Fuzzy Logic Based Resource Manager for a Team of UAVs

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***Abstract* -A fuzzy logic resource allocation algorithm that enables a collection of unmanned aerial vehicles (UAVs) to automatically cooperate to make meteorological measurements will be discussed. Once in flight no human intervention is required. Planning and real-time control algorithms determine the optimal trajectory and points each UAV will sample, while taking into account the UAVs' risk, risk tolerance, reliability, mission priority, fuel limitations, mission cost, and related uncertainties. The approach is illustrated by a discussion of the fuzzy decision tree for UAV path assignment and related simulation. Simulations also show the ability of the control algorithm to allow UAVs to effectively cooperate to increase the UAV team's likelihood of success.**

I. 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 aerial 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 preplanned, and cooperate with other UAVs.

Section II 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 III discusses the electromagnetic measurement space, UAV risk, UAV risk tolerance and the planning algorithm. Section III also discusses 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 IV discusses 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 V provides a summary.

II. 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.

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 omnidirectional 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

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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.

III. Planning 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 this section.

The planning algorithm allows the determination of the minimum number of UAVs needed for the mission subject to fuel constraints, risk, UAV cost, 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. The planning algorithm automatically establishes the order in which to send the UAVs taking into account the UAV's value; 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.

The notion of a desirable neighborhood is motivated by the fact that a sample point may also be a taboo point or reside within an undesirable neighborhood. In the case the sample point coincides with or is near a taboo point and at least part of the sample point's desirable neighborhood falls within the taboo point's undesirable neighborhood, the UAV may only sample within a desirable neighborhood that is consistent with its risk tolerance.

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 this section. 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. Depending on the UAV's risk tolerance a UAV may pass through various neighborhoods of the taboo point, subsequently experiencing various degrees of risk. Both the concepts of risk and risk tolerance are based on human expertise and employ 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 and risk tolerance in terms of fuzzy logic.

A. Risk Fuzzy Decision Tree

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),

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

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

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

where the "taboo point," $\vec{q}_{taboo}$ is the point at which the risk phenomenon has been observed. The root concepts used on the risk subtree are given in (4), and the subscript α is an element of the root concept set , *RC*, i.e.,

$\alpha \in$ ***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}* (4)

The norm in equation (2) is typically taken as an Euclidean distance. 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

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

B. Optimal Paths and AUP Fuzzy Decision Tree

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

$$path\_cost(\vec{r}_A,\vec{r}_B) = \frac{d(\vec{r}_A,\vec{r}_B) + \beta \cdot \sum_{i=1}^{n_{taboo}} \mu_{risk}(\vec{t}_i,\vec{r}_B)}{v(\vec{r}_A,\vec{r}_B)}. \tag{6}$$

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

$$Taboo \equiv \left[\vec{t}_1,\vec{t}_2,\ldots,\vec{t}_{n_{taboo}}\right] \tag{7}$$

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 (8),

$$Path_i = [\vec{r}_1, \quad \vec{r}_2, \quad \ldots, \quad \vec{r}_n], \tag{8}$$

then the total path cost is defined to be

$$total\_cost(Path_i) \equiv \sum_{j=1}^{n-1} path\_cost(\vec{r}_j,\vec{r}_{j+1}). \tag{9}$$

Determining the optimal path for the i^{th} UAV consists of minimizing the total path cost given by (9) 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 tree for path assignment described in this section.

The planning algorithm must assign UAVs to the flight paths determined by the optimization procedure described below in this section. This is referred to as the UAV path assignment problem (UPAP). The planning algorithm makes this assignment using the following fuzzy logic based procedure. To describe the decision tree 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,

$$Path = \left[\vec{P}_1, \vec{P}_2, \ldots, \vec{P}_{n_{path}}, \vec{P}_1\right] \tag{10}$$

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 (7). 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 (MR) is

$$mission\_risk(Taboo, Path_k) \equiv \sum_{i=1}^{n_{taboo}} \sum_{j=1}^{n_{path}} \mu_{risk}\left(\vec{t}_i, \vec{P}_j\right) \tag{11}$$

The degree to which the k^{th} path belongs to the related fuzzy concept MR is given by

$$\mu_{MR}(Taboo, Path_k) \equiv \frac{mission\_risk(Taboo, Path_k)}{\max_j\left\{mission\_risk\left(Taboo, Path_j\right)\right\}} \tag{12}$$

The "*max*" operation in (12) is taken over the set of all possible UAVs that can be assigned to the mission.

