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Multi-UAV Task Allocation using Team Theory

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Abstract— A multiple UAV search and attack mission in a battlefield involves allocating UAVs to different target tasks efficiently. This task allocation becomes difficult when there is no communication among the UAVs and the UAVs sensors have limited range to detect the targets and neighbouring UAVs, and assess target status. In this paper, we propose a team theoretic approach to efficiently allocate UAVs to the targets with the constraint that UAVs do not communicate among themselves and have limited sensor range. We study the performance of team theoretic approach for task allocation on a battle field scenario. The performance obtained through team theory is compared with two other methods, namely, limited sensor range but with communication among all the UAVs, and greedy strategy with limited sensor range and no communication. It is found that the team theoretic strategy performs the best even though it assumes limited sensor range and no communication.

I. INTRODUCTION

Unmanned aerial vehicles are being extensively used for military purposes, like search, surveillance and as munitions in the battlefield [1] - [10]. They play a crucial role in information gathering from hostile and unknown regions. These UAVs can also be used as munitions to search for, attack and destroy targets in unknown regions. The UAVs used for these applications may have limited capabilities and may not have the required stealth capability and ammunition payload to complete the task single-handedly. Hence, there is a case for such UAVs to be deployed in swarms. A desirable feature for these UAV swarms would be to have autonomous decision making and coordinating capability. As the UAVs perform search, they may find several targets in the search region. The number of UAVs may be more than the number of targets available or the number of targets available may be more than the number of UAVs. In either case, we need an efficient task allocation method for assigning the UAVs to the targets. However, this algorithm must be decentralized and suitable for implementation in a multiple agent UAV swarm. An efficient task allocation strategy should complete the mission (that is, destroy all targets) in minimum time by cooperating and coordinating with other UAVs [1]. Cooperation can be achieved by communication with neighbouring UAVs, explicitly or implicitly. When the UAVs do not communicate with each other, decision making

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becomes a difficult task. The classical solution for task allocation problem would be to have a centralized task allocation system that generates the necessary commands for the UAVs. But, centralized task allocation system have well known limitations and do not address scalability issues too well. Hence, there is a necessity to develop a decentralized task allocation algorithm. Here, we use concepts from team theory to develop such a decentralized task allocation algorithm for multiple UAVs that do not communicate with each other while performing search and attack tasks in an unknown region.

The UAVs that we consider are small in size, have limited fuel capacity (limited flight time), and limited sensing capabilities. The UAVs can detect the presence of neighbouring UAVs and targets within its sensor range only. The UAVs do not communicate with their neighbours and make their decisions based only on the information they receive from their sensors. All the UAVs are assumed to be homogeneous, have constant speed and have no turn radius constraints. The UAVs have to carry out the mission within the given flight time. Collision avoidance between UAVs is not an issue here.

The UAVs can perform search, attack, speculative and battle damage assessment (BDA) tasks. Search task refers to searching for targets in the unknown region. Once a target is found by the UAV, it executes a speculative task to ensure that the target is a real target and not a false target. The target that has been verified as a real target is attacked by the UAV. After attacking the target, battle damage assessment is carried out. The BDA task gives an estimate about the amount of damage caused to the target. The speculative and BDA tasks yield information about the target status, the former before the attack and the latter after the attack is performed. Since there is no communication among UAVs, a UAV does not have any information about whether a target which is not in its sensor range has been attacked by any other UAV. So, it has to perform a BDA with some probability. Since the BDA task and the speculative tasks are similar in nature, we classify the BDA task also as a speculative task.

The speculative task is performed in the following way: Once a UAV finds a target, it estimates the status of the target with some probability. The target can have three different status – (a) Not Attacked (NA) (b) Partially Destroyed (PD) (c) Completely Destroyed or False target (CDF). The probability of the target status is a function of the distance between the UAV and the corresponding target. The estimate about the status of the target is updated as the UAV moves towards the target. So, the speculative task is performed on its way to the target, at every time step.

Each UAV performs decision-making independently, based

on the estimate of the target status. The decision taken by the UAV also depends on the number of neighbouring UAVs. Here, we assume that the UAVs do not have sufficient memory to remember the path travelled so far, as well as the location of the targets already attacked.

