Information Exchange and Decision Making in Micro Aerial Vehicle Networks for Cooperative Search

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***Abstract*—This paper considers a network of autonomous micro aerial vehicles (MAVs) cooperatively searching for multiple stationary targets. The objective is to minimize the search time while considering sensing and communication limitations. We derive limits for the required number of sensor observations considering false alarms and miss detections, to declare the existence or absence of a target. To minimize the search time, we formulate the cooperative search as a traveling salesman problem and use the calculated sensor observation's limits in each predicted location of the target. Moreover, the design options in multi-MAV cooperative search are explored and classified in two dimensions: information merging and decision making where each dimension can be either centralized or distributed. Algorithms are then introduced to analyze the effects of centralized or distributed coordination for minimizing the search time. We show that depending on the availability of information and capability of making decisions, the MAVs can search an area more efficiently if both information merging and decision making are distributed. We compare our proposed algorithms with a traditional lawnmower search pattern and a distributed cooperative search algorithm.**

***Index Terms*—Multi-MAV system, cooperative search, coordination, cooperative control, motion planning, decision making.**

I. Introduction

Micro aerial vehicles (MAVs) have recently undergone significant technological advances and even small-scale MAVs, e.g., quadrotors, provide a variety of sensing, embedded processing, and wireless communication capabilities nowadays. The use of teams of MAVs for civil applications such as search and rescue [1], [2], disaster management [3], surveillance [4], multispectral monitoring [5], forest fire [6], target detection [7], goods delivery and construction [8] is therefore steadily increasing. An emerging domain that can utilize teams of MAVs is search operations, where the missions are typically time critical and span a large geographical area. Such missions require the coordination of MAVs, referred to as multi-MAV cooperative search [9]. Coordination has to consider sharing of information, task assignment and decision making to operate as a team and to minimize the search time.

In multi-MAV cooperative search, generally, each MAV maintains a map of the search area (search map) [9], [10] that serves as the MAV's knowledge base about the state of the search region. The MAVs move around and observe parts of the search region, gaining information using the on-board surveillance sensors (e.g., cameras). The ultimate goal is to determine the necessary actions in order to gain as much information as possible about target locations potentially considering energy, communication, time, and processing power constraints. The MAVs must therefore decide *what search action* to take (i.e., when and where to move in the search region), *what information* to send or receive, and *when to share* information to complete the search efficiently. Multi-MAV cooperative search is thus defined by three components [11]: (i) *sensing* the search region and updating the search map by individual MAVs, (ii) *making decisions* about search actions based on the available information, and (iii) *sharing* local information.

This paper analyzes multi-MAV cooperative search from two dimensions: information merging and decision making where each dimension can be either centralized or distributed. *Representative* algorithms are proposed to analyze the effects of these two dimensions in the presence of sensing and communication limitations on minimizing the search time. Several information merging techniques to maintain maps have already been investigated in [11], where the amount and type of information exchanged between the MAVs varied for fixed pre-computed paths of the MAVs. In this paper, we include decision making into the coordination process in addition to information merging. Both the information merging and decision making components of coordination can be processed at a centralized entity or on each MAV in a distributed way enabling four processing options. The goal is to identify the design space, and to analyze the trade-offs introduced by different coordination methodologies. We envision that such exploration of the design space, where the impact of information exchange and decision making is quantified, can be valuable to other researchers in designing search strategies.

At the beginning of the search the ground station generates a pre-computed movement plan for the *team* of MAVs. After this initial phase, representative algorithms are proposed for four possibilities with (i) centralized decision making and information merging with team movement plans (CCT), (ii) centralized decision making and distributed information

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merging with individual MAV movement plans (CDI), (iii) distributed decision making and information merging with individual MAV movement plans (DDI), and (iv) distributed decision making and centralized information merging with individual MAV movement plans (DCI).

A distinct feature of the proposed algorithms is calculation of limits for the required observations for deciding on the target existence at a specified confidence level. These limits are derived considering an imperfect surveillance sensor (i.e., with miss detections and false alarms) and a Bayesian update model for the cell's occupancy probability. Once an MAV updates its map information based on sensor observations, it exchanges the updated information with other neighboring MAVs. Utilizing the map information, the MAVs then select a search action which is a combination of two sub-actions: (i) how many observations to take in a given cell and (ii) which cells to visit and in which order (path). Each MAV selects a subset of cells that are more likely to contain a target. Based on the well-known Traveling Salesman Problem (TSP) and the Multiple Traveling Salesmen Problem (MTSP) [12], efficient paths for the MAVs are planned to visit the selected cells.

The key contributions of this research are: (i) a formal system model for cooperative search with constraints in sensing, information exchange, and network connectivity, (ii) an analytical derivation of the number of required observations to declare the absence or existence of a target, (iii) the application of a TSP and MTSP for the selection of MAV paths, (iv) the introduction of information merging strategies, and (v) simulation results to compare our proposed algorithms with state-of-the-art approaches.

The rest of the paper is organized as follows. Section II discusses the related work in multi-MAV cooperative search. Section III introduces the problem formulation and the system model. Section IV analyzes the required number of observations to declare the absence or existence of a target. Section V explains the approach for information merging, and Section VI describes the algorithms for decision mechanisms. We present simulation results in Section VII. Finally, Section VIII concludes the paper with a brief discussion.

II. Related Work

Coordination in MAVs for search operations can be traced back to the work of Passino et al. [13] who proposed a framework of cooperative search focusing on efficient coverage and uncertainty reduction of the whole search region. Much of the early work relies on centralized maps for information merging and distributed decision making for movement [14]. The MAVs plan their own paths using the search map and locations of other MAVs in the team. This early work has been extended using artificial potential fields [15], machine learning techniques [9], group dispersion patterns [16], mixed integer linear programming [17], and evolutionary algorithms [18] to argue that reducing the overlap in look-ahead planned paths can improve the efficiency of search operations. Considering false alarms and miss detections in the sensor model, a centralized search map with distributed decision making was proposed in [19], where an information-theoretic sensor management was used. This sensor management directs the movement of an MAV to a cell, where the expected information gain is maximized by future sensor observations. Although these methods reduce the uncertainty about the search region, they do not consider assumptions about sensing and communications in a single search strategy.

The authors in [20], [21], [7] proposed distributed coordination of decision making among MAVs without having a search map. As these coordination methods do not keep a record of target location information, they are not able to find the exact location of a target. However, they generate promising results for spatial and temporal coverage of a search region. None of these methods considers a complete sensor model with both types of errors and limitations in communications; only [7] includes communication range limitations.

Instead of having a centralized search map and sharing position information, the authors in [22], [23], [24] proposed a concept of a distributed search map and sharing of sensor observations. Each MAV has its own search map and updates both its search map and search action individually to locate the target efficiently. The goal is to show how information on a single target location can be maintained in a distributed manner between a team of MAVs. However, these methods do not include limitations in communication and false alarms in their sensor model. The authors in [25] proposed a distributed information merging and decision making strategy that considers the communication range limitation. One unique characteristic of this coordination method is that MAVs can agree on actions using mutual decision making based on an exchange of multiple messages. Although the method assumes limitations in communication, it does not apply a realistic sensor model. Another distributed information merging and decision making strategy was proposed in [26] where MAVs coordinate in terms of sharing binary sensor observations. The method considers a realistic sensor model with both types of errors but does not include limitations in communications. The work of Hu et al. [27] in this category of cooperative search uses both the limitations in communication and sensing (both types of errors). However, the approach focuses on consensus among MAVs to maintain similar maps on each MAV with a finite number of observations, and not on increasing the efficiency of the search operation.

