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Evidential Map-Building Approaches for Multi-UAV Cooperative Search

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Abstract— **This paper addresses the map building problem for cooperative search by a team of Uninhabited Air Vehicles (UAVs) operating in an unknown and uncertain environment . We present and compare two evidential map-building approaches based on Bayesian theory and Dempster-Shafer theory respectively. We illustrate how to utilize the generated maps into the UAVs path planning procedure so that they could cooperatively localize targets in the environment. The simulation results illustrate the effectiveness of the proposed strategies.**

I. INTRODUCTION

Control of networked multi-vehicle systems designed to perform complex coordinated tasks is currently an important and challenging field of research [1], [2], [3], [4]. One of the key questions is how to coordinate the behavior of multiple vehicles especially in an environment whose structure is unknown and dynamic. This paper focuses on the multi-vehicle cooperative search problem where a team of Uninhabited Air Vehicles (UAVs) seek to find targets in an unknown and uncertain environment [5], [6], [7], [8], [15]. Since the environment is unknown, there is limited or even no *a priori* information about the environment such as the distribution of targets and threats. The UAVs need to search the environment so that they can incrementally obtain knowledge of the environment and locate targets. The decision on where to search next is driven by the objective to increase the chance of locating targets and possibly avoiding threats. For this purpose, the UAVs require a good model of the environment and they should be able to construct and consistently update their environment models based on the sensory information. The efficiency and quality of the environment model will consequently affect the UAVs short-term and long-term planning and decision-making activities.

Since there always exist various kinds of inaccuracies and uncertainties in UAVs sensory information about the real world, sensory information from multiple sensors and different vehicles needs to be combined to obtain the best knowledge of the environment. One common method is to treat sensor observations as *evidence* and uses evidential reasoning techniques to fuse the sensor information, extract and share knowledge. Most available evidential fusion methods are broadly based on Bayesian Theory, Dempster-Shafer Theory and Fuzzy theory based techniques [9]. These methods have already been successfully utilized in various applications, e.g., the mobile robot exploration and navigation problems [10], [11], [12], [13], [14].

In this paper, we present two evidential methods to incrementally build cognitive maps for directing a group of UAVs to perform cooperative search tasks. Both of the formulations are suitable for sensor measurements obtained in a sequential manner and they also allow the information to be incorporated into a previously formulated finite horizon optimal control problem for the multi-UAV cooperative path planning problem in the search mission [8]. Some simulation results and analytical discussions are given to demonstrate the feasibility of using these map building methods in the cooperative search problem and to compare the performance of these two methods.

II. PROBLEM DEFINITION

We consider a team of UAVs engaged in searching for targets in an environment with the objective to identify as many targets as possible and minimize the loss or damage of the UAVs. The *environment* is a bounded $L_x \times L_y$ cellular area, populated by stationary non-threatening targets and threats. There are M threats, $\gamma_i,\ i = 1,\ldots,M$, located at (x_i^γ, y_i^γ) and each of them has *a priori* known attack region ϕ_i over which the threat is capable of destroying the UAVs with *a priori* known kill probability $p_{kill}^i \in [0,1]$. However, the number and locations of the targets are initially unknown and we assume that there is at most one target in each cell. A team of N identical UAVs move synchronously in discrete time and search the given environment using the equipped sensors (with imperfect detection accuracy). They can also communicate with each other for exchanging information. Here, to simplify the problem, we assume that each UAV can receive all the information from other UAVs without any delay. This assumption will be relaxed later.

At time t, UAV i has cell position $\lambda_i(t) = (x_i(t), y_i(t))$, and can be in one of eight possible orientations, $o_i(t)$: 0 (north), 1 (northeast), 2 (east), 3 (southeast), 4 (south), 5 (southwest), 6 (west), and 7 (northwest). It also has an *alive* state flag $\delta_i(t) \in \{0,1\}$ to indicate whether it has been destroyed at time t, where $\delta_i(t) = 1$ means that the UAV i is alive at time t. Thus the state of UAV i at time t can be denoted by $v_i(t) = [\lambda_i(t), o_i(t), \delta_i(t)]$.

