# Fuzzy decision trees for planning and autonomous control of a coordinated team of UAVs

James F. Smith III[*], ThanhVu H. Nguyen

Naval Research Laboratory, Code 5741, Washington, D.C., 20375-5000

## ABSTRACT

A fuzzy logic resource manager 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 control algorithm permits newly obtained information about weather and other events to be introduced to allow the UAVs to be more effective. The approach is illustrated by a discussion of the fuzzy decision tree for UAV path assignment and related simulation. The different fuzzy membership functions on the tree are described in mathematical detail. The different methods by which this tree is obtained are summarized including a method based on using a genetic program as a data mining function. A second fuzzy decision tree that allows the UAVs to automatically collaborate without human intervention is discussed. This tree permits three different types of collaborative behavior between the UAVs. Simulations illustrating how the tree allows the different types of collaboration to be automated are provided. Simulations also show 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 planning and control algorithms that allow a collection of unmanned aerial vehicles (UAVs) and an interferometer platform (IP) to automatically collaborate will be discussed[1, 2]. In particular, the fuzzy decision trees[1-6] (FDTs) that "assigns UAVs to paths" (AUP) and the FDT for "priority for helping" (PH) are discussed. The AUP FDT is used by both the planning and control algorithms. The PH FDT is used by the real-time control algorithm to allow automatic cooperation between the UAVs through communications.

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 algorithm determines the best flight paths by minimizing a cost function[1, 2]. Once flight paths are determined the AUP FDT and a defuzzification algorithm explained below are used for UAV flight path assignments.

The AUP FDT incorporates fuzzy concepts related to UAV sensor reliability, UAV non-sensor reliability, the UAV's value, the UAV custodian's risk-tolerance, and the UAV's speed. The AUP FDT also incorporates fuzzy concepts related to the path the UAV might fly including: mission risk and mission priority.

Each UAV has onboard its own fuzzy logic based real-time control algorithm that uses the PH FDT. 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. The PH FDT incorporates the fuzzy concepts related to UAV

[*] Correspondence: Email: jfsmith@drsews.nrl.navy.mil

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properties used by the AUP FDT as well as path concepts somewhat different than those previously used. There will be two different types of cooperation allowed by the PH FDT 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 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.

Section 2 develops a fuzzy logic based approach for assigning UAVs to paths. Section 3 emphasizes real-time UAV control and the fuzzy decision tree (FDT) that allows UAVs to automatically cooperate. Section 4 provides results of computational experiments. Finally, section 5 gives a summary.

## 2. AUP FUZZY DECISION TREE

The planning algorithm[1, 2] 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 it assigns UAVs to paths (AUP) using the AUP FDT which is developed below.

Points in the measurement space are considered taboo if they are threatening to the UAVs, e.g., because of local turbulence or the presence of physical obstructions such as mountain tops. Position vectors measured from the origin for the taboo points are denoted as $\vec{t}_i, i = 1,2,\ldots,n_{taboo}$ where $n_{taboo}$ is the number of taboo points.

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,

$$Path = \left[\vec{P}_1, \vec{P}_2, \ldots, \vec{P}_{n_{path}}, \vec{P}_1\right] \tag{1}$$

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 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

$$mission\_risk(Taboo, Path_k) \equiv \sum_{i=1}^{n_{taboo}} \sum_{j=1}^{n_{path}} \mu_{risk}(\vec{t}_i, \vec{P}_j) \tag{2}$$

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

$$\mu_{MR}(Taboo, Path_k) \equiv \frac{mission\_risk(Taboo, Path_k)}{\max_j \{mission\_risk(Taboo, Path_j)\}} \tag{3}$$

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

$$\mu_{LR}(Taboo, Path_k) \equiv min(1, \alpha + 1 - \mu_{MR}) \tag{4}$$

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

Within the path specified by (1), 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, $prio(\vec{S}_j)$ is the priority of the $j^{th}$ sample point. The values that $prio(\vec{S}_j)$ 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

$$mission\_prio(Path_k) \equiv \sum_{i=1}^{n_{sp}} \frac{1}{prio(\vec{S}_i)}. \tag{5}$$