Decision making can also be centralized with either centralized [28], [29], [30] or distributed [31] information merging. Some techniques use centralized decision making without any information merging [32]. The subregions that need to be visited by MAVs are repeatedly assigned by a centralized entity without any merging of information [32] or MAVs can merge information in terms of collecting observations from other team mates [31]. The approaches in [28], [29], [30] are centralized in both dimensions. The coordination in decision making is to restrict the motion of each MAV to a disjoint subregion of the whole search region. A classification of MAV coordination approaches for search operations is given in Table I.

A common task in all the methods mentioned so far is to increase the number of observations in a given cell of the search map to reduce uncertainty within the cell. Analytical

TABLE I: Classification of coordination approaches for search operations, C: Centralized, D: Distributed.

		Information Merging		
		None	C	D
Decision	C	[32]	[28], [29], [30]	[31]
	D	[20], [21], [7]	[13], [14], [15] [9], [16], [17] [18], [19]	[1], [2], [22] [23], [24], [25] [26], [27]

derivation of expressions for required number of observations in a given cell to determine the existence or absence of a target is not properly addressed in the literature. A closely related work can be found in [10], but it does not include probability of miss detection and probability of false alarm into a single expression and requires additional prior information about the uncertainty reduction. Strong assumptions on the selection of sensor model and threshold selection also make the work in [10] very limited. Expressions for calculating the required number of observations considering probability of miss detection, probability of false alarm, modeling observations as a binomial distribution, and relaxing assumptions on the selection of sensor model are derived in this paper. In addition to calculating the required number of observations, we propose algorithms to update the movement plans of MAVs using the required number of observations along with TSP and/or MTSP formulation. Investigating the effects of centralized and distributed coordination in multi-MAV cooperative search is another contribution in this paper which has not been covered in the literature.

III. Problem Formulation

A. Environment

Inspired from [33], [27], [34] the rectangular search region Ω is represented by $L \cdot W$ equally-sized, disjoint cells, where L and W represent the number of rows and the number of columns, respectively. Each cell is identified by $c = (l, w)$, where $l \in \{1, 2, ..., L\}$ and $w \in \{1, 2, ..., W\}$ are the coordinates of its center. Thus, $C = \{1, 2, 3, ..., LW\}$ represents the set of cells in the discretized search region. The search map with C cells can be maintained either in a centralized or decentralized way.

B. Target

Let $G = \{G_1, G_2, ..., G_Q\}$ be the set of Q stationary targets present in Ω. A target is assumed to occupy at most a single cell in Ω and a cell is allowed to have at most one target. A cell is termed as target cell if it contains a target and as empty cell if it does not. The occupancy probability [33] P_c 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 cell c is represented as $P_c = 1$ or $P_c = 0$, respectively. No knowledge about target existence in cell c is thus represented as $P_c = 0.5$ [33]. It is assumed that no prior knowledge is available about Ω or the locations of G, which may require the MAVs to search every cell of Ω at least once. Cell c is considered as containing a target if $P_c \geq B^+$ and as an empty cell if $P_c < B^-$, where B^+ and B^- are predefined thresholds.

C. MAVs

Let $U = \{U_1, U_2, ..., U_N\}$ be the set of N homogeneous MAVs. Each MAV, denoted by U_i $(i = 1, 2, ..., N)$, moves at a slightly different altitude above the search region to avoid collisions with each other. The MAV U_i is equipped with (i) a position sensor which facilitates the MAV to know its position within the resolution of a cell at any time, (ii) a surveillance sensor for observing Ω, (iii) a wireless communication unit for exchanging information with the ground station and with other MAVs in the team, and (iv) a computing unit for performing local map updates.

D. Movement and Path Planning

The movement of U_i is discretized in space (*cells*) and time (*time step*). It is assumed that U_i has sufficient battery life or flight time to remain part of the search mission until Q targets are found. The MAV U_i makes movement decisions only at discrete time intervals referred to as time step. The duration of a single time step t is sufficient for U_i to move to a horizontal or vertical adjacent cell, to take a sensor observation, to update its local map, and to exchange information with other MAVs. The discretized movement of U_i is represented as $c_i^{t+1} \in \{(l+1, w)_i^t, (l-1, w)_i^t, (l, w+1)_i^t, (l, w-1)_i^t\}$, where c_i^{t+1} (location of U_i at time step $t + 1$) must stay within the boundary of Ω. Each MAV U_i traverses a path R_i which is an ordered sequence of cells, and R represents the set of search paths for all MAVs in U. The cells constituting a search path for an MAV are considered as way-points and determine the sub-regions where the number of observations should be increased.

The predicted cells where the number of observations should be increased are termed as candidate cells, represented by set $S \subseteq C$. Depending on the initial observations and P_c, S is updated iteratively after each time a path is traversed (Section VI). The Euclidean distance between the candidate cells is considered as cost, and paths for N MAVs are determined to visit cells in S. The start and end of the paths depend on centralized (path computation at the ground station) or distributed (path computation at MAVs) coordination. Consider a graph $G = (S, A)$, where A is the set of edges connecting cells $\alpha \in S$ and $\beta \in S$ $(\alpha \neq \beta)$ and $d_{\alpha\beta}$ is the Euclidean distance associated with edge $(\alpha, \beta) \in A$. Finding shortest paths to visit each cell in S exactly once resembles with solving the well-known TSP and/or MTSP [12] depending on the number of MAVs. The work in [12] also provides a survey on a subset of exact and heuristic solutions for the TSP and the MTSP. Any existing solution (exact or heuristic) for TSP and MTSP can be applied as an off-the-shelf component to compute the path for visiting candidate cells, thus computational complexity and limitations of TSP and MTSP solutions are inherited in the proposed approach.

E. Observations

The independent sensor observation by the surveillance sensor of U_i in cell c at time step t is denoted as $O_{i,c}^t$. Two observation results are defined for each cell, i.e., $O_{i,c}^t = 0$

(negative observation) or $O_{i,c}^t = 1$ (positive observation). Depending on the target's true presence or absence and the made observation, the following probabilities are defined [27], [35], [19]:

$$\begin{aligned} P(O_{i,c}^t = 1|X_c = 1) = p, P(O_{i,c}^t = 0|X_c = 1) = 1 - p \\ P(O_{i,c}^t = 1|X_c = 0) = q, P(O_{i,c}^t = 0|X_c = 0) = 1 - q \end{aligned} \quad (1)$$

where sensor parameters $p, q, 1-p$ and $1-q$ denote probabilities of detection, false alarm, false miss and true miss, respectively. Considering an informative sensor with $0.5 < p < 1$ and $0 < q < 0.5$, this paper assumes that only one observation per cell can be taken at a single time step and the field of view of surveillance sensor coincides with a single cell. The number of observations in a given cell c is denoted by m. Thus, if c contains a target $P_c \to 1$ as $m \to \infty$, and if c is empty $P_c \to 0$ as $m \to \infty$ [27]. The minimum and average number of sensor observations required to declare c as a target cell are represented by (m_{min}^+) and (m_{avg}^+), respectively. Similarly, the minimum and average number of sensor observations required to declare c as an empty cell are represented by (m_{min}^-) and (m_{avg}^-), respectively.