A. Literature

Task allocation of UAVs is an active research area for the past few years. Nygard et al. [1], propose a network flow optimization model for allocating UAVs to targets. The network optimization problem is formulated as a linear programming problem to obtain decisions for allocating the UAVs. The authors assume that global communication between UAVs exists. The network flow model has been further extensively studied by Schumacher ([2], [3], [4]) for wide area search munitions with variable path lengths, assignment with timing constraints and path planning. Chandler et al. ([5], [6]), explore various other techniques like iterative network flow, auctions, linear programming, and mixed integer linear programming, for multi-UAV task allocation. The effect of communication delays on the task allocation using the iterative network flow model is dealt with in Mitchell [7]. Curtis [8] presents a task allocation methodology for simultaneous search and target assignment, where the search and task assignments are posed as a single optimization problem. Turra et al. [9] present a task allocation algorithm for multiple UAVs performing search, identification, attack, and verification tasks in an unknown region for targets that move in real time. These authors also address the problem of obstacle avoidance for the UAV. Jin et al. [10] propose a probabilistic task allocation scheme for the scenario presented in [5], [6].

In most of the algorithms presented in the papers cited above, global communication between agents is assumed although the agents themselves have limited sensor range. So, information obtained by an agent is communicated to all the other agents. However, the task allocation decision algorithm is autonomously executed by the agents. The team theoretic approach allows the UAVs to perform decision-making independently when there is no exchange of information with other UAVs, or when there is no communication between UAVs. The UAVs can only sense the location of their neighbours. Radner [11] was the first to show that decentralized optimal team decision problems can be formulated and solved using linear programming techiniques. An example of applying team theory to a manufacturing firm and obtaining team optimal decisions is described in [12] and [13]. Waal and Van Schuppen [14] provide optimal team decision solution for team problem with discrete action spaces. Rajnarayan and Ghose [15] pose a multiple agent search problem as a problem in the team theory framework and propose optimal solution to determination of search regions. Rusmevichientong and Van Roy [16] show that local information sensing with a chain of agents can produce near optimal decisions for the entire team of agents.

In this paper, we present a task allocation algorithm for multiple UAVs performing search, attack, speculative, and battle damage assessment tasks in an unknown region using concepts from team theory for the scenario given in the next section. This is one of the very few applications available that exploits the esoteric team theoretic results to solve a practical problem of decision-making.

B. Problem Scenario

Consider a planar search space consisting of an unknown number of targets. The location of the targets are not known *a priori* to the UAVs. A search and destroy mission would be undertaken by sending a fleet of UAVs to search a region and destroy as many targets as possible within flight endurance time of the UAVs. The task involved in such missions are search, attack, and speculate/battle damage assessment (BDA). A search task involves searching the environment for targets, while attack task involves attacking the target, speculate/BDA task involves estimating the value of the target. The UAVs have to coordinate among each other so as to accomplish the mission faster. Coordination between UAVs has to be achieved without communication. The UAVs also have limited sensor range. The UAVs can sense the exact position of all the targets within its sensor range, but not the exact target values. The location of all the neighbouring UAVs within a UAV's sensor region are also assumed to be detected. This information is utilized to accomplish the mission. The UAVs should perform task allocation so that as much of the mission as possible is completed.

C. Basics of Team Theory

Team theory deals with problems where there are several decision makers who have different but correlated observations about a random state. Each decision maker uses pre-determined strategies to make a decision based on his observations. Depending on the decision taken, the team realizes a common payoff or incurs a common cost. The goal is to minimize this total cost or maximize the global profit in an expected sense.

Let $T = \{1, 2, \ldots, N\}$ denote a team of N decision makers and S denotes the set of alternate states of the world or the environment. We consider the set S to be finite, i.e., there are only a finite number of configuration of the environment. Moreover, there is a probability function $\gamma(s)$ defined on the set S of the possible states of the environment.

Each decision maker receives information about a state $s \epsilon S$. The information received by the ith decision maker is given by

$$y_i = \eta_i(s) \tag{1}$$

where η_i is called the information function of the ith decision maker. The set of all information that the ith decision maker can receive is given by $Y_i = \{y_i\}$. The set $\eta = \{\eta_1, \eta_2, \ldots, \eta_N\}$ is called the information structure for the team.

