potential icing conditions. The objective of this paper is to present the integration of planning algorithms of the autonomy architecture, and demonstrate its potential for real missions application.

The results presented here are simulated search and locate missions based on actual environmental data. The path planning algorithms are based on Evolutionary Computation (EC) techniques. When planning for multiple vehicles these planning techniques are combined with market-based cooperation strategies. The path planning algorithms are integrated with search and stand-off observation maneuvers. The initial direction of these maneuvers is determined based on sun location to avoid glare into the camera. The observation maneuvers allow the observer to keep the debris in view as it moves with the ocean and wind driven currents, and allow direction of debris recovery vehicles to the site.

The algorithms accept weather data imported from standard atmospheric data files (GRIB 4–D). These files provide wind field information and weather parameters used for predicting regions of potential icing conditions based on the Integrated Icing Forecast Algorithm (IIFA).

In the following, Section 2 presents the planning techniques and the integration with trajectory generation algorithms. Section 3 indicates how weather and aircraft performance information is used for planning and mission simulation. In Section 4, simulation results are presented. Remarks and conclusions are provided in Section 5.

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II. Path Planning and Trajectory Generation

Long term remote missions as considered here benefit from autonomous operation, which requires a means to respond to environmental dynamics. Given measurement of key environmental variables (world states), autonomy implies an efficient response to these measurements without further external input. A response is 'efficient' if it serves the mission goal. The planning and trajectory generation algorithms presented here constitute high level components of a complete autonomy architecture, Figure 1. This section provides a brief overview with references for the planning algorithms used here, and explains how they are combined with mission tasks. The trajectory following guidance algorithm is found in Rysdyk.[3]

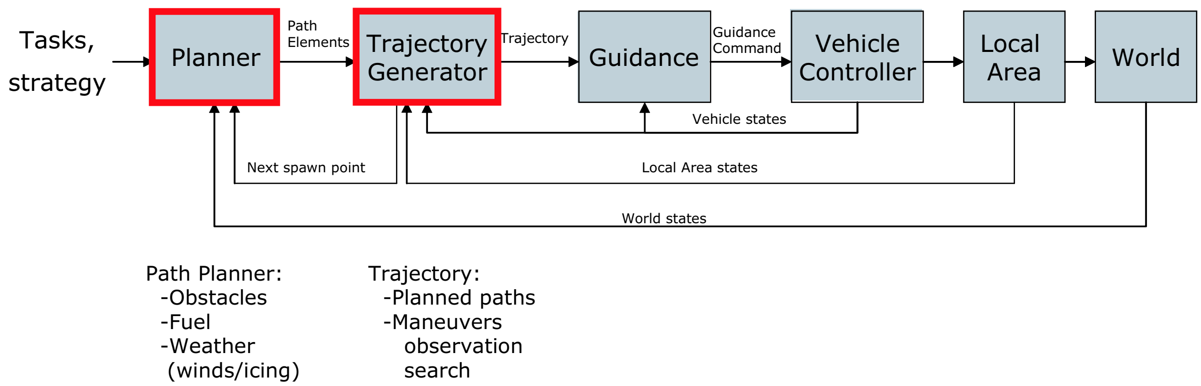

Figure 1. Autonomy System Architecture.

A. Task and Path Planning Algorithms

Many approaches have been used to solve task and path planning problems. Most conventional methods search for solutions assuming fixed world states. The search for the optimal solution is computationally expensive. Without adaptations, these methods are not suitable for a dynamic environment in which limited computational time and power is available. EC is based on a search technique that resembles the evolutionary process. The EC search technique is not as efficient in finding an optimal solution, but its important advantage is that a viable solution is available at any time, and that it approaches an optimum as more processing time is available. When the EC search technique is applied to a 'population' of possible vehicle paths it can be used for path planning. EC has shown promising results for path planning where complex environments play an important role, e.g. Fogel[4] and Capozzi.[5]

The path planning concept used in this paper is presented in Figure 2. The algorithm performs a random search for a feasible solution by mutating, evaluating, and selecting members with higher fitness within a population of possible solutions. This cycle is repeated until a criterion is met. Details of the path planning algorithm for a single vehicle are presented in Rathbun and Capozzi[6] and Rathbun et al.[7] The use of these techniques for long range missions is addressed in Rubio.[8]

The multiple vehicle cooperation problem has also been addressed with EC techniques in Fogel[4] and Xiao.[9] These are centralized approaches that showed good results but have some limitations, such as difficulties in finding optimal solutions for large and complex scenarios, and lack of robustness with respect to communication problems. For such scenarios, distributed approaches have had a continuous research interest with good results. A powerful formulation combines Market-Protocol algorithms with the EC techniques mentioned above. This combination in task planning problems has been proposed by Wellman and Wurman[10] and Dias and Stenz.[11] Algorithms used for multiple vehicle cooperation presented in this paper are described in Pongpunwattana.[12,13]