Each UAV moves from one cell to another neighboring cell at each time step and it can only change its orientation by at most one step, that is, $o_i(t+1) \in \{o_i(t) - 1, o_i(t), o_i(t)+1\}\ mod\ 8$. In this way, each UAV has three possible positions for the next time step, i.e. turn left, turn right or go straight, designated by $\{l$ (left), f (front), r (right)$\}$. This essentially means that the UAV's maximum

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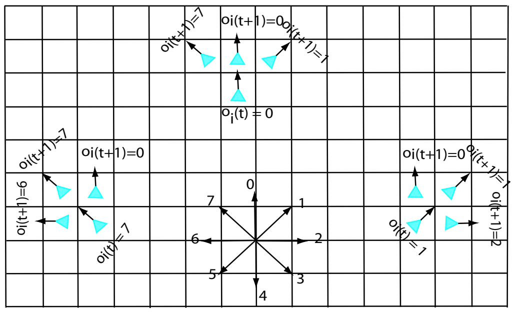

Fig. 1. Possible transition choices for agents (UAVs) in all 8 orientations.

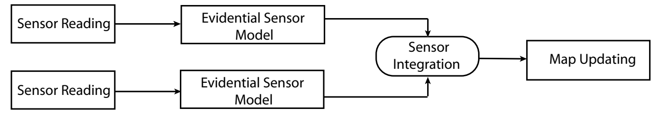

Fig. 2. Block diagram representation of evidential map building.

turning capability is $45°$. The control decision for UAV i is its path selection at each time step t, which can be denoted by $u_i(t) \in \{l, f, r\}$. Figure 1 shows this dynamics graphically for various orientations.

The threat actions in the environment, denoted by $\omega(t) = [\omega_1(t), \omega_2(t), \ldots, \omega_M(t)]$, will stochastically determine the transition of UAVs' alive state $\delta_i(t)$ since UAV i will be destroyed with probability p^j_{kill} in threat j's attack region, thus causing $\delta_i(t) = 1$ change into $\delta_i(t) = 0$. In summary, a vehicle's transition function can be expressed as:

$$v_i(t+1) = f_v(v_i(t), u_i(t), \omega(t)) \tag{1}$$

In our model, UAVs use the q-steps-ahead path planning method, that is, each UAV plans its path q steps ahead of its current location, adding a new move at each time-step. For simplicity, in this paper we use $q = 1$, but the extension to $q > 1$ is straightforward. Thus, at time-step t, the UAV i makes its path decision $u_i(t+1)$.

The UAV's decision on where to search is based on its model of the environment, which can be utilized to quantify the values to search certain areas of the environment and it should be able to be consistently updated based on the sensory information. In our method, the UAVs use *cognitive maps* as their environment model and maintain these maps in their *information base*. Cognitive maps are Cartesian grids containing cells, where each cell is assigned a certain value representing the probability or vehicles' belief in the corresponding region being occupied by a target or threat. As UAVs search the environment, the cell values are incrementally updated by incorporating the UAVs' sensor readings using the sensor fusion algorithm and using the appropriate sensor model so that the non-ideal sensor measurements could be accounted for. Here, we present two evidential methods for UAVs to incrementally build cognitive maps, which will help UAVs to cooperatively localize possible targets in the environment.

III. Evidential Map Building Methods

The basic idea of the evidential map building methods is to treat sensor observations as *evidence* and use evidential reasoning techniques to fuse sensor information and hence to extract and share knowledge. This map building procedure is illustrated in Figure 2. An initial map of the environment usually can be created based on the *a priori* knowledge. Afterwards, the map is successively refined by processing additional sensory information as it becomes available. Most available evidential fusion methods are based on Bayesian and Dempster-Shafer theories [9]. In Bayesian based evidential methods, the sensor evidence is represented probabilistically and is fused with other information using Bayes rule. On the other hand, the Dempster-Shafer based evidential methods consider sensor evidence as *belief* and use Dempster-Shafer rule to incorporate the sensor information. Another important difference between the Bayesian and Dempster-Shafer approaches lies in their methods to assign initial values to the states which are completely unknown prior to any measurements. In the following parts, we will discuss these two approaches in detail and show how to apply them into the target cognitive map building problem for the UAV cooperative search task.

