Ant Colony Optimisation based Cooperative Search and Attack using multiple UAVs in unknown environment

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***Abstract*—This study investigates the application of the Ant Colony Optimisation Algorithm(ACO) for multiple UAVs. A dynamic environment with unknown target locations is searched using a probabilistic pheromone update formulation for the transition of states. Firstly, the dynamic environment model with multiple UAVs, Targets, and threats is established. Secondly, state transition rules were stated for UAVs by improving the behavior criterion of the ant colony algorithm and the updating principle of the pheromone map. Further, another improved Ant colony algorithm is adapted for multiple constraints and a search-attack mission has been accomplished for determining the performance measures. Finally, the improved algorithm is compared with the former ACO algorithm, random and parallel search algorithms with simulation results.**

***Index Terms*—Ant Colony Optimisation, Pheromone, Cooperative search and attack, Unmanned Aerial Vehicles, dynamic environment.**

I. INTRODUCTION

Unmanned Aerial vehicles-based exploration of unknown environments has been an open area of research in the interest of using advanced technology in modern warfare. Considering the limit in the range of exploration in a given time by a single UAV, a few multiple UAV-based exploration techniques have been formulated for a faster search of the given region. A large number of algorithms have been studied and formulated from the biological inspiration in the literature such as Ant Colony, Bee Colony, Simulated Annealing algorithm, Particle Swarm Algorithm, Tabu search, etc.,

A cooperative predictive control multi-UAV search algorithm in free flight mode has been proposed which considers a regional probability map with communication constraints in Reference [1].In [2] a coordination mechanism is used in guiding the UAVs for potential area exploration. A collaborative search method for multi-target cooperative search with multiple UAVs based on the Multi Ant Colony Algorithm is proposed in [3]. Furthermore, some improved heuristic algorithms were proposed such as a multi-objective Genetic Algorithm (MOGA) for solving a complex mission planning problem. [4], [5]. Although these algorithms reduce the computation, they are still computationally expensive for online planning in dynamic environments with complex constraints.

One of the most successful algorithms for these problems is ACO known as Ant Colony Optimization based on Ants. (Design and Implementation). ACO is inspired by the foraging behavior of ant colonies targeting discrete optimization problems. This Algorithm studies a model derived from the observation of real ants' behavior, and uses these models for the design of novel algorithms for the solution of optimization and distributed control problems. Ant Colony Algorithms are applicable to both static and dynamic optimization problems. Static optimization problems include those where the problem characteristics defined in the beginning, do not change while the problem is being solved. Dynamic problems are those where these characteristics will be a function of model dynamics. However, ACO proves to be a promising approach to both kinds of optimization problems. In this project, we investigate the implementation of Ant colony Algorithms and their limitations for the task of cooperative search and attack. First, we start with an improved ACO algorithm as in [6], thereby imposing multiple constraints such as no-fly zones and threats along with collision-avoidance and maneuverability constraints [7].

The rest of the paper is organized as follows. Section II introduces the problem formulation for a cooperative search and attack. This section describes the formulation of the Mission environment model, state transition rules, and pheromone update rules for two different ACO algorithms. Simulation results are illustrated and discussed in Section III. Section IV involves the conclusion.

II. PROBLEM FORMULATION

In this section, the mission-environment model, heuristic state transition rules, and rules for pheromone update are discussed. Assumptions under consideration and definitions to be used in further sections are stated here.

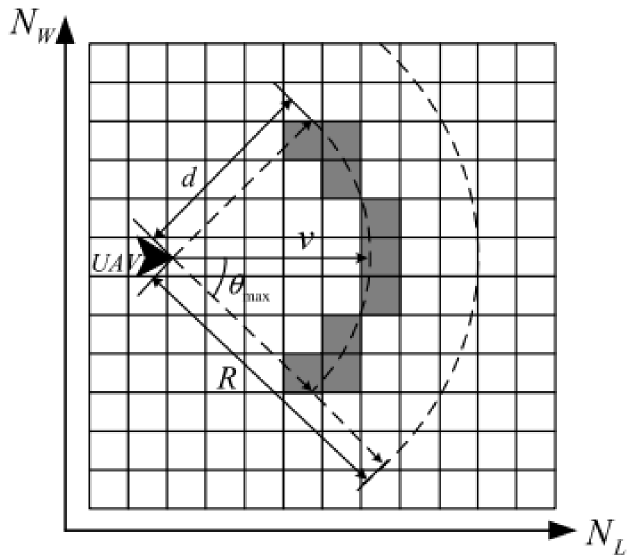
A. Mission-environment model

The search areas is modeled as a dynamic environment with the following assumptions:

Assumption 1: All the UAVs are identical and can perform both search and attack missions.