B. Integration of Strategic Path Planning and Tactical Maneuvers

For most problems involving operation in uncertain environmental changes, dynamic path planning is required. EC adapts to changes without the need to recompute a completely new solution.[6] This characteristic is computationally efficient and also allows for easy integration with maneuvers that are triggered by the

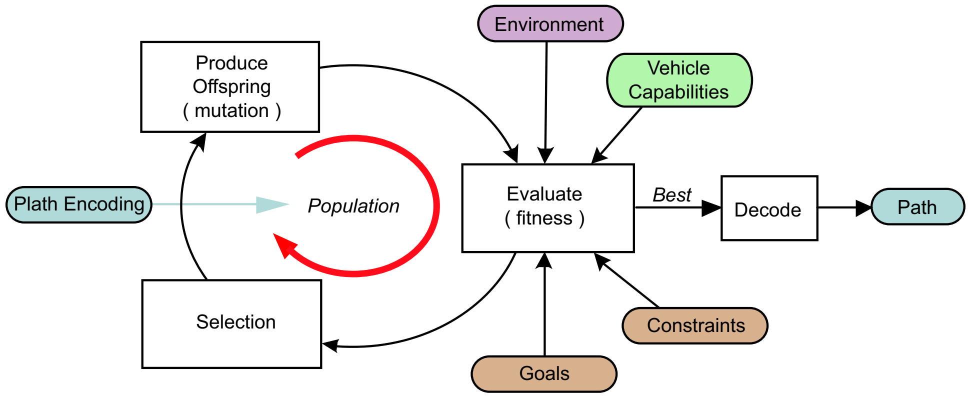

Figure 2. Evolutionary Computation based path planning algorithm.

environment. For those maneuvers, the timing, place, or occurrence is not precisely known. The path planner aims to approach the region wherein a desired interaction with the environment is expected. If this interaction occurs, the planned strategic path switches to a local tactical maneuver. With the use of EC path planning, the execution of a local maneuver is simply interpreted as an environmental change.

To allow for dynamic planning, vehicles commit to flying only a portion of the planned path in any trajectory generation cycle, as shown in Figure 3. Once a tactical maneuver is commanded, the vehicle commits to it, and the planner takes the end point of the maneuver as the next 'spawn point'. Interactions with the environment are continuously monitored, allowing for further tactical maneuvers to command the current path if necessary. The planner adapts by continuously considering the end of the current maneuver as the next spawn point.

For the mission presented here, two tactical maneuvers are used; a search and an observation maneuver as shown in Figure 4. The maneuvers are designed for a UAV with nose-mounted sensors. The nature of the lower level guidance and control laws favors the use of smooth paths consisting of segments with constant curvature.[3] Hence, the maneuver patterns consist of lines and semi-circles. The length and curvature of the segments is adapted to the size of the search area, the size of the target, the range of the sensor equipment, the vehicle performance. Orientation of the maneuver is based on the estimated sun angles, which are determined from the vehicle's position and local time. The stand-off observation maneuver provides a flight pattern that maximizes target exposure for observation, while avoiding sun glare.

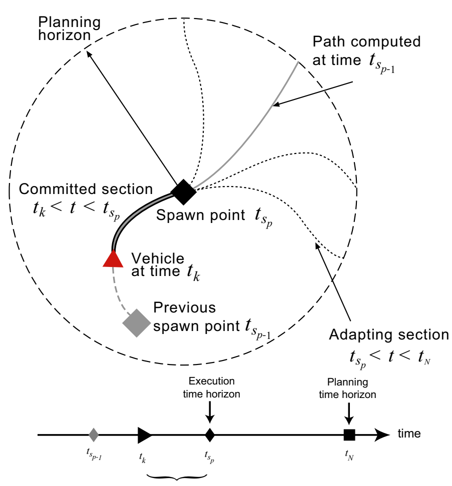

Figure 3. Dynamic Planning Concept; a vehicle (at time t_k) is moving along a path previously computed at time t_{s_p-1}, shown as a gray line. The current spawn point at time t_{s_p} is shown as a black diamond.