A. Bayesian Map Building Formulation

In the cellular environment used in this paper, considering the target information, the only state of interest for each cell is target present or not, written as $s(x, y) \in \{0, 1\}$, where $s(x, y) = 1$ indicates a target present in cell (x, y), and $s(x, y) = 0$ indicates no target present in that cell. The cognitive map used to store the target information is called the *target probability map*, denoted by $P(t)$. In $P(t)$, each cell has a *target probability* $p(x, y, t) \in [0, 1]$ defined as:

$$p(x, y, t) = P(s(x, y) = 1 \mid B_t) = P(A \mid B_t) \tag{2}$$

where A denotes an event that $s(x, y) = 1$ and B_t is the vector of all sensor readings for cell (x, y) taken upto time t. $p(x, y, t)$ actually represents the probability of a target present in cell (x, y) according to the vehicle's current knowledge. The higher the target probability is, the more likely the vehicle believes the cell is occupied by a target. This formulation allows the use of Bayesian inference to fuse sensor readings, which can be expressed as

$$P(A \mid b) = \frac{P(b \mid A)P(A)}{P(b)} \tag{3}$$

where b denotes the new sensor reading. $P(A)$ is the required *a priori* probability of the target state in that cell. If there is no such *a priori* information available, one standard approach is to assign the *a priori* probability as 0.5, that is $P(A) = P(s(x, y) = 1) = 0.5$. If some target distribution knowledge is available, then it can be represented using different initial probability values. The normalization term $P(b)$ in (3) can be calculated as follows

$$P(b) = P(b \mid A)P(A) + P(b \mid \bar{A})P(\bar{A}) \tag{4}$$

where $P(b \mid A)$ and $P(b \mid \bar{A})$ depend on the sensor model, which qualitatively describes the probability of obtaining a sensor reading b given certain target present situations. Therefore, we define two parameters to characterize the sensor's uncertainty: the sensor detection rate p_c and the false alarm rate p_f:

$$p_c = P(b(x,y) = 1 \mid A) \quad (5)$$
$$p_f = P(b(x,y) = 1 \mid \bar{A}) \quad (6)$$

where $b(x,y) = 1$ indicates a target detection in cell (x,y) and $b(x,y) = 0$ indicates no target detection. So we can see that p_c quantifies the probability of a correct target detection given the actual target present and p_f represents the probability of a false reporting of the target detection given no target present. Based on these definitions, the target probability map $P(t)$ can be updated to combine each sensor scan data $b(x,y,t)$ using the following update rule derived from Bayesian inference (3) and (4):

$$p(x,y,t) \;=\; b(x,y,t)\Lambda_1 + (1 - b(x,y,t))\Lambda_2 \quad (7)$$

where

$$\Lambda_1 \;=\; \frac{p_c p(x,y,t-1)}{p_c p(x,y,t-1) + p_f(1 - p(x,y,t-1))}$$
$$\Lambda_2 \;=\; \frac{(1-p_c)p(x,y,t-1)}{(1-p_f)(1-p(x,y,t-1)) + (1-p_c)p(x,y,t-1)}$$

The Bayesian map-building approach provides a scheme to incrementally estimate the target distribution information by incorporating the new sensor readings. It can also easily incorporate the *a priori* knowledge and even can permit the use of subjective probability estimates. However, the Bayesian approach has some shortcomings when applied to some sensor fusion tasks [13]. In some situations, it is difficult to specify the *a priori* probabilities and then they could only be approximated. When there is no *a priori* information exists, the probability $p(x,y,0)$ is usually initialized to 0.5 since the Bayesian theory requires $P(A) + P(\bar{A}) = 1$. This is essentially means that "with 50% certainty, the cell (x,y) is occupied," yet, no sensor readings have been collected. Moreover, this kind of initialization make it impossible to distinguish between the ignorance and contradiction. For example, with cell value as $p(x,y,t) = 0.5$ when $t > 0$, one cannot deduce whether the cell has simply not been searched yet, or whether the information received was contradictory, thus making it likely that the particular cell (x,y) will continue being close to the high uncertainty value. Such information, if it was available could be used to make decisions on the utilization of different sensors. These disadvantages limit the applicability of the Bayesian inference method in many complex situations.

