

Information Merging in Multi-UAV Cooperative Search

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Abstract—In this paper, we propose strategies for merging occupancy probabilities of target existence in multi-UAV cooperative search. The objective is to determine the impact of cooperation and type of information exchange on search time and detection errors. To this end, we assume that small-scale UAVs (e.g., quadrotors) with communication range limitations move in a given search region following pre-defined paths to locate a single stationary target. Local occupancy grids are used to represent target existence, to update its belief with local observations and to merge information from other UAVs. Our merging strategies perform Bayes updates of the occupancy probabilities while considering realistic limitations in sensing, communication and UAV movement—all of which are important for small-scale UAVs. Our simulation results show that information merging achieves a reduction in mission time from 27% to 70% as the number of UAVs grows from 2 to 5.

I. INTRODUCTION

The coordination of small-scale unmanned aerial vehicles (UAVs) for search operations, referred to as multi-UAV cooperative search, is an emerging research area and is applied in areas such as search & rescue [1], [2], disaster management [3], forest fire [4] and target detection [5]. Since search missions are typically time critical and span a large geographical area, a single UAV is often not able to complete the mission on time. A team of UAVs provides more resources and can therefore perform the search more efficiently. However, cooperation among individual UAVs is necessary to operate as team.

Generally, in multi-UAV cooperative search each UAV maintains a map of the search area (known as search map, cognitive map or probability map) that serves as the UAV's knowledge base of the state of the search region. At the beginning of the search mission, the initial map reflects prior knowledge about the search region. As the UAV moves around and observes some parts of the search region, the corresponding parts of the map are updated to incorporate the information gained by the UAV's surveillance sensor. The ultimate goal of each UAV is to gain as much information as possible about potential target locations. The UAV must therefore decide *what information* to send or receive to/from other UAVs, *when to share* information and *how to utilize* the shared information to plan their movement actions in the most effective way. These decisions are important as each UAV is likely to perceive (parts of) the search region differently due to some deviations in the available information at the UAVs.

We can define multi-UAV cooperative search by three components: (i) sensing the search region and updating the

search map by individual UAVs, (ii) sharing local information with each other, and (iii) making mutual decisions about actions, e.g., where to move in the search region to minimize the time of search. In this paper, we focus on the first two components and advance the state of the art by a new approach of distributed information merging considering limitations in sensing performance, information exchange and connectivity. In the presented approach we do not assume perfect sensing and consider detection and false alarm probabilities for the surveillance sensors. We model the search space by a discrete 2D map where each cell represents the occupancy probability of a target. Whenever a new observation is available, the UAV performs a Bayes update for the corresponding occupancy probability in its local map. By exchanging and merging local map information the team of UAVs is able to achieve a faster search mission and an improved detection performance as compared to non-cooperative search. Our key contributions include (i) a formal system model for cooperative search considering limitations in sensing, information exchange and network connectivity, (ii) the introduction of resource-efficient merging strategies of information from multiple UAVs and (iii) a detailed comparison of the proposed strategies. Our simulation results show that information merging achieves a reduction in mission time from 27% to 70% as the number of UAVs grows from 2 to 5.

The rest of the paper is organized as follows. Section II discusses the related work in cooperative search. In Section III, we introduce the problem formulation. Section IV describes our approach of information merging among UAVs. In Section V, we present and discuss the simulation results. Section VI concludes the paper with a brief discussion.

II. RELATED WORK

In cooperative search, a team of UAVs shares its local information such as past trajectories, current position, (parts of) the search map or planned movement actions of UAVs. The UAVs then merge the information and coordinate their actions to efficiently and effectively accomplish the search mission. In centralized coordination, the merging and coordination is either performed on a single UAV or a ground station—both equipped with sufficient computing equipment and connected with all other UAVs during the mission. The team's performance is highly sensitive to a failure of the centralized node and communication limitations. In distributed coordination, control, information merging and decision making are distributed among the UAVs. Distributed coordination increases the robustness of the team, but introduces control overhead and may lead to performance

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degradations due to decisions based on limited information.

We can classify existing multi-UAV search operations into three approaches. The first approach focuses on efficiently covering the search region, the second approach concentrates on decentralized data fusion, and the third approach is based on mutual decision making using shared information. Essentially, all approaches require sharing of some information among UAVs, but the amount and type of shared information varies. Similarly, decision-making can be performed at the UAV level or the group level. Challenges for all approaches include the representation of the search space, the information merging as well as the various limitations of the UAVs such as physical maneuverability, sensing range, flight time and communication.