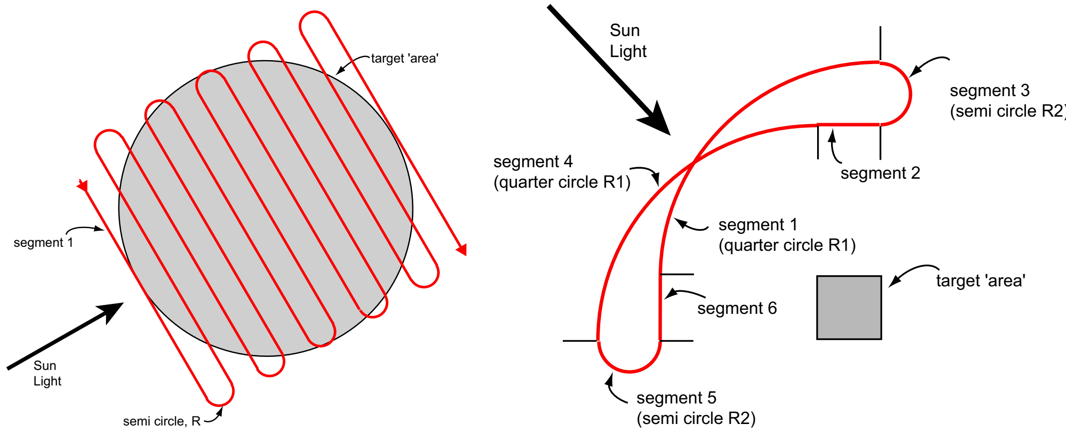

Figure 4. Mission Tactical Maneuvers: Search (left) and Observation (right).

III. Environmental and Vehicle Models

A. 'World State' Information: Wind and Icing Potential

In 1985 the World Meteorological Organization approved the GRIB format (GRIdded Binary) as the standard for weather data management.[14] It is a compact bit-oriented format that allows an efficient transmission of large volumes of gridded data, and that serves as a data storage format with similar benefits. Therefore, numerous weather products are available in GRIB format.

The two main sources used in the simulations are GFS and Reanalysis products. GFS refers to the Global Forecast System, which provides real-time numerical weather forecasts for the entire globe out to 16 days four times per day (00UTC, 06UTC, 12UTC, and 18UTC). Reanalysis products provide new historical analyses. These products contain horizontal gridded data at different pressure altitudes and forecast times.

For our current mission, the extracted parameters ('world states') are: horizontal wind vectors (VGRD and UGRD in m/s), temperature (TMP in K), relative humidity (RH in %), and geopotential height (HGT in gpm). The first two items directly provide wind field information. The latter three parameters are used to compute regions of icing potential with a modified version of the Integrated Icing Potential Algorithm which is the basis of the Forecast Icing Potential product (FIP).[15,16] The use of this adapted IIFA is not expected to provide the exact results that the FIP may generate, but it has the advantage of providing the planner with 1) estimates of icing potential areas for any region on the planet (the current FIP product is limited to the continental U.S.) and 2) extended forecasts, not available from regular FIP reports. Figure 5 compares the icing potential as computed with our implemented algorithm with an actual FIP report.

Wind fields and an estimate of potential icing hazard are provided to the planning system, which takes these into account as major environmental factors particularly affecting small aircraft. Figure 6 presents the steps in the processing of this weather data. Further detail on the use of weather information is provided in Rubio.[8,17]

B. Aircraft Performance Characteristics

Because of the low bandwidth nature of the maneuvers, the aircraft is represented as a kinematic performance model. The guidance and control loops are assumed to provide perfect tracking of the commanded path. To ensure paths are flyable, the strategic planner and tactical maneuver generator are constrained by vehicle characteristics such as descent and climb rates, flight path angles, airspeeds, minimum turn radius, and maximum altitude. As these characteristics depend on vehicle weight and altitude, the vehicle's fuel consumption is continuously estimated and the path constrained appropriately. Information is provided through look-up tables of performance characteristics.

Aircraft ice accumulation and its effect on performance are of much interest to aviation, and are topics of continuous research. As indicated above, vehicle performance characteristics constrain the generated paths, and therefore it is important to consider the effect of icing on the vehicle. To model this effect, we currently