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

$$\mu_{MP}(Path_k) \equiv \frac{mission\_prio(Path_k)}{\max_j \{mission\_prio(Path_j)\}}. \tag{6}$$

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

$$\mu_V(UAV(i)) \equiv \frac{Value(UAV(i))}{\underset{j}{max}\{Value(UAV(j))\}}. \tag{7}$$

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:

$$\mu_{fast}(UAV(i), Path) \equiv \Lambda_{rrtmp} \cdot \min\left(1, \alpha + 1 - \frac{T(UAV(i), Path)}{\max_j \{T(UAV(j), Path)\}}\right) \tag{8}$$

and

$$\Lambda_{rrtmp} \equiv \chi\left[\min(\mu_{sr}, \mu_{nsr}) - \varepsilon_{1,rel} \cdot \min\left[1 - \mu_{risk-tol}, \max(1 - \mu_{MP}, \varepsilon_{2,MP})\right] - \varepsilon_{3,rel}\right] \tag{9}$$

where $\varepsilon_{1,rel}, \varepsilon_{2,MP}, \varepsilon_{3,rel} \in (0,1]$ are expert assigned parameters. The Heaviside step function denoted as $\chi$ in (9) 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 (9) can result in $\Lambda_{rrtmp}$ going to zero if $\mu_{risk-tol}$ or $\mu_{MP}$ 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 $\mu_{VMR}$ is defined as

$$\mu_{VMR} \equiv min(min(\mu_{risk-tol}, 1 - \mu_V), AND_2(\mu_{fast}, \mu_{LR})) \tag{10}$$

The use of $AND_2$ in (10) allows distinctions to be made between various values of $\mu_{fast}$ and $\mu_{LR}$. If $AND_2$ were replaced by a $min$ in (10) then if $\mu_{fast}$ is low enough then $min(\mu_{fast}, \mu_{LR})$ would take the value $\mu_{fast}$ independent of the value of $\mu_{LR}$ this would not allow fine distinctions to be made.

The logical connective $AND_2$ is defined as

$$AND_2(\mu_A, \mu_B) \equiv \mu_A \cdot \mu_B \tag{11}$$

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

$$\mu_{RMP} \equiv min(\mu_{sr}, \mu_{nsr}, \mu_{MP}) \tag{12}$$

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

$$\mu_{AUP} \equiv AND_2[\mu_{RMP}, AND_2(\mu_{RMP}, \mu_{VMR})] = \mu_{RMP}{}^2 \cdot \mu_{VMR} \tag{13}$$

The fuzzy membership function for AUP is a decision tree that combines both "VMR" and "RMP" as subtrees. The use of $AND_2$ in (13) in two places renders $\mu_{AUP}$ more sensitive to the values of $\mu_{RMP}$ and $\mu_{VMR}$ than it would be if the membership function for AUP took the value $min(\mu_{RMP}, \mu_{VMR})$. If $\mu_{AUP}$ were to take the value $min(\mu_{RMP}, \mu_{VMR})$ then a small value of $\mu_{RMP}$ such that $\mu_{RMP} < \mu_{VMR}$ would cause $\mu_{AUP}$ to take the value of $\mu_{RMP}$ independent of the value of $\mu_{VMR}$. The use of $AND_2$ instead of $min$ allows finer distinctions to be made. The second degree dependence of $\mu_{RMP}$ in (13) results in a small value of $\mu_{AUP}$ if $\mu_{RMP}$ is small, but $\mu_{AUP}$ is still dependent on $\mu_{VMR}$. This is consistent with expertise. If the sensor or non-sensor reliabilities or mission priority are small, $\mu_{AUP}$ should be small. Low reliability or priority results in a faster decline in $\mu_{AUP}$ 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 Figure 1. For both FDTs described in this paper the following conventions are observed. 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 $\mu_A$ be the fuzzy membership function for the fuzzy concept *A* then membership function for *not A* is given by $1-\mu_A$. A diamond on an edge refers to a function related to *not* which has a lower bound of $\alpha$ which is generally not zero. The mathematical form of this modifier is $\min[1, \alpha + 1 - \mu_A]$. The quantity $\alpha$ is an expert defined quantity. This is a bounded sum[7, 8] between the complement of *A* and the crisp number $\alpha$. An ellipse label as "$Pow_q$" indicates that the value of the input fuzzy grade of membership is raised to the power "*q*". The value "*q*" is taken as two for this paper.

