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Multi-UAV Task Allocation: A Team-Based Approach

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***Abstract*—This paper presents a team-search based decentralized task allocation scheme for multiple homogeneous unmanned aerial vehicles (UAVs) to provide protection to static convoys of ground vehicles. The UAVs, during operation, protect the ground convoy by searching their vicinity for imminent threat, analyzing/confirming threat level, attacking it and finally assessing the damage to confirm if the threat has been nullified. The proposed approach utilizes search maps to form a common information base for intelligent decision making. A decentralized scheme is developed based on team theory, wherein the best course of action for each UAV is selected to minimize resource use of the team. This scheme is generic enough to handle different types of UAVs and control technique and caters to a dynamic environment.**

The proposed convoy protection scheme is evaluated by software simulation with multi-UAV-multi-targets. Different experiments were performed to analyze the efficacy of this approach. The performance comparison with greedy task allocation highlights the advantage of the proposed scheme.

I. Introduction

Unmanned vehicles are expected to play a more important role in future civilian and military applications. In particular, recent trends indicate that unmanned ground vehicles would be used in transportation of convoys, and their protection. Although these ground vehicles would be capable of protecting the convoys, Unmanned Aerial Vehicles (UAVs) possess the dynamic ability to provide coverage, surveillance, and protection to the ground vehicles [3]. As a result, various research works are being conducted in the domain of UAVs, such as maneuvering, decision control, and path calculation. A natural problem that occurs during the use of UAVs is that of coordination among UAVs. This is especially true when UAVs are required to protect the ground convoy while satisfying multiple kinematics as well as resource constraints. Hence, various UAV coordination techniques have been formulated for efficient decision control [5].

Numerous generic task allocation schemes have been developed under the domains of Mobile Robot Systems (MRS), Multi-Agent Systems (MAS) and Distributed Artificial-Intelligence (DAI). MAS and DAI typically deal with distributed computers and software agents respectively, while MRS focuses on applications in physical robot systems. Within MRS, Multiple Mobile Robot Systems (MMRS) has been studied extensively for similar-skilled homogeneous robots as well specialized heterogeneous robots .The task assigned to the robots can be competitive, as in the case of a soccer playing robot teams, or cooperative, as in the case of search&rescue robots [2]. For unknown operating environments with limited knowledge of it, calls for a dynamic task allocation scheme. Popular schemes include free market architecture [9], auction based schemes [6] and trade based schemes [11]. These methods elegantly simplify the assignment problem by considering costs and/or benefit of every action for every agent and assign tasks to maximize the individual profits. However, they do not explicitly discuss how dropped tasks (tasks that are not performed by any agent due to a negative profit margin) are handled. In a dynamic environment, tasks that may be unproductive to perform at a specific point in time may become attractive at a later point. Use of certainty maps for maintaining history of the environment is popularly used by localization & mapping robot teams and is employed in this work.

In the context of convoy protection considered in this work, an early attempt employed traveling salesperson (assignment problem) [4] based approach to solve this problem. Due to the time-complexity of this approach, an alternative is an auction based game-theory approach [1], where each UAV is considered as an agent who bid on the task they like to be assigned. In [8], a decentralized approach is proposed where the solution feasibility is optimized rather than cost function. However, the above solutions assume that the number of threats are pre-specified. However in real-world convoy protection problem, the number of threats are unknown and the environment is dynamic.

In [7], search maps were used and a dynamic task allocation scheme was proposed for a team of UAVs applied to a search & destroy mission. However, this method like many others, employs a centralized task allocation scheme. For convoy protection, centralized allocation imposes non-line-of-sight communication, longer information loop time and difficult coordination. This highly bolsters the need for a decentralized approach, where coordination can be done directly by convoy. In this work, we develop a decentralized decision control mechanism for multiple UAVs using team-theory inspired

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approach [10]. Team-theory deals with problems where several agents have different yet correlated observations about a given state. Each agent uses predetermined strategies to make a decision based on their observations. Depending on the decision taken, the team incurs a common cost.

It is assumed that each UAV has limited communication capability restricted to a communication radius. Also, each UAV has a limited sensing radius. The aim of a team of multiple-UAVs (UAV team) is to search a given area for possible threats, detect the threats in real-time basis and destroy it, such that the convoy is protected. To achieve this, each UAV consists of four actions: search a given region, confirm the presence of target, attack a target and assess battle damage. During the operation time, each UAV senses the environment and stores the information in its database. It uses this database to assess the information and chooses the best strategy for itself such that individual and hence the total cost is optimized.