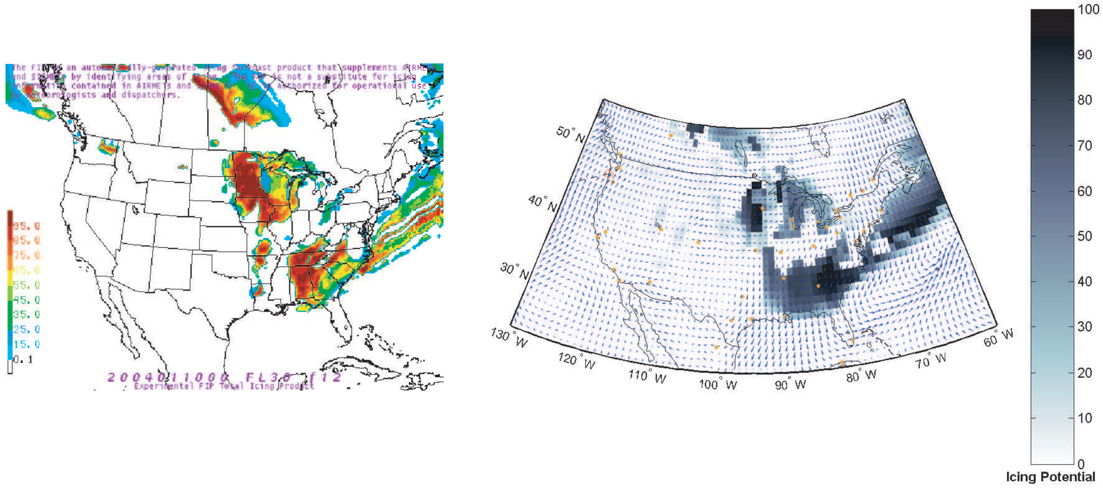

Figure 5. Forecast Icing Potential Comparison. ***Left*****: FIP report on Jan10,2004 at 00UTC for 12UTC forecast.** ***Right*****: Computed Icing Potential for path planner using GFS report of Jan10,2004 at 00UTC for 12UTC forecast. Altitude: FL030 (915m).**

use an assumption that relates the amount of aircraft icing with exposure to icing potential determined by the IIFA. The planner is provided with both *clean* and *iced* aircraft data. The parameters of interest are determined using a linear interpolation of an accumulated icing potential factor, based on the icing regions already traversed and assuming no de–icing occurs.

IV. Simulation Results

In this section, simulation results are presented for three different case scenarios: a) a single vehicle search in similar conditions as those of actual manned searches[1] that took place in the Summer of 2003, b) a single vehicle search in icing conditions, and c) a multiple vehicle search case. The results are presented primarily with a series of map snapshots of the simulated flight. Planned paths are shown in black, and committed trajectories are depicted in red. Search areas are shown as big black circles; the smaller circles in red indicate the location of the ghostnets, which is unknown to the planner. We assume there is only one target (a ghostnet) per search area. The vehicle is shown as a blue triangle, and its sensors range is shown in green. The vehicle performance model used corresponds to a Seascan UAV.[18] In addition, maps contain the following information:

- Fuel committed: amount of fuel for the trajectory committed to fly.
- Level of icing expected: accumulated icing level for the trajectory committed to fly, based on the assumption stated previously.
- Altitude: current altitude of vehicle (weather conditions shown on map correspond to this altitude).
- Elapsed time: estimated hours from launch to current vehicle position.
- Max/Min winds: provide a reference to the maximum and minimum wind vectors on the current map (location of the maximum and minimum vectors are indicated by corresponding green and red dots).
- When icing risk is predicted, a colorbar accompanies the map; the darker the color indicates higher icing potential.

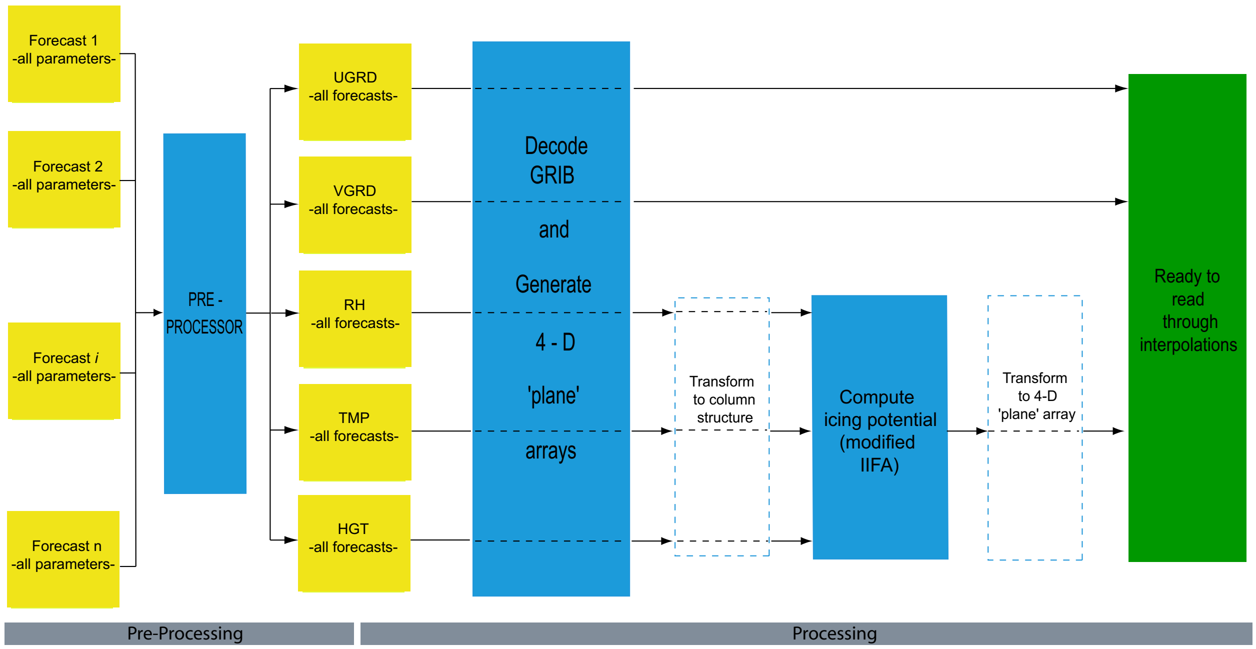

Figure 6. Processing of Weather Information.