Assumption 2: At any time instant, UAV will always lie within a grid.

Assumption 3: UAV altitude is fixed i.e. search is only 2 dimensional.



(a) Discretised Area

Mission Area: The UAV mission area is discretised into $N_L \times N_W$ grids. Targets appear randomly in this discretised area at the grid centers. Threats and No-fly zones are modeled as circular regions in the grid area. A UAV can move from its position to next position depending on maneuverability constraints on turning radius **R** and turning angle $\boldsymbol{\theta}$ as shown in fig[1].

B. Heuristic State Transition

A UAV transitions from one state to another following maneuverability, threat avoidance, and collision constraints. A state of a UAV is defined as

$$\begin{cases} \text{State}_i(k) = \{\text{State}_{j,i}(k_j), \text{Ant}_j \in AC\} \\ \text{State}_{j,i}(k_j) = \{(x_{j,i}(k_j), y_{j,i}(k_j)), PSI_{j,i}(k_j)\} \end{cases} \quad (1)$$

where $State_{j,i}(k_j)$ is the information of Ant_j stored by Ant_i.$\{(x_{j,i}(k_j), y_{j,i}(k_j))$ is the position of Ant_j at time k_j, $PSI_{j,i}(k_j)$ is the direction of movement of Ant_j at time k_j.

$$grid_1{}^*(k+1) = arg \max_{GRID(k+1)} (\boldsymbol{\tau}^{\alpha}(GRID(k+1)) \times \eta^{\beta}(GRID(k+1)). \quad (2)$$

where $GRID(k+1)$ is the set of candidates at the next time instant,α is the importance degree of pheromone concentration in transition and β is the heuristic transition importance degree. If 2 has multiple solutions, then a factor of minimum steering angle is chosen.
In (2),τ is pheromone concentration and η is the benefit which is given by

$$\eta = P = \frac{\sum_{x=1}^{N_L} \sum_{y=1}^{N_W} \text{ grid }_{(x,y)}}{N_L \times N_W} \quad (3)$$

C. Constraints

This subsection gives detailed descriptions of different types of constraints imposed on the UAV models
(1) Maneuverability constraints: the maximum turning angle θ_{max} of each UAV which limits its turning radius and rate is considered as

$$C_m : \theta_i(k) - \theta_{max} \le 0 \, (i = 1, 2, 3, ...N_v) \quad (4)$$

(2) Collision-avoidance constraints: a safe distance is considered between the UAVs for avoiding collision as

$$C_c : d_{min} - d_{ij}(k) \le 0 \; (i = 1, 2, 3, ...N_v; i \ne j) \quad (5)$$

where $d_i j(k)$ is the distance between the i-th and j-th UAVs at time k, and d_m

(3) Threat-avoidance constraints: a safe distance is considered between the UAVs for avoiding collision as

$$C_t : R^l{}_T - d^{il}{}_T(k) \le 0 \; (i = 1, 2, 3, ...N_v; l = 1, 2, 3...N_T) \quad (6)$$

where $d^{il}{}_T(k)$ is the distance between the i-th UAV and l-th threat, and $R^l{}_T$ is the radius of the l-th threat.

