Human-in-Loop Hierarchical Control of Multi-UAV Systems

Shripad Gade[1] and Ashok Joshi[2]
[1,2] *Department of Aerospace Engineering, Indian Institute of Technology Bombay, Mumbai, 400076.*
{shripad.gade@iitb.ac.in ,ashokj@aero.iitb.ac.in}

Unmanned Aerial Systems (UAS) possess tremendous capabilities to perform search, tracking and situation assessment in hazardous environments. However, it sometimes becomes critical to include a human component and offset the limited reasoning of agents. This paper presents Human-in-Loop (HiL) control architecture for distributed and cooperative target search. Hierarchical autonomy provides tight control over the system, enhancing operational reliability, search efficiency and effectiveness. Human feedback also provides significant edge in terms of mission reconfiguration.

I. Introduction

Automatic Target Recognition (ATR) is autonomous and remote search of targets based on characterizing patterns. ATR finds application in civilian and military missions alike. Several methods have been used for ATR including Satellite Imagery, Radars and Unmanned Aerial Systems (UAS). Technological advancements in the fields on onboard computers, image processing and communication technology on Unmanned Aerial Vehicles (UAV's) have opened up a host of applications for UAS. Swarm based classification [01-02], cooperative classification [03], opportunistic learning [04] and coverage methods [05] have been proposed for performing ATR missions using UAS.

Intelligent systems are in nascent phase of their implementation and hence are rarely deployed in a fully autonomous fashion. Levels of autonomy awarded to UAS depend upon the criticality of the mission. Example would be UAV's flown in Rescue operation after hurricane Katrina required three operators per UAV [06]. Whereas cleaning robots are expected to be fully functional without any human intervention at all.

The focus of this work is to present a hierarchical control structure to enable Human-in-the-Loop control of UAS especially in situations where UAV to operator ratio is less than one. It will require high level control and behavioral specifications to be provided to the UAS. Intelligent control practices and intelligent control architecture are presented for UAV's in [07]. Heterogeneous swarm control for aerial robotic networks is presented in [08] involving Motherships and Daughterships to cooperatively solve search and tracking problems. We address the need of generic control architecture to incorporate human feedback in multi-agent system operation.

Swarm based methods are inherently decentralized making UAS immune to malevolent attacks. Localized decision making introduces increased scalability. Swarm systems are also protected from possible agent loss, data loss and communications failure. We prove our theory through simulations on a swarming based automatic target recognition algorithm [01]. Section II talks about the target search problem and swarming algorithm used for ATR. Section III and IV describe the Hierarchical control structure and mission reconfiguration aspects respectively. Simulation results and conclusions follow.

II. Swarming Algorithm for ATR

The search problem is defined as automatic target search using UAV's in dynamic, noisy and uncertain environment in presence of no-fly-zones. Target search is performed in bounded search domain and divided into home-zones. Targets are capable of motion in 2D. No prior information about the targets is available. Environment is filled with popup targets and popup target cluster; and they become active at random time instants. UAV's are capable of motion in 3D and are equipped with GPS (for self localization), wireless modules (for inter-agent communication), sensors and onboard computational capacity. Hostile entities, capable of shooting down UAV's are present in the search domain.

UAV teams are made of heterogeneous group of UAV's. Super Agents outperform agents in terms of motion dynamics, sensor characteristics and communication capabilities. Each agent team is led by a super-agent. Speed advantage provided by super-agents results in faster gathering of target information. Better sensors with an increased vision range result into quicker target sightings. Better communication with longer ranges will ensure greater information dissemination and hence will better prepare the swarm for search. These leadership qualities can drastically improve search performance

Each agent maintains the following datasets:

1. Target uncertainty map:

Multiple sightings are necessary during classification in noisy and uncertain environments. Target uncertainty map is a target knowledge map and has information about perceived certainties of target location. Every sighting reduces the uncertainty associated with a target point by a factor (η). This factor (η) is modeled to be altitude dependent, and reduces with decrease in altitude, implying that sighting at lower altitudes is more information rich and will reduce uncertainty by a larger factor. A target becomes completely classified when the uncertainty goes below a threshold level.