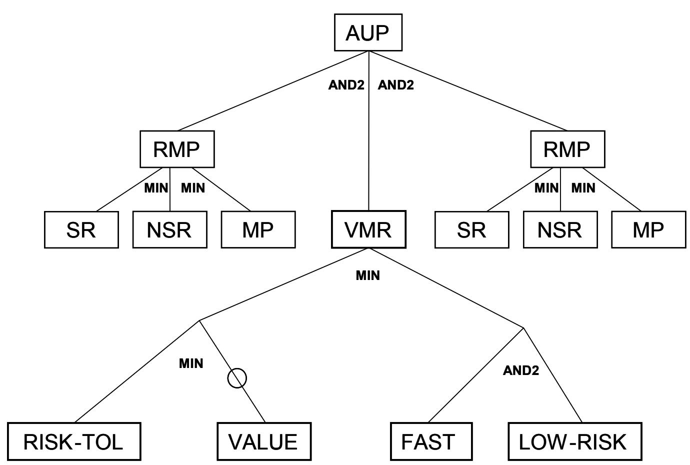


Figure 1: The AUP fuzzy decision tree.

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 $\mu_{AUP}$ 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 $n_{UAV} < n_{path}$.

The decision tree for AUP given in (13) 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[2]. An alternate method of obtaining (13) is to evolve it using a genetic program[9] (GP). 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[10] to create the decision tree in (13). 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 (13) 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.

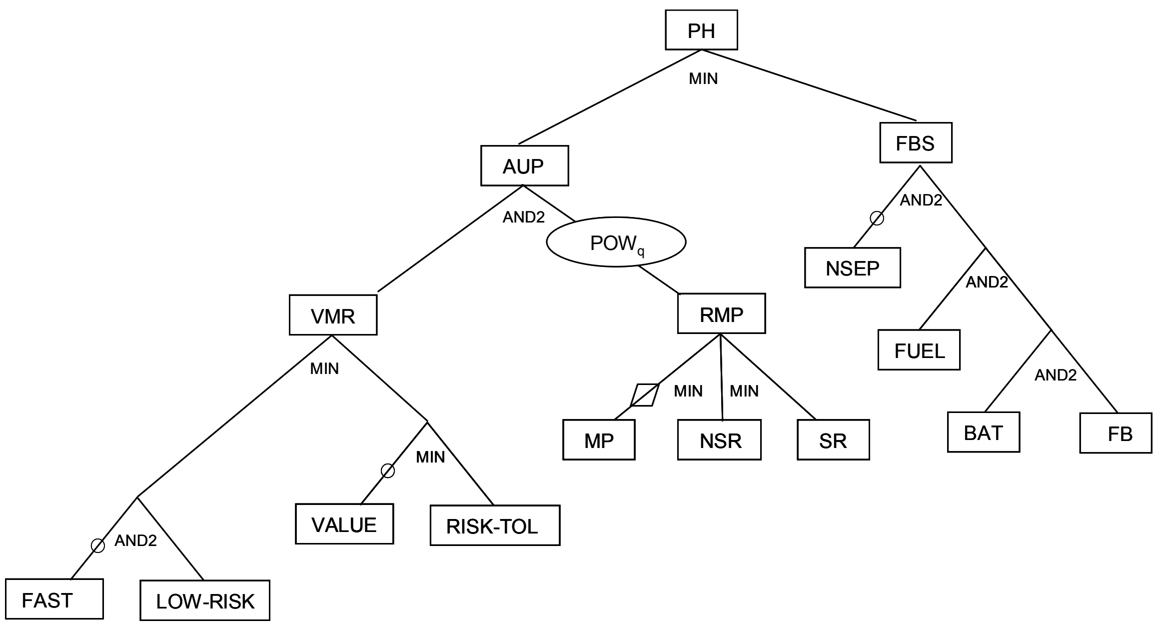


Figure 2: PH fuzzy decision tree

## 3. 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. Other routing algorithms may be considered for this application in the future[12].

