Distributed autonomous systems: resource management, planning, and control algorithms

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ABSTRACT

Distributed autonomous systems, i.e., systems that have separated distributed components, each of which, exhibit some degree of autonomy are increasingly providing solutions to naval and other DoD problems. Recently developed control, planning and resource allocation algorithms for two types of distributed autonomous systems will be discussed. The first distributed autonomous system (DAS) to be discussed consists of a collection of unmanned aerial vehicles (UAVs) that are under fuzzy logic control. The UAVs fly and conduct meteorological sampling in a coordinated fashion determined by their fuzzy logic controllers to determine the atmospheric index of refraction. Once in flight no human intervention is required. A fuzzy planning algorithm determines the optimal trajectory, sampling rate and pattern for the UAVs and an interferometer platform while taking into account risk, reliability, priority for sampling in certain regions, fuel limitations, mission cost, and related uncertainties. The real-time fuzzy control algorithm running on each UAV will give the UAV limited autonomy allowing it to change course immediately without consulting with any commander, request other UAVs to help it, alter its sampling pattern and rate when observing interesting phenomena, or to terminate the mission and return to base. The algorithms developed will be compared to a resource manager (RM) developed for another DAS problem related to electronic attack (EA). This RM is based on fuzzy logic and optimized by evolutionary algorithms. It allows a group of dissimilar platforms to use EA resources distributed throughout the group. For both DAS types significant theoretical and simulation results will be presented.

Keywords: fuzzy logic, resource management, evolutionary computing, robotic control, distributed autonomous systems

1. INTRODUCTION

A DAS is a collection of machines, such that many of them have an algorithm onboard that allows them to make decisions, adapt to changing conditions in real-time, and cooperate through communications with the other machines making up the DAS to increase the probability of mission success for the group.

Although not necessarily part of the definition of a DAS, it is desirable that the decision algorithms allow each machine to exercise judgment at the quality level of the best human experts, but much faster. Also, the decision algorithms should make optimal use of the many sensors and other resources distributed over the DAS. The machines should work together in an optimal fashion. The machines should be able to take into account many different constraints in making their decisions. Finally, only processed information should be sent between machines to reduce communications bandwidth requirements.

Two DASs will be considered. Primary attention will be given to a DAS that facilitates localization of an electromagnetic source (EMS) using matched field processing[1,2] (MFP). This DAS, referred to as the EMS DAS, consists of multiple UAVs each under the control of its own decision theoretic algorithm (DTA), an interferometer platform (IP) also under the control of a DTA and guide stars. The IP is actually an airplane with an interferometer onboard that measures emissions from the electromagnetic source whose position is to be estimated. The UAVs will measure the index of refraction of the atmosphere in real-time to facilitate estimation of the EMS position through matched field processing. In MFP, measured field emissions from a source whose position is unknown are compared to theoretically calculated electromagnetic fields, referred to as replica fields. To calculate the replica fields the index of

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refraction of the propagation medium is essential, thus the reason for the UAV measurements. The guide stars are objects of known position, magnitude and phase that have been placed in position by the blue force. The blue force is the group desiring to know the position of the EMS. The guide stars' properties are used to correct for wavefront distortion (WFD) in a fashion similar to WFD correction methods in astrophysics and ultrasonics[3,4]. The DTA aboard the UAVs will allow them to determine their own course, change course to avoid danger, sample phenomena of interest that were not pre-planned, and cooperate with other UAVs and other machines in the DAS.

The second DAS problem to be considered is multi-platform cooperative electronic attack (MEA). The MEA DTA was evolved for it by a symbolic evolutionary algorithm[5] (SEA). The MEA algorithm assumes data has already been fused, including IDs. This DTA allows a group of platforms to automatically engage in cooperative electronic attack (EA). They will automatically help each other, and combine EA techniques and power for greater success. Also, the group remains stable if platforms are lost, and late arriving platforms may join the DAS without hesitation and contribute to its success. This DTA does not require human intervention. There is no human commander central or local.