2. Ψi is the pheromone landscape of agent a_i

It is populated by adding perceived target points obtained from sensors and gossip. Pheromone Map is a knowledge map and it stores information about targets, obstacles and hostile entities. Pheromone point is represented by ψ = {loc, pher, phertime, vel, bearing, weight}.where, ψ.loc is the location of the potential target.

ψ.pher is the pheromone associated with the point and depends upon the severity and confidence perceived by the agent. ψ.phertime is the time of first pheromone deposition and is used in comparing relative life of information. ψ.vel and ψ.bear are estimated velocity and bearing of target as seen by agent. ψ.weight is a Boolean value assigned during prioritization. Pheromone values decay with time. It helps in removing false identifications and noise from pheromone map.

3. Γ_i is the task set corresponding to the agent a_i.

4. State information of other agents.

Swarming algorithm used here has two main components. It behaves as a deterministic fashion in the absence of any potential targets and behaves like a swarm in the presence of target information.

A. Deterministic Foraging

Deterministic foraging is a type of non-swarming and exhaustive demining type of behavior shown when no information about targets is present. It searches the domain with the intention to gather first sets of target points. A waypoint based deterministic foraging algorithm is used here.

B. Swarming

Swarming is the emergence of intelligent behavior based on simple coordination rules between agents. We use Ant-Colony metaheuristic based on food-foraging behavior of ants. ACO provides high level planning in terms of prioritization of targets and APF (Artificial Potential Functions) provides local path planning. The priority is dynamically calculated for each possible task based on other possible tasks, their distance estimates and the probability of them prioritizing it.

III. Hierarchical Control Structure

A hierarchical control structure is presented here. This control structure takes advantage of individual strengths of heterogeneous swarm of UAV's. A 3-tier structure consisting of Agents, Super-Agents and Human Mission Control is implemented here.

Consider a group of agents ($\mathbf{A}$), consisting of two types of UAV's – Super-Agents ($SA \in \mathbf{A}$) and Agents ($A \in \mathbf{A}$). Each super agent ($sa_i \in SA$) has a team of agents ($a_i \in A$) at its command and can enforce decisions on them. Agents however are not restricted from sharing information with other agents or super agents. Mission Control (MC) has authority over the super agents and hence over the entire UAV network. Together they form the Human-in-Loop Unmanned Aerial System.