On the basis of the received information y_i, the ith decision maker takes decision x_i which is given as

$$x_i = \delta_i(y_i) \tag{2}$$

where, δ_i is called the decision function. Let $X_i = \{x_i\}$ be the set of alternative decisions that the ith decision maker can take. Then, δ_i maps $Y_i \rightarrow X_i$. The vector $\delta = \{\delta_1, \delta_2, \ldots, \delta_N\}$ is the team decision function. Depending on the problem, the team decision $x = \{x_1, x_2, \ldots, x_N\}$ may be constrained to satisfy some conditions, i.e., x may be forced to remain within some closed convex set $k(s) \subseteq \mathbb{R}^N$.

The outcome of the team is determined by the state s and the team decision x and it is given by

$$\omega = u(s, x) \tag{3}$$

where, $\omega(s, x)$ is called the *payoff function*. Since, the state of the environment is a random variable with a given probability distribution, we find the expected payoff $E[\omega(s, x)]$. Thus, the objective of the decision maker is to

$$\max_{x \in k(s)} E[\omega(s, x)] \tag{4}$$

If the payoff function is linear, $\omega(s, x)$ can be written as $\omega = \sum_i C_i x_i$, where C_i is a function of the state and it is a random variable. Then, the objective function is given as

$$\max_{x \in k(s)} E\left[\sum_i C_i x_i\right], \tag{5}$$

II. PROBLEM FORMULATION

Considering the scenario described in Section I, let N number of UAVs be deployed for the search and attack operation. The objective of the UAVs is to attack and destroy the maximum number of targets within their endurance time. Each UAV is an autonomous decision maker. We assume that there are M targets in the search space whose exact location or number is not known to the UAVs. The state of the environment, S, consists of the UAV position (q_x, q_y), target position (t_x, t_y) and the target values V_j, $j = 1, \ldots, M$. A UAV can sense the presence of a target and estimate its value with probability $p(d_j)$, which depends on the distance d_j between the UAV and the target T_j.

Let us assume that at time step t_s, UAV i can sense m_i number of targets and n_i number of UAVs within its sensor range. The ith UAV calculates the probabilities $p(d_j), j = 1 \ldots, m_i$ for m_i targets values. The UAV has to decide on its action using this information. The decision that the ith UAV takes is given by the decision vector $x_i = [x_{i,1}, x_{i,2}, \ldots, x_{i,m_i}]$, where $x_{ij} \in \{0, 1\}$ denotes whether the ith UAV will perform the task j or not.

The decision of the ith UAV is based on the benefit C_{ij} obtained by performing task j. The ith UAV uses information of only those of its neighbouring UAVs that are within its sensor range. So, the objective of the team is to maximize the total benefit which is given by

$$\omega = \sum_{i,j} C_{ij} x_{ij}, \quad i = 1, \ldots, n_i \quad j = 1, \ldots, m_i + 1 \tag{6}$$

where, tasks $j = 1, 2, \ldots, m_i$ denote whether UAV i will attack target T_j, and $j = (m_i + 1)$ is the search task. The objective function ω and the constraints are linear. Hence,

we can use the linear programming algorithms to solve the above optimization problem.

Each UAV is at a different geographical position and the environment sensed by each UAV may be different. Hence ω for each UAV would also be different. Moreover, each UAV can perform only one task at any one time instant, so

$$\sum_j x_{ij} = 1 \tag{7}$$

For the mission to be effective, it is necessary that only one UAV should be assigned to one target at a time step. So, we also have the following condition,

$$\sum_i x_{ij} = 1, \quad i = 1, \ldots, n_i, \quad j = 1, \ldots, m_i + 1 \tag{8}$$

But, with the above constraint, the solution might still become infeasible as it may so happen that the number of targets present is more than the number of UAVs and hence it may not be possible to assign all the targets. Hence, we relax the above constraint to

$$\sum_i x_{ij} \leq 1 \tag{9}$$

Thus, the problem can be framed as an LP problem with each UAV solving its own LP. The optimization problem is rewritten as:

$$\max w = \sum_{ij} C_{ij} x_{ij} \tag{10}$$
$$i = 1, \ldots, n_i, \quad j = 1, \ldots, m_i + 1$$

subject to

$$\sum_j x_{ij} = 1, \quad \forall i, \; j = i, \ldots, m_i, m_i + 1$$

$$\sum_i x_{ij} \leq 1 \quad \forall j, \quad i = 1, \ldots, n_i \quad x_{ij} = \{0, 1\}$$

The above LP problem is formulated without using any team theoretic concepts. Now, we describe the LP formulation using team theory.