The proposed approach has been evaluated on an area of 10m $\times$ 10m with varying number of UAVs, threats and UAV database size. The performance is compared with a variant of greedy algorithm in a similar setting. The performance comparison indicates the advantage of the proposed approach over greedy algorithm.

The rest of the paper is organized as follows. In Section II, we present the dynamic task allocation framework and explain in detail how each of the action and their benefit is calculated. The performance of the proposed scheme is evaluated in Section III. The paper is concluded and future work outlined in Section IV

II. Team Based Task Allocation for Convoy Protection

Bulk transport convoys, unit convoys for brigade support and other special purpose convoys need protection in hazardous terrains. UAVs have been increasingly used in this context due to their aerial surveillance capability and ability to quickly neutralize threats. When multiple UAVs are deployed in such a mission, we propose a scheme to facilitate self regulation and coordination with only high level commands from the ground convoy. We employ team-theoretic approach to decentralize decision making and utilize search maps to store and share environmental information for effective search and attack. The convoy protection mechanism employed here is annihilation of the threats. Other protection mechanisms such as rerouting the convoys are also possible but are not investigated here.

Each UAV considered in this work is capable of performing four different actions: search, confirm, attack and battle damage assessment. To integrate the four actions, a finite state machine is employed. We shall now describe each of the four actions in detail. Finally, this section concludes by describing the finite state machine for the mission.

A. Search Action

In this work it is assumed that the UAVs do not possess any information about the number and location of the threats.

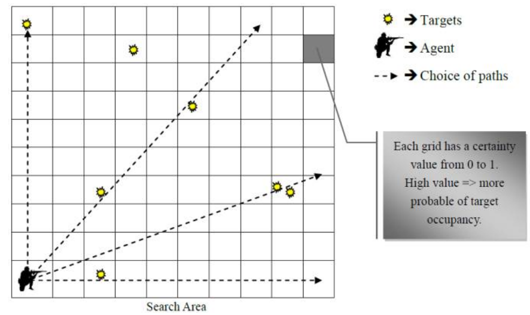


Fig. 1: Zoning of search area (certainty map)

As a result, each UAV during operation does proactive search of its vicinity for any threats. The search mechanism in each UAV zones a given search area into multiple grid of equal size, as shown in the Fig. 1. Associated with each grid is a threat certainty value in the range $[0,\ 1]$ with 0 indicating that UAV is confident about the absence of a threat in a given grid, while 1 represents complete confidence in its presence. At each point in time, the UAV updates this certainty value based on a certain criteria. Let the threat presence certainty of a UAV u about a grid (x, y) at time t be represented as $CertMat_u^{(x,y,t)}$. This certainty is calculated and updated as,

$$CertMat_u^{(x,y,t)} = CertC_u^{x,y} \tag{1}$$

if threat is detected within the UAV's sensor radius with a sensor certainty of $CertC$, and

$$CertMat_u^{(x,y,t)} = 0.5 \times CertMat_u^{(x,y,t-1)} \tag{2}$$

otherwise. It should be noted that the threat certainty value is initialized with 1, i.e., it is assumed that each grid has equally high probability of the threat occurring. As the UAV searches the given grid, this certainty is either reinforced or reduced. It should also be noted that the certainty score for a given grid will never reach zero. These two criteria help the UAV in conducting efficient search of a given space while allowing for uncertainties due to erroneous sensing or mobility of the targets.

At each time step, UAVs update their local certainty map and broadcast this information using a publish/subscribe communication model. UAVs listen to other UAVs within their communication range and update their map based on other team members. This sets up a common information base on the environment, within the team. Since a continuous exchange of the certainty information between agents may impose high overheads in communication, members within a team can be made to exchange information on updates done to their maps rather than the entire data. Bulk information exchange will then be limited to the event when a new member joins the team. Based on the communication radius, multiple groups organize themselves to exchange information. Due to the independent mobility of the team members, information is also shared across groups.