D. Pheromone Update

Each UAV maintains a local pheromone map of size $N_L \times N_W$. As each UAV moves from one grid to the other,the neighbouring grids of the UAV current state sees a decrement in the pheromone which is inversely proportional to the distance from the grid. The local pheromone update equations are as follows

$$\begin{cases} \tau^i_{(x,y)}(k+1) = \tau^i_{(x,y)}(k) - \Delta\tau^i_{l(x,y)}(k) \\ \Delta\tau^i_{l(x,y)}(k) = \sum_{j \in T^i_{\text{neighbor}}} \Delta\tau^{(i,j)}_{l(x,y)}(k) \end{cases} \quad (7)$$

where $\Delta\tau^i_{l(x,y)}(k)$ is the pheromone decrement of the $grid(x,y)$, is the sum of the pheromone decrement by $\Delta\tau^{(i,j)}_{l(x,y)}(k)$ due to Ant_j and

$$\Delta\tau^{(i,j)}_{l(x,y)}(k) = \begin{cases} \Delta\tau_{l_0} \times \frac{R^4 - d^4\left((x,y),\left(x^*_{j,i}(k), y^*_{j,i}(k)\right)\right)}{R^4}, \\ \quad d^4\left((x,y),\left(x^*_{j,i}(k), y^*_{j,i}(k)\right)\right) \le R^4 \\ 0, \quad d^4\left((x,y),\left(x^*_{j,i}(k), y^*_{j,i}(k)\right)\right) > R^4 \end{cases} \quad (8)$$

where $\Delta\tau_{l_0}$ is the local pheromone attenuation coefficient,$d\left((x,y),\left(x^*_{j,i}(k), y^*_{j,i}(k)\right)\right)$ represents the distance between the two grids .The above equations apply to only grids in the detection range R.

Global Pheromone Update: During the search, new targets may appear in the area which has been searched before. Hence the uncertainty in the mission area will increase as time passes by and accordingly the concentration of pheromones of the grids needs to be enhanced. Therefore, a global pheromone update mechanism is designed as follows:

$$\tau^i_{(x,y)}(k+1) = \tau^i_{(x,y)}(k) + F \times \Delta\tau_{g_0} \quad (9)$$

where F is the environmental uncertainty and $F \in (0, 1)$. Saturation values of τ_min and τ_max are applied to prevent too high or too low pheromone values at any grid.

Algorithm 1 ACO for Search and Attack

```
Initialize MAP, Targets, Threats, UAVs
Position each UAV in Starting Positions
while stopping criteria not met do
    for each ant do
        find candidate grids
        update candidate grids by removing infeasible grids
        if target in candidate grids then
            choose max value target grid
        else
            choose grid as per equation
        end if
        Move UAV
    end for
    for each ant do
        update local pheromone as in (7),(8)
        update local pheromone as in (9)
    end for
end while
```

E. Alternate ACO formulation

In this subsection, an alternate approach for finding the next state for UAVs is discussed. The grid selection for the next state follows the rule:

$$P_{ij}^{k} = \frac{\tau_j^{\alpha} \cdot \eta_{ijk}^{\beta}}{\sum_{j \in J_k} \tau_j^{\alpha} \cdot \eta_{ijk}^{\beta}}, j \in J_i^k \tag{10}$$

where,

$$\eta_{ijk} = \begin{cases} 1/4 \times \eta_{ij}, \theta = 0° \\ 5/24 \times \eta_{ij}, \theta = 45° \\ 1/6 \times \eta_{ij}, \theta = 90° \\ 0, \text{ others} \end{cases} \tag{11}$$

where,

$$\eta_{ij}(t) = \begin{cases} 1.4, D(i,j) = 100 \\ 1, D(i,j) = 100\sqrt{2} \\ 0, \text{ others} \end{cases} \tag{12}$$

The pheromone update using this alternate approach is as follows:

$$\tau_j(t+1) = \tau_j(t) - \Delta\tau_j(t) \tag{13}$$

where,

$$\Delta\tau_j(t) = \sum_{k=1}^{m} \Delta\tau_{ij}^{k}(t) \tag{14}$$

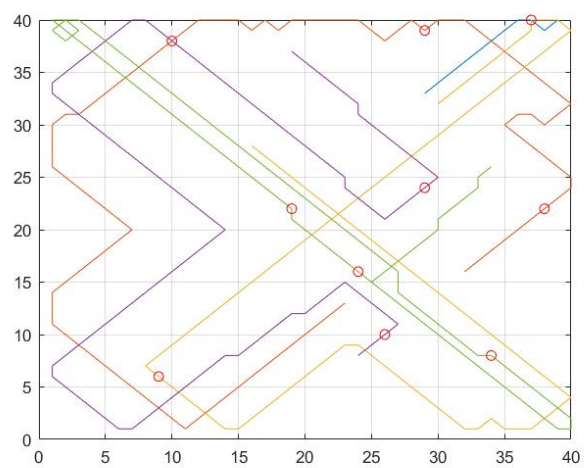
where,

$$\Delta\tau_{ij}^{k}(t) = \begin{cases} \frac{1}{2\sqrt{2\pi}} \exp\left(-\frac{\left(\frac{Q}{D(i,j)}\right)^2}{2}\right), D(i,j) < 500 \\ 0.9, D(i,j) = 0 \end{cases} \tag{15}$$