To overcome the confusion between ignorance and contradiction, we define a *certainty* value for each cell (x,y), denoted as $\chi(x,y,t) \in [0,1]$, which corresponds to the degree to which the cell has been searched. If $\chi(x,y,t) = 0$ then the cell has not been searched until time t. As the cell is searched repeatedly, $\chi(x,y,t)$ approaches 1. The cognitive map to store this information is called the certainty map $\mathcal{X}(t)$, in which most cells typically begin with a certainty 0. Each time a UAV visits cell (x,y) and makes a scan, the certainty changes according to the rule

$$\chi(x,y,t+1) = \chi(x,y,t) + 0.5(1 - \chi(x,y,t)) \quad (8)$$

This is a simple way to track the number of useful "looks" each cell has had and capture the notion of diminishing returns with each look. Although the simulation results show that the use of the certainty value into the UAV's decision procedure could enhance the performance of cooperative search and could allow the distinction between ignorance and contradiction, the certainty definition equation to compute the uncertainty value is ad-hoc.

Another cognitive map the UAVs use is the *threat probability map*, $K(t)$. It stores the *threat probability* of each cell (x,y) denoted as $k(x,y,t) \in [0,1]$ which represents the probability that the UAV will be destroyed at cell (x,y) by any threat. We have

$$\begin{aligned} k(x,y,t) &= P(UAV \text{ destroyed at } (x,y) \text{ by threats}) \\ &= 1 - \prod_{j=1}^{n}(1 - p^j_{kill}(x,y)) \end{aligned} \quad (9)$$

where n is the number of threats whose attack regions cover position (x,y). Due to assumption that the threats are all stationary and known *a priori*, the threat probability map is time-invariant, that is $K(t) = K(0)$. When the threat information is unknown, it can be built incrementally using similar methods as described above to build the target cognitive map.

B. Dempster-Shafer Map Building Method

Dempster-Shafer's evidence method can be viewed as a generalized Bayesian approach. It has some advantages over the Bayesian method, especially in the ability to clearly distinguish between the ignorance and contradiction[13] [14]. In this part, we present an approach for using Dempster-Shafer's evidential method to build the target cognitive map. To aid the reader in following the application of Dempster-Shafer theory to cognitive map building, the basics of Dempster-Shafer theory are briefly reviewed and then its application to target map building procedure is described.

1) Dempster-Shafer Theory: The basic entity in Dempster-Shafer theory is a set of exclusive and exhaustive hypotheses about some problem domain, called the *frame of discernment*, denoted as Θ. The degree of belief of each hypothesis is represented by a real number in [0,1]. The *basic probability assignment* (BPA) is a function $m : \Psi \rightarrow [0,1]$, where Ψ is the set of all subsets of Θ, the power set of Θ, $\Psi = 2^{\Theta}$. The function m can be interpreted as distributing belief to each element of Ψ, with the following criteria satisfied:

$$\sum_{A \subseteq \Psi} m(A) = 1 \quad (10)$$

$$m(\emptyset) = 0 \tag{11}$$

Thus, the element A is assigned a basic probability number $m(A)$ describing the degree of belief that is committed to exactly A. Note that a situation of total ignorance is characterized by $m(\Theta) = 1$. It can easily be verified that the belief in some hypothesis A and the belief in its negation $\bar{A}$ do not necessarily sum to 1, which is a major difference compared to probability theory. Given two belief function over the same frame of discernment, but induced by two independent sources of information, they can be combined into a new belief function over that frame of discernment using Dempsters rule of combination

$$\begin{aligned} m_1 \oplus m_2(A) &= \frac{\sum_{B \cap C = A} m_1(B) m_2(C)}{1 - \sum_{B \cap C = \emptyset} m_1(B) m_2(C)} && (12) \\ m_1 \oplus m_2(\emptyset) &= 0 && (13) \end{aligned}$$

