Resource manager for an autonomous coordinated team of UAVs

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ABSTRACT

A recently developed fuzzy logic resource allocation algorithm that enables a collection of unmanned air vehicles (UAVs) to automatically cooperate as they make meteorological measurements will be discussed. The goal of the UAVs' coordinated effort is to measure the atmospheric index of refraction. Once in flight no human intervention is required. A fuzzy logic based planning algorithm determines the optimal trajectory and points each UAV will sample, while taking into account the UAVs' risk, reliability, and mission priority for sampling in certain regions. It also considers fuel limitations, mission cost, and related uncertainties. The real-time fuzzy control algorithm running on each UAV renders the UAVs autonomous allowing them to change course immediately without consulting with any commander, requests other UAVs to help, changes the points that will be sampled when observing interesting phenomena, or to terminate the mission and return to base. The control algorithm allows three types of cooperation between UAVs. The underlying optimization procedures including the fuzzy logic based cost function, the fuzzy logic decision rule for UAV path assignment, the fuzzy algorithm that determines when a UAV should alter its mission to help another UAV and the underlying approach to quantifying risks are discussed. Significant simulation results will show the planning algorithm's effectiveness in initially selecting UAVs and determining UAV routes. Likewise, simulation shows the ability of the control algorithm to allow UAVs to effectively cooperate to increase the UAV team's likelihood of success.

Keywords: resource management, fuzzy logic, planning algorithms, decision support algorithms, cooperative behavior

1. INTRODUCTION

Knowledge of meteorological properties is fundamental to many decision processes. Due to personnel limitations and risks, it is useful if related measurement processes can be conducted in a fully automated fashion. Recently developed fuzzy logic based algorithms that allow a collection of unmanned air vehicles (UAVs) and an interferometer platform (IP)[1] to automatically collaborate will be discussed. The UAVs measure the index of refraction in real-time to help determine the position of an electromagnetic source (EMS). The IP is actually an airplane with an interferometer onboard that measures emissions from the electromagnetic source whose position is to be estimated. Each UAV has onboard its own fuzzy logic based real-time control algorithm. The control algorithm renders each UAV fully autonomous; no human intervention is necessary. The control algorithm aboard each UAV will allow it to determine its own course, change course to avoid danger, sample phenomena of interest that were not pre-planned, and cooperate with other UAVs.

Section 2 provides an overview of the meteorological sampling problem, and a high level description of the planning and control algorithms that render the UAV team fully autonomous. Section 3 discusses the electromagnetic measurement space, UAV risk, and the planning algorithm. Section 3 also describes the UAV path construction algorithm that determines the minimum number of UAVs required to complete the task, a fuzzy logic based approach for assigning paths to UAVs and which UAVs should be assigned to the overall mission. Section 4 describes the control algorithm that renders the UAVs autonomous. Section 4 also describes the priority for helping (PH) algorithm, a part of the control algorithm based on fuzzy logic that determines which UAV should help another UAV requesting help. The three subclasses of help requests are also discussed in this section. Section 5 presents experimental results including UAV path determination, UAV path assignment, determination of which UAVs should fly the mission and the result of a request for help during the mission. Finally, section 6 provides a summary.

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2. METEOROLOGICAL SAMPLING AND COOPERATIVE AUTONOMOUS PLATFORMS

For many applications it is useful to be able to make meteorological measurements in real-time. Examples include determining the index of refraction of the atmosphere to facilitate geo-location[1]; determination of the presence and extent of such phenomena as radio holes and ducts, which may interfere with communications; tracking atmospheric contaminants[2]; and sand suspended in the atmosphere that can interfere with sensors.

The fuzzy logic based planning and control algorithms that have been developed allow a collection of UAVs making up the UAV team to engage in cooperative sampling of the atmosphere in real-time without human intervention. Each UAV will have its own control algorithm allowing it to determine new optimal trajectories in real-time subject to changing conditions. Also, the control algorithm on the UAVs will allow them to cooperate to increase the probability of mission success. There will be two different types of cooperation allowed by the control algorithm and three classes of help requests which are discussed in section 4.

The first type of cooperation that the UAVs may exhibit is to support each other if there is evidence that an interesting physical phenomenon has been discovered. If one UAV seems to have discovered a radio hole, it can request that another UAV or UAVs help determine the extent of the radio hole so the IP can fly around it. Similar cooperation can be carried out if a UAV may have discovered other elevated extended weather systems.

The second type of cooperation that the UAVs can exhibit through their control algorithm is when a UAV is malfunctioning or may be malfunctioning. If a UAV's internal diagnostics indicate a possible malfunction, then it will send out an omni-directional request to the other UAVs for help. Each UAV will calculate its priority for providing help using a fuzzy logic procedure described below. The UAVs send their priority for providing help message back to the requesting UAV. The requester subsequently sends out a message informing the group of the ID of the highest priority UAV. The high priority UAV then proceeds to aid the requester.

The support provided by the helping UAV can take on different forms. If the requester suspects a malfunction in its sensors, the helper may measure some of the same points originally measured by the UAV in doubt. This will help establish the condition of the requester's sensors. If additional sampling indicates the requester is malfunctioning, and represents a liability to the group it will return to base. In this case the supporter may take over the mission of the requester, whether or not the supporter samples all the remaining sample points of the requester; subsequently, abandoning its original points depends on the sample points' priorities. A fuzzy logic based procedure for determining sample point priorities is discussed below. If it is established that the requester is not malfunctioning or the requester can still contribute to the mission's success it may remain in the field to complete its current mission.

3. MEASUREMENT SPACE, THE PLANNING ALGORITHM, AND RISK

The measurement space consists of the electromagnetic propagation environment where UAVs and the IP make their measurements. This environment includes sample points and the desirable neighborhoods that surround them. The sample points or the desirable neighborhoods are where the UAVs will make measurements. The method of determining the sample points and desirable neighborhoods is described below.

The measurement space also includes taboo points and the undesirable neighborhoods that surround them. The taboo points are points of turbulence and other phenomena that could threaten the UAVs. The undesirable neighborhoods surrounding them also represent various degrees of risk. The method of specifying taboo points and quantifying the degree of risk associated with their undesirable neighborhoods employs fuzzy logic and is discussed in subsection 3.2.

3.1 Planning algorithm

The planning algorithm allows the determination of the minimum number of UAVs needed for the mission subject to fuel constraints, risk, UAV cost, UAV speed, and importance of various points for sampling. Risk refers to turbulent regions or regions undesirable for other reasons, e.g., the presence of enemy observers or physical obstructions. Risk may also be incurred if the UAV's propulsion or sensor systems are considered unreliable. The planning algorithm automatically establishes the order in which to send the UAVs taking into account the UAV's value; speed; onboard sensor payload; onboard resources such as fuel, computer CPU and memory; etc. The priority of sample points and their desirable neighborhoods are taken into account. The planning algorithm also calculates the optimal path around undesirable regions routing the UAVs to or at least near the points to be sampled.

In the planning phase, the location of the EMS is unknown. Some positions are more likely than others for the EMS's location. When establishing likely positions for the EMS, human experts are consulted. The experts provide subjective probabilities of the EMS being located at a number of positions. These likely EMS locations are referred as *hypothesis positions*. Ray-theoretic electromagnetic propagation[3] is conducted from each hypothesis position to each interferometer element on the IP. The points on the sampling grid nearest the points of each ray's passage are the sample points. The priority of a sample point is related to the subjective probability of the hypothesis position from which the associated ray emerges. Sample points arising from the highest probability hypothesis positions have priority one; sample points associated with lower probability hypothesis positions, priority two; etc.

Each sample point is surrounded by what are referred to as *desirable neighborhoods*. Depending on local weather, topography, etc., the desirable neighborhoods are generally concentric closed balls with a degree of desirability assigned to each ball. The degree of desirability characterizes the anticipated variation in the index of refraction. If for that region of the measurement space, the spatial variation of the index of refraction is slow, the degree of desirability may assume its maximum value of unity for a ball of radius measured in miles. For regions of space where the index of refraction's spatial variation is greater, the degree of desirability may fall off much more rapidly, approaching the minimum value of zero after just a mile or two.

The desirable region need not have spherical geometry. Rotational symmetry may be broken by a variety of processes, e.g., an elevated duct, a radio hole, etc.

3.2 UAV risk and the fuzzy risk tree

A point may be labeled taboo for a variety of reasons. A taboo point and the undesirable neighborhoods containing the point generally represent a threat to the UAV. The threat may take the form of high winds, turbulence, icing conditions, mountains, etc. The undesirable neighborhoods around the taboo point relate to how spatially extensive the threat is.
A method of quantifying risk and incorporating it into the path assignment algorithm is presented that offers conceptual improvements over an approach previously developed[1]. This section uses fuzzy logic to quantify how much risk a given neighborhood poses for a UAV. This quantitative risk is then incorporated into the UAV's cost for traveling through the neighborhood as described in subsection 3.3. Once the cost is established an optimization algorithm is used to determine the best path for the UAV to reach its goal.

When determining the optimal path for the UAVs to follow both the planning algorithm and the control algorithm running on each UAV take into account taboo points and the undesirable neighborhood around each taboo point. The path planning algorithm and control algorithm will not allow a UAV to pass through a taboo point. The concept of risk is based on human expertise and employs rules each of which carry a degree of uncertainty. This uncertainty is born of linguistic imprecision[4], the inability of human experts to specify a crisp assignment for risk. Owing to this uncertainty it is very effective to specify risk in terms of fuzzy logic.

Risk is represented as a fuzzy decision tree[5-10]. The risk subtree defined below is a subtree of the larger risk tree that was actually used. The risk tree is used to define taboo points and the undesirable neighborhoods surrounding the taboo points.

The root concepts on the risk tree use the membership function defined in (1-3),

$$\mu_{root\_concept}\left(\vec{q}_{taboo},\vec{x}\right)=\begin{cases} 1, & if \quad r=0 \\ 3/4, & if \quad 0<r\le 1\cdot\Delta l \\ 1/2, & if \quad 1\cdot\Delta l<r\le\sqrt{2}\cdot\Delta l \\ 1/4, & if \quad \sqrt{2}\cdot\Delta l<r\le\sqrt{3}\cdot\Delta l \\ 0, & if \quad r>\sqrt{3}\cdot\Delta l \end{cases} \tag{1}$$

$$r=\left\|\vec{x}-\vec{q}_{taboo}\right\|, \tag{2}$$

$$\vec{q}_{taboo} = \text{position of taboo point.} \tag{3}$$

where "taboo point" is the point at which the risk phenomenon has been observed. The root concepts used on the risk subtree are given in (4).

$$Root\_concept \in \boldsymbol{RC}=\{Mountains,\ High\ Tension\ Wires,\ Buildings,\ Trees,\ Smoke\ Plumes,\ Suspended\ Sand,\ Birds/Insects,\ Other\ UAVs,\ Air\ Polution,\ Civilian,\ Own\ Military,\ Allied\ Military,\ Neutral\ Military,\ Cold,\ Heat,\ Icing,\ Rain,\ Fog,\ Sleet,\ Snow,\ Hail,\ Air\ Pocket,\ Wind,\ Wind\ Shear,\ Hostile\ Action/Observation\} \tag{4}$$

The values taken by the quantity Δl will be discussed in a future publication.

The fuzzy membership function for the composite concept "risk" is defined as

$$\mu_{risk}\left(\vec{q}_{taboo},\vec{x}\right)=\max_{\alpha\in RC}\mu_{\alpha}\left(\vec{q}_{taboo},\vec{x}\right), \tag{5}$$

with the "Undesirable Neighborhood" defined as follows:

$$\text{Undesirable Neighborhood} =\left\{\vec{x}\,\middle|\,\sum_{i=1}^{n_{taboo}}\mu_{risk}\left(\vec{t}_i,\vec{x}\right)\ge\tau_i\right\}. \tag{6}$$

The parameter, τ_i, of the i^{th} UAV, UAV(i) is defined such that it is preferred that UAV(i) not fly through the undesirable neighborhood given in (6). Instead it is preferred that UAV(i) should only fly through points within an "Acceptable Neighborhood" as defined in (7), the complement of the set defined in (6).

$$\text{Acceptable Neighborhood} =\left\{\vec{x}\,\middle|\,0<\sum_{i=1}^{n_{taboo}}\mu_{risk}\left(\vec{t}_i,\vec{x}\right)<\tau_i\right\}. \tag{7}$$

3.3 Cost matrix

The best path algorithm is actually an optimization algorithm that attempts to minimize a cost function to determine the optimal trajectory for each UAV to follow, given a priori knowledge. The cost function for the optimization algorithm takes into account various factors associated with the UAV's properties, mission and measurement space. Two significant quantities that contribute to the cost are the effective distance between the initial and final proposed positions of the UAV and the risk associated with travel.

For purposes of determining the optimal path, the UAV is assumed to follow a rectilinear path consisting of connected lines segments, where the beginning and ending points of each line segment reside on the UAV's sampling lattice. Let

A and B be two grid points on the UAV's sampling grid with corresponding position vectors, $\vec{r}_A$ and $\vec{r}_B$, respectively. Denote the Euclidean distance between A and B as $d(\vec{r}_A,\vec{r}_B)$. Let $v(\vec{r}_A,\vec{r}_B)$ be the speed at which the UAV travels in going from $\vec{r}_A$ to $\vec{r}_B$. If both $\vec{r}_A$ and $\vec{r}_B$ are sample points then the UAV travels at sampling velocity, otherwise it travels at non-sampling velocity. The path cost is given by

$$path\_cost(\vec{r}_A,\vec{r}_B) = \frac{d(\vec{r}_A,\vec{r}_B) + \beta \cdot \sum_{i=1}^{n_{taboo}} \mu_{risk}(\vec{t}_i,\vec{r}_B)}{v(\vec{r}_A,\vec{r}_B)} . \tag{8}$$

where n_{taboo} is the number of taboo points, i.e., columns in the taboo point matrix

$$Taboo \equiv \left[\vec{t}_1,\vec{t}_2,\ldots,\vec{t}_{n_{taboo}}\right] \tag{9}$$

and $\vec{t}_i, i = 1,2,\ldots,n_{taboo}$ are the taboo points determined to exists in the measurement space when $path\_cost(\vec{r}_A,\vec{r}_B)$ is calculated. The quantity, β, is an expert assigned parameter. Note that $path\_cost(\vec{r}_A,\vec{r}_B)$ is an effective time. When risk is not present, i.e., $\beta \cdot \sum_{i=1}^{n_{taboo}} \mu_{risk}(\vec{t}_i,\vec{r}_B)$ is zero, then $path\_cost(\vec{r}_A,\vec{r}_B)$ is the actual travel time. When risk is present then the travel time is increased. The time increase will be significant if the risk is high.

If the candidate path for the mission consists of the following points on the UAV lattice given by the path matrix in (10),

$$Path_i = [\vec{r}_1, \quad \vec{r}_2, \quad \ldots, \quad \vec{r}_n], \tag{10}$$

then the total path cost is defined to be

$$total\_cost(Path_i) \equiv \sum_{j=1}^{n-1} path\_cost(\vec{r}_j,\vec{r}_{j+1}) . \tag{11}$$

Determining the optimal path for the the i^{th} UAV consists of minimizing the total path cost given by (11) such that there is enough fuel left to complete the path.

The planning algorithm determines the path each UAV will pursue, which points will be sampled, the minimum number of UAVs required for sampling the points and makes assignments of UAVs for measurements at particular points. UAVs are assigned as a function of their abilities to sample high priority points first. The planning algorithm determines flight paths by assigning as many high priority points to a path as possible taking into account relative distances including sampling and non-sampling velocity, risk from taboo points, and UAV fuel limitations. Once flight paths are determined, the planning algorithm assigns the best UAV to each path using the fuzzy logic decision rule for path assignment described in section 3.4.

3.4 Decision rule for UAV path assignment

The planning algorithm must assign UAVs to the flight paths determined by the optimization procedure described in section 3.3. The planning algorithm makes this assignment using the following fuzzy logic based procedure. To describe the decision rule it is necessary to develop some preliminary concepts and notation.

Each UAV will fly from lattice point to lattice point, i.e., grid point to grid point, let one such route be given by the matrix of points,

$$Path = \left[\vec{P}_1,\vec{P}_2,\ldots,\vec{P}_{n_{path}},\vec{P}_1\right] \tag{12}$$

where the ordering of points gives the direction of the route, i.e., starting at $\vec{P}_1$ and ending at $\vec{P}_1$. Let the taboo points be those given in (9). Let the degree of undesirability of the neighborhood associated with taboo points, $\vec{t}_i, i = 1,2,\ldots,n_{taboo}$ be denoted $\mu_{risk}\left(\vec{t}_i, \vec{P}_j\right)$ for the route points $\vec{P}_j, j = 1,2,\ldots,n_{path}$. The definition of the mission risk is

$$mission\_risk(Path) \equiv \sum_{i=1}^{n_{taboo}} \sum_{j=1}^{n_{path}} \mu_{risk}\left(\vec{t}_i, \vec{P}_j\right) \tag{13}$$

Within the path specified by (12), let there be the following sample points to be measured, $\vec{S}_j, j = 1,2,\ldots,n_{sp}$. Let the function $prio$ assign priorities to the sample points, i.e, $prio\left(\vec{S}_j\right)$ is the priority of the j^{th} sample point. The values that $prio\left(\vec{S}_j\right)$ can take are positive integers with one representing the highest priority, two the next highest priority, etc. The mission priority for $Path$ is defined to be

$$mission\_prio(Path) \equiv \sum_{i=1}^{n_{sp}} \frac{1}{prio\left(\vec{S}_i\right)}. \tag{14}$$

Furthermore, let the $T(UAV(i), Path)$ be the amount of time it will take UAV(i) to fly and make measurements along $Path$.

The fuzzy degree of reliability experts assign to the sensors of UAV(i) is denoted as $\mu_{sr}(UAV(i))$. This is a real number between zero and one with one implying the sensors are very reliable and zero that they are totally unreliable. Likewise, $\mu_{nsr}(UAV(i))$ is the fuzzy degree of reliability of other non-sensor systems onboard the UAV(i). This fuzzy concept relates to any non-sensor system, e.g., propulsion, computers, hard disk, deicing systems, etc. The value of UAV(i) in units of \$1000.00 is denoted as $V(UAV(i))$. The amount of fuel that UAV(i) has at time t is denoted $fuel(UAV(i), t)$. All the UAVs participating in a mission are assumed to leave base at time, $t = t_o$.

Let UAV(i)'s fuzzy grade of membership in the fuzzy concept "risk tolerance" be denoted as $\mu_{risk-tol}(UAV(i))$. The quantity, $\mu_{risk-tol}(UAV(i))$, is a number between zero and one and will be simply referred to as UAV(i)'s risk tolerance. If the risk tolerance is near zero then the UAV should not be sent on very risky missions. If the UAV's risk tolerance is near one then it can be sent on very risky missions. It seems natural to compare risk tolerance to value. So the comparison can be carried out on the same footing, a fuzzy concept of value should be defined.

The fuzzy grade of membership of each UAV that can be assigned to the mission in the fuzzy concept "Value" is defined as

$$\mu_V(UAV(i)) \equiv \frac{Value(UAV(i))}{\max_j \{Value(UAV(j))\}} \tag{15}$$

The "*max*" operation in (15) is taken over the set of all possible UAVs that can be assigned to the mission.

The advantage of the concept of "risk tolerance" is that it gives the user an extra concept to exploit. If the UAV is not of great relative value, but it still might be needed for a crucial mission after the current one, it might be useful to give it a low risk tolerance so that it is not lost on the current mission. This may allow it to be used on the following mission.

The final concept and related fuzzy membership function that will be defined is "slow". A UAV is said to be slow if it takes a long time to travel a particular path. The fuzzy membership function for the concept "slow" is defined as follows:

$$\mu_{slow}(UAV(i),Path) \equiv \frac{T(UAV(i),Path)}{\max_j \{T(UAV(j),Path)\}} \tag{16}$$

A "slow" UAV experiences a higher relative mission risk since it is in the field longer and may be exposed to risk longer.

To construct the fuzzy membership function for the fuzzy concept, "Assign UAV to Path" (AUP), make the following definitions:

$$factor_1(UAV(i),Path) \equiv \chi\left(fuel(UAV(i),t_o) + \varepsilon_{fuel} - T(UAV(i),Path)\right) \ , \tag{17}$$

$$factor_2(UAV(i),Path) \equiv \frac{min[\mu_{sr}(UAV(i)),\mu_{nsr}(UAV(i))] \cdot mission\_prio(Path)}{denom(UAV(i),Path)} , \tag{18}$$

$$\begin{aligned} &denom(UAV(i),Path) \equiv \\ &1 + min[1 - \mu_{risk-tol}(UAV(i)),\mu_V(UAV(i))] \cdot \mu_{slow}(UAV(i),Path) \cdot mission\_risk(Path), \end{aligned} \tag{19}$$

$$num(UAV(i),Path) \equiv factor_1(UAV(i),Path) \cdot factor_2(UAV(i),Path). \tag{20}$$

The Heaviside step function denoted as χ in (17) takes the value one when its argument is greater than or equal to zero and is zero otherwise. The quantity ε_{fuel} is added to the fuel term to make sure the UAV selected has more than enough fuel. Given the definition of $num(UAV(i),Path)$ the fuzzy membership function that gives the grade of membership of UAV(i) in the fuzzy concept "assign UAV to Path" is defined as

$$\mu_{AUP}(UAV(i),Path) \equiv \frac{num(UAV(i),Path)}{\max_j num(UAV(j),Path)} , \tag{21}$$

where the "*max*" operation in the denominator of (21) is taken over the set of all UAVs that can be assigned to the path.

Given the fuzzy grade of membership it is necessary to defuzzify, i.e., make definite UAV-path assignments. Simply assigning the UAV with the highest fuzzy grade of membership for a particular path to that path can give less than desirable results. Another approach to defuzzification is as follows: assume that the following matrix has been determined $\mu_{AUP}(UAV(i),Path_j); i = 1,2,\ldots,n_{UAV}; j = 1,2,\ldots,n_{path};$ where n_{UAV} and n_{path} are the number of UAVs and paths, respectively. Further assume that $n_{UAV} \geq n_{path}$. There must be an assignment of a one UAV to each path. The number of ways of doing this is $P_{n_{path}}^{n_{UAV}} = \binom{n_{UAV}}{n_{path}} \cdot n_{path}!$. Let the set of paths be denoted as $Path\_set$. Let the p^{th} assignment of UAVs to paths be denoted by the set of ordered pairs

$$Perm(p) \equiv \{(index(j,p),j) \mid j = 1,2,\ldots,n_{path}\}, \qquad p = 1,2,\ldots,P_{n_{path}}^{n_{UAV}} . \tag{22}$$

where $index(j,p)$ is defined to be a function that gives the UAV index as a function of path index $j = 1,2,\ldots,n_{path}$, and permutation index $p = 1,2,\ldots,P^{n_{path}}_{n_{UAV}}$. Let $Perm\_set \equiv \{Perm(p) \mid p = 1,2,\ldots,P^{n_{path}}_{n_{UAV}}\}$ The approach to defuzzification currently used is to select the permutation p such that the following cost function is maximized

$$Cost_{AUP}(p, Path\_set) = \sum_{k=1}^{n_{path}} \mu_{AUP}(UAV(index(index(k,p))), Path_k), \quad p \in Perm\_set. \tag{23}$$

If the number of paths exceeds the number of UAVs a similar procedure is taken where all possible permutations of path assignment to UAVs are considered and the assignment that is made is the one that maximizes a cost function analogous to (23).

4. CONTROL ALGORITHM

Each UAV has a real-time algorithm onboard it that allows recalculation of paths during flight due to changes in environmental conditions or mission priorities. These changes typically become apparent after the planning algorithm has run during the pre-flight stage. As in the case of the planning algorithm the control algorithm uses an A-star algorithm[11] to do the best path calculation, employs fuzzy logic and solves a constrained optimization problem.
This has proven successful for real-time application.

The control algorithms' recalculation of flight paths can be triggered by a number of events such as weather broadcasts that indicate new taboo regions or emergence of new or elimination of old sample points. For those changes that do not require UAVs supporting each other, the control algorithm does not differ from the planning algorithm. The control algorithm is faster by virtue that it only need process those parts of the measurement space where there have been changes relative to sample or taboo points.

A UAV may requests help if it discovers a potential elevated system like a radio hole, malfunctions or suspected malfunctions. All of these conditions can result in help messages being transmitted between the UAVs. These help messages can result in interactions between the UAVs based on transmission of the results of priority calculations for rendering support to the requesting UAVs.

Currently in the control stage, when a UAV discovers an interesting physical phenomenon, is malfunctioning, or suspects due to internal readings that it is malfunctioning, it sends out a request for help. Each UAV receiving this message calculates its priorities for providing assistance to the UAV in need. This priority calculation gives rise to a number between zero and one, inclusive, which is subsequently transmitted to the original UAV desiring support. The requesting UAV sends out an omni-directional message with the ID of the UAV with highest priority for contributing support. The high priority UAV then flies into the necessary neighborhood of the requesting UAV to provide help.

There are three classes of help request. The first occurs when a UAV, the requester, determines it may have discovered an interesting physical phenomenon. This phenomenon may be an elevated duct, radio hole, rain system or some other type of system with physical extent. The requester desires to determine if the phenomenon has significant extent. It will request that a helping UAV or UAVs sample likely distant points within this phenomenon.

The second class of help request relates to a UAV that according to internal diagnostics may be experiencing a sensor malfunction. This UAV will requests that another UAV or UAVs measure some of the points that the requesting UAV measured. This will help determine if the UAV is actually malfunctioning. If the requesting UAV is determined to be malfunctioning, then it will fly back to base, if it is capable. The determination of whether it is actually malfunctioning requires some consideration. Since the second UAV will probably be measuring a distant point at a time different than the original requesting UAV made its measurements, potential variation in the index of refraction over time must be taken into account.

When a UAV sends out an omni-directional request for help, those UAVs receiving the message will calculate their fuzzy priority for helping, denoted as "PH". The UAV that will ultimately help the requester is the one with the highest fuzzy priority for helping. The fuzzy priority for helping takes into account a variety of properties of the potential helper. The set of UAVs that receive the request for help from UAV(i) at time t is denoted as $help(i,t)$. If UAV(i) requests help at time t and UAV(j) receives the message then UAV(j) will take into account the amount of time, denoted, $help\_time(UAV(j))$, it will take to fly from the point where it received the request to the point where it would provide support. It also takes into account the amount of fuel UAV(j) has left at the time of the request, denoted $fuel(UAV(j),t)$; UAV(j)'s fuzzy concept of price denoted as *"price"*, and UAV(j)'s fuzzy concept of "*mission priority*" at time, t. Let the set of relevant UAV properties be denoted as UAV_prop and be defined as

$$UAV\_prop = \{help\_time, fuel, mission\_prio, price\}. \tag{24}$$

The fuzzy priority for helping denoted as μ_{PH} takes the form

$$\mu_{PH}(UAV(i), UAV(j)) = \sum_{\alpha \in UAV\_prop} w_\alpha \cdot \mu_\alpha(UAV(j)). \tag{25}$$

The quantities w_α and μ_α, for $\alpha \in UAV\_prop$ are expert defined weights and fuzzy membership functions, respectively. The fuzzy membership functions are defined in (26-29) and given below,

$$\mu_{help\_time}(UAV(i), UAV(j)) = \left[\frac{help\_time(UAV(j))}{\max\limits_{k \in help(i,t)} \{help\_time(UAV(k))\}} + 1 \right]^{-1}, \tag{26}$$

$$\mu_{fuel}(UAV(i), UAV(j)) = \frac{fuel(UAV(j))}{\max\limits_{k \in help(i,t)} \{fuel(UAV(k))\}}, \tag{27}$$

$$\mu_{mission\_prio}(UAV(i), UAV(j)) = \left[\frac{mission\_prio(UAV(j))}{\max\limits_{k \in help(i,t)} \{mission\_prio(UAV(k))\}} + 1 \right]^{-1}, \tag{28}$$

$$\mu_{price}(UAV(i), UAV(j)) = \left[\frac{Value(UAV(j))}{\max\limits_{k \in help(i,t)} \{Value(UAV(k))\}} + 1 \right]^{-1}. \tag{29}$$

It is assumed that all evaluations are processed at time, t, so time dependence is suppressed in (25-29) for notational convenience. A more sophisticated version of the control logic that takes path risk, changes in risk, UAV reliability, UAV, risk tolerance and missed sample points into account will be the subject of a future publication.

5. COMPUTATIONAL EXPERIMENTS

The planning and control algorithms described in the previous sections have been the subject of a large number of experiments. This section provides a description of a small subset of these experiments. They serve to illustrate how the algorithms were tested. Due to space limitations only experiments involving one or two UAVs are discussed.

UAV experiments using only one UAV demonstrate how the planning and control algorithm, while avoiding taboo points, will determine the route the UAV flies so that it is successful in making measurements at sample points in space. Experiments using two UAVs illustrate how the control algorithm allows the UAVs to automatically support each other to increase the probability their joint mission is successful.

Figures 1-4 use the same labeling conventions. Sample points are labeled by concentric circular regions colored in different shades of gray. The lighter the shade of gray used to color a point, the lower the point's grade of membership in the fuzzy concept "desirable neighborhood." The legend provides numerical values for the fuzzy grade of membership in the fuzzy concept "desirable neighborhoods". If the fuzzy degree of desirability is high then the index of refraction is considered to be close to the index of refraction of the sample point at the center of the desirable neighborhood. This allows the UAV to make significant measurements while avoiding undesirable neighborhoods.

Each sample point is labeled with an ordered pair. The first member of the ordered pair provides the index of the sample point. The second member of the ordered pair provides the point's priority. For example, if there are n_{sp} sample points and the q^{th} sample point is of priority p ,then that point will be labeled with the ordered pair (q,p).

Points surrounded by star-shaped neighborhoods varying from dark grey to white in color are taboo points. As with the sample points, neighborhoods with darker shades of gray have a higher grade of membership in the fuzzy concept "undesirable neighborhood." The legend provides numerical values for the fuzzy grade of membership in the fuzzy concept "undesirable neighborhood." UAVs with high risk tolerance may fly through darker grey regions than those with low risk tolerance. When comparing planning and associated control pictures, if a point ceases to be taboo, the neighborhood where it resides is marked by a very dim gray star as well as being labeled by a dialog box as being an "old taboo point." New taboo points and their associated undesirable neighborhoods are labeled with dialog boxes indicating that they are "new."

UAVs start their mission at the UAV base which is labeled with a diamond-shaped marker. They fly in the direction of the arrows labeling the various curves in Figures 1-4.

Figure 1 provides the sample points, taboo points and sample path for one UAV as determined by the planning algorithm. It is important to notice that the UAV's path passes directly through each sample point, i.e., through the center of the concentric circular regions representing the fuzzy degree of desirability of neighborhoods. Fortuitously, the taboo points and their neighborhoods are so positioned that they do not interfere with the UAV's measurement process or its return to base.

Figure 2 depicts the actual path the UAV flies as determined by the UAV's real-time control algorithm. The path determined by the control algorithm differs from the one created by the planning algorithm due to real-time changes in taboo points. After leaving the UAV base new weather data was acquired informing the UAVs that the exact position of the third sample point, i.e., the one labeled (3,1) actually resides within an undesirable neighborhood. Due to the high priority of the sample point, the UAV flies into the taboo points' undesirable neighborhood as indicated in Figure 2.

In both the planning and control algorithms the UAV measures sample points of two different priorities, with the direction of the flight path selected so that the higher priority points are measured first. By measuring high priority points first, the likelihood of an important measurement not being made is diminished, if the UAV can not complete its mission due to a malfunction, change in weather, etc.

Also, due to movement of old taboo points or the emergence of new taboo points which are marked "New", the path determined for the UAV using the control algorithm is significantly different than the one created by the planning algorithm. The path change represents the control algorithm's ability to reduce UAV risk.

Figure 3 depicts the sampling path determined by the planning algorithm for an experiment involving two UAVs. The first, UAV(1) follows the dashed curve; the second, UAV(2), the solid curve. The UAVs were assigned to the different paths by the fuzzy path assignment decision rule described in section 3. UAV(1) is assigned to sample all the highest priority points, i.e., the priority one points. UAV(2) samples the lower priority points, i.e.; those with priority two. Due to the greedy nature of the point-path assignment algorithm, the highest priority points are assigned for sampling first.

Figure 4 depicts the actual flight path the UAVs take during real-time. Initially, UAV(1) is successful in measuring sample points one and two as assigned it by the planning algorithm. Just beyond sample point two, UAV(1) experiences a malfunction. UAV(1)'s real-time control algorithm subsequently sends out a help request informing the only other UAV in the field, UAV(2) of the malfunction. UAV(2)'s control algorithm determines a new path for UAV(2) to fly so that the priority one points, labeled (3,1) and (4,1), that UAV(1) was not able to sample are subsequently measured. After UAV(2) measures sample point five, its new flight path allows it to measure sample points three and four. UAV(2)'s control algorithm determined it was very important that these priority one points be measured. Unfortunately, due to the extra fuel expended in reassigning sample points three and four to UAV(2), UAV(2) did not have enough fuel to measure sample points seven and eight which were of priority two. UAV(2)'s real-time control algorithm determined the best possible solution in the face of changing circumstances and limited resources.

It is important to note that the control algorithms running on UAV(1) and UAV(2) direct both UAVs to alter their return flight to the base due to the emergence of new taboo points making the planning algorithm determined flight paths too dangerous. The control algorithm uses each UAV's fuzzy risk tolerance to determine how close each UAV may approach a taboo point.

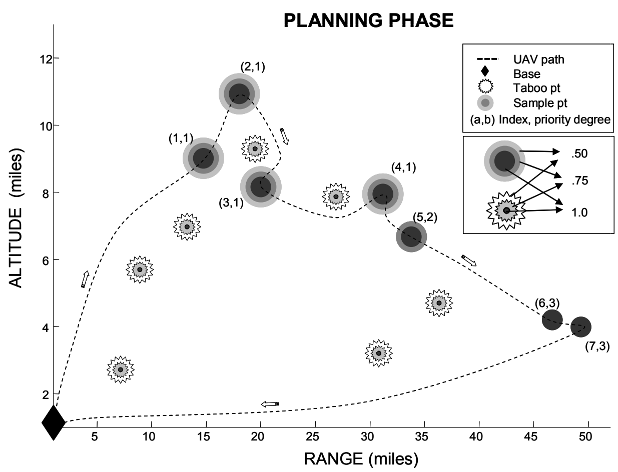

Figure 1: One UAV trajectory as determined by the planning algorithm.

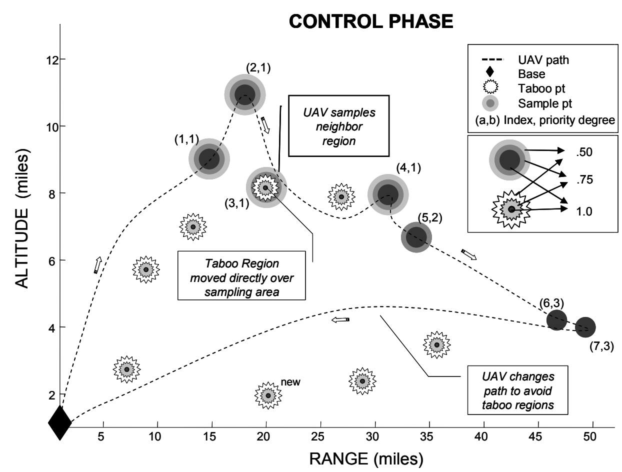

Figure 2: One UAV trajectory as determined by the real-time control algorithm.

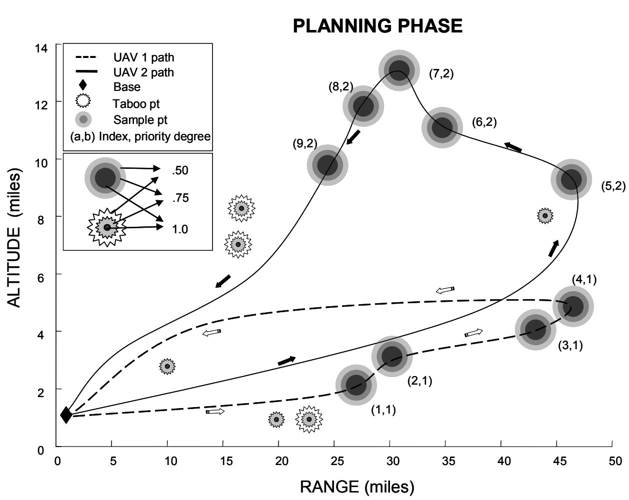

Figure 3: Trajectory of two UAVs as determined by the planning algorithm.

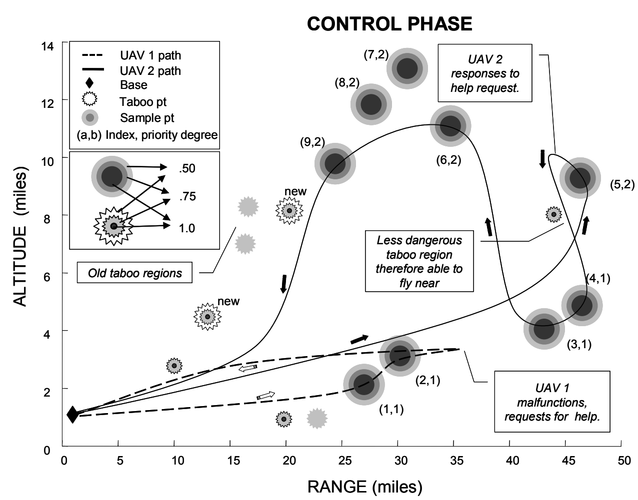

Figure 4: During flight, updates about environmental changes cause the real-time control algorithms on the two UAVs to change their trajectories.

6. SUMMARY

Fuzzy logic based planning and control algorithms that allow a team of cooperating unmanned air vehicles (UAVs) to make meteorological measurements have been developed. The planning algorithm including the fuzzy logic based optimization algorithm for flight path determination and the UAV path assignment algorithm are discussed. The control algorithm also uses these fuzzy logic algorithms, but also allows three types of automatic cooperation between UAVs. The fuzzy logic algorithm for automatic cooperation is examined in detail. Methods of incorporating environmental risk measures as well as expert measures of UAV reliability are discussed as they relate to both the planning and control algorithms. Experimental results are examined.

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