A fuzzy concept related to "mission risk" is "low risk." The fuzzy membership function for "low risk" denoted as μ_{LR} is defined as

$$\mu_{LR}(Taboo, Path_k) \equiv \min(1, \alpha + 1 - \mu_{MR}) \tag{13}$$

where $\alpha \in (0,1)$ is an expert defined parameter. The function of α is to make sure that "low risk" does not dominate calculations developed below.

Within the path specified by (10), 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 (MP) for the k^{th} $Path_k$ is defined to be

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

The degree to which the k^{th} path belongs to the related fuzzy concept MP is given by

$$\mu_{MP}(Path_k) \equiv \frac{mission\_prio(Path_k)}{\max_j\left\{mission\_prio\left(Path_j\right)\right\}}. \tag{15}$$

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

$$\mu_V(UAV(i)) \equiv \frac{Value(UAV(i))}{\max_j\{Value(UAV(j))\}} \tag{16}$$

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.

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

$$\mu_{fast}(UAV(i), Path) \equiv \Lambda_{rrtmp} \cdot min\left(1, \alpha + 1 - \frac{T(UAV(i), Path)}{\max_j\{T(UAV(j), Path)\}}\right) \quad (17)$$

and

$$\Lambda_{rrtmp} \equiv \chi\lfloor min(\mu_{sr}, \mu_{nsr}) - \varepsilon_{1,rel} \cdot min(1 - \mu_{risk-tol}, max(1 - \mu_{MP}, \varepsilon_{2,MP})) - \varepsilon_{3,rel}\rfloor \quad (18)$$

where $\varepsilon_{1,rel}, \varepsilon_{2,MP}, \varepsilon_{3,rel} \in (0,1]$ are expert assigned parameters. The Heaviside step function denoted as χ in (18) takes the value one when its argument is greater than or equal to zero and is zero otherwise.

The term $\varepsilon_{1,rel} \cdot min(1 - \mu_{risk-tol}, max(1 - \mu_{MP}, \varepsilon_{2,MP}))$ in the Heaviside step function's argument in (18) can result in Λ_{rrtmp} going to zero if $\mu_{risk-tol}$ or μ_{MP} are small enough. If "Risk tolerance" and "mission priority" take low values then depending on the value of $\varepsilon_{1,rel}$, the membership function for the fuzzy concept "fast" may take the value zero. The parameter $\varepsilon_{2,MP}$ limits the effect of "mission priority." Even if the mission priority is very high, risk tolerance plays an important role. If the UAV has high risk tolerance and the path, high mission priority the UAV must have a minimum reliability given by $\varepsilon_{3,rel}$. Finally, the motivation for the concept "fast" is that a fast UAV experiences a lower relative risk since it is in the field less time and may be exposed to risk for a shorter duration.

A fuzzy concept that combines "Value" and "mission risk" is "VMR" and its membership function denoted as μ_{VMR} is defined as

$$\mu_{VMR} \equiv min(min(\mu_{risk-tol}, 1 - \mu_V), AND_2(\mu_{fast}, \mu_{LR})) \quad (19)$$

The use of AND_2 in (19) allows distinctions to be made between various values of μ_{fast} and μ_{LR}. If AND_2 were replaced by a min in (19) then if μ_{fast} is low enough then $min(\mu_{fast}, \mu_{LR})$ would take the value μ_{fast} independent of the value of μ_{LR} this would not allow fine distinctions to be made.

The logical connective AND_2 is defined as

$$AND_2(\mu_A, \mu_B) \equiv \mu_A \cdot \mu_B \quad (20)$$

The fuzzy concept "RMP" combines the fuzzy concepts "sr," "nsr," and "MP." The fuzzy membership function for "RMP," denoted as μ_{RMP} is defined as

$$\mu_{RMP} \equiv min(\mu_{sr}, \mu_{nsr}, \mu_{MP}) \quad (21)$$

Both the membership functions for "VMR" and "RMP" can be represented as fuzzy decision trees.

Finally, the fuzzy membership function for the fuzzy concept "assignment of UAV(i) to the path" (AUP) is defined as

$$\mu_{AUP} \equiv AND_2[\mu_{RMP}, AND_2(\mu_{RMP}, \mu_{VMR})] = \mu_{RMP}^{\ 2} \cdot \mu_{VMR} \quad (22)$$

The fuzzy membership function for AUP is a decision tree that combines both "VMR" and "RMP" as subtrees. The use of AND_2 in (22) in two places renders μ_{AUP} more sensitive to the values of μ_{RMP} and μ_{VMR} than it would be if the membership function for AUP took the value $min(\mu_{RMP}, \mu_{VMR})$. If μ_{AUP} were to take the value $min(\mu_{RMP}, \mu_{VMR})$ then a small value of μ_{RMP} such that $\mu_{RMP} < \mu_{VMR}$ would cause μ_{AUP} to take the value of μ_{RMP} independent of the value of μ_{VMR}. The use of AND_2 instead of min allows finer distinctions to be made. The second degree dependence of μ_{RMP} in (22) results in a small value of μ_{AUP} if μ_{RMP} is small, but μ_{AUP} is still dependent on μ_{VMR}. This is consistent with expertise. If the sensor or non-sensor reliabilities or mission priority are small, μ_{AUP} should be small. Low reliability or priority results in a faster decline in μ_{AUP} than high mission risk, high UAV value, low UAV risk tolerance or the fact that a reliable and risk-tolerant UAV is slow.

The fuzzy concept AUP is depicted as a tree in Fig. 1. Leaves of the tree, i.e., those vertices of degree one are labeled by the names of the fuzzy concepts described above. Vertices are labeled by the specific logical connective used, i.e., *min* or AND_2. A circle on an edge indicates the fuzzy logic modifier *not*. The fuzzy modifier *not* is defined as the complement of the fuzzy set, i.e., let μ_A be the fuzzy membership function for the fuzzy concept A then membership function for *not* A is given by $1 - \mu_A$.

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. The approach to defuzzification taken is as follows: if the number of UAVs is denoted as n_{UAV} and likewise, the number of paths is denoted by n_{path}, where $n_{UAV} \geq n_{path}$ then consider the set of all possible permutations of the n_{path} UAVs selected from a total of n_{UAV} UAVs. For each assignment of n_{path} UAVs to the paths, add up the values of μ_{AUP} for that assignment over the paths. This sum is referred to as the assignment benefit (AB). The assignment with the highest AB is the one selected. Finally, a similar procedure is followed if $n_{UAV} < n_{path}$.

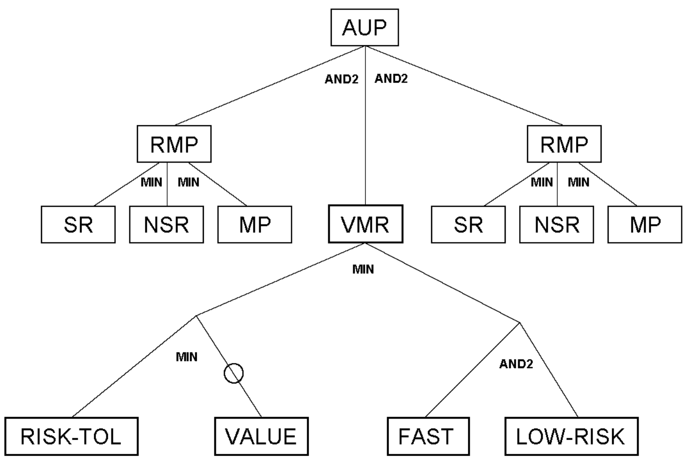

Figure 1: The AUP subtree for the UAVRM.

The decision tree for AUP given in (22) was constructed using expertise provided by human experts. It is a significant improvement over a previously developed fuzzy decision rule for path assignment also constructed from expertise [11]. An alternate method of obtaining (22) is to evolve it using a genetic program (GP) [12]. A GP is a computer program based on the theory of evolution that evolves mathematical expressions or computer programs that can be considered optimal in a sense. The GP has been used as a data mining function [12] to create the decision tree in (22). The GP data mined a scenario database where each scenario had been labeled by an expert. Expert rules were also incorporated to guide the evolutionary process and improve convergence time. The decision tree in (22) has been evolved many times. The GP finds the same AUP decision tree, over and over again independent of the seed of the random number generator used to simulate a random evolutionary process.

IV. 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 two or three UAVs are discussed.

In Figs. 2 and 3, 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. Fig. 4 summarizes a three UAV experiment that exhibits the AUP decision tree's ability to assign UAVs to paths in a fashion that makes effective use of available resources.

Figs. 2-4 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 Figs. 2-3.

Fig. 2 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 AUP fuzzy decision tree described in section III. 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.

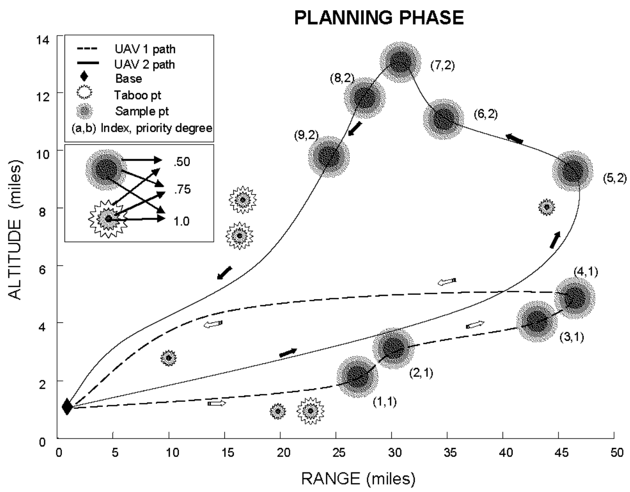

Figure 2: Trajectory of two UAVs as determined by the planning algorithm and their paths assigned by AUP.

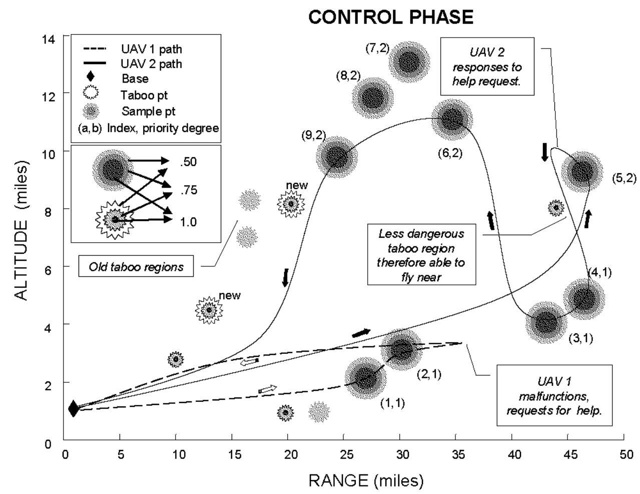

Figure 3: During flight, updates about environmental changes cause the real-time control algorithms on the two UAVs to change their trajectories.

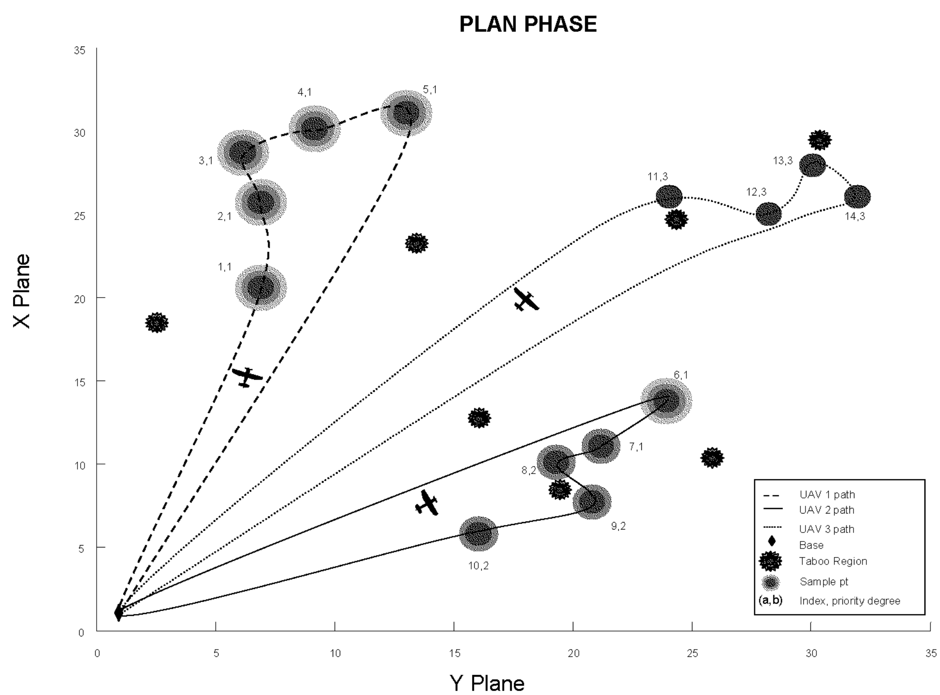

Figure 4: Three UAV mission that provides an example of the AUP decision tree's assignments.

Fig. 3 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.

Additional mathematical details about the fuzzy decision algorithm that permits UAVs to help each other are provided in [11]. A more sophisticated GP evolved fuzzy decision tree that permits greater cooperation between UAVs will be the subject of a future publication.

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 near each UAV may approach a taboo point.

Fig. 4 provides an example of the AUP decision tree's assignment of three UAVs to three paths. The highest priority locations are assigned to UAV(1) as it has the greatest fuel capacity, i.e., 90 minutes. UAV(1) however does not have enough fuel to handle the high priority points located at positions six and seven and therefore UAV(2) is assigned these points along with the second degree high priority locations.

V. Summary

Fuzzy logic based planning and control algorithms that allow a team of cooperating unmanned aerial 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. 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 provided. The experiments show the algorithms' effectiveness.

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