2) Dempster-Shafer Target Map Building Algorithm: In our problem, the target map is used to represent the belief that a target is present (or not) in a particular cell. Each cell is characterized by two states, *empty* and *full*. Thus, we define the field of discernment Θ, by the set

$$\Theta = \{E, F\} \tag{14}$$

where E and F correspond to the states that the cell is empty (no target present) or full (target present), respectively. The set of all subsets of Θ is the power set

$$\Lambda = 2^{\Theta} = \{\emptyset, E, F, U\} \tag{15}$$

where $U = \{E, F\}$ represent $unknown$. The state of cell (x, y) is described by assigning basic probability numbers to each element in Λ satisfying

$$\begin{aligned} m_{x,y}(\emptyset) &= 0 && (16) \\ \sum_{A \subset \Lambda} m_{x,y}(A) &= m_{x,y}(E) + m_{x,y}(F) + m_{x,y}(U) \\ &= 1 && (17) \end{aligned}$$

Considering this linear dependence, it is sufficient to store $m_{x,y}(F)$ and $m_{x,y}(U)$ to represent the state of cell (x, y). The cognitive map used to store $m^t_{x,y}(F)$ is called the *target map*, denoted as $T(t)$ and the map to store $m^t_{x,y}(U)$ is called the *Ignorance map*, denoted as $I(t)$. If there is no available *a priori* information about target present or not in cell (x, y), that is, we are completely ignored of the target state, cell (x, y) is initialized as $t(x, y, 0) = m^0_{x,y}(F) = 0$ and $i(x, y, 0) = m^0_{x,y}(U) = 1$ in the cognitive maps. Each UAVs' sensor reading about that cell is a source of evidence for the target state and it can be incrementally fused into maps through the sensor models.

The sensor model converts the sensor readings into the belief assignments and it can be represented as its basic probability assignment (BPA) function. When the sensor reading reports a target detection in cell (x, y) at time t, that is $b(x, y, t) = 1$, this sensor reading can be regarded as a piece of evidence that increases our belief in state F, that is, there is a target present in cell (x, y). However, this piece of evidence does not by itself provide 100% certainty due to the sensor's inaccuracy. So this can be expressed by saying that only some part of our belief is committed to the target present. Since this sensor reading does not provide any information about the state E, the rest of our belief can not be distributed to E and can only be assigned to U. This item of evidence can therefore be represented by the basic probability assignment (BPA) function defined as

$$\begin{aligned} m_b(E) &= 0 && (18) \\ m_b(F) &= m_f && (19) \\ m_b(U) &= 1 - m_f && (20) \end{aligned}$$

where m_f denotes our belief in the target being present given a sensor reporting a target detection. Similarly, when $b(x, y, t) = 0$, the sensor reporting increases our belief in state E and provide no information about state F, so the basic probability assignment(BPA) function can be given as

$$\begin{aligned} m_b(E) &= m_e && (21) \\ m_b(F) &= 0 && (22) \\ m_b(U) &= 1 - m_e && (23) \end{aligned}$$

where m_e denote our belief in the state of no target present given a sensor reporting no target detection. Note m_f and m_e are sensor's characteristics. Following the approach in [13], the relationships between m_f, m_e and p_f, p_c can be obtained as $m_f = 1 - p_f / p_c$ and $m_e = 1 - (1 - pc)/(1 - pf)$.

Based on the given sensor model, each sensor reading can be fused into the cognitive map using the following map updating rule derived from (12):

$$\begin{aligned} &t(x, y, t+1) && (24) \\ &= \frac{t(x,y,t) m_b(F) + t(x,y,t) m_b(U) + i(x,y,t) m_b(F)}{1 - (1 - t(x,y,t) - i(x,y,t)) m_b(F) - t(x,y,t) m_b(E)} \\ &i(x, y, t+1) && (25) \\ &= \frac{i(x,y,t) m_b(U)}{1 - (1 - t(x,y,t) - i(x,y,t)) m_b(F) - t(x,y,t) m_b(E)} \end{aligned}$$

where $t(x, y, t) = m^t_{x,y}(F)$ and $i(x, y, t) = m^t_{x,y}(U)$. It can be shown that $i(x, y, t)$, representing the UAVs' ignorance of the target information in (x, y), will decrease as the search time increases. This provides a theoretical basis for using the uncertainty function defined as (8) to represent the state of the environment.