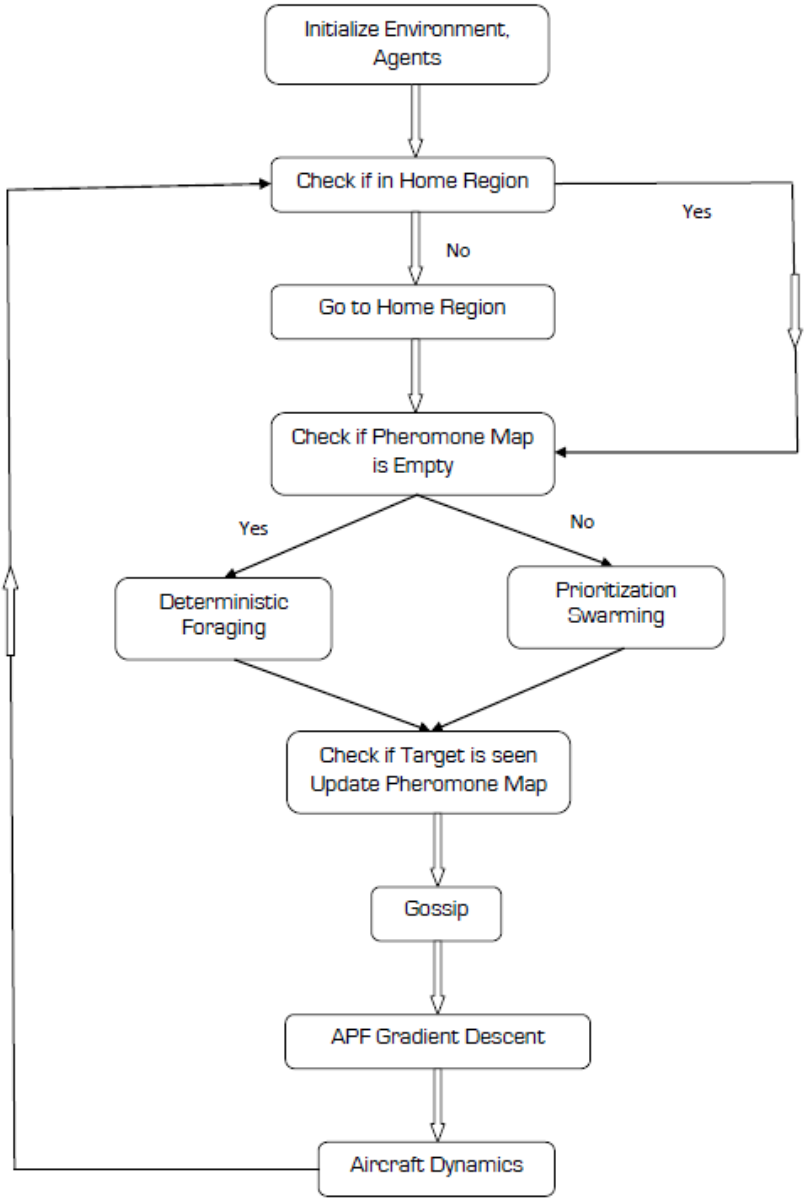

Fig. 1: Flowchart for Swarming Search Algorithm

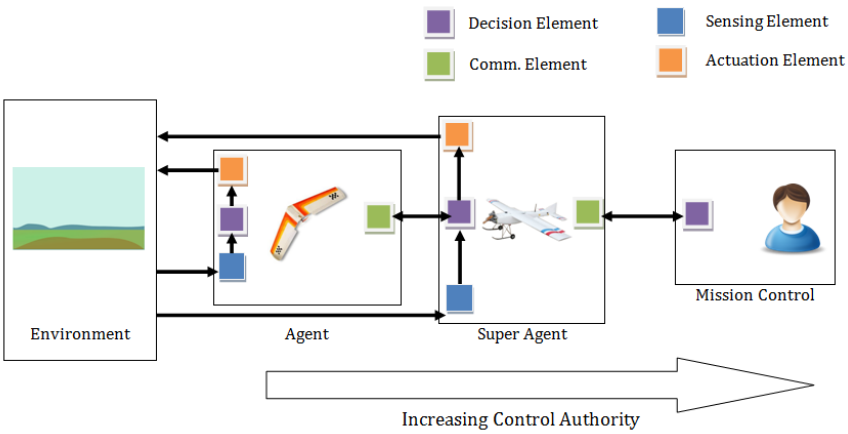

Fig. 2: Hierarchical Control Structure [09]

At the lowest echelon are agents (a_i) capable of sensor fusion, communication, path planning and local decision making. Middle echelon consists of super agents (sa_i) who act as leaders or hubs of the team, gathering and transmitting data much effectively. At the highest echelon is the mission control (MC) who has highest level of control and makes decisions on the basis of feedback from the UAS. It has the ability to assign/reassign resources based on team goals, system health, search performance and dynamics of the search zone. Mission Control is an add-on layer over the autonomous system and hence in case of communication failure, the system will degenerate to an autonomous swarming search system. Search agents employ the USAR algorithm whereas super-agents maintain foraging behavior to ensure maximum communication with the teams. Sensor characteristics, payloads and motion dynamics of the agent depends upon the type of agent they are and the architecture tries to extract maximum utility out of it. Fig. 3 shows the Human-in-Loop philosophy. The aim of this architecture is to add a supervisory Mission Control that will provide feedback to the autonomous system and enhance performance.