A. Efficient area coverage based approaches

Initial work in multi-UAV cooperative search [6] focuses on how to efficiently visit all cells of the search region multiple times. This early work performs lookahead path planning and considers maneuverability constraints of the UAVs. Coordination is limited to sharing position information of the UAVs and does not consider any sensor model. To increase efficiency, this work is extended to reduce overlapping in UAV paths by using artificial potential field [7]. Neural network, reinforcement learning [8], group dispersion pattern [9], K-shortest path search [10], [11] and mixed integer linear programming [12] have also been explored for efficient area coverage. Similarly, Voronoi partitioning [13], [14], [15], [16] has also been used to restrict the movement of each UAV to a specific partition to avoid overlaps in their paths. In contrast to the previous approaches, [5] efficiently covers the search region for detecting targets without storing the history of visits. In all these approaches no merging of target information in the individual search maps is performed.

B. Decentralized data fusion based approaches

Instead of sharing a centralized map and UAV motion information for path planning, the UAVs exchange sensor observations and update their own search maps in this approach [17]. The entries of the search map represent a probability distribution of the target location. All UAVs update their probability map based on their own and shared sensor observations using a Bayesian approach considering a sensor model which only includes the sensor's detection probability. The UAVs assume that the target is always present in the search region and terminate the search mission when the cumulative probability of target existence exceeds a threshold [18], [19]. Probability of detection and probability of false alarm have also been included in the sensor model to reach a decision about the target existence or absence in the search region [20], [21]. The decision strategy for each approach differs and the performance depends on the prior probability distribution about the target location. The goal is to show how information on a single target location can be maintained in a distributed manner between a team of UAVs. These approaches do not consider communication limitations among the UAVs.

C. Mutual decision making based approaches

As opposed to the previous approaches where the UAVs share data and each UAV individually decides what to do next (passive coordination), mutual decision making based approaches use active coordination, i.e., the UAVs agree on actions and mutually decide what to do next. An example of this work is to search a target where UAVs arrange themselves to move in equally-spaced parallel tracks [22]. UAVs exchange messages to maintain proper distance among them in order to cover the whole search region uniformly. Negotiation among UAVs [23] is another approach that has been used to reduce the uncertainty about the target existence and to avoid covering the same area by multiple UAVs simultaneously. In a similar method, neighboring UAVs exchange proposals and mutually decide using self-assessment based decision making to cover a specific sub-region [24]. Coordination in UAVs for the selection among a discrete set of pre-computed trajectories [25] and the selection of information to be shared [26] also involve limited mutual decision making.

This paper introduces a generic framework for cooperative multi-UAV search and compares different strategies for information merging. The key differences to related work include the consideration of limited communication and sensing as well as the efficiency of the merging strategies in terms of computation and memory requirements—all of which are essential in small-scale UAVs.

III. SYSTEM MODEL

We model the search region Ω as a rectangular ground plane where a team of UAVs search for a target of interest. The search region is logically divided into C equally-sized, disjoint cells, and each cell is identified by $c = (x, y)$ where x and y are the coordinates of its center. This two dimensional grid of cells is used to maintain the occupancy probability of target and therefore serves as our search map. A target may be any object of interest a-priori defined by the user, e.g., a lost person or a fire source in the forest, and is assumed to occupy at most a single cell. A single stationary target is either present or absent throughout the entire search mission. The occupancy probability is modeled as a Bernoulli distribution, i.e., $X_c = 1$ (a target is present in cell c) with probability P_c and $X_c = 0$ (no target is present in cell c) with probability $1 - P_c$. Definite knowledge about target existence or absence in a specific cell c is represented as $P_c = 1$ or $P_c = 0$, respectively. No knowledge about target existence is thus represented as $P_c = 0.5$.

There are N homogeneous UAVs moving at a fixed altitude¹ above the search region and each UAV maintains its own search map. At each time step the UAVs can move to a single distinct cell and take a single observation. For sake of simplicity, we represent the location of a UAV $_i$ ($i = 1, 2, \dots, N$) at time step t by the coordinates of the cell in the search map $c_{i,t} = (x_{i,t}, y_{i,t})$. We assume that each

¹This assumption is made for simplicity. The proposed strategies are applicable to UAVs with different altitudes as well.

UAV is equipped with (i) a position sensor which facilitates the UAV to know its location within the resolution of a cell at any time; (ii) a surveillance sensor that is able to cover the entire cell; (iii) a wireless communication unit for exchanging information with other UAVs in the team; and (iv) a computing unit for performing local map updates. The independent sensor observation by UAV_{*i*} in cell *c* at time step *t* is represented as $O_{i,c,t}$. Two observation results are defined for each cell, i.e., $O_{i,c,t} = 0$ or $O_{i,c,t} = 1$. However, we do not assume perfect sensing and represent the sensor's detection probability and false alarm probability by the constant parameters *p* and *q*, respectively, i.e., $P(O_{i,c,t} = 1|X_c = 1) = p$ and $P(O_{i,c,t} = 1|X_c = 0) = q$, for all cells and UAVs. Whenever a UAV_{*i*} visits a given cell *c*, the information associated with that cell P_c is updated in the search map of UAV_{*i*} based on its sensor observation and prior probability in cell *c*.

The mobility of each UAV is discretized in time by allowing the vehicle to make only decisions at discrete time intervals, referred to as *time steps*. The mobility is also discretized in space by only allowing the vehicle to move to left, right, forward, backward or stay at the current cell at each time step. This discretization of mobility in time and space is well suited for small-scale, battery powered quadrotor UAVs. Currently, we assume predefined paths for the UAVs to move, i.e., a sweep mobility model, and do not bias the mobility of UAVs by information gained during the mission. We assume the wireless communication onboard the UAVs have range limitations. Thus, information can only be exchanged when the UAVs are within the specified communication range. We further assume that there are no delays or failures in communication once the UAVs are within this range. We ignore mutual decisions on UAV movement, and hence concentrate on coordination in terms of information sharing and merging, where the key is to show how information of one UAV can be combined with information from other UAVs so that the team can work together to locate the target more efficiently in terms of mission time and location errors.

Primarily, each UAV updates its own search map using its own sensor observations. Due to different UAV locations, errors in the surveillance sensor, number of visits to a given cell and especially limited communication range, the UAVs may have different probabilities of target existence for a given cell. Individual probabilities by various UAVs for a given cell should be merged to calculate a probability that best represents information about the target existence in that cell. Utilizing the information from other team-mates a UAV can improve the search in two ways: (i) by increasing its observability of the search region by taking into consideration other UAVs' observations and (ii) by improving its knowledge in a given cell by merging probabilities in that cell by other UAVs. In the following section we discuss the information merging strategies in more detail.

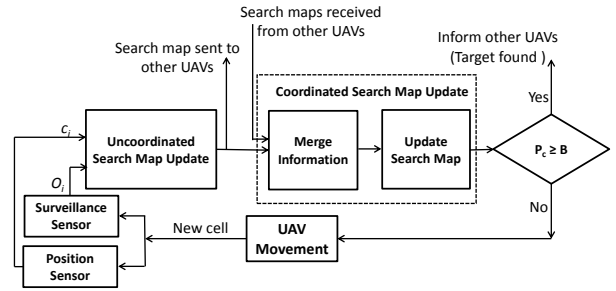


Fig. 1. Information merging for multi-UAV cooperative search (process within single UAV). Coordinated update depicted in the dashed box is not deployed for the search strategies without merging.

IV. INFORMATION MERGING

As the mission starts, *N* UAVs initialize their search maps with $P_{i,c,0} = 0.5$ for $i = 1, \dots, N$ and for all *c*, which represents complete uncertainty or lack of prior knowledge about the search region Ω . Each UAV in the team starts taking sensor observation at its current location. Based on the sensor observation $O_{i,c,t}$ and prior probability $P_{i,c,t-1}$ in the current cell c_i , $\forall i$, the UAVs update the occupancy probability to $P_{i,c,t}$ in their own search maps. This *uncoordinated* map update by individual UAVs depend on the detection and false alarm probabilities of surveillance sensor on board the UAVs. Each UAV then broadcasts the updated information to other UAVs in the team. Depending on the communication range, the UAVs in the team now have at most *N* values for the visited c_i 's at time *t*. A merging strategy takes into consideration all values corresponding to c_i that are visited at time *t* and determines a new occupancy probability that best represents the existence of target at the current cells of each UAV. Each UAV then moves to the next cell in the search region according to its mobility model and continues the merging process at the new cell. The process is depicted in Fig. 1 which is executed by each UAV at every time step. The search is finished when any of the *N* UAVs identifies a cell *c* with $P_c \geq B$, where *B* is a predefined detection threshold to stop the search.

Fig. 2 represents a small search region with a single target and the local 4×4 search maps of three UAVs having unlimited communication. Fig. 3 shows the information contents of UAV₁ after exchange of information with all other UAVs. Sharing and merging of information result in at most *N* cell updates in each individual search map. To avoid confusion, we use the notation c_i to represent location of UAV_{*i*} and P_{i,c_j} to represent occupancy probability of UAV_{*i*} at the location of UAV_{*j*} ($j = 1, 2, \dots, N$). As indicated in Fig. 1 there are two different updates performed by each UAV at each time step: *uncoordinated map update* and *coordinated map merging*. Uncoordinated map update requires only local information and results in the "uncoordinated" occupancy probability. Coordinated map merging combines this local uncoordinated probability with information from other UAVs and computes the actual probability P_{i,c_i} which is stored in the search map. Obviously, when no information from other UAVs is available, coordinated map merging is not

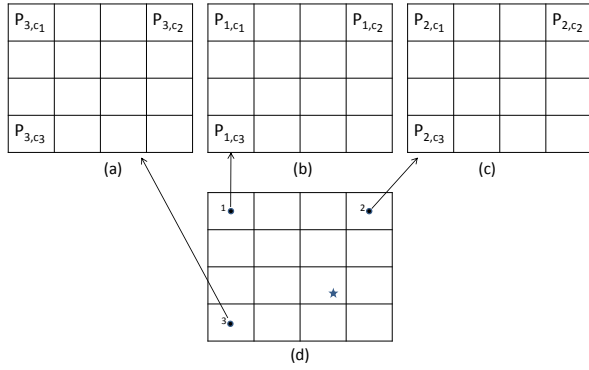


Fig. 2. Local 4×4 search maps of three UAVs (a, b and c) and the search region (d) marked with the UAVs' positions (dots) and the target position (star).

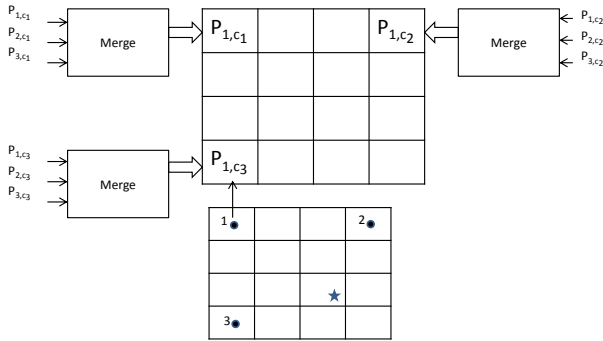


Fig. 3. The coordinated map merging for UAV₁ having unlimited communication.

possible and we simply use the uncoordinated occupancy probability as new cell value.² In the following, we describe the uncoordinated update and propose several strategies for map merging in more detail.

A. Uncoordinated search map update

The probability in the current cell c is updated using Bayesian rule [27], [16], which uses the sensor characteristics (p and q), sensor observation $O_{i,c,t}$ and prior probability in cell c . The Bayesian rule is given by

$$P_{i,c,t} = \begin{cases} \frac{pP_{i,c,t-1}}{pP_{i,c,t-1} + q(1-P_{i,c,t-1})} & \text{if } O_{i,c,t} = 1 \\ \frac{(1-p)P_{i,c,t-1}}{(1-p)P_{i,c,t-1} + (1-q)(1-P_{i,c,t-1})} & \text{if } O_{i,c,t} = 0 \end{cases} \quad (1)$$

It can be shown from Eq. (1) that $P_{i,c,t} = 1$ if $P_{i,c,0} = 1$ and $P_{i,c,t} = 0$ if $P_{i,c,0} = 0$ for all $t > 0$. If $p = 0$, $P_{i,c,t}$ becomes 0 once UAV _{i} gets a sensor observation equal to 1, and will remain unchanged regardless of future observations. We consider $0 < P_{i,c,0} < 1$, $0 < p < 1$, and $0 < q < 1$.

B. Map merging

In this section, we propose four strategies to merge information from multiple UAVs. We consider different types

²For the sake of simplicity, we do not distinguish between uncoordinated and merged occupancy probabilities throughout the remainder of this paper.

of information and communication limitations. We start with *unlimited* communication and then elaborate on the modifications required for efficient implementation of each strategy under limited range condition.

1) *Belief update*: Each UAV _{i} computes the uncoordinated occupancy probability for cell c_i , stores it at its search map and broadcasts the updated probability value to the other UAVs. All UAVs which receive this information, overwrite the previous probability value at c_i in their own maps. Thus, a UAV _{i} receives updated information from other UAVs and updates its search map by

$$P_{i,c_j} = P_{j,c_j} \quad (2)$$

where $j = 1, 2, \dots, N$ assuming that UAVs don't visit a cell concurrently.

2) *Average*: Each UAV _{i} computes the uncoordinated occupancy probability for cell c_i , stores it at its search map and broadcasts the updated probability value to the other UAVs. The UAVs receiving this updated value for cell c_i update their own maps depending on the previous value of cell c_i . UAV _{j} overwrites the occupancy probability in cell c_i by the received value, if the previous probability value is 0.5 and replaces it by the average of the values in its own map and the received messages otherwise. UAV _{i} has to fully believe UAV _{j} for a given cell, if only UAV _{j} has some information in that cell. Otherwise UAV _{i} averages the information contributed by itself and UAV _{j} . UAV _{i} updates its map by

$$P_{i,c_j} = \begin{cases} P_{j,c_j}, & \text{if } P_{i,c_j} = 0.5 \\ \frac{1}{n} \sum_{k=1}^n P_{k,c_j} & \text{otherwise, } (n \leq N) \end{cases} \quad (3)$$

where n depends on the communication range. If the communication range is limited, the probability values for c_j may differ in the local search maps due to updates at different time steps (Section IV-C). In this case n is equal to the number of UAVs with different values for c_j within the communication range. If the communication range is unlimited, all UAVs ($j \neq i$) have up-to-date knowledge for the probability value in c_j in their local search maps. Thus, we compute the average only from the UAV currently observing c_j and the UAV _{i} , i.e., $n = 2$.

3) *Modified occupancy grid map merging*: Integrating occupancy grids [28] is a well-known technique used in simultaneous localization and mapping (SLAM). We propose a modified version of this strategy which better fits to the search process and include it as a comparison with the state-of-the-art. The original merging rule is given as

$$P_{c_i}^{iogm} = \frac{odds_{c_i}}{1 + odds_{c_i}} \quad (4)$$

$$odds_{c_i} = \prod_{j=1}^n odds_{j,c_i} \quad (5)$$

$$odds_{j,c_i} = \frac{P_{j,c_i}}{1 - P_{j,c_i}} \quad (6)$$

TABLE I

MERGING OCCUPANCY PROBABILITIES IN A GIVEN CELL MULTIPLE TIMES USING INTEGRATING OCCUPANCY GRIDS METHOD.

Time	$O_{1,c}$	$O_{2,c}$	$P_{1,c}$	$P_{2,c}$
t_0	-	-	0.5	0.5
t_1	1 (false alarm)	-	0.9	0.9
t_2	-	0 (true negative)	0.9	0.9

where $P_{c_i}^{iogm}$ is the probability of occupancy at c_i calculated through integrating occupancy grid maps (OGMM)³.

In our cooperative search, we model the target existence also as occupancy probability of a cell. The OGMM method aims to reinforce cell values and thus reaches low or high probability values very fast. This property supports quick decision making but results in a considerable amount of detection errors, if the repetitive observations include false alarm and false negatives. Table I shows an example of this problem for specific values of $p = 0.9$ and $q = 0.1$, where at time t_1 one UAV receives false alarm from its sensor and the other UAV has no observation at cell c . The merging results in updating both the maps at $P_{1,c}$ and $P_{2,c}$ with value 0.9. At a later time t_2 , one of the UAVs observes true negative at cell c but merging of values brings no change in both the maps. The probability of occupancy at c is now fixed to 0.9 and can not be reduced by even infinite numbers of correct observations in that cell. The detection of another false alarm at c will further increase the value of P_c leading to exceeding the threshold value and terminating the search with an erroneous result. Thus, integrating occupancy grid maps in its original form is not suitable for cooperative search scenario.

The effect of this problem can be reduced if we restrict the output of the integrating occupancy grid technique to change slowly. In order to do so, we combine the average value of occupancy probabilities at c_i and occupancy value using integrating occupancy grids at c_i by a weighted average.

$$P_{c_i} = v(P_{c_i}^{avg}) + (1 - v)(P_{c_i}^{iogm}) \quad (7)$$

where

$$P_{c_i}^{avg} = \frac{1}{n} \sum_{j=1}^n P_{j,c_i} \quad (8)$$

The weight v can be chosen based on the sensor parameters and search constraints.

4) *Sensed data sharing*: Instead of sharing probability values, the UAVs can share their current locations and sensor observations with each other. In this strategy, each UAV keeps a record of sensor observations for each and every cell in the search region and updates the P_c iteratively based on the total number and type of observations in cell c . The strategy enables UAVs to share full information but requires more memory, computation power and bandwidth if surveillance sensors are heterogeneous with different characteristics

³This rule is adopted from SLAM where robots develop partial maps using occupancy grids and integrate the partial occupancy grids at the end of the SLAM process by using Eq. (4).

(p and q). The updated probability in cell c by a UAV can be calculated by iteratively using Eq. (1) for all consecutive observations from all UAVs.

C. Communication range limitations

When the communication range is unlimited, the presented strategies do not need to utilize the time index of a given observation, since each UAV can hear the broadcast of every other UAV at all times. However, in situations where the communication range is limited, each UAV can only communicate to UAVs that are within its communication range. This likely results in different probability maps at each UAV and it is essential to correctly interpret the maps, e.g., to avoid double counting of observations in the sensed data sharing strategy.

In order to maintain the timeliness of the occupancy probabilities we introduce a simple time stamping mechanism. Whenever a probability value is changed, we capture the time stamp of this update. If this update is caused by an observation of the cell, we capture the current time. If this update is caused by merging cell values from different UAVs, we take the most recent time stamp among the contributing cell values as new time stamp. The time stamps are stored in the search maps and are exchanged together with the probability values of the cells. Map merging is only performed in those cells which have different time stamps wrt. the neighboring UAVs.

Observe that adding time stamps (i.e., history of observations) to the search map increases the information to be exchanged and processed by the UAVs. Therefore, the performance of each strategy will depend on not only the communication range but also the available bandwidth for data transmission. The effect of bandwidth limitations on cooperative search will be analyzed in future work.

D. Best case analysis for a single cell

Given the values of p , q and the threshold B , we can calculate the minimum number of observations required in cell c to satisfy the condition $P_c \geq B$, if the target is present in cell c . This condition is satisfied when all observations taken at the target cell equal 1. According to Eq. (1), for a cell c , the first updated probability in case of positive observation is given by,

$$P_1 = \frac{pP_0}{pP_0 + q(1 - P_0)} \quad (9)$$

where P_0 represents initial probability in cell c and is equal to 0.5. Assume that target is present in cell c and each time step the sensor generates positive observation $O_c = 1$. The iterative solution of this equation yields

$$P_m = \frac{pP_{m-1}}{pP_{m-1} + q(1 - P_{m-1})} \quad (10)$$

$$P_m = \frac{p^m P_0}{p^m P_0 + q^m (1 - P_0)} \quad (11)$$

where P_m represents the updated value in cell c at m^{th} observation. To find the minimum number of observations

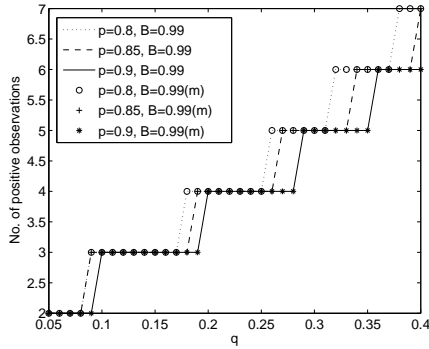


Fig. 4. Minimum number of observations required in a single cell to satisfy condition $P_c \geq B$ (corresponds to the best case, i.e., when a target is present in the visited cell and the observation is equal to 1.)

such that, $P_m \geq B$, we need to find the value of m which can be obtained by

$$m \geq \log \left(\frac{P_0(1-B)}{B(1-P_0)} \right) / \log \frac{q}{p} \quad (12)$$

Given the values of p , q , and B , Eq. (12) can be used to estimate the minimum number of observations ($P_m \geq B$) required in a cell if there is a target. Fig. 4 shows the analytical number of observations obtained using Eq. (12) (represented with m in the legend) and simulation results. In simulation results, we iteratively update the initial probability of 0.5 and count the number of observations (that are always positive) till the probability is equal to or greater than B .

V. SIMULATION RESULTS

To evaluate the effectiveness of our proposed merging strategies, we simulate a search region of 10×10 cells with a single stationary target located at $(6, 7)$. We initialize the location of upto $N = 5$ UAVs at randomly selected cells and consider a standard sweep model for the mobility of UAVs. We consider $B = 0.99$ which means the search is finished if one of the UAVs finds a cell c in its own map with $P_c \geq 0.99$ and that cell is designated as location of the target. If the result of search is a cell other than $(6, 7)$, we record a detection error. We perform simulations to compare the results of our proposed strategies in case of no communication, limited communication and full communication among UAVs. We use the communication range in terms of cells and consider two UAVs in range when the Euclidean distance between them is less than or equal to the specified communication range. All results are based on 1000 runs of simulations and $v = 0.7$ in modified OGMM merging strategy. We also present results for uncoordinated search, where UAVs only use their own observations to update their maps as reference.

First, we consider full communication, where all UAVs can exchange information at each time step and evaluate our strategies for various values of q and N . Fig. 5 and Fig. 6 show the average number of time steps required and the percentage of erroneous results versus the false alarm

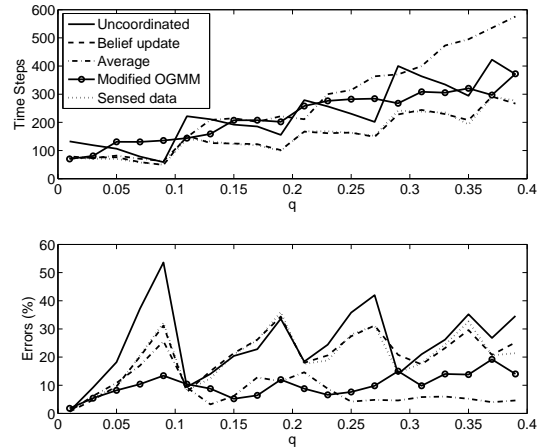


Fig. 5. The effect of increasing q on the search time (time steps) and location errors with 2 UAVs ($p = 0.9$, unlimited communication).

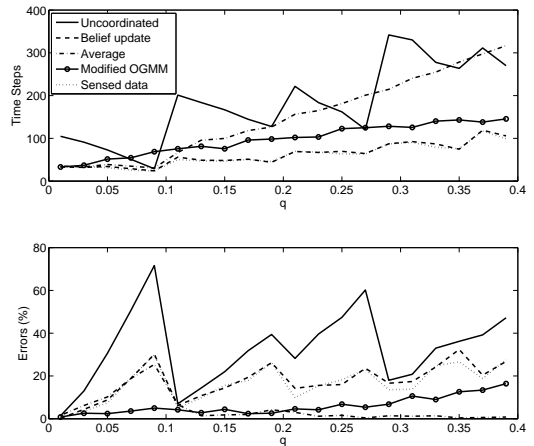


Fig. 6. The effect of increasing q on the search time (time steps) and location errors with 5 UAVs ($p = 0.9$, unlimited communication).

rate q for 2 and 5 UAVs, respectively. The figures show that degrading the quality of the sensor (increasing the value of q) increases the number of time steps to locate the target in all strategies. Comparing the results in these figures, in contrast to other strategies, the errors for the *average* strategy reduces as the value of q increases. This reduction in errors comes with a cost of overshoot in time steps. The repetitive behavior or jumps in the plots are due to the fact that there are a fixed number of observations required to exceed the threshold for certain ranges of q (as explained in Fig. 4). As the value of q increases within a given range, the number of false alarms increases but the number of steps required to reach a decision remains constant. Having consecutive false alarms in a cell will end up in an erroneous result. While not presented here due to space limitations, decreasing the value of p for fixed value of q increases the number of time steps required to terminate the search.

Second, we show the effect of increasing the number of

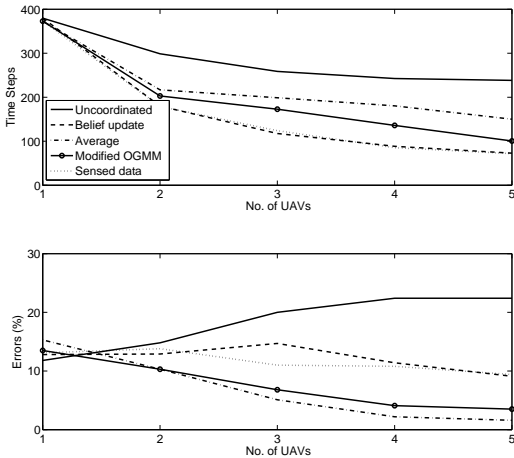


Fig. 7. The effect of increasing the number of UAVs on the search time and the location errors ($p = 0.9, q = 0.2$, unlimited communication).

UAVs on our merging strategies with unlimited communication. Fig. 7 shows the effect of increasing the number of UAVs with fixed values of $p = 0.9$ and $q = 0.2$ on the search time. Note that increasing the number of UAVs with coordinated map updates is more efficient than increasing the number of UAVs in uncoordinated search. It is evident from Fig. 7 that sensed data merging and belief update require less time to search the region but at the cost of higher location errors. We can tune the value of v in the modified OGMM strategy to obtain better results depending on the values of p, q and the number of UAVs.

Third, we evaluate our proposed strategies for limited communication with fixed values of p, q and the number of UAVs. Fig. 8 and Fig. 9 show the effect of increasing the communication range on time steps required to terminate the search and percentage of erroneous results for 2 and 5 UAVs, respectively. We show the results for no communication to unlimited communication (in a 10×10 grid with communication range < 14). As the communication range increases, the performance of these strategies converge to a point that is consistent with the results of Fig. 7.

Finally, we show the percent gain for the various merging strategies with respect to uncoordinated search in Table II. We define the percent gain as $((T_u - T_c)/T_u) * 100$, where T_u and T_c represent time steps for uncoordinated and coordinated search respectively. In general, the improvements rise with increasing the number of UAVs. In our simulations, the minimum gain we can achieve for minimum number of UAVs (i.e., 2 UAVs) is 27% and the maximum gain that we can reach for maximum number of UAVs (i.e., 5 UAVs) is 70%. The improvement is also increasing with enlarging the communication range but saturates once the communication is stable. Note that when there is unlimited communication, exchanging the probability maps (i.e., belief update) is sufficient to perform as good as sharing all observations. As the communication range reduces, the improvements with belief

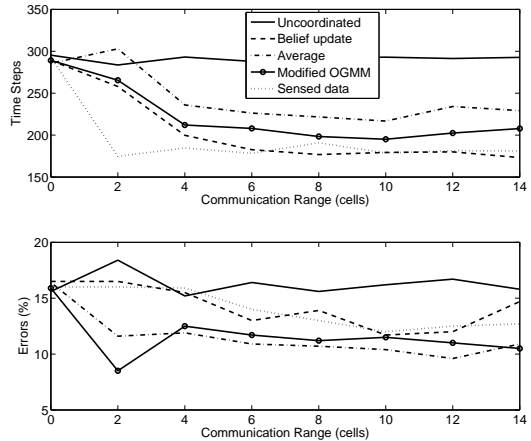


Fig. 8. The effect of increasing the communication range on the search time and the location errors (2 UAVs, $p = 0.9, q = 0.2$).

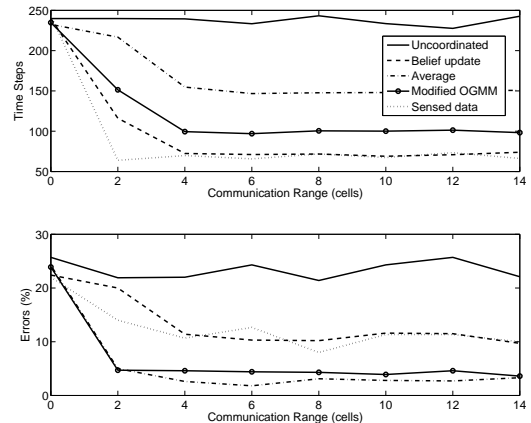


Fig. 9. The effect of increasing communication range on time steps (5 UAVs, $p = 0.9, q = 0.2$).

update also reduce (from 70% to 41%) since the UAVs meet each other at different times and keep different maps, while sharing observations still sustains high improvements. In this case, increasing the number of UAVs is also not sufficient. Therefore, under stringent communication, deployed merging strategy needs to be chosen carefully.

VI. CONCLUSIONS

We presented merging strategies for information from multiple UAVs in a cooperative search scenario. We showed that the proposed strategies enable cooperative search better than uncooperative search even with pre-defined and fixed path mobility of UAVs. The strategies are well suited for higher number of UAVs as increasing the number of UAVs increases the gain (in terms of time and errors) compared to uncooperative search. The improvement due to increase in communication range saturates once the communication is stable. Sharing of full information, as discussed in sensed data sharing strategy, is efficient time-wise but requires

TABLE II

PERCENTAGE GAIN IN TERMS OF TIME STEPS WITH RESPECT TO UNCOORDINATED SEARCH ($p = 0.9, q = 0.2$)

	Communication range = 2 (cells)				Communication range = 6 (cells)				Communication range = 14 (cells)			
	BU	AVG	MOGM	SDS	BU	AVG	MOGM	SDS	BU	AVG	MOGM	SDS
N=2	15.6	-7.2	14.7	36.7	30.9	22.9	32.6	37.0	39.8	27.4	32.1	39.9
N=3	20.4	-2.1	16.2	48.0	50.6	14.5	36.8	52.3	54.5	23.1	33.1	52.0
N=4	39.6	5.8	28.7	67.6	64.0	23.9	51.3	68.6	63.5	25.6	43.8	64.8
N=5	41.6	8.0	29.7	70.9	70.0	40.0	61.1	69.5	69.4	37.0	57.8	69.8

BU=Belief update, AVG=Average, MOGM=Modified OGMM, SDS=Sensed data sharing

more resources. Other strategies are resource efficient and involve trade-off in time-to-search and number of errors. We did not consider biasing the mobility of UAVs and did not plan cooperative paths based on information obtained from sharing and merging which will be included in our future research. We also plan to include the mobility of target and communication bandwidth limitations in our future publications.

ACKNOWLEDGEMENTS

This work was supported in part by the EACEA Agency of the European Commission under EMJD ICE FPA n^o 2010-0012. The work has also been supported by the ERDF, KWF, and BABEG under grant KWF-20214/24272/36084 (SINUS). It has been performed in the research cluster Lakeside Labs.

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