IV. Cooperative Path Planning Method

In this section, we describe how to utilize the developed cognitive maps for cooperative path selection and search. The decision function is based on the expected rewards associated with each of the three possible paths of the next time step. The expected immediate reward for a UAV searching cell (x, y) at time $t + 1$, denoted as $\rho(x, y, t + 1)$, is the payoff for target confirmation and UAV survival. It is represented as a multi-objective cost function which is a linear combination of four types of rewards corresponding to the four sub-goals:

$$\rho(x,y,t+1) = \omega_1\rho_f(x,y,t+1) + \omega_2\rho_e(x,y,t+1) + \omega_3\rho_t(x,y,t+1) + \omega_4\rho_c(x,y,t+1) \quad (26)$$

where $\rho_f(x,y,t+1)$ is the target confirmation reward, $\rho_e(x,y,t+1)$ is the environment exploration reward, $\rho_t(x,y,t+1)$ is the threat avoidance reward and $\rho_c(x,y,t+1)$ is the cooperation reward. The definitions of these rewards are given below.

Target Confirmation Reward: To achieve the goal of maximizing the number of confirmed targets, a UAV will get a reward in one cell if it can confirm a new target there. This kind of reward can direct the UAVs to the regions with high target likelihood. In the Bayesian map-building method, the expected target confirmation reward in cell (x,y) at time $t+1$ is defined as:

$$\rho_f(x,y,t+1) = [(p_c - p_f)p(x,y,t) + p_f] \quad (27)$$

and in the Dempster-Shafer map-building method, the corresponding reward is defined as:

$$\rho_f(x,y,t+1) = e^{t(x,y,t)-i(x,y,t)} \quad (28)$$

Environment Exploration Reward: Since targets are usually relatively sparse in the practical situations, it is important for the UAVs to explore the environment in order to obtain new information on potential targets. This corresponds to a requirement to decrease the uncertainty or ignorance of target information in the whole environment. Hence, for exploration purposes, it is better for the UAVs to visit cells with lower certainty values $\chi(x,y,t)$ or with higher ignorance values $i(x,y,t)$. In the Bayesian map-building method, the environment exploration reward, ρ_e, can be defined as the expected certainty increase caused by a UAV's visit to cell (x,y):

$$\rho_e(x,y,t+1) = 0.5(1-\chi(x,y,t)) \quad (29)$$

And in the Dempster-Shafer based map-building method, the reward ρ_e is defined as the ignorance value stored in its Ignorance map $I(t)$:

$$\rho_e(x,y,t+1) = i(x,y,t) \quad (30)$$

Threat Avoidance Reward: Due to the presence of threats, UAVs can be destroyed, resulting in a reduction in the terminal payoff. The threat avoidance reward ρ_t is defined as the avoided loss if a UAV is not destroyed in cell (x,y) at time $t+1$:

$$\rho_t(x,y,t+1) = (1-k(x,y,t+1))(\pi_v + \bar{n}(t+1)\pi_t) \quad (31)$$

where $\bar{n}(t+1)$ denotes the estimated average number of targets which could be identified by the UAV from time $t+2$ until the terminal time. π_v and π_t represent the value of a vehicle or a target respectively. To gain threat avoidance rewards, a UAV needs to avoid cells with high threat probabilities.

Cooperation Reward: The cooperative reward is a cost function that penalizes vehicles being close to each other and heading in the same direction so as to reduce the possible overlaps on their paths caused by their intentions to obtain high individual rewards. In this paper, we utilize the cooperation cost function generated based on the "rivaling force" method. The rivaling force approach is based on treating paths of other vehicles as soft obstacles, which are to be avoided. A type of artificial potential field method is used to derive an algorithm for generating the rivaling force that neighboring agents' paths may exert on a certain vehicle. The cooperation reward, ρ_c, is defined as the negative of the "rivaling force", F_i:

$$\rho_c(x,y,t+1) = -F_i(x,y,t+1) \quad (32)$$

where $F_i(x,y,t+1)$ is a function of other vehicles' positions $\lambda_j(t+1)$ and orientations $o_j(t+1), j \in \{1,2,\ldots,N\},\ j \neq i$. Detailed information regarding the generation of the rivaling force function F is given in [15], [8].

The reward defined in (26) can be thought of as an *immediate reward* since it considers the estimated reward for the next step only. However, a good algorithm should not be based only on the immediate reward but also lead to a path that will bring more rewards over the long term. Therefore, UAVs use a limited look-ahead policy to select their paths in the proposed path planning method. An approach to take into consideration both short-term and long-term rewards is described in [5], [8].