To be consistent with terminology used in artificial intelligence and complexity theory[6], the term "agent" will sometimes be used to mean platform, also a group of allied platforms will be referred to as a "meta-agent." Finally, the terms "blue" and "red" will refer to "agents" or "meta-agents" on opposite sides of a conflict, i.e., the blue side and the red side.

Section 2 provides an overview of electromagnetic source localization through MFP using mutiple UAVs for realtime index of refraction measurement and motivates the need for the algorithms described in subsequent sections. Section 3 discusses the electromagnetic measurement space, UAV risk, UAV risk tolerance and the planning algorithm. Section 4 discusses DAS interactions and the control algorithm. Section 5 discusses the MFP based post-processing algorithm and validation. Section 6 provides a comparison of DAS interaction models. Finally, section 7 provides a summary.

2. ELECTROMAGNETIC SOURCE LOCALIZATION THROUGH MFP

It is frequently desirable to be able to estimate the position of an electromagnetic source. One approach involves the use of hybrid time-difference-of-arrival[7] (TDOA) methods to rapidly geo-locate threats based on RF emissions. These techniques require multiple platforms with sophisticated sensor suites and very high bandwidth data links to determine unambiguous geo-location. Another approach that escapes the requirements for sophisticated sensors and ultra-high bandwidth communications is MFP. In MFP an interferometer detects the electromagnetic emissions of the EMS. Estimates are made for the possible positions of the EMS. For each possible position a theoretical electromagnetic field is calculated as if there were an EMS at that position. These theoretical fields are known as replica fields. The replica fields are compared through an inner product with the measured field. The position corresponding to the maximum value of the inner product is the EMS's MFP position estimate. The MFP procedure has been applied extensively in acoustics[1,2] and shows promise for electromagnetic source localization.

To calculate the replica fields essential to the MFP algorithm, it is necessary to known the index of refraction of the atmosphere between the EMS and the IP. The index of refraction is subject to short time scale fluctuations and over longer periods of time can change significantly. In addition, there can be phenomena that can seriously impact the MFP position estimates. An example is the formation of a radio hole[8]. If the IP should fly into a radio hole then it will not be able to record emissions from the EMS. If some of the elements of the interferometer should happen to be in the radio hole and others not, and the radio hole is not modeled in the replica field calculations, then the MFP position estimation error can be significant. For the reasons outlined, it is useful to have real-time updates of the index of refraction.

The function of the EMS DAS will be to conduct real-time measurements of the index of refraction. Each UAV will have its own DTA allowing it to determine new optimal trajectories in real-time subject to changing conditions. Also, the DTAs 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 DTA and three classes of help requests which are discussed in section 4.2.

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 DTAs 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 support using a fuzzy logic procedure described below. The UAVs send their priority for providing support 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.

Figure 1 provides an overview of the process. The filled circle represents an EMS. The double-arrow represents an interferometer that will measure emissions from the EMS. The unfilled triangles are UAVs that work in a coordinated fashion to measure the index of refraction. These index of refraction measurements are sent to the interferometer platform to be incorporated into the replica field calculations, which is part of the MFP estimation process. The star shaped objects are the guide stars. The guide stars are inexpensive multi-spectral electromagnetic sources of known position, magnitude and phase. Their positions are pre-calculated by the planning algorithm allowing them to be deposited in optimal locations. Since they will be beacons of known position, magnitude and phase they can be used to correct for wavefront distortion (WFD) due to inhomogeneities in the propagation environment. This ultimately should improve the EMS position estimate. This process of WFD correction is kindred to what is done in observational astrophysics when using a Knox-Thompson algorithm[3]. Given a star of unknown magnitude and phase within a turbulence cell where there is a star of known magnitude and phase, the Knox-Thompson algorithm effectively allows the estimate of the unknown star's magnitude and phase while subtracting out the effect of the earth's turbulent atmosphere.

