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On-Board Multi-Objective Mission Planning for Unmanned Aerial Vehicles

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Abstract—A system for automated mission planning is presented with a view to operate Unmanned Aerial Vehicles (UAVs) in the National Airspace System (NAS). This paper describes methods for modelling decision variables, for en-route flight planning under Visual Flight Rules (VFR). For demonstration purposes, the task of delivering a medical package to a remote location was chosen. Decision variables include fuel consumption, flight time, wind and weather conditions, terrain elevation, airspace classification and the flight trajectories of other aircraft. The decision variables are transformed, using a Multi-Criteria Decision Making (MCDM) cost function, into a single cost value for a grid-based search algorithm (e.g. A*). It is shown that the proposed system provides a means for fast, autonomous generation of near-optimal flight plans, which in turn are a key enabler in the operation of UAVs in the NAS. [1 2]

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1. INTRODUCTION

Mission planning is an integral component in the integration of Unmanned Aerial Vehicles (UAVs) within the National Airspace System (NAS). In order to gain access to the NAS, it is necessary to demonstrate an Equivalent Level of Safety (ELOS) to that of human piloted aircraft [1]. ELOS comprises three major requirements: (i) see and avoid capability, (ii) compliance with existing aviation rules and regulations, and (iii) transparency of operation [1]. Mission planning, which comprises pre-flight (strategic) planning and in-flight (tactical) replanning, ensures conformance with the rules of the air [2], and thus helps to address ELOS.

UAV mission planning is a complex multi-objective decision problem that must consider not just the *rules of the air*, but also mission *efficiency* objectives and *safety* objectives. Pre-flight planning is necessary in the risk management and subsequent approval of flight operations. In-flight replanning, on the other hand, is required when changes to the operating environment, to the UAV or to mission goals, invalidate the strategic plan. Because the UAV operates in a dynamic, outdoor environment, it is impossible to predict with certainty true operating conditions. Replanning is used to mitigate this uncertainty. For fixed wing UAVs, there is significant time pressure on in-flight planning as the vehicle is in constant motion.

The benefits of automating the mission planning process onboard the UAV are twofold. Firstly, onboard mission planning can help increase the level of autonomy of the UAV. Onboard replanning ensures continued compliance with the rules of the air despite changes to the operating environment, even in the event of a communications failure. This is crucial for operation in the NAS [1]. In order to realise this capability, a level of autonomy is required whereby the UAV executes decisions made autonomously unless the human operator intervenes [3]. Given the size of the search space and the complexity of the decision problem, an automated mission planner can also serve as a decision support tool to aid the human operator. This can be especially beneficial in the scenario where the human operator is controlling multiple UAVs.

This paper presents a framework for UAV mission planning that adapts the human operator's multi-objective decision rules in generating a flight plan. For the purposes of demonstration, this paper adopts an example mission scenario involving delivery of a medical package to a remote location, using a small UAV. Such a mission, due to the non-standard locale and low altitude ceiling of small UAVs [4] is performed under Visual Flight Rules (VFR) [5]. Examples of small UAVs include the RQ-2 Pioneer (100nm range), RQ-7 Shadow (68nm range), and Aerosonde (3000km range), all of which have a ceiling of 15000ft [4]. However, the proposed framework is applicable to en-route flight planning in general.

Mission planning, in the context of UAV en-route flight planning, is a path planning problem. It involves finding a

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sequence of waypoints (or nodes) in 3D along with the estimated time of arrival at each waypoint, that link the start waypoint to a specified goal waypoint. In an intelligent control architecture, these waypoints are passed to the aircraft's autopilot controller through a sequencer [6]. The integration of planning and control is beyond the scope of this paper. In determining intermediary waypoints, it is necessary to evaluate multiple decision criteria. A mission objective is satisfied when that objective's constituent decision criteria are satisfied. For example, satisfaction of fuel and flight time criteria leads to satisfaction of the mission efficiency objective.

Existing work (as described in section 2) fails to address the simultaneous requirements for computational efficiency, and multi-criteria decision making, necessary to on-board mission planning. Section 3 discusses the decision criteria relevant to en-route flight planning. The proposed algorithm, which combines a candidate method for multi-objective aggregation with an efficient path planning algorithm, is presented in section 4. Finally, the simulation outcomes are discussed in section 5.

It is shown through simulation that the proposed multi-objective planning approach is fast enough to meet the requirements of on-board mission planning. This is a key enabler in the operation of UAVs in the NAS.

2. BACKGROUND

Mission planning belongs to the class of planning problems referred to as the weighted region problem [7]. For these problems, the transition costs between nodes are non-binary, i.e. regions of the search space can not be classified as purely untraversable or purely free space [8]. This is because it is necessary to distinguish between path segments which may lie in "free space" (as in free of obstacles), but have different degrees of attractiveness when evaluated against multiple decision criteria. Note that mission planning is a form of path planning [8], as it finds a sequence of waypoints that link the start to the goal (destination) waypoint. This differs from trajectory planning [8], where the solution path is expressed in terms of the degrees of freedom of the vehicle and velocity/angle rates.

Existing methods for UAV flight planning, have focused predominantly on finding paths that satisfy vehicle dynamics while avoiding obstacles (e.g. [8-16]). This is similarly the case for many generic path planning algorithms (refer [8] for a comprehensive survey).

There are many examples of multi-objective path planners in the field of HAZardous MATerials (HAZMAT) transportation [17-19]. This is due to the need to make trade-offs between risk and transportation costs. Existing work in HAZMAT route planning almost exclusively adopts the approach of combining a multi-criteria cost function (typically a weighted sum) with a search algorithm (such as A* [20]). This framework is described in [21]. It is necessary to aggregate decision variables into a single cost value because of "exponential growth in planning time and memory usage with dimensionality" [22]. Existing HAZMAT route planning methods, however, are constrained to 2D environments and do not consider variables such as wind.

Rubio [23] presents a 3D UAV path planner that incorporates wind conditions to find a path that minimises fuel consumption. However, the rules of the air were not incorporated into the planning process. Gu [24] proposes a bi-objective UAV flight planner that optimises for risk and fuel costs; but wind information is not used.

There are also generic multi-objective search algorithms such as MOA* [25] and Fujimura's [26] algorithm. MOA* only works for acyclic graphs (graphs derived from grids are cyclic) and Fujimura's algorithm is not scalable to large search spaces.

It can be seen that existing work does not adequately address the requirements for UAV mission planning. Furthermore, it is necessary to minimise the dimensionality of the problem due to the intractability of path planning [8, 22]. A minimum of three spatial dimensions are required for UAV flight planning. In addition, because of the presence of dynamic obstacles (e.g. weather, other aircraft), variable wind conditions, and a need to optimise for flight time, it is desirable to include a time dimension. This guarantees resolution completeness [8] and path optimality when using an algorithm like A*. For the following section on decision criteria, it is assumed that the search space is four dimensional.

3. DECISION CRITERIA

A number of key decision criteria for UAV en-route planning under VFR [5] are presented. This section discusses, for each criterion, the potential data source, data storage structure, and impact on the medical package delivery mission. For the planning task at hand, it is desirable to find the optimal (or least cost) path, where the cost represents the combined degree of satisfaction of all the decision criteria.

Time

Emergency delivery of a medical package to a remote location requires reaching the goal destination in minimal time. The time of arrival at each waypoint corresponds to a unique node in the 4D search space. This arrival time is conditional on the wind vector, selected cruise velocity, and the predicted flight trajectory between waypoints.

The predicted flight trajectory is contingent on the structure of the search space. Much of the recent work for vehicle planning has focused on techniques in computational geometry using a grid [9, 23, 24, 27-35]. However, for conventional grid based planning (using a 4/8-connected or 6/26-connected neighbourhood for 2D or 3D respectively), the resultant flight trajectory has limited track angle resolution. For example, in 2D planning, the resolution is limited to increments of 45°. This can lead to sub-optimal paths even after application of path smoothing [28].

A number of methods have been proposed which increase the angular resolution of the search space [27, 28, 30, 32, 35]. However, [30] does not find the least cost path and [35] requires *a priori* cell decomposition; this is computationally infeasible given the presence of dynamic obstacles. As well, it is not possible to use the methods described in [27, 28] as the track angle is derived from *a priori* knowledge of path costs. This is not possible since, for en-route planning, the path cost is itself dependent on the track angle (due to wind effects).

Consider the approach presented in [32] whereby predefined trajectory segments are used to connect nodes (which are placed in the centre of cells). Unlike the 26-connected neighbourhood, successive nodes do not necessarily lie in adjacent cells (see Figure 1). This is sometimes referred to as a vector neighbour [8]. It is possible to have arbitrary angular resolution using vector neighbours. However, [32] focuses on trajectory planning for a 2D vehicle. For the purposes of UAV mission planning, it is sufficient to approximate the actual path costs by assuming linear trajectories (as in Figure 1). This is possible when the cell size is large compared to the aircraft's tracking error and turn radius, and the time spent manoeuvring between tracks is small compared to time spent on track. Such an assumption forgoes the need for inclusion of horizontal and vertical track angle dimensions, as turning circles are not considered. In addition, computation of ground speed is simplified when using linear tracks. This assumption is necessary to avoid "the curse of dimensionality" [22].

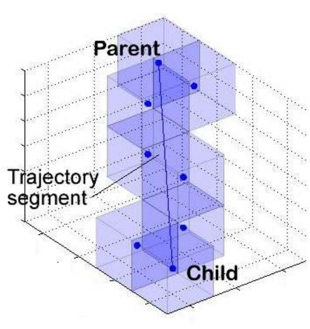

Figure 1 – A vector neighbour

The adopted neighbourhood operator is shown in Figure 2. It provides an average horizontal angle increment of 15° and allows for flight path angles of up to ±6° in approximately 3° increments for cells of size 1nm×1nm×1000ft (equivalent to 1852m×1852m×304.8m).

The estimated time of arrival at a node can be expressed as a simple recurrence relation:

$$t(s') = t(s) + \tau(s, s') \qquad \textbf{(1)}$$

where s, s' are parent and child nodes respectively, t is the time of arrival at a node, and τ is the transition time between nodes.

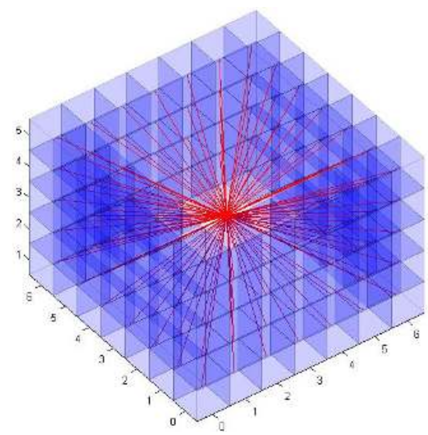

Figure 2 – 3D Neighbourhood operator

Using predefined, linear, flight trajectories, the transition time is thus:

$$\tau(s, s') = \frac{d(s, s')}{\left|\underset{\sim}{v}_c + \underset{\sim}{v}_w\right|} \qquad \textbf{(2)}$$

where d is the horizontal distance between the nodes, v_c is the cruise velocity vector and v_w the wind velocity. Wind and weather forecasts in Australia are obtainable from Airservices Australia [36]. For long range flight, wind forecasts are available in GRIdded Binary (GRIB) format [23] with 1×1.25° resolution. As small UAVs have limited engine power [4], the wind can drastically affect flight time and constrain potential paths. Therefore, v_w can not be ignored.

Fuel

A decision criterion that is in direct contention with minimisation of travel time is minimisation of fuel consumption. Calculation of fuel usage is based on a specified cruise velocity, traversal time between nodes (equation (2)), flight altitude, climb/descent angle, aircraft parameters (e.g. fuel mixture, throttle, propeller pitch), and atmospheric temperature and pressure. Such fuel calculations are platform specific. For the purposes of this simulation, a simple look up table is used based on the Aerosim fuel model [37].

Altitude Above Ground Level (AGL)

Australian civil air regulation CAR157 stipulates that flight must be conducted at altitudes of at least 1000ft Above Ground Level (AGL) over populous areas, and 500ft AGL otherwise [2]. For each cell in the search grid, AGL is calculated by subtracting terrain elevation from the altitude of that cell. Because of the relatively short range of small UAVs [4], the curvature of the earth can be neglected. Thus, it is possible to use the 3D grid discussed previously. The altitude levels (on the *z* axis) on this grid are expressed in feet Above Mean Sea Level (AMSL). Terrain elevation information can be obtained from a Digital Elevation Map (DEM), such as the National Aeronautics and Space Administration (NASA) Shuttle Radar Topography Mission (SRTM) map [38]. Elevation information is available at a resolution 90m for many regions in the world [38].

Airspace Classes

En-route path planning is constrained by the different classes of airspace and the requirements for operation in each class. For the purposes of simulation, it is assumed that the UAV operates under VFR and has access to the NAS. In Australia, there are five major categories of airspace, namely class A, C, D, E and G [5]. Regions of airspace, as shown in Figure 3, are defined using altitudes (e.g. en-route airspace, class A and E) or, in terms of altitude and proximity to an aerodrome (class C, and D). Class G airspace covers all regions not defined otherwise. Only in a small number of cases are there more complicated airspace designations (such as special use airspace or military airspace). Airspace charts can be obtained from Airservices Australia [36].

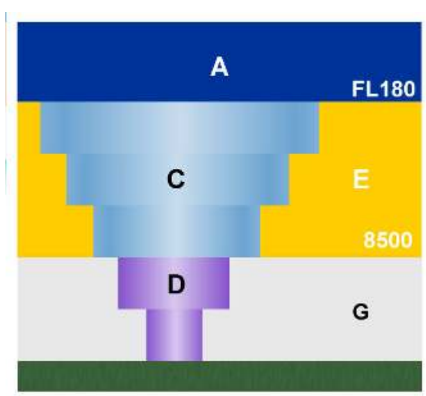

Figure 3 – Example airspace regions

The airspace is suited to a polyhedron based representation, especially cylinders (for class C, D airspace), and rectangular prisms (for class A, E, G). For the mission at hand, the en-route flight path avoids restricted airspace, and classes A, D and C airspace. These obstacle regions *O* are represented as the conjunction of half-spaces *H*:

$$O = H_0 \wedge H_1 \wedge \ldots \wedge H_n \qquad \textbf{(3)}$$

where H_i is defined based on the cells, *x*, *y*, *z* in the grid (which represents the world space) *W*:

$$H_i = \{(x, y, z) \in W, W \mid f_i(x, y, z) \leq 0\} \qquad \textbf{(4)}$$

It is beneficial to model half spaces using both flat (6) and curved (7) surfaces, due to the presence of cylindrical regions.

$$ax + by + cz - d \qquad \textbf{(5)}$$

$$(x - x_c)^2 + (y - y_c)^2 - r^2 \qquad \textbf{(6)}$$

From (6) and (7), it can be seen that only the parameters *a*, *b*, *c*, *d*, *r* are stored – thus, this is significantly more memory efficient than a grid.

Aircraft Separation Risk

Another requirement in the design of a flight path is the avoidance of other aircraft. By incorporating *a priori* knowledge of aircraft movement, it is possible to strategically avoid collision scenarios without activating emergency collision avoidance systems. Potentially, this information can be obtained from flight plans lodged with the regulatory body. Alternatively, it is also possible to obtain position and velocity information of other aircraft from surveillance systems such as Automatic Dependent Surveillance Broadcast (ADS-B) [39].

Aircraft must maintain a minimal vertical separation of 1000ft as part of the Reduced Vertical Separation Minimum (RVSM) requirement [40]. However, lateral separation standards vary depending on aircraft flight vectors, and navigation systems used. For the purposes of simulation, it is assumed that the lateral separation is 5nm. This is the proposed separation for aircraft in conflict that use ADS-B [39]; it is identical to the standard used for operations under Route Surveillance Radar (RSR) [40]. It can be seen that other aircraft can be modeled as cylindrical obstacles (using (4), (5)) with a radius of 5nm, and height of 2000ft. Unlike regions of airspace, where the position and extents are static and known, there is uncertainty in the predicted position of a moving aircraft. This uncertainty grows with time [14].

Uncertainty can be modeled using probabilistic methods (refer [41]), or approximated probabilistic methods (such as [14]). Consider the case where initial position uncertainty is purely a result of Global Positioning System (GPS) uncertainty. GPS error is typically modeled using the Gaussian distribution [42]. Present day GPS systems have a horizontal accuracy of 5-10m (95% confidence) and vertical accuracy approximately 1.4 times the horizontal accuracy [43]. These errors are small when compared to the cell size (1852m×1852m×304.8m). However, the accumulated position uncertainty can be much greater given uncertainty in the predicted velocity vector. Where there is no further information regarding the performance, and operator intentions of other aircraft, this uncertainty is assumed to be Gaussian.

For the purposes of simulation, a simple bivariate Gaussian model was employed, extending the approximation technique described in [14, 44] to a 3D grid. Given independent specifications for GPS horizontal and vertical accuracy, the aircraft position density function p can be expressed as:

$$p\left(r,z,\sigma_r,\sigma_z\right)=\frac{1}{2\pi\sigma_r\sigma_z}e^{-\left(\frac{r^2}{2\sigma_r^2}+\frac{\left(z-z_c(t)\right)^2}{2\sigma_z^2}\right)} \quad \textbf{(7)}$$

where $r=\sqrt{\left(x-x_c\left(t\right)\right)^2+\left(y-y_c\left(t\right)\right)^2}$, and σ_r, σ_z is the standard deviation. The expected position, $\left(x_c\left(t\right),y_c\left(t\right),z_c\left(t\right)\right)$ is assumed to be a piecewise linear function of the form:

$$x_c\left(t\right)=v_x^i t+c^i \quad \textbf{(8)}$$

where v^i is the predicted velocity vector for segment i. The probability density field for the aircraft separation zone (5nm by 2000ft cylinder), given independence between r and z, can derived from (7) using:

$$\beta\left(r,z,\sigma_r,\sigma_z\right)= \frac{\int_{z+H}^{z-H}\int_{r+R}^{r-R}\Pi_R\left(r'\right)\Pi_H\left(z'\right)p\left(r',z',\sigma_r,\sigma_z\right)dr'dz'}{\int_{-\infty}^{\infty}\int_{-\infty}^{\infty}\Pi_R\left(r'\right)\Pi_H\left(z'\right)p\left(r',z',\sigma_r,\sigma_z\right)dr'dz'} \quad \textbf{(9)}$$

where Π is the rectangle (or gate) function, R is the radius (5nm), and H the half-height RVSM (1000ft). From an implementation perspective, (9) can be approximated using numerical means. For a given trajectory segment, the risk of encroachment (or aircraft separation risk) is the sum of the probabilities calculated using (9) for each cell on the trajectory. This is possible given that the cell size is small relative to $2R$ and $2H$.

In actuality, the estimated velocity v is also a random variable; however, recall that (10) has to be evaluated at every iteration in a search. To minimise computational complexity, the methodology presented in [14] is adopted by modelling σ as some function of time. For example, [14] proposes a model for σ based on the acceleration capability of the aircraft.

By applying thresholds to (10), it can be seen that the separation zone is cylindrical (refer Figure 4 in section 5). Consider the scenario where two risk thresholds (p_t, p_b) are selected. Note that the (p_t, p_b) do not correspond to the likelihood of a fatal event (i.e. midair collision); they instead describe the likelihood of encroachment on the minimal separation requirement. The safety threshold, p_t, is the maximum allowable risk for a give flight path (i.e. sequence of cells), whereas the risk floor, p_b is some minimum bound below which the risk is deemed negligible. For example, if the UAV never approaches within 2σ of the mean, then the maximum risk of encroachment p_b is less than 0.028.

Storm Cell Risk

An important safety consideration for UAV operation is the avoidance of storm cells and their associated turbulence. Information about storm cells and their movements are provided by the Bureau of Meteorology [45]. It is possible to model storm cells in the same manner as for aircraft (described previously). The primary difference would be a higher degree of uncertainty, not just in the velocity vector, but the size (radius and height) would also vary with time. For simulation purposes, these were assumed to be piecewise linear in time.

Cruising Levels

In Australia, civil air regulation CAR173 [2] assigns cruising altitudes to aircraft operating under VFR based on their heading angle. This minimises the risk of head-on collisions. Permissible cruising altitudes for aircraft on headings from 0° to 179° are at odd multiples of 1000ft plus 500ft AMSL (e.g. 1500ft, 3500ft, 5500ft AMSL). For headings between 180° and 359°, aircraft should cruise at even multiples of 1000ft AMSL plus 500ft (e.g. 2500, 4500, 6500ft AMSL). CAR173 is not mandatory below 5000ft, but, for safety purposes, it is preferable to conduct flight in accordance with CAR173 where terrain, weather, and traffic conditions permit.

Population Risk

The two primary safety concerns for operation of UAVs in the NAS are that of midair collision and flight termination in a populated area [46]. For the simulation studies, the risk presented to people on the ground as a result of flight termination is incorporated into the decision process. This risk value, which can be calculated using [46], is expressed as the number of ground casualties per flight hour.

4. MULTI-OBJECTIVE PATH PLANNING

The preceding section highlighted the numerous decision criteria and constraints involved in UAV mission planning. These extend beyond simply finding a shortest path that avoids obstacles. It can be seen that the decision space comprises 9 dimensions: x, y, z, t, *fuel*, *aircraft separation risk, storm cell risk, heading angle*, and *population risk.* Clearly, this highlights the intractability of path planning [8]. However, it can be noted that, based on the models presented in section 3, it is possible to derive all decision variables uniquely, given a waypoint x, y, z, t. An aggregated cost value can then be calculated based on the previously described decision variables using a Multi-Criteria Decision Making (MCDM) cost function.

Planner Architecture

The proposed planner adopts the approach of combining a heuristic search algorithm with a MCDM cost function [17-19, 21]. Heuristic search algorithms are based on the dynamic programming equation [8]:

$$g(s') = g(s) + c(s, s') \tag{10}$$

where s, s' are parent and child nodes, $g(s)$ is the total cost of the least cost path P from the start node to s, and c is the cost incurred by the trajectory segment between s and s'. Each node, s, is located in the centre of a grid cell in a four dimensional search space. Using the adopted planner architecture, c is a MCDM cost function. When using A*, c must be non-negative, and non-zero [20].

A* [20] has been selected as a suitable heuristic search algorithm as it finds the least cost path efficiently [8]. Despite the need for in-flight re-planning, a heuristic re-planning algorithm (e.g. D* Lite [29]) was not selected because of the presence of dynamic elements. For example, changing wind conditions and storm cell or aircraft movements can invalidate prior search results for a large number of nodes in the search space. In these scenarios, re-planning algorithms are *less* efficient than planning from scratch using A* [47].

Decision Function

Mission planning is a task that is performed proficiently at present by human experts [48]. Therefore, by capturing the decision strategies and preferences of a human expert, it is possible to find paths that best satisfy mission objectives. The decision variables, also referred to as attributes, are incommensurate; for example, a fuel consumption of 0.2kg is not comparable with a storm cell risk of 0.03. One approach for calculating a cost from such incommensurate variable values is to use Multi-Attribute Utility Theory (MAUT) [49].

MAUT provides a methodology for modelling decision maker preferences where preferences are represented as binary relations between objects (i.e. prefer A to B). The methodology comprises a two step process: (i) mapping of all decision variables onto a common scale using a set of value (or utility) functions, and (ii) computation of a single cost or utility value on the common scale. Typically, the output utility value is defined on (0,1). Methods for implementing step (ii) include the Choquet integral and weighted sum aggregation. The Choquet integral is a powerful, generic aggregation function that degenerates into the weighted sum when all decision variables are independent. However, weighted sum aggregation was chosen over the Choquet integral due to the computational complexity of evaluating a Choquet integral at every iteration, for every candidate child node. [49]

5. Simulation and Discussion

Preliminary analysis of the proposed planning framework for UAV mission planning was conducted in simulation. The planning algorithm was evaluated on a number of randomly generated UAV medical delivery scenarios to ascertain performance (Figure 4). This was measured in terms of computation time and path cost (when comparing a near-optimal to the optimal path). Each scenario has a search space size of 100nm×100nm×20000ft×250min. All simulations were run in Matlab on a 3.3GHz Intel Core 2

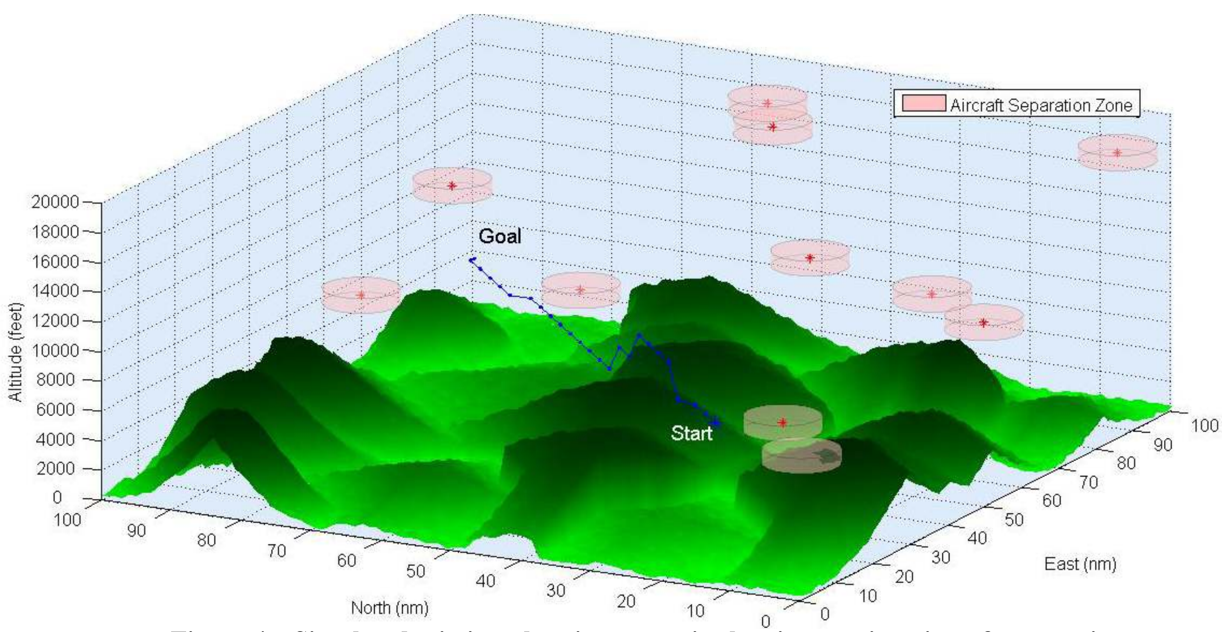

Figure 4 – Simulated mission planning scenario showing moving aircraft separation zones

Duo CPU with 4GB of RAM running 32-bit Windows XP.

An example of the decision criteria for a simulated scenario is depicted in Figure 4, Figure 5 and Figure 6. Note the complexity of the planning problem, which is compounded by an operating environment that contains dynamic elements, such as weather and other aircraft. Despite the presence of multiple path constraints and decision criteria, the planner finds always finds a path that meets these constraints (when one exists). The planned path tends to follow that of a straight line connecting the start and the goal waypoints. This is to be expected as A* finds the least cost path, and all trajectory transition costs between nodes are non-zero and non-negative.

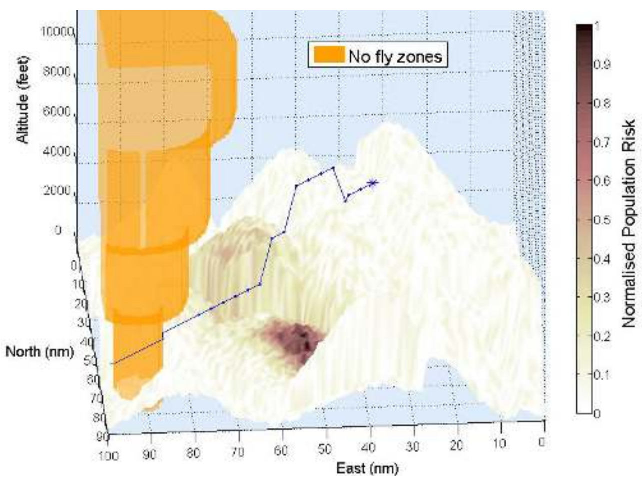

Figure 5 – Illustration of restricted airspace

The use of a multi-objective decision function enables the planner to find a path that addresses multiple, disparate, decision objectives. Consider for instance Figure 5 where the planner selects a path that does not overfly highly populated regions (darker region) whilst avoiding restricted airspace. Simultaneously, the path also meets the altitude requirements as per the cruising levels rule where the flight is operated at altitudes of 3500, 5500 and 7500ft given a north-easterly heading (Figure 4). Additionally, the flight path also takes into account wind and storm cells (Figure 6) in the minimisation of flight time and fuel consumption.

Finding a path that satisfies multiple objectives is just one aspect of on-board UAV mission planning. The planner itself must be fast enough to meet the time constraints imposed on in-flight replanning. To analyse the computational efficiency of the algorithm, a number of complex mission scenarios were simulated; the simulation cases are complex in terms of the number of and movement of dynamic obstacles, terrain shape, and varying wind conditions.

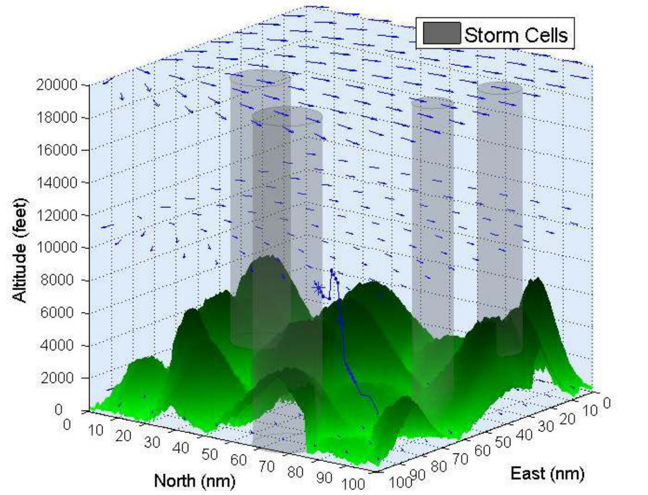

Figure 6 – Illustration of wind and storm cells (gray cylinders) over green terrain

An optimal solution, calculated using A* is compared with a near-optimal solution using an inflated heuristic [50]. A statistical box plot of computation time is shown in Figure 7.

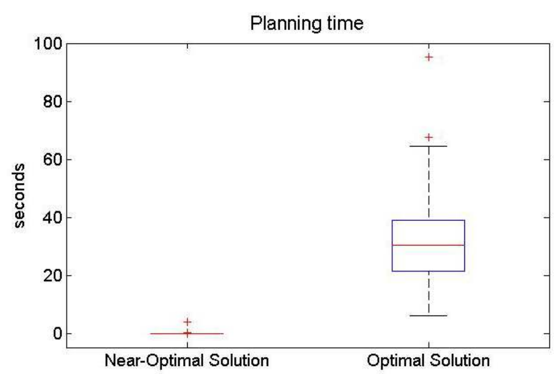

Figure 7 – Algorithm computation time

It is clear that inflating the heuristic drastically reduces computation time. Over 184 different simulations, a near-optimal solution is obtained with a mean computation time of 0.104s and an inter-quartile range of 3.3ms. This compares with a mean time of 32.1s and inter-quartile range of 17.8s for the optimal solution. The near-optimal solution is, on average, 30% more costly (in terms of the unit-less, aggregated cost) than the optimal. An increase in path cost is traded for a significant saving in computation time. The near optimal solution is obtained, by inflating (multiplying) the heuristic term in the optimal algorithm (e.g. A*), by a constant factor ε. It has been shown that total cost of the near-optimal solution is at most ε times the optimal [47].

The proposed algorithm not only meets the requirements of multi-objective en-route planning, but also meets the time-constraints of in-flight re-planning. Selection of an optimal or near-optimal solution is dependent on the time available for planning, which in turn depends on the current position, flight trajectory, and environmental conditions. Given the neighbourhood operator defined in section 3, all path waypoints have a minimum displacement of 3nm, which, at 50m/s, is traversed in 111.1s. Hence, it may be possible to find an optimal solution. There are no such time constraints on pre-flight planning.

6. Conclusion

This paper presented a system for automated, on-board mission planning for the purpose of operating UAVs in the NAS. In order to meet the rules of the air, safety objectives and mission efficiency objectives, it is shown that multi-objective planning is required. For the purposes of UAV en-route planning under VFR, the relevant planning criteria were found to be time, fuel, AGL altitude, airspace type, aircraft separation, the cruising levels rule, storm cells and population risk. To improve the modelling of time and fuel, a 3D vector neighbourhood operator was proposed to enable arbitrary angular resolution. Additionally, it was shown that airspace is suited to geometric modelling using cylinders and polyhedrons. This concept is extensible to the modelling of other aircraft and storm cells.

Through simulation studies, it was found that the proposed planner, which combines a weighted sum MCDM cost function with A*, is efficient, and finds a path that satisfies multiple decision objectives. This algorithm finds a near-optimal solution (with a cost that is on average 30% greater than the optimal) in a mean time of 0.104s, and an optimal one in 32.1s. Hence, the algorithm is suited to meeting the mission planning requirements for operation of UAVs in the NAS.

Ongoing work includes improving existing probability density field approximations (equation (9)), and application of the algorithm to different planning scenarios. Of particular interest are missions conducted in windy conditions over mountainous terrain (updrafts and downdrafts). This is of interest due to the significant impact of wind on the safety and fuel efficiency of a small UAV.

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