III. TEAM THEORETIC FORMULATION

The problem defined in Section II assumes that the optimization problem is solved globally. However, in the scenario that we consider, the UAVs do not have global information. Each UAV solves the optimization problem with only local information available to it.

The benefits that the ith UAV calculates for different tasks' are defined as follows:

Search task:

$$C_{is} = \frac{\text{time left}}{\text{total flight time}} \tag{11}$$

Attacking target j:

$$C_{ij} = V_{T_j} w_r - S_t \tag{12}$$

where, V_{T_j} = value of target T_j, w_r = the weight given to search task over the task of attacking a target, S_t = (time to reach the target T_j)/(total flight time). However, the ith

UAV knows the values of the target j with some probability. The probability distribution is assumed to be linear and is shown in Figure 1. Let $p_r(d_j)$ define the probability of target j to have a value r at a distance d. Here, $r = \{0, 0.5, 1\}$ where, when $r = 1$ the target is not attacked, when $r = 0.5$ the target is partially destroyed, and when $r = 0$ the target is fully destroyed. Thus, C_{ij}'s are random variables with probability $p(d_j) = \{p_r(d_j)\}$.

Speculation/BDA: Since speculation on the target is done at every time step, and is reflected on the value of targets, we are not attaching a separate benefit for the speculative task.

Each UAV also estimates the benefits that its neighbouring UAVs (say the kth UAV) will get from the different tasks that it can perform as follows:

Search task: The search task is similar to that defined above, hence the search value is same for all UAVs.

Attacking target j: If target j is within the sensor radius of the kth UAV then

$$C_{kj} = V_t w_r - S_t \tag{13}$$

where,

$$S_t = \frac{\text{time to reach the target } j \text{ by UAV } k}{\text{total flight time}} \tag{14}$$

If, target j is not in the sensor range of the kth UAV then $C_{kj} = 0$. Here, we have assumed that all the UAVs have the same sensor range and hence the ith UAV can estimate whether the jth target is within the sensor range of kth UAV.

Attacking virtual target: The concept of virtual target is used to estimate the environment beyond the sensor range of the ith UAV (see Figure 2). The ith UAV cannot see the shaded region which j^{th} UAV can see. Depending on the number of targets present in that shaded region, the behaviour of the jth UAV will vary. To estimate the number of targets that might be there, we assume that the targets are uniformly distributed. We take into consideration the combined effect of all these target, which we assume to be placed at a point p, equidistant from point (a, b). This combined target is called the virtual target for the kth UAV. The benefit that the kth UAV gets for attacking this virtual target $\hat{k}$ is

$$C_{k\hat{k}} = (\text{average value of target})n_k w_r - S_{\hat{d}} \tag{15}$$

where, n_k is the number of targets that can be present in the shaded region. Therefore, $n_k = n_i (\text{area of shaded region})/\pi(s_r)^2$ and $C_{l\hat{k}} = 0, \forall\ l = 1, \ldots, n_i\ \ l \neq k$, and s_r is the sensor range. That is, for any other UAVs, the benefit of attacking the virtual target $\hat{k}$ of the kth UAV is zero.

Since, C_{ij}s' are random variables, the ith UAV will maximize the expected payoff. The expectation is calculated on the basis of the joint probability $P_i(s)$ of the state. Here, we assume that the value of the targets are independent events, therefore

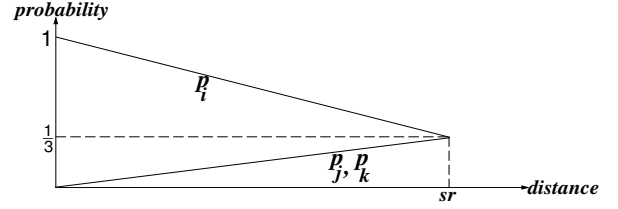$$P_i(s) = \prod_{j=1}^{m_i} p(d_j) \tag{16}$$

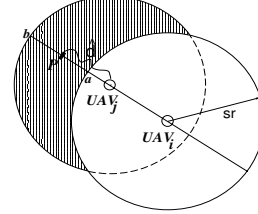Fig. 1.   probability distribution of the values of the targets