V. SIMULATION RESULTS

In this section, a simulation study is included to illustrate the feasibility of implementing these evidential approaches and to demonstrate the importance of environment representation to the performance of cooperative search. The simulation scenario consists of a team of 5 UAVs searching a 20×20 cellular environment with 20 targets and 2 threats. It is assumed that there is some minor a priori topographical information but no other sources of information on target distribution. For all the simulation runs in this paper, the homogeneous targets and threats are randomly assigned into the environment and the UAVs' initial locations and orientations are also randomly assigned. The threats' attack regions are set to $\phi = 1$, the threat probability $p_{kill} = 0.2$. A target is considered located in cell (x,y) if the number of sensor readings reporting target detection in (x,y) is two times larger than the number of sensor readings reporting no target detection.

To assess the performance of different approaches described in this paper, we run the simulations using two different map-building approaches and using two different search algorithms. They are Bayesian map-building method, Dempster-Shafer map-building method, cooperative search method and greedy search method. In the greedy search strategy, the vehicles move at each step to the candidate

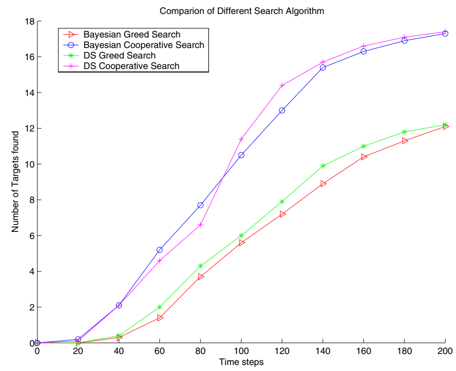

Fig. 3. Number of targets found as a function of time: Comparison between Bayesian method and Dempster-Shafer Method with high sensor accuracy.

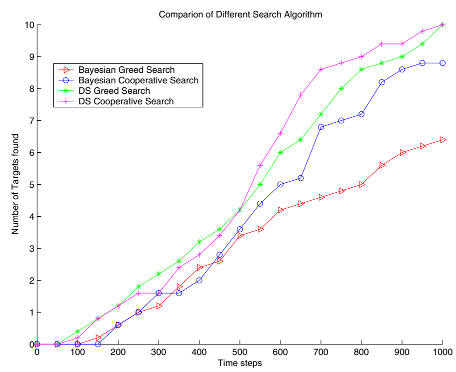

Fig. 4. Number of targets found as a function of time: Comparison between Bayesian method and Dempster-Shafer Method with low sensor accuracy.

cells with highest reward for target confirmation and avoidance of UAV losses, but they perform little distributed path selection in order to coordinate their actions.

The performance was evaluated by the number of targets found as a function of time. Figure 3 shows the performance comparison for four different approaches when the UAVs carry highly accurate sensors (specifically, the sensor detection rate is $p_c = 0.9$ and the sensors' false alarm rate is $p_f = 0.1$). Figure 4 shows the performance comparison when the UAVs carry lower accuracy sensors, where the sensor detection rate $p_c = 0.6$ and the sensors' false alarm rate $p_f = 0.4$.

The simulation results shown that the cooperative search method can always outperform the greedy search method no matter which map-building method is used. We can see that when the sensor accuracy is high, there is no big difference between the Bayesian theory based map-building and the Dempster-Shafer method based approach. However, when the sensor accuracy is low, which means there is more possibility to have contradictory sensor readings, the Dempster-Shafer method based map-building method can direct the UAVs to find more targets than the Bayesian theory based map-building.

VI. Conclusion

In this paper, we present two evidential map-building approaches for the UAV cooperative search problem based on Bayesian theory and Dempster-Shafer theory. We illustrate how to utilize these maps into the UAVs path planning procedure so that they could cooperatively localize targets in an unknown and uncertain environment. The simulation results illustrate the use of both approaches for the cooperative search problem. The Dempster-Shafer theory approach yields significantly better performance in the case that the sensor uncertainty is high. This is due to the capability of the Dempster-Shafer approach to differentiate between ignorance and contradiction scenarios. Future work includes the extension of evidential map-building approaches to more complex problems and the more thorough study of the performance analysis.

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