From the above equations, we can observe that the pheromone decrement around the current grid follows an exponential decrease. Here the equation (10) calculates the probability of the candidate grid to be the next state in the state transition. We observe that η accounts for the ease of steering as compared to the previous instance where η accounts for the search benefit.The equations (13),(14),(15) give the pheromone update rules using this alternate algorithm.

III. SIMULATION ANALYSIS

A Matlab simulation and results for the above-mentioned algorithm are illustrated in this section.The parameters chosen are grid size $N_L \times N_W$=1000 $\times$ 1000 of map size 50x50 km.The number of UAVs chosen is 2. The number of Targets is 18. Speed of each UAV is 250m/s. The detection radius is 1km Maximum steering angle $\boldsymbol{\theta_{max}}$=45 degree.$\Delta\tau_{l0}$=1,$\Delta\tau_{g0}$=100, and F=0.022,$\alpha$=1,$\beta$=5..The simulation is run for 1000 iterations for both algorithms and a comparison has been made with Random and Parallel search methods.

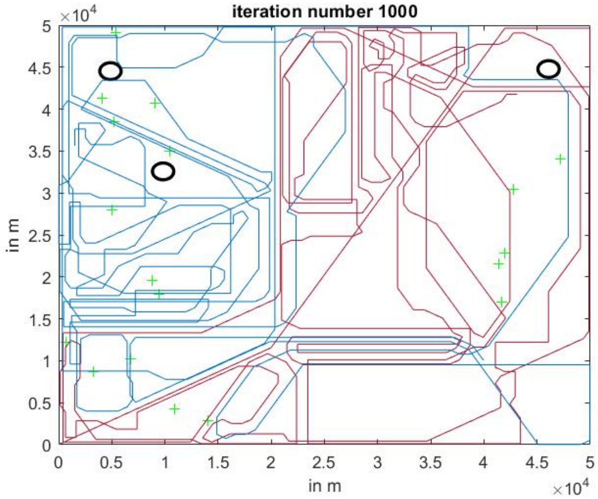


(a) Alternate Ant Colony optimization with no.of UAVs 5

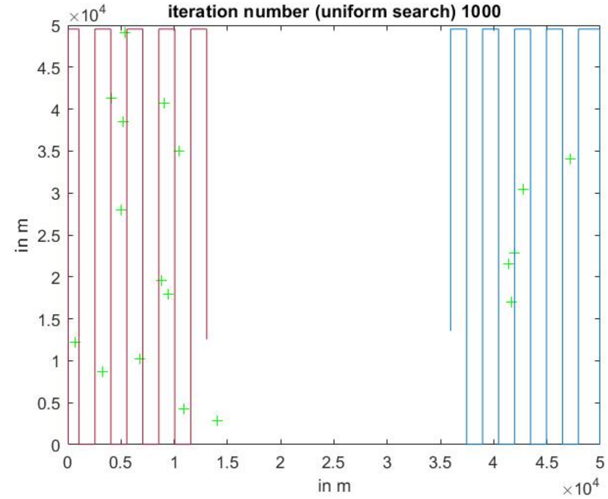
As we can see from the fig(2a), fig(3a), fig(4a) and fig(5a) the Alternate ACO and improved ACO (SAMSOA) has better search performance than traditional Random and Parallel search methods. Also the table fig(6a) shows the information about the performance measures i.e. Coverage rate and number of Targets found where the coverage rate is the ratio of sum of all the visited nodes by an algorithm to the maximum possible nodes that can be visited in a given number of iterations. It is observed from the table that improved ACO finds thrice the number of Targets found by Random search with a high coverage rate. Also, as the number of iterations increases, the coverage rate is decreasing because of the overlapping of the search areas. However, this decrease is lesser in improved ACO than compared with the Random Search Algorithm