The control algorithm allows UAVs to cooperatively help each other without human intervention. 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.

Each UAV receiving this message calculates its priorities for providing assistance to the UAV in need using the priority for helping (PH) FDT which is developed in this section. The fuzzy grade of membership in the concept PH 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.

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 $fuel(UAV(j),t)$ and UAV(j)'s fuzzy concept of "*mission priority*" at time, $t$.

### 3.1 Fuzzy decision tree for providing help

The next fuzzy decision tree to be developed is the "priority for helping"(PH) decision tree. This tree allows the UAVs to determine how they should support each in real-time as the need arises. When a UAV requires help in making a measurement, its diagnostic systems indicate a sensor might be malfunctioning or there is a clear indication of a malfunction, a UAV can request that another UAV provide help. The request for help is sent out as an omni-directional message. When a UAV sends out an omni-directional request for support, those UAVs receiving the message will calculate their fuzzy priority of providing help, denoted as $\mu_{PH}$. The UAV that will ultimately help the requester is the one with the highest value of $\mu_{PH}$. The fuzzy concept, priority for helping, takes into account properties of the potential supporter. 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 necessary travel time it will consume in helping UAV(i), as well as the relative amounts of fuel and battery life the potential helper, UAV(j), has at the time the request is received. Define the relative degree of fuel and battery power left at time, $t$, that UAV(j) might use to help UAV(i) as

$$\mu_{fuel}(i,j,t) = \frac{fuel(UAV(j),t)}{\max\limits_{k \in help(i,t)} fuel(UAV(k),t)} \tag{14}$$

and

$$\mu_{battery}(i,j,t) = \frac{battery(UAV(j),t)}{\max\limits_{k \in help(i,t)} battery(UAV(k),t)} \tag{15}$$

Define the relative degree of UAV(j)'s "not-separation" from UAV(i) as

$$\mu_{nsep}(i,j,t) = \min\left[1, \beta + 1 - \frac{T(UAV(j), Q_{req}(j,i))}{\max\limits_{k \in help(i,t)} T(UAV(k), Q_{req}(j,i))}\right] \tag{16}$$

where $T\left(UAV(j), Q_{req}(j,i)\right)$ is the time it would take UAV(j) to travel the path $Q_{req}(j,i)$ from the point $\overrightarrow{pos}(j,t)$ where UAV(j) receives request for help at time, $t$, from UAV(i) to the final point , $\vec{q}_{n_{request}(i),i}$, where it would start helping UAV(i). The subscript *"req"* on $Q_{req}(j,i)$ is an abbreviation for "requested path." The quantity, $n_{request}(i)-1$, is the number of points that UAV(j) would pass through in going from its position at time, *t*, to the first new sample point, $\vec{q}_{n_{request}(i),i}$.

The travel time $T\left(UAV(j), Q_{req}(j,i)\right)$ is determined by an A-star algorithm[1, 2, 11] and includes sampling and non-sampling velocities.