3. MEASUREMENT SPACE, RISK, RISK TOLERANCE AND THE PLANNING ALGORITHM

The measurement space consists of the electromagnetic propagation environment where UAVs and the IP make their measurements. This environment includes sampling points and the desirable neighborhoods that surround them. The sampling points or the desirable neighborhoods are where the UAVs will make measurements. The method of determining the sampling 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, 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; onboard sensor payload; onboard resources such as fuel, battery, computer CPU and memory; etc. The priority of sampling 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[8] 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 sampling points. The priority of a sampling point is equal to the subjective probability of the hypothesis position from which the associated ray emerges.

Each sampling 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 sampling point may also be a taboo point or reside within an undesirable neighborhood. In the case the sampling point coincides or is near a taboo point and at least part of the sampling 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.

3.2 UAV risk, the fuzzy risk tree and 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. 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 subject to risk, risk tolerance and many other issues.

3.2.1 Quantifying UAV risk and risk tolerance

When determining the optimal path for the UAVs to follow both the planning algorithm and the control algorithm running on each UAV takes 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[9], 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.

Risk is represented as a fuzzy decision tree[5,10-14] as depicted in Figure 2. 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),

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

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

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

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 ∈ ***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 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

$$\mu_{RISKt}^{(\vec{x})} = \bigvee_{\alpha \in RC} \mu_{\alpha}^{(\vec{x})}, \tag{5}$$

with the "Undesirable Neighborhood" defined as follows:

$$\text{Undesirable Neighborhood} = \left\{ \vec{x} \middle| \mu_{RISK}^{(\vec{x})} \ge \frac{1}{4} \right\}. \tag{6}$$

The concept of *risk tolerance* is used to specify the subset of the undesirable neighborhood that a UAV may fly through. The risk tolerance, τ_i, of the i^{th} UAV, UAV(i) is defined such that UAV(i) may fly through the following subset of the undesirable neighborhood of taboo point, q_{taboo},

$$\text{Risk Tolerant Subset} = \left\{ \vec{x} \middle| 0 < \mu_{RISK}^{(\vec{x})} \le \tau_i \right\}. \tag{7}$$

The concept of risk tolerance is defined to allow higher risk settings for the UAVs. By letting the UAVs have greater risk tolerance it is anticipated that the probability of mission success will be greater. It is also anticipated that the probability of the mission's cost exceeding a higher threshold will also be higher. The effect of a variable risk tolerance on the DAS's probability of mission success and probability of cost exceeding a certain threshold will be investigated in detail in the near future. For now risk tolerance is simply a parameter to be set. In the future it will be rendered as a function of the value of the UAV in dollars, the UAV's propulsion system properties and estimated reliability, the sampling points' priority, etc.

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 effective distance between A and B as $d(\vec{r}_A,\vec{r}_B)$. 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. If both $\vec{r}_A$ and $\vec{r}_B$ are sample points then the effective distance is the Euclidean distance between the points multiplied by the ratio of the sampling speed to the non-sampling speed; otherwise, it is simply the Euclidean distance between the points. If only the effective distance between points A and B and the travel risk are taken into account the path cost is given by $d(\vec{r}_A,\vec{r}_B)+\mu_{RISK}(\vec{r}_B)\cdot V(i)$, where $V(i)$ is defined to be the relative value of the i^{th} UAV in $10,000 units.

Two other concepts contributing to the path cost are estimates of the reliability of the i^{th} UAV's sensors and propulsion system. Let these reliability estimates be denoted as μ_{rs} and μ_{rp}, respectively. These fuzzy grades of membership in the concepts "sensor reliability" and "propulsion reliability", abbreviated as "rs" and "rp", respectively, assume values between zero and one, inclusive. A value of unity implies high reliability; and a value of zero, that the system is totally unreliable. A form of the path cost that incorporates Euclidean distance, travel risk, and reliability is

$$path\_cost(A,B) = d(\vec{r}_A,\vec{r}_B)+\mu_{RISK}(\vec{r}_B)\cdot V(i)+\left({}^{1}\!/\!{}_{\mu_{rs}(\vec{r}_A,\vec{r}_B)} + {}^{1}\!/\!{}_{\mu_{rp}(\vec{r}_A,\vec{r}_B)} - 2\right)\cdot V(i). \tag{8}$$