Each UAV then computes the benefit function for traversing in a particular direction. Based on the calculated benefit, the direction that maximizes the benefit is chosen by the UAV for path planning. This path planning has been simplified to 2D in the current work and the UAV is assumed to be single point in space. The benefit of searching a particular region (x, y) for a UAV u at time t is $BSearch$ calculated as

$$BSearch_u^t = \sum_{\forall x,y} K_S \times Fuel_u \times CertMat^{(x,y,t)} \times f(x, y, u) \quad (3)$$

where, $f(x, y, u)$ is the distance of the UAV u from the grid encompassing (x, y), given as

$$f(x, y, u) = \exp\left(-\left((x - u_x)^2 + (y - u_y)^2\right)\right), \quad (4)$$

$Fuel_u$ is the percentage of fuel available with UAV u and K_S is a scaling factor associated with search operation. It is assumed that there is only fuel constraint on the UAV during search operation. The above given search benefit accounts for three aspects of search:

- Benefit decreases with distance of target
- Benefit increases with certainty of target presence
- Benefit decreases with amount of fuel remaining

This formulation also automatically ensures open areas are favored over corners since the direction will span more grids, maximizing the summation.

B. Confirm Action

The UAV can employ any technique to detect a threat, such as computer vision based techniques. In this study, the modality of threat detection is not explored. A threat is discovered if it is within the sensor radius r_u of the UAV u. In the simulation study conducted in this work, the target certainty is assumed to be radially diminishing as the distance to the target increases, while within the sensor radius. The threat presence certainty $CertC$ for a UAV u, at grid (x, y) is given as,

$$CertC_u^{x,y} = \exp\left(-\frac{\left((x - u_x)^2 + (y - u_y)^2\right)}{r_u^2}\right) \quad (5)$$

When approaching the target, if the certainty of target presence increases above a particular confirm-threshold T_C, the UAV confirms the presence of a threat. Upon confirmation of the threat, there are multiple options available to the UAV-convoy system. It can either engage the threat or it can avoid the threat without confrontation by requiring the convoy to change the path. These decisions are made upon perceiving the strength of the threat. However, in this work, the UAV can only attack the threat. It moves in the direction of the threat in order to increase its confidence and to bring the threat within its attack radius.

C. Attack Action

Once it is confirmed which UAV u would attack a given target T, the UAV progress to attacking the target. During attack, a benefit function $BAttack$ is calculated to decide who should attack the target and whether to continue attacking or not. The attack benefit is given by

$$BAttack_u^T = K_A \times I^T \times exp\left(1 - \frac{\|T - u\|}{r_u}\right) * (100 - Fuel_u) \quad (6)$$

where, K_A is a scaling factor associated with attack. I^T denotes the UAV's perceived intensity or strength of the target with 0 indicating target is fully annihilated and 1 indicating its full strength. This is a subjective quantity and different techniques could be employed to gauge the target intensity. In the simulation study presented in this work, the target intensity is calculated as

$$I^T = \frac{\mathbb{N}(0, 1)}{\#attacks\ on\ the\ target} \quad (7)$$

where $\mathbb{N}(0, 1)$ denotes a random value in standard normal distribution. The above benefit function captures three aspects. The attack benefit,

- Increases with the amount of fuel remaining
- Increases with target strength
- Decreases with distance of the UAV from the threat

When a UAV confirms target presence in its vicinity, the team is updated on this. The team keeps track of the list of targets and their perceived strength. The individual decision making on which team member to attack which target uses team theory principles [10]. Each UAV solves a simple optimization problem to maximize the benefit of the team rather than its own. This ensures the UAVs are not greedy and unnecessarily expend energy in attacking targets when some other member can perform the same action more efficiently. Further, constraining that not more than one UAV should be assigned to a particular target ensures conflict resolution.

D. Battle Damage Assessment Action

The UAV, upon attacking, assesses the damage inflicted upon the target. Based on its assessment, it estimates whether the threat has been nullified or if it should continue with the attack. A threat is assumed to be destroyed if its target intensity is below a given threshold.

E. Finite State Machine

In the above subsections, different UAV actions were described and the benefit associated with each were calculated. In this subsection, technique for combining these four actions would be detailed. A finite state machine is designed as shown in Fig. 2. The use of the finite state machine enables decentralized decision making by the UAVs based on the benefits calculated.