The quantity, $\beta$, is added so that $\mu_{nsep}(i,j,t)$ remains nonzero even for the UAV in the set $help(i,t)$ that will take the maximum amount of time, which leaves open the possibility of the slowest UAV participating in the coordinated team. The quantity, $\beta$, is an additive constant to be determined such that

$$0 < \beta \leq 1 . \tag{17}$$

Let the path from $\vec{q}_{n_{request}(i)+1,i}$, the first flight point beyond $\vec{q}_{n_{request}(i),i}$, to $\vec{P}_{base}$, the position of the base that UAV(j) returns to after helping UAV(i) be denoted as $Q_{sar}(j,i)$, where the subscript "*sar*" denotes "sample and return." The full path that UAV(j) will fly in support of UAV(i) is denoted as

$$SPath(j,i) \equiv \left[Q_{req}(j,i), Q_{sar}(j,i)\right] \tag{18}$$

where the notation *SPath* is an abbreviation for "support path." It should be recalled that $Q_{req}(j,i)$ is a matrix of order $\left(1+n_{request}(i)\right)\times 3$ where the "3" arises from representing points in three spatial dimensions. If the path $Q_{sar}(j,i)$ has $n_{sar}(j,i)$ points then $Q_{sar}(j,i)$ is a $n_{sar}(j,i)\times 3$ matrix. The path $SPath(j,i)$ is then represented by a $\left(1+n_{request}(i)+n_{sar}(j,i)\right)\times 3$ matrix. The path $Q_{sar}(j,i)$ and subsequently $SPath(j,i)$ can contain non-sampling points, new sampling points contributed by UAV(i) and old sampling points originally assigned to UAV(j), assuming UAV(j) has enough fuel and battery time left to sample all these points.

As an intermediate step define the quantity below

$$\begin{aligned} &FB\left(UAV(j), SPath(j,i)\right) \equiv \\ &\qquad \chi\left(\min\left[fuel\left(UAV(j),t\right)+\varepsilon_{fuel}, battery\left(UAV(i),t\right)+\varepsilon_{battery}\right]-T\left(UAV(j), SPath(j,i)\right)\right) \end{aligned} \tag{19}$$

The parameters $\varepsilon_{fuel}$ and $\varepsilon_{battery}$ are added to make sure that UAV(j) has sufficient fuel and battery time in the face of travel uncertainties such as head winds which may prolong flight times. The notation, "FB," in the name of the function in (19) is an abbreviation for "fuel and battery."

Let UAV(j)'s fuzzy degree of membership in the fuzzy concept "fuel-battery-separation" (FBS) be defined as

$$\mu_{FBS}\left(UAV(j), UAV(i), SPath(j,i)\right) \equiv FB\left(UAV(j), SPath(j,i)\right)\cdot \mu_{nsep}(i,j,t)\cdot \mu_{fuel}(i,j,t)\cdot \mu_{battery}(i,j,t) \tag{20}$$

The FBS fuzzy decision tree is depicted in Figure 2.

Finally, enough formalism has been developed to define the membership function for the fuzzy concept "priority for helping" (PH) for UAV(j) to help UAV(i). This membership function is defined as

$$\mu_{PH}(UAV(j),UAV(i),SPath(j,i)) \equiv \min[\mu_{FBS}(UAV(j),UAV(i),SPath(j,i)),\mu_{AUP}(UAV(j),UAV(i),SPath(j,i))] \tag{21}$$

The UAV that has the largest degree of membership in "priority for helping" is the one that will be assigned by UAV(i) to provide support. The PH fuzzy decision tree is depicted in Figure 2.

## 4. COMPUTATIONAL EXPERIMENTS

This section considers computational examples related to multi-UAV assignment during the control stage for four measurement processes. During the actual operation of the measurement processes different events arise resulting in the PH tree making various assignments.

The measurement space in the planning and control stages consists of an atmospheric volume 60 miles wide, by 60 miles long, and 15 miles in maximum altitude measured from the ground which is assumed to be a flat plane. There are initially nine points to be sampled. The points are assumed to be surrounded by spherical neighborhoods of desirability. The degree of desirability of each sample point varies with distance. The degree of desirability of different sample points at different ranges can vary.

There are many taboo points. These taboo points and their associated neighborhoods of undesirability give rise to significant degrees of mission risk for each of the paths ultimately selected by the planning and control algorithms.