If the total candidate path for the mission consists of the following points on the UAV lattice,

$$Path(i) = \{A_1,\quad A_2,\quad \ldots,\quad A_n\}, \tag{9}$$

then the total path cost is defined to be

$$total\_cost(Path(i)) \equiv \sum_{j=1}^{n-1} path\_cost(A_j, A_{j+1}). \tag{10}$$

The form of the path cost given in (8, 10) is non-unique, a variety of expressions might be used. The expression on the right-side of (8) has the advantage that if either the sensors or propulsion systems are totally unreliable, the cost goes to infinity, which is appropriate since such an extremely unreliable UAV should not be used. If both sensors and propulsion are extremely reliable, then the contribution to the path cost related to reliability issues is zero due to the subtraction of two on the right-side of (8). Finally, the reliability terms in (8) can be made a function of time or the end points of the line segment being traversed, this allows the modeling of decaying reliability, automatic repair processes or a UAV that automatically switches to a redundant sensor system when the previous sensor fails.

Determining the optimal path for the the i^{th} UAV consists of minimizing (10) such that the total travel time remains less than the amount of fuel and battery life measured in time. Also, the fuzzy membership functions corresponding to sensor and propulsion risk must remain below their associated thresholds.

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 assigns as many high priority points to a UAV as possible with the UAV's fuel, battery life, estimated reliability and effectiveness being the limiting constraints. When the planning algorithm determines a UAV has been assigned as many points as it can handle, assignments are made to the next highest priority UAV. This process is continued until the points required for sampling are exhausted. It is important to observe that a single UAV can sample points of different priority if that is efficient. Finally, if there are not enough UAVs to sample all the points, the approach underlying the planning algorithm assures the highest priority points are sampled first, leaving the lowest priority sampling point to the last.

4. DAS INTERACTION AND THE CONTROL ALGORITHM

The planning algorithm determines based on the best a priori knowledge the minimum number of UAVs required for the measurement process, the order in which UAVs are used, the paths the UAVs will fly, the priority of points to be sampled and regions to avoid. During the travel and measurement process it is inevitable that priority of points for sampling will change, new interesting physical phenomena will be discovered and old points will prove to be uninteresting. Also regions, initially thought to be threatening will prove to be benign and it will become more efficient to reroute UAVs through these previously excluded regions. Sampling new points, ignoring points that are no longer of interest and rerouting through new regions require an algorithm that allows changes in real-time. This section will describe the real-time control algorithm and the types of interactions it allows between the UAVs and the IP.

4.1 Overview of real-time control

Each UAV has a real-time algorithm onboard it that allows recalculation of paths during flight. As in the case of the planning algorithm the control algorithm uses an A-star algorithm[15] to do the best path calculation, employs fuzzy logic and solves a constrained optimization problem. Although this can require a number of minutes of computation on a two to three gigahertz computer, this is considered adequate given the required UAV flight time between points.

A recalculation of flight paths can be triggered by a number of events such as a weather broadcast that indicates new taboo regions, the discovery by a UAV of 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. The current formulation of the control algorithm gives the UAVs significant autonomy in making decisions about travel, measurement, and rendering support to other UAVs. This approach is still under evaluation.

4.2 Methods of assigning priority for providing support

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.

4.2.1 The three request classes

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.

The third request class occurs when a UAV has definitely determined that it is malfunctioning and should not or can not continue to sample. The supporting UAV will take over the requester's sampling task. The requester returns to base if possible.

4.2.2 Determining the priority of contributing support

The determination of priority of contributing support (PCS) currently uses fuzzy logic and is a weighted sum of four contributing terms. These terms are the value in dollars of the UAV, the distance of the potential helper from the position where help is to be rendered, the amount of fuel the supporting UAV has, and the priority of the points the potential supporting UAV was scheduled to sample.