A. Single Vehicle Search

Figure 7 presents the sequence for the flight. Launch is set from Kodiak Island, AK, on July 30, 2003 at 15:00UTC (early morning local time). The flight is constrained between 300m and 500m.

The planner itself focuses on finding paths to approach the search areas. This is shown on the first map of Figure 7, which is a straightforward solution. Once the flight has begun and the vehicle effectively approaches the first search area, the system switches to a search maneuver with a direction determined by the estimated sun position. Notice how the system subsequently replans based on the estimated end position of the search pattern. When the target is found, the vehicle initiates a stand-off maneuver (its direction determined by the sun location at that time) to maintain it in-sight as would be required to direct surface debris recovery vehicles. The planner once again adapts the path based on the new maneuver to direct the vehicle to the second search area. The vehicle returns to base once the mission is accomplished.

B. Single Vehicle Search in Icing Conditions

In the interest of showing the response to icing conditions, a similar flight was simulated taking place on January 27, 2004. As seen in Figure 8, a considerable amount of icing potential is estimated in the region.

The system response depends on how the fitness function in the path planner is formulated. For example, if icing is to be completely avoided, the cost of this factor is set high enough that for this particular case the vehicle will in fact decide not to leave the base. On the other hand, the cost of icing may be set sufficiently low, so that the vehicle will attempt the search in both areas regardless of the estimated icing risk, for which a result not very different from the previous case (July 30, 2003) would be obtained. For this case, we set the cost associated with icing such that it increases sharply when the icing level reaches 100%. As seen in Figure 8, this setting results in the system planning to attempt only one search, where the icing risk is lower. As the vehicle approaches the search area, it switches to a search maneuver. In this particular case, as the vehicle prepares to initiate the maneuver, it coincidentally flies over the target, cancelling the search and initiating the observation maneuver. The vehicle returns to base without attempting the search on the second area. In this case, the linear interpolation was set such that aircraft performance was 80% for a 100% icing level.