An idealized model of UAV behavior has been selected for these computational examples. The UAVs are assumed to have operational efficiencies that vary with altitude. At higher altitudes the engines are considered less efficient. When the UAVs change altitude more fuel is consumed than when they fly in a plane parallel to the earth. The UAV's fuel consumption efficiency, when descending is assumed to be much better than when ascending.

Although not depicted, there are many taboo points. It is largely the taboo points that determine at which points sampling is conducted. Given the neighborhoods of desirability around the ideal sample points, there are many points at which sampling can occur.

The planning and control algorithms ultimately determine that given the UAV properties in terms of fuel consumption efficiency described above and the extent of the neighborhood of desirability around sample points, sampling should be conduced in three planes parallel to the ground plane. These three planes are located at altitudes of 5 miles, 10 miles, and 15 miles above the ground and labeled as the "1 plane," "2 plane," and "3 plane," respectively.

In the five figures in this section, the following notation is used. Each point to be sampled is labeled by an "o" and an ordered triple of numbers. The ordered triple gives each sample point's "point index," "point priority," and "path index." The "point index" gives the order in which the point is sampled along the path with a given "path index." A point with a "point index" of one is sampled first, followed by the sample point with "point index" of two and so on. The "path index" is the number of the UAV that is assigned to do the sampling. The "point priority" gives the point's priority or importance for sampling. Points with priority one are the most important followed by priority two points and so on. Finally, points will also be referred to as being at the position (x, y, z) miles where "x" refers to the horizontal axes, "y" the vertical axes, and "z" the altitude of the planes depicted in Figures 3-7.

Figure 3 depicts the planning stage. The planning algorithm determines that three UAVs are required for the measurement process. The UAVs were deliberately selected so that fuel and battery life would not be the only determining factor for point measurement assignments. The fact that the planning and control algorithms have the UAVs sample in planar regions at particular altitudes reflects fuel efficiency of the UAVs. The UAVs use less fuel when flying parallel to the earth than when ascending. They use less fuel flying equal distances in planes nearer the earth than those at higher altitudes. The distribution of points to be sampled ultimately determined that three sample planes and hence three UAVs are required.

Plane 1 of Figure 3 has four points to be sampled. The planning algorithm using the AUP FDT determined that three of the points are to be sampled by UAV(1) and one of them by UAV(2). Given the proximity of the points to be sampled by UAV(2) to the base at (0, 0, 0) miles it was determined that UAV(2) should sample in plane 2 first and subsequently sampling its third point in plane 1 while it is descending.

Plane 2 contains the first two points that UAV(2) is to sample. Plane 3 contains all three of the points that UAV(3) is to sample.

Figure 4 depicts the control stage for example 1. Initially, the UAVs follow the paths determined by the planning algorithm. Unfortunately, UAV(2) fails immediately after sampling the point at (10, 20, 10) miles in plane 2. UAV(2) sends out an omni-directional message to the other two UAVs in the field. They calculate their priority for helping using their PH FDTs. It is determined by the PH tree that UAV(3) should sample those points missed by UAV(2). So UAV(1) samples those points assigned during planning, UAV(2) samples the first point assigned to it and fails after transmission and UAV(3) samples those points missed by UAV(2).

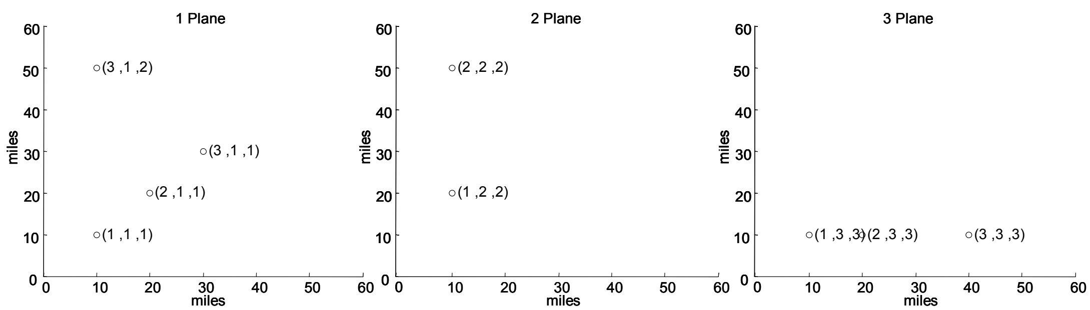


Figure 3: Sampling by three UAVs as determined in the planning stage.