It could be observed from the figure that a UAV is initialized with search action. The UAV continues to perform search and confirm actions until it encounters a threat. Upon encountering the threat and confirming its presence beyond doubt, it moves to attack action with the aim of annihilating the threat. Once the threat is confirmed and the UAV that would engage the threat is decided, the chosen UAV changes its action to attack. Upon attacking the target, the UAV moves to battle

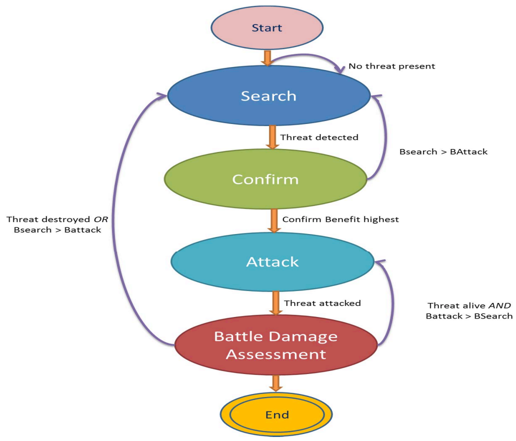


Fig. 2: Finite state machine realization

damage assessment state, to assess the amount of damage done to the threat. During damage assessment, the UAV will recalculate the attack benefit as well as search benefit, to decide whether to continue with the attack or return to search mode. It will continue to attack the threat until the threat is minimized or the search benefit calculated is higher than that of attack benefit. This will help in balancing exploration and exploitation, minimizing the effect of the threat while optimizing the amount of resource available (primarily fuel).

Next, we shall evaluate the performance of the proposed method for convoy protection.

III. Performance Evaluation

In this section, we shall first describe the experimental/environment setup, followed by the type of experiments conducted and the performance measures employed. Then we shall discuss each of the experiments in detail and provide a comparison with a well-known greedy algorithm that forms the basis of popular schemes such as free market architecture, auction based approach and trade based approach.

A. Experiment Setup

The environment considered in this study is a 10m $\times$ 10m area at the center of which is located the convoy. The environment is planar with no obstacles and the UAVs and the threats are initialized at random location. The aim of the UAVs is to search the given area for any threats and protect the convoy from them. Each UAV in this region is set to have a search grid of size 0.5m $\times$ 0.5m. Its target sensing radius is set as 0.5m and its communication radius is set as 2.5m. It is assumed that each UAV can take a decision on its own action 10 times (iterations) in one second.

B. Simulation Settings

The proposed convoy protection mechanism is simulated on Matlab$^{(R)}$ R2014b. To study the effect of the mechanism, a monte-carlo simulation study was conducted where each experiment was repeated 1000 times. At each repetition, the threats and the UAVs were initialized at different locations.

C. Performance Measures

In this study, two performance measures are employed:

- Percentage Threat Destroyed: $\frac{\#Targets\ Destroyed}{\#Targets}$
- Percentage Target Strength Reduced: $\frac{\sum_{\forall Targets} Strength\ After\ Attack}{\sum_{\forall Targets} Initial\ Strength}$.

Both the performance measures are calculated for a given period of time. Since targets may be mobile, the time for complete neutralization of targets may vary significantly and hence not used as the performance measure for the monte-carlo simulation. The percentage targets destroyed is done in comparison to ground truth. It should be noted that percentage targets destroyed is given only for the sake of comparison and in the UAVs do not have information about the number or the location of the threats. Also, in some scenarios, it is not required to fully annihilate the threats and incapacitating them would be sufficient. This would help in decreasing the threat while conserving resources. To ascertain this, the second performance measure of the percentage reduction in target strength is used.

D. Performance Comparison - Time to Task Completion

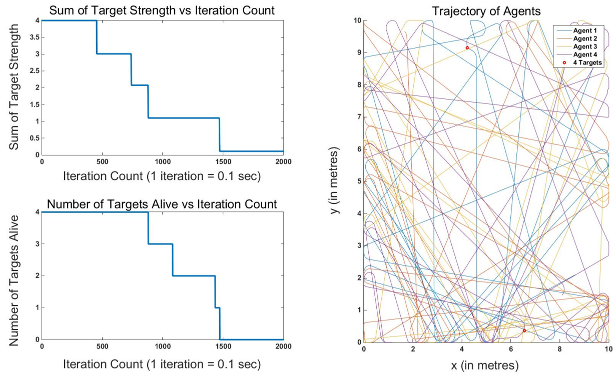
In the first study, the number of UAVs and the number of threats were assumed to be 4 each. The two algorithmic settings were simulated, greedy algorithm and the proposed decentralized team algorithm. The target strength, number of targets destroyed and the search map during this period for one simulation is given in Fig. 3.