F. Communication

Following a discussion [36] on the communication requirements of MAV networks, we simplify the assumptions that suit to our problem. Let the communication range among MAVs, measured by the Euclidean distance, be limited to r cells. Thus, information can only be exchanged when the MAVs are within distance r. Communication is considered free of any delays or failures, once the MAVs are within range r. Let $H(U_i) = \{U_j \in U : j = 1, ..., N \wedge \|c_i - c_j\| \leq r\}$ be the set of MAVs that are within the communication range r of U_i ($H(U_i) \subseteq U$) and $1 \leq |H(U_i)| \leq N$. Note that $H(U_i) = \{U_i\}$ and $|H(U_i)| = 1$, if $r = 0$ or $\|c_i - c_j\| > r$ for $i \neq j$.

G. Coordination

The MAVs coordinate in terms of sharing information and decisions about the search action. Primarily, each MAV updates its own search map without coordination with other MAVs (cp. Section IV). Due to different MAV locations, errors in the surveillance sensor, number of visits to a given cell and especially limited communication range, the MAVs may have different search maps. The MAVs coordinate by exchanging and merging individual search maps to best represent the search region. In addition to the exchange of information, the MAVs also coordinate the decision making about their paths by using MTSP. Coordination in terms of information merging and path planning is discussed in Section IV and Section V, respectively.

H. Objectives

The objective of each MAV is to find the locations of Q targets as fast as possible. Let m_c be the number of observations in cell c and the value of m_c increases as the time spent by an MAV in cell c increases. The objective function of each MAV becomes

$$\text{minimize } \{t : Q = \sum_{c \in C} f(c)\} \quad (2)$$

where

$$f(c) = \begin{cases} 1 & \text{if } P_c \geq B^+ \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

and

$$P_c \to \begin{cases} 1 & \text{if } m_c \to \infty \text{ and } c \text{ contains a target} \\ 0 & \text{if } m_c \to \infty \text{ and } c \text{ is empty} \end{cases} \quad (4)$$

The constraint in Eq. 4 shows that the value of P_c depends on target existence and time spent by an MAV in cell c. Once this objective is achieved by any of the MAVs or the ground station, the search is finished.

IV. Required Number of Observations

Given the sensor parameters, the sensor observation and the prior occupancy probability, the posterior occupancy probability can be determined using the Bayesian update rule [37], [27] as

$$P_{i,c}^t = \begin{cases} \frac{pP_{i,c}^{t-1}}{pP_{i,c}^{t-1} + q(1-P_{i,c}^{t-1})} & \text{if } O_{i,c}^t = 1 \\ \frac{(1-p)P_{i,c}^{t-1}}{(1-p)P_{i,c}^{t-1} + (1-q)(1-P_{i,c}^{t-1})} & \text{if } O_{i,c}^t = 0 \end{cases} \quad (5)$$

where $P_{i,c}^t$ and $P_{i,c}^{t-1}$ denote the updated and prior occupancy probabilities in cell c by U_i, respectively. This update rule is exploited to calculate the minimum (m_{min}^+) and average (m_{avg}^+) number of observations required in a given cell c to satisfy the condition $P_c \geq B^+$.

A. Required Number of Observations for Target Cell

Consider a single target cell where a sensor takes m independent observations. The sequence of consecutive binary observations has a binomial distribution with probability of success $= p$, frequency of successes $= \kappa$ and can be written as

$$p_{m,\kappa} = \binom{m}{\kappa} p^\kappa (1-p)^{m-\kappa}. \quad (6)$$

If all observations are positive, the probability of occupancy for m observations can be calculated by iteratively solving Eq. (5). In this case the updated occupancy probability in cell c for m positive observations is given by

$$P_c^m = \frac{p^m P_c^0}{p^m P_c^0 + q^m (1 - P_c^0)} \quad (7)$$

where P_c^0 is the initial occupancy probability of cell c. Given the values of p, q and B^+ and the target is present, the minimum number of observations m_{min}^+ required in a cell c to satisfy the condition $P_c^m \geq B^+$ can be computed, if the target is present. By transforming Eq. (7) with some simple algebra, the number of observations is computed by

$$m = \left\lceil \log\left(\frac{P_c^0(1-P_c^m)}{P_c^m(1-P_c^0)}\right) / \log\frac{q}{p} \right\rceil \quad (8)$$

$$m_{min}^+ \geq \log\left(\frac{P_c^0(1-B^+)}{B^+(1-P_c^0)}\right) / \log\frac{q}{p}. \quad (9)$$

where $\lceil\cdot\rceil$ denotes the ceiling function to ensure positive integral time steps. It is clear from Eq. (9) that increasing the value of q or decreasing the value of p increases the minimum number of observations required to decide whether a target is in the cell.

The probability of having m consecutive negative observations in a target cell is given as $(1-p)^m$ (using Eq. 6). In case of positive and negative observations the average number of observations required to satisfy the condition $P_c^m \geq B^+$ can be determined as follows. Suppose x and y represent the number of negative and positive observations such that $m = x + y$. The binomial distribution has a mean of mp which shows that $y = mp$ and $x = m - mp$. The probability of occupancy after y number of positive observations P_c^y can be calculated using Eq. (7). The probability of occupancy after x number of negative observations P_c^x can be derived in a similar way and is given by

$$P_c^x = \frac{(1-p)^x P_c^0}{(1-p)^x P_c^0 + (1-q)^x (1-P_c^0)}. \tag{10}$$

Considering P_c^y as a prior probability in cell c and using Eq. (10) to find the probability of occupancy after x consecutive negative observations, yields

$$P_c^m = \frac{(1-p)^x p^y P_c^0}{(1-p)^x p^y P_c^0 + (1-q)^x q^y (1-P_c^0)}. \tag{11}$$

By replacing the values of x and y, and using some algebra the average number of observations m_{avg}^+ required to satisfy the condition $P_c^m \geq B^+$ is calculated as

$$m = \left\lceil \frac{\log\left(\frac{P_c^0(1-P_c^m)}{P_c^m(1-P_c^0)}\right)}{(1-p)\log\frac{1-q}{1-p} + p\log\frac{q}{p}} \right\rceil \tag{12}$$

$$m_{avg}^+ \geq \frac{\log\left(\frac{P_c^0(1-B^+)}{B^+(1-P_c^0)}\right)}{(1-p)\log\frac{1-q}{1-p} + p\log\frac{q}{p}}. \tag{13}$$

B. Required Number of Observations for Empty Cell

In analogy we can derive the probability of occupancy after m observations in an empty cell. Given the threshold B^- such that $P_c^m < B^-$, the minimum number of observations m_{min}^- and the average number of observations m_{avg}^- required to declare a cell empty are

$$m_{min}^- = \left\lceil \log\left(\frac{P_c^0(1-P_c^m)}{P_c^m(1-P_c^0)}\right) / \log\frac{1-q}{1-p} \right\rceil \tag{14}$$

and

$$m_{avg}^- \geq \frac{\log\left(\frac{P_c^0(1-B^-)}{B^-(1-P_c^0)}\right)}{(1-q)\log\frac{1-q}{1-p} + q\log\frac{q}{p}}. \tag{15}$$

With probability q^m, the sensor will provide false alarms in all the m observations and eventually the cell will be erroneously declared a target cell (false alarm).