It is likely this weighted sum, if it is to be used in the future should include other terms. The new terms would involve the estimated reliability of the helping UAV's sensors and propulsion systems, the priority of the points that the requesting UAV desires to be sampled as well as the priority of the points other adjacent UAVs are sampling. This last priority related to adjacent UAVs is introduced because, if the potential supporter flies a great distance to help a UAV with relatively low priority sample points and a UAV that was adjacent fails, then some very high priority points may not be sampled.

5. MFP POST-PROCESSING ALGORITHM AND VALIDATION

While the UAVs make index of refraction measurements they are sending this information to a base facility or the IP. Once sufficient index of refraction measurements are received and the IP has recorded sufficient emissions from the EMS, then MFP post-processing can be conducted. The MFP yields an estimate of the location of the EMS, which is the ultimate goal of the cooperative measurement behavior of the IP and the UAVs. In a simulation environment where "truth" is known the MFP step can be used to show the effectiveness of the entire process. This section discusses the three main MFP processors used including techniques that take advantage of the fact that the IP is a moving platform. The section concludes with a discussion of MFP results.

5.1 MFP processors

Many MFP processors have been applied in the undersea acoustics literature[1]. For this initial electromagnetic effort three processors were applied: the simple linear processor, the gradient processor and the extended linear processor.

As previously noted, MFP compares the EMS emission measurements made by an interferometer. The interferometer used will typically have multiple elements. Each element will be used to make a measurement. The measured values are used to form a vector referred to as the measurement vector (MV). From various hypothesis positions replica fields are calculated and the results of measurement by each interferometer element are simulated. The simulated measurements are used to form a vector analogous to the one formed from the measurement process and referred to as a replica vector (RV). There is a RV calculated for each replica field.

5.1.1 The simple linear MFP processor

For the case of the simple linear MFP processor (SLMP) measurement and replica vectors are determined at only one position of the IP. The use of the word "simple" in the designation "simple linear MFP processor" refers to formation of the vectors after making measurements at only one position of the IP. Both the measurement vector and the replica vectors are rendered as unit vectors by dividing by their respective norms. The resulting unit vectors are referred to as the unit measurement vector (UMV) and unit replica vector (URV), respectively. The SLMP is the inner product of the UMV and the URV. For the SLMP, the best position estimate corresponds to the hypothesis position that maximizes the SLMP.

5.1.2 The gradient MFP processor and IP motion

The IP is a moving platform and over time the EMS will make multiple emissions. The gradient MFP processor (GMP) takes advantage of the motion of the IP and multiple emissions in time of the EMS. For the GMP, the difference between MVs at two IP positions is recorded. For a single position of the IP, the difference in measured values across the interferometer elements is also recorded. The two types of differences allow partial derivatives and hence the field gradient to be approximated as ratios of finite differences. The MV vector is replaced by a measurement matrix (MM) whose entries correspond to the gradient of the measured electromagnetic field. An analogous replica MFP matrix (RMM) is calculated for each replica field. Both the MM and the RMM are normalized by dividing by the square root of the sum of the squares of each matrix's respective elements. This normalization procedure is carried out so that when a sum of squares of each normalized matrix's elements is computed, the result is unity for non-zero matrices. These normalized matrices are referred to as the unit MM (UMM) and unit RMM (URMM), respectively. The GMP consists of forming the sum of the product of corresponding elements of the UMM and URMM. The best GMP position estimate arises from the hypothesis position that maximizes the GMP.

5.1.3 The extended linear array MFP processor and IP motion

The extended linear array MFP processor (ELAMP) also takes advantage of the IP's motion. Instead of restricting measurements to two IP positions, the ELAMP can incorporate measurements at many positions, typically four.
For the ELAMP, the MV consists of concatenations of the MVs for each position. The UMV is formed by dividing by the concatenated vector's norm. The URV is formed in an analogous fashion for each replica field calculation. The ELAMP is the inner product between the UMV and the URV. The hypothesis position that maximizes the ELAMP corresponds to the best MFP position estimate.