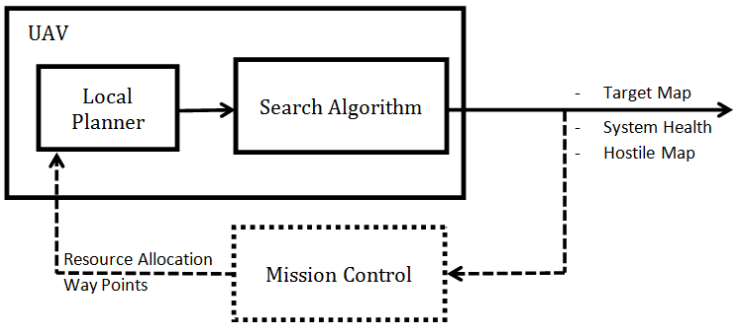

Fig. 3: Human-in-Loop Philosophy

IV. Online Mission Planning

Hierarchical control architectures allow for human intervention over autonomous UAS and provide great advantage in terms of mission planning and reconfiguration. Human mind with its immense capabilities can add significant edge to mission planning, pattern search and task assignment. Mission control provides commands to the super agents in terms of available resources and priority search domains. Super-agents in turn influence their team by increasing/decreasing weights of target areas based on control commands. Three strategies are given below to perform online mission planning and reconfiguration.

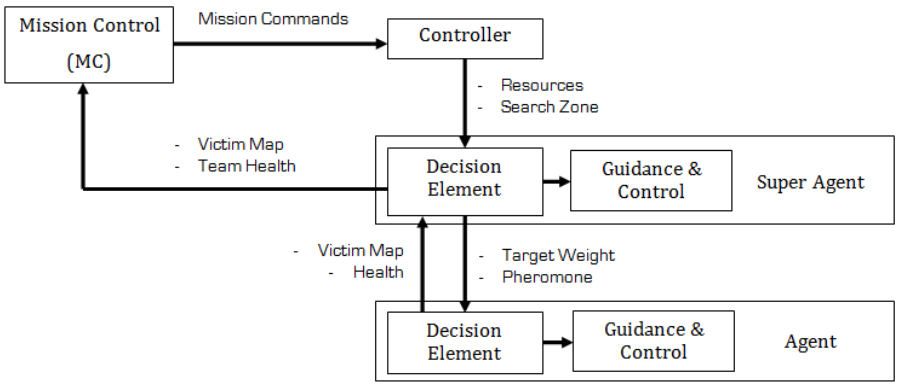

Fig. 4: Mission Planning and Reconfiguration

A. Team Reassignment

Agents are a part of the team and ideally belong to the same team throughout the mission. Team Reassignment is a strategy employed by the Mission Control to reassign agents from one team to another. This

strategy forcibly changes team topology creating new team topologies in process. Reassignment is also possible in terms of the team - home-zone mapping that is predefined at the start of the mission.

B. Agent/Team Rerouting

Agent/Team Rerouting is a strategy that allows for the mission control to force agents to visit specific locations within the search domain. Rerouting has huge applications in missions where some information about victims or clusters is known a priori. It is also has applications in areas where help/searching is critical and is needed on an urgent basis or if the search zone suffers from agent depletion.

C. Home-Zone Reshaping

Home zones are primary action areas for UAV teams. This strategy involves reshaping and resizing of home zones. Possible applications of this strategy include resizing for accounting uneven target distribution and facilitating continuous tracking of special targets.

V. Simulation

The unmanned search algorithm has been implemented in MATLAB. The search is to be conducted in a square zone of side 30 km (=1000u). UAV agents have a speed of 45 m/s (=1.5 u/tick), a communication range of 6 km(=200 u), sensor field of view of 60^0.

The square search domain is divided into four home zones of equal area. There are varying numbers of victims and three obstacles randomly scattered in the search domain. Each simulation is run for 10000 ticks (each tick is an execution step and is equivalent to 1s). The simulation time is hence ~166 min.

Artificial Potential Function approach is used for path planning. Obstacles are provided with positive potential, targets are given negative potential and potential walls are provided to ensure that agent stays within the simulation environment. Fig. 5a and 5b show the potential functions used in simulation.