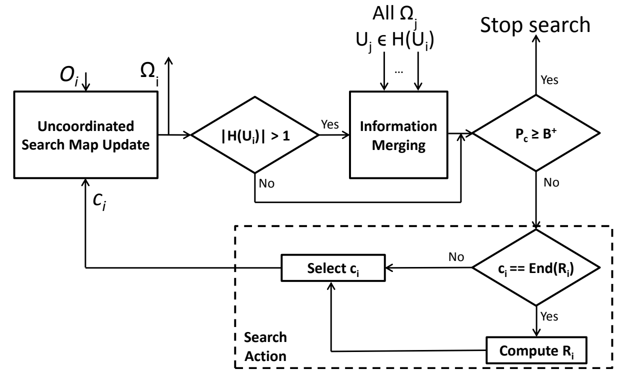


Fig. 1: Processing diagram for cooperative search of an individual MAV U_i.

V. INFORMATION MERGING

Fig. 1 depicts the processing diagram on an individual MAV. At each time step t, an MAV U_i updates its search map using Eq. (5) and exchanges information (search maps) with neighboring MAVs $H(U_i)$. In a given cell c, MAV U_i may now receive different values for P_c which are merged to determine a new value for P_c that best represents the collected information on target existence in c. MAV U_i then selects a search action for the next observation and repeats this process. Depending on r, U_i can now have $1 \leq n \leq N$ occupancy probability values for a given cell c at time t. If $r = 0$, then $|H(U_i)| = 1$ and cell c has only one ($n = 1$) value contributed by the local search map Ω_i of U_i. If the communication range is limited, the neighbors $H(U_i)$ may have different values for a given cell c and U_i can now have at most ($n = N$) values for cell c. In the case of unlimited communication, there are $n = 2$ values for each cell, one contributed by Ω_i and the other by Ω_j, where $U_j \in H(U_i)$. In case of perfect communication, the MAVs have consistent maps as complete and updated information is available to each MAV.

In order to maintain the timeliness of the occupancy probabilities, a simple time stamping mechanism is introduced. Whenever a P_c is updated by U_i, time stamp $\tau_{i,c}$ of this update is captured. If the update is caused by an observation of the cell, the current time step is captured as a time stamp. If the update is caused by merging cell values from different MAVs, the most recent time stamp among the contributing cell values is taken as the 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 with respect to the neighboring MAVs.

Obviously, when no information from other MAVs is available to MAV U_i, $|H(U_i)| = 1$ and information merging is not possible. MAV U_i simply uses the uncoordinated occupancy probability in the search map[1]. If $|H(U_i)| > 1$, U_i receives n occupancy probability values for cell c represented as $\mathbf{P} = \{P_{i,c}, P_{j,c} : j \neq i \wedge U_j \in H(U_i)\}$. Similarly, U_i receives n time stamps for cell c represented as $\mathbf{t} = \{\tau_{i,c}, \tau_{j,c} : U_j \in$

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

$H(U_i)\}$. The information merging method can be expressed as

$$P_{i,c} = f(\mathbf{P}, \mathbf{t}). \tag{16}$$

There are different methods for merging probability values in $\mathbf{P}$ to calculate a new value for $P_{i,c}$. Some of these merging methods and their effects on search time and search errors have already been discussed in [11]. The belief update merging strategy [11] is applied here as it is efficient in reducing the time and memory requirements of cooperative search.

According to the belief update merging strategy, the occupancy probability associated with the latest time step is given more importance to prioritize the most recently collected information. $P_{i,c}$ is replaced with a value from $\mathbf{P}$ with the most recent corresponding time stamp. $\tau_{i,c}$ is updated as $\tau_{i,c} = max(\mathbf{t})$. A specific example is to consider N MAVs in distinct locations with unlimited communication. An MAV U_i receives P_{j,c_j} from MAV U_j and Eq. 16 reduces to

$$P_{i,c_j} = P_{j,c_j} \tag{17}$$

where P_{i,c_j} represents the occupancy probability of U_i at the location of U_j $(j = 1, 2, \ldots, N)$. Here the value P_c in Ω_i is simply replaced by the latest updated value coming from any MAV in $H(U_i)$.

VI. Decision Mechanisms

We present four search algorithms based on centralized or distributed information merging as well as centralized or distributed decision making. Centralized and distributed strategies have different characteristics [38] and we want to explore the design space in the presence of resource limitations. The initial observation of an informative sensor (cp. Eq. (5)) greatly affects the occupancy probability which in turn determines whether a cell remains a candidate cell (if $P_c \geq B^-$). For further observations, the search actions of the MAVs are updated to focus only on the candidate cells. Such search strategy reduces the resource usage and increases the efficiency of the cooperative search.

A. Centralized Decision Making and Information Merging with Team Movement Plans (CCT)

CCT is a completely *centralized* algorithm (Alg. 1), where all MAVs have access to a single search map Ω on the ground station, and the ground station is responsible for the selection of the MAV paths R throughout the mission. Exemplified paths of two MAVs following CCT algorithm are shown in Fig. 2a. The number of targets found Q^+ is initialized with 0, the set of candidate cells S is initialized with C, and the number of negative observations is set to zero for each cell ($Z = \{z_c = 0 : 1 \leq c \leq C\}$). The paths are traversed a fixed number (J) of times to have at least J number of observations per cell as shown in line 5 of Alg. 1. Based on the initial J observations, some cells (with J negative observations) are removed from the search (Alg. 2) while others become candidate cells and new paths are computed (lines 8 to 13) by the ground station to focus only on candidate cells. Thus, the number of cells to be visited for additional observations at each iteration is reduced. Each path is then traversed only once (line 17) and the process of updating S and R continues until Q targets are found. An empty set S indicates that the search process completely missed the target, in which case the search is re-initialized (line 15).

At each iteration, the ground station waits for all the MAVs (some MAVs are in open-loop mode) to complete their paths and then updates both S and R. While the paths are the best possible paths with the given information, the time to search is long due to the wait times. There are two reasons that stop the ground station from frequent re-planning. Firstly, due to limited communication the information available at the ground station may be incomplete. Secondly, the decision made by the ground station may not be communicated to all the MAVs on time. This centralized algorithm is motivated by [28] where new paths for MAVs are computed once the previous paths are completely traversed and information along those paths is collected. Distributed algorithms where autonomy is provided to MAVs will take implicit advantage of frequent updates based on locally available information.

1) Criteria for Candidate Cell Selection: The selection of the value for J depends on p and the probability that a sensor can miss the target in initial $J-1$ observations but detects it in the J^{th} observation. The probability that the J^{th} observation is the first success in a target cell and $J-1$ initial observations miss the target (Geometric distribution) is

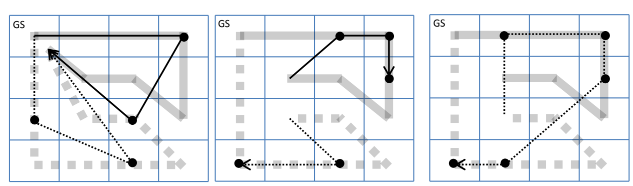
$$Y_J = (1-p)^{J-1} p \tag{18}$$

and

$$J = \frac{log(Y_J/p)}{log(1-p)} + 1 \tag{19}$$

For example, if $p = 0.9$ there is a less than 10% $(Y_J = 0.09)$ chance that a sensor will miss the target in the first observation and will detect it in the second ($J = 2$) observation. If Y_J is given (by the operator), the number of initial observations necessary to predict a cell as a candidate can be selected.

2) Coordinated Movement of MAVs: If $|S| > N$, the ground station updates R by using MTSP otherwise it assigns a single MAV (TSP path) to visit the candidate cells (lines 10 to 12 of Alg. 1). As the MAV U_i can only move to neighboring



(a) (b) (c)

Fig. 2: Exemplified search paths for (a) CCT, (b) CDI and (c) DDI for two MAVs. Paths in gray represent initial iterations, paths in black represent the second iteration. Solid lines correspond to U_1 and dotted lines to U_2. In CCT, all MAVs start from and return to the ground station (GS) at each iteration. In CDI, the GS selects R^0 during the first iteration and each U_i selects S_i and R_i in the second iteration (note that $R_i \in R_i^0$). In DDI, U_2 traverses its path R_2^0 and selects new S_2 and R_2, while U_1 is still on R_1^0 (note that $R_i \notin R_i^0$).

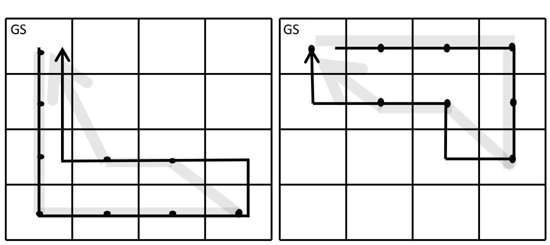
cells, U_i may cover multiple cells while moving from one cell of R_i to another. Fig. 3 shows an example of paths taken by MAVs. The paths generated by the TSP and MTSP solutions are drawn with edges that cut corners of the cells and MAVs use straight-edge distances between cells in our computations. Spending one complete time step by U_i in each cell of R_i is necessary for time step synchronization among the MAVs.

Algorithm 1 CCT runs on the ground station.

procedure CCT(Ω, N, Q, B^+, J)
  $Q^+ = 0$
  $S = C$
  $Z = \{z_c = 0 : 1 \leq c \leq C\}$
  traverse $R = MTSP(S, N)$**,** J **times**
  while $Q^+ < Q$ **do**
    $S = CANDIDATECELLS1(S, Z, J)$
    if $0 <$ **size(**S**) then**
      if size(S**)** $< N$ **then**
        $R_1 = TSP(S)$ ▷ $R_j = \varnothing : j = 2, ..., N$
      else
        $R = MTSP(S, N)$
      end if
    else
      initialize search
    end if
    traverse $R, 1$ **times**
    $Q^+ =$ **number of cells having** $P_c \geq B^+$
  end while
end procedure

Algorithm 2 Selection of candidate cells in S for CCT algorithm.

procedure CANDIDATECELLS1(S, Z, J)
  if $z_c \geq J$ **then** ▷ $\forall c : c \in S$
    remove c **from** S
  end if
end procedure



(a) (b)

Fig. 3: (a) Path R_1 and (b) path R_2 of two MAVs. The gray line shows the path computed by MTSP and the black line shows the actual path taken by an MAV. Cells with dots represent candidate cells, and GS represents the ground station.

B. Centralized Decision Making and Distributed Information Merging with Individual MAV Movement Plans (CDI)

In contrast to CCT, CDI (Alg. 3) is distributed where each MAV U_i has its own search map Ω_i, a set of candidate cells S_i, and the ability to compute a TSP path for itself. The centralized part in this algorithm is the initial assignment of MTSP paths R^0 (line 3) by the ground station, which restricts an MAV U_i to a distinct cluster of cells R_i^0 for the rest of the algorithm execution. Exemplified paths of two MAVs following CDI algorithm are shown in Fig. 2b.

While traversing R_i MAV U_i determines the number of observations to take in cell c based on P_c and O_c (lines 6 to 12). If $P_c == 0.5$ (no prior visits to c), MAV U_i takes observation $O_{i,c}$ and based on the value of $O_{i,c}$ the MAV U_i decides either to stay in c taking m^+_{min} observations ($O_{i,c} == 1$) or to move to the next cell ($O_{i,c} == 0$). If $P_c \neq 0.5$, (c has already been visited) m^+_{avg} number of observations are taken in c. As soon as an MAV moves to a cell with probability p^m, the cell will be declared as target cell in m number of observations.

Once R_i is completely traversed and not all Q targets are found, MAV U_i updates S_i (line 15) and R_i (line 19) for itself. The selection of candidate cells in S_i is also distributed where a candidate cell can only be a cell from the initial path R_i^0. The selection of a candidate cell based on J negative observations is not possible here (each cell has a different number of observations) and can be based on P_c. If $P_c < B^-$, cell c is considered empty and is removed from S_i (Alg. 4). The MAV U_i iteratively updates S_i and path R_i independently of the other MAVs and the ground station. The independent selection of S_i and R_i eliminates the waiting time of the individual MAVs at the ground station as in CCT. If there is no candidate cell the MAV U_i starts again with the initial path (line 17). CDI cannot benefit fully from sharing and merging of information because the MAVs have only a small overlap in their paths and a given cell c is most likely visited only by a single MAV.

C. Distributed Decision Making and Information Merging with Individual MAV Movement Plans (DDI)

DDI differs from CDI only in the selection of candidate cells (Alg. 5). Once the initially assigned paths R^0 are traversed by the MAVs and the targets are not found, the selection of candidate cells takes into account all cells C in the search region (Fig. 2c). The cells in the search region that have an occupancy probability $P_c \geq B^-$ are selected for further visits.

In contrast to CCT and CDI, the distributed coordination in DDI consists of information merging as well as decision making about search actions. The selection of R_i considers the whole search region including the cells that are in R_j, $i \neq j$. This in turn introduces an overlap in the paths and redundant observations in a given cell c by multiple MAVs and results in benefits in terms of search time reduction. The system's intelligence is completely embedded into each MAV, thus raising the level of autonomy of the MAVs. An MAV can now decide by itself, even if communication and availability of information is limited.

D. Distributed Decision Making and Centralized Information Merging with Individual MAV Movement Plans (DCI)

DCI and DDI are exact replicas of each other with the only difference being the location for information merging. In

Algorithm 3 CDI on each MAV U_i.

procedure CDI(R_i^0, Q, B^+, B^-)
  $Q^+ = 0$
  $R_i = R_i^0$
  $S_i = \{c : c \in R_i^0\}$
  while $Q^+ < Q$ **do** ▷ $\forall c : c \in R_i$
    if $P_c == 0.5$ **then**
      if $O_c == 1$ **then**
        Take m^+_{min} **observations**
      end if
    else
      Take m^+_{avg} **observations**
    end if
    $Q^+ =$ **number of cells having** $P_c \geq B^-$
    if $c_i == End(R_i)$ **then**
      $S_i = CANDIDATECELLS2(S_i, B^-)$
      if $S_i == \varnothing$ **then**
        $S_i = R_i^0$
      end if
      $R_i = TSP(S_i)$
    end if
  end while
end procedure

contrast to DDI, DCI depends on a global map Ω at the ground station for information merging. Each observation made by the MAV U_i updates Ω_i as well as Ω. There is no communication among the MAVs and the only communication possible is between MAVs and the ground station. If the communication is limited and the MAV U_i is out of communication range ($\|c_i - GS\| > r$), then the MAV U_i uses only its own map for information updates.

VII. Simulation Results

A. Simulation Set-up

In our simulation study we measure the effect of various parameters on the search time and the search error of our proposed algorithms. We further compare our algorithms to two algorithms which perform only information merging with predefined paths and one algorithm which performs distributed decision making as a reference.

Algorithm 4 Selection of candidate cells in S_i for CDI.

procedure CANDIDATECELLS2(S_i, B^-)
  if $P_c < B^-$ **then** ▷ $\forall c : c \in R_i$
    remove c **from** S_i
  end if
end procedure

Algorithm 5 Selection of candidate cells in S_i for DDI.

procedure CANDIDATECELLS3(B^-)
  if $P_c < B^-$ **then** ▷ $\forall c : c \in C$
    remove c **from** S_i
  end if
end procedure

In our simulations, the search region Ω is composed of $L \times W = 10 \times 10$ cells with an initial value of $P_c = 0.5$. The targets are randomly placed in the search region for each simulation run. The start location of all MAVs and the ground station are set to cell $c = (1, 1)$. Note that in our setup, the communication range $r \geq 14$ corresponds to unlimited communication.

All experiments are based on $M = 1000$ simulation runs. The average search time (T), the average search errors (e) and the false discovery rate (FDR) [39] are used as performance metrics. T is defined as the time of completion of the search algorithm, i.e., when at least Q cells with $P_c \geq B^+$ have been detected. A completed search is erroneous, if at least one target has not been properly detected ($\exists c \mid P_c \geq B^+ \wedge X_c = 0$). Thus, the error rate is given as $e = \frac{e_s}{M}$ where e_s represents the number of erroneous searches. For $Q > 1$, FDR is defined as $FDR = \frac{1}{M}\sum(f_s/Q)$ where f_s represents the number of faulty target detections in a single search run ($0 \leq f_s \leq Q$).

All simulations are performed for specific parameters of $p = 0.9, q = 0.2$ to represent an informative sensor with probability of detection near one and probability of false alarms near zero. The value of $B^+ = 0.99$ is used to show that 99% confidence in the search result is required to stop the search. Degrading the quality of the sensor (p and q) increases the number of time steps to locate the target (cf. [11]). In all simulations, nearest neighbor heuristic[2] is used for solving TSP and a heuristic based on genetic algorithm[3] is used for solving MTSP and thus algorithms proposed in this research inherit all the limitations of TSP, MTSP and applied heuristics.

The proposed algorithms are compared with traditional sweep search or lawnmower-type search [40] where MAVs move straight from one boundary of the search region to other. To avoid multiple MAVs following the same path concurrently, some initial randomness has been introduced in the sweep search. Each MAV starts from the ground station in a random direction (either along the rows or along the columns of the search region) and follows that direction for a random number of cells (less than L or W). Then the MAVs continue with the traditional sweep pattern in the opposite direction. Uncoordinated sweep search (US) does not use information sharing and coordinated sweep search (CS) shares and merges information using the belief update strategy. The proposed algorithms are also compared with distributed cooperative search (DCS) [16], [41], a recent sophisticated algorithm for minimizing the time of multi-MAV cooperative search.

B. Threshold Selection

Simulations are performed for three different threshold values $J = 1$, $J = 2$ and $J = 3$ in CCT and two different threshold values $B^- = 0.5$ and $B^- = 0.1111$ in CDI, DDI and DCI. Setting $B^- = 0.5$ means that the MAVs include a cell c in S if $P_c \geq 0.5$. Otherwise, c is removed from the S which means that a single observation in cell c is sufficient to include

[2] http://www.mathworks.co.uk/matlabcentral/fileexchange/35178-tspsearch

[3] http://www.mathworks.co.uk/matlabcentral/fileexchange/19049-multiple-traveling-salesmen-problem-genetic-algorithm

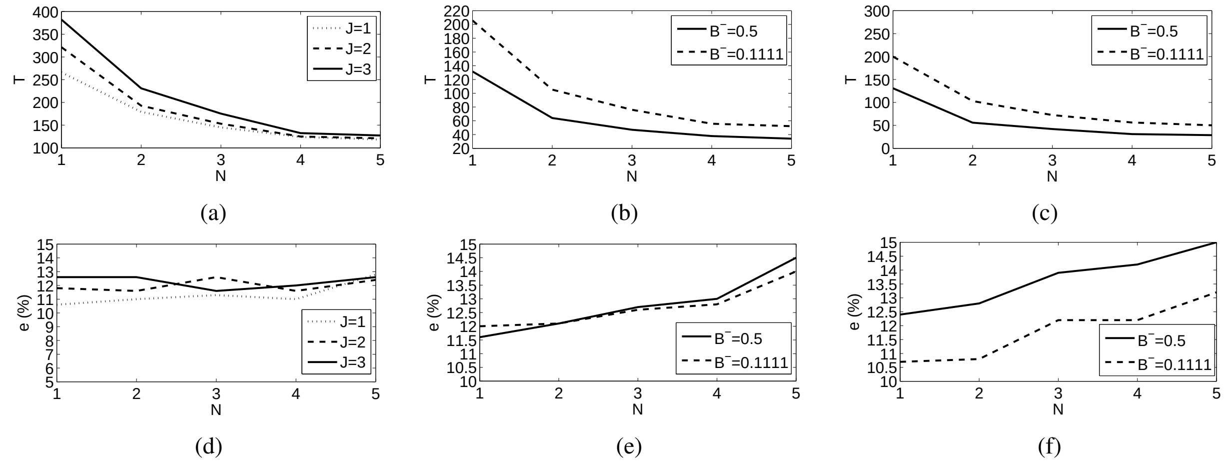


Fig. 4: The effect of increasing the number of MAVs and increasing the threshold values (J and B^-) on the search time (a) CCT, (b) CDI, and (c) DDI and the effect of increasing the number of MAVs and increasing the threshold values on the search errors (d) CCT, (e) CDI, and (f) DDI ($p = 0.9, q = 0.2, B^+ = 0.99, Q = 1, r = 14$).

or remove it for further search. Similarly, setting $B^- = 0.1111$ (a cell is a candidate if $P_c \geq 0.1111$) in CDI, DDI and DCI, corresponds to two negative observations in a cell to remove it from S. Fig. 4 shows the effect of different threshold values (J and B^-) on CCT, CDI and DDI. DCI and DDI generate the same results when communication range is unlimited (see Section VII-C) and that is why Fig. 4 does not show results for DCI. Since increasing J or decreasing B^- increases the number of independent observations the path lengths of the MAVs have to increase as well which in turn increases the search time. Fig. 4 shows the trade-off between search time and search errors as the number of MAVs increase.

C. The Effect of Communication Range

Varying the communication range for CCT does not affect the search time as MAVs do not share information and make decisions while they are traversing the paths. Similarly, the effects of communication range on the performance of CDI are small, as overlapping paths for information merging are unlikely and MAVs cannot fully benefit from information merging. However, the communication range influences the search time of DDI and DCI (Fig. 5).

If no communication among the MAVs is possible, CDI performs better than DDI and DCI. The reason is that the length of path R_i for the MAV U_i does not exceed the length of R_i^0 in subsequent iterations of CDI. While it is more likely that the length of R_i in subsequent iterations of DDI exceeds the length of R_i^0 to consider the whole search region Ω. This increase in length of paths does not facilitate other MAVs in searching the whole region Ω and, thus, increases the overall search time. If communication is possible, the overlap in paths in subsequent iterations of DDI increases information merging among the MAVs. This increase in information merging reduces the number of candidate cells and the length of paths leads to a reduction in the overall search time of DDI (Fig. 5). This improvement increases as the communication range enlarges but saturates as the MAV network becomes fully connected.

An MAV running DCI algorithm is isolated if it is not in communication range with the ground station, even if there are other MAVs in its neighborhood. This makes the DCI algorithm slower than the DDI algorithm, as shown in Fig. 5. As compared to CDI, the improvement in DDI is greater than 13% for 100 cells and full communication. This improvement enhances with increasing number of cells (Section VII-E). Moreover, it is clear from Fig. 5 that DDI and DCI generate exactly the same results when either $r == 0$ or r covers the whole search region. In such cases, keeping information merging either centralized or distributed makes no difference. Therefore, results for DCI algorithm are not shown in the remaining sub-sections where full communication is assumed.

D. Comparison of Algorithms

The goal is to illustrate the impact of information merging and decision making on cooperative search. As shown in Fig. 6, CCT, CDI and DDI significantly reduce the search time as compared to US, CS, and DCS. An interesting observation is that CS performs better than CCT for larger numbers of MAVs, which is caused by the longer waiting times for MAVs

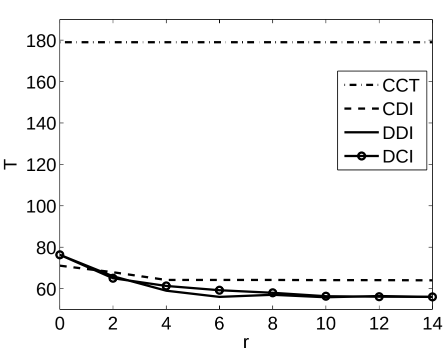


Fig. 5: The effect of increasing communication range (r) on average time steps (T) for $N = 2,\ Q = 1,\ p = 0.9,\ q = 0.2,\ B^+ = 0.99$, and $B^- = 0.5$.

at each iteration in CCT. As the number of MAVs increases DCS outperforms US, CS and CCT due to its ability to frequently update the search action on-line and independent of other MAVs or the ground station. Due to the coordinated decision making, information merging and more intelligent search action selection CDI and DDI clearly outperform the other algorithms.

The proposed algorithms reduce the number of candidate cells in each iteration and increase the number of observations only in candidate cells. The increase of observations only in candidate cells makes the distribution of observations in the search region very skewed towards a subset of cells in the search region. This skewed distribution of observations increases the chances of finding the target without covering the whole search region multiple times and causes a reduction in search time. The distributions of observations in terms of standard deviation of the observations per cell for CCT, CDI, DDI and DCS algorithms are shown in Fig. 7. The standard deviation of number of observations per cell σ for no target in the search region and 140 time steps is computed regardless of which MAV visited the cell. It is clear from Fig. 7 that DDI introduces abrupt variation in number of observation per cell as time increases, which causes significant reduction in search time.

E. The Effect of Search Region Size

Increasing the size of search region, on average, increases the search time of all algorithms. Fig. 8 shows the effects of increasing the size of the search region on performance of proposed algorithms. Simulations in this section are performed for nine different search region sizes, starting from $C = 4 \times 4$ cells to $C = 20 \times 20$ cells. Both the number of rows and number of columns were incremented by two to get different search region sizes. The increase in the size of the search region rises the variation in lengths of paths and number of candidate cells at different iterations of all the proposed algorithms. This variation increases the waiting time in CCT and thus significantly reduces the speed of cooperative search. It is also clear from Fig. 8 that the difference in the results generated by CDI and DDI enlarges with the increase in the size of search region.

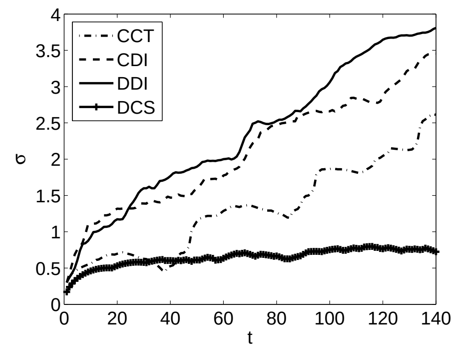


Fig. 7: Standard deviation of the number of observations per cell for 140 time steps and a single simulation run for $N = 3,\ Q = 0,\ p = 0.9,\ q = 0.2,\ B^{+} = 0.99,\ J = 1,\ B^{-} = 0.5$, and $r = 14$.

F. Multiple Targets

Fig. 9 shows the impact of the number of MAVs for three targets ($Q = 3$) on T, e and FDR. Increasing the number of MAVs for a fixed number of targets gradually reduces T but has no considerable effect on e and FDR. On the contrary, increasing the number of targets increases T and e but reduces FDR. The reason is that a larger number of MAVs increases the observations per cell which helps to reduce the number of false positives and, thus, FDR. The search error increases since the probability of missing one out of Q targets also increases.

CDI does not work for multiple targets, if the MAVs are unable to communicate ($r = 0$). The reason is that each MAV tries to find Q targets and not all of them might be present in its assigned initial path (cluster of cells). In that case each MAV may continue its search for an infinite number of iterations. Similarly, the communication range does not affect CCT as explained in Section VII-C. Therefore, the effect of varying communication range is shown only for DDI (Fig. 10). It is evident from Fig. 10, that enlarging the communication range reduces the search time and FDR while increasing the search errors. FDR and e converge to a single point in the case of unlimited communication range.

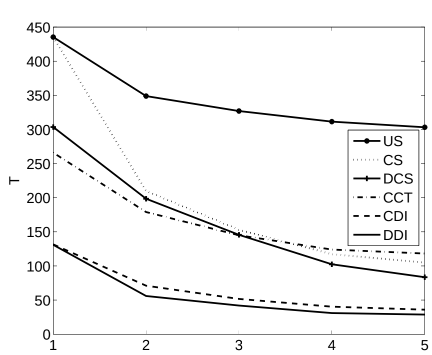


Fig. 6: Comparison of algorithms for $Q = 1,\ p = 0.9,\ q = 0.2,\ B^{+} = 0.99,\ J = 1, B^{-} = 0.5$, and $r = 14$.

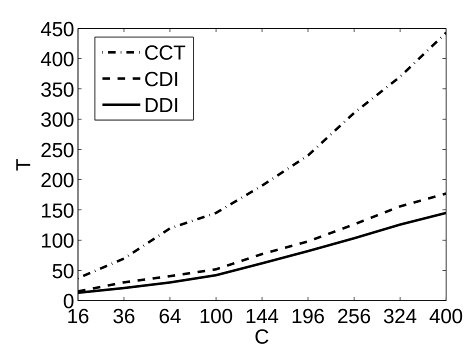


Fig. 8: The effect of increasing the number of cells in search region for $N = 3,\ Q = 1, p = 0.9,\ q = 0.2,\ B^{+} = 0.99,\ J = 1,\ B^{-} = 0.5$, and $r = 14$.

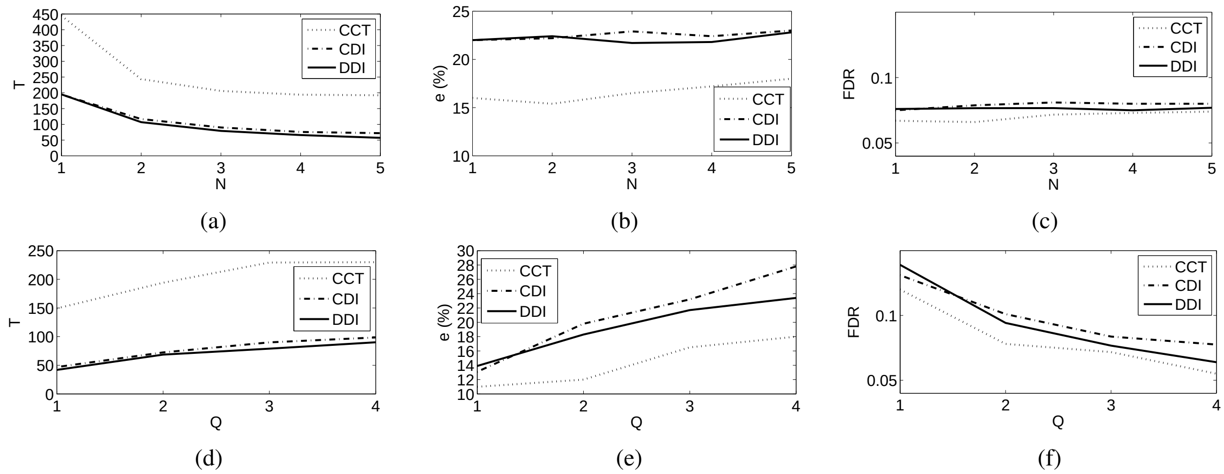


Fig. 9: The effect of increasing the number of MAVs (with $Q = 3$) on (a) T, (b) e, and (c) FDR, and increasing the number of targets (with $N = 3$) on (d) T, (e) e, and (f) FDR ($p = 0.9, q = 0.2, B^+ = 0.99, J = 1, B^- = 0.5, r = 14$).

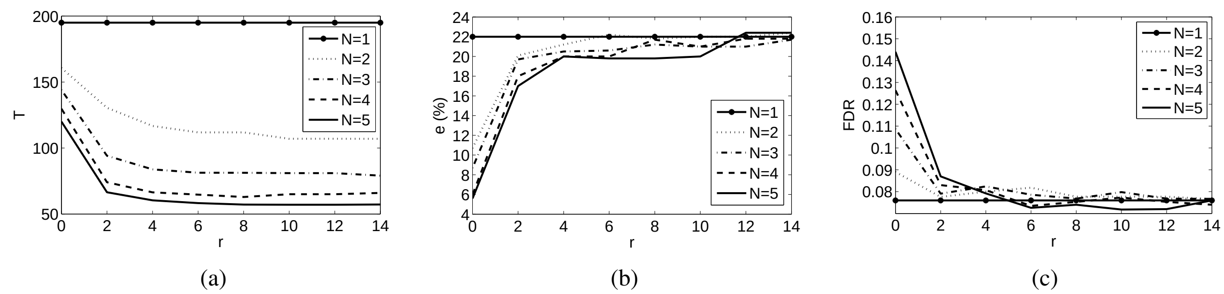


Fig. 10: The effect of increasing the communication range ($Q = 3, p = 0.9, q = 0.2, B^+ = 0.99, B^- = 0.5$) for DDI.

G. Discussion

A limitation of the proposed algorithms is their sensitivity to the values of the sensor parameters (p and q). Determining these parameters is a challenging task because of their dependency on various factors, e.g., type of the sensor (hardware and software), environmental conditions and altitude of the sensor. Deficiencies in the sensor parameters will naturally have a negative effect on the performance of the proposed algorithms. The actual duration of a single time step (t) depends on the overall processing time (Fig. 1). The computation of the TSP/MTSP solution can become the dominant component, especially in case of large search areas. In case of heterogeneous sensors more sophisticated information merging strategies are required. To avoid collisions, the algorithms keep the MAVs at slightly different altitudes. This may cause considerable variations in accuracies and the field of views of the sensors. Moreover, the target location accuracy is modelled at the cell level which in turn depends on the sensor's field of view and, thus, the proposed algorithms cannot determine the position of a target within the field of view or the cell.

VIII. Conclusion

Information merging and decision making represent two important coordination dimensions for cooperative multi-MAV search. In this paper we have investigated four search methods—which differ in whether these two coordination dimensions are centralized or distributed—with limited sensing and communication capabilities. All methods rely on a discretized search map with a Bayesian update rule for the occupancy probabilities. We analytically derived the number of independent observations in order to decide on target absence or existence at a given confidence level. In our simulations we showed that distributed coordination significantly reduces the search time as compared to uncoordinated or centralized coordinated approaches.

Naturally there is much room for improvement in cooperative multi-MAV search. One example is to analyze the coordinated on-line decision making where each MAV has no path information but decides its movement at each time step. Another example is to include additional resource constraints such as the flight time of MAVs. A third example is to consider alternative inference processes for cell updates and dynamic grid sizes to focus the search. Finally, heterogeneous sensors and a 3D representation of the search area and the flight paths could serve as interesting research directions.

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