5.2 MFP results

Computational experiments were conducted using a variety of meteorological conditions and all three processors. Guide star based WFD correction was not incorporated, but will be included in future publications. The simulated EMS was assumed to have a frequency of one gigahertz. It is well known that at such high frequencies there can be significant fluctuations in the EMS field due to small inhomogeneities in the propagation environment. These fluctuations can have a significant effect on the SLMP, resulting in a reduction of EMS position estimate quality. For an EMS and IP separated by 50 miles in a propagation environment with a vertically stratified index of refraction field, small random azimuthal variations in the index of refraction could produce an estimation error of the EMS position of a mile or more even after correction of the index refraction using UAV measurements and an index of refraction interpolation model.

Due to the use of measurements at two different positions, the GMP was able to produce better MFP position estimates. The error in position estimate after using measured index values and interpolation was typically well under one mile.

In some experiments, presumably due to the inclusion of additional measurements made by the IP, the ELAMP showed results superior to the SLMP and the GMP. After replacing the original index of refraction field with one constructed from UAV measurements that were subsequently interpolated, the ELAMP yielded position estimates with an error typically on the order of feet or less.

All three processors exhibited errors in position estimates of a mile or more over 50 miles if extreme horizontal variation in the index of refraction was permitted. An initial examination of experimental data and consultation with experts seems to show that such extreme horizontal variation in index of refraction over the space of one to five miles is not observed in nature most of the time so this is not considered a significant difficulty with the MFP procedure.

For all three MFP processors there were fluctuations in performance that must be explored and explained. Notably, when some interferometer elements were turned off, resulting in a smaller number of measurements, the MFP estimate improved. Presumably, this relates to the model of the index of refraction allowing random horizontal variation in value. If for a particular element the random variation was large and this was not modeled in the replica field then a particular interferometer element could bias the MFP estimate. Fortunately, as observed above this type of phenomenon seems to be rare in nature.

6. COMPARISON OF DAS INTERACTION MODELS

It is interesting to compare the EMS DAS to the previously referenced MEA DAS. The MEA DAS has been under development longer than the EMS DAS. Both DAS allow interaction between the agents making up the DAS. In some versions of the MEA DAS, like the EMS DAS help request are radiated in an omni-directional fashion with potential supporters each sending a priority score to the requester. The requester then sends a confirmation to the agent with highest priority that it may help. The MEA DAS shows greater flexibility in behavior by virtue of it fuzzy parameter selector tree (FPST), a fuzzy decision tree that allows the MEA RM to change its parameters and hence behavior significantly in real-time. A FPST has not been introduced into the EMS DAS controller as of yet. This will be a subject of future consideration.

The MEA DAS also shows difference forms of cooperation between agents since for different threats the RM can select different combined electronic attack (EA) techniques. This reflects the different problem that motivated the MEA DAS's design. It is likely the different types of interactions that the UAVs are subject to, for the EMS DAS will increase in future versions.

7. SUMMARY

A distributed autonomous system (DAS) consists of a collection of machines or agents, most of which have some autonomous decision making ability that allows them to interact through communication for the mutual benefit of the DAS. A DAS consisting of a collection of unmanned aerial vehicles (UAVs), an interferometer platform (IP) and guide stars has been discussed as well as three related algorithms that are under development. The IP measures emissions from an electromagnetic source (EMS) and the UAVs measure the index of refraction of the propagation environment in real-time. The emissions and index of refraction measurements are used in a process known as matched field processing (MFP) to estimate the position of the EMS. Three algorithms are discussed that facilitate the MFP process. The first is the planning algorithm that determines which points to sample and which UAV will sample them, the path that each UAV and IP will fly, and the position of the guide stars. The second algorithm is the control algorithm. This algorithm resides on each UAV and allows it to changes its path, sampling points and cooperative behavior with respect to the IP and other UAVs in real-time. Both the planning algorithm and control algorithm employ best path algorithms, fuzzy logic and constrained optimization. The final algorithm discussed is the post-processing algorithm that incorporates the measured quantities into a MFP estimate of the EMS position. Experimental and validation results are discussed. Comparisons are drawn between the EMS DAS control algorithm and a resource manager developed previously for a DAS dedicated to multiple platform cooperative electronic attack.