From the figure, it can be observed that the team based task allocation algorithm attained better performance than greedy algorithm. Team search destroyed all targets within 80sec whereas the greedy algorithm took 150sec. Further, the total target strength was reduced to a minimal value within 60sec by team search as opposed to 140sec by the greedy algorithm. These observations were consistent across multiple simulation studies. Thus, the team based task allocation approach is able to achieve the team's objective of destroying maximum threats while balancing resource usage.

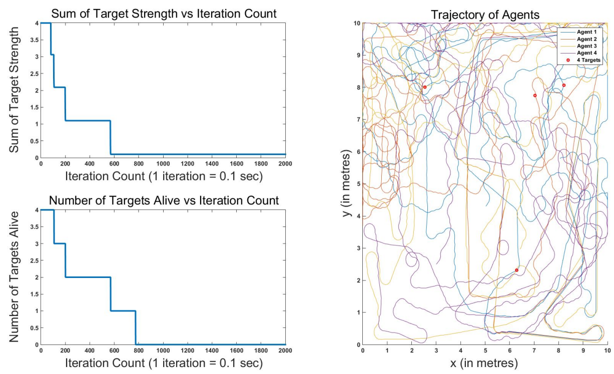
E. Performance Comparison - Varying Number of UAVs

In order to analyze the effect of varying the number of UAVs, their number was varied from 1 to 10, keeping the number of targets fixed at 4. The simulation time was kept short at 50sec to challenge the algorithms. A search grid of size 0.5m $\times$ 0.5m was used for the certainty map. The result of monte-carlo simulation of varying the number of UAVs is given in Fig. 4. The result was averaged over 1000 simulations. The figure plots the number of UAVs versus % threats annihilated and % target strength reduced.

It can be seen from the figure that the performance of the team-search is better than greedy algorithm in both performance measures by a range of 10 to 35%. This is consistent across different team sizes. Also, as expected, performance of both algorithms improve with team size. However, the difference in performance between the two algorithms is



(a) Greedy Algorithm



(b) Team-based Algorithm

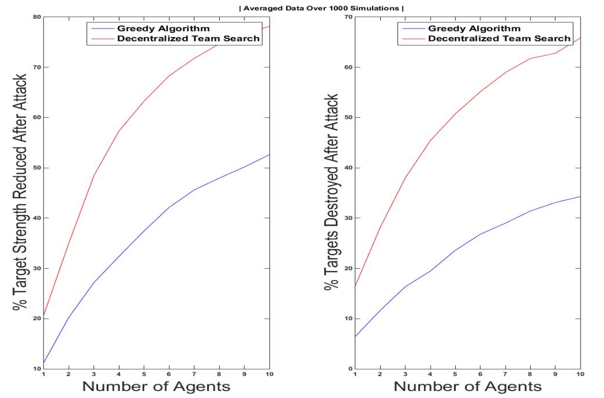
Fig. 3: Performance comparison of (a) Greedy Algorithm and (b) Decentralized Team-based Algorithm (time to task completion)

higher for larger teams. This directly relates to the fact that larger teams will have better information hopping in team-search since communication radius is restricted. Thus the team members will be equipped with more accurate information of their environment.

F. Performance Comparison - Varying Number of Targets

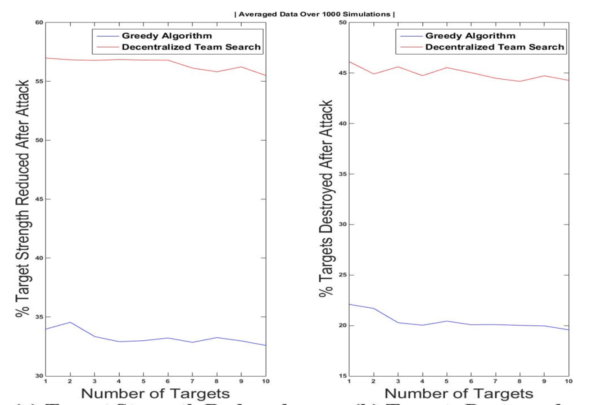
In this study, number of threats is varied from 1 to 10 and are randomly initialized at every study. The number of UAVs is fixed at 4. The simulation time was kept short at 50sec. A search grid of size 0.5m $\times$ 0.5m was used for the certainty map. The result of monte-carlo simulation of varying the number of UAVs is given in Fig. 5. The result was averaged over 1000 simulations. The figure plots the number of targets versus % threats annihilated and % target strength reduced.

Once again, the figure illustrates that team-search is better than greedy algorithm in both performance measures by a range of 20 to 25%. This is consistent across different number of targets. Also, as expected, performance of both algorithms show a small reduction when larger number of targets are present.