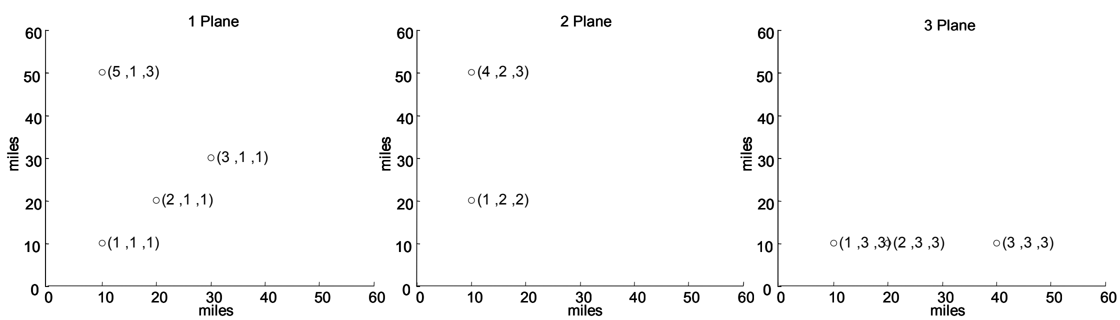


Figure 4: The control stage for example 1.

Figure 5 illustrates the control stage for example 2. The planning stage is the same as in example 1 except changes in risk evaluation during the planning stage result in the point at (10, 50, 5) miles being assigned to UAV(1) instead of UAV(2). After the point in Figure 5 at (10, 20, 10) miles is sampled, a message is sent out that the points at (40, 50, 5) and (40, 60, 5) miles should be sampled. The PH tree determines that UAV(2) should do the sampling of the new points. So UAV(2) samples its old points and then samples the points at (40, 50, 5) and (40, 60, 5) miles in that order. The other UAVs sample the points that were originally assigned**.**

Figure 6 depicts the control stage for example 3; the planning stage assignments are the same as in example 2. Sampling by three UAVs is conducted as determined in the control stage. After the point labeled (2, 1, 1) in Figure 6 is sampled, a general request is sent out for the neighborhood of two sampled points to be re-sampled. The new points to be sampled are at (10, 15, 5) miles and (20, 25, 5) miles. The PH tree determines that UAV(2) should sample the two new points. UAV(1) is the UAV that made measurements in those neighborhoods the first time. So UAV(2) completes its originally assigned points and then flies back to sample the new points. The other two UAVs sample only those points originally assigned to them.

Figure 7 represents the control stage for example 4, an extension of example 3. The first phase of this example is the same as example 3. Once again, UAV(2) samples the new points at (10, 15, 5) and (20, 25, 5) miles. After the point in Figure 7 at (10, 15, 5) miles is sampled, a request is made to make a measurement at a new point at (20, 25, 10) miles. UAV(2) is selected by the PH FDT calculations to sample the new point because of the lateness of the request.

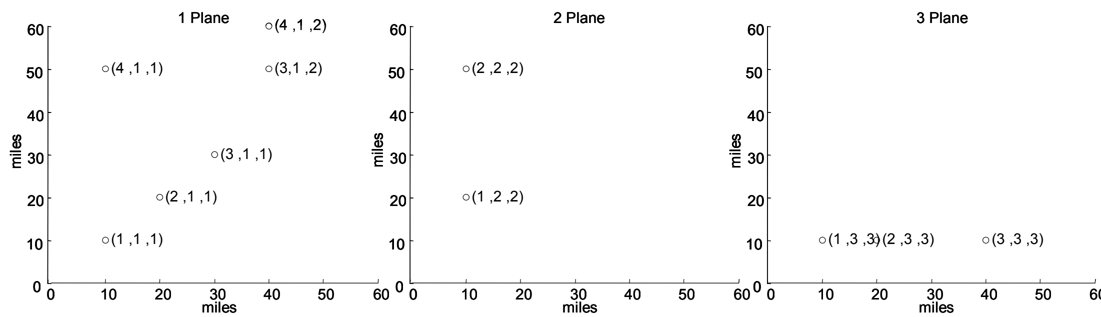


Figure 5: The control stage for example 2.