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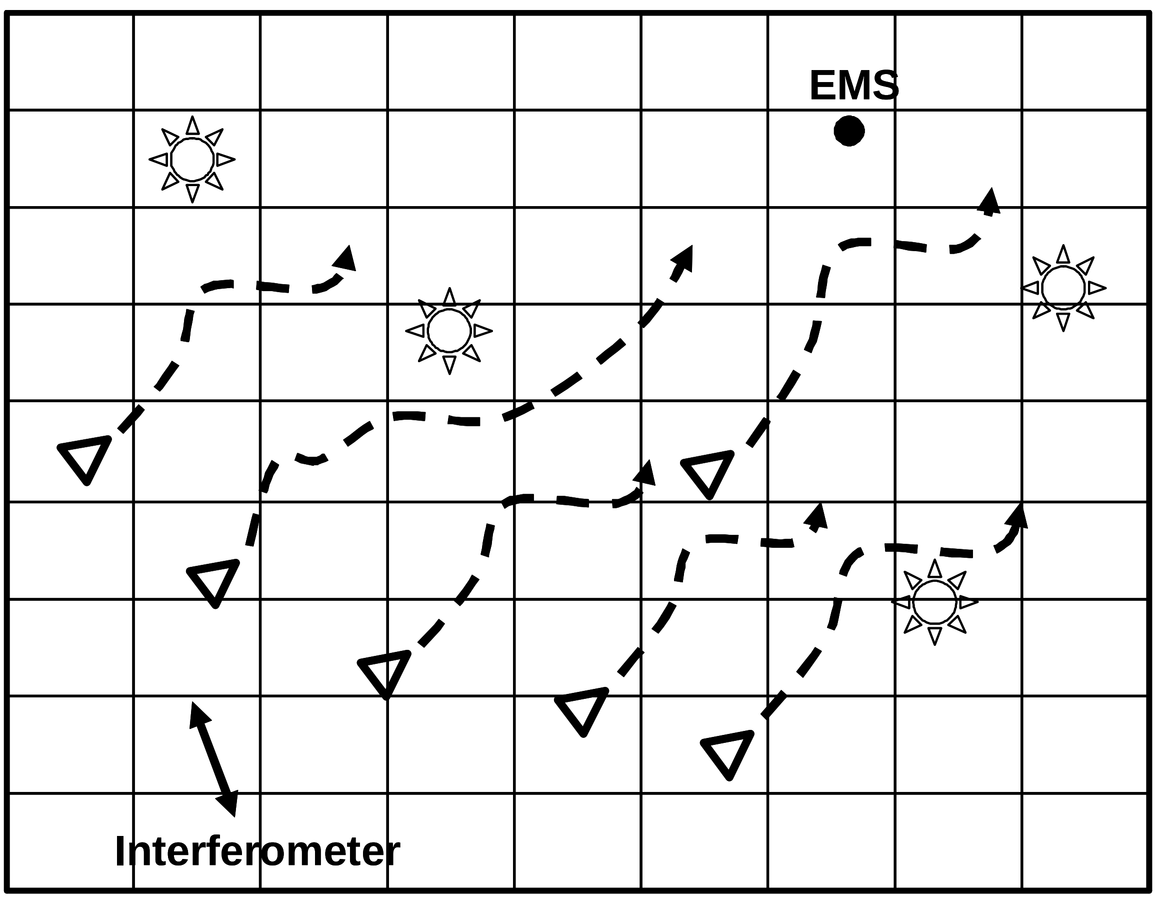

Figure 1: The grid represents the electromagnetic propagation environment; the filled circle, the EMS whose position is to estimated, the double-headed arrow, the IP platform; unfilled triangles, UAVs; and the star shapes, guide stars.