Fig. 2.   Determination of virtual targets

The objective is to maximize the expected payoff $E(\omega)$ with the constraints defined in Section II, thus each UAV solves the following linear programming problem:

$$\max\quad E(\sum_{ij} c_{ij} x_{ij}) \tag{17}$$

$$i = 1, \ldots, n_i$$
$$j = 1, \ldots, m_i, m_i + 1,$$
$$(m_i + 1) + 1, \ldots, (m_i + 1) + (n_i - 1)$$

$$\text{subject to}\qquad \sum_j x_{ij} = 1, \qquad \forall i$$
$$\sum_i x_{ij} \leq 1 \qquad \forall j$$
$$x_{i,\hat{j}} = 0, \quad \forall i, \hat{j} = \text{virtual targets}$$

where $j = m_i + 1$ is a search task, $\hat{j} = j = (m_i + 1) + 1, \ldots, (m_i + 1) + (n_i - 1)$ represents the virtual targets.

IV. SIMULATION RESULTS

We demonstrate the effectiveness of using team theory for a multi-UAV task allocation problem using a simulation environment. Consider a geographical search space of 100×100 with 20 targets present in the geographical region, as shown in Figure 3. The search and attack operation is carried out for 200 time steps, which also represents the flight time of the UAVs. The sensor range of each UAV is 20. The location of the target are not known a *priori* to the UAVs. All the targets in the search space have the same target value for these set of simulations, however, in general, the target may have different target values depending on their threat level. The targets are located randomly in the search space. We use 7 UAVs for the mission. The UAVs perform search, attack and speculative tasks on the target. We compare the results when UAVs use team theory based decision making with other types of task allocations, namely, greedy allocation, and limited sensor range with full communication.
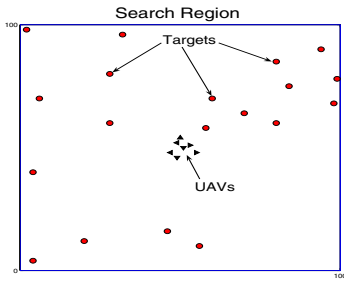
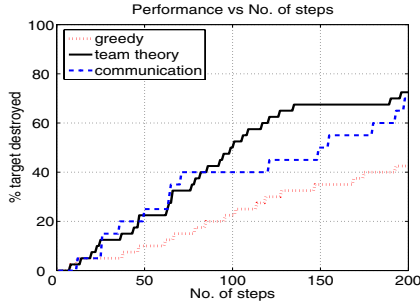Fig. 3.   Search region with UAVs and targets

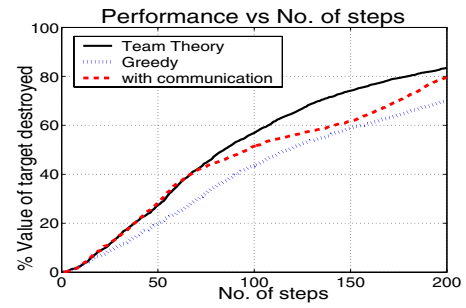Fig. 4.   Number of targets destroyed completely

Fig. 5.   Average target value destroyed; performance for averaging over 20 different maps
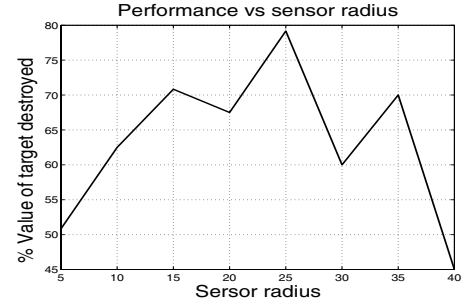
Fig. 6.   Performance of target value destroyed with variation in sensor range for the UAVs

A. Greedy allocation

In this allocation scheme, each UAV decides to move to a target that would give maximum benefit. Since the value of the targets are random variables, we consider the expected value of the target to calculate the benefit C_{ij}. Hence, i^{th} UAV's decision is given by:

$$\max_j C_{ij} = \max_j [E(V_j)w_r - S_t] \qquad (18)$$

where $S_t = \frac{\text{time to reach the target } j}{\text{total flight time}}$

B. Limited sensor range with full communication

Here, each UAV has limited sensor range s_r but can communicate with all the other UAVs. Whenever a new information is sensed by a UAV, the UAV broadcasts the information to all the other UAVs. We assume that there are no communication delays. Hence, all the UAVs have the same information about the state of the environment at any given time. So, all the UAVs solve the same LP problem. Moreover, the concept of virtual target does not apply here, as the ith UAV knows the number of target present in the neighbours sensor region through communication. Similar to greedy strategy, the UAV would like to maximize the expected value of the target. The ith UAV solves the following problem

$$\max_{x_{ij}} \quad \sum C_{ij}x_{ij} \qquad (19)$$

$$\text{subject to} \quad \sum_j x_{ij} = 1$$
$$\sum_i x_{ij} \leq 1 \qquad (20)$$

where $i = 1, \ldots, N$ and $j = 1, \ldots, t_a$, with t_a representing all the targets detected so far.