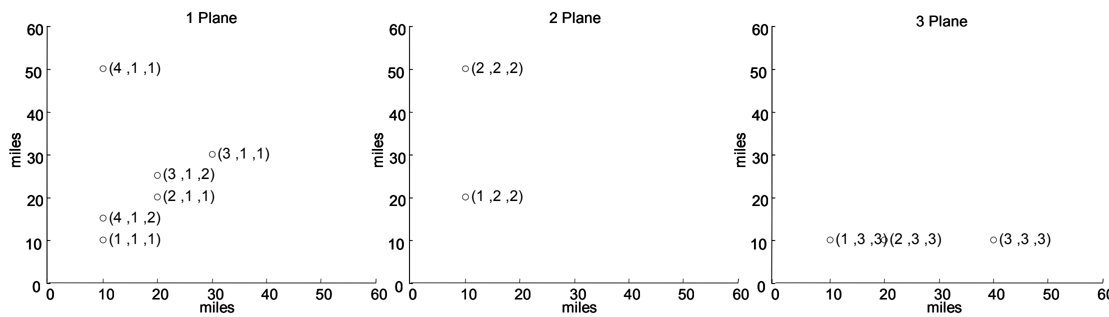


Figure 6: The control stage for example 3

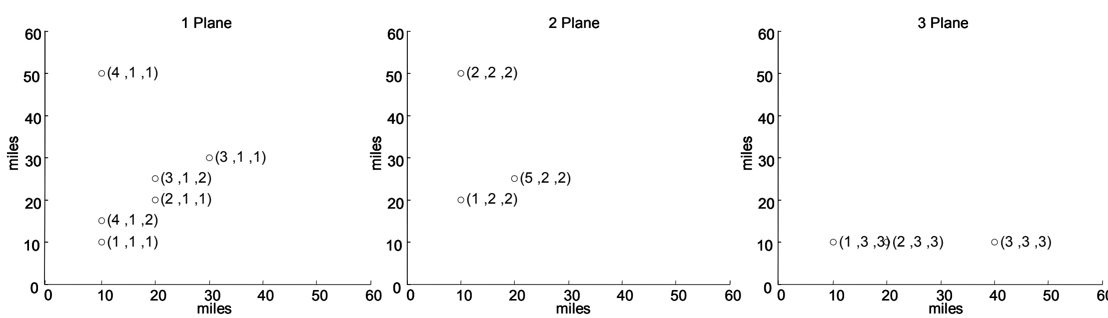


Figure 7: This is the control stage for example 4 an extension of example 3.

## 5. 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. Two fuzzy decision trees (FDTs) fundamental to the planning and control algorithms are provided in detail. The first of these assigns a UAV to a path (AUP). A related defuzzification algorithm is provided. The AUP FDT incorporates fuzzy concepts related to UAV sensor reliability, UAV non-sensor reliability, the UAV's value, the UAV custodian's risk-tolerance, and the UAVs speed. The AUP FDT also incorporates fuzzy concepts related to the path the UAV might fly including: mission risk and mission priority.

The FDT that is used for multi-UAV cooperation is developed. When a UAV requests help each UAV receiving the requests will calculate its priority for helping (PH) the requester using the PH FDT. This tree can be used by the UAV for three different types of automatic cooperation. The PH FDT permits the UAVs to collaborate without human intervention. The PH FDT incorporates the fuzzy concepts related to UAV properties used by the AUP FDT as well as path concepts somewhat different than those previously used. Experimental results are examined.

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