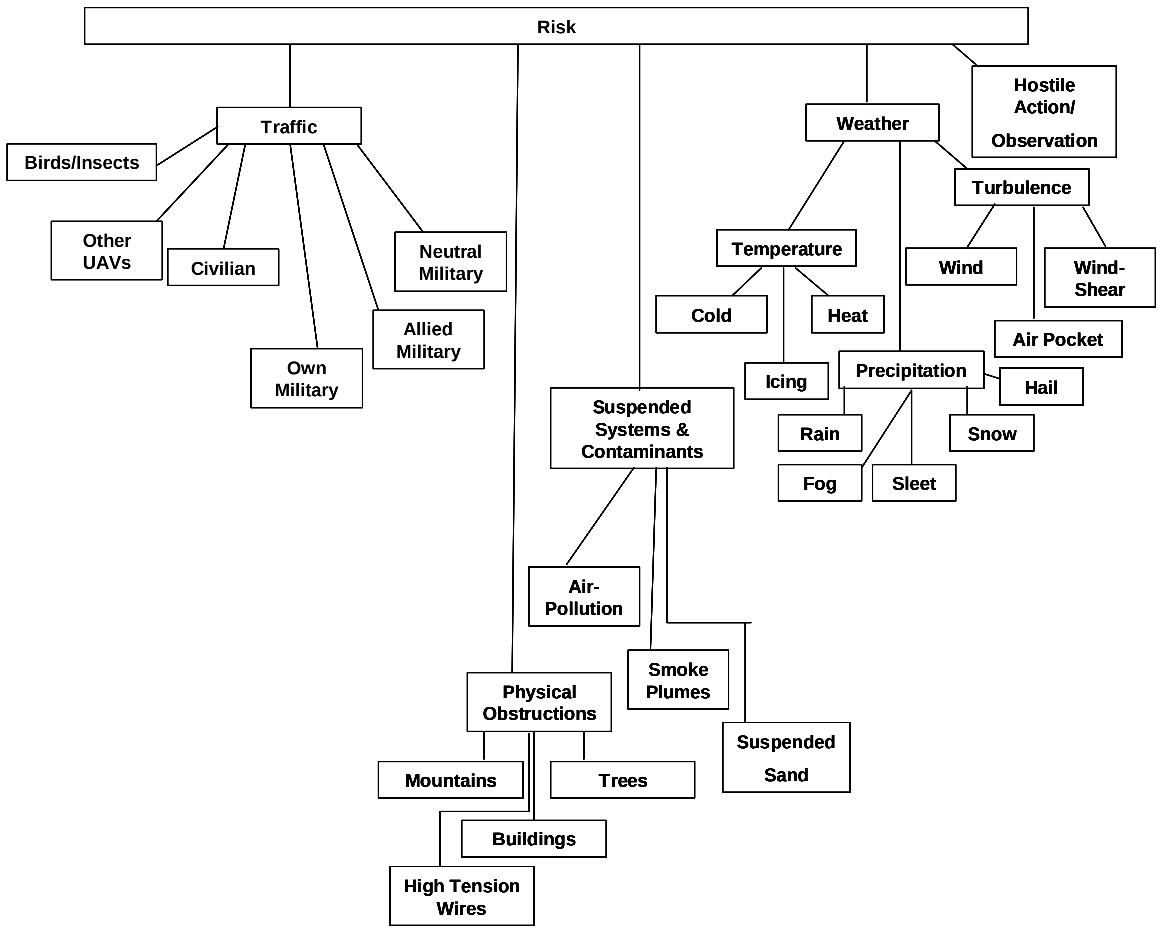

Figure 2: The fuzzy risk tree and its 25 fuzzy root concepts.