Popup targets and popup clusters are randomly added to the system. Each cluster has 4 targets and inter-target distance has a maximum of 20 units. Fig. 6b shows the target distribution as a function of time. Fig. 7a and 7b show target scenario at t = 0 ticks and t = 6000 ticks.

We compare search time requirements for both Automatic search and Human-in-Loop search to gauge the efficiency of the HiL strategy. The three online mission reconfiguration strategies described above are implemented for HiL search. We use 12 agents (including 4 super-agents) to perform search in a square domain. Search effectiveness can be measured by the number of agents that remain unclassified after search time is elapsed.

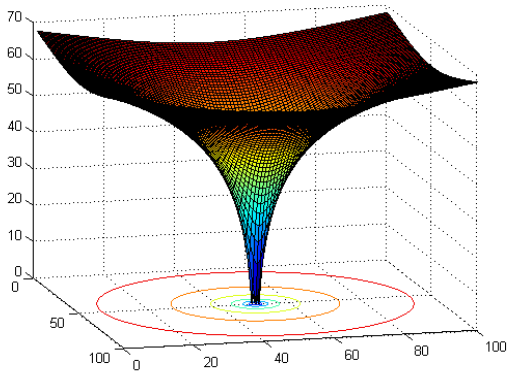

Fig. 5a: Potential Function for Target

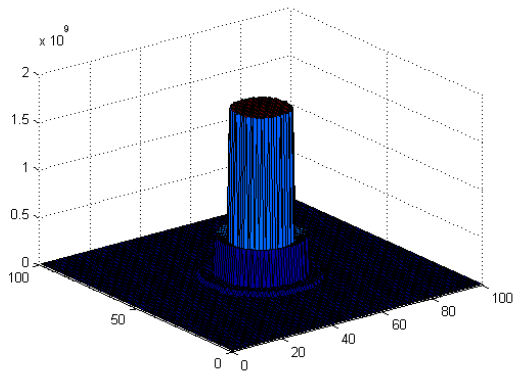

Fig. 5b: Potential Function for Obstacle

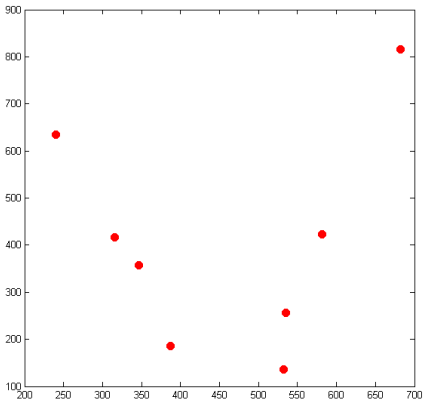

Fig. 7a: Target Map at t = 0;