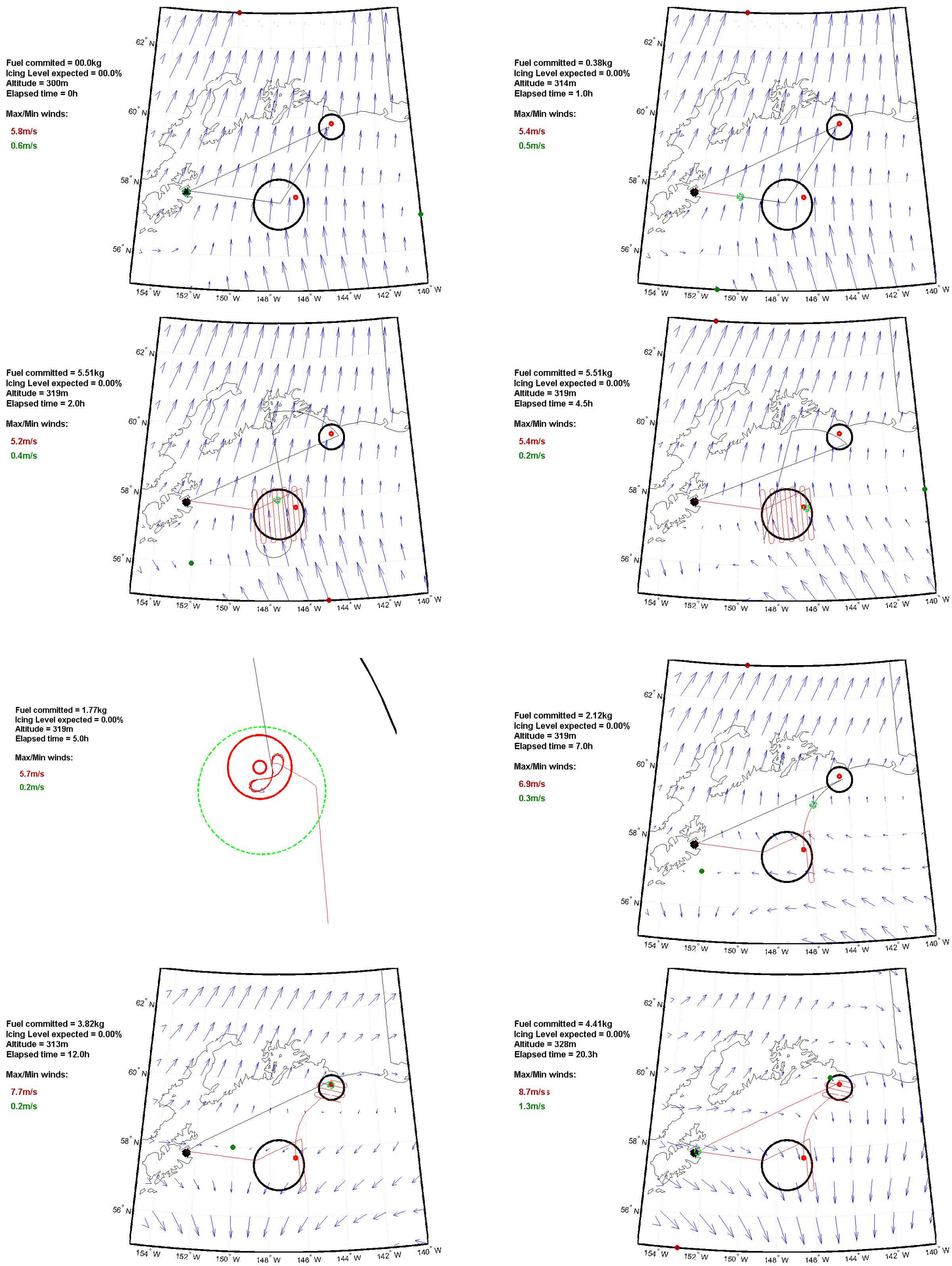

Figure 7. Single Vehicle, Launch July 30, 2003, 15h00UTC.