Figure 4 shows the performance curves for 7 UAVs performing search and attack tasks on a 100×100 search space shown in Figure 3. For evaluation of the performance by each strategy we use the percentage values of the target destroyed (T_d). For instance, at time step t_i, if, say, t_c targets are completely destroyed (hence their value is equal to 0), t_h targets are half destroyed and t_n targets are not attacked, then

$$T_d = t_c + 0.5t_h + 0t_n \qquad (21)$$

The target value destroyed (T_d) provides an insight about how many targets are half and full destroyed in the search space. We can see that as time passes the number of targets being destroyed increases and hence the target value destroyed (T_d) increases. The performance of greedy strategy is the worst compared to other two strategies as expected. However, team theoretic strategy performs the best in spite of their being no communication between UAVs.

Figure 4 show the performance of a particular simulation. To obtain the average performance of all the strategies, we carry out the simulation for 20 different random target maps for 200 time steps each with same UAV positions. During the search task, it is logical that, after some time during which search is carried and if no targets are found, the UAV has to change its direction, so that there is a better chance of finding a target. Hence, after every 10 steps of search task, the UAVs change their direction of search by a random angle. Hence, the performance of the target destroyed sometimes depends on the random change in search direction. Hence, to average out the randomness of search we simulate each target map

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three times and consider the average performance. Figure 5 shows the average performance of each strategy for 20 such randomly generated target maps. From the figure we can see that initially all the strategies perform almost at the same level but with time, team theoretic strategy outperforms the other strategies. This is a significant outcome since the team theoretic strategy assumes no communication between UAVs and has limited sensor range. In case of full communication, the communication costs are incurred and the computational costs are more with respect to the team theoretic strategies as the UAV has to consider all the UAVs information about the targets. The greedy strategy has a tendency to move in groups and of not effectively using the resources of having multiple UAVs for the mission. Team theory perform better and is scalable to large scale systems as the information sensing is local and consequently the computational effort is less.

Figures 4 and 5 have shown that the team theoretic strategy performs better than the other strategies. Another study examines the effect of sensor radius on T_d (Figure 6). Here, we considered a random target map and carried out three simulations for each sensor radius. The effect of sensor radius shown is the average of the three simulations. The figure shows that for this particular case sensor radius of about 25 gives the best performance than any other sensor radius. The performance of team theory, greedy and full communication strategies depends on sensor range. If the sensor radius is small, a UAV can sense very small area and the decision taken will not be effective. We expect that with increase in sensor range the performance will also improve. In the case of team theory, this is not true because if we consider a large sensor range, the estimated value of the virtual target will be incorrect. This is because the area sensed by the kth UAV can include regions beyond the search region space where there are no targets. But, the ith UAV does not consider this fact and assumes equal density of targets everywhere. This unnecessarily gives more weightage on the virtual target and the overall performance decreases. This effect can be seen in Figure 6. This problem can be resolved if we consider other parameters such as target density gradients or restriction to the search space. These aspects are being invistigated and will be reported later.

The ratio of search value to the target value also plays a crucial role. If we give equal priority to search and target then the UAV may opt for search task even though there is a target near it. On the other hand, if we increase the value of the target then there is a possibility that the UAV may loiter around a target which is already destroyed. In our simulations, we considered search value to be 25% of the target value and this seemed to yield good results. But, a more focused study is necessary to study this aspect of the problem.

V. Conclusion

In this paper, we proposed a team theoretic strategy for efficient task allocation for multiple UAVs performing search and attack task in an unknown region consisting of unknown number of targets with no communication between UAVs

and having limited sensor range. The performance of team theory for task allocation studied through simulations show that team theory performs better than other strategies. The scheme is applicable to situations were communications delays or lack of communication becomes a deciding factor in UAV task performance as this scheme does not require any communication at all. The task allocation algorithm can be scalable to large number of UAVs and does not have communication overhead. This is one of the few applications in the literature where team theory has been used effectively to solve a practical problem.

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