IV. CONCLUSION

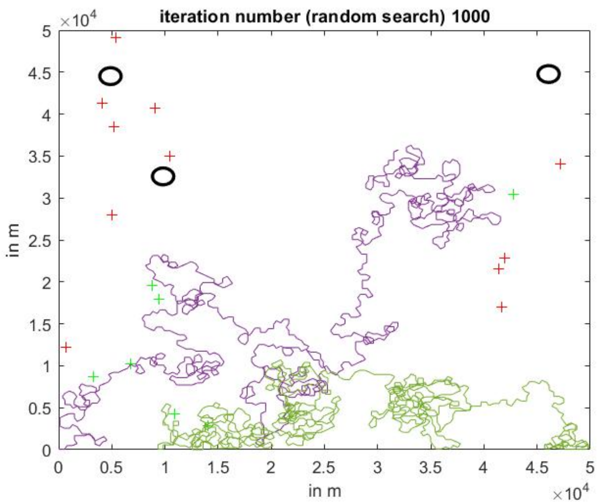
This study investigates the application of two different ACO-based algorithms for the cooperative search and attack



(a) Improved Ant colony Optimization with no.of UAVs 2



(a) Parallel Search method with no.of UAVs 2



(a) Random Search method with no.of UAVs 2

Algorithm	Num of Iterations	Coverage Rate (in percentage)	Num of targets found
SAMSOA	500	82.3	11.67
Random Search	500	78.6	4
SAMSOA	1000	67.6	14
Random Search	1000	59.6	5.33
SAMSOA	1500	54.5	17.33
Random Search	1500	48.1	6.67

1. No. Of ants = 2 in each case
2. Coverage rate is sum of all visited nodes divided by max possible visited nodes
3. Each case is average of 3 times

(a) Comparison Table

mission. The alternate ACO though found to locate more targets, carries an inherent assumption that all the UAVs track a known global pheromone map. However, the improved ACO takes individual local pheromone maps and hence the algorithm is more practical towards the imposed constraints. But, as the Ant Colony Algorithm is stochastic, it is highly susceptible to finding local minima than global minima with high convergence time. Also, ACO highly depends on the hyper-parameters defined which makes it design of the algorithm difficult for general environments.

References

[1] FU Xiao-wei, WEI Guang-wei, GAO Xiao-guang.“ Cooperative area search algorithm for multi-UAVs in uncertainty environment[J]”. *Systems Engineering and Electronics*, doi: 10.3969/j.issn.1001-506X.2016.04.15.

[2] M. G. C. A. Cimino, A. Lazzeri, and G. Vaglini, “Combining stigmergic and flocking behaviors to coordinate swarms of drones performing target search,” in International Conference on Information, Intelligence, Systems and Applications, 2016, pp. 1-6.

[3] X. Sun, C. Cai and S. O. Automation, ”A Cooperative Target Searching Method Based on Multiple Ant Colony Optimization Algorithm,”Tactical Missile Technology, 2014

[4] C. Ramirez-Atencia, G. Bello-Orgaz, M.D. R-Moreno, D. Camacho, Solving complex multi-UAV mission planning problems using multi-objective genetic algorithms, in Soft Computing, 2016, pp.1–18.

[5] C. Ramirez-Atencia, S. Mostaghim, D. Camacho, A knee point based evolutionary multi-objective optimization for mission planning problems, in Proceed-ings of the Genetic and Evolutionary Computation Conference, Berlin, Germany, 2017, pp.1216–1223.

[6] F. Yang, X. Ji, C. Yang, J. Li and B. Li, ”Cooperative search of UAV swarm based on improved ant colony algorithm in uncertain environment,” 2017 IEEE International Conference on Unmanned Systems (ICUS), 2017, pp. 231-236, doi: 10.1109/ICUS.2017.8278346.

[7] Ziyang Zhen, Dongjing Xing, Chen Gao, Cooperative search-attack mission planning for multi-UAV based on intelligent self-organized algorithm,Aerospace Science and Technology,Volume 76,2018,Pages 402-411,ISSN 1270-9638, https://doi.org/10.1016/j.ast.2018.01.035.