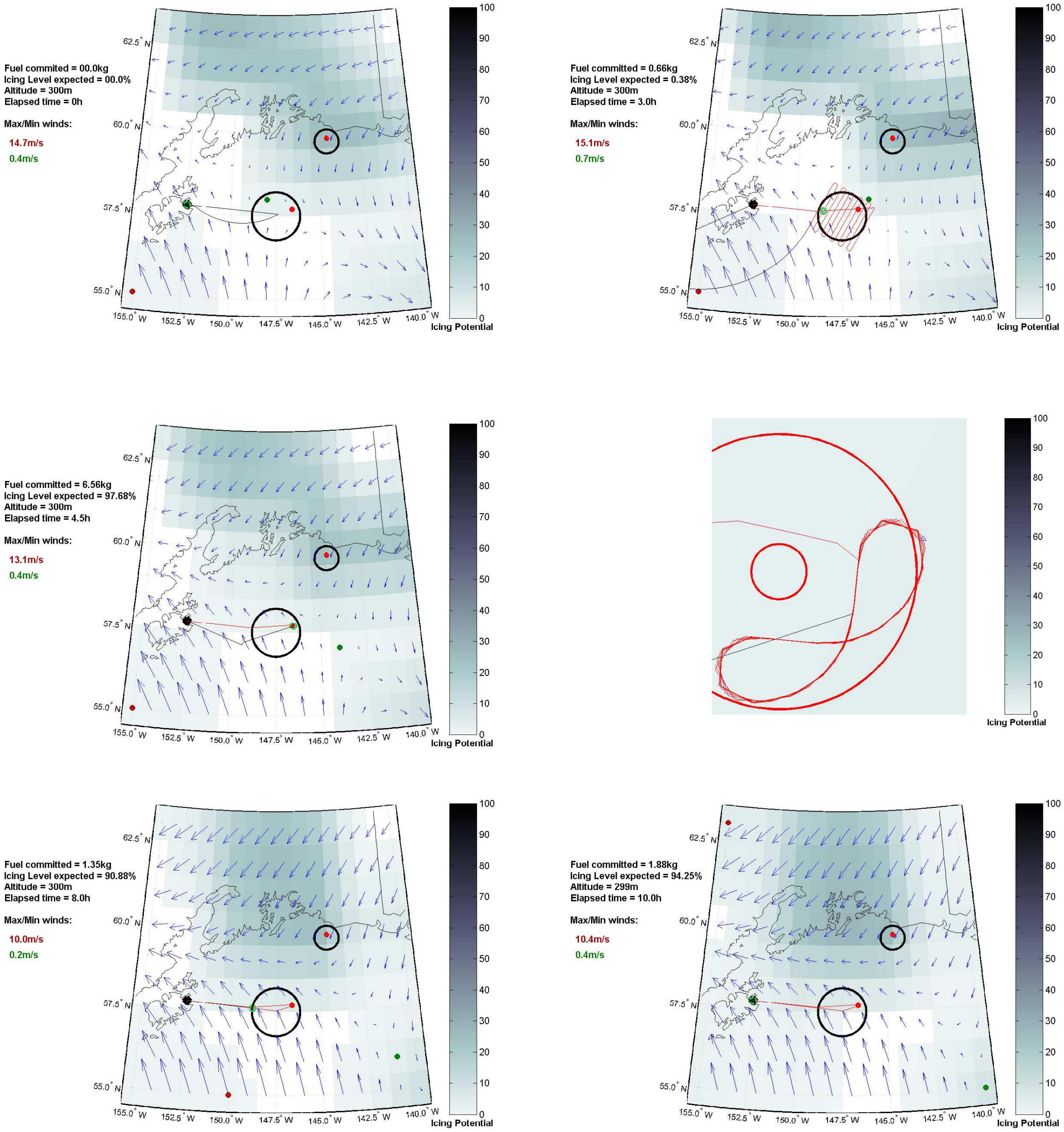

Figure 8. Single Vehicle, Launch January 27, 2004, 15h00UTC.

C. Multiple Vehicle Search

This last case is an example of how this system provides implicit vehicle cooperation (Figure 9). Launch is set on July 30, 2003, at 15:00UTC. Flights are constrained to a 500m altitude. Three vehicles are used to search in four different regions. The first map presents the initial plan, where the two closest search areas are assigned to a single vehicle, and the other two areas are each assigned to separate vehicles. The indicated fuel commitment for each vehicle corresponds to right, middle, and left vehicles respectively, according to the search areas assigned. The middle vehicle finds its target quickly after 6 hours of flight time. This results in some re-planning in which this vehicle is assigned another search area to aid one of the other team members. All vehicles return to base once their final target search is accomplished.

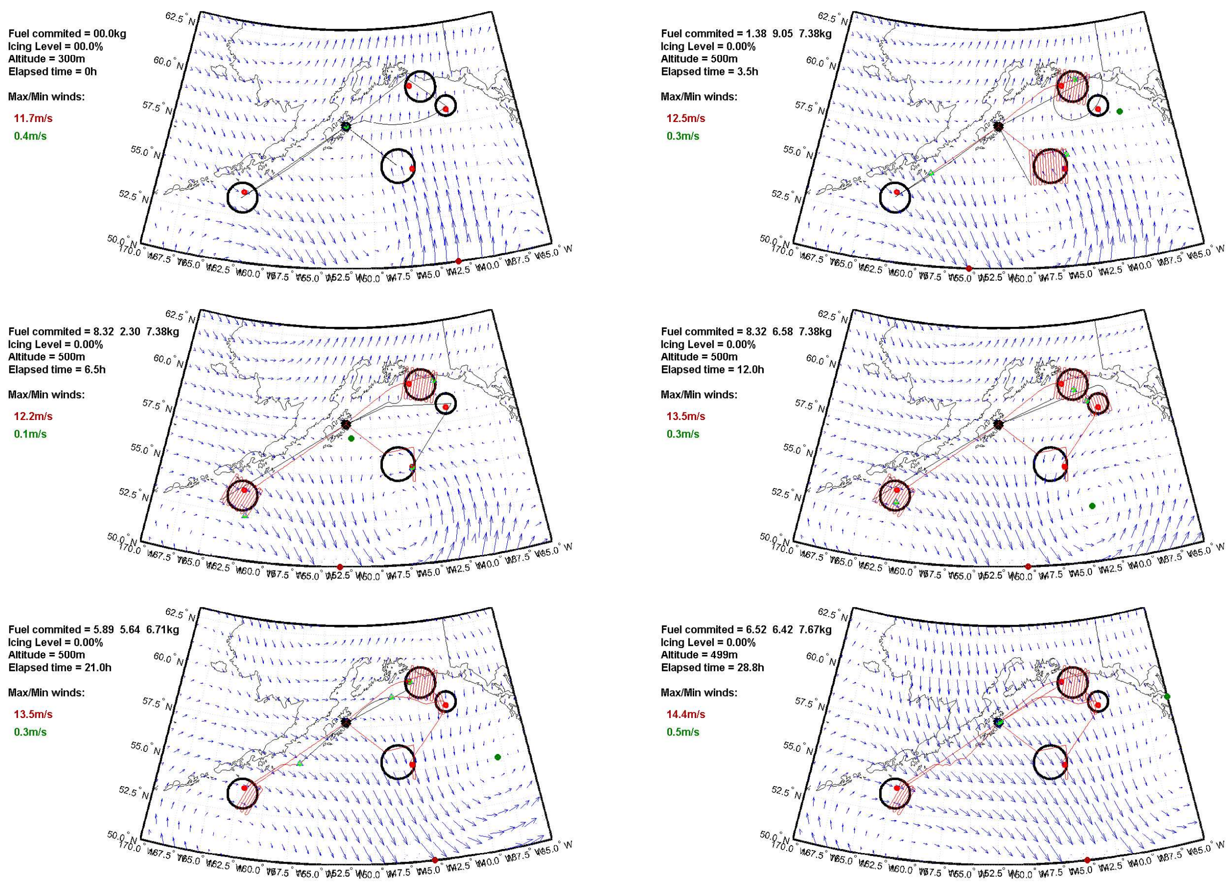

Figure 9. Multiple Vehicles, Launch July 30, 2003, 15h00UTC.

V. Conclusion

Simulations for autonomous flight path planning have been presented. The system combines an evolution based dynamic planner with trajectory generation algorithms, and can consider realistic weather information and vehicle performance data. This system is intended to provide autonomy which, combined with appropriate guidance algorithms and low level controllers, may constitute a feasible means of conducting low-cost oceanic search missions for the recovery of abandoned fishing nets ('ghost-nets'), reducing risks, costs, and limitations associated with manned missions.

Acknowledgments

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References

[1]www.highseasghost.net

[2]Ocean and Coastal Law Memo Issue 34, Ocean and Coastal Law Center, School of Law, University of Oregon, Eugene, OR, July 1990

[3]Rysdyk, R. "UAV Path Following for Constant Line of Sight", *2nd AIAA Unmanned Systems Conference*, San Diego, CA, September 2003

[4]Fogel, D. and L. Fogel, "Optimal Routing of Multiple Autonomous Underwater Vehicles through Evolutionary Programming", in it Symposium on Autonomous Underwater Vehicle Technology, Washington, D.C., 1990

[5]Capozzi, B. *Evolution-based Path Planning and Management for Autonomous Vehicles*, Ph.D. thesis, University of Washington, 2001

[6]Rathbun, D. and B.J. Capozzi, "Evolutionary Approaches to Path Planning through Uncertain Environments", in *1st AIAA Unmanned Aerospace Vehicles, Systems, Technologies, and Operations Conference*, Portsmouth, VA, May 2002

[7]Rathbun, D., S. Kragelund, A. Pongpunwattana, and B. Capozzi, "An Evolution Based Path Planning Algorithm for Autonomous Motion of a UAV through Uncertain Environments", in *21st Digital Avionics Systems Conference*, Irvine, CA, Oct 2002

[8]Rubio, J.C. *Long Range Evolution-based Path Planning for UAVs through Realistic Weather Environments*, M.Sc. thesis, University of Washington, 2004

[9]Xiao, J. et al., "Adaptive Evolutionary Planner/Navigator for Mobile Robots", it IEEE Transactions on Evolutionary Computation, Vol. 1, April 1997, pp. 18-28

[10]Wellman, M.P. and P.R. Wurman, "Market-aware Agents for a Multi-agent World", *Robotics and Autonomous Systems*, Vol. 24, September 1998, pp 115-125

[11]Dias, M.B., and A. Stenz, "A Free Market Architecture for Distributed Control of a Multirobot System", in *Proceedings of the 6th International Conference on Intelligent Autonomous Systems*, July 2000

[12]Pongpunwattana, A., R. Rysdyk, J. Vagners and D. Rathbun, "Market-based Co-evolution Planning for Multiple Autonomous Vehicles", *2nd AIAA Unmanned Systems Conference*, San Diego, CA, September 2003.

[13]Pongpunwattana, A. *Real-Time Planning for Teams of Autonomous Vehicles in Dynamic Uncertain Environments*, Ph.D. thesis, University of Washington, 2004.

[14]World Meteorological Organization, *Guide to the WMO Table Driven Code Form Used for the Representation and Exchange of Regularly Spaced Data in Binary Form: FM 92 GRIB Edition 2*, Geneva, January 2003.

[15]Brown,B.G., T.L. Fowler, J.L. Mahoney, *Verification Results for the Integrated Icing Forecast Algorithm (IIFA)*," tech. rep., Quality Assessment Group, Aviation Forecast and Quality Assessment Product Development Team, July 2001.

[16]McDonough,F., B.C. Bernstein, M.K. Politovich, C.A. Wolff, "The forecast icing potential (FIP) algorithm", in *Proceedings of the AMS 20th International Conference on Interactive Information and Porcessing Systems (IIPS) for Meteorology, Oceanography and Hydrology*, Seattle, WA, January 2004

[17]Rubio, J.C. and S. Kragelund, "The Trans-Pacific Crossing: Long Range Adaptive Path Planning for UAVs through Variable Wind Fields", it 22nd Digital Avionics Systems Conference, Indianapolis, IN, October 2003

[18]www.insitugroup.net