(a) Target Strength Reduced vs Number of Agents **(b) Targets Destroyed vs Number of Agents**

Fig. 4: Performance comparison of greedy and team-based task allocation algorithms : Effect of varying the number of UAVs (averaged metric over 1000 simulations)



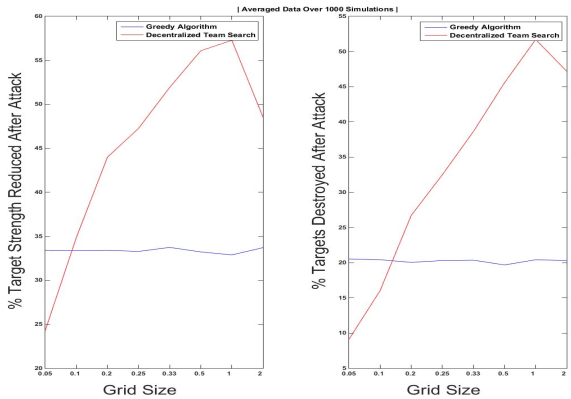
(a) Target Strength Reduced vs Number of Targets **(b) Targets Destroyed vs Number of Targets**

Fig. 5: Performance comparison of greedy and team-based task allocation algorithms : Effect of varying the number of targets (averaged metric over 1000 simulations)

G. Performance Comparison - Varying Grid Size

The final study conducted is to analyze the performance of the proposed approach on varying the grid size. The number of UAVs and targets are fixed at 4 each. The simulation time was kept short at 50sec. The grid size is varied such that different granularity of the environment is achieved, i.e., from 0.05m $\times$ 0.05m to 2m $\times$ 2m ($4*10^4$ grids to 25 grids). This influences the memory required for maintaining the database, the computation for path planning and communication overhead in sharing the information between UAVs. The result of monte-carlo simulation of varying the number of UAVs is given in Fig. 6. The result was averaged over 1000 simulations. The figure plots the variation in grid size versus % threats annihilated and % target strength reduced.

The figure illustrates an interesting aspect of varying the grid size. For grid sizes below 0.2m $\times$ 0.2m, the greedy



(a) Target Strength Reduced vs Grid Size **(b) Targets Destroyed vs Grid Size**

Fig. 6: Performance comparison of greedy and team-based task allocation algorithms : Effect of varying the grid size (averaged metric over 1000 simulations)

algorithm performs better than the team search. This may be counter-intuitive since more granularity of information should mean better performance. However, smaller grid size means the UAV updates the certainty map with information of a smaller area every iteration. This causes slower information update on the environment. Since the UAV's sensing radius is 0.5m, there is no advantage of having a granular information beyond 0.2m grids. For grid sizes between 0.2m and 1m, the team search outperforms greedy algorithm in both performance criteria by a range of 7 to 22%. But beyond this, as expected, with lesser granularity of information about the environment, the performance of team search deteriorates. Thus, it is optimal to keep the grid size small but not smaller than half the sensing radius of the UAV.

IV. Conclusion

In this paper, a decentralized team based task allocation algorithm inspired by team-theory was proposed for convoy protection. The algorithm utilizes a search certainty map to historize information, ensuring no dropped tasks of eliminating known targets. Further, decision making by the UAV ensures minimum resource requirement for team rather than itself. The performance of the proposed approach was analyzed by simulating a search space with unknown number and location of targets and UAVs. Various studies were conducted to understand the effect of varying the number of UAVs, the number of targets and the grid size, on the performance of the algorithm. It could be concluded that, larger the team, more the information exchange and better the performance. Further, the algorithm eliminates threats effectively within a given time, irrespective of the number of targets. Also, it was observed that the grid size setting for the search map should be close to the sensing radius for most optimal performance. The algorithm was compared with a decentralized greedy algorithm that forms the basis of popular schemes such as free market architecture, auction based approach and trade based approach. Results indicated significant performance improvement in convoy protection problem.

In the future, we aim to explore other methodologies of convoy protection such as re-routing. We intend to improve the benefit formulation and introduce adaptation and learning into it. This will help to make the algorithm versatile to different scenarios. Further, it will provide a better handle to balancing exploration versus exploitation. Another area for improvement is optimizing search through better path planning and extending this to 3D. This technology could be employed in multiple arenas of search and destroy, autonomous robots for verification, etc.

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