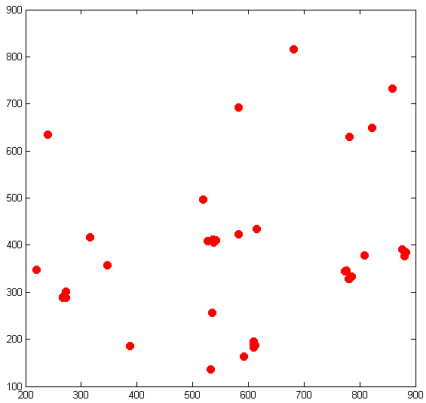

Fig. 7b: Target Map at t = 6000

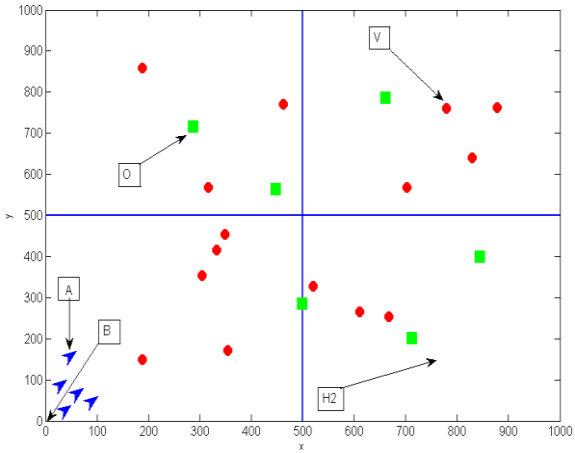

Fig. 6a: Simulation Setting {O-Obstacles, V-Target, A-Agents, H2- Home-Zone2}

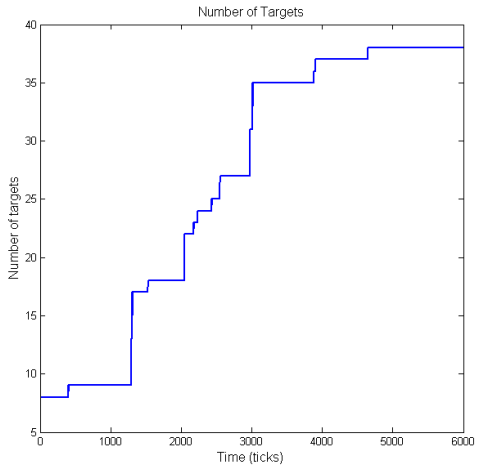

Fig. 6b: Variation in number of targets with time

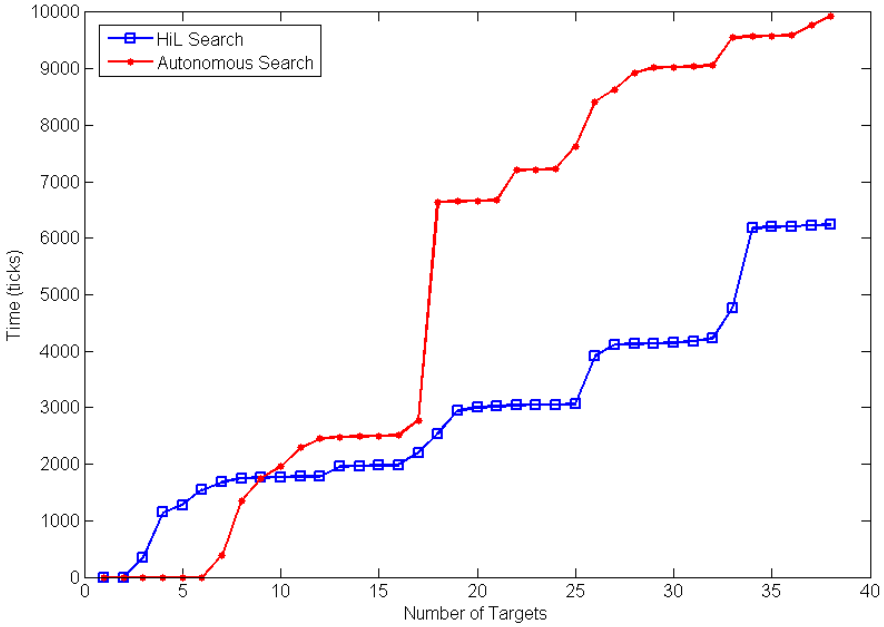

Fig. 8: Comparison of search performance for Human-in-Loop and Autonomous Search

Fig. 8 shows the time requirement for Human-in-Loop strategy to be much lower as compared to Autonomous search. Human intervention allows the system to account for knowledge biases about targets and helps immensely in task assignment of teams and agents.

Tab. 1 shows the number of unclassified targets is much lesser in HiL strategy. Number of unclassified targets directly relates to the search effectiveness and talks about failure scenarios of the search algorithm. Results show the superiority of HiL over autonomous search.

Tab. 1: Number of unclassified Targets

Strategy	Unclassified Targets	% of Unclassified Targets
Autonomous Search	6/38	15.79%
Human-in-Loop Search	2/38	5.26%

VI. Conclusion

Human-in-Loop hierarchical control architecture is presented for multi-agent systems. HiL architecture tries to extract maximum utility out of heterogeneous UAV swarm ensuring tight feedback of system performance and human insight. Three strategies are presented and implemented for human assisted search operation. Simulations prove that Human-in-Loop search is much more efficient compared to autonomous search in terms of time taken to search targets. Human assisted search is also more reliable and effective in